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Editorial

"Algorithms in Multi-Objective Optimization": Foreword by the Guest Editor

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Many real-world optimization problems typically involve multiple (conflicting) objectives. In such problems, the aim is to find the set of non-dominated (Pareto-optimal) solutions, producing different image vectors that are indifferent to each other when no other selection criterion is available [1]. Determining the whole set of Pareto-optimal solutions, as well as its image, i.e., the Pareto-front, is a difficult problem even though objectives and constraints are linear. Some algorithms (e.g., the Weighting method and the ε-Constraints method), in the attempt to (fully or partially), accomplish this task, rely on iteratively solving proper single-objective mathematical formulations derived from the original problem, each one returning a non-dominated solution, possibly requiring a large computing time when such a single-objective problem is NP-hard. Other solution approaches, such as Evolutionary Algorithms, due to their inherent parallelism, have the potential of finding multiple Pareto-optimal solutions in a single run. Other classes of algorithms (e.g., the Utility Function method, Lexicographic method, and Goal Programming), even more differently, try to overcome the burden hidden behind finding the Pareto-front by reducing the multi-objective problem into a unique single-objective problem, assuming the knowledge of additional information, e.g., a utility value for each solution or a ranking among the objectives.

This Special Issue aimed to collect original manuscripts dealing with algorithms and applications in a Multi-Objective Optimization (MOO) environment. Four papers have been collected, each one touching an important field of application of MOO, as reported in the following paragraphs.

Production planning and scheduling are among the most studied applications when it comes to multi-objective optimization, as witnessed, e.g., by the recent survey by Ojstersek et al. [2]. Related to this field of research is the first paper of this Special Issue, "A Multi-Objective Model and Algorithms of Aggregate Production Planning of Multi-Product with Early and Late Delivery" by Liu and Yang [3]. Here, the authors dealt with production planning and tackled a scenario where, due to the influence of insufficient production capacity or a shortage of production materials, production enterprises may produce products in advance or on backorder. To improve the adaptability of enterprises and reduce production costs, the authors analyzed the impacts of early delivery and delayed delivery and proposed a method to determine the loss threshold. Moreover, the maximum allowable shortage of customers with different tardiness is calculated, and the cost of delayed delivery and loss of sales is determined. Considering the production cost, raw material cost, inventory cost, staff cost, stockout, and lost sales cost, an early/delay multi-objective optimization model is developed for an aggregate production planning problem to minimize total production costs and instability in the workforce. Three algorithms and three different hybrid strategies were designed and tested to solve the model.

Another important field of application of multi-objective optimization is cloud computing. As per the forecast report by Moore [4], Gartner predicted that 41% of global IT spending will shift from traditional services to public cloud services in 2022. By 2025, this percentage will increase to 51%. In the booming cloud market, cloud providers are

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facing the challenge of optimizing both the cost and performance of cloud services. Cloud service brokering plays an important role in finding suitable cloud services for application providers to deploy their applications in cloud data centers [5]. As the number of cloud services from multi-cloud providers grows, the selection of proper cloud services to optimize multiple, potentially conflicting, objectives simultaneously is an issue. In the second paper of this Special Issue, titled "Classification and Merging Techniques to Reduce Brokerage Using Multi-Objective Optimization" by Kengegowda et al. [6], the authors analyzed cloud computing with effective resource utilization and cost optimization. To overcome the high resource cost, the authors proposed a new model called Classification and Merging Techniques for Reducing Brokerage Cost (CMRBC) designed for effective resource utilization and cost optimization in the cloud. CMRBC appears to have two benefits. Firstly, it is a cost-effective solution for service providers and customers. Secondly, for every job, Virtual Machine (VM) creations are avoided to reduce brokerage. The allocation, creation, or selection of resources of VM is carried out by the broker. The main objectives considered are to maximize resource utilization and minimize brokerage in cloud computing by using MOO. Likewise, CMRBC implements efficient resource allocation to reduce the usage cost of resources, as demonstrated in the experimental campaign carried out by the authors.

Credit scoring is an important tool for banks and financial institutions to measure credit risk. It consists of a statistical analysis performed by lenders and financial institutions to determine the creditworthiness of a person or a company. Typically, these problems are tackled with Linear Discriminant Analysis (LDA), which, according to the score of each credit applicant, categorizes these applicants by a cutoff and is a comprehensible and robust method in the credit scoring domain. However, enhancing credit scoring models based on LDA is an important research target, as observed in, e.g., Guo et al. [7], placing particular emphasis on improving the sensitivity of the classifier by using multi-objective optimization.

The third paper of the Special Issue titled "Comparison of Profit-Based Multi-Objective Approaches for Feature Selection in Credit Scoring" by Simumba et al. [8] concentrates its focus exactly on the latter topic and in particular on feature selection, which is crucial to credit-scoring process, allowing for the removal of irrelevant variables with low predictive power. Indeed, conventional credit-scoring techniques treat this as a separate process wherein features are selected based on improving a single statistical measure, such as accuracy; however, recent research has focused on meaningful business parameters such as profit. More than one factor may be important to the selection process, making multi-objective optimization methods relevant in attaining such a goal. However, the comparative performance of multi-objective methods has been known to vary depending on the test problem and specific implementation. This research employed a recent hybrid non-dominated sorting binary Grasshopper Optimization Algorithm and compared its performance on multi-objective feature selection for credit scoring to that of two popular benchmark algorithms in this space. Further comparison is made to determine the impact of changing the profit-maximizing base classifiers on algorithm performance. The experimental campaign carried out by the authors demonstrated that the neural network classifier improved the profit-based measure and minimized the mean number of features in the population the most. Additionally, the authors' algorithm gave relatively smaller hypervolumes and increased computational time across all base classifiers, while giving the highest mean objective values for the solutions.

The last application considered in this Special Issue is related to the COVID-19 pandemic outbreak. Pandemic influenza has been an important public health concern, with several historical outbreaks. During an influenza pandemic, hospitals are often overwhelmed by the surging demand from influenza patients, and therefore, it is important to react preparing ffective response plans. Multi-objective optimization approaches have been used to cope with such problems; to cite just one, the reader is referred to Sun et al. [9]. In the fourth paper of this Special Issue titled "A Multi-Objective Optimization Method for Hospital Admission Problem—A Case Study on COVID-19 Patients" by AbdelAziz et al. [10], the authors considered the effects of the spreading of COVID-19, which has infected a huge number of patients simultaneously. This resulted in a massive number of requests for medical care, all at the same time. During the first wave of COVID-19, many people were not able to be admitted to proper hospitals because of the immense number of patients, and it is clear how admitting patients to suitable hospitals can decrease the in-bed time of patients, which can lead to saving many lives. In addition, optimizing the admission process can minimize the waiting time for medical care, which can save the lives of severe cases as well. The admission process needs to consider two main criteria: the admission time and the readiness of the hospital that will accept the patients. With these two objectives, the admission problem has been converted into a MOO. A Pareto Optimization (PO)-based algorithm was proposed to deal with admitting COVID-19 patients to hospitals. The method uses PO to choose the most suitable hospital for the patient with the least admission time. The method also considers patients with severe cases by admitting them to hospitals with the least admission time regardless of their readiness. The method has been tested over a real-life dataset of patients from King Faisal hospital in Saudi Arabia and was compared with the lexicographic multi-objective optimization method regarding admission time and accuracy.

In conclusion, we hope that the approaches presented and the applications dealt with in this Special Issue will be found interesting, constructive, and appreciated by the international scientific community. It is also expected that they will inspire further contributions on these topics, which certainly deserve further investigation.

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