Towards a description of correlations between heuristic parameters for a scheduling problem

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1 Introduction

In Operations Research (OR), heuristics generally rely on some parameters that need to be specified in advance. Their values are crucial as they significantly affect the algorithm's performance. In practice, these values are typically determined empirically and manually. This process is time-consuming and most of the time does not guarantee the best choice of parameters, but rather enables finding a "suitable" set of parameters. The process is complicated by the fact that there isn't a single ideal set of parameters for the algorithm: rather, it varies depending on the instance that is used [1].

Parameter tuning typically involves four essential components: the target algorithm A, which addresses the operational research (OR) problem; the configuration space C; the parameter tuning algorithm, which explores the configuration space to identify the optimal configuration c^*; and the performance metric m, which helps guide the search. This method aims to independently determine the optimal parameter values to maximise the algorithm's performance [2].

Although automated tuning is widely used in Artificial Intelligence (AI) and machine learning (ML), its adoption in Operations Research (OR) is still at an early stage. A number of recent studies have shown growing interest in parameter tuning and parameter control, whether dynamic or static [1], yet the practice remains relatively uncommon compared with the AI community. Our work addresses this gap and proposes an approach to automatically determine an efficient set of parameter values in a static manner. We also investigate how the different parameters are correlated and how they influence the efficiency of the algorithm.

For our experiments, we focus on a two-machine flowshop scheduling problem and on a classical ant colony optimisation (ACO) algorithm that solves it [3]. This algorithm includes three parameters: the number of ants, the number of iterations, and the evaporation coefficient.

In the original publication, the authors propose a set of parameters that yields an efficient heuristic with respect to the literature. More precisely, it is suggested to consider an evaporation coefficient of 0.9, 20 ants, and 100 iterations. In the remainder, we first show that by means of Bayesian optimisation, we can derive parameter values that depend on the instance size and lead to a better configuration. Next, we investigate the links and correlations between some of these parameters.

2 Bayesian optimisation for ACO tuning

A popular approach for global black box function optimisation is Bayesian optimisation, which is model-based, iterative, and primarily utilised in machine learning, but rarely used in OR. This approach relies on two important components :

- A surrogate model: a Gaussian process approximating the performance of a configuration;
- An acquisition Function: The predictive distribution of the surrogate model is used to assess the benefit of evaluating a new point.

We apply this method to tune two parameters of the ACO algorithm: the number of iterations (Nb_{iter}) and the number of ants (Nb_{ants}).The evaporation coefficient is fixed at 0.9, following consistent evidence in the literature that this value performs well [3].

Regarding Bayesian optimisation, we first need to define the function f for which the maximum must be found. It's the equivalent of the performance metric (m) specified in the parameter tuning definition. This function takes as input the parameters to learn and returns the expected average gain with respect to the default parameters proposed in the literature. More precisely, let us denote by $\sum_j C_j^A(I)$ (resp. $\sum_j C_j^{bA}(I)$) the value of the objective function computed by the ACO heuristic with the default values (resp. with parameter values γ).

On a given instance I of the scheduling problem, we have:

$$f(\gamma) = \sum_{I \in B_{learn}} \frac{\sum_j C_j^A(I) - \sum_j C_j^{bA}(I)}{\sum_j C_j^A} \tag{1}$$

With B_{learn} a learning database containing a representative set of randomly generated instances of the scheduling problem.

We formulate the hypothesis that the parameters are linearly dependent on the size of the instances n. So, instead of tuning directly the parameters $Nbants$ and Nb_{iter}, we consider the learning model: $Nb_{ants} = \alpha_1 \times n + \alpha_2$ and $Nb_{iter} = \beta_1 \times n + \beta_2$. Thus, Bayesian optimisation searches for "optimal" coefficients $\alpha_1, \alpha_2, \beta_1, \beta_2$.

Our tests show that Bayesian Optimisation enables us to find a set of coefficients $\alpha_1, \alpha_2, \beta_1$ and β_2 such that the corresponding ACO outperforms the version with state-of-the-art parameters. These results show that a relationship between the instance size and the parameters exists and can be exploited to improve the algorithm's performance.

3 Perspectives

This work shows that Bayesian optimisation can already be used to outperform manual-based tuning and is a first step towards automated configuration in Operations Research. However, it remains limited because it treats the configuration as independent parameters and does not model dependencies between the parameters or the instance features.

The goal is more to identify such correlations and build predictive models capable of recommending parameter values tailored to each problem instance. We will present the first elements at the time of the conference.

References

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