Perspectives in Dynamic Optimization Evolutionary Algorithm

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Abstract. Dynamic Optimization Evolutionary Algorithm(DOEA) is an intrinsic development of traditional Evolutionary Algorithm. Different to the traditional Evolutionary Algorithm which is designed for stationary or static optimization functions, it can be used to solve some dynamic optimization problems. The traditional Evolutionary Algorithm is hard to escape from the old optimum after the convergence when dealing with dynamic optimization problems, therefore, it is necessary to develop new algorithms. After reviewing the relative works, three directions are proposed: first,by treating the time variable as a common variable, DOPs can be extended as a kind of special Multi-objective Optimization Problems, therefore, Multi-objective Optimization Evolutionary Algorithm would be useful to develop DOEAs; second, it would be very important to theoretically analyze Dynamic Optimization Evolutionary Algorithm; finally, DOEA can be applied into more fields, such as industrial control etc..

Keywords: Evolutionary Algorithm, Dynamic Optimization, Multi-objective Optimization.

1 Introduction

Since 1960s, the researches on Evolutionary Algorithms(EAs) have been greatly promoted. The most important application of EAs certainly is optimization. In many circumstances, the optimization problems can be represented as the minimization of functions, and the minimum values is irrelative to time, that is, they would not vary with the elapsing time variable. But with the intrinsic development of EAs, the researchers are paying more and more attention to Dynamic Optimization Problem(DOP), or say, Non-stationary Optimization Problem, and develop Dynamic Optimization Evolutionary Algorithms (DOEAs) to deal with this kind of problems.

Dynamic Optimization Problems come from the industry, actually, many control problems can be transferred into DOPs. But in general, the researchers did not achieve a consensus on the definition and the taxonomy of DOPs, since "Dynamic" is too complex and complicated.

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Formally, DOP can be depicted as equation 1.

$$
\begin{aligned}
&\min f(\boldsymbol{x},t) = \begin{cases} \min f_1(\boldsymbol{x},t) & \mathrm{t_1}< \mathrm{t} \leq \mathrm{t_2} \\ \min f_2(\boldsymbol{x},t) & \mathrm{t_2}< \mathrm{t} \leq \mathrm{t_3} \\ \dots & \\ \min f_n(\boldsymbol{x},t) & \mathrm{t_n}< \mathrm{t} \leq \mathrm{t_{n+1}} \end{cases} \\
&s.t. g(\boldsymbol{x},t) \leq 0 \\
&g(\boldsymbol{x},t) = \begin{cases} g_1(\boldsymbol{x},t) & \mathrm{t_1}< \mathrm{t} \leq \mathrm{t_2} \\ g_2(\boldsymbol{x},t) & \mathrm{t_2}< \mathrm{t} \leq \mathrm{t_3} \\ \dots & \\ g_n(\boldsymbol{x},t) & \mathrm{t_n}< \mathrm{t} \leq \mathrm{t_{n+1}} \end{cases}
\end{aligned} \tag{1}
$$

When $n \to \infty$, the solution of a DOP can be expressed as a sequence of the solutions of a series of optimization problems. When $n = 1$ and for constant t, DOP degenerates as a single-objective optimization problem.

Notice that DOP defined here is quite different to the current researches in some details, although this equation seemly expressed similar ideas. First, the definition here can be explained as that EAs can have prior knowledge on the problems, EAs can know the period, the value of n, the functions themselves, so EAs can take appropriate actions according to the knowledge. Second, the definition here somehow ignores "the dynamic environment"."The dynamic environment" may imply that the environment is not predictable, this implication would confuse the researchers and make the communications between the scientists inefficient. Actually, we agree on that the researches on DOP, or say, DOEA, would be built on a solid foundation, that is, based on clear and specific problems, not an algorithms for universal aims.

Although the researchers have put various implicit preconditions on DOPs, some basic principles are regarded reasonable. For examples, the dynamic environment should change continuously, the dynamic environment after a change should have exploitable similarities to the environment before the change and so on. Actually, these principles demand that the environment should not be random, such that there are some interests to research these problems.

This paper is organized as follows. First, this paper introduces the current advances, include the current algorithms, the performance evaluation indictors, the test-bed functions and the theoretical researches in section 2. Second, according to the-state-of-the-art researches, this paper discusses the open issues. Finally, this paper makes conclusions.

2 Current Works

Although the researchers did not reach consensus on DOPs, the researchers proposed several DOEAs to deal with this kind of problems. They also proposed several evaluation indicators to measure the performance of DOEAs, and several test-bed functions to standardize the comparisons. Moreover, they made some progresses on the theoretical analysis.

2.1 Current Algorithms

Since 1960s, a couple of DOEAs had been proposed, but these algorithms mainly focused on keeping the population's diversity or storing the historical best solutions based on memory.

Generally speaking, these algorithms can be categorized by two means, one is based upon the employed techniques, the other is based upon the characters of problems.

The taxonomy by the techniques. J. Branke categorized DOEAs into four classes[3,6,29].

1. Increasing the diversity after the environmental change.
   The simplest method is the re-starting method. The idea of this method is that when the environment changes, every individual will be randomly generated again. Since this method did not save the information in the evolution, many problems will take a long time to restart the process of evolution and cannot get good results.
   Hyper-mutation is the representative of this type of method[20], and the basic idea of this method is that population's mutation ratio should be increased sharply in some generations after environment changes. The improvement of this method includes [25] and [24], they gradually increase the mutation ratio and adaptively increase the mutation ratio.
2. Maintaining the diversity.
   Evolutionary algorithm tends to converge to one solution, which is inappropriate for the dynamic optimization problems. If all the individuals converge to the only one point, the population is hard to come out from this point to search better solutions when the environment changes. Therefore, some methods are proposed to prevent the algorithm to converge. An approach is that a number of randomly generated individuals will be inserted into population in every generation[11], which can be thought as the compromise version of the re-starting method.
3. The method based on memory.
   There are two ways to reflect the idea of memory, one of them is the implicit memory method, and the other is the explicit memory method. The implicit memory method was proposed earlier, and redundancy can be regarded as the original version. The explicit memory method is attracting current researchers now, such as [4][2].
   By employing the memory, DOEAs can keep diversity and record the history, and the history may be useful of predicting the hopeful spaces when the environment changes.
4. Multi-population method and migration method.
   The basic idea of this kind of methods is to divide the whole population into some sub-populations to trace multiple peaks in the fitness landscape [5,33,22,27]. Every sub-population is responsible of several hopeful areas, so this method can be regarded as an improvement of the memory method.

Besides the method proposed above, there are some algorithm can not be categorized, such as the futurist approach[12].

The taxonomy by the characters of DOPs. Different to the taxonomy of J. Branke, Yamasiki[26,15] points out that when the optimal solutions jump from here to there at every time, adaption of evolutionary algorithms would not perform well, moreover, periodical environments are not the environments of all the real-world DOPs. He also proposed that the aim of adaption is not for the optimal solutions, but for how the environment changes, therefore, the adaption in current algorithms is used for the characters of changing environments.

Yamasiki categorized current DOEAs into four classes, that is, the algorithms utilized the reappearance,the algorithms utilized the continuity,the algorithms utilized the sparsity, the algorithms utilized the predictable property.

1. The reappearance.
   The reappearance means that the best solution will appear after n times changes of the environment. Obviously, the best method to deal with the problems with such a character would be the methods based on memory.
2. The continuity. That is, the next best solution will appear nearby the historical best solutions. For this kind of problem, the best method is to use Neighborhood Search Operators.
3. The sparsity. That is, few environmental changes would happen. If the environment changes greatly, then the frequency of the changes of environment would be small. To deal with this kind of problems, the best algorithms would be the algorithms based on keeping diversity, include the algorithms which keep the diversity for the while evolving process and increase the diversity drastically in a certain time.
4. The predictable property. That is , the environment is predictable. Here, the futurist approach[12] would be a good method. Moreover,Literature [1] proposed two variants of ecGA to deal with dynamic environment, called dcGA(1) and dcGA(2) respectively. In these algorithm, implicit predication approach is employed. Literature[16] emphasized the predication method, because the predication method is also a kind of adaption. But since now, a few works utilized the prediction approach. Some work, such as literature[21] explored how to avoid the collision of boats by the predication approach, literature[17] discussed DOPs in automobile industry.

Moreover, because DOPs have tight relationships with MOPs, some researchers have proposed some DOEAs based on MOEAs. Of course, people can also use DOEAs to develop MOEAs.

2.2 The Evaluations on Performance

Single-objective optimization evolutionary algorithms aim to the capability of “finding” the optimal solution. But DOEAs aim to the capability of “tracking” the sequence of optimal solutions for various time variable. So there is a trade-off in the evaluation of the performance, that is , on one hand, it is very important to obtain the best solution at certain time; on the other hand, it is also very important to obtain good solutions at all the time. A saying goes that the worst clock would have two times to signal absolutely right, but the best clock would never run right. Based on different viewpoint, the evaluation would be very different.

Currently, some performance indicators have been proposed. For examples, online performance, offline performance, adaptation, accuracy, etc.

Online performance. In stationary single-objective optimization, online performance is the average value of the fitness of all historical individuals. It can be used to measure the performance of DOEAs.

Here Let f_{ti} is the fitness of $i-th$ evaluation at the $t-th$ environment, T is the total number of environmental change, I_t is the total number of all evaluations in the $t-th$ environment, thus, online performance can be depicted as equation 2.

$$ONP = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{I_t} f_{ti} \tag{2}$$

Offline performance. Offline performance means the average value of the fitness of all the historical best solution. Here Let$f_{best(t)}$ is the best fitness at the $t-th$ environment, offline performance can be defined as equation 3.

$$OFP = \frac{1}{T}\sum_{t}^{1} f_{best(t)} \tag{3}$$

Adaptation. Mori et al. proposed *adaption* as the measure of performance[18] as equation 4.

$$Ada = \frac{1}{T}\sum_{t=1}^{T}\frac{f_{best(t)}}{f_{opt(t)}} \tag{4}$$

here, $f_{opt(t)}$ represents the best fitness at time t.

Accuracy. Mori[19] et al. and Trojanowski et al.[23] proposed *accuracy* as the measure of performance as equation 5.

$$Acc = \frac{1}{T}\sum_{t=1}^{T}(f_{best(t)} - f_{opt(t)}) \tag{5}$$

Besides, some researchers have proposed some other evaluation indicators.

In general, for any indicator, there must exist a basic hypothesis that the algorithms should converge, that is, when $t \to \infty$ the algorithm would certainly track the optimal solutions. However, current designs on the evaluation indicators did not emphasize, even mention this precondition. Actually, if the algorithms do not converge, all the indicators above can not deterministically measure the performances, since the future is not predictable for the algorithms and therefore the deviation is also unpredictable. Thus, the values of the indicators would depend on the choice of time variable t. It would be possible that if $t = 100$, algorithm A is better than B; but if $t = 200$, B is better than A.

Current DOEAs did not pay enough attention to the convergence, so the evaluation indicators should be improved. Only if the compared algorithms are convergent, the comparisons are trustable.

2.3 The Test-Bed Functions

As to the constructed test-bed functions, they would have some features. Commonly, they should be efficiently calculated to save the computation cost; they would be easy to implement various dynamic features; they would be easy to control the complexity of fitness landscape; they would also be easy to obtain the trajectory of the optimal solutions by catalytical means.

Currently, the popular test-bed functions include Dynamic Bit-Matching, moving parabola, Moving Peaks Function, Dynamic TSPs etc.

Dynamic Bit-Matching. Dynamic Bit-Matching Problem [8] is the simplest dynamic problem. This problem is constructed to solve a bit sequence which change randomly with time, that is, the bit sequence would change with time in the dynamic environment, and the objective function si to summarize the same bits between the dynamic environment and the chromosomes of the individuals.

Moving Parabola. Moving Parabola is a popular test-bed problem[7], described as equation 6.

$$Min\ f(x,t) = \sum_{i=1}^{n} (x_i(t) + \delta_i(t))^2 \tag{6}$$

Here, t is the time variable, $x_i(t)$ is $i-th$ decision variable, and $\delta_i(t)$ can be depicted as equation 7.

$$\begin{aligned} &\delta_i(0) = 0, \forall i \in \{1, 2, \cdots, N\} \\ &\delta_i(t+1) = \delta_i(t) + S, \forall i \in \{1, 2, \cdots, N\} \end{aligned} \tag{7}$$

Here, S commonly is 1.

Dynamic TSPs. Lishan Kang et al.[14] proposed a series of test-bed functions called CHN144+M based on CHN144 problem, that is, based on the original CHN144 problem and add M satellites. They also used a real-time evolutionary algorithm[32] to solve these problems. Among this series of problems, CHN144+1 is the simplest. This problem can be depicted as follows,

Based on the original CHN144 problem, add a satellite, this satellite circles with the center (2531,1906) and a radius of 2905, the time variable is the real time, the algorithms are asked to obtain the shortest TSP distance of 145 nodes.

Moving Peaks. J. Branke proposed a test-bed function with multi-modal and slight move[4] as equation 8.

$$f(x(t)) = \max_{i=1,..m} \left[H_i(t) - R_i(t) \times \sqrt{\sum_{j=1}^{n} (x_j - X_{ij}(t))^2} \right] \tag{8}$$

Here, $H_i(t) = H_i(t-1) + k_H\sigma$,$W_i(t) = W_i(t-1) + k_W\sigma$,$\sigma \in N(0,1)$, $X(t) = X(t-1) + \omega(t)$,$\omega(t) = \frac{s}{|r+\omega(t-1)|}((1-\lambda)r + \lambda\omega(t-1))$.

The other test-bed functions. Yang and Yao et al. proposed that the test-bed instances can be generated by a XOR generator[28], Farina [9,10] and Jin [13] et al. also proposed dynamic multi-objective optimization problems which integrate the multi-objective optimization problems.

2.4 Theoretical Analysis

Currently, few works focused the theoretical analysis of DOESs. Zheng et al. [30,31] defined the convergence of DOEAs and designed an algorithm to deal with predictable DOPs, and proved that this algorithm can converge under certain conditions. However, this problem can not deal with the DOPs with randomness and noise, also can not deal with the DOPs with implicit functions.

The theoretical analysis is necessary to be promoted.

3 Perspectives

In contrast to hundreds of Multi-objective Optimization Evolutionary Algorithms, current researchers only proposed tens of DOEAs. There are great room for the development of DOEAs. For examples, the new branches such as Particle Swarm Optimization, Culture Algorithm and Quantum Inspired Algorithm etc. could be applied into this field, thus to improve DOEAs. Moreover, there are still many works to do in the metrics of performance and the test-bed functions.

But the most important directions would be: integration with MOEAs, theoretical analysis and application.

3.1 Integration with MOEAs

DOPs are very similar to MOPs. Actually, the nature of DOPs is to solve a sequence of minimum values. This sequence can be regarded as a sampling on the dimension of time for dynamic functions. Similarly, the nature of MOPs is a sampling on the true Pareto fronts.

In MOEAs, histogram method is a feasible method to obtain the approximated Pareto front. That is, only considering to the bi-objective optimization problem, this method divides the functional value region of the first objective function into many parts, and for each parts, to obtain the minimum (or maximum) of the second objective function, finally, calculates the non-dominated set of all the minimum values.

We can reasonably extend DOPs to MOPs by adding an additional objective functions. Assume that a DOP is defined as $F(x,t)$, we can rewrite it as $F_1(x,t)$, and add another objective function as $F_2(x,t) = t$. Hence, DOP is transferred as MOP, and "tracking the optimal solutions" means a sampling on the second objective function. As to the solutions of the extended DOP and MOP, the only difference is that DOP would not need a calculation of "non-dominated solution set".

Although DOP is quite similar to MOP, there are still many difference.

First, the time variable. The time variable is independent variable, and its value is predefined and belongs to $[0, +\infty]$.

Second, the aims are different. MOEAs hope to obtain a spatial sampling, and then the results of sampling is refined to suit for the definition of Pareto front. But DOEAs just want to obtain the minimum value sequence, not to be Pareto, and the sampling should base on the time variable.

When we regard the time variable as the real time, DOEA would have a concept of "trade-off solutions".

In the stationary single-objective optimization problems, the solutions are stable and invariant, if the computing time is infinite, the well-designed algorithm would certainly obtain the best solutions. But DOPs are different. Assume that the time variable is the real time, the computing time would be limited, so the algorithms should trade off between the better solutions and the time.

3.2 Theoretical Analysis

Theoretical analysis on DOEAs is very difficult, but the difficulties partly owe to the unclear definition on DOPs. If treating the time variable in DOP as a variable, not the real time, it would be simple to reduce them as special MOEAs. If not, theoretical analysis would be possible only in some special circumstances.

If the time variable is just a variable, the most important issue would be the convergence of DOEAs. Different to MOEAs, there are at least two definition on it[30]. First, DOEAs may converge only when $t \to \infty$, we can call it "asymptotic convergence". Second, DOEAs may converge for each t, here, the time variable t is fully treated as a variable, we can call it "full convergence". Different definitions show different viewpoints on time variable. Another important issue would be the convergent rate. These issues would be very important directions.

If the time variable is not a common variable, the convergence of DOEAs would base on a hypothesis that the environment would be predictable. Otherwise, even the asymptotic convergence is not obtainable. Considering that some MOEAs are capable of convergence, so we can surely find the convergent DOEAs.

3.3 Applications

Currently, the fields of application of DOEAs still are a bit narrow, mainly in sea transportation, telecommunication etc.. Actually, if we treat the time variable as a common variable, most control problems can be transferred into DOPs, and then DOEAs can be used to solve them. This issue would be another important direction.

4 Conclusions

This paper reviewed the development of dynamic optimization evolutionary algorithms. According to the-state-of-the-art researches, this paper proposed that: since DOP can be extended as MOP, DOEAs are very similar to MOEAs, the experience of MOEAs can be applied into DOEAs; moreover, theoretical analysis is very important to the furthermore development of DOEAs.

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