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# WIENER MODEL IDENTIFICATION BASED ON ADE ALGORITHM

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**ABSTRACT**

DE algorithm is a population-based heuristic global search technology. The algorithm has simple principle, fewer control parameters, but has strong robustness, and good optimization performance. This paper uses differential evolution algorithm for parameters identification of Wiener model. Firstly, we analyze the influence of mutation rate F on global parallel search ability and convergence in the process of identification. Secondly, an adaptive mutated differential evolution algorithm (ADE) is proposed. The algorithm keeps individual diversity to avoid premature convergence during the early stage and reduces the mutation rate gradually so as not to damage the optimal solution obtained during the later stage of the search process. Finally numerical simulation is performed on Wiener model. The results show that ADE algorithm has more effectiveness in parameter identification problem than PSO. On the other hand, compared with the general DE algorithm, ADE algorithm identifies the parameters of Wiener model with higher precision as well as shows lower sensitivity to the algorithmic parameters.

**Keywords:** *Differential Evolution; Adaptive Mutation; Parameter Identification; Wiener Model; Particle Swarm Algorithm*

## 1. INTRODUCTION

The actual industrial processes usually have strong nonlinear characteristic, Nonlinear model often can better describe the characteristics of the whole production process. Therefore, the nonlinear model parameter identification and establishment are the key of the model-based control method. Wiener model established by Masry and Cambanis is a linear subsystem and a static (no memory) nonlinear gain in series. Wiener model identification is mentioned in reference [1], wiener model identification based on particle swarm optimization (PSO). However, the disturbance has a certain influence on algorithm performance and identification results. Reference [2] using GA algorithm approximates inverse function of nonlinear gain, and applies least-square method to identify parameter of linear subsystem, identification accuracy can not reach the requirements; Reference [3] based on quantum particle swarm optimal(QPSO), QPSO algorithm has stronger nonlinear identification ability, however, to some extent, increases the complexity of the identification operation.

Differential evolution is a kind of heuristic global random search algorithm based on individual differences among population. As an important branch of evolutionary algorithm, DE is gradually attented by domestic and foreign scholars, it is proposed by Rainer Storn and Kenneth Price for solving the Chebyshev polynomials[4-6].Compared with the general evolutionary algorithm(such as GA,PSO),DE principle is simple, easy to implement, strong robustness, fast convergence, also has less controlled parameters. It is widely used in the constrained optimization[7],neural network optimization[8],nonlinear optimization control[9],filter design[10] and other aspects. At present, apply DE to the system parameter identification is still less, therefore, it has a certain significance and potential application.

Since DE principle is simple, strong robustness, etc, combines it with the system parameter identification. The identification problem of Wiener model is equal to the nonlinear minimization problem with the estimated parameters as the optimized variables. Via the simulation experiment, analyzes the influence of mutation rate F on global parallel search ability and convergence, on this basis, analysis of the improved differential evolution algorithm, proposing an adaptive differential evolution algorithm with the combination of the improved DE and the nonlinear

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system identification, searches the optimal estimation of Wiener model in the whole parameters space. Compare the identification results of DE to PSO and QPSO, meanwhile, analysis shows that ADE is more advanced than DE. The simulation results show that the model parameter identification by ADE is more effective than other algorithm this paper introduced.

In this paper, section 2 introduces the Wiener nonlinear model ; section 3 describes the Wiener model identification based on ADE algorithm; section 4 , we present the numerical simulation; and the section 5 gives the conclusion of this paper; than section 6 is the acknowledgement of the work we do.

## 2. WIENER NONLINEAR MODEL

Wiener model is a linear subsystem and a memoryless nonlinear gain links in series, connection mode is shown in figure 1, its differential equation is:

$$\begin{cases} A(q^{-1})z(k) = q^{-d}B(q^{-1})u(k) \\ y(k) = f[z(k)] + e(k) \end{cases} \quad (1)$$

where $A(q^{-1}) = 1 + a_1 q^{-1} + \cdots + a_n q^{-n}, B(q^{-1}) = b_0 + b_1 q^{-1} + \cdots + b_m q^{-m}$ are $n$ , $m$ order polynomial backward-shift operator, $d$ is system delay, $u(k)$ , $y(k)$ are system input and output, $e(k)$ is Gaussian white noise, $z(k)$ is the output of the linear part, not measured, $f(\cdot)$ is memoryless nonlinear gain. In order to identify Wiener model, assuming $m, n, d$ and $f(\cdot)$ are known, that is the model structure is known.

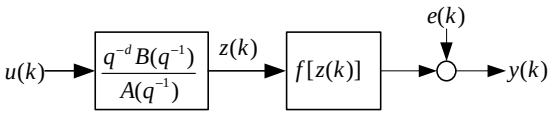


*Figure 1 Wiener model*

Definition vector parameter is $\theta = [a_1 \cdots a_n \quad b_0 \cdots b_m]^T$ , identification target is to estimate $\theta$ according to the given input $u(k)$ and output $y(k)$ ,set estimate $\theta$ is $\hat{\theta} = [\hat{a}_1 \cdots \hat{a}_n \quad \hat{b}_0 \cdots \hat{b}_m]^T$ ,make the squares of output estimation bias minimum at $k$ moment.

$$\min_{\hat{\theta}} J(k) = \sum_{j=1}^{L} [y(k-j) - \hat{y}(k-j)]^2 \quad (2)$$

where $L$ is identification window length, $y(k-j), \hat{y}(k-j)$ are output measurement signal and estimated value at $k-j(j=1,\cdots,L)$ moment, $\hat{y}(k-j)$ can be obtained by the following formula:

$$\begin{cases} \hat{z}(k-i) = -\hat{a}_1 \hat{z}(\text{k-i-1}) - \cdots - \\ \qquad \hat{a}_n \hat{z}(\text{k-i-n}) + \\ \qquad \hat{b}_0 \hat{u}(\text{k-i-d}) + \cdots + \\ \qquad \hat{b}_m \hat{u}(\text{k-i-d-m}) \\ \hat{y}(\text{k-i}) = f\left[\hat{z}(k-i)\right] + e(\text{k-i}) \end{cases} \quad (3)$$

Meanwhile, parameters of Wiener model to meet:

$$\theta^{\min} \le \hat{\theta} \le \theta^{\max} \quad (4)$$

So identification problem of Wiener model is equivalent to identifying nonlinear minimum optimization problem in formula (2) under solving the problem of equality constraints in formula (3) and inequality constraints in formula (4),parameter estimation $\hat{\theta}$ is optimization variable.

## 3. WIENER MODEL IDENTIFICATION BASED ON ADE ALGORITHM

### 3.1. The Basic Principle of De algorithm

The basic idea of the DE algorithm is described as below. Firstly, initializes population randomly in the feasible solution space, using the difference vector between the individuals of current parent to disturbance to realize individual variation. Secondly, according to a certain probability, parent individual and variation individual to cross than getting the test individual. Finally, selects individual between parent individual and test individual according to the fitness value, take the individual of better fitness as the offspring. DE algorithm process is described as follows:

1) Initialize population. NP D-dimensional real parameter vector, each individual is expressed as: $x_i(G)(i=1,2,\cdots,NP)$ ( $i$ is individual sequence in the population, $G$ is evolution generation).Initial population generated randomly:

$$x_{i,j}(0) = x_{i,j}^L + rand * (x_{i,j}^U - x_{i,j}^L) \quad (5)$$

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where $x_{i,j}(0)$ represents the first $j$ gene of the first $i$ individual of the first 0 generation. $NP$ is population size, $D$ is the dimension of the optimization problem; $x_{i,j}^{U}$ , $x_{i,j}^{L}$ are parameters boundaries, *rand* is uniformly distributed random number between $(0,1)$.

2) Mutation. For each target vector, mutant vector is generated as bellow:

$$v_i(g+1) = x_{t1}(g) + F\cdot(x_{t2}(g)-x_{t3}(g)) \ (i \neq t_1 \neq t_2 \neq t_3) \quad (6)$$

Where $F$ is mutation rate, The randomly integers $t_1, t_2, t_3 \in [1, NP]$ are chosen to be different from the running index i . $F$ controls the amplification of the differential variation( $x_{t2}(g)-x_{t3}(g)$ ), $x_i(g)$ represents the number $i$ individual of the number $g$ generation.

3) Crossover: once the mutant vector is generated, the perturbed individual, $v_{i,j}(g+1)=(v_{1,i}(g+1)\ldots v_{n,i}(g+1))$, and the current population member, $x_{i,j}=(x_{1,i,g,\ldots}x_{n,i,g})$, are then subject to the crossover operation, that finally generates the population of candidates, or "trial" vectors, $u_{i,j}(g+1)=(u_{i,1}(g+1),\cdots,u_{i,n}(g+1))$, as follows:

$$u_{i,j}(g+1)=\begin{cases} v_{i,j}(g+1), & if \ \ rand \le CR \ \text{or} \ j=j_{rand} \\ x_{i,j}(g), & otherwise \end{cases} \quad (7)$$

where $CR$ is crossover probability, $j_{rand}$ is random integer between $[1,2,\cdots,D]$ , *rand* is uniformly distributed random number between $(0,1)$.

4) Selection. If the new individual is better than the original one then the new individual is to be an offspring n the next generation $G=t+1$ else the new individual is discarded and the original one is retained in the next generation.

$$x_i(g+1)=\begin{cases} u_i(g+1), & if \ \ f(u_i(g+1)) \le f(x_i(g)) \\ x_i(g), & otherwise \end{cases} \quad (8)$$

Where $f()$ is the fitness function, $f(u())$ is the fitness values of trial individual.

### 3.2. Adaptive Mutation De algorithm

In the identification of the process of DE algorithm, mutation rate generally is selected a fixed real number between $[0,1]$ , it is used to control the amplification of the differential variation $(x_i(g)-x_j(g))$. The algorithm is difficult to determine the variation rate F and it is big in the concrete implementation process. DE algorithm is similar to random search, having low search efficiency, and its accuracy about getting the global optimal solution is low; small mutation rate leads to reducing the diversity of population, easy to appear premature. Therefore, proposes adaptive mutation operator, Early in the algorithm, adaptive mutation operator was $F_0-2F_0$ , it has great value and makes the individuals diversity in the population at the initial generations to overcome the premature. With the algorithm progress, mutation operator gradually reduced, mutation rates is closed to $F_0$ later, preserve the excellent individuals, enhance the probability of obtaining the global optimum.

Adaptive mutation operator is designed as follows:

$$F = F_0 \cdot 2^{(1-\frac{gen\_\max}{gen\_\max+1-count})} \quad (9)$$

Where $F_0$ is mutation parameter, $gen\_\max$ is maximum evolution generation, *count* is current evolution generation. At the beginning of the algorithm, mutation rate is $F=2F_0$ , with large mutation rate, so as to keep the individual diversity; mutation rate is reduced gradually with the algorithm progress, mutation rate close to $F_0$ at the end of algorithm, avoiding the destruction of the optimal solution. In ADE algorithm, mutation rate $F$ is determined by adaptive mutation operator (ie, formula (9)).

### 3.3. Wiener Model Identification Based on ADE

For Eq(2) the optimization problem, set $x=\hat{\theta}$ , particle dimension is $D=n+m+1$ ,fitness function is $F(k)=J(k)$ .The specific steps for wiener model identification based on ADE are as follows:

Step 1 Parameter settings and produce uniform white noise $e(k)$;

Step 2 Set the range of the individual position $x^L$ and $x^U$ , iterations $k=0$ ,initial population( $x_i(0)\ (i=1,2,\cdots,NP)$ ) generated randomly: $x_{i,j}(0)=x_{i,j}^{L}+rand*(x_{i,j}^{U}-x_{i,j}^{L})$;

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Step 3 Calculate the fitness $F_i(0)$ of each individual of initial generation, getting the optimal fitness value $F_{best}$ and optimal individual $X_{best}$;

Step 4 Calculate mutation rate F according to formula (9);

Step 5 Realize individual variation for the first $k$ generation $\{x_i(k)\}$ according to formula (6), generate intermediates $\{v_i(k+1)\}$ and limit the range of individuals;

Step 6 Crossover between the first $k$ generation population $\{x_i(k)\}$ and variable intermediates $\{v_i(k+1)\}$ according to formula (7) to get $\{u_i(k+1)\}$;

Step 7 Adopt greedy algorithm for selecting operation according to formula (8), choose individuals to enter the next generation of population;

Step 8 Compare $F_{best}$ with $F_i(k)$ for the first $i$ individual, if $F_i(k) < F_{best}$, make $F_{best} = F_i(k)$, $X_{best} = x_i(k)$;

Step 9 Set $k = k+1$, go to Step 4 to repeat the above steps, if reach maximum iterating times $gen_{\max}$, iteration is terminated.

The algorithm flow chart is shown in Figure 2.

## 4. NUMERICAL SIMULATION

Consider Wiener model in reference [2]

$$\begin{cases} x(k)=1.5x(k-1)-0.7x(k-2)+ \\ \qquad u(k-1)+0.5u(k-2), \\ y(k)=f[x(k)]+e(k), \\ f[x(k)]=\begin{cases} \sqrt{x(k)/2}, & x(k)\ge 0, \\ -\sqrt{-x(k)/2}, & x(k)<0. \end{cases} \end{cases} \quad (10)$$

Where $e(k)$ is the noise, variance $\sigma_e = 0.1$; input signal $u(k)$ is zero mean Gaussian white noise sequence, variance $\sigma_u = 1$. To identify the true parameter vector is $\theta = [a_1\ a_2\ b_0\ b_1]^T = [-1.5\ 0.7\ 1.0\ 0.5]^T$, set $L = 500$, $gen_{\max} = 300$, $x_i^L = -2, x_i^U = 2$, $D = 4$.

The definition of root mean square error measures the identification accuracy.

$$RMSE = \sqrt{\frac{\sum_{j=1}^{M}[y(j)-\hat{y}(j)]^2}{M}} \quad (11)$$

Where $M$ is the amount of data for verification, set $M = 500$, $y(j), \hat{y}(j)$ are output measured value and estimate value of the first j process. $ITERATION$ is a minimum iterations when identified the estimated parameters.

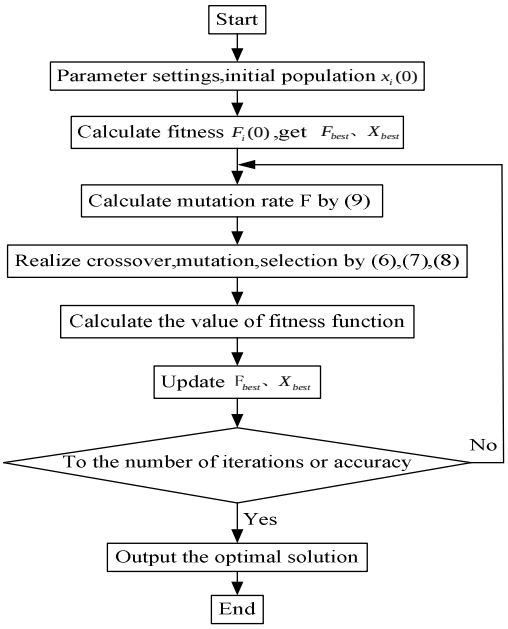


*Fig. 2 Flow chart of ADE algorithm*

DE algorithm mainly involves population scale $NP$, mutation rate $F$, crossover probability $CR$ this 3 control parameters. Population scale $NP$ generally takes a value between $5D$ and $10D$, $D$ is the number of decision variables about objective function, no less than 4,otherwise you can not carry on the mutation opetation; Mutation rate $F$ is used to control the population diversity and convergence, generally takes $F \in [0,1]$; Crossover probability $CR$ is used to control each dimension of individual participation of the crossover, generally takes $CR \in [0,1]$. In the test, set $NP = 40$, $CR = 0.9$, mutation rate $F$ for different values the influence of identification results shown in table 1.

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*Tab. 1 $NP = 20$、$CR = 0.9$, Different F To Identification Results Influence*

| *NP* | F | *CR* | $a_1$ | $a_2$ | $b_0$ | $b_1$ | *RMSE* | *ITERATION* |
|---|---|---|---|---|---|---|---|---|
| 40 | 0 | 0.9 | 0.0908 | -0.6314 | 0.9051 | 1.1156 | 0.8989 | 5 |
| 40 | 0.1 | 0.9 | -0.6109 | -0.1808 | 0.6938 | 1.8083 | 0.5173 | 15 |
| 40 | 0.2 | 0.9 | -1.3880 | 0.6010 | 0.6503 | 0.9781 | 0.2087 | 25 |
| 40 | 0.3 | 0.9 | -1.4957 | 0.6941 | 1.1605 | 0.4903 | 0.0488 | 40 |
| 40 | 0.4 | 0.9 | -1.5000 | 0.7000 | 0.9999 | 0.5000 | 6.67e-005 | 35 |
| 40 | 0.5 | 0.9 | -1.5000 | 0.7000 | 1.0000 | 0.5000 | 1.28e-012 | 40 |
| 40 | 0.6 | 0.9 | -1.5000 | 0.7000 | 1.0000 | 0.5000 | 4.81e-015 | 50 |
| 40 | 0.7 | 0.9 | -1.5000 | 0.7000 | 1.0000 | 0.5000 | 1.42e-012 | 70 |
| 40 | 0.8 | 0.9 | -1.5000 | 0.7000 | 1.0000 | 0.5000 | 5.92e-009 | 90 |
| 40 | 0.9 | 0.9 | -1.5000 | 0.7000 | 1.0000 | 0.5000 | 4.16e-007 | 115 |
| 40 | 1.0 | 0.9 | -1.5000 | 0.7000 | 1.0000 | 0.5000 | 3.31e-006 | 140 |

As can be seen from Table 1, when $F$ is large, *DE* algorithm can identify the estimation parameters, but algorithm approximates random search, the smallest iterations corresponding increse when identified the estimate value, search efficiency is low, and the accuracy of getting the global optimal solutions is low; when $F$ is small, the population diversity decreases, easily falling into local optimal solution, thus appearing premature phenomenon with low identification accuracy. Therefore, this paper proposes adaptive mutation operator, according to the progress of the search algorithm, mutation rate is determined adaptively, the algorithm in the initial has larger mutation rate remaining individual diversity and avoiding premature; later in the algorithm, mutation rate gradually reduces and keeps good information, than avoids damaging the optimal solution, increases the probability of searching the global optimal solution.

The simulation experiment indicates that the ideal control parameters of *ADE* algorithm are $NP = 40$, $F_0 = 0.4$, $CR = 0.9$. Identification results of *ADE* algorithm and *PSO*, *QPSO*, *DE* algorithm are shown in Table 2. Table 2 shows that *ADE* algorithm can accurately convergence to the real value of parameter, fully displays the feasibility and effectiveness of applicating *ADE* identification method. Compared with *PSO*, *QPSO* and *DE* identification results, *ADE* algorithm can more accurately getting the real value.

*Tab. 4 Comparison Of Four Algorithms Identification Results*

| Parameters | True value | Estimate | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | PSO | RMSE | QPSO | RMSE | DE | RMSE | ADE | RMSE |
| $a_1$ | -1.5 | -1.4998 | 2.47e-008 | -1.4999 | 1.07e-009 | -1.5000 | 1.32e-012 | -1.5000 | 4.2e-014 |
| $a_2$ | 0.7 | 0.6998 | | 0.7000 | | 0.7000 | | 0.7000 | |
| $b_0$ | 1.0 | 1.0000 | | 0.9998 | | 1.0000 | | 1.0000 | |
| $b_1$ | 0.5 | 0.4999 | | 0.5000 | | 0.5000 | | 0.5000 | |

Figure 3, 4, 5 and 6 are identification results of Wiener model based on *PSO*, *QPSO*, *DE* and *ADE* algorithm. Even if the influence of noise, *ADE*, *DE*, *PSO*, *QPSO* algorithm can identify the true value of Wiener model within 50 iterations. but the accuracy of *ADE* identification is more highter.

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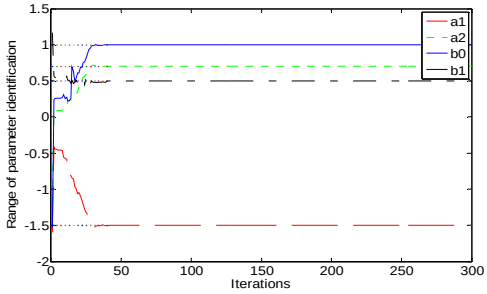


*Fig. 3 Real Value And Estimate Of Wiener Model Identification Based On PSO*

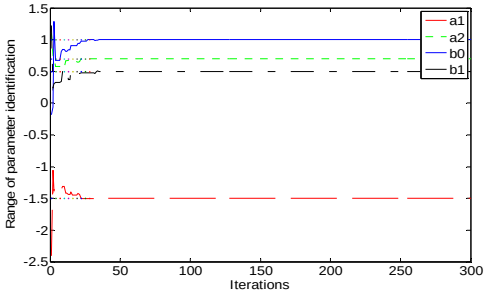


*Fig. 4 Real Value And Estimate Of Wiener Model Identification Based On QPSO*

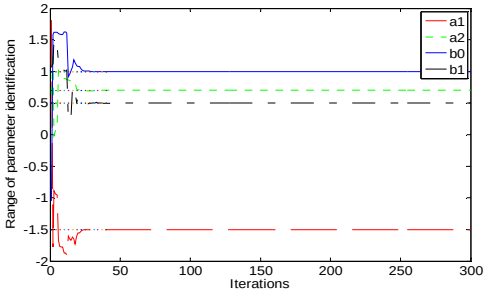


*Fig. 5 Real Value And Estimate Of Wiener Model Identification Based On DE*

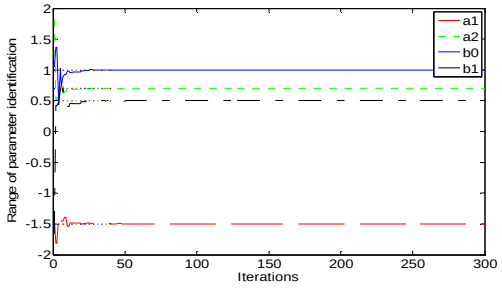


*Fig. 6 Real Value And Estimate Of Wiener Model Identification Based On ADE*

Parameter sensitivity analysis between *ADE* and *DE* algorithm:

Set the same operating parameters of the two algorithms, including the same initial population, population scale $NP = 40$ ,crossover probability $CR = 0.9$ ,variation parameter $F_0$ **is** $0.1, 0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6, 1.8$ respectively , maximum evolution generation is 300 .When variation parameter $F_0$ takes each value, the two algorithms reciprocity for 10 different randomly generated initial population respectively. Then analyzes the number of getting optimal solution in all 10 times optimization process, the result is shown in Figure 7.

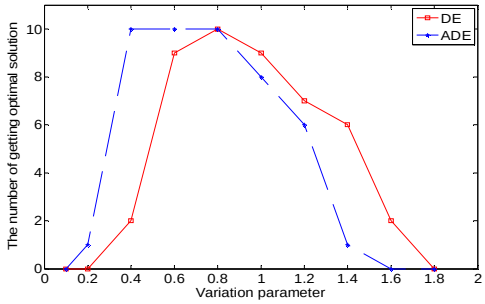


*Fig. 7 Compare The Number Of Getting Optimal Solution Between ADE And DE*

Abscissa of the figure is variation parameter $F_0$ ,ordinate is the number of times getting optimal solution; in the figure, star represents the number of times getting optimal solution in different variation parameter $F_0$ based on *ADE* ,square represents the number of times getting optimal solution in different variation parameter $F_0$ ( $F$ ) based on *DE* .As can be seen from the figure, when $F_0 \in [0.4, 0.8]$ , *ADE* algorithm reaches the best optimization results, all getting optimal solution 10 times; however, only when $F_0$=0.8 *DE* algorithm reaches the best optimization results, all getting the optimal solution 10 times. When $F_0 \in [0.4, 1]$ , *ADE* algorithm has better optimization performance; but only when $F_0 \in [0.8, 1]$, *DE* algorithm has better optimization performance. The sensitive degree of variation parameter by *ADE* algorithm is significantly lower than that by *DE* algorithm.

## 5. CONCLUSION

In this paper, using *ADE* algorithm for a class of known model structure in industrial process which can be described as Wiener model of nonlinear system to obtain optimal estimation of model parameters by searching parallel. First, via simulation experiment, analyzes the influence of mutation rate on identification results; on this basis,

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making using of improved differential evolution algorithm to identify parameters of Wiener model. Simulation results show that the sensitive degree of variation parameter by *ADE* algorithm is significantly lower than that by *DE* algorithm, it reflects that *ADE* is more advanced than *DE* . ADE algorithm has less parameters to select, strong robustness and it is easy to implement and simulation results shows that identification accuracy is satisfied based on *ADE* and *DE* , indicating the feasibility and effectiveness of this method. This next work is aiming at applying the algorithm to concrete engineering examples.

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