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Case Study

A Self-adaptive Cloud Co-evolution Genetic Algorithm for Parameter Identification of Advanced Manufacturing Mode Diffusion

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Abstract

Background: To solve the parameter identification of a multiple advanced-manufacturing-mode competitive diffusion (ACD), this study proposes an improved self-adaptive cloud co-evolution genetic algorithm (ISCCGA) combining a cloud differential evolution model with competitive strategies. **Materials and Methods:** First, the multiple-ACD model is described and the parameter identification model is formulated. Then, to solve the parameter identification of multiple-ACD model, ISCCGA is proposed in which differential evolution of a cloud model and competitive strategies are introduced into the crossover operator to improve the convergence speed and global search ability. In addition, the co-evolution and mutation probabilities are improved to implement nonlinear adaptive adjustment. And then optimal parameters are obtained. **Results:** Finally, the influences of parameters on the algorithm are investigated and the validity of ISCCGA is verified. **Conclusion:** This experimental results show that ISCCGA is more efficient for parameter identification problem in terms of accuracy and convergence than simple genetic, adaptive genetic and co-evolution adaptive genetic algorithms.

Key words: Parameter identification, genetic algorithm, co-evolution, cloud differential evolution, multiple-ACD model

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INTRODUCTION

With globalization of international markets and intense competition enterprises are taking advantage of new manufacturing modes to improve their core competitiveness and make adjustment to various markets. Advanced manufacturing modes refer to methods that effectively organize various production factors to achieve satisfying manufacturing effect in a particular environment[1]. These methods have become standardized concepts, philosophies and structures and can be adopted by enterprises according to their different environments and manufacturing goals. Considerable literatures on advanced manufacturing modes have been concentrated on: (1) Philosophy, definition and characteristics of various manufacturing modes, (2) Relative technologies in manufacturing modes and (3) Applications of advanced modes in different environments. As an example of (1) Sun *et al.*[1] made classification on advanced manufacturing modes in terms of mode philosophies, methods and technologies. As an example of (2) Bai *et al.*[2] introduced the concept, construction and key technologies of virtual manufacturing, as well as its relationship with other modes. In terms of (3) Dong and Guo[3] studied the practice of Computer Integrated Manufacturing Systems (CIMS) in a company named high speed wire plant of Tangshan Iron and Steel Corporation. However, few quantitative studies have been on the rules of practical advanced mode implementation.

In this study, the implementation of manufacturing modes includes accepting, adapting and applying standardized concepts, philosophies, structures and advanced manufacturing methods collectively[4]. This is a diffusion process, called advanced-manufacturing-mode diffusion (ACD). In practice, it is impossible a process of a kind of mode. It is a process of competitive diffusion among different modes, called multiple advanced-manufacturing-mode competitive diffusion. Thus far, most researches on the ACD are qualitative studies and the limited existing work on ACD can be briefed: (1) Diffusion mechanisms, (2) Diffusion models, (3) Problems related to mode diffusion and (4) Empirical studies on mode diffusion. As an example of (1) Xu and Sun[5] discussed how to promote the implementation of green manufacturing from such aspects as market incentives, government and enterprise behavior. In terms of (2) studies can be divided into two categories: The macro level (aggregate level) based on overall statistical behavior and micro level (individual level) based on the adoption decision of potential adopters[6-11]. The macro level models dominate. For example, the diffusion behavior of the Computer Integrated Manufacturing (CIM) philosophy was studied by Xue *et al.*[11] and its diffusion model was given without considering enterprise capacity and competition. In another study[4], competition diffusion model was built about mode diffusion in a cluster environment, which considered enterprise capacity, competition and government influence. In terms of (3) some specific issues in application fields, such as multi-stages, influencing factors and the diffusion mode are addressed. Xu and Sun[5] studied the implementation environment of a green manufacturing mode. In terms of (4) they are mainly about the applications of specific advanced manufacturing modes in the company[12]. For instance, Li *et al.*[12] studied the dynamic evolution path of an advanced mode in HUAWEI (a telecommunication equipment company in China) through a field investigation and proposed some countermeasures and suggestions for the development of an advanced manufacturing mode. Our prior study proposed mode diffusion and built different ACD models by considering competition among multiple modes, multi-stages and external influence so as to master their diffusion rules[4,11,13-15].

In order to reveal mode diffusion rules more precisely, the parameters of mode diffusion model must be identified. Parameter identification means choosing parameters, which are best meeting real data, so that mathematical models conform to real systems. At present, studies on system parameter identification can be divided into two aspects: (1) Identification methods and (2) Applications of parameter, identification in different fields. In terms of (1) Sun *et al.*[16] utilized a traditional genetic algorithm to solve specific optimization problems and proposed an improved genetic algorithm for system parameter identification. Xue *et al.*[17] studied parameter identification method of mode diffusion by improved GA. In terms of (2) Huang and Ding[18] used genetic algorithms to identify motor parameters, thus obtaining a motor vector control system. System parameter identification has been utilized in various application environments successfully and some simple application had been conducted[17], but parameter identification of diffusion models with efficient algorithms has not been studied.

To better solve the problem, an improved self-adaptive cloud co-evolution genetic algorithm (ISCCGA) is proposed. Evolutionary Algorithms (EA) are stochastic study and optimization methods, which derived from natural biological evolution[19]. Evolutionary algorithms are highly robust and powerful search and optimization methods. At present, there are three types of EAs: Evolutionary Programming (EP), Evolution Strategies (ES) and Genetic Algorithms (GA)[20]. Compared with EP and ES, genetic algorithms are the most widely used evolutionary optimization methods. The GA is stochastic global study methods that solve complicate problems through the imitation on natural evolution[21]. They are considered as intelligent optimization methods for heuristic random searching in discrete spaces. Holland[20] developed the theoretical foundation of GA based on the concept of schema firstly. Then, in the 1980s, Goldberg presented the Simple Genetic Algorithm (SGA), which unified all essential features of genetic algorithms. In recent years, increasingly widespread attentions have been focused on genetic algorithms for academic and engineering applications. The GAs have been widely used in many fields, including optimization computing, job scheduling, automation, robotics, machine learning, data mining and image processing[22].

However, genetic algorithms perform mutation, crossover and selection operations to achieve an optimization search based on the fitness of present individuals. The GAs have some limitations that are similar to other evolutionary algorithms, including low optimization efficiency, tendency to easily fall into a local optimum and premature convergence. In recent years, many scholars have proposed strategies and methods to mitigate these deficiencies, such as Immune Genetic Algorithm (IGA), Adaptive Genetic Algorithm (AGA) and co-evolution adaptive genetic algorithm (CEAGA)[23-25].

These improved GAs overcome the problems of premature convergence and the tendency to fall into local optimums. However, their local search ability, convergence speed and optimization accuracy still need to be strengthened. In this study, it is propose an improved self-adaptive cloud co-evolution genetic algorithm (ISCCGA). It can overcome shortcoming of GAs and provide an effective algorithm for solving optimization problems. In this practical parameter identification problem, it can evaluate the applying status more accurately so as to make best decisions.

MODE DIFFUSION MODEL

An ACD process is influenced by many factors, which can be divided into external, internal and technological ones. External factors exist outside an enterprise, e.g., government policies, social networks, social capital, competitiveness, industrial associations and business climate. Internal factors are those inside enterprises, mostly influencing the enterprise's capacity, such as enterprise schema, innovation infrastructure and enterprise culture. In reality, ACD is a limited rational process. Influenced by current adopters, external environment and potential and enterprises may transfer to other advanced modes. Meanwhile, if one mode is more advantageous over other mode, enterprises implementing the first one may transfer to modes with more advantages. Thus, enterprises can be divided into the following types:

- x_1, enterprises with ability to implement advanced modes, but yet to do so
- x_2, enterprises without capacity themselves to implement advantage mode, but may do so by external intervention)
- y_1, enterprises implementing mode 1
- y_2, enterprises implementing mode 2
- y_n, enterprises implementing mode n

Implementing advanced modes enables enterprises to gain advantages over others. Advanced manufacturing modes may have their improved versions and they share a same philosophy. Advanced manufacturing modes have good performance and reliability. At a given time, the number of enterprises that may implement advanced modes is finite i.e., the number is a constant in the model $x_1+x_2+y_1+y_2+...+y_n = m$, where, m is the total number to implement advanced modes. At a specific time, the multi-ACD model is listed in Eq. 1:

$$\begin{cases} \dfrac{dx_1}{dt} = -\beta x_1 - \sum\limits_{k=1}^{n}\left(p_k + q_{1k}\dfrac{am - x_1}{am}\right)x_1 \\ \dfrac{dx_2}{dt} = -\beta x_1 - \sum\limits_{k=1}^{n}\left(p_k + gq_{2k}\dfrac{bm - x_2}{bm}\right)x_2 \\ \dfrac{dy_1}{dt} = \left(p_1 + q_{11}\dfrac{am - x_1}{am}\right)x_1 + \left(p_1 + gq_{21}\dfrac{bm - x_2}{bm}\right)x_2 - \sum\limits_{j=2}^{n}\theta_{1j}y_1 \\ \quad\vdots \\ \dfrac{dy_k}{dt} = \left(p_k + q_{1k}\dfrac{am - x_1}{am}\right)x_1 + \left(p_k + gq_{2k}\dfrac{bm - x_2}{bm}\right)x_2 \\ \qquad + \sum\limits_{i}^{k-1}\theta_{ik}y_i - \sum\limits_{j=k+1}^{n}\theta_{kj}y_k \\ \quad\vdots \\ \dfrac{dy_n}{dt} = \left(p_n + q_{1n}\dfrac{am - x_1}{am}\right)x_1 + \left(p_n + gq_{2n}\dfrac{bm - x_2}{bm}\right)x_2 + \sum\limits_{i=1}^{n-1}\theta_{1n}y_i \end{cases} \tag{1}$$

where, β is the competitive transfer coefficient from x_1-x_2, p_k is the coefficient of potential adopters on mode k, g is government influence coefficient on potential adopters without capacity, a is the proportion of capable enterprises, q_{1k} and q_{2k} are the inherent diffusing rates of x_1-y_k and x_1-y_k and θ_{ij} is the competitive transfer coefficient from y_i-y_j.

PARAMETER IDENTIFICATION MODEL

The parameters in multi-ACD model include p, g, q, a, θ, b and β. Due to the mode diffusion and practical meaning of parameters, a, b and β can be obtained through field investigation and statistical data and it still need to identify p, g, q and θ. To obtain the optimal parameters, a new parameter identification model of mode diffusion has to be built. Actually, optimal parameters of mode diffusion can make the mode diffusion model obtain minimal error contrasted with real conditions. Therefore, parameters to be identified can be taken as decision making variables and error between model prediction and real data can be taken as objective. In this way, parameter identification of mode diffusion can be taken as an optimization problem.

To do this, the objective function should first be obtained. As the diffusion model means the adopting status of manufacturing modes, the distance between estimated values y_{ij} and their actual values can be used as the error. Meanwhile, the constraints of multi-ACD model should be satisfied. Thus, the parameter identification model of competitive mode diffusion model (Model (1)) is proposed to obtain optimal parameters. The specific model is listed below:

- Objective function:

$$\min \sum_{i=1}^{M} \sum_{j=1}^{N} \left(y_{ij} - y_{ij}^{*} \right)^2$$

where, y_{ij} is the estimated number of enterprises adopting the jth mode in ith year and y_{ij}^{*} is the actual value in practice.

- Constraints:

$$\begin{cases} \dfrac{dx_{i1}}{dt} = -\beta x_{i1} - \left(p_1 + q_{11} \dfrac{am - x_{i1}}{am} \right) x_{i1} - \left(p_2 + q_{12} \dfrac{am - x_{i1}}{am} \right) x_{i1} \\ \qquad - \left(p_3 + q_{13} \dfrac{am - x_{i1}}{am} \right) x_{i1} \\ \dfrac{dx_{i2}}{dt} = \beta x_{i1} - \left(p_1 + gq_{21} \dfrac{bm - x_{i2}}{bm} \right) x_{i2} - \left(p_2 + gq_{22} \dfrac{bm - x_{i2}}{bm} \right) x_{i2} \\ \qquad - \left(p_3 + gq_{23} \dfrac{bm - x_{i2}}{bm} \right) x_{i2} \\ \dfrac{dy_{i1}}{dt} = \left(p_1 + q_{11} \dfrac{am - x_{i1}}{am} \right) x_{i1} + \left(p_1 + gq_{21} \dfrac{bm - x_{i2}}{bm} \right) x_{i2} \\ \qquad - \theta_{12} y_{i1} - \theta_{13} y_{i1} \\ \dfrac{dy_{i2}}{dt} = \left(p_2 + q_{12} \dfrac{am - x_{i1}}{am} \right) x_{i1} + \left(p_2 + gq_{22} \dfrac{bm - x_{i2}}{bm} \right) x_{i2} \\ \qquad + \theta_{12} y_{i1} - \theta_{23} y_{i2} \\ \qquad \vdots \\ \dfrac{dy_{in}}{dt} = \left(p_n + q_{1n} \dfrac{am - x_{i1}}{am} \right) x_{i1} + \left(p_n + gq_{2n} \dfrac{bm - x_{i2}}{bm} \right) x_{i2} \\ \qquad + \sum_{i=1}^{n-1} \theta_{in} y_i \\ x_{i1} + x_{i2} + y_{i1} + y_{i2} + \cdots + y_{in} = m \\ q_L \le q_{11}, q_{12}, q_{13}, q_{21}, q_{22}, q_{23} \le q_U \\ p_L \le p_1, p_2, p_3 \le p_U \\ \theta_L \le \theta_{12}, \theta_{13}, \theta_{23} \le \theta_U \end{cases}$$

where, q_L, p_L and θ_L are the lower bound of q, p and θ, respectively. The q_U, p_U and θ_U are the upper bound.

This is a nonlinear minimum optimization with constrains, whose optimal results cannot be obtained by programming techniques such as linear programming. However, it can be solved by connotative enumerative methods, such as GAs, particle swarm optimization method. In system identification genetic algorithms can quickly obtain better estimates of parameter values. To better solve this parameter identification problem, it is propose an improved self-adaptive cloud co-evolution genetic algorithm.

MATERIALS AND METHODS

Improved self-adaptive cloud co-evolution genetic algorithm: First, based on multiple species evolution, the population of ISCCGA is divided into global and local populations. In the process of co-evolution, the global population carries out co-evolution operation and implements the improved promotion operation (Fig. 1). At the same time, local populations conduct local evolution operations. Figure 1 shows the global and local populations implement corresponding evolution operations. Finally, the algorithm determines whether to choose the environment selection operation according to the number of global and local populations. The optimum solution in the local population can be obtained using this multiple loop. The purpose of the promotion operation is to copy outstanding individuals in global population into local population.

Algorithm 1: The promotion operation algorithm:

Step 1 : Rank the individuals in global population according to their fitness. Based on a certain probability, copy a number of outstanding individuals to local populations

Step 2 : Sort the individuals in local population according to their fitness. Delete the worst performing individuals to ensure the superiority of local population and retain its original size

Improvements of ISCCGA: To make the local population rapidly converge to optimal solution, it was use local adaptive evolution. In this method, if the fitness of a mutated individual is better after the variation, it was replaced the primary individual. The adaptive mutation probability is defined as in Eq. 2:

$$P_m(t) = 0.01 + NG \times cof \qquad (2)$$

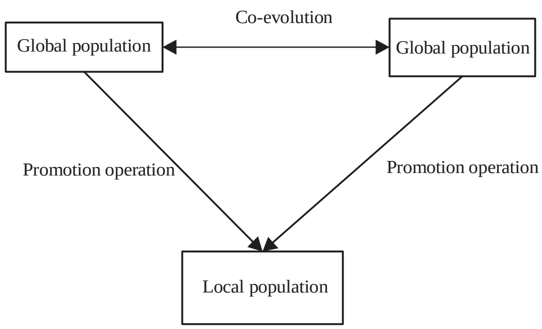

Fig. 1: Co-evolution model of the algorithm

where, t is the current iterative generation, NG is the differential value between the last optimal solution and the current algebra and cof is the coefficient of variation.

As can be seen from Eq. 2, there will be a larger mutation probability when more optimum solutions do not appear during the evolutionary process and the highest variation rate can reach 100%. Although there is no such case in natural evolution, this operation exists in the algorithm so that it can be find the optimum solution as soon as possible.

The co-evolution of individuals is influenced by individual fitness, living environment and competition[26]. In ISCCGA, this process is divided into two operations: The co-evolution algorithm and the environment selection algorithm. The population density variation can be simplified to Eq. 3:

$$\frac{dN_i}{dt} = N_{i\_t} - N_{i\_t-1} \qquad (3)$$

where, N_{i_t} is the size of the population i at time t.

Algorithm 2: The co-evolution of global population:

Step 1 : Calculate the variation of population density $\frac{dN_i}{dt}$, according to Eq. 3

Step 2 : If $\left|\frac{dN_i}{dt}\right| < \delta$ for a given threshold $\delta>0$, insert mm randomly generated new individuals into the sub-population

Step 3 : If $\left|\frac{dN_i}{dt}\right| > \delta$ and $\frac{dN_i}{dt} < 0$, insert $\left|\frac{dN_i}{dt}\right|$ randomly generated new individuals into the sub-population. If $\frac{dN_i}{dt} > 0$, delete $\left|\frac{dN_i}{dt}\right|$ low fitness individuals from the sub-population

In Algorithm 2, m randomly generated individuals will be inserted into the sub-populations when the finite population density change is not large. This improves the diversity of the algorithm. Otherwise, if the density of the sub-populations increases, then the worst individuals are deleted. If the density of the sub-populations decreases, then some randomly generated individuals are created. Through this adjustment, the sub-populations improve the overall fitness and competitive power in the evolution process.

The main purpose of the environment selection operation is to keep the size of sub-populations (N_i) constant. Once the environment load capacity (K_i) is reached, some of the worst individuals are deleted according to "survival of the fittest". The environment selection algorithm in ISCCGA is as follows.

Algorithm 3: The environment selection algorithm:

Step 1 : For each sub-population i, calculate its size N_i and environment load capacity K_i

Step 2 : If $N_i>K_i$, delete the worst $0.2\times K_i$ individuals from sub-population i

This method uses the differential evolution of a cloud model[27] to improve the crossover probability P_C in Eq. 4-6:

$$P_c = \begin{cases} P_{c\max}, & f \le \delta \\ P_{c\min} + \left(P_{c\max} - P_{c\min}\right)\exp\left(-\frac{1}{2}\frac{\left(x - E_X\right)^2}{E_n^{'} x^2}\right), & f > \delta \end{cases} \qquad (4)$$

$$\begin{cases} E_n^{'} = G\left(E_n, \quad H_e\right) \\ x = G\left(E_x, \quad E_n^{'}\right) \end{cases} \qquad (5)$$

$$\begin{cases} E_x = \max\left(f_i\right) \\ E_n = \frac{E_x - f_i}{c_1} \\ H_\varepsilon = \frac{E_n}{c_2} \end{cases} \qquad (6)$$

where, δ is the individual difference threshold, E_x is the fitness value of the worst individuals in a population, E_n are individuals in a population and its deviation, H_e is the excess entropy of the population, f_i is the individual fitness value, c_1 and c_2 are constant (generally taken as 2.8 and 12.8) and G (E_n, H_e) is a normal random number x with expectation and standard deviation of E_n and H_e, respectively.

In Eq. 4, when there is little difference in the individuals of a population and it is in the later stages of its evolution, we set P_c to be the maximum value and try to increase the diversity of the population. Otherwise, it is in the early stages of its evolution and so it can be use cloud differential evolution of the crossover probability model. Then, the competitive strategy parents and their children to the crossover process was introduced. It can be believe that higher fitness of an individual's parents results in a higher survival probability. This preserves excellent individuals, saves the winning genes and means that the algorithm converges faster.

The mutation probability uses the sigmoid function[28] in the neural network in Eq. 7:

$$P_m = \begin{cases} \dfrac{P_{m\max} - P_{m\min}}{1+\exp\left(A\left(\dfrac{2\left(f_i - f_{avg}\right)}{f_{\max} - f_{avg}} - 1\right)\right)} & f \geq f_{avg} \\ P_{m\min}, & f < f_{avg} \end{cases} \quad (7)$$

Equation 7 solves the maximum adaptive mutation probability optimization problem. The P_{mmax} and P_{mmin} are constants, A is 9.903438, f_{avg}, f_{min} and f_{max} are the average, minimum and maximum fitness of the individuals in the population[24].

ISCCGA: Based on the above improvement on genetic algorithm, an improved self-adaptive cloud co-evolution genetic algorithm (ISCCGA) was proposed as follows:

Algorithm 4: ISCCGA:

Step 1 : Initialize the global and local populations. Randomly divide the global population into multiple sub-populations

Step 2 : Code each individual and calculate its fitness

Step 3 : Improve each sub-population according to algorithm 1. Copy the outstanding individuals into the local populations

Step 4 : Use the improved evolution operation for the local population with the adaptive evolution algorithm

Step 5 : Apply co-evolution operations for each sub-population using algorithm 2

Step 6 : Apply selection operations to each sub-population and copy the best individuals to the next generation

Step 7 : Apply adaptive evolution operations to each sub-population using the adaptive evolutionary operation for the global population

Step 8 : Apply the environment selection operation to the global and local populations using algorithm 3

Step 9 : End the process if the termination condition is met, otherwise go to step 3

SOLUTION OF PARAMETER IDENTIFICATION MODEL

The ISCCGA has some advantages such as improving convergence rate, avoiding local optimum and avoiding premature convergence. Thus, it is an effective algorithm for solving optimization problems. The ISCCGA is used to solve parameter identification model of mode diffusion.

RESULTS

The case study of three mode diffusion in reference[4] is taken as an example. Supply chain management (A), green manufacturing (B) and total quality management (C) are utilized to show the application of multi-ACD model and the proposed parameter identification model. Data of the three modes are obtained through different ways such as statistical data, investigation, as well as evaluation on statistical as shown in Table 1.

In this case, m = 29774, a = 0.08, b = 0.92 and β = 0.12. Based on the data in Table 1, the parameter identification model was built. According to the above parameter identification model, the optimal parameters of g, p, q and θ can be obtained by ISCCGA using MATLAB 7.1, as shown in Table 2.

To verify the convergence and robustness of the proposed algorithm, it is compared the performance of ISCCGA with other algorithms. In this experiments, the population size NP = 500, the initial crossover probability P_c = 0.8 and the initial mutation probabilities are $P_m = 0.1$, $P_{cmin} = 0.6$, $P_{cmax} = 0.8$, $P_{mmin} = 0.1$ and $P_{mmax} = 0.5$. The improved probability is 0.4, the co-evolution probability is 0.4, δ = 5, m = 4 and the initial mutation coefficient probability of the growth probability is 0.01.

Table 1: Number of enterprises implementing three modes

	Time					
Mode	2005	2006	2007	2008	2009	2010
A	58	132	230	370	743	1061
B	328	335	704	1180	1340	1742
C	1000	1238	1771	2139	2405	2617

Table 2: Optimal parameter values

Parameters	m	a	b	γ	g
Value	29774	0.08	0.92	0.12	1.0045
Parameter	p_1	p_2	p_3	q_{11}	q_{12}
Value	0.0017	0.0040	0.0006	0.4598	0.6434
Parameter	q_{13}	q_{21}	q_{22}	q_{23}	θ_{12}
Value	0.6746	0.2039	0.2117	0.2762	0.0305
Parameter	θ_{13}	θ_{23}			
Value	0.0934	0.0688			

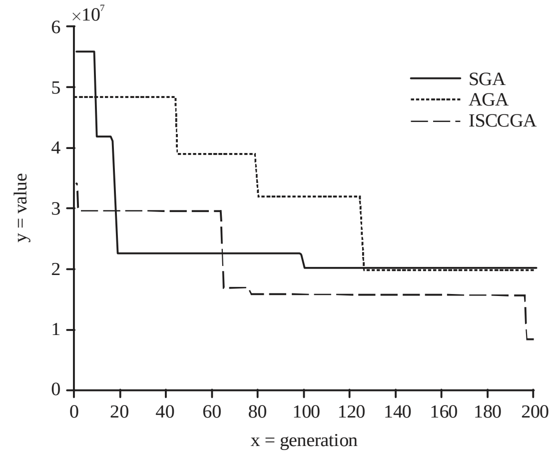

Fig. 2: Iterative process of algorithms

Table 3: Experiments on the influence of P_c

[P_{cmin} and P_{cmax}]	Optimal value	Convergence algebra
[0, 0.2]	8.6733+006^e	123
[0.2, 0.4]	1.7228+007^e	199
[0.4, 0.6]	1.9018+007^e	153
[0.6, 0.8]	1.4326+007^e	89
[0.8, 1.0]	1.4226+007^e	31

Table 4: The influence of K_i

Sub-population size (N_i)	Optimal value	Convergence algebra
$N_i = 1.5\times K_i$	1.2032+007^e	76
$N_i = 2\times K_i$	1.2472+007^e	108
$N_i = 3\times K_i$	1.5851+007^e	113

Table 5: Comparison results for different algorithms

Algorithm	Optimal value	Mean value	Success rate (%)
SGA	1.3751+007^e	1.4196+007^e	98
AGA	1.2373+007^e	1.3126+007^e	100
ISCCGA	1.0263+007^e	1.2315+007^e	100

Influence of parameters: The initial crossover probability P_c and the initial mutation probability P_m must be user-defined in the ISCCGA algorithm.

P_{cmin} and P_{cmax}: The crossover probability is the key influence on ICEAGA and P_{cmin} and P_{cmax} have direct influences. To simplify the calculation, the difference between P_{cmin} and P_{cmax} was set to 0.2 and it is varied them between [0, 1]. The results are shown in Table 3.

Environment load capacity K_i: In ISCCGA, it was selected 80% of the population if the size of the sub-population is beyond the environment load capacity (K_i). The $N_i = 1.5\times K_i$, $N_i = 2\times K_i$ and $N_i = 3\times K_i$ for these experiments was chosen, as shown in Table 4.

Comparison with other algorithms: To investigate the effectiveness of the ISCCGA for solving the practical problem, we compared the experimental results of the ISCCGA with those commonly used algorithms: SGA and AGA, as shown in Fig. 2 and Table 5.

Figure 2 demonstrates that the ISCCGA has better convergence. Compared with SGA, ISCCGA can converge more quickly and has more optimal value. And compared with AGA, it has more optimal value. The results in Table 5 demonstrate that the ISCCGA performed better than SGA and AGA, the optimal value is 1.0263+007^e and the mean value is 1.2315+007^e.

DISCUSSION

From the optimization by ISCCGA, it can concluded: (1) Parameter optimization of mode diffusion can be realized by ISCCGA. As parameter identification of advanced manufacturing mode diffusion is a complex practical problem, which has many parameters. Xue *et al.*[17] firstly studied its parameter identification through optimization method by an improved GA. This study also realize its optimization by a different method, i.e., ISCCGA and (2) As to parameter identification, better results can be obtained by ISCCGA. In this study, commonly used GA methods, i.e., SGA and AGA are also used in parameter identification problem and ISCCGA can obtain better results as can be seen in Table 5. The ISCCGA is more efficient than SGA and AGA[17,18,24]. In future study, in one way ISCCGA will be used in other complex optimization problems to verify its converge. And more optimization methods instead of GA class methods, such as ant colony algorithm (AA), Particle Swarm Optimization (PSO) algorithm will be compared in other way so as to better verify the ISCCGA.

CONCLUSION

In order to better reveal the rules of multi-ACD process and make best decisions, parameter identification methods and an improved self-adaptive cloud co-evolution genetic algorithm to obtain more reasonable parameters of the model was proposed. The multi-ACD model provides a better explanation for advanced manufacturing mode diffusion, the parameter identification model provides a new way to find optimal parameters and ISCCGA provides new solution to optimization problems.

In ISCCGA, the mutation probability and parts of the co-evolution algorithm are improved using a basic co-evolution adaptive genetic algorithm. Then, the differential evolution of a cloud model and competition strategies into crossover operator are introduced. Thus, a nonlinear adaptive adjustment to the rate of crossover have been achieved. The proposed ISCCGA have been verified by applying it to a practical problem, i.e., parameter identification of multi-ACD. This experimental results demonstrate that ISCCGA has some advantages, such as improving convergence rate, avoiding local optimum and avoiding premature convergence. Thus, ISCCGA is an effective algorithm for solving parameter identification problems of mode diffusion.

Given necessary mode diffusion parameters, which can be obtained through field investigation and proper parameters of ISCCGA, optimal parameters of mode diffusion with minimize predict error can be obtained by our proposed methods. This study helps to provide a new approach to predict the implementation status more accurately, so that enterprises and governments can master the rules of advanced mode diffusion to the greatest degree and make best decisions. By the way, the proposed ISCCGA provide a new way to solve other practical optimization problems.

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