Research of Model Identification for Control System Based on Improved Differential Evolution Algorithm

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Abstract. Differential evolution algorithm is a heuristic global search technology based on population, which has received extensive attention from the academic community. Evolution algorithm is applied to the identification and optimization of double-tank system in this article. Firstly, the paper introduces the basic principle of the system identification and differential evolution algorithm. Secondly, design the identification scheme of double-tank system based on differential evolution algorithm. Identify the system according to the data measured in the experiment. Based on the commonly used three models and combined with DE/rand/1/bin, the model structure which best complies with the original experimental data is selected, and the improved form of the difference algorithm is further studied on the basis of the model structure. A large number of experiments have been carried out, the algorithm in other references may only improve one of CR or F, and the two will be all compared in this paper. The results of comparative analysis show that the improved differential evolution algorithm is, to some extent, superior to the basic differential evolution algorithm on identification accuracy of double-tank.

Keywords: Differential evolution algorithm · System identification · Two-tank

1 Introduction

People's research on process behavior has been paid more and more attention. The mastery of process behavior has largely determined the performance of process control system, which has promoted the development of process modeling and identification. There are two ways to build a mathematical model: analytic method and system identification. This paper mainly studies the method of establishing the mathematical model of the process to be studied by system identification. System identification, a kind of science and technology, establishes the dynamic system model by examining the input and output data of the system. When faced with some systems which are more complex, the classic system identification method will be ineffective.

Evolutionary computation has many advantages, such as self-organization, self-adaptation, self-learning, and it is not limited by the type and nature of the problem to be studied. The differential evolution (DE) algorithm uses the population-based global

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search strategy and uses real number coding and simple variation based on the difference, which effectively reduces the complexity of genetic operation. In addition, the DE algorithm has the ability of memory, it can dynamically track the current search situation of the algorithm and adjust its search strategy. The algorithm does not need to know the characteristic information of the problem studied in advance, so it can solve the optimization problem in some complicated environment. DE algorithm has been widely concerned and applied because of its obvious advantage in the continuous domain optimization problem, which has led to the upsurge in the field of evolutionary algorithm research.

2 Principle and Process of Differential Evolution Algorithm

The DE algorithm is usually composed of four operations: initialization, mutation, crossover and selection. Combined with the evaluation of the fitness value, the optimal solution can be approximated by repeated iterations. In general, the global optimization problem can be transformed into solving the minimum or maximum problem. The step of solving the minimum problem of the function is shown in Eq. (1).

$$\begin{cases} \min f(X), X = [x_1, x_2, \ldots, x_D] \\ s.t.\ a_j \le x_j \le b_j,\ j = 1, 2, \ldots, \ldots D \end{cases} \tag{1}$$

In the formula (1), b_j is used to express the upper limit of x_j, and a_j is used to express the lower limit of x_j.

The process of differential evolution algorithm is shown as follows.

2.1 Initialize the Population

$$\left\{X_i(0) | X_i(0) = [x_{i,1}, x_{i,2}, \ldots, x_{i,D}], i = 1, 2, \ldots NP\right\} \tag{2}$$

$$\begin{cases} x_{i,j} = a_j + rand \cdot (b_j - a_j) \\ i = 1, 2, \ldots, NP; j = 1, 2, \ldots, D \end{cases} \tag{3}$$

$X_i(0)$ is used to express the i-th individual of the initial population, and $x_{i,j}$ is used to express the i-th individual of the j-th dimension.

2.2 Mutation Operation

$$V_i(g + 1) = X_{r_1}(g) + F \cdot (X_{r_2}(g) - X_{r_3}(g)) \tag{4}$$

$i \ne r_1 \ne r_2 \ne r_3$, $i = 1,2,\ldots,NP$, r_1, r_2, r_3 are the random integers in the closed interval [1, NP], and g represents the current number of iterations. X_i(g) Represents the i-th individual in the g-th iteration population. V_i(g + 1) represents a new population generated after the mutation.

2.3 Cross Operation

$$u_{i,j}(g+1) = \begin{cases} V_{i,j}(g+1)\ if\ rand \le CR\ or\ j = j_{rand} \\ x_{i,j}(g), \quad otherwise \end{cases} \tag{5}$$

$i = 1,2,\ldots,NP, j = 1,2,\ldots,D$, $U_i(g+1) = [u_{i,1}, u_{i,2}, \ldots, u_{i,D}]$ represents the new population after the cross operation, j_{rand} is a random integer within the interval [1, D] (Fig. 1).

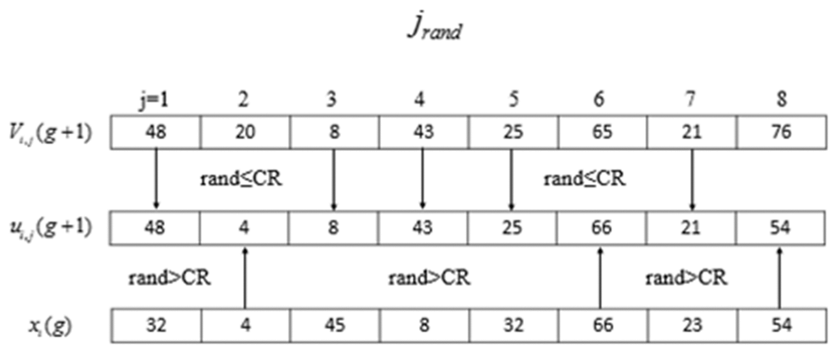

Fig. 1. Binomial cross process

2.4 Selection Operation

$$X_i(g+1) = \begin{cases} U_i(g+1), if\ f(U_i(g+1)) \le f(X_i(g)) \\ X_i(g), \quad otherwise \end{cases} \tag{6}$$

2.5 Termination Condition

The judgment condition here is that the number of evolutionary iterations reaches its maximum value, that is to say, the operation of the algorithm can be stopped only if g (the number of iterations) is greater than G_m (the maximum number of iterations); otherwise, the algorithm will continue until the termination condition is satisfied.

3 Improved Differential Evolution Algorithm

3.1 New Mutation Operation

The differential vector of the parent is the most basic component of the mutation operation of the DE algorithm, and each differential vector consists of two different individuals of the parent. According to a variety of generating methods of mutation individual, a variety of different differential evolution algorithm has be formed. The equations for the DE/rand/1 and DE/best/1 are:

$$v_i^t = x_{r1}^t + F(x_{r2}^t - x_{r3}^t) \tag{7}$$

$$v_i^t = x_{best}^t + F(x_{r2}^t - x_{r3}^t) \tag{8}$$

In the Eqs. (7) and (8), $X_{r1}^t, X_{r2}^t, X_{r3}^t$ are random individuals different from each other, X_{best}^t is the best individual in the population, F ∈ [0,1] is Scale factor. From Eq. (7) we can see that the mutation individual consists of three different random individuals. Since the base vector is a random individual, which do not need any fitness information, the mutation operation shown in Eq. (7) contributes to the diversity of the population and global search capability of differential evolution algorithm, at the same time, the convergence rate of the algorithm will be reduced. From Eq. (8) we can see that mutation individual X_{best}^t is the base vector of V_i^t, therefore, its local search ability is high, the precision is high, however, the fast convergence speed may cause the algorithm fall into the local optimal point. Combine the characteristics of these two different mutation patterns, take the effects of random individuals X_{r3}^t and optimal individuals X_{best}^t into account when make the mutation strategy of the mutation equation. In this paper, a new mutation strategy is adopted, the mutation equations are:

$$v_i^t = \lambda x_{r1}^t + (1 - \lambda)x_{best}^t + F(x_{r2}^t - x_{r3}^t) \tag{9}$$

$$\lambda = (T_{\max} - t)/T_{\max} \tag{10}$$

In Eq. (10), T_{max} is used to express the maximum number of iterations, t indicates the current number of iterations, λ ∈ [0,1]. If λ = 1, then Eq. (9) is equivalent to Eq. (7), which refers to DE/rand/1; If λ = 0, then Eq. (9) is equivalent to Eq. (8), which refers to DE/best/1. A well-performing algorithm generally requires strong global search capability at the initial stage of the search to find possible global optimizations as much as possible, and at the end of the search it should have strong local search capability. Combine the global search capabilities and local search abilities, then the accuracy and convergence rate of the algorithm can be improved. Therefore, the simulated annealing strategy is introduced, λ is set as the annealing factor, as it is shown in Eq. (10). In the process of running the DE algorithm, λ will be gradually reduced from 1 to 0, so that the weight of X_{r3}^t gradually reduces and the weight of X_{best}^t gradually increases, so as to ensure the strong global search and faster convergence rate and search accuracy of the differential evolution algorithm.

3.2 The Strategy of Adaptive Scaling Factor

In the standard differential evolution algorithm, the scaling factor F is generally a fixed value. The scaling factor F affects the degree of disturbance to the base vector, so the size of F will affect the convergence and convergence speed of the algorithm. Das and so on proposed F dynamic adjustment strategy, F gradually reduces with the increase of the number of iterations, so that the algorithm can make multi-directional exploration in the early stages of evolution, and in the late stages of evolution, the gradual reduction of the scaling factor is conducive to adjust the search direction of the vector, which contributes to the development in the region where the global optimal solution are. The following gives a strategy for adaptive scaling factor F, in which F decreases with the increase of the number of iterations:

$$F = F_{\max} - \frac{t(F_{\max} - F_{\min})}{T_{\max}} \tag{11}$$

3.3 The Strategy of Crossover Probability Factor

CR determines whether the test vector of the individual in the population is taken from the mutation vector or the target vector. When the CR is large, the information of the test vector will be taken from the mutation vector more, and when CR is small, the information of the test vector will be taken from the target vector more, so as to achieve the desired cross effect. When the fitness value of the mutation vector is better, the test vector should be taken from the mutation vector with a larger probability, and the value of CR should be increased. When the fitness value of the mutation vector is poor, the test vector should be taken from the mutation vector with a smaller probability, and the value of CR should be reduced. The crossover probability factor chosen in this paper is shown in Eq. (12).

$$CR = CR_{\min} + \frac{t(CR_{\max} - CR_{\min})}{T_{\max}} \tag{12}$$

4 Application and Verification of Improved DE Alogorithm

In order to verify the effect of model identification based on differential evolution algorithm, the process control experiment device is adopted, and the tank level is the controlled amount. Give the output data collected from the experiment back to the computer to study the dynamic characteristics of dual capacity tank. A total of two sets of experimental data were collected, the first group receives a 5% step signal, and the second group receives a 15% step signal.

From the literature [2] and the literature [3] we can see that the transfer function of the dual-capacity tank can be expressed as three models as shown in Table 1.

Table 1. Three models of the dual-capacity tank

Model 1	$G_1(s) = \dfrac{K}{(T_1 s + 1)(T_2 s + 1)}$
Model 2	$G_2(s) = \dfrac{K}{(T_1 s + 1)(T_2 s + 1)} e^{-\tau s}$
Model 3	$G_3(s) = \dfrac{K}{Ts + 1} e^{-\tau s}$

In this paper, the precision index shown in Eq. (13) is chosen as the fitness function. y_p is the output value obtained from the simulation of the model, y is the real output data measured from the experiment.

$$J = \sum_{i=1}^{n} \frac{1}{2}(y_p - y)^2 \tag{13}$$

The differential evolution algorithm uses DE/rand/1/bin. After a large number of experiments, it is found that the influence of the range of the parameters to be identified on the performance of the algorithm is poor than the influence of the algorithm parameter on the performance of the algorithm. Therefore, after several tests, identify the upper limit of the range of parameters. The three models identified by the basic differential evolution algorithm are shown in Table 2.

Table 2. The three models of the double tank identified

Model 1	$G_1(s) = \dfrac{93.7977}{(64.0501s+1)(291.6566s+1)}$
Model 2	$G_2(s) = \dfrac{93.8236}{(59.9938s+1)(296.2190s+1)}e^{-0.9874s}$
Model 3	$G_3(s) = \dfrac{94.2152}{340.5260s+1}e^{-42.7492s}$

From Table 3, the model 1 is also applicable to the second set of experimental data, and the accuracy is high and the time is short (Fig. 2).

Table 3. The model parameters identified by the second set of experimental data

	J	K	T/T_1 T_2	τ	Time
Model 1	0.0816	94.64	66.6 285	/	79.4
Model 2	0.0817	94.65	66.4286	0.1	128
Model 3	0.2939	97.19	330	47	123

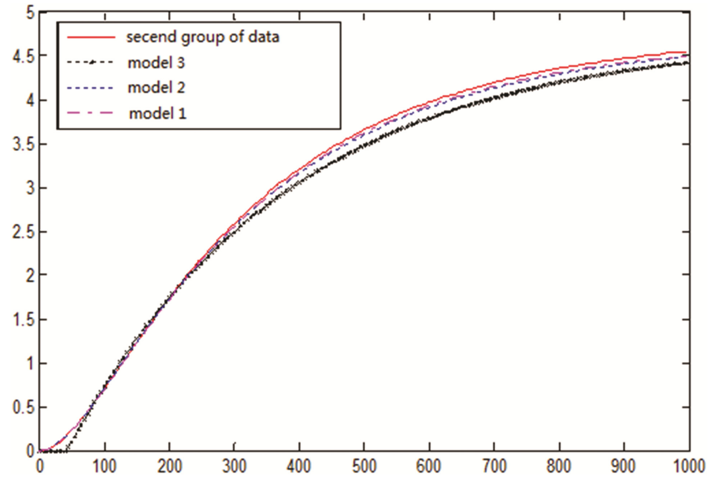

Fig. 2. Validation of model accuracy

The step response curve of model 3 identified by the first set of experimental data is far from the second set of experimental data, and the step response curve of model 1 is closer to the real experimental data. Therefore, model 1 is used as the object of further study (Fig. 3).

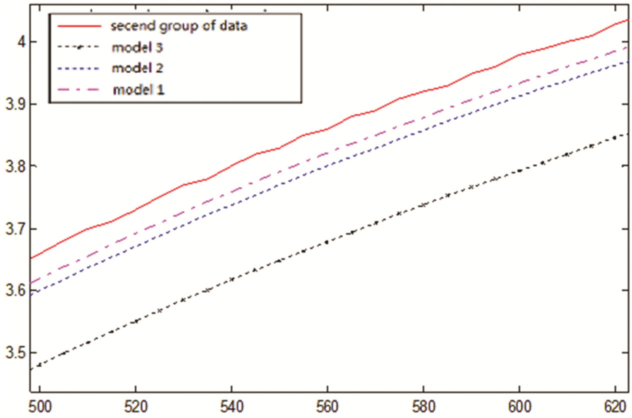

Fig. 3. Proximity between three models and experimental data

Dynamically changing the value of the parameter allows the parameters of the differential evolution algorithm to be adapted to the algorithm process automatically, while improving the mutation operation to apply it to the identification of the system model. The MATLAB experiments were carried out with the mutation operations shown in Eqs. (8) and (9). The PC system is win10 Professional Edition, and the MATLAB version is 2011b.

$$v_i^t = \lambda x_{r1}^t + (1 - \lambda)x_{best}^t + F(x_{r2}^t - x_{r3}^t) \tag{14}$$

$$\lambda = (T_{\max} - t)/T_{\max} \tag{15}$$

Now select the following two adaptive parameter strategy to identify.

$$CR = CR_{\min} + \frac{t(CR_{\max} - CR_{\min})}{T_{\max}} \tag{16}$$

$$F = F_{\max} - \frac{t(F_{\max} - F_{\min})}{T_{\max}} \tag{17}$$

4.1 Application of Improved Mutation Operator Algorithm

Under the premise that the population size NP, the maximum evolutionary algebra. T_{max} and the scaling factor F are not changed, the system is identified by the mutation strategy shown in Eqs. (14) and (15). The change of the optimal solution with the evolutionary algebra is shown in Fig. 4. It can be seen that the recognition accuracy based on the basic differential evolution algorithm and the recognition accuracy based on the improved mutation operator are not very different and the convergence rate of the improved differential evolution algorithm is superior to the basic differential evolution algorithm to a certain extent. It can be seen that the convergence rate of the differential evolution algorithm with improved mutation operator is faster than that of the basic mutation operator. So we can know that the performance of the improved mutation operator algorithm is better than that of the basic differential evolution algorithm.

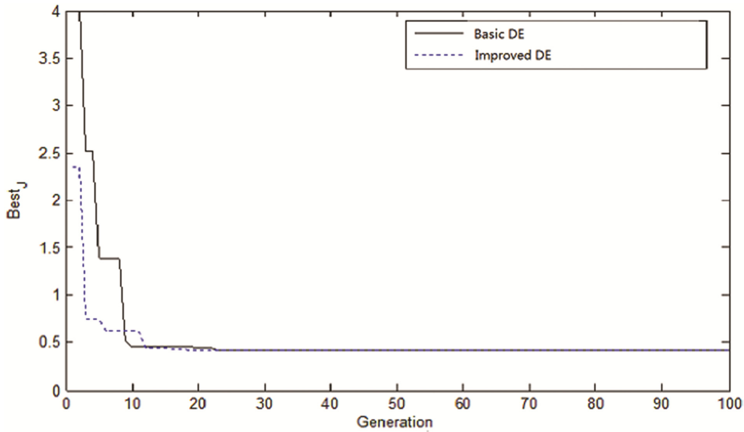

Fig. 4. Effect of mutation operator

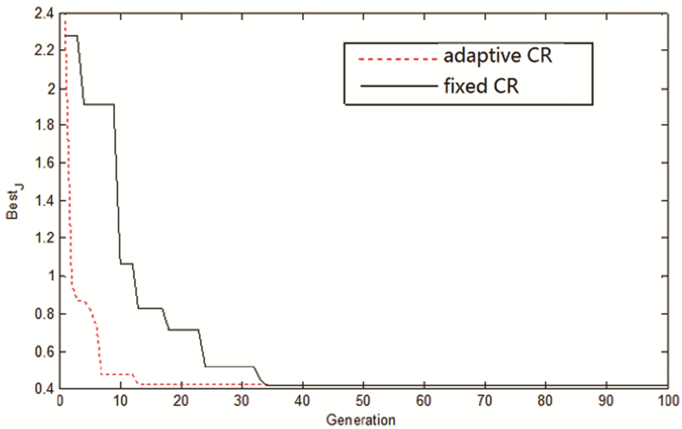

Fig. 5. Effect of cross factor strategy

4.2 Application of Improved Crossover Probability Factor Algorithm

Under the premise that the population size NP, the maximum evolutionary algebra T_{max} and the scaling factor F are invariant, we choose the crossover probability factor strategy as shown in Eq. (16) to identify the parameters of the mathematical model of the double-tank test system. The change of fitness value with evolutionary algebra is shown in Fig. 5.

From Fig. 5, the convergence rate of the differential evolution algorithm with the adaptive cross factor parameter strategy is faster than that of the fixed CR value. It can be seen that the performance of adaptive crossover factor algorithm is better than that of fixed cross factor algorithm.

4.3 Application of Improved Scaling Factor Algorithm

Similarly, under the premise that the population size NP, the maximum evolutionary algebra T_{max} and the cross factor CR are invariant, we choose the following adaptive scaling factor F strategy, in which F decreases with the increase of the number of iterations:

$$F = F_{\max} - \frac{t(F_{\max} - F_{\min})}{T_{\max}} \tag{18}$$

Now study the effect of adaptive parameter scaling factor, where t is the current number of iterations, parameters $F_{max} = 0.8$, $F_{min} = 0.2$. The change of the optimal solution with the evolutionary algebra t is shown in Fig. 6.

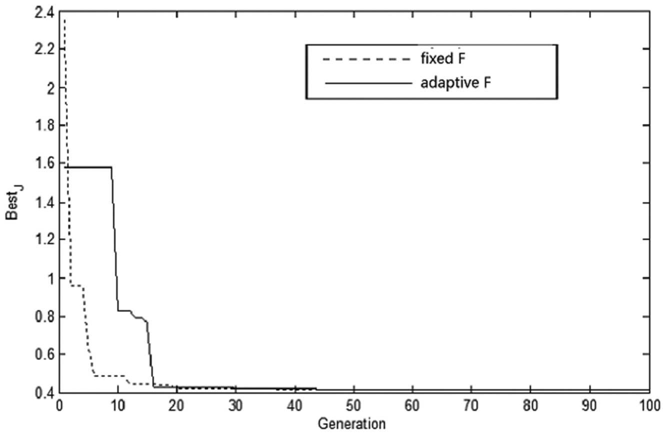

Fig. 6. The effect of scaling factor strategy

It can be seen from Fig. 6 that the convergence rate of the differential evolution algorithm with the scaling factor parameter adaptive selection strategy is faster than that of the fixed F-value differential evolution algorithm. Which proves that the superiority of the differential evolution algorithm which adopts the adaptive scaling factor strategy.

4.4 Comparison of Identification Results of Double-Capacity Water Tank System Based on Improved DE Algorithm

The three improved DE algorithms are used to identify the parameters of the dual-tank system. After selecting the best parameters, three new transfer functions can be formed, and then the simulation is carried out by MATLAB. The step response curve is shown in Fig. 7.

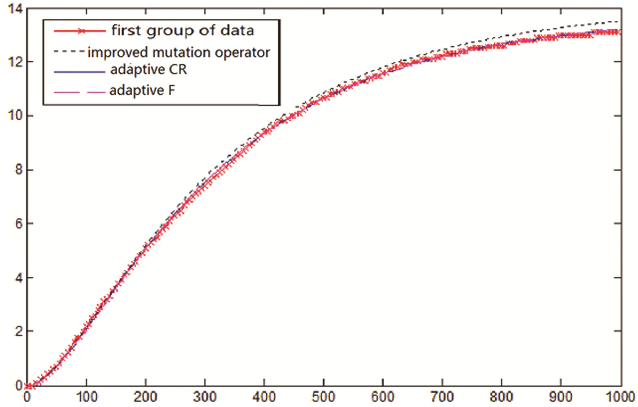

Fig. 7. Improved DE algorithm to identify the results of the response curve and experimental data comparison

It can be seen from Fig. 7 that among the three improved differential evolution algorithms, the result of the improved mutation operator strategy is relatively poor, while the accuracy of the other two improved differential evolution algorithms is similar to each other.

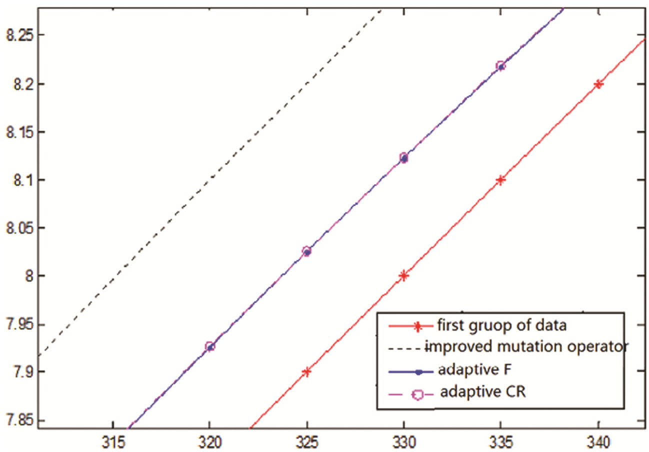

Fig. 8. Comparison of the results of the improved algorithm and the experimental data

After further enlarging the curve graph shown in Fig. 8, it can be seen that the accuracy of the improved F and adaptive CR differential evolution algorithm is similar to that of the improved CR, and then compare the recognition result of improved CR differential evolution algorithm with the recognition result of the basic differential evolution algorithm, the result is shown in Fig. 9.

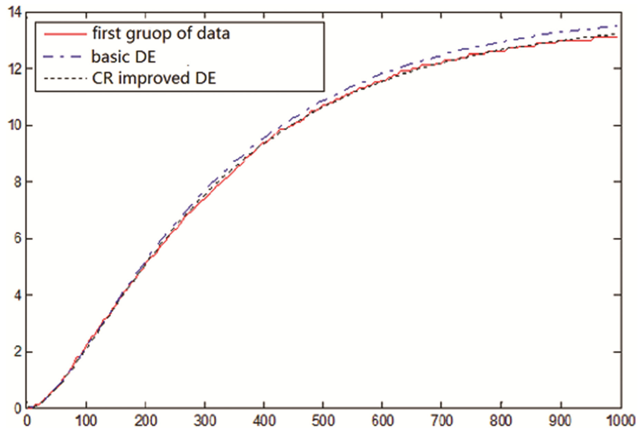

Fig. 9. Comparison of improved DE and basic DE identification results

From Fig. 9, we can see that the step response curve of the parametric model identified by the basic differential evolution algorithm is far from the first group of experimental data, and the step response curve of the parametric model identified by the improved differential evolution algorithm is almost overlaps with the curve of the experimental data, thus it can be seen that the improved differential evolution algorithm is superior to the basic differential evolution algorithm in the accuracy of the dual-tank model.

5 Conclusion

This paper introduces the differential evolution algorithm and the principle of improved differential evolution algorithm and its several different forms. The performance of improved differential evolution algorithm is verified by the case of double - capacity water tank. In this paper, the operation flow of the basic differential evolution algorithm is given and used in the model identification of the system. The influence of the parameters in the differential evolution algorithm on the performance of the algorithm is studied by repeated comparative experiments.

Because of the strong and rapid optimization ability of the differential evolution algorithm, In this paper, the differential evolution algorithm is used to identify the parameters of the model, and the individuals of differential evolutionary algorithms is composed of the parameters of the model to be identified. The results show that the improved differential evolution algorithm is superior to the basic evolutionary algorithm in terms of system identification.

DE algorithm has become a new research hotspot in the field of evolutionary computation, however DE algorithm still has a wide range of research space worthy of mining in its theoretical analysis, algorithm improvement and applied research. For example, we can consider the diversity of the population and the change of the individual fitness value in the process of the algorithm, and introduce the adaptive adjustment mechanism. When the population converges to a certain range near the optimal solution, take the reverse direction, and this will cause greater perturbation to mutation vector, which can increase the diversity of the population and prevent local optimum; we can take advantage of the high degree of parallelism in the operation of the DE algorithm to divided the initial population into multiple subpopulations, and the subpopulations are interconnected according to the von Neumann topology, and the migration mechanism allows the information to be shared periodically throughout the population; DE can also be combined with other algorithms with respective advantages within a certain scope of the solution to produce a new algorithm which surpass the parent algorithm.

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References

1. Guo, L.-H., Zhu, L.-H., Gao, W.: Characteristics and simulation of least squares system based on MATLAB. J. Xuchang Univ. **29**(2), 24–27 (2010)
2. Liu, Z.-Q., Wang, S.-X.: Study on modeling and PID control algorithm of liquid level control system for double-tank. J. Appl. Sci. **9**, 95–96 (2015)
3. Wang, Z.: Process Control Systems and Instruments. Mechanical Industry Press, Beijing (2006)
4. Zhang, C.: Differential Evolution Algorithm Theory and Application. Beijing University of Science and Technology Press, Beijing (2014)
5. Liu, Y., Gu, F.: Study on differential evolution algorithm. Technol. Square **03**, 20–23 (2013)
6. Li, Q., Guo, Y., Ying, P.: Comparison of water level model DE and PSO and LS identification of double-capacity water tank. Comput. Simul. **32**(11), 407–409 (2015)
7. Li, X.-L., Li, J., Shi, L.-H.: Construction and simulation of tank level system. J. Syst. Simul. **22**(4), 829–832 (2010)
8. Tasgetiren, M.F., Suganthan, P.N.: A multi-populated differential evolution algorithm for solving const rained optimization problem. In: IEEE Congress on Evolutionary Computation (2006)
9. Das, S., Suganthan, P.N.: Differential evolution: a survey of the state-of-the-art. IEEE Trans. Evol. Comput. **15**(1), 4–31 (2011)
10. Liu, J., Lampinen, J.: A fuzzy adaptive differential evolution algorithm. Soft. Comput. **9**(6), 448–462 (2005)
11. Vu, C.C., Bui, L.T., Abbass, H.A.: DEAL: a direction-guided evolutionary algorithm. In: Bui, L.T., Ong, Y.S., Hoai, N.X., Ishibuchi, H., Suganthan, P.N. (eds.) SEAL 2012. LNCS, vol. 7673, pp. 148–157. Springer, Heidelberg (2012). doi:10.1007/978-3-642-34859-4_15
12. Gong, W., Cai, Z., Ling, C.X.: Enhanced differential evolution with adaptive strategies for numerical optimization. IEEE Trans. Syst. Man Cybern. B Cybern. **41**(2), 397–413 (2011)