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A New Strategy of Dynamically Adjusting Population Size for Coevolutionary Algorithms

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Abstract- **How to dynamically adjust population size is one of the most important research topics in coevolutionary computation. This paper proposes a new strategy to dynamically adjust population size during a coevolutionary process. Three factors are considered in the strategy to describe the influence on population size. They are the natural growth of sub-populations, the internal competition of individuals from same sub-population and the interaction between individuals from different sub-populations. It is proven that the proposed strategy is globally asymptotically stable and also the convergence of a coevolutionary algorithm with the strategy is investigated. Finally, the behavior of the proposed strategy in practical use is illustrated.**

***Index terms*—coevolutionary algorithm, dynamic population size, global asymptotic stability, convergence**

1. INTRODUCTION

Coevolutionary algorithm (CEA) is a new kind of *evolutionary algorithm* (EA) and is receiving increased attention. In CEA, the set of individuals is divided into several sub-populations. The fitness value of an individual is determined not only by its interaction with the individuals in the same sub-population, but also by the individuals in different sub-populations [1][2]. Like other EAs, the population size is one of the most important parameters affecting the behavior of CEA greatly. If the population size is too small, CEA may suffer from premature convergence. If it is too big, it results in excrescent computation cost. Although the selection of the size of each sub-population is very important, traditional CEAs do not support the dynamic adjustment of the population size.

Although much work has been done to adjust the population size self-adaptively during an evolutionary process, most of it focuses on how to vary the population size for *genetic algorithms* (GA). Among them, some researchers proposed new methods. In [3], Arabas *et al* propose the GAVaPS in which the population size is varied by giving each individual a lifetime. In [4], Miller *et al* introduce a mechanism called dynamic niche sharing into GA to directly adjust the population size. In [5], Ahn *et al* suggest to control the population size with an enhanced and generalized equation based on the gambler's ruin model. In [6], Tan *et al* propose a technique similar to simulated annealing to decrease the population size gradually. Some other researchers try to investigate the effects of varying the population size in GA. For example, In [7], Fernandes *et al* present a study on the effects of non-random mating and varying the population size in GA performance. Other related work includes Shi [8], Chen [9], and Costa [10]. On the other hand, in order to adjust population size in CEA, the interactions among different sub-populations should be investigated additionally. Therefore, such adjusting strategy is more difficult to design. DMOEA, proposed by Yen *et al.*[11] in 2003, is one of few studies focused on varying the population size in CEA. In DMOEA two sub-populations are used for the optimization of rank and density, and the corresponding population growing strategy and population declining strategy are designed.

Focusing on GA or CEA, the previous work is aimed to solve specific problems. Specific population adjusting strategies are thus designed. Actually, their methods perform well in solving some special problems. However, a strategy, which can adjust population size dynamically during a coevolutionary process and is also independent of specific CEA, remains open.

The major contribution of this paper is to propose a new strategy of *dynamical population size* (DPS) for CEA. The strategy is independent of specific CEA and can ensure the global asymptotic stability of the population size.

The rest of this paper is organized as follows. In Section 2, we describe the strategy and the corresponding CEA structure. In Section 3, we prove its global asymptotic stability. In Section 4, the convergence of a CEA with this strategy is investigated. In Section 5, the behavior of the strategy in practical use is illustrated. The conclusion is given in the last section.

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2. ADJUSTING DYNAMIC POPULATION SIZE AND THE CORRESPONDING CEA

Let P_i denote the i-th sub-population, and $N_i = |P_i|$ the population size of P_i.

2.1. The strategy for dynamic population size

In the strategy, there are three factors that influence N_i.

(1) The natural growth of sub-populations

During a coevolutionary process, sub-populations grow naturally by reproducing offspring continuously. Simultaneously, to make the population size under control, we need to restrict the number of the offspring produced by one individual per generation.

We sort the individuals of P_i by fitness value, and set their reproductive abilities as a linear distribution. The worst individual of P_i can produce offspring with the expectation of q_i and the best one with the expectation of r_i. It is required to point out that q_i and r_i need not to be an integer because they are the mathematical expectation of the number of offspring.

There are $\frac{q_i + r_i}{2} N_i$ new individuals produced per generation.

(2) The internal competition among individuals from same sub-population

The internal competition among individuals from the same sub-populations aims to prevent a sub-population from increasing unlimitedly. For all pairs of individuals $a, b \in P_i$, $a \neq b$, the worse one may be eliminated with the probability of λ_i.

There are $N_i^2 / 2$ pairs of individuals in P_i, so $\frac{1}{2}\lambda_i N_i^2$ individuals are eliminated per generation.

(3) The interaction among individuals from different sub-populations

Because the evolutionary system is evolving as a whole, the interaction among individuals from different sub-populations must be taken into account. For each pair of individuals $a \in P_i$, $b \in P_j$, $P_i \neq P_j$, let coefficient w_{ab} denote the influence of b upon a. w_{ab} can be positive if b benefits a, or negative if b impairs a, or 0 if a is independent of b. Positive w_{ab} gives a additional offspring with the expectation of w_{ab}, whereas negative w_{ab} causes a to be eliminated with the probability of $-w_{ab}$.

For each sub-population $P_j \neq P_i$, the influence of P_j upon P_i can be described as $\sum_{a \in P_i} \sum_{b \in P_j} w_{ab}$, and total influence upon P_i is $\sum_{P_j \neq P_i} \sum_{a \in P_i} \sum_{b \in P_j} w_{ab}$.

Assume that $w_{ij} = \sum_{a \in P_i} \sum_{b \in P_j} w_{ab} / (N_i N_j)$ is average influence of P_j upon P_i, $\dot{x} \equiv \frac{dx}{dt}$ is the first derivative of variable x to generation t. Then we have the dynamics of the proposed strategy:

$$\dot{N}_i = \frac{q_i + r_i}{2} N_i - \frac{\lambda_i}{2} N_i^2 + \sum_{P_j \neq P_i} w_{ij} N_i N_j \quad (1)$$

Additionally, parameters q_i, r_i, λ_i and w_{ab} need to satisfy the following conditions:

$$\det \mathbf{A} > 0$$
$$\overline{\mathbf{N}} > 0 \quad (2)$$

where

$$\mathbf{A} = \begin{pmatrix} -\frac{\lambda_1}{2} & w_{12} & w_{13} & \cdots & w_{1k} \\ w_{21} & -\frac{\lambda_2}{2} & w_{23} & \cdots & w_{2k} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ w_{k1} & w_{k2} & w_{k3} & \cdots & -\frac{\lambda_k}{2} \end{pmatrix},$$

$$\mathbf{N} = \begin{pmatrix} N_1 \\ N_2 \\ \vdots \\ N_k \end{pmatrix}, \quad \mathbf{b} = \begin{pmatrix} \frac{q_1 + r_1}{2} \\ \frac{q_2 + r_2}{2} \\ \vdots \\ \frac{q_k + r_k}{2} \end{pmatrix},$$

and $\overline{\mathbf{N}}$ is the solution vector of $\mathbf{AN} + \mathbf{b} = \mathbf{0}$.

With the condition (2) being satisfied, equation (1) can be proven globally asymptotically stable. The proof is presented in section 3.

2.2. The corresponding CEA structure

We give the pseudo code of a general CEA with the proposed strategy:

Initialize sub-populations $P_1, P_2, \ldots,$ and P_k

For each generation

evaluate the fitness value of each individual in P_i

/*The natural growth of sub-populations*/

for each P_i

for each $a \in P_i$

calculate required offspring number for a *(denoted as* N_a*)*

produce offspring by crossover and mutation with the expectation of N_a

/*The internal competition of same sub-population*/

for each P_i

for each $a, b \in P_i, a \neq b$

eliminate the worse one with the probability of λ_i

/*The interaction between individuals from different sub-populations*/

for each $P_i \neq P_j$

for each $a \in P_i, b \in P_j$

calculate w_{ab}

if $w_{ab} > 0$ **then** *produce bonus offspring for* a *with the expectation of* w_{ab}

if $w_{ab} < 0$ **then** *eliminate* a *with the probability of* $-w_{ab}$

End for

From its description and CEA structure, we can see that the proposed strategy is independent of specific CEA.

First, for each P_i, if $\frac{q_i + r_i}{2} N_i^0 = \frac{\lambda_i}{2} N_i^{02}$ and $\forall w_{ab} = 0$, N_i^0 is initial population size of P_i, then the CEA degenerates to a traditional CEA without dynamic population size. That means the latter can be regarded as a special case of our CEA. Second, we don't care how offspring is produced. Selection, crossover, mutation, and other genetic operators if needed, can be chosen freely according to specific problems. The only requirement is the expected number of offspring and probability of elimination.

It is worth mentioning that the strategy can be simplified. In the algorithm described above, in order to obtain total influence of internal competition and interaction between sub-populations, we calculate it from every pair of individuals. However, we can also use only a proportion of total pairs as samples instead. Through that, the time complexity of the algorithm can be decreased drastically.

3. The Global Asymptotic Stability

In this section, we prove the global asymptotic stability of the proposed strategy. The proof is given in three steps:

(1) Prove the local asymptotic stability under the circumstance of two sub-populations.
(2) Prove the global asymptotic stability under the circumstance of two sub-populations.
(3) Extend the result to the circumstance of N sub-populations.

3.1. The local asymptotic stability under the circumstance of two sub-populations

If there are only two sub-populations: P_1 and P_2, the dynamics Eq. (1) becomes

$$\begin{aligned} \dot{N}_1 &= \frac{q_1 + r_1}{2} N_1 - \frac{\lambda_1}{2} N_1^2 + w_{12} N_1 N_2 \\ \dot{N}_2 &= \frac{q_2 + r_2}{2} N_2 - \frac{\lambda_2}{2} N_2^2 + w_{21} N_1 N_2 \end{aligned} \tag{3}$$

The condition Eq. (2) becomes

$$\begin{aligned} \det \mathbf{A} &= \frac{\lambda_1 \lambda_2}{4} - w_{12} w_{21} > 0 \\ \overline{N}_1 &= \frac{\lambda_2 (q_1 + r_1) + 2 w_{12} (q_2 + r_2)}{\lambda_1 \lambda_2 - 4 w_{12} w_{21}} > 0 \\ \overline{N}_2 &= \frac{\lambda_1 (q_2 + r_2) + 2 w_{21} (q_1 + r_1)}{\lambda_1 \lambda_2 - 4 w_{12} w_{21}} > 0 \end{aligned} \tag{4}$$

It is obvious that $(\overline{N}_1, \overline{N}_2)$ is the only one non-trivial positive steady state of Eq. (3).

Theorem 1. In Eq. (3), steady state $(\overline{N}_1, \overline{N}_2)$ is locally asymptotically stable as long as condition (4) is satisfied.

Proof. Let $x_i = N_i - \overline{N}_i$ and linearization, Eq. (3) becomes

$$\dot{x}_1 = -\frac{\lambda_1 \overline{N}_1}{2} x_1 + w_{12} \overline{N}_1 x_2$$

$$\dot{x}_2 = w_{21} \overline{N}_2 x_1 - \frac{\lambda_2 \overline{N}_2}{2} x_2$$

From Routh-Hurwitz condition and condition (4), we know (x_1, x_2) locally asymptotically converges to $(0,0)$. That means $(\overline{N}_1, \overline{N}_2)$ is locally asymptotically stable. □

Theorem 2. In Eq. (3), steady state $(\overline{N}_1, \overline{N}_2)$ is globally asymptotically stable as long as condition (4) is satisfied.

Proof. To prove the global asymptotic stability, we need a Liapunov function $V(N_1, N_2)$ subject to:

1) $V(N_1, N_2) > 0$, $\forall (N_1, N_2) \neq (\overline{N}_1, \overline{N}_2)$
2) $V(\overline{N}_1, \overline{N}_2) = 0$
3) $\dot{V}(N_1, N_2) < 0$, $\forall (N_1, N_2) \neq (\overline{N}_1, \overline{N}_2)$
4) $N_1^2 + N_2^2 \to \infty \Rightarrow V \to \infty$

Construct Liapunov function as:

$$\begin{aligned} V(N_1, N_2) &= c_1 (N_1 - \overline{N}_1 - \overline{N}_1 \ln \frac{N_1}{\overline{N}_1}) \\ &+ c_2 (N_2 - \overline{N}_2 - \overline{N}_2 \ln \frac{N_2}{\overline{N}_2}) \end{aligned} \tag{5}$$

where c_1 and c_2 are positive constants. It is easy to prove that $V(N_1, N_2)$ satisfies conditions 1), 2) and 4) above. If we can find appropriate constants c_1 and c_2 such that condition 3) is satisfied, the global asymptotic stability can be proven.

Because $(\overline{N}_1, \overline{N}_2)$ is a steady state, we have

$$\frac{q_1 + r_1}{2} - \frac{\lambda_1}{2} \overline{N}_1 + w_{12} \overline{N}_2 = 0$$

$$\frac{q_2 + r_2}{2} - \frac{\lambda_2}{2} \overline{N}_2 + w_{21} \overline{N}_1 = 0$$

which can be transformed to

$$\begin{aligned} \frac{q_1 + r_1}{2} &= \frac{\lambda_1}{2} \overline{N}_1 - w_{12} \overline{N}_2 \\ \frac{q_2 + r_2}{2} &= \frac{\lambda_2}{2} \overline{N}_2 - w_{21} \overline{N}_1 \end{aligned} \tag{6}$$

Substitute Eq. (6) into (3), we get

$$\begin{aligned} \dot{N}_1 &= N_1 [-\frac{\lambda_1}{2} (N_1 - \overline{N}_1) + w_{12} (N_2 - \overline{N}_2)] \\ \dot{N}_2 &= N_2 [w_{21} (N_1 - \overline{N}_1) - \frac{\lambda_2}{2} (N_2 - \overline{N}_2)] \end{aligned} \tag{7}$$

Substitute Eq. (7) into (5), we get

$$\dot{V}(N_1,N_2)=c_1(N_1-\overline{N}_1)\frac{\dot{N}_1}{N_1}+c_2(N_2-\overline{N}_2)\frac{\dot{N}_2}{N_2}$$

$$=c_1(-\frac{\lambda_1}{2})(N_1-\overline{N}_1)^2+c_1w_{12}(N_1-\overline{N}_1)(N_2-\overline{N}_2)$$

$$+c_2w_{21}(N_2-\overline{N}_2)(N_1-\overline{N}_1)+c_2(-\frac{\lambda_2}{2})(N_2-\overline{N}_2)^2$$

$$=\frac{1}{2}(\mathbf{N}-\overline{\mathbf{N}})^{\mathrm{T}}(\mathbf{CA}+\mathbf{A}^{\mathrm{T}}\mathbf{C})(\mathbf{N}-\overline{\mathbf{N}})$$

where $\mathbf{N}=\begin{pmatrix}N_1\\N_2\end{pmatrix}$, $\mathbf{C}=\begin{pmatrix}c_1 & 0\\0 & c_2\end{pmatrix}$,

$$\mathbf{A}=\begin{pmatrix}-\frac{\lambda_1}{2} & w_{12}\\ w_{21} & -\frac{\lambda_2}{2}\end{pmatrix}$$

Therefore condition 3) is equivalent to finding a positive diagonal matrix $\mathbf{C}$ such that $\mathbf{CA}+\mathbf{A}^{\mathrm{T}}\mathbf{C}$ is negative definite.

$\mathbf{CA}+\mathbf{A}^{\mathrm{T}}\mathbf{C}$ is negative definite *iff.*

$$c_1c_2\lambda_1\lambda_2-(c_1w_{12}+c_2w_{21})^2>0 \qquad (8)$$

Let's discuss Eq. (8) from three aspects:

a) $w_{12}w_{21}=0$

Without loss of generality, suppose $w_{12}=0$. Then Eq. (8) becomes $c_2(c_1\lambda_1\lambda_2-c_2w_{21}^2)>0$. Choose c_1 and c_2 such that $c_1\lambda_1\lambda_2-c_2w_{21}^2>0$ and (8) is satisfied.

b) $w_{12}w_{21}>0$

Transform (8) to

$c_1c_2(\lambda_1\lambda_2-4w_{12}w_{21})-(c_1w_{12}-c_2w_{21})^2>0$.

Because $w_{12}w_{21}>0$, we can choose c_1 and c_2 such that $c_1w_{12}-c_2w_{21}=0$. And from $\lambda_1\lambda_2>4w_{12}w_{21}$ we have $\lambda_1\lambda_2-4w_{12}w_{21}>0$ and (8) is satisfied.

c) $w_{12}w_{21}<0$

Choose c_1 and c_2 such that $c_1w_{12}+c_2w_{21}=0$ and (8) is satisfied.

To sum up, we can choose positive constants c_1 and c_2 such that $\mathbf{CA}+\mathbf{A}^{\mathrm{T}}\mathbf{C}$ is negative definite, so condition 3) can be satisfied. Then $V(N_1,N_2)$ is an appropriate Liapunov function and equation (3)'s global asymptotic stability is proven. □

3.2. The global asymptotic stability under the circumstance of N sub-populations

The result in Theorem 2 can be extended easily to the circumstance of k sub-populations.

Theorem 3. Equation (1) has a globally asymptotically stable positive steady state as long as conditions (2) is satisfied.

Proof. It can be proven in the similar way as Theorem 1 and Theorem 2. □

3.3. The global asymptotic stability of a simplified strategy

The similar analysis can be given for the simplified strategy described at the end of Section 2. It uses a proportion of total pairs of individuals, hence Eq. (1) is changed to:

$$\dot{N}_i=\frac{q_i+r_i}{2}N_i-\frac{\lambda_i}{2}(d_1N_i)^2+\sum_{P_j\neq P_i}w_{ij}(d_2N_i)(d_3N_j)$$

where d_1, d_2 and d_3 are the proportion actually used. After changing $\tilde{\lambda}_i$ and $\tilde{w}_{ij}$ as $\tilde{\lambda}_i=d_1^2\lambda_i$, $\tilde{w}_{ij}=d_2d_3w_{ij}$, it is clear that we can educe the same result.

With the use of the simplified strategy, the time complexity of the algorithm is decreased drastically. Assume T_1 is the time cost of producing offspring for one individual in the first part of our strategy, T_2 and T_3 are the time costs of the second and the third parts for one pair of individuals. For each generation, the additional time cost of the original strategy is

$$T=T_1\sum_{P_i}N_i+T_2\sum_{P_i}\frac{N_i^2}{2}+T_3\sum_{P_i\neq P_j}N_iN_j$$

Contrastively, the additional time cost of the simplified strategy is

$$\tilde{T}=T_1\sum_{P_i}N_i+d_1^2T_2\sum_{P_i}\frac{N_i^2}{2}+d_2d_3T_3\sum_{P_i\neq P_j}N_iN_j$$

Obviously, $\tilde{T}\ll T$.

4. The Convergence of CEA with Our Strategy

Firstly, a CEA with the proposed strategy is still a stochastic process and can be analyzed by a Markov Chain model. Similar to the analysis by Rodolph [12], a CEA with our strategy converges to the globally optimal solution with the probability of 1 as long as an elitism strategy is being used.

Then we present a qualitative analysis of the optimization ability with a Markov Chain model. Consider a CEA with k sub-populations, and sub-population P_i consists of N_i individuals. Let S_i be the state space of P_i, which consists of all possible individuals of P_i. Since the solution consists of individuals from each sub-populations, we can express the solution state space S in terms of $S=S_1\times S_2\times\cdots\times S_k$ and the feasible solution space

Ω is a subset of S. On the other hand, sub-population P_i consists of N_i individuals, meaning the population state $E_i = S_i^{N_i}$, and the total system state space $E = S_1^{N_1} \times S_2^{N_2} \times \cdots \times S_k^{N_k}$.

Generally, the cardinality of different S_i and S_j is different. Without loss of generality, we suppose $|S_i| > |S_j|$. In a CEA without varying population size, there may be $N_i = N_j$ while no priori is known. By using the strategy, we may have $\tilde{N}_i > \tilde{N}_j$ while $\tilde{N}_i + \tilde{N}_j = N_i + N_j$. The system state space $|\tilde{E}|$ of CEA with the strategy becomes

$$|\tilde{E}| = |S_1|^{N_1} |S_2|^{N_2} \cdots |S_i|^{\tilde{N}_i} \cdots |S_j|^{\tilde{N}_j} \cdots |S_k|^{N_k}$$

$$= |E| \left(\frac{|S_i|}{|S_j|} \right)^{\tilde{N}_i - \tilde{N}_j} > |E|$$

In the evolution theory, with the expansion of system state space, the possibility for searching for globally optimal solution increases; meanwhile, the quality of solutions improves. Because the system state space becomes larger after using our strategy, a CEA with the strategy has a better ability to search for global optimal solutions.

5. Behavior of Our Strategy in Practical Use

On the base of Theorem 3, it has been proven that, when using a CEA with our strategy, giving arbitrary initial states, the population size is bound to converge to a steady state with given parameter value subject to Eq. (2) in Section 2.1. The steady state is determined by parameters q_i, r_i, λ_i and w_{ab}, and has nothing to do with the initial states of sub-populations. To assign proper parameter value to q_i, r_i, λ_i and w_{ab} then becomes the primary problem.

First, consider the situation of constant parameter assignment. From Theorem 3, if the value of parameters keeps constant throughout the whole coevolutionary process, the population size converges to a steady state and then remains stable (Fig. 1).

In order to guarantee the globally asymptotic stability, the value of parameters can not change at will. However, that does not mean that they are unchangeable. In practice, we can still alter the parameter value when the population size has almost converged to the current steady state, just as shown in Fig. 2.

At first, a group of parameter value, as $q_i^{\ 1}$, $r_i^{\ 1}$, $\lambda_i^{\ 1}$ and $w_{ab}^{\ 1}$, is given; at the same time, the current steady state, as $(N_1^{\ 1}, N_2^{\ 1})$, is fixed. The population size begins converging to the steady state similar to which is shown in Fig. 1. We keep the parameters constant so as to guarantee the steady state. As time goes on, the population size $(N_1(t), N_2(t))$ comes close and closer to the steady state $(N_1^{\ 1}, N_2^{\ 1})$. Till a certain generation (T_1), we think that the current population size $(N_1(T_1), N_2(T_1))$ is close enough to $(N_1^{\ 1}, N_2^{\ 1})$. Then a new group of parameter value $q_i^{\ 2}$, $r_i^{\ 2}$, $\lambda_i^{\ 2}$ and $w_{ab}^{\ 2}$ is generated, and the convergence of

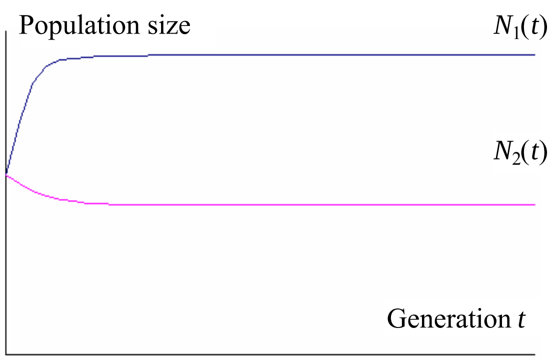

Fig.1.Variation of population size with constant parameters

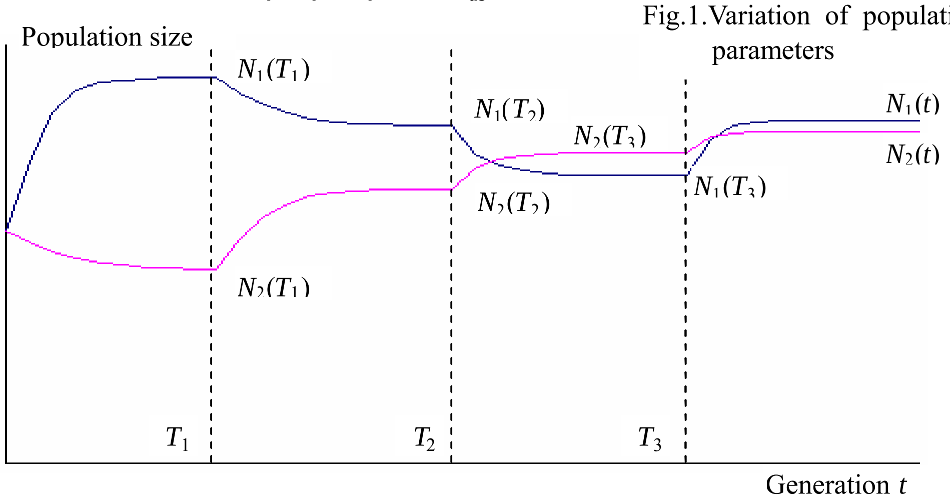

Fig. 2: Variation of population size with variable parameters

population size reaches a new target (N_1^2, N_2^2). With the repetition of this process again and again, the whole coevolutionary process is divided into many steps, and the parameter value keeps constant throughout every single step. If only every group of parameter value satisfies condition (2) in Section 2.1, the population size will converge to the steady state of each step successively. It is easy to know that the global asymptotic stability still holds.

Obviously, our CEA with constant parameters is a special case of that with variable parameters. The latter one is more flexible, and has better performance when the most appropriate population size for the CEA changing along with time.

6. CONCLUSION

This paper proposes a new strategy of dynamically adjusting population size for CEA. Its globally asymptotic stability is proven, the convergence of a CEA with it is investigated, and its behavior in practical use is also illustrated. Our strategy, compared with the previous strategies proposed, is independent of specific CEA, and can be easily used. At the same time, our strategy enables a CEA to adjust population size self-adaptively to a proper level, no matter what the initial state is. Moreover, the population size after convergence can be controlled by varying the parameter value. That means our strategy has the ability to solve the problems in which the most appropriate population size changes along with time.

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