G Model
ASOC-3895; No. of Pages 15
ARTICLE IN PRESS
Applied Soft Computing xxx (2016) xxx–xxx
Contents lists available at ScienceDirect
Applied Soft Computing
journal homepage: www.elsevier.com/locate/asoc

Solving online dynamic time-linkage problems under unreliable prediction

Chenyang Bu[a], Wenjian Luo[a,*], Tao Zhu[b], Lihua Yue[a]

[a] Anhui Province Key Laboratory of Software Engineering in Computing and Communication, School of Computer Science and Technology, University of Science and Technology of China, Hefei 230027, Anhui, China
[b] School of Computer & Communication Engineering, University of Science & Technology, Beijing, China

ARTICLE INFO

Article history:
Received 1 October 2015
Received in revised form 26 October 2016
Accepted 3 November 2016
Available online xxx

Keywords:
Evolutionary dynamic optimization
Time-linkage
Unreliable prediction
Stochastic ranking

ABSTRACT

Dynamic time-linkage optimization problems (DTPs) are a special class of dynamic optimization problems (DOPs) with the feature of time-linkage. Time-linkage means that the decisions taken now could influence the problem states in future. Although DTPs are common in practice, attention from the field of evolutionary optimization is little. To date, the prediction method is the major approach to solve DTPs in the field of evolutionary optimization. However, in existing studies, the method of how to deal with the situation where the prediction is unreliable has not been studied yet for the complete Black-Box Optimization (BBO) case. In this paper, the prediction approach EA + predictor, proposed by Bosman, is improved to handle such situation. A stochastic-ranking selection scheme based on the prediction accuracy is designed to improve EA + predictor under unreliable prediction, where the prediction accuracy is based on the rank of the individuals but not the fitness. Experimental results show that, compared with the original prediction approach, the performance of the improved algorithm is competitive.

1. Introduction

There is an important problem feature that few papers in the field of evolutionary dynamic optimization (EDO) [1–3] have covered, which is named time-linkage by Bosman [4,5]. Time-linkage refers to that any solution chosen by the problem solver could influence how the problem would be in the future [6].

The feature of time-linkage widely exists in real-world applications [7–10]. Nguyen has shown that most of the surveyed real-world dynamic optimization applications have the property of time-linkage (see Figs. 3.9–3.10 in [11]). A typical example is the dynamic vehicle routing problem [9,10]. The problem is to plan the routes for a fleet of vehicles to transport loads, where the locations of the loads are announced over time [10]. The dynamic vehicle routing problem is a DTP, because any decision of the current route would influence the future states of the vehicles, e.g., the future locations and the remaining capacity of the vehicles.

Although time-linkage is widespread in practice, it has not drawn much attention yet, especially in the field of EDO. An example is the inventory management (IM) problem [7]. In [7], Bosman has pointed out that IM is a DTP, because whether a customer is satisfied or not, when he requests goods, influences his future behavior. A high level of satisfaction could bring about future profits to the vendor. However, this feature has not been taken into consideration in most of related literature.

To address online DTPs, Bosman pointed out that the feature of time-linkage requires the problem solver, while evaluating a solution, to take its future influence into account instead of acting myopically [4], and the method of "optimizing both the present and the future" is suggested to solve DTPs, instead of the traditional method of "optimizing only the present" (illustrated in Section 2.2). A prediction approach [4], called EA + predictor, has been proposed, where the decision is made based on both the current fitness and the predicted fitness of the future.

The major problem of the Bosman's approach is that it does not take into consideration the situation where the prediction is unreliable. However, in practice, this situation is common, because the form of the real optimization problems are usually completely unknown or partially known at most. Based on the collected data, it could be very difficult to learn a function that gives a globally correct approximation of the actual future. The optima of the predicted function could be far from the optimum of the real function (see the example given in Fig. 1). In this case, it is very likely

* Corresponding author.
E-mail addresses: bucy1991@mail.ustc.edu.cn (C. Bu), wjluo@ustc.edu.cn (W. Luo), tzhu@ustb.edu.cn (T. Zhu), llyue@ustc.edu.cn (L. Yue).

http://dx.doi.org/10.1016/j.asoc.2016.11.005
1568-4946/

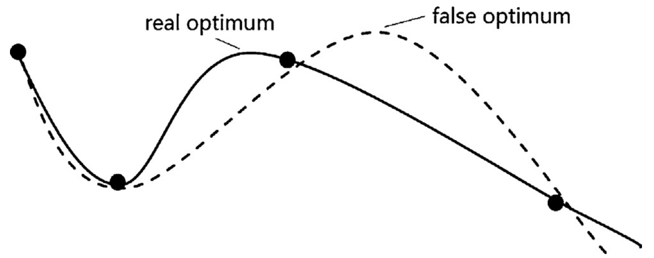

Fig. 1. An example of false optimum. The solid line represents the real function, and the dashed line represents a predicted function based on the collected data (the black dots).

that the evolutionary algorithm would be misled to converge to a false optimum. If we make decisions based on such an unreliable predicted function, the consequent performance could be even worse than that without prediction (see the example given in [6]). Therefore, it is not commendable to make decisions based on the predicted function alone regardless of whether the predictor is reliable.

In this paper, we focus on improving the Bosman's approach (i.e., EA + predictor) under unreliable prediction for the complete Black-Box Optimization (BBO) case, i.e., no prior knowledge about the problem is provided. The improved algorithm is named EASR + predictor. A stochastic-ranking selection scheme based on the prediction accuracy is designed to improve EA + predictor under unreliable prediction, where the prediction accuracy is based on the rank of the individuals but not the fitness. The experimental results show that, compared with the original prediction approach, the performance of the improved algorithm is competitive.

The remainder of this paper is structured as follows. Section 2 introduces the backgrounds of dynamic time-linkage optimization. Related methods are introduced in Section 3. Section 4 describes the motivation and the details of the improved method. The experimental results are provided in Section 5. Finally, the last section concludes this paper.

2. Backgrounds

2.1. Online dynamic time-linkage optimization

If a dynamic optimization problem (DOP) contains the feature of time-linkage, it is a dynamic time-linkage optimization problem (DTP). Time-linkage is defined as that "...there exists at least one time $0 \le t \le t^{end}$ for which the dynamic optimization value at time t is dependent on at least one earlier solution..." [4,5].

DTPs have been distinguished from common DOPs from the perspective of the two types of influence, i.e., **system influence** and **control influence** [4,5]. System influence is the "inherent reason" that leads to the optimization problem changing over time, regardless of which choices have been made. Control influence, however, refers to that the choices made in the past could lead to the response of the dynamic system.

The form of DTPs is given as follows [4,5]:

$$\text{Maximize} \int_0^{t^{end}} f_{\gamma(t,Z(t,x))}(t, x(t))\mathrm{d}t \tag{1}$$

where $Z(t, x)$ contains the decisions made before time t, and $\gamma(t, Z(t, x))$ is the set of parameters, determining the current form of the dynamic optimization function f.

Different from the common DOPs, at the current time t^{now}, the set of parameters of the current objective function (i.e., $\gamma(t, Z(t, x))$) may depend not only on the current time, but also on the previous decisions, i.e., $Z(t, x)$.

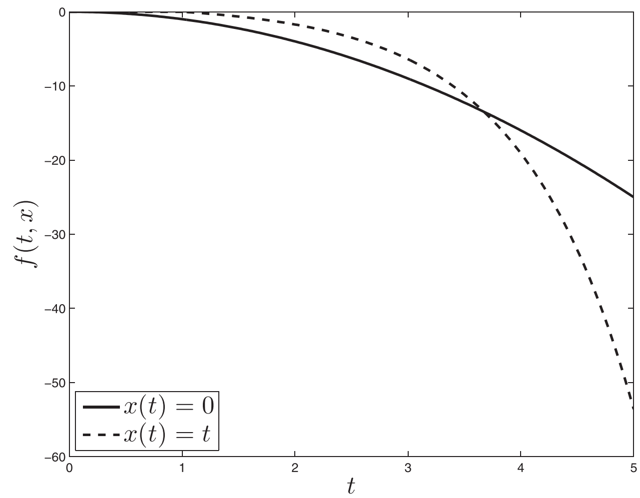

Fig. 2. The optimization value trajectories of $f(t, x)$, reproduced from [4], where $l = 1$ and $\psi(|x(t-1)_i|) = e^{x(t-1)_i} - 1$.

DTPs should be solved online in most real-world applications, i.e., making decisions continuously as time goes by. For the complete Black-Box Optimization (BBO) problems, additional information could only be gained by evaluating the fitness of solutions at current time, while the fitness in the future can not be evaluated.

2.2. Challenges of online DTPs

The characteristic of time-linkage makes that the traditional method of "optimizing only the present" may not suitable to solve DTPs [4,5]. "Optimizing only the present" means the often-used method to optimize the current form of the dynamic optimization function continuously [4]. The reason of the ineffectiveness of the traditional method in solving DTPs is illustrated by the following example proposed in [4].

The form of the DTP is given as follows:

$$f(t, x(t)) = \begin{cases} -\displaystyle\sum_{i=0}^{l-1} (x(t)_i - t)^2 & \text{if } \ 0 \le t < 1 \\ -\displaystyle\sum_{i=0}^{l-1} ((x(t)_i - t)^2 + \psi(|x(t-1)_i|)) & \text{otherwise} \end{cases} \tag{2}$$

where $x(t)$ is the decision made at time t, and l is the dimension. The problem is a DTP because the decision made at time $(t-1)$ influences the function value of time t when t is larger than one.

For any t, $f(t, x(t))$ is just a hyper-parabola with a unique optimum for $x(t)_i = t$. The decision of $x(t)$ brings a penalty of $\psi(|x(t-1)|)$ to the value of $f(t+1, x(t+1))$. Fig. 2, reproduced from [4], shows that the optimization value trajectory of $f(t, x)$ when the present is always optimally optimized (i.e., $x(t)_i = t$), is worse than the trajectory when $x(t)_i$ is simply set to zero.

It is the construction of $\psi(|x(t-1)_i|)$, which contains time-linkage, that deceives the method of "optimizing only the present". As the characteristic of time-linkage is not taken into account, the method of "optimizing the present" reduces the overall performance even though the decision made at each time step is the optimum for each present. And even worse, the overall performance could be reduced at an arbitrary rate, dependent on the form of $\psi(\cdot)$ [4].

Please cite this article in press as: C. Bu, et al., Solving online dynamic time-linkage problems under unreliable prediction, Appl. Soft Comput. J. (2016), http://dx.doi.org/10.1016/j.asoc.2016.11.005