Chapter 1

Introduction

1.1 Background

Optimization aims to make the most effective or functional use of resources. Mathematically speaking, optimization is the problem of finding the best feasible solution with respect to an objective function which is used to evaluate solutions for determining the best one. Most real-world optimization problems necessitate optimization of multiple, conflicting objectives, they are referred to as multi-objective optimization which is much more challenging but has extremely practical importance. We can find multi-objective optimization applications in every aspect of our real world, such as engineering, computer science, ecology, sociology, economics, agriculture, aviation, automotive, medicine, and so on.

Classically multi-objective optimization problems were handled by deterministic methods [77]. These methods have a limited scope and require functions to have certain properties, such as convexity or differentiability, and often computationally-intensive to find an exact solution. The more flexible metaheuristic approaches were introduced in some early work by Schaffer [92], Fonesca and Fleming [46], Srinivas and Deb [99], Horn et al. [59], Kursawe [70], etc. They were popularized by Deb's book "Multi-Objective Optimization using Evolutionary Algorithms" [22]. Among powerful metaheuristic techniques, evolutionary algorithms (EAs) have been used extensively and proven to be suited for solving complex optimization problems. Multi-objective evolutionary algorithm (MOEA) has already become the major approach to solve multi-objective optimization (MOO) problems.

The process of evolutionary computing is inspired by biological evolution. EA mimics evolutionary processes in nature, such as nature selection and variation (mutation, crossover). Candidate solutions are represented as chromosomes, for instance, integer vectors or real vectors, depending on the real world application. The steps of an EA can be described as follows: a set of solutions (population) is created usually randomly (initialization). In each iteration (generation), new solutions (offspring) are created by genetic operators: selecting top members by the quality (fitness) function as parents (mating selection); recombining portions of these parents to create offspring solutions (crossover); producing a small modification to offspring solutions (mutation). From the set of old and new solutions (parents and offspring), a new set of solutions (new generation) is chosen based on the quality function, where better solutions are preferred (survivor selection). With the iteration of this process (generational loop), the solutions become better and better, and approach optimal values closer and closer (evolution). Unlike single-objective optimization, when dealing with multiple conflicting objectives, the ranking mechanism of EA needs to be designed because it is no longer obvious which solutions are better or worse than others. Moreover, to present a wide variety of trade–off solutions, diversity maintenance in the population is required.

Due to the historical development, one distinguishes different methods of evolutionary computing to: genetic algorithms (GA), evolution strategies (ES), evolutionary programming (EP), and genetic programming (GP) [5]. The major technical difference between them is the preferred representation. For example, GAs work better at binary representation, ES concentrate on real-valued representation, EP focuses on finite state machines, and GP relies on tree structured representations in order to evolve mathematical expressions. Today, these representatives are converging and the distinction between them is getting vague. It was suggested by Bäck to unify these branches under the common term "evolutionary algorithms". Therefore, EAs will be used in this thesis as the general term.

This thesis focuses on the application of scheduling optimization which is a typical and important branch of optimization problem. Thinking of many tasks, such as production tasks, maintenance tasks or service tasks, how to allocate these tasks to the workers or machines, for example, when to perform a task and what is the execution sequence, is usually an NP-hard problem, especially when multiple objectives are pursued, like resource consumption, completion time, economic cost, etc. The features of scheduling optimization make it a meaningful and interesting research topic. This thesis discusses two types of scheduling problems: flexible job shop scheduling and dynamic prediction-based maintenance scheduling problem. The flexible job shop scheduling problem is one of the best known combinatorial optimization problems.

It is realistic for modeling a wide range of real-life applications because it captures key features of modern manufacturing and service systems. Dynamic prediction-based maintenance scheduling problem comes from a real world application that was studied in this PhD thesis. Its goal is to optimize the maintenance schedule based on the predicted life-span of components and the condition of available workshops. Especially, the process of optimizing the schedule needs to be performed in a rolling horizon fashion.

1.2 Research Questions

To thoroughly explore MOEA and apply them in the domain of scheduling optimization, the following research questions are investigated in this thesis.

RQ1 (Chapter 3) How can an MOEA be developed that generates uniformly distributed sets on the Pareto front regardless of the shape of the Pareto front?

Many MOEAs have been suggested in the literature since the first real implementation of an MOEA in 1984 [91]. But none of these algorithms is perfect and can behave well in all MOO problems. One special open challenge is to devise MOEA that are invariant to the shape of the Pareto front [40, 64]. In this thesis, we want to therefore study methods and techniques which can generate uniformly distributed sets on the Pareto front regardless of the shape of the Pareto front.

RQ2 (Chapters 3) How can the performance of MOEAs be improved generally?

MOEAs need to consider convergence and diversity properties of the obtained solution set. For this reason, most MOEAs have two design criteria: to find a solution set, the solutions of which are close to the Pareto front and also well-spread across the Pareto front. Although it can be non-trivial, we study whether there can be a method which can improve MOEA in general with respect to these design criteria as compared to existing EAs.

RQ3 (Chapter 4) Instead of the whole Pareto front, how can preferred solutions which are of real interest to the decision maker (DM) be obtained?

Over the past decade, the research on preference-based multi-objective optimization has been strongly motivated by real-world applications. In reality, the DM is often not interested in discovering the whole Pareto front, but rather in approximating the portion of the front that best matches his/her preferences.

Incorporating the preference information in MOEA allows the algorithm to focus on the part of the objective space, which is most interesting to the DM. The question arises of how the algorithms can adapt the search to focus on the interesting regions.

RQ4 (Chapter 5) How to solve multi-objective flexible job shop scheduling optimization problems?

Due to the NP-hard characteristic of flexible job shop scheduling problems, it is difficult to propose exact algorithms with satisfactory running time for them. Moreover, the consideration of multiple objectives further complicates the situation. However, research work on these problems is essential, and can be used as the foundation for solving our real-world scheduling optimization problems. This thesis seeks to design MOEAs to tackle these important combinatorial optimisation problems.

RQ5 (Chapter 5) How to represent and solve a real-world scheduling optimization problem in the EA world?

To solve a problem with an MOEA, the representation of the problem for evolutionary computation is an important step and defining a good representation can have a substantial impact on the performance of MOEAs. Solving an MOO problem involves the formulation of the real-world problem, the choice of the data structure used for representing solutions as the chromosomes and the genetic operators, and also many other problem specific issues.

RQ6 (Chapter 6) How to apply and adapt the developed algorithms to the dynamic prediction-based maintenance scheduling optimization problem?

In the process of generating the prediction-based maintenance schedule periodically, the time-varying characteristics, i.e., the dynamics of the optimization, are considered to find the optimal solutions at different moments. This should also lead to dynamic optimization.

1.3 Outline

This thesis is structured as follows. The content, corresponding research question(s) and publication(s) are introduced for each chapter.

Chapter 2 gives a brief introduction on optimization, multi-objective optimization, evolutionary computation. Especially, different order relations for multi-objective optimization have been discussed. The work presented in this chapter has been (partially) published in:

1) André Deutz, Michael Emmerich and Yali Wang. Many-Criteria Dominance Relations. In Dimo Brockhoff, Michael Emmerich, Boris Naujoks, and Robin Purshouse, editors, Many-Criteria Optimization and Decision Analysis, Springer, Natural Computing Series (2022). [33]

In Chapter 3, to answer RQ1 and RQ2, first, a diversity-indicator based multi-objective evolutionary algorithm is proposed. After that, the performance of the standard Pareto dominance relation is improved to enhance the behaviour of general multi-objective evolutionary algorithms [114]. The work presented in this chapter has been (partially) published in:

2) Yali Wang, Michael Emmerich, André Deutz, and Thomas Bäck. Diversity-indicator Based Multi-Objective Evolutionary Algorithm: DI-MOEA. In International Conference on Evolutionary Multi-Criterion Optimization, pages 346–358. Springer, 2019. [116].

3) Yali Wang, André Deutz, Thomas Bäck, and Michael Emmerich. Edge-Rotated Cone Orders in Multi-Objective Evolutionary Algorithms for Improved Convergence and Preference Articulation. In 2020 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 165-172. IEEE, 2020. [115].

4) Yali Wang, André Deutz, Thomas Bäck, and Michael Emmerich. Improving Many-Objective Evolutionary Algorithms by Means of Edge-rotated Cones. In International Conference on Parallel Problem Solving from Nature, pages 313–326. Springer, 2020. [114].

Chapter 4 extends the basic static multi-objective optimization to preference-based multi-objective optimization. The corresponding preference-based multi-objective evolutionary algorithms are proposed with the aim of answering RQ3 and have been published in:

5) Yali Wang, Longmei Li, Kaifeng Yang, and Michael Emmerich. A New Approach to Target Region Based Multiobjective Evolutionary Algorithms. In 2017 IEEE Congress on Evolutionary Computation (CEC), pages 1757–1764. IEEE, 2017. [117].

6) Longmei Li, Yali Wang, Heike Trautmann, Ning Jing, and Michael Emmerich. Multiobjective Evolutionary Algorithms Based on Target Region Preferences. Swarm and Evolutionary Computation, 40:196–215, 2018. [73].

7) Yali Wang, Steffen Limmer, Markus Olhofer, Michael Emmerich, and Thomas Bäck. Automatic Preference Based Multi-Objective Evolutionary Algorithm on Vehicle Fleet Maintenance Scheduling Optimization. Swarm and Evolutionary Computation, p.100933, 2021. [118].

In Chapter 5 the flexible job shop scheduling problem is introduced due to its practical importance. A multi-objective evolutionary approach is developed to address multi-objective flexible job shop scheduling problems with three considered objectives: minimizing makespan, total workload and critical workload [121], this answers RQ4. After the analysis of the multi-objective flexible job shop scheduling problem, the problem of vehicle fleet maintenance scheduling optimization is formulated for our real-world application. On the basis of this formulation, the representation and corresponding algorithm are developed to solve this multi-objective optimization problem [119], this answers RQ5. The work presented in this chapter has been (partially) published in:

8) Yali Wang, Steffen Limmer, Markus Olhofer, Michael Emmerich, and Thomas Bäck. Vehicle Fleet Maintenance Scheduling Optimization by Multi-Objective Evolutionary Algorithms. In 2019 IEEE Congress on Evolutionary Computation (CEC), pages 442–449. IEEE, 2019. [119].

9) Yali Wang, Bas van Stein, Thomas Bäck, and Michael Emmerich. Improving NSGA-III for Flexible Job Shop Scheduling Using Automatic Configuration, Smart Initialization and Local Search. In Proceedings of the 2020 Genetic and Evolutionary Computation Conference Companion, pages 181–182, 2020. [121].

10) Yali Wang, Bas van Stein, Thomas Bäck, and Michael Emmerich. A Tailored NSGA-III for Multi-Objective Flexible Job Shop Scheduling. In 2020 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 2746-2753, IEEE, 2020. [122].

Chapter 6 gives attention to RQ6, it looks at the performance of proposed (preference-based) multi-objective evolutionary algorithms on our real-world vehicle fleet maintenance scheduling optimization problem. Especially, to apply the dynamic algorithm on this application problem, the scenario of a taxi fleet is simulated, the maintenance schedule is based on the prediction of remaining useful life (RUL) of components in each car. The dynamic algorithm is used to update the maintenance schedule of the vehicles based on the predicted RUL which keeps changing with the execution of driving tasks. Moreover, an empirical comparison of different maintenance strategies is presented. The work presented in this chapter has been (partially) published in:

11) Yali Wang, Steffen Limmer, Duc Van Nguyen, Markus Olhofer, Thomas Bäck and Michael Emmerich. Optimizing the Maintenance Schedule for A Vehicle Fleet: A Simulation-based Case Study. Engineering optimization, pp. 1-14. 2021. [120].

Chapter 7 concludes the thesis and closes with a discussion of future work.