Challenges and Opportunities in Dynamic Optimisation

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ABSTRACT

Dynamic optimisation has been studied for many years within the evolutionary computation community. Many strategies have been proposed to tackle the challenge, e.g., memory schemes, multiple populations, random immigrants, restart schemes, etc. This talk will first review a few of such strategies in dealing with dynamic optimisation. Then some less researched areas are discussed, including dynamic constrained optimisation, dynamic combinatorial optimisation, time-linkage problems, and theoretical analyses in dynamic optimisation. A couple of theoretical results, which were rather unexpected at the first sight, will be mentioned. Finally, a few future research directions are highlighted. In particular, potential links between dynamic optimisation and online learning are pointed out as an interesting and promising research direction in combining evolutionary computation with machine learning.

Categories and Subject Descriptors

I.2 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search; I.2.8 [**Problem Solving, Control Methods, and Search**]: Heuristic methods

General Terms

Algorithms

Keywords

Evolutionary dynamic optimization, dynamic constraints, online learning, evolutionary algorithms

1. DYNAMIC OPTIMISATION

Dynamic optimisation has been a topic of research for a long time in different fields. In evolutionary computation, it can be traced back to some early pioneering work [5, 8]. It is now often studied under a broader umbrella — optimisation under uncertainty [10], and even grown into the domain of software engineering (see Mark Harman's keynote talk at GECCO 2013).

Many solution methods [4, 16] have been proposed to tackle some of the above challenges, such as memory schemes, multiple populations, random immigrants, restart schemes, prediction, etc.

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2. CHALLENGES

In spite of a large body of research papers and books in dynamic optimisation, some topic areas seem to be less well studied. We will mention just a few here.

2.1 Dynamic Constrained Optimisation

Constraints are ubiquitous in the real world. However, the research in dynamic constraints has been few [14]. This is an interesting research topic because some implicit assumption made under static constraints may not hold any more. For example, given a dynamic optimisation problem with static constraints, one often assume that the solution quality will deteriorate when a change occurs. However, this does not have to be the case with dynamic constraints, because an infeasible solution with a high fitness value may become feasible after a change. In such a case, the solution quality will actually be higher, rather than lower, after a change. Dynamic changes in constraints can have a dramatic impact on the shape and structure of the feasible solution space. As argued in [14], new algorithms need to be specifically designed to deal with dynamic constrained optimisation problems.

2.2 Robust Optimisation Over Time (ROOT)

Adaptation to dynamic environments has usually been regarded as good and is the goal that has been pursued by researchers in dynamic optimisation. However, adaptation has cost. For example, in route optimisation of gritting trucks [9], every change of the optimised routes implies that the drivers have to get used to the new routes, which increases the inconvenience and the chance of mistakes. Such costs should be taken into consideration in our research. In fact, one does not have to adapt to a change if the solution quality is still very good, e.g., above certain threshold, after the change. An interesting challenge here is how to find a robust solution over time (ROOT) [17, 6, 7], which can be used with its performance above certain threshold for longest possible time. It adapts to a change only when the solution quality is expected to drop below a threshold. There are numerous unanswered questions related to this new challenge, including an appropriate mathematical definition of the problem.

2.3 Dynamic Optimisation and Online Learning

Dealing with a dynamic and uncertain environment is not a unique challenge to evolutionary computation, or optimisation in general. There are active research activities within the machine learning community that try to tackle similar challenges. There are striking similarities between the challenges faced by dynamic optimisation and online learning researchers. There is an excellent opportunity for cross-fertilisation.

When characterising dynamics, both communities focus on the frequency, severity and periodicity of the changes. Both communities design their change detection methods. Both communities used diversity as a means to adapt to changes quickly and to minimise the performance degradation due to changes [12, 11]. Both communities are developing prediction methods to anticipate and adapt to changes more promptly. While most work in dynamic optimisation so far has been based on heuristics, online learning community has mostly treated a dynamic environment as a data stream or time-series, which is well-suited to model the dynamic lankage problem in dynamic optimisation [13].

2.4 Theoretical Foundations

Theoretical analysis of evolutionary algorithms for static optimisation problems is challenging. It is even more so for any theoretical analysis of dynamic optimisation problems. However, efforts have been made since early 2000s [3, 1]. More recently, further insight has been gained into the difficulty of solving dynamic optimisation problems. More specifically, rigorously analyses have been carried out to understand how the magnitude and frequency of changes may affect the expected runtime of an evolutionary algorithm [15]. Some counter-intuitive examples were shown, where the expected runtime of an evolutionary algorithm to relocate the dynamic optimum is no more than a polynomial if the magnitude of change is large, but is at least exponential is the magnitude of change is small. Similarly, one could prove that the expected runtime of an evolutionary algorithm to relocate the dynamic optimum is no more than a polynomial if the frequency of change is high, but is at least exponential is the frequency of change is low.

Self-adaptive mutation and time-varying mutation have often been used in dynamic optimisation to create and maintain population diversity. However, it was shown rigorously that for certain dynamic optimisation problems, no self-adaptive and time-varying mutation can do better than simple static mutation [2].

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