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Confidence measure: A novel metric for robust meta-heuristic optimisation algorithms

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ABSTRACT

In meta-heuristic optimisation, the robustness of a particular solution can be confirmed by re-sampling, which is reliable but computationally expensive, or by reusing neighbourhood solutions, which is cheap but unreliable. This work proposes a novel metric called the confidence measure to increase the reliability of the latter method, defines new confidence-based operators for robust meta-heuristics, and establishes a new robust optimisation approach called confidence-based robust optimisation. The confidence metric and five confidence-based operators are proposed and employed to design two new meta-heuristics: confidence-based robust Particle Swarm Optimisation and confidence-based robust Genetic Algorithm. A set of fifteen robust benchmark problems is employed to investigate the efficiencies of the proposed algorithms. The results show that the proposed metric is able to calculate the confidence level of solutions effectively during the optimisation process. In addition, the results demonstrate that the proposed operators can be employed to design a confident robust optimisation process and are readily applicable to different meta-heuristics.

1. Introduction

Meta-heuristics have become the most popular optimisation techniques over the last decade. The main reasons for this are their simplicity, flexibility, inexpensive computational cost, and derivation-free mechanism. In addition to the huge number of theoretical studies, the application of meta-heuristics have been investigated in a wide range of real problems. Despite the merits of meta-heuristics in solving real problems, the three critical issues of multi-objectivity, constraint, and uncertainty must be considered during the optimisation process.

Real-world, challenging problems mostly have multiple objectives. Optimisation in a multi-objective search space is quite different and challenging compared to a single-objective search space. In a single-objective problem, there is only one objective function to be optimised and only one global solution to be found. However, in multi-objective problems there is no longer a single solution for the problem, and a set of solutions representing the trade-offs between the multiple objectives, the Pareto optimal set, must be found.

In real applications optimisation problems are usually restricted by a set of constraints. The constraints can take the form of equality and inequality criteria. The final optimum solutions must satisfy all the constraints to be acceptable. Constraints

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can be considered as dividing the search space into feasible and infeasible regions. An optimisation algorithm should be equipped with suitable mechanisms to avoid infeasible regions and discover promising feasible areas of the search space.

The last issue is uncertainty, in which different components of a system may face perturbations. The resulting uncertainties make the optimisation process very challenging since they change the search space unpredictably. An optimisation technique should be able to handle different types of uncertainties in order to find reliably optimal solutions for a particular problem. An optimisation process considering possible uncertainties, mostly in design parameters and operating conditions, is called robust optimisation, in which the solutions with the least variability are preferable.

These issues have been studied in the field of meta-heuristics over the last decade. Different methods of handling multiple objective meta-heuristics have been proposed. For instance, Genetic algorithm (GA) [20] and Particle Swarm Optimisation algorithm (PSO) [22] were extended to multi-objective algorithms by Deb et al. (NSGA-II) [15] and Coello Coello et al. (MOPSO) [9], respectively. Different constraint handling mechanisms also have been integrated with these algorithms, as discussed in [11,16,10]. For robust optimisation, there are also some studies that consider uncertainties during the optimisation process utilising PSO [17], GA [28], MOPSO [25], and NSGA-II [14].

However, robust optimisation has unfortunately received much less attention compared to the other issues. This might be due to the novelty of this area in meta-heuristics and its complexity. This is the motivation of this work, in which we identify and attempt to fill a current substantial gap in the literature. A novel metric called the Confidence (C) measure is proposed to calculate the confidence placed on estimates of robustness of solutions and drive a computationally inexpensive, confidence-based, robust optimisation process.

The remainder of the paper is organised as follows: Section 2 provides a comprehensive literature review and identifies the current gap in robust optimisation. The Confidence measure, confidence-based operators, and Confidence-based Robust Optimisation (CRO) are then proposed in Section 3. The results and discussion are provided in 4. Finally Section 5 concludes the work and suggests some directions for future studies.

2. Related works – robust optimisation

2.1. Key concepts and types of uncertainty

In 2005 Yaochu and Branke provided a comprehensive survey of evolutionary optimisation in uncertain environments and relevant techniques to address them [30]. Another survey with the same purpose was performed by Beyer and Sendhoff in 2007 [3]. According to these studies, the uncertainties have been divided into three main categories:

1. **Type A:** this uncertainty occurs in the environmental and operating conditions. Perturbation in speed, temperature, moisture, angle of attack in airfoil design, and speed of the vehicle in propeller design are some examples of this type of uncertainty.
2. **Type B:** in this case the parameters may be changed after determining the optimal solution(s). One of the major sources of this kind of uncertainty is manufacturing tolerance.
3. **Type C:** in this case the system itself produces noisy outputs. It might be due to sensory measurement errors or randomised simulations. Simulators which approximate outputs of systems generate this type of uncertainty as well. This also may happen when the evaluation of a fitness function is so expensive or an analytical fitness function is not available *e.g.* in Computational Fluid Dynamics (CFD). The main difference between this type of uncertainty and type A is that the error is deterministic. Time-varying (dynamic) systems are also considered as having type C uncertainty.

Fig. 1 shows where these three types of uncertainties happen during and after optimisation. Type A and B uncertainties are the most important types in optimising real-world problems, which is the focus of this work. Fig. 2 illustrates an example of type B uncertainty.

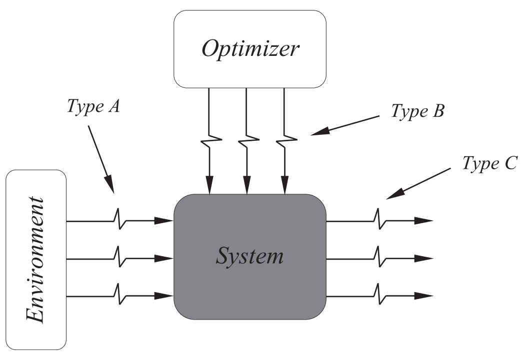

Fig. 1. Different types of uncertainties: (A) environmental and operating conditions, (B) parameters, (C) output.