Multi-population techniques in nature inspired optimization algorithms: A comprehensive survey

Haiping Ma [a,*], Shigen Shen [a], Mei Yu [a], Zhile Yang [b], Minrui Fei [c], Huiyu Zhou [d]

[a] Department of Electrical Engineering, Shaoxing University, Shaoxing, Zhejiang, 312000, China
[b] Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, Shenzhen, 518055, China
[c] Shanghai Key Laboratory of Power Station Automation Technology, School of Mechatronic Engineering and Automation, Shanghai University, Shanghai, 200072, China
[d] Department of Informatics, University of Leicester, Leicester, LE1 7RH, UK

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ABSTRACT

Multi-population based nature-inspired optimization algorithms have attracted wide research interests in the last decade, and become one of the frequently used methods to handle real-world optimization problems. Considering the importance and value of multi-population methods and its applications, we believe it is the right time to provide a comprehensive survey of the published work, and also to discuss several aspects for the future research. The purpose of this paper is to summarize the published techniques related to the multi-population methods in nature-inspired optimization algorithms. Beginning with the concept of multi-population optimization, we review basic and important issues in the multi-population methods and discuss their applications in science and engineering. Finally, this paper presents several interesting open problems with future research directions for multi-population optimization methods.

1. Introduction

Nature-inspired optimization algorithms, including evolutionary algorithms (EAs) and swarm intelligence (SI), are part of the computer intelligence discipline that has become increasingly popular over the past few decades [1–4]. EAs and SI are inspired by natural phenomena, evolution processes, and the collective behaviors of swarms of ants and bees, and flocks of birds when they search for food or a better environment. The popularity of nature-inspired optimization algorithms is due to the fact that they can be used to solve complex problems in different domains. EAs begin with a set of random candidate solutions, iteratively generate offspring solutions, and render the fittest until an acceptable solution is found. Popular algorithms in this category are genetic algorithms (GAs) [5], evolution strategy (ES) [6], evolutionary programming (EP) [7], genetic programming (GP) [8], estimation of distribution algorithms (EDAs) [9], differential evolution (DE) [10,11], biogeography-based optimization (BBO) [12,13] and fireworks algorithm (FWA) [14]. SI algorithms start with a set of candidate solutions, and in each iteration, a new set of candidate solutions is created based on historical and other related information. Some examples include ant colony algorithms (ACO) [15], particle swarm optimization (PSO) [16], artificial bee colony (ABC) algorithm [17], firefly algorithm (FA) [18],

krill herd (KH) algorithm [19], and others [20–23].

In the last decade, multi-population based methods were often discussed and used to improve the optimization performance of nature-inspired optimization algorithms. Researchers tend to divide the original population into multiple small subpopulations for some specific purposes, for example, solving large-scale optimization and dynamic optimization problems. Then, some evolution operations, for example, selection, crossover and mutation for GAs, are executed to implement individual evolution. Finally, these subpopulations interact with each other via merging, communication and re-division process to avoid premature convergence and maintain population diversity when people tackle various optimization problems.

Existing studies on multi-population optimization demonstrate that it is easily integrated within various nature-inspired optimization algorithms, and it often performs better than single-population optimization algorithms, including global benchmark functions and real-world applications. Why a multi-population approach is popular and effective [47, 77,118]: (1) it divides the whole population into multiple subpopulations, in which the population diversity can be maintained because different subpopulations can be located in different search spaces; (2) it is able to search different areas simultaneously, allowing it to find promising optimal solutions efficiently, and (3) various

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nature-inspired optimization algorithms can be rapidly and easily embedded into multi-population methods. The main objective of this survey is to provide an exhaustive summary of the work published on multi-population methods in nature-inspired optimization algorithms, whilst presenting remaining challenges and research objectives. This survey includes two main areas: basic research issues and applications.

Other reviews and surveys on multi-population methods have also been published in the past few years [24–26], in which the concepts of multi-population is described using other terms such as 'parallel', 'cooperative', 'co-evolution', 'islands', and so on. Our survey introduces the research progress made in the last few years with comprehensive discussion on remaining problems and possible research directions. In addition, we discuss hardware implementations of multi-population including traditional CPU, parallel GPU, and AMD Accelerated Processing Unit (APU) with multi-core architectures. Their features of multi-thread and parallel processing significantly speed up implementation time. Implementation details can be found in the literature [27–29].

This survey is prepared using the database of Web of Science. Fig. 1 shows the chronological distribution of the papers published in the last 10-year related to nature-inspired optimization algorithms with "multi-population (multipopulation)" or "multi-swarm (multiswarm)" in their titles. Note that the concept of multi-population is often used in EAs whilst the concept of multi-swarm is often used in SI related papers. Table 1 shows the top 10 countries with the largest number of the research papers, and Table 2 shows the top 5 journals with the largest number of papers on multi-population methods in nature-inspired optimization algorithms. These figure and tables clearly show the breadth, depth, and growth of interest in multi-population methods.

To further analyze the development of multi-population methods, we use CiteSpace software [30], which generates the co-occurrence networks of authors, keywords, and institutions; and co-citation networks of the cited authors, references, and journals, to generate a journal co-citation analysis network. The top 5 multi-population methods related co-cited journals are shown in Table 3. Based on the analysis of the publications and co-citation counts, IEEE Transactions on Evolutionary Computation is identified as the major journal for publishing multi-population methods. We also use the CiteSpace to generate keyword co-occurrence, which is a useful approach to explore knowledge structures and hot topics, and the top 5 multi-population methods related keywords are shown in Table 4.

The organization of this paper is as follows. The basic issues of multi-population methods and their integration with nature-inspired
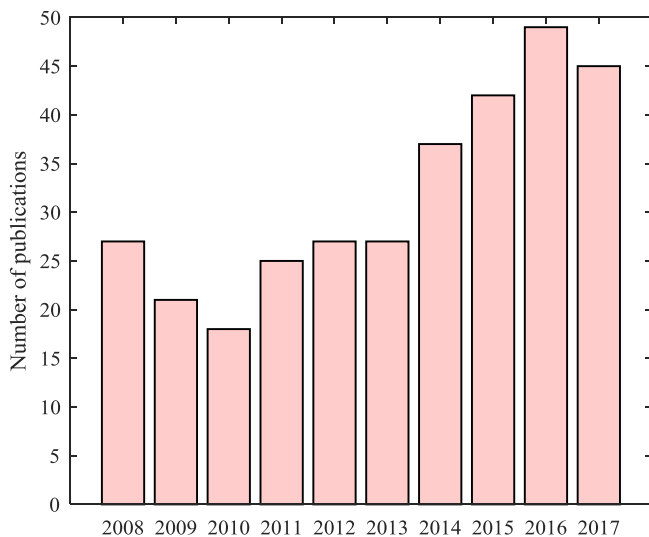
Table 1

The top 10 countries with the largest number of the papers on multi-population methods.

Rank	Country	Number of papers	Rank	Country	Number of papers
1	China	196	6	India	16
2	USA	45	7	Spain	14
3	UK	23	8	Japan	13
4	Canada	22	9	Australia	13
5	Brazil	17	10	Italy	13

Table 2

The top 5 journals with the largest number of the papers on multi-population methods.

Rank	Journal	Number of papers
1	Applied Soft Computing	15
2	Information Sciences	10
3	Soft Computing	7
4	Expert Systems with Applications	6
5	IEEE Transactions on Evolutionary Computation	4
	Advances in Engineering Software	
	Applied Mathematics and Computation	
	Applied Mechanics and Materials	
	Computers Operations Research	
	PLoS One	

Table 3

The top 5 co-cited journals related with multi-population methods, where "Count" denotes the number of times each journal is co-cited by other journals.

Rank	Journal	Count
1	IEEE Transactions on Evolutionary Computation	315
2	Applied Soft Computing	104
3	Information Sciences	75
4	European Journal of Operational Research	72
5	Applied Mathematics and Computation	69

Table 4

The top 5 keywords related with multi-population methods, where "Count" denotes the number of times each keyword is found in the term of keywords in the published papers.

Rank	Keywords	Count
1	Optimization	112
2	Genetic algorithm	80
3	Particle swarm optimization	76
4	Multi-population	61
5	Multi-swarm	46

optimization algorithms are provided in Section 2, and the literature review of multi-population methods in relation to the classes of optimization and areas of applications are given in Section 3. Finally, further development of multi-population methods is outlined in Section 4.

2. Multi-population methods

This section presents basic and important issues of multi-population methods, as well as how they are integrated with nature-inspired optimization algorithms.

2.1. Basic issues of multi-population methods

Existing work on multi-population methods demonstrate that using multi-population is one of the most effective methods to maintain population diversity. In nature-inspired optimization algorithms, diversity is indicated as the difference between candidate solutions, and evolution progress lies fundamentally on the existence of population variations.

Fig. 1. Publication number of multi-population methods in nature-inspired algorithms by years.

Population diversity may greatly influence the convergence and optimization of solutions. The main purpose of multi-population methods is to maintain population diversity by spreading candidate solutions over the entire search space. This feature helps nature-inspired optimization algorithms efficiently find global optimal solutions.

To make multi-population methods more efficient, several basic and important issues of the algorithm design are discussed, which are shown in Fig. 2. These issues include the number of subpopulations, the communication between subpopulations, the search area of subpopulations, and the search strategy of subpopulations. In the following subsections, these issues are discussed in detail.

2.1.1. The number of subpopulations

The first issue is how to determine the number of subpopulations. If too many subpopulations exist in the optimization process, they may waste the limited computation resources. However, if there are a small number of subpopulations, the effect of multi-population is not significant for one to render optimal solutions. According to the number of subpopulations, this issue is addressed in two ways. The first way is to use a fixed number of subpopulations. Most of the existing multi-population methods belong to this group. In Ref. [31], a three-population architecture of EAs was applied to solve non-stationary optimization tasks, where one population supplied the historic estimates while the others were used in the searching process. Experimental results showed that the proposed algorithm had good performance in non-stationary environments. Niu et al. [32] proposed a multi-population cooperative PSO, in which the population consists of one master swarm and a fixed number of slave swarms, and the former executed PSO independently to maintain the diversity of particles, while the latter enhanced their particles based on their own knowledge and the knowledge of the particles in the other slave swarms. Simulation results demonstrated the effectiveness of the proposed algorithm. In Ref. [33], Togelius et al. used multi-population competitive co-evolution for car racing controllers, where nine-subpopulation co-evolution was compared with single-population co-evolution and standard evolution strategies. Experimental results showed that the proposed strategy had better performance. Li et al. [34] proposed new GAs based on multi-population competitive co-evolution, where the method comprised three simultaneously coevolving populations including learner population, evaluator population and fame hall, and the competitive exclusion principle in the ecological theory was applied in populations to maintain chromosome diversity. Experimental results showed that the proposed algorithm was more likely to avoid the occurrence of premature convergence, and outperformed the counter-parts. In Ref. [35], a multi-population cooperative cultural algorithm was proposed by integrating the cooperative GA into the population space of a culture algorithm, where the population was divided into several subpopulations and GA was adopted in each subpopulation.

Simulations indicated that the proposed algorithm effectively sped up the convergence and improved the optimization performance. A new hybrid multi-population GA with the fixed number of subpopulations was proposed in Ref. [36] to solve the multi-level capacitated lot-sizing problem with backlogging. The proposed algorithm was tested on a set of multi-item lot-sizing with a backlogging library, and the results showed that it had better performance for most of the testing problems. In Ref. [37], a multi-population cultural algorithm with two subpopulations was proposed for artifact selection, in which agents in one subpopulation consistently outperformed the other agents due to the prior knowledge about certain artifacts. The study showed that the evolving agents significantly improved artifact selection knowledge. Yu [38] proposed a multi-population ABC algorithm for numerical optimization, which employed a new multi-population strategy with the fixed subpopulation numbers to enhance the population diversity. The results showed that the proposed algorithm achieved better performance than the standard ABC algorithm. In Ref. [39], Aimi and Suyama proposed a multi-swarm PSO for the IIR filter design, and the experimental results showed that the effectiveness of the proposed method through several design examples. Chatterjee and Zhou [40] presented a DE algorithm within a multi-population strategy, which divided an initial set of solutions into several subsets, and each subset evolved independently and finally connected with each other. The experimental results revealed the relationship between the number of subpopulations and the performance of DE. The advantage of using fixed subpopulation numbers is that it can be implemented simply, and we only need to create a fixed number of subpopulations for the problem. However, the number of subpopulations is only determined by researchers' experience, and it is hard to obtain unified and effective rules to determine the numbers of subpopulations for different practical problems.

The second way is to use a varying number of subpopulations. To maintain population diversity, the subpopulation numbers may be different at different phases during the evolution process. For example, in the early phase, a method needs a large number of subpopulations because the candidate solutions can scatter over the entire search space, which leads to high population diversity. But in the later phase, a small number of subpopulations help reducing diversity and the solution can quickly converge to a global minimum or maximum. So it is wise to dynamically increase or decrease the subpopulation numbers during the optimization. In many cases, a method often divides a main population into sub-groups or vice versa. In Ref. [41], Bongard proposed to use co-evolutionary dynamics of a multi-population GP system, in which the proposed method used a master/slave architecture, and the number of the client populations dynamically evolved to promote continuous search. The experimental results showed that the proposed method led to the discovery of better solutions in some numerical cases. In Refs. [42, 43], Liang and Suganthan proposed a dynamic multi-swarm PSO by local
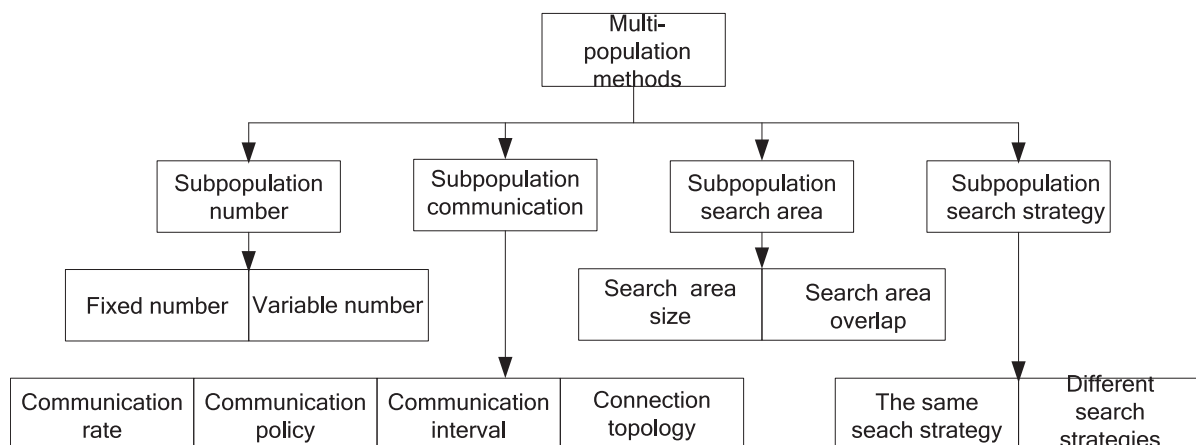

Fig. 2. Diagram of basic and important issues of multi-population methods.

searching, in which the whole population was divided into many small swarms, whose number could be determined using regrouping schedules. The simulation results showed the proposed method had better performance than the other standard algorithms. A clustering PSO was proposed by Yang and Li [44] for locating and tracking multiple optima in a dynamic environment. The proposed algorithm used a hierarchical clustering method to dynamically adjust the subpopulation numbers to track multiple peaks. The experimental study was conducted to test the performance of the proposed algorithm, and the results showed its effectiveness for tracking multiple dynamic optima. In Ref. [45], Zhao and Suganthan proposed a dynamic multi-swarm particle optimizer with sub-regional harmony search, where the whole population was divided into a large number of sub-swarms that were regrouped using various regrouping schedules. The simulation results showed that the proposed system achieved good performance for most of the numerical benchmarks. In Ref. [46], a fuzzy C-means (FCM) multi-swarm competitive PSO was proposed for optimization control of an ethylene cracking furnace, in which FCM clustering was used to categorize swarms adaptively into different clusters. This method was evaluated by benchmark functions and optimization control of the cracking depths of an ethylene cracking furnace. Nseef et al. [47] proposed an adaptive multi-population ABC algorithm for dynamic optimization problems, where the number of subpopulations changed over time for the algorithm to adapt to a dynamic environment. The simulations showed that the proposed algorithm was superior to the standard algorithm on all the test datasets. In Ref. [48], cooperative co-evolutionary algorithms were proposed to solve high-dimension problems, in which a dynamic multi-population framework was incorporated into the proposed algorithms to enhance the global optimization ability. The simulation results verified the effectiveness of the proposed algorithm.

2.1.2. Communication between subpopulations

The second issue is how to handle the communication between subpopulations. Many studies show that the communication between subpopulations can help exchange information and, hence, will accelerate the search process and find the promising solutions. The communication between subpopulations is controlled by the following four parameters: (i) a communication rate that defines the number of the solutions in a subpopulation to be shared with other subpopulations; (ii) a communication policy that determines which solutions are to be replaced by those of other subpopulations; (iii) a communication interval that sets up the frequency for executing communication; (iv) a connection topology that defines how to connect subpopulations. The literature [49] firstly focused on the communication issues in designing cooperative multi-thread parallel search techniques, and attempted to identify the key issues to be addressed in the design of an algorithm in this class. In Ref. [50], the topologies and migration rates of multi-population parallel GAs were discussed in detail. The study revealed the explicit relation between the probability of reaching a desired solution with a specific population size, the migration rate and the degree of the connectivity graph. Middendorf et al. [51] discussed information exchange in multi colony ant algorithms, and the results showed that the exchange of only a small amount of solutions helped efficient and effective search. In Ref. [52], El-Abd and Kamel discussed the factors governing the behavior of multiple cooperating swarms, and these factors included the communication strategy used, and the number of the cooperative swarms. The experimental results showed that a circular topology communication strategy produced better performance than those of sharing the global best of all the swarms. In Ref. [53], Chen and Chang applied a real-coded multi-population GA to multi-reservoir operation, in which a hyper-cubic topology was used to connect various subpopulations to exchange information. The results showed that the proposed algorithm provided much better performance than the conventional GA in terms of minimizing the water deficit of a reservoir system. A different topology multi-swarm PSO was proposed in Ref. [54] to deal with problems in a dynamic environment. The proposed

algorithm integrated two different topological sub-swarms, and they exchanged their best particles at the checkpoints. The experiments demonstrated that the proposed algorithm was effective and stable in a dynamic environment. Li and Zeng [55] presented a multi-population agent based co-genetic algorithm with a chain-like agent structure for parallel global numerical optimization, where a close chain-like agent connection structure, a cycle chain-like agent connection structure, and a dynamic neighborhood were adopted to realize the parallel optimization. The results showed that the proposed algorithm had better optimization precision and efficiency than the GA. A novel multi-swarm PSO was presented in Ref. [56], where the proposed method extended a single population model to an interacting multi-swarm model by constructing a hierarchical interaction topology. The simulation results proved that the proposed method had significantly better performance than four variants of the standard PSO. In Ref. [57], an adaptive migration revisiting schemes was proposed for multi-population GAs, where fitness- and diversity-based migration schemes were used for preventing premature convergence. The experimental results on 0/1 knapsack problems showed that both of the new approaches were better than the standard methods. Biswas et al. [58] presented a multi-swarm ABC with forager migration, which maintained multiple swarm populations that applied different perturbation strategies and gradual migration of the population. The simulation results on 25 benchmark problems showed the superiority of the proposed method. In Ref. [59], Campos et al. evaluated the impact of several topologies on asynchronous multi-swarm particle optimization, and the experimental results provided the ranking of different topologies. Turky and Abdullah [60] proposed a multi-population electromagnetic algorithm with different migration mechanisms including a random immigrant scheme and a memory-based immigrant scheme. The purpose of these schemes is to determine which solutions are migrated to maintain population diversity. The simulation results showed the proposed algorithm was very effective on moving peak benchmarking problems. Michalak [61] proposed an evolutionary algorithm based on problem similarity, which was called Sim-EA. The proposed method utilized the concept of multi-population optimization, and each subpopulation was assigned to solve one of the instances which were similar to each other. Furthermore, the same author [62] used the same technology to propose a multi-population estimation of distribution algorithm (EDA), called Sim-EDA, where each subpopulation was assigned to a different instance and a migration mechanism was used for transferring information between the subpopulations. The experimental results confirmed that the performance of the proposed algorithm was better than the others when information was transferred between subpopulations assigned to similar instances of the problem. In Ref. [63], an ABC optimizer with bee-to-bee communication and multi-population co-evolution was proposed for multilevel threshold image segmentation, where individuals could share information from the elites through the bee-to-bee communication model. The experimental results on a set of benchmark datasets demonstrated the performance of the proposed algorithm. Kommenda et al. [64] studied the effects of multi-population GPs for symbolic regression problems, where several subpopulations were parallelly evolved according to unidirectional ring migration to maintain genetic diversity. The effects of multiple populations with a data migration strategy were compared to the standard genetic programming algorithms on several symbolic regression benchmark problems. In Ref. [65], Xu et al. proposed a dynamic multi-swarm PSO with cooperative learning strategy. In the proposed strategy, for each sub-swarm, each dimension of the two poor particles learns from the better particle of two randomly selected sub-swarms using a tournament selection strategy so that particles can have more excellent examples to learn and can find the global optimum more easily. The simulation results showed that the proposed algorithm had superior performance in comparison with several popular PSO variants. In Ref. [66], Upadhyayula and Kobti studied population migration using the dominance in multi-population cultural algorithms, in which multiple subpopulations utilized the evolutionary dominance to improve system performance.

The preliminary results showed that the proposed algorithm outperformed the traditional methods. In Ref. [67], a multi-swarm bat algorithm was proposed for global optimization, where an immigration operator was used to exchange information between different swarms with necessary parameter settings, and the best individual of swarms was used as the elite swarm through the selection operator. The experimental results showed that the proposed method was able to search satisfactory function values on most of the benchmark datasets. Niu et al. [68] proposed a symbiosis-based alternative learning multi-swarm PSO algorithm, where the communication policy used a learning method to select one example out of the center position, the local best position, and the historical best position including the experience of the internal and external multiple swarms, to keep the diversity of the population. The experimental results exhibited better performance in terms of the convergence speed and optimality. An orthogonal multi-swarm cooperative PSO algorithm with a particle trajectory knowledge based method was proposed in Ref. [69], where the proposed algorithm used a matrix recording the information of the particle trajectory, and a new adaptive cooperation mechanism to implement the information interaction between swarms and particles, to greatly decrease the computational cost. The simulation results showed that the proposed algorithm had better performance compared with the traditional algorithms. Apparently, communication between subpopulations is very useful for optimization since information exchanging is able to improve the search ability of algorithms.

2.1.3. Search area of subpopulations

The third issue is how to determine the search area of each subpopulation. If the search area of a subpopulation is too small, there is a potential problem that the small isolated subpopulation often converges to a local optimal solution. On the contrast, if the search area of a subpopulation is too large, it is almost equal to the search area of the original population. Another case is that the search area may be overlapped, that is, two subpopulations search in the same sub-area, which may waste computational resources. To handle this problem, in Ref. [70], Li and Yang proposed a general multi-population method with clustering, where different subpopulations were distributed in different sub-areas in the fitness landscape, and then it applied the random immigrant method without change detection based on a mechanism that could automatically reduce redundant individuals in the search space. The simulation results on the benchmark functions showed that the proposed algorithm provided much better performance than the other algorithms. Pourvaziri and Naderi [71] presented a hybrid multi-population GA for the dynamic facility layout problem. In this study, the proposed algorithm separated the potential solution space into different parts by using a heuristic procedure and each subpopulation represented a separate part to assure population diversity. The results showed that the proposed algorithm performed better than the other methods. Kobti [72] proposed a heterogeneous multi-population cultural algorithm, which firstly incorporated a decomposition technique to divide the given problem into a number of sub-problems, and then it assigned the sub-problems to different subpopulations to be optimized separately in parallel in order to evaluate the proposed architecture. The simulation results showed that the proposed algorithm outperformed the other state-of-the-art methods presented in the literature. In Ref. [73], Raeesi et al. proposed a heterogeneous multi-population cultural algorithm with a dynamic dimension decomposition strategy, where two dynamic dimension decomposition techniques including the top-down and bottom-up approaches were used to decompose the dimensions of a given problem as different subsets, and each subpopulation was designed to optimize these subsets. The comparison results revealed that the proposed method was effective and outperformed the other standard approaches in terms of efficiency. In Ref. [74], Ufnalski and Grzesiak proposed a multi-swarm plug-in direct PSO algorithm for the sine-wave constant-amplitude and constant-frequency voltage-source inverter, where a dynamic optimization problem was divided into multiple lower dimensional swarms and

each swarm was optimized independently by PSO. Ei Dor et al. [75] presented a multi-swarm PSO algorithm using charged particles in a partitioned search space for continuous optimization, in which the auxiliary swarms were initialized in different areas, and then an electrostatic repulsion heuristic method was applied in each area to increase its diversity. In Ref. [76], Bolufe and Chen studied the effects of sub-swarms in multi-swarm systems, and used a separate search mechanism to identify different regions of the solution space for each swarm with different goals and features. The comprehensive study provided a new set of general guidelines for the configuration of sub-swarms in multi-swarm systems. The common ground of these methods is that they use empirical experience to determine the search area of each subpopulation. Therefore, it is required to identify a proper search area for each subpopulation for different optimization problems.

2.1.4. Search strategy of subpopulations

The fourth issue is how to determine the search strategy of each subpopulation. Search strategies can significantly affect the performance of multi-population methods on different optimization problems. Different search strategies with different advantages can complement one another when a multi-population method is applied to an optimization problem. If each subpopulation is used to support a search strategy, and is responsible for either exploring or exploiting the search space, it is a promising way to enhance the optimization performance. In Ref. [77], Wu et al. proposed a DE algorithm with multi-population based ensemble of mutation strategies for global optimization, in which each subpopulation employed different mutation strategies, including "current-to-pbest/1", "current-to-rand/1" and "rand/1", during the evolution. After a certain number of iterations, the current best performing mutation strategy would be found according to the ratios between the quantitative performance improvements and function evaluations. As a result, better mutation strategies may require more computational resources. The simulation results showed that the proposed algorithm performed better than the other variants of DE on the benchmark functions. Another version that adopted a multi-population based ensemble mutation method for solving a single objective bi-level optimization problem was proposed by Li et al. [78]. Wang and Tang [79] proposed an adaptive multi-population DE algorithm for continuous multi-objective optimization, where each of subpopulation evolved according to the assigned different crossover operators borrowed from various GAs to generate perturbed vectors. Computational results on benchmark datasets showed that the proposed algorithm was superior to some previous algorithms in the literature. In Ref. [80], Godio presented a multi-population GA for estimating snow properties from the GPR data. In this study, each subpopulation was associated with an independent variant of GA to explore different promising regions of the search space. The experimental results showed that the proposed algorithm successfully estimated layer thickness and the porosity, saturation and structural exponents of snow. A multi-swarm cooperative PSO was proposed by Niu et al. in Ref. [81], where a population consists of one master swarm and several slave swarms. The slave swarms executed the variants of PSO independently to maintain the diversity of particles, and the master swarm evolved based on its own knowledge and also the knowledge of the slave swarms. The simulation results showed that the proposed algorithm had better performance compared with the standard PSO. Zhao et al. [82] proposed a multi-swarm cooperative multistage perturbation guiding PSO, where the three-stage perturbation guiding idea was used to separate the execution process of algorithm into three stages, and each stage used a DE mechanism with different perturbation to balance the exploration and the exploitation. The simulation results showed that the proposed strategy was a promising algorithm compared with the other particle swarm optimizers and state-of-the-art algorithms. In Ref. [83], Ali and Suganthan proposed an adaptive multi-population DE with dynamic population reduction, in which the population was clustered in multiple tribes and used an ensemble of different mutation and crossover strategies. That is, a different adaptive scheme was used in each tribe to

define the scaling factor and the crossover rate, and to guarantee that successful tribes with the best adaptive scheme were the one that guided the search toward the optimal solution. The simulation results justified the robustness of the proposed approach compared to the other state-of-the-art algorithms. In Ref. [84], Biswas and Das proposed a multi-swarm based ABC algorithm for global search, in which the proposed algorithm deployed a multiple swarm population characterized by unique perturbation strategies, that is, each subpopulation used the different evolving operators in the landscapes. The experimental results had indicated the statistical superiority of the proposed approach. Cheng and Jin [85] presented a multi-swarm evolutionary framework based on a feedback mechanism, where the framework consisted of several operators similar to those in PSO and a mutation strategy, applied in different sub-swarms, on the top of the feedback mechanism. The simulation results showed that the proposed method enhanced the algorithm's global search ability. In Ref. [86], a multi-swarm bare bones PSO with distribution adaption was proposed, where four methods were developed using Gaussian or multivariate Gaussian distributions, and then the cellular learning automata model was incorporated with the proposed bare bones PSO, which was able to adaptively learn suitable updating strategies for the swarms. The experimental results indicated the superiority of the proposed approach in terms of accuracy and speed in finding appropriate solutions. The advantage of these methods is that different search strategies are used with different subpopulations, which is better than a single search strategy throughout the evolution.

2.2. Integration with nature-inspired algorithms

Now we present how to integrate the multi-population methods with nature-inspired optimization algorithm. Simply speaking, it starts by setting parameters for different conditions, randomly creates a population of solutions and then evaluates them. Next, the population is divided into multiple subpopulations. Each subpopulation performs certain evolutionary operation to generate its own offspring. Based on the requirements of the algorithm design, the communication between subpopulations is used to help the evolution. Finally, the process stops if the stopping criteria is met. In this way, multi-population methods can flexibly manage the subpopulations, leading to better performance than single-population algorithms. The flowchart of multi-population methods integrating with nature-inspired optimization is shown in Fig. 3.

The main steps are further described below:

Step 1 Set parameters, and initialize the population of solutions. The key parameters of multi-population methods integrating with nature-inspired optimization include the parameters of EA or SI paradigms, the maximum number of iterations, the size of population, the number of subpopulations, and the communication parameters between subpopulations.

Step 2 Evaluate the population, and the fitness of the generated solutions is calculated using the objective function. Divide the entire population into multiple subpopulations, and each subpopulation
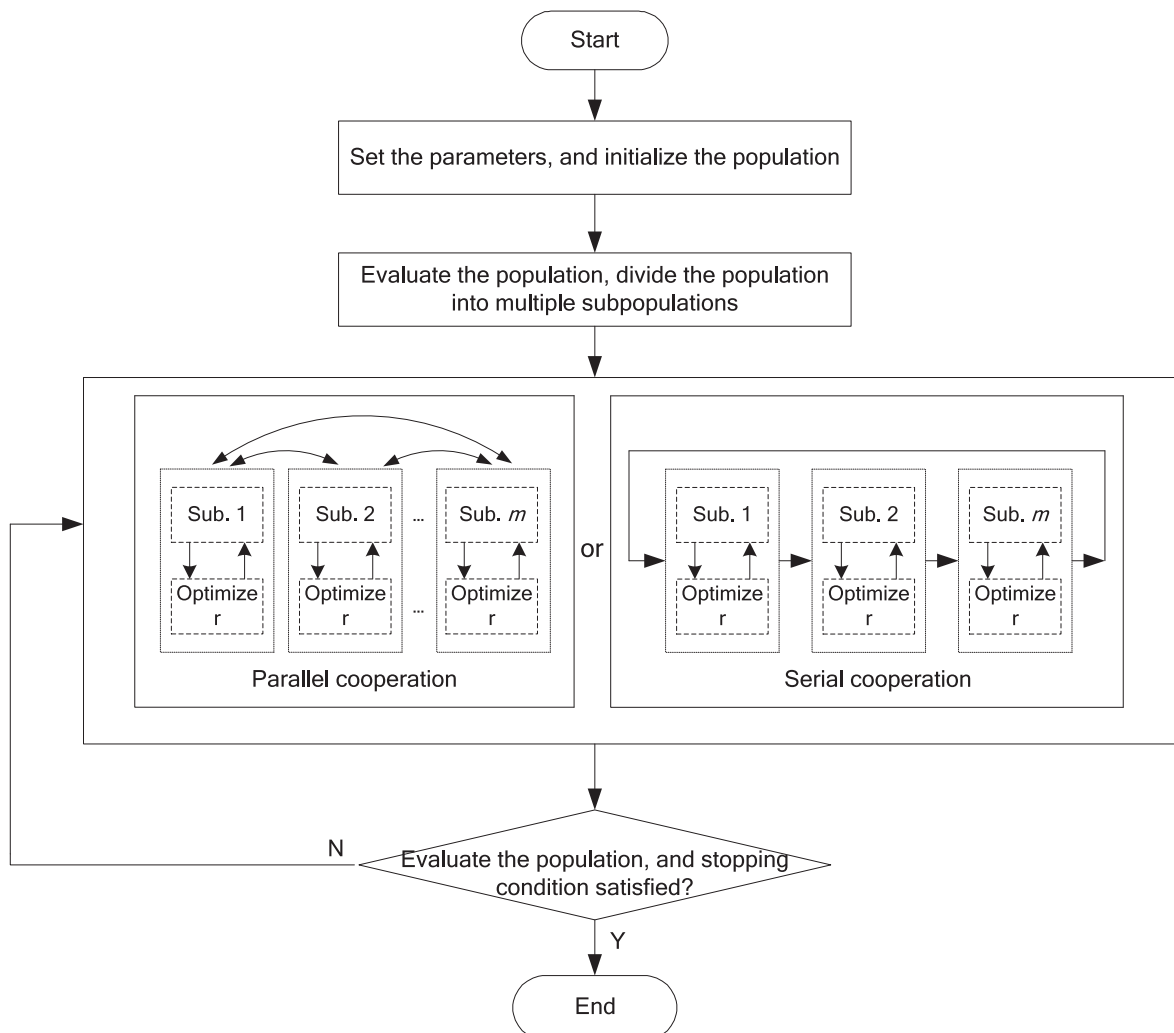

Fig. 3. Flowchart of multi-population methods integrating with nature-inspired optimization algorithms.

may have different sizes of populations. Each subpopulation can be randomly or orderly assigned from the solutions.

Step 3 Create offspring subpopulations, which is the most important part for multi-population methods integrating with nature-inspired optimization. In this step, we can use a fix or variable number of subpopulations, and we also can use a complex communication mechanism between subpopulations. Different subpopulations can be executed independently or dependently by EA or SI paradigms to generate their own offspring subpopulations. For these EA or SI paradigms, we can use the same strategy for all the subpopulations, or use different strategies for each subpopulation. In addition, for different optimization problems, we can allow all the subpopulations to search in the entire solution space.

Step 4 Evaluate offspring subpopulations and check the stopping condition. If the termination criterion is not met, go to Step 3; otherwise, terminate and output the evaluation results.

3. Applications of multi-population methods

The literature reports numerous applications of multi-population methods to benchmark datasets and real-world problems. This section first provides a summary of optimization problem categories: multimodal optimization, dynamic optimization, multi-objective optimization, large-scale optimization, combinatorial optimization, constrained optimization, and noisy optimization. Then we review the applications of multi-population methods to in different practices.

3.1. Classes of optimization

3.1.1. Multi-modal optimization

Many multi-population methods were used to solve multi-modal benchmark functions [68,78]. Siarry et al. [87] presented a multi-population GA for multi-modal optimization, which created subpopulations within the niches defined by the multiple optima to warrant good diversity. The empirical results showed the reliability of the proposed algorithm. In Refs. [88,89], a multi-population cultural algorithm using fuzzy clustering was proposed for multi-modal function optimization, where fuzzy clustering was used to partition the single population into several communicating subpopulations which evolved in parallel whilst cultural exchange ensured population diversity. The simulation results on several multi-modal test functions showed that the proposed method had good performance. A bi-objective multi-population GA was proposed in Refs. [90,91] for multi-modal function optimization, in which two separate but complementary fitness objectives were designed to enhance the diversity of the overall populations and exploration of the search space. The experimental results on five multi-modal functions showed that the proposed algorithm outperformed four multi-modal GAs. Zhang and Ding [92] proposed a multi-swarm self-adaptive and cooperative PSO for complex multi-modal functions, in which particles in each sub-swarms shared the best optimum to enhance the cooperative capability. The simulation results showed that the proposed algorithm had better performance than the other algorithms. In Ref. [93], Kwasnicka and Przewozniczek proposed a multi-population pattern searching algorithm, which is a new evolutionary method based on the standard messy genetic algorithm for solving optimization problems. In this study, the authors used some of the messy GA ideas like coding and operators in different subpopulations to solve the bottleneck of effectiveness dropdown. The simulations on a set of test functions including multi-modal benchmarks showed that their method had highly competitive performance. In Ref. [94], Bolufe and Chen proposed a multi-swarm hybrid algorithm for multi-modal optimization, where some ideas from DE algorithms and EDAs were used to address the new design in multi-swarm systems. The experimental results showed that the proposed hybrid system could perform better than each of the individual components. In Ref. [95], Fieldsend presented a new multi-modal evolutionary optimizer, the niching migratory multi-swarm optimizer (NMMSO), which

dynamically managed many particle swarms. In the proposed method, sub-swarms were concerned with optimizing separate local modes, and employed measures to allow swarm elements to migrate away from their parent swarm and to merge swarms together under some conditions. The simulation results on multi-modal test problems showed that the proposed method obtained competitive performance. In Ref. [96], a pseudo multi-population differential evolution (p-MPDE) was proposed for multi-modal functions, in which the proposed p-MPDE employed a small exemplar population to conduct standard DE operation, and each other individual used the differential of two randomly chosen members in the exemplar population to mutate themselves and evolve. The simulation results showed that the proposed p-MPDE outperformed other state-of-the-art multi-modal algorithms. Xiao et al. [97] presented a novel multi-population co-evolution immune optimization algorithm for most of the existing multi-modal benchmarks, where co-evolution of three subpopulations was promoted through a self-adjusted clone operator to enhance exploration and exploitation. The authors proved that their method outperformed three known immune algorithms and several EAs. A general-purpose asynchronous adaptive multi-population model for a distributed differential evolution (AsAMP-dDE) algorithm was proposed in Ref. [98], where the asynchronous migration mechanism and the adaptive procedure allowed reducing the number of the control parameters to be set in the distributed multi-population models. The experimental results showed that this algorithm achieved good performance for the investigated benchmarks including the most of multi-modal functions.

3.1.2. Dynamic optimization

Multi-population methods have also been used to solve dynamic optimization problems [44,47,54,60,70,71]. Branke et al. [99] presented a multi-population approach to dynamic optimization problems, where the proposed algorithm used concepts from a multi-population evolutionary algorithm, which is to find multiple peaks in a multi-modal landscape, to enhance solution search in a dynamic landscape. The experimental results showed that this approach was indeed suitable for moving peak benchmarks. In Ref. [100], authors presented new variants of PSO which worked well in dynamic environments, where the main idea was to extend the single population PSO by constructing interacting multi-swarms. The results showed that the proposed multi-swarm optimizer significantly outperformed the single population PSO on the moving peaks benchmarks. In Ref. [101], authors proposed a mixed multi-swarm optimization approach applied to dynamic environments, where a set of particles was divided into multiple sub-swarms, and every sub-swarm consisted of two types of particles: classic and quantum ones. Both of them were based on stable symmetric distributions. The experimental results showed that the proposed method had achieved satisfactory efficiency. Another version adopting a multi-swarm PSO based on the concept of quantum for dynamic optimization was proposed in Ref. [102]. Yazdani et al. [103] presented a novel multi-swarm PSO algorithm for benchmark functions in dynamic environments. In this study, several mechanisms based on the changes of velocity vectors and particle positions were used to increase the diversity of swarms. The simulation results conducted on moving peak benchmarks showed the superiority of the proposed method. Multi-swarm optimization with chaotic mapping was proposed in Ref. [104] for dynamic optimization problems, in which the proposed algorithm adopted an improved multi-swarm approach and employed PSO as a global and local search method. Furthermore, a modified chaotic mapping mechanism was presented to overcome the challenge of diversity loss. The simulation results showed that the proposed algorithm outperformed the others on most of the test cases. Other studies about multi-population methods combining with PSO were presented in the literature [105–110]. Furthermore, a multi-population based geometric collaborative evolutionary algorithm was presented in Ref. [111] to solve complex dynamics problems. The numerical results demonstrated that the proposed algorithm was effective. Wu et al. [112, 113] designed a multi-population and diffusion univariate marginal

distribution algorithm, and the results showed that the proposed algorithm was effective for the function with a moving optimum and could adapt to the dynamic environments. In Ref. [114], a simple but effective self-adaptive strategy to control the behaviors of a DE based multi-population algorithm was proposed for dynamic environments. Specifically, the proposed scheme was aimed to control the creation of random individuals by the self-adaptation of the involved parameters. The simulation results showed that the proposed algorithm was as competitive as other efficient methods. Kundu et al. [115] published a similar study which used a multi-population based DE with speciation-based response to dynamic environments. The introduction of external archiving into a multi-population harmony search algorithm to solve dynamic optimization problems was presented by Turky and Abdullah [116]. The results on moving peak benchmarks showed that their modified version was better than the original harmony search algorithms. In Ref. [117], Li et al. proposed an adaptive multi-swarm optimizer for dynamic optimization problems, which addressed how to adapt the number of populations to change and how to adaptively maintain the population diversity in a situation where changes were hard to detect or predict. The performance of the proposed algorithm was compared with a set of the standard algorithms based on multi-population methods. Li et al. [118] presented some great challenges for multi-population methods in unconstrained dynamic environments, and analyzed them through experimental studies from the algorithm design point of view. The simulation results showed that the multi-population performance was significantly affected by several crucial issues, including how to adapt the number of subpopulations to dynamic environments, how to determine the search area of each subpopulation, and so on. Li et al. [119] used an adaptive multi-population optimization framework for locating and tracking multiple optima, which was taken as a dynamic optimization problem. In this study, PSO and DE were implemented into the multi-population framework, and the authors discovered that the proposed framework was quite good for dynamic optimization problems. Another version about multi-population optimization framework for dynamic environments was proposed by Uludag et al. [120]. Ozsoydan and Baykasoglu [121] employed a multi-population firefly algorithm to tackle dynamic optimization problems. The experiments on moving peak benchmarks showed that the proposed algorithm significantly improved system performance. A multi-swarm artificial bee colony (MABC) algorithm was proposed in Ref. [122] for dynamic optimization problems, where the proposed MABC had a similar framework to the original ABC but used an environment detection technique to track the moving of the optimal solutions of dynamic problems. The experimental results showed that the proposed MABC performed better in terms of offline errors, convergence speeds, and robustness.

3.1.3. Multi-objective optimization

Multi-population methods have sometimes been used to solve multi-objective optimization problems [79]. Leong et al. [123] extended multi-population methods to PSO-based multi-objective optimization in order to create multi-population multi-objective PSO, which made use of a dynamic population size and adaptive local archives to improve the diversity within each subpopulation. The computational experiments showed that their method worked better than the other standard methods. Zhang et al. [124] handled multi-objective optimization problems using a multi-swarm cooperative PSO, where each sub-swarm was designed to optimize one specific objective function of the multi-objective problem. The simulation results indicated that the proposed algorithm was highly competitive in solving multi-objective problems. In Ref. [125], Yu et al. used a multi-swarm comprehensive learning PSO algorithm to solve the multi-objective sustainable operation problem of the Three Gorges cascaded hydropower system. The experimental results demonstrated that the proposed method had satisfactory convergence and diversity for the cases studied. Liu et al. [126] proposed a co-evolutionary technique based on a multi-swarm PSO for the dynamic

multi-objective problem. The simulation results indicated that the proposed algorithm was promising for tackling dynamic multi-objective problems. Other studies using multi-swarm PSO for multi-objective optimization problems were reported in Refs. [127–132]. In addition, Kersting and Zabel [133] proposed a new multi-population multi-objective evolutionary algorithm for optimizing NC-tool paths for simultaneous five-axis milling. Their results showed the effectiveness of this multi-population algorithm for optimizing the previously available solutions. Xiao [134] formulated an improved multi-objective evolutionary memetic algorithm by using a multi-population approach. The airport ground services were optimized by the authors to test the performance of their method, and it showed that their method was better than the existing ones in terms of solution quality and Pareto dominance. Shang et al. [135] developed a multi-population cooperative co-evolutionary algorithm for the multi-objective capacitated arc routing problem, where the divide-and-conquer method was applied to decompose the whole population into multiple subpopulations according to different direction vectors, and then each subpopulation was used to search different objective sub-regions simultaneously. The results showed the effectiveness of this multi-population multi-objective algorithm for optimizing the capacitated arc routing problem. In Ref. [136], Shi et al. introduced a multi-objective immune algorithm based on a multi-population co-evolutionary strategy, where subpopulations evolved independently, and the unique characteristics of each subpopulation could be effectively maintained. The diversity of the entire population was effectively increased. The results showed that the proposed algorithm achieved satisfactory results in terms of convergence, diversity metrics, and running time on most of the problems. In Ref. [137], the author proposed a multi-population Sim-EA algorithm with operator auto-adaptation for the multi-objective firefighter problem, where a new migration mechanism was used to improve the effectiveness of the algorithm. The simulation results showed that the proposed multi-population Sim-EA algorithm produced better results than a decomposition-based algorithm. Castro et al. [138] presented a competent multi-swarm approach for more than three objectives known as many-objective optimization problems (MaOPs). On each sub-swarm, an EDA was used to ensure proper convergence. The empirical results fully demonstrated the superiority of the proposed method on almost all test instances.

3.1.4. Large-scale optimization

Multi-population methods have also been used to solve large-scale optimization problems [45]. Fan and Chang [139] presented a dynamic multi-swarm PSO based on parallel PC cluster systems for optimizing large-scale functions, in which multiple swarms worked in parallel, and used a message passing interface for information interchange among swarms. The simulation results showed that the proposed algorithm was promising in solving large-scale problems. Another version adopting a dynamic multi-swarm PSO with local search for large-scale global optimization was presented in Ref. [140]. Moeini et al. [141] introduced a colonial multi-swarm method with modular characteristics to the administration of PSO in large-scale problems, which ensured a decent degree of exploration by administrating a number of parallel swarms. The simulation results on 28 large-scale benchmark problems exhibited significant improvement as the problem dimensionality arose. A novel parallel multi-swarm algorithm based on comprehensive learning PSO was proposed in Ref. [142] for large-scale benchmark functions. In this study, multiple swarms had a master-slave relationship and worked cooperatively and concurrently to reach proper convergence. The simulation results showed that the proposed algorithm had good performance over the other variants of PSO. An enhanced version was implemented to handle another set of 20 large-scale optimization functions by Ge et al. [143]. In the meantime, Guo et al. [144] presented a novel multi-population cultural algorithm adopting knowledge migration, where implicit knowledge extracted from each subpopulation directly reflected the information of the

dominant search space in order to enhance diversity. The authors proved that their method had better performance than the other methods for large-scale optimization functions. In Ref. [145], a new multi-swarm multi-objective optimization method was proposed for dealing with large-scale structural problems. In this method, a multi-objective optimization method combining with clustering and particle regeneration procedure was presented to deal with large scale optimization problems. The experimental results showed that the proposed method outperformed several state-of-the-art approaches. Ali et al. [146] proposed multi-population DE with balanced ensemble of mutation strategies for large-scale global optimization, where the population was divided into independent subpopulations, each with different mutation and updating strategies. The performance of the proposed algorithm was investigated using 19 large-scale optimization functions and the results showed that it had competitive performance. A large-scale optimization application of multi-population differential ABC algorithm was presented by Zhou and Yao [147] for service composition in cloud manufacturing. In their study, the proposed algorithm adopted multiple parallel subpopulations, each of which evolved according to different mutation strategies from differential evolution to generate perturbed sources for foraging bees, and the mutation parameters were adapted independently. The authors found that the proposed algorithm outperformed other hybrid and single population algorithms in the literature.

3.1.5. Combinatorial optimization

Sometimes, multi-population methods have been used to solve combinational optimization problems [57,62]. A study on multi-population GAs for 0/1 knapsack problem was proposed by Lin et al. [148], and the experimental results showed that the proposed approach was comparable to single-population GAs. Another similar study on multi-population GA for multiple-choice multidimensional knapsack problems was proposed by Zhou and Luo [149]. A case on the dynamic vehicle routing problem, which was one of dynamic combinatorial problems, was handled by multi-swarm PSO [150]. In their study, the population of particles was split into a set of interacting swarms. The effectiveness of the approach was tested on a set of benchmarks, and the results showed that the proposed approach significantly outperformed the other meta-heuristics. Xiong and Wei [151] presented a multi-population binary ACO algorithm based on the distribution of food quantity, in which subpopulations learned from each other by the means of ant pheromones. The simulations on the 0/1 multi-knapsack problem demonstrated that their method could obtain satisfactory optimization performance. In Ref. [152], the authors discussed adaptive tuning of all the parameters used in a multi-swarm PSO algorithm, and applied the method to the probabilistic traveling salesman problem. The experimental results on a number of benchmark instances showed that the proposed algorithm had better performance than a number of algorithms reported in the literature.

3.1.6. Constrained optimization

Multi-population methods have also been used to solve constrained optimization problems. In Ref. [153], a multi-population EA was proposed for solving constrained optimization problems, where the proposed method adopted three populations with different multi-parent crossover operators. During the optimizing process, three populations exchange the best solution in each generation to adjust its search direction to possible optimum solution. The numerical results showed that the proposed method was highly competitive against the other algorithms. Liang and Suganthan [154] presented a dynamic multi-swarm PSO with a novel constraint-handling mechanism. The simulation results on CEC 2006 benchmark functions showed that the modified algorithm had better performance. Another version using a hybrid multi-swarm PSO for solving constrained optimization problems was proposed by Wang and Cai [155]. Applications of a parallel multi-population GA were presented by Gonçalves and Resende [156] for two-dimensional orthogonal packing problems with constraints. The effectiveness of the proposed

algorithm was verified on a set of instances, and the results of the study showed that their method outperformed a standard GA. In Ref. [157], a scalable multi-swarm based algorithm with Lagrangian relaxation was proposed for the constrained problems, in which the proposed method used a set of techniques in parallel to find near optimal solutions for these problems. The effectiveness of this approach was demonstrated in a rail scheduling problem. In Ref. [158], a novel quantum-behavior multi-swarm algorithm based on a parallel architecture was applied to the constrained engineering design. In this study, the method was focused at generating a solution which included better quality of search and higher speed of convergence by using evolutionary strategies. The results showed that the proposed method could obtain better performance. In Ref. [159], Srivastava and Singh proposed a hybrid multi-swarm PSO for solving a reactive power dispatch, which was a non-linear and multi-objective constrained optimization problem. The experimental results verified that the effectiveness of the proposed algorithm. In Ref. [160], Aimi and Suyama designed IIR filters with constraints using multi-swarm PSO, where the design problem was formulated as the non-linear optimization problem. The effectiveness of the proposed method was verified through several examples.

3.1.7. Noisy optimization

Some real-world problems are of noisy measurements. In Ref. [161], the noisy environment of GA was described, and the effect of noise on GA was analyzed. Then cluster based multi-population GA was proposed for handling the noisy environment. The numerical experiment showed that the performance of the proposed algorithm was better than the traditional GAs. Szeto and Guo [162] applied a multi-population GA for locating multi-optima in a noisy environment. The noise interfered with precision and covering degrees, and affected the optimization performance. In their work, the authors incorporated a multi-population method with adaptive migration to control the information exchange between different subpopulations. The experimental results showed that the proposed algorithm performed better than the other algorithms for handling benchmark functions with noise.

3.2. Areas of applications

3.2.1. Applications to scheduling problems

Various paradigms of multi-population methods have been applied to scheduling problems, which comprise some of the most important advances [163–170]. In Ref. [171], Qi et al. applied parallel multi-population GA to dynamic job-shop scheduling, where a modified genetic technique was adopted using a specially formulated genetic operator to conduct efficient search. The simulation results indicated that the proposed GA successfully improved the solution obtained from the conventional approaches, particularly in coping with the job-shop scheduling problem. Cochran et al. [172] applied a multi-population GA algorithm to handle parallel machine scheduling problems. The authors concluded that their approach was promising for practical scheduling problems. Zandieh and Karimi [173] studied the performance of an adaptive multi-population GA technique for the multi-objective group scheduling problem in hybrid flexible flowshop with sequence-dependent setup. The computational results showed that the proposed algorithm performed better than the standard GAs. In Ref. [174], a multi-population GA was proposed for multi-objective scheduling simulation of flexible job-shop. This study took into account the shortest processing time and the balanced usage of machines, and put forward the multi-population GA solution based on the multi-objective scheduling of flexible job-shop. The experimental results showed that the total machine load and the machine load's variance were gradually decreased by the proposed algorithm. Other studies that adopted the multi-population GA approach for scheduling problems were presented by Chakraborti and Kumar [175], Zegordi and Nia [176], Toledo et al. [177], and Huang et al. [178]. In Ref. [179], an improved multi-population hybrid PSO was proposed for the flexible job-shop

scheduling problem, in which searching efficiency was improved and the best processing sequence was found for flexible job-shop scheduling via simultaneous evolution of multiple populations. The proposed method was proved to be valid for flexible job-shop scheduling problems. Liang et al. [180] used a dynamic multi-swarm PSO method for solving the blocking flow shop scheduling problem, in which small multi-swarms and a regrouping schedule were used to minimize makespan. The computational results and comparisons indicated that the proposed algorithm had better performance than the other established algorithms in the literature. In Ref. [181], the authors applied a multi-swarm PSO-based optimization approach to handle multi-reservoir operation rules, which was one of the real-world applications of scheduling problems. In their study, the proposed method incorporated multi-swarm into PSO to improve the performance of the standard algorithm. The experimental results on the real-time operation of the Three Reservoir System showed that the proposed approach significantly outperformed the standard stochastic optimization approaches. Other studies that adopted the multi-population PSO for scheduling problems were presented by Liu et al. [182], Li and He [183], and Liu et al. [184]. Moreover, Digalakis and Margaritis [185] proposed a multi-population cultural algorithm for the electrical generator scheduling problem. In the proposed model a variety of selection mechanisms, operators, communication methods, and local search procedures were applied to each subpopulation. The experimental results showed that the proposed framework was useful. A multi-population interactive co-evolutionary algorithm for the flexible job shop scheduling problem was discussed in Ref. [186], where the quality of population was improved effectively by the interaction, competition and sharing mechanism among subpopulations. The simulation results showed that the proposed algorithm was an effective method for the flexible job shop scheduling problem. In Ref. [187], the authors employed a hybrid multi-population evolutionary algorithm to solve glass container production scheduling, in which a multi-population hierarchically structured GA scheme combined with a simulated annealing and cavity heuristic algorithm to improve system performance. The simulation results demonstrated that their algorithm was more effective than a state-of-the-art commercial solver and a non-hybridized multi-population GA. Recently, Gao and Pan [188] proposed a shuffled multi-swarm micro-migrating birds optimizer for a multi-resource-constrained flexible job-shop scheduling problem, in which a random shuffle process applied to the entire population was invoked periodically to propagate the good information that was found in some of the micro-swarms, and an adaptive search operator based on a problem-specific crossover and two-vector crossover helped to balance exploitation and exploration. The experimental results showed that the proposed method performed significantly better than the existing algorithms.

3.2.2. Applications to path planning

Multi-population methods are important optimization tools for path planning. Cheng et al. [189,190] presented an immigrants-enhanced multi-population GA for dynamic shortest path routing problems in mobile ad hoc networks, which were taken as a dynamic optimization problem. The experimental results showed that the proposed algorithm could quickly adapt to environmental changes and produce high-quality solutions after each change. Other studies that used a multi-population memetic algorithm and a multi-memory multi-population memetic algorithm for dynamic shortest path routing in mobile ad-hoc networks were presented by Turky et al. [191] and Sabar et al. [192] respectively. In Ref. [193], multi-swarm sharing PSO was applied to UAV path planning problem, in which the proposed method was employed to explore a better solution and the variable-length crossover concept was used to share information among different dimension swarms. The simulation result showed that the proposed method had the ability to determine suitable characteristics for flight path. Arantes et al. [194] used a hybrid multi-population GA for unmanned aerial vehicle (UAV) path panning, where the environment was non-convex by the presence of no-fly zones

such as mountains, cities and airports. Experimental results demonstrated the effectiveness of the algorithm relative to other methods. In other research, Liang et al. [195,196] solved path planning based on a dynamic multi-swarm PSO with crossover and different constraint handling methods. Experimental results demonstrated the effectiveness of the proposed algorithms. Kuczkowski and Smierzchalski [197] compared single and multi-population evolutionary algorithms for path planning in the navigation situation. The results showed that the multi-population method was better than the single-population method for the studied path planning. Similar problems were solved based on the modified multi-population DE and multi-population GA in Refs. [198, 199]. PSO with adaptive multi-swarm strategy was proposed in Ref. [200] for the capacitated vehicle routing problem with pickups and deliveries, which included goods delivery/pickup optimization, vehicle number optimization, routing path optimization and transportation cost minimization. In this study, the proposed method employed multiple PSO algorithms and an adaptive algorithm with the punishment mechanism to search an optimal solution. The simulation results proved that the method could solve the capacitated vehicle routing problem with the least number of vehicles and less transportation cost simultaneously. Osaba and Diaz [201] designed and implemented a multi-population meta-heuristic for solving the vehicle routing problem, in which the proposed algorithm combined multi-population DE with an elite pool scheme to keep population diversity and avoid prematurely trapping into local optima. The computational results indicated that the method outperformed other algorithms relative to the given criteria. Similar vehicle routing problems with time windows and stochastic travel and service times were solved based on multi-population memetic algorithm in Ref. [202].

3.2.3. Applications to data analysis

Data analysis is another important application area for multi-population methods [203–215]. A layered multi-population GP for designing a classifier was presented in Ref. [216], where the layer architectures were used to arrange multiple subpopulations to construct a new training set. The authors compared their method to the other algorithms and found that it was an effective approach to the classification problem. Another version was performed on clustering temporal data using a co-operative multi-population approach in Ref. [217]. Clustering applications of large probabilistic graphs using a multi-population evolutionary algorithm was presented by Halim et al. [218], in which each subpopulation represented a deterministic version of the same probabilistic graph. The computational experiments showed that the proposed algorithm gave better performance than the baseline methods and the state-of-the-art algorithms. In Ref. [219], a multi-population parallel GA for the direct-space crystal structure solution from the powder diffraction data, in which the multi-population GA was based on the independent evolution of different subpopulations, with occasional interaction allowed to occur between different subpopulations. The experimental result showed that the proposed method could create the opportunity for structure determination of molecular crystals of increasing complexity. Other studies that used niche GA and multi-population competition for feature extraction of nonparametric curves was presented by Wei et al. [220]. Yao et al. [221] proposed a multi-population GA for robust and fast ellipse detection from an image, where a number of subpopulations were evolved, and each was clustered around an actual ellipse in the target image. Simulation results indicated that the proposed algorithm significantly outperformed the other algorithms. Li et al. [222] developed a multi-population agent GA which realized parallel search for feature selection. The computational results indicated that the proposed method outperformed the other algorithms relative to the given criteria. Garcia-Nieto and Alba [223] proposed parallel multi-swarm optimizer for gene selection in DNA microarrays datasets. In this work, the proposed method consisted of running a set of independent PSOs following an island model, where a migration policy exchanges solutions with a certain frequency. The experimental results

on four well-known cancer datasets showed that the proposed method was able to identify specific genes as significant ones for an accurate classification. In Ref. [224], Xiao and Cheng used a multi-swarm PSO method for DNA encoding. In Ref. [225], a multi-population GA was used based on the extended finite state machine, which was a popular algorithm used to describe states and actions of software system. The authors proved that their method had better performance comparable to other methods. Podgorelec et al. [226] studied evolving balanced decision trees using a multi-population GA, and the simulation results showed that the proposed method outperformed the other methods. On the other hand, a multi-population multi-strategy DE algorithm for structural optimization of metal nanoclusters was presented in Ref. [227], where the product design and downstream life cycle descriptions were modeled by a multi-level graph data structure. Industrial case studies had been implemented to show the effectiveness of the proposed algorithm. Mausa and Grbac [228] proposed a co-evolutionary multi-population GP which combined colonization and migration with three ensemble selection strategies for classification in software defect prediction. Computational results demonstrated the efficiency of the proposed method.

3.2.4. Applications to network

Quintero and Pierre [229] presented sequential and multi-population memetic algorithms for assigning cells to switch in mobile networks. The proposed algorithms were tested on moderate- and large-sized cellular mobile networks. A similar strategy was implemented for the same problem by Niu et al. [230]. In Ref. [231], Liang et al. improved the performance of fiber Bragg grating (FBG) sensor networks using a novel dynamic multi-swarm PSO. Experimental results showed that the proposed algorithm achieved higher accuracy with less computational cost compared to the other conventional methods. A multi-swarm PSO algorithm for energy-effective clustering in wireless sensor networks was presented in Ref. [232]. Simulation results revealed that the suggested method outperformed the other methods. In Ref. [233], the authors used a multi-swarm PSO for RFID network planning, which was an optimization model for planning the positions of readers in the RFID network. Simulation results showed that the proposed algorithm proved to be more effective for planning RFID networks than the canonical PSO, and GA with elitism and self-adaptive ES. Xu and Liu [234] proposed a multi-population firefly algorithm for correlated data routing in underwater wireless sensor networks. The simulation results showed that the proposed method achieved better performance than the existing methods in the metrics of packet delivery ratio, energy consumption and network throughput. Another version adopted an improved dynamic deployment method based on multi-swarm PSO for wireless sensor network was presented by Ni et al. [235]. Fontes and Goncalves [236] proposed a multi-population hybrid biased random key GA for hop-constrained trees in nonlinear cost flow networks. The results proved the efficiency and effectiveness of the proposed method. A multi-population GA was used for internet of things [237], where web service composition was modeled as a multi-criteria goal programming problem. Simulation results showed that the proposed algorithm was capable to solve the large-scale service composition problem in terms of efficiency and scalability. A multi-population cultural algorithm was proposed in Ref. [238] for community detection in social network, which was viewed as a reflection of the real world to study to gain insight into the real life societies and events. The comparison results between the proposed algorithm and other well-known algorithms showed that it was able to fast and more accurately find the true communities. In Ref. [239], a multi-population cooperative bat algorithm was used for an artificial neural network model, which mainly depended on the connection weights and network structure. Experimental results showed that there was a significant improvement by applying the proposed algorithm to all the test cases. An active multi-population pattern searching algorithm for flow optimization in computer networks and routing spectrum allocation was studied by Przewozniczek [240,241]. In their study, a novel co-evolution schema was combined with linkage learning to tackle high-dimensional and hard

optimization problems. The experimental results showed that the proposed algorithm was an effective method for the studied problems. In Ref. [242], the authors discussed the possibility of generating complex networks using multi-swarm PSO, and advised employed advanced complex network analysis to improve the performance of multi-swarm PSO. Lin et al. [243] used a multi-population harmony search algorithm for extending the lifetime of dynamic underwater acoustic sensor networks, which was a dynamic optimization problem due to the underwater environment changes. The simulation results showed that the proposed method outperformed the other algorithms.

3.2.5. Applications to parameter estimation and control

Parameter estimation and control is also another important application area for multi-population methods [244–253]. In Ref. [254], a multi-population GA based on the dynamic exploration of local optima was proposed to estimate the parameters of a micro-population model of risk-group dynamics. Simulation results showed that the proposed algorithm performed better than the other algorithms. Su and Hou [255] employed a multi-population intelligent GA to find the Pareto-optimal parameters for a nano-particle milling process. Simulation results indicated that the proposed algorithm provided better performance than regular GAs. In Ref. [256], an active contour model was solved by multi-population PSO, where the objective was to enhance the concavity searching capability for the control points of the active contour model. Their method was tested on the proposed problem and was compared to other algorithms. A multi-population GA was modified by Angelova and Pencheva [257] for parameter identification of yeast fed-batch cultivation. The experimental results showed that the modified multi-population GA outperformed the standard ones. In Ref. [258], Toledo et al. presented a multi-population GA for PID controller auto-tuning. Computational results showed the superior performance of the proposed algorithm. Mukhopadhyay and Banerjee [259] proposed a chaotic multi-swarm PSO for global optimization of an optical chaotic system, where the control and estimation of unknown parameters of chaotic systems were a daunting task. The numerical results showed that for the given system parameters, the proposed algorithm could identify the optimized parameters effectively. A multi-population GA was presented in Ref. [260] for optimizing multi-size micro-perforated panel absorbers. In this study, the proposed problem depended on four structure parameters, and the aim was to find an appropriate combination to provide good performance. The results demonstrated the effectiveness of their method on multi-size micro-perforated panel absorbers. Mao and Li [261] used a multi-population GA for dust particle size distribution inversion, which is to characterize aerosol optimal properties and physical properties. The simulation results showed that the proposed method was an important tool for the studied problem. Folly et al. [262] used multi-population PBIL for a design of a power system controller, and simulation results showed that the multi-population PBIL approach performed better than the standard PBIL. Furthermore, the same authors [263] also compared multi-population PBIL and adaptive learning rate PBIL in designing a power system controller, and simulation results showed that multi-population PBIL was as effective as adaptive learning rate PBIL. In Refs. [264,265], authors proposed multi-swarm fruit fly optimization algorithm for structural damage identification, which was transformed into an optimization problem. Numerical results showed that the proposed algorithm had a better capacity for structural damage identification than the other methods.

3.2.6. Electrical engineering problems

Challenges in electrical engineering problems were often solved by multi-population methods [266–268]. In Ref. [269], the authors applied node-depth encoding and multi-objective EA to large-scale distribution system reconfiguration, which was a nonlinear and multi-objective problem. In this study, a multi-objective EA based on subpopulation tables adequately modeled several objectives and constraints, enabling a better exploration of the search space. Tests with networks ranging from

632 to 5166 switches indicated that the proposed method could find network configurations corresponding to power loss reduction of 27.64% for very large networks requiring relatively low running time. In Ref. [270], a multi-objective EA was employed for single and multiple fault service restoration in large-scale distribution systems. In this study, two multi-objective EAs used node-depth encoding to efficiently generate adequate service restoration plans for the large distribution systems. Experimental results showed that the number of switching operations required implementing the service restoration plans generated by the proposed method increased in a moderate way with the number of faults. Alves and De Sousa [271] proposed a multi-population GA to solve the multi-objective remote switches allocation problem in distribution systems. In this study, the proposed method obtained the optimal solution considering a priori articulation of preferences established by the decision maker in terms of an aggregating function which combined individual objective values in a single utility value. Simulation results on a 282-bus test system confirmed the efficiency of the proposed method. Furthermore, Alves [272] proposed a multi-population hybrid algorithm to solve the similar problem in distribution systems. The simulation results confirmed the efficiency of the proposed method. In Ref. [273], the authors obtained optimal VAR control for real power loss minimization and voltage stability improvement using hybrid multi-swarm PSO. In this study, PSO was implemented as the search engine for each sub-swarm, and DE was applied to improve the personal best of each particle. Effectiveness of the proposed algorithm was proved on the IEEE 30-bus system. In Ref. [274], the authors presented a multi-swarm optimization based adaptive fuzzy multi-agent system for micro-grid multi-objective energy management. In the proposed architecture each agent presented a different micro-grids unit. Fuzzy logic was used by each agent to estimate the amount of energy to be generated in order to cover the uncertainty and imprecision related to renewable energy sources and micro-grid constraints, and multi-population PSO was used by a coordinator agent to find the best compromised solution to satisfy economical/environmental objectives based on agent proposals. Simulation results showed the importance of the proposed method compared to the basic PSO. Jena and Chauhan [275] used multi-swarm cooperative PSO to solve distribution feeder reconfiguration and concurrent DG installation problems for power loss minimization, and the effectiveness of the proposed approach was tested with IEEE 33-bus and 69-bus test systems with encouraging results. In Ref. [276], authors employed hybrid particle multi-swarm optimization to solve convex and non-convex static and dynamic economic dispatch problems. In their study, the proposed method conducted deep search with fast response, and convex and non-convex cost functions along with equality and inequality constraints had been used to evaluate the performance of the proposed approach. Comparison against the previous techniques showed that the proposed algorithm had better performance.

3.2.7. Applications to mathematical equation problems

In other research, Mera et al. [277] employed a multi-population GA for tackling ill-posed problems, and the authors proved that their method was able to obtain highly accurate solutions. Another version that adopted entropy-based multi-population GA for nonlinear programming problems was proposed by Li et al. [278]. Simulation results demonstrated the accuracy and efficiency of the proposed algorithm. In Ref. [279], authors used multi-population DE for searching nonlinear systems, and one of these nonlinear problems was the boundary value problem. Simulation results showed that the proposed method got better solutions together with a simple convergence analysis. A multi-population parallel imperialist competitive algorithm was presented in Ref. [280] for solving systems of nonlinear equations, which were taken as NP-hard problems. In their study, the optimal solutions were obtained by the proposed algorithm, and experimental results demonstrated that the proposed algorithm had good performance. Yeh et al. [281] presented layered multi-population genetic programming for learning ranking functions, which was a complex optimization problem

in information retrieval. Experimental results were compared with other approaches and indicated the superiority of the proposed algorithm.

3.2.8. Applications to other problems

A penalty-guided multi-population GA was presented in Ref. [282] for reservoir system optimization. Several real-world applications were used to show the competitiveness of their approach. Li et al. [283] presented an improved multi-population GA for fast flexible docking program. Numerical results demonstrated that their method was able to obtain competitive performance. A similar study that adopted a parallel multi-population biased random-key GA for a container loading problem was proposed by Goncalves and Resende [284]. In another similar study, Zheng et al. [285] developed a multi-objective multi-population biased random-key GA to solve a 3-D container loading problem. Comparisons with other algorithms on hard and weak heterogeneous cases showed that the proposed algorithm had better performance. Xu et al. [286] employed a multi-population cultural algorithm with adaptive diversity preservation to optimize ammonia synthesis process. Results showed that the optimized model improved the prediction accuracy of ammonia synthesis system. The performance of a novel multi-population GA was investigated for a complex system which combined cooling, heating and power system with ground source heat pump system in Ref. [287]. A multi-population optimization algorithm for the optimization of wind turbine layout was discussed in Ref. [288]. Lastly, multi-population optimization algorithms had been applied to injection molding optimization [289], truss structure optimization [290], ultra-short-term load forecasting [291], fashion design [292], speed synthesis [293], inverse problem in hydrogeology [294], landscape mapping [295], virtual enterprise [296], highway alignment optimization model [297], community detection [298], space manipulators [299], and optimal mass customisation production [300].

4. Discussions and conclusions

Tables 5 and 6 summarize the literature review of the multi-population methods for nature-inspired optimization. In-depth analyses and findings are achieved based on discussed literature, which provide a deep insight into how to design efficient multi-population methods for solving optimization problems. Note that another two techniques related to multi-population methods, including "cooperative coevolution" [301, 302] and "species" [303–306], are not carefully considered in this paper. Cooperative coevolution is an explicit means of problem decomposition in multi-population evolutionary algorithms. For cooperative coevolution, each subpopulation is responsible for optimizing a subset of variables (i. e., a subcomponent), and different subpopulations are likely to have different contributions to the improvement of the best overall solution to the problem. For the species technique, a species is a subpopulation, defined as a group of individuals in a population that have similar characteristics and are dominated by the best individual, and different species are able to optimize toward different optima simultaneously. The publications in the tables are organized according to issues and applications of multi-population methods, as discussed above.

4.1. Suggestions for future research

The development of multi-population methods is diverse and rapidly expanding, but there are still many open research areas. The first and important area for future research is to appropriately handle four fundamental issues of multi-population methods in nature-inspired optimization algorithms, including the number of subpopulations, the communication between subpopulations, the search area of subpopulations, and the search strategy of subpopulations. Currently, most existing multi-population methods just use pre-defined parameters, which are based on empirical experience, to determine the parameter setting of subpopulations. Some of the other studies assume that some prior information of optimization problems has been known. In this case,

Table 5
Basic issues of multi-population methods.

Basic issues	References and methods	Analysis and findings
Number of subpopulations	Trojanowski and Wierzchon [31]: Multi-population heuristic method Niu et al. [32]: Multi-population cooperative PSO Togelius et al. [33]: Multi-population competitive coevolution algorithm Li et al. [34]: Multi-population competitive coevolution GA Guo et al. [35]: Multi-population cooperative cultural algorithm Toledo et al. [36]: Hybrid multi-population GA Mokom and Kobti [37]: Multi-population cultural algorithm Yu [38]: Multi-population ABC Aimi and Suyama [39]: Multi-swarm PSO based on particle reallocation strategy Chatterjee and Zhou [40]: Multi-population DE Bongard [41]: Multi-population GP Liang and Suganthan [42,43]: Dynamic multi-swarm PSO Yang and Li [44]: Clustering PSO Zhao et al. [45]: Dynamic multi-swarm PSO Xia et al. [46]: Multi-swarm competitive PSO Nseef et al. [47]: Adaptive multi-population ABC Peng and Shi [48]: Multi-population cooperative coevolutionary algorithm	The number of subpopulations to be increased or decreased may be related to the phases during the evolution process, and the historical changes of the number of the survived subpopulations.
Communication between subpopulations	Toulouse et al. [49]: Cooperative multi-thread heuristics method Cantú-Paz [50]: Multi-population parallel GA Middendorf et al. [51]: Multi-colony ant algorithms El-Abd and Kamel [52]: Multi-swarm cooperative PSO Chen and Chang [53]: Real-coded multi-population GA Zheng and Liu [54]: Multi-swarm PSO Li and Zeng [55]: Multi-population co-genetic algorithm Chen et al. [56]: Multi-swarm coevolution PSO Lin et al. [57]: Multi-population GA Biswas et al. [58]: Multi-population ABC Campos et al. [59]: Asynchronous multi-swarm PSO Turky and Abdullah [60]: Multi-population electromagnetic algorithm Michalak [61,62]: Multi-population EA based on problem similarity Li et al. [63]: Multi-population ABC Kommenda et al. [64]: Multi-population GP Xu et al. [65]: Multi-swarm PSO with cooperative learning strategy Upadhyayula and Kobti [66]: Multi-population cultural algorithm Wang et al. [67]: Multi-population bat algorithm Niu et al. [68]: Symbiosis-based alternative learning multi-swarm PSO Yany et al. [69]: Orthogonal multi-swarm cooperative PSO	Communication between subpopulations always is helpful for most of the multi-population methods. It is able to significantly improve the search ability when communication parameters including communication rate, communication policy, communication interval, and connection topology, are reasonably set.
Search area of each subpopulation	Li and Yang [70]: Multi-population GA, PSO and DE Pourvaziri and Naderi [71]: Hybrid multi-population GA Kobti [72] and Raeesi et al. [73]: Heterogeneous multi-population cultural algorithm Ufnalske and Grzesiak [74]: multi-swarm PSO El Dor et al. [75]: Multi-swarm PSO Bolufe and Chen [76]: Multi-swarm PSO	Decomposition based strategy is considered as one of the most helpful approaches to determine the search area of each subpopulation, which is able to effectively enhance the optimization performance.
Search strategy of each subpopulation	Wu et al. [77]: Multi-population DE Li et al. [78]: Multi-population based ensemble mutation method Wang and Tang [79]: Adaptive multi-population DE Godio [80]: Multi-population GA Niu et al. [81]: Multi-swarm cooperative PSO Zhao et al. [82]: Multi-swarm cooperative multistage perturbation guiding PSO Ali et al. [83]: Adaptive multi-population DE Biswas et al. [84]: Multi-swarm ABC Cheng et al. [85]: Multi-swarm PSO Vafashoar and Meybodi [86]: Multi-swarm bare bones PSO	Each subpopulation using different search strategies is better than a single search strategy throughout the evolution.

problem information can be used to guide the configuration of multi-population parameters. However, for the most of cases, we need to deeply explore these issues to develop good multi-population methods to more effectively solve a variety of problems. It should also be possible to design automatic schemes so that multi-population methods can adaptively self-tune. One may need to adaptively adjust the number of subpopulations for different phases during the evolution process, or adaptively determine the search area and search strategy for each subpopulation according to the historical information. One may need to develop learning based approaches to explore communication strategy between subpopulations, to avoid premature convergence of multi-population algorithms.

Another area for the future research is additional mathematical tools for the theoretical analysis of multi-population methods. There are few

publications about the theoretical aspects of multi-population methods to help investigate the impact of multi-population for optimization problems [307,308], which greatly limits the further generalizations, improvements and applications of multi-population methods. Therefore, it is challenging to obtain quantitative results for optimization problems using theoretical analysis. Quantitative results such as theoretical comparisons with other optimization methods could be of great interest to the multi-population optimization research community. Furthermore, theoretical analysis could provide insights as to what types of multi-population methods are hard or easy for what types of optimization problems.

Another area for the future research is new algorithmic frameworks. The current popular frameworks of multi-population methods are parallel cooperation and serial cooperation. But there are still other new

Table 6
Applications of multi-population methods.

Problems		References and methods	Analysis and findings
Classes of optimization	Multi-modal optimization	Niu et al. [68]: Symbiosis-based alternative learning multi-swarm PSO Li et al. [78]: Multi-population based ensemble mutation method Siarry et al. [87]: Multi-population GA Alami and El Imrani [88,89]: Multi-population culture algorithm Yao et al. [90,91]: Bi-objective multi-population GA Zhang and Ding [92]: Multi-swarm self-adaptive and cooperative PSO Kwasnicka and Przewoznickek [93]: Multi-population pattern searching algorithm Bolufe and Chen [94]: Multi-population hybrid DE and EDA Fieldsend [95]: Niching migratory multi-swarm PSO Li et al. [96]: Pseudo multi-population DE Xiao et al. [97]: Multi-population coevolution immune optimization algorithm De Falco et al. [98]: Asynchronous adaptive multi-population DE	Reference [68] demonstrates that symbiosis-based alternative learning multi-swarm PSO outperforms other multi-swarm versions of PSO for solving multi-modal optimization. Reference [78] shows that ensemble-based method is one of the best alternative multi-population methods.
	Dynamic optimization	Yang and Li [44]: Clustering PSO Nseef et al. [47]: Multi-population ABC Zheng and Liu [54]: Topology multi-swarm PSO Turky and Abdullah [60]: Multi-population electromagnetic algorithm Li and Yang [70]: Multi-population GA, PSO and DE Pourvaziri and Naderi [71]: Hybrid multi-population GA Branke et al. [99]: Multi-population EA Blackwell and Branke [100]: Multi-swarm PSO Trojanowski [101,102]: Quantum multi-swarm PSO Yazdani and Nasiri [103,104]: Multi-swarm PSO Wang et al. [105]: Cooperative multi-swarm PSO Hu et al. [106]: Multi-swarm PSO with Cauchy mutation Del Amo et al. [107,108]: Multi-population PSO Nabizadeh et al. [109]: Multi-swarm cellular PSO Liu et al. [110]: Multi-swarm PSO with orthogonal learning Gog et al. [111]: Multi-population geometric collaborative EA Wu et al. [112,113]: Multi-population univariate marginal distribution algorithm (UMDA) Novoa-Hernandez et al. [114]: Self-adaptive multi-population DE Kundu et al. [115]: Multi-population DE with speciation-based response Turky and Abdullah [116]: Multi-population harmony search algorithm Li and Yang et al. [117]: Adaptive multi-population PSO Li and Nguyen et al. [118,119]: Adaptive multi-population PSO and DE Uludag et al. [120]: Multi-population based incremental learning algorithms (PBIL) Ozsoydan and Baykasoglu [121]: Multi-population firefly algorithm (FA) Jia et al. [122]: Multi-swarm ABC	Reference [119] demonstrates that heuristic clustering-based adaptive multi-population PSO and DE outperforms other multi-swarm versions of PSO and other multi-population EAs for solving dynamic optimization.
	Multi-objective optimization	Wang and Tang [79]: Adaptive multi-population DE Leong and Yen [123]: Multi-swarm PSO with dynamic population size and adaptive local archives Zhang et al. [124]: Multi-swarm cooperative PSO Yu et al. [125]: Multi-swarm comprehensive learning PSO Liu et al. [126]: Multi-swarm coevolutionary PSO Wang and Yang [127]: Interactive multi-swarm PSO Sun et al. [128]: Multi-swarm multi-objective PSO Liang et al. [129]: Dynamic multi-swarm PSO Britto et al. [130,131]: Iterated multi-swarm PSO and Reference-point based multi-swarm PSO Yao et al. [132]: Cooperative multi-swarm PSO Kersting and Zabel [133]: Multi-population multi-objective EAs Xiao [134]: Multi-population multi-objective evolutionary memetic algorithm Shang et al. [135]: Multi-population cooperative coevolutionary algorithm	References [126] and [138] demonstrate that multi-swarm coevolutionary PSOs and competent multi-swarm PSOs outperform the other multi-swarm versions of PSOs for solving multi-objective optimization.

Table 6 (*continued*)

Problems		References and methods	Analysis and findings
	Large-scale optimization	Shi et al. [136]: Multi-population coevolutionary multi-objective immune algorithm Michalak [137]: Sim-EA algorithm with operator auto-adaptation Castro et al. [138]: Competent multi-swarm PSO Zhao et al. [45]: Multi-swarm PSO with sub-regional harmony search Fan and Chang [139]: Dynamic multi-swarm PSO Zhao et al. [140]: Dynamic multi-swarm PSO with local search Moeini et al. [141]: Colonial multi-swarm PSO Gulcu and Kodaz [142]: Parallel multi-swarm PSO Ge et al. [143]: Diversity-based multi-population DE Guo et al. [144]: Multi-population cultural algorithm with knowledge migration Kaveh and Laknefadi [145]: Multi-population multi-objective PSO Ali et al. [146]: Multi-population DE with balanced ensemble of mutation strategies Zhou and Yao [147]: Multi-population parallel self-adaptive differential ABC	Reference [147] demonstrates that multi-population parallel self-adaptive differential ABC outperforms the other multi-population algorithms for large-scale optimization.
	Combinatorial optimization	Lin et al. [57]: Multi-population GA Michalak [62]: Multi-population estimation of distribution algorithm (EDA) Lin et al. [148]: Multi-population GA Zhou and Luo [149]: Multi-population GA Khouadjia et al. [150]: Multi-swarm PSO Xiong and Wei [151]: Multi-population binary ACO Marinakis et al. [152]: Multi-swarm PSO	Reference [62] demonstrates that the multi-population estimation of distribution algorithm is one of the best multi-population algorithms for combinatorial optimization.
	Constrained optimization	Chen and Kang [153]: Multi-population EAs Liang and Suganthan [154]: Dynamic multi-swarm PSO Wang and Cai [155]: Hybrid multi-swarm PSO Goncalves and Resende [156]: Parallel multi-population GA Gomez-lglesias et al. [157]: Scalable multi-swarm PSO with Lagrangian relaxation Souza et al. [158]: Quantum-behavior evolutionary multi-swarm PSO Srivastava and Singh [159]: Hybrid multi-swarm PSO Aimi and Suyama [160]: Multi-swarm PSO	Reference [159] demonstrates that a multi-population PSO hybridizing DE outperforms the other versions of PSO for constrained optimization.
	Noisy optimization	Li et al. [161]: Cluster based multi-population GA Szeto and Guo [162]: Multi-population GA	There are only a few references discussing multi-population algorithms for noisy optimization.
Area of applications	Scheduling problems	Kapanoglu and Koc [163]: Multi-population parallel GA Wang and Li [164]: Multi-population GA Morady and Dal [165]: Multi-population parallel GA Sun et al. [166]: Multi-population and self-adaptive GA Wang et al. [167]: Adaptive multi-population GA Yu et al. [168]: Cooperative multi-swarm PSO Li et al. [170]: Multi-swarm PSO Qi et al. [171]: Parallel multi-population GA Cochran et al. [172]: Multi-population GA Zandieh and Karimi [173]: Adaptive multi-population GA Zhang et al. [174]: Multi-population GA Chakraborti et al. [175]: Multi-population GA and DE Zegordi and Nia [176]: Multi-population GA Toledo et al. [177]: Multi-population GA Huang et al. [178]: Multi-population GA Chen et al. [179]: Multi-population hybrid PSO Liang et al. [180]: Dynamic multi-swarm PSO Ostadrahimi et al. [181]: Multi-swarm PSO Liu et al. [182]: Multi-swarm PSO Li and He [183]: Cooperative multi-swarm PSO Liu and Ma [184]: Multi-population PSO based memetic algorithm Digalakis and Margaritis [185]: Multi-population cultural algorithm	Reference [188] demonstrates that the multi-population methods combining with new nature inspired optimization algorithms are a hot research trend in recent years, and shuffled multi-swarm micro-migrating birds optimizer outperforms the other multi-population algorithms for solving scheduling problems.

Table 6 (*continued*)

Problems		References and methods	Analysis and findings
	Path planning	Cheng et al. [189]: Multi-population interactive GA with immigrants scheme	Reference [191] demonstrates that multi-population memetic algorithm outperforms the other multi-population algorithms for solving path planning problems.
		Toledo et al. [190]: Multi-job multi-population memetic Algorithm	
		Salman and Han [192]: Multiffed multi-population migration joint optimizer	
		Huo et al. [193]: Multi-swarm sharing PSO	
		Arantes et al. [194]: Hybrid multi-population GA	
		Liang et al. [195,196]: Dynamic multi-swarm PSO with crossover	
		Kuczkowski et al. [197]: Multi-population EAs	
		Li et al. [198]: Multi-population DE	
		Da Silva Arantes et al. [199]: Multi-population GA	
		Chen et al. [200]: PSO with adaptive multi-swarm strategy	
		Osaba and Diaz [201]: Multi-population meta-heuristic algorithm	
		Gutierrez et al. [202]: Multi-population memetic algorithm	
	Data analysis	Keyhanipour et al. [203]: Layered multi-population GP	Reference [228] demonstrates that coevolutionary multi-population genetic programming method outperforms the other multi-population algorithms for solving data analysis problems.
		Mao et al. [204]: Multi-population GA	
		Heraguemi et al. [205,206]: Multi-population cooperative bat algorithm	
		Podgorelec et al. [207]: Multi-population GA	
		Cao [208]: Multi-population elitists shared GA	
		Zhu et al. [209]: Multi-population GA	
		Chen and Zhong [210]: Multi-population GA	
		Li and Zeng [211]: Multi-population agent GA	
		Lin et al. [212]: Layered multi-population GP	
		Keyhanipour and Moshiri [213]: Layered multi-population GP	
		Liu and Liu [214]: Multi-population collaborative optimization	
		Aimi and Suyama [215]: Multi-swarm PSO	
		Lin et al. [216]: Layered multi-population GP	
		Georgieva and Engelbrecht [217]: Cooperative multi-population PSO	
		Halim et al. [218]: Multi-population EAs	
		Habershon et al. [219]: Multi-population parallel GA	
		Wei et al. [220]: Niche GAs and multi-population competition	
		Yao et al. [221]: Multi-population GA	
		Li et al. [222]: Multi-population agent GA	
		Garcia-Nieto and Alba [223]: Parallel multi-swarm PSO	
		Xiao and Cheng et al. [224]: Multi-swarm PSO	
		Zhou et al. [225]: Multi-population GA	
		Podgorelec et al. [226]: Multi-population GA	
		Fan et al. [227]: Multi-population multi-strategy DE	
		Mausa and Grbac [228]: Coevolutionary multi-population GP	
	Network	Quintero and Pierre [229]: Sequential and multi-population memetic algorithm	Reference [241] demonstrates that the multi-population pattern searching algorithm is a new optimization algorithm, and outperforms the other multi-population algorithms for solving network optimization problems.
		Niu et al. [230]: Multi-population cooperative PSO	
		Liang et al. [231]: Dynamic multi-swarm PSO	
		Suganthi and Rajagopalan [232]: Multi-swarm PSO	
		Chen et al. [233]: Multi-swarm PSO	
		Xu and Liu [234]: Multi-population firefly algorithm	
		Ni et al. [235]: Multi-population PSO	
		Fontes and Goncalves [236]: Multi-population hybrid biased random key GA	
		Li et al. [237]: Multi-population GA	
		Zadeh and Kobti [238]: Multi-population cultural algorithm	
		Jaddi et al. [239]: Multi-population cooperative bat algorithm	
		Przewozniczek [240,241]: Multi-population pattern searching algorithm	
		Pluhacek et al. [242]: Multi-swarm PSO	
		Lin et al. [243]: Multi-population harmony search algorithm	
	Parameter estimation and control	Roeva [244]: Multi-population GA	Reference [265] demonstrates that the multi-swarm fruit fly optimization algorithm outperforms the other popular multi-population GAs and PSO algorithms for solving parameter estimation and control problems.
		Gao et al. [245]: Multi-population PSO	
		Chen et al. [246]: Multi-population GA	
		Li et al. [247]: Multi-population PSO	

Table 6 (*continued*)

Problems	References and methods	Analysis and findings
	Chang and Wang [248]: Multi-population parallel EDAs	
	Li and Chiang [249]: Multi-population PSO	
	Lu et al. [250]: Multi-population GA	
	Saini et al. [251]: Hierarchical multi-swarm cooperative PSO	
	Lin et al. [252]: Multi-population GA	
	Yuan et al. [253]: Multi-swarm fruit fly optimization algorithm	
	Elketroussi and Fan [254]: Multi-population GA	
	Su and Hou [255]: Multi-population intelligent GA	
	Tseng et al. [256]: Multi-population PSO	
	Angelova et al. [257]: Modified multi-population GA	
	Toledo et al. [258]: Multi-population GA	
	Mukhopadhyay and Banerjee [259]: Chaotic multi-swarm PSO	
	Qian et al. [260]: Multi-population GA	
	Mao and Li [261]: Multi-population GA	
	Folly et al. [262,263]: Multi-population PBIL	
	Li and Lu [264,265]: Multi-swarm fruit fly optimization algorithm	
Electrical Engineering problems	Li and Li et al. [266]: Multi-population GA	Reference [276] demonstrates that the hybrid particle multi-swarm optimization outperforms other versions of PSO for solving electrical engineering problems.
	Li and Zhang et al. [267]: Dynamic multi-population PSO	
	Zhou et al. [268]: Multi-objective multi-population ACO	
	Santos et al. [269]: Node-depth encoding and multi-objective EA	
	Sanches et al. [270]: multi-objective EA	
	Alves et al. [271,272]: Multi-population GA	
	Singh and Srivastava [273]: Hybrid multi-population PSO	
	Serraji et al. [274]: Multi-swarm PSO	
	Jena and Chauhan [275]: Multi-swarm co-operative PSO	
	Nawaz et al. [276]: Hybrid particle multi-swarm optimization	
Mathematical equation problems	Mera et al. [277]: Multi-population GA	Reference [281] demonstrates that the layered multi-population GP outperforms the other state-of-the-art methods for solving mathematical equation problems.
	Li et al. [278]: Entropy-based multi-population GA	
	Liu et al. [279]: Multi-population DE	
	Majd et al. [280]: Multi-population parallel imperialist competitive algorithm	
	Yeh and Lin [281]: Layered multi-population GP	
Other problems	Ndiritu [282]: Multi-population GA	Reference [298] demonstrates that Multi-population methods combining with new nature inspired optimization algorithms can result in good optimization performance. Meanwhile, reference [300] demonstrates that effective multi-population techniques combined with classical optimization algorithms can also obtain satisfying performance.
	Li et al. [283]: Improve multi-population GA	
	Goncalves and Resende [284]: Parallel multi-population biased random-key GA	
	Zheng et al. [285]: Multi-objective multi-population biased random-key GA	
	Xu et al. [286]: Multi-population cultural algorithm with adaptive diversity preservation	
	Zeng et al. [287]: Multi-population GA	
	Gao et al. [288]: Multi-population GA	
	Wu et al. [289]: Distributed multi-population GA	
	Wu and Tseng [290]: Adaptive multi-population DE	
	Liang et al. [291]: Dynamic multi-swarm PSO	
	Gong et al. [292]: Interactive GA with multi-population adaptive hierarchy	
	Brito and Rodriguez [293]: Multi-population GA	
	Karpouzos et al. [294]: Multi-population GA	
	LGuo and Szeto [295]: Multi-population GA	
	Lu et al. [296]: Multi-swarm PSO	
	Chen et al. [297]: Adaptive GA based on multi-population parallel EA	
	Liu et al. [298]: Multi-population fruit fly optimization algorithm	
	Zhang et al. [299]: Multi-population PSO	
	Yu et al. [300]: Multi-population coevolutionary GP	

frameworks that have not yet been experimented, or combinations of these frameworks have not yet been explored in any depth. These frameworks will also raise other new researches and opportunities.

Additional research is additional applications of multi-population methods. As we have seen from this review, the multi-population applications are very diverse. The applications of multi-population methods to complex optimization problems, including many-objective optimization, large-scale optimization, and their combinations, would be of great interest. Many more applications of multi-population methods integrating with nature-inspired optimization algorithms can emerge with wide applications.

Many of these open research questions are common across different fields of computer intelligence. The open questions in the research of multi-population methods are similar to those in the other areas of computer intelligence. Research which is first driven by practical problems, and which is then generalized to broad results and conclusions, has the greatest likelihood to make a strong impact on the field, and so this is the research approach that is recommended for future work in the area of multi-population methods.

4.2. Summary

This review has summarized the development of multi-population methods during the last 10 years. The review has shown some basic issues of multi-population methods, but these basic issues are always challenging and important for the development of multi-population methods. The review has also shown that multi-population methods can be practically applied to any optimization problem domain. Multi-population methods have been applied to multi-modal optimization, dynamic optimization, large-scale optimization, multi-objective optimization, combinatorial optimization, constrained optimization, and noisy optimization. Multi-population methods are simple, versatile, and flexible, and have proven to be efficient for solving a wide variety of real-world problems. The applications of multi-population methods include scheduling problems, path planning, network, parameter estimation and control, electrical engineering problems, mathematical equation problems and many others. Multi-population methods have proven to be useful to the optimization and engineering community, as well as to researchers who are currently working or will work in these areas.

Acknowledgment

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.swevo.2018.04.011.

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