Desalination and Water Treatment
www.deswater.com
doi:10.5004/dwt.2017.20228

66 (2017) 229–234
March

Comprehensive evaluation of integrative drip-irrigation and fertilization using a projection pursuit model based on the improved double chains quantum genetic algorithm

Bai Wang[a,*], Yanfeng Li[b], Yan Meng[a], Xiao Liu[a]

[a]*Heilongjiang Water Conservancy Institute, Harbin 150080, China; Tel. +86 15846601103, Fax +86045186689241, email: wangbai1980@163.com (B. Wang), Tel. +86 18204600530, email: hljskynt@163.com (Y. Meng), Tel. +86 13684502945, email: 0319xiaoxiao@163.com (X. Liu)*

[b]*Institute of Food Science and Engineering, State Key Laboratory of Simulation and Regulation of Water Cycle in River Basin, China, Institute of Water Resources and Hydropower Research, Beijing 100048, China, Tel. +86 13810650918, email: liyf@iwhr.com (Y. Li)*

Received 20 March 2016; Accepted 11 September 2016

ABSTRACT

Finding the optimal solution in a single-treatment drip-irrigation and fertilizer scheme is nontrivial because of the inherent difficulty in evaluating the overall benefit of such a scheme. To address this problem, we have developed the project pursuit model based on the improved double chains quantum genetic algorithm, and applied it to integrative drip-irrigation and fertilization. The double chains quantum genetic algorithm was introduced to optimize the projection index function and seek the optimum projection vector. This algorithm was improved by introducing an immunity operator, a simulated annealing operator, and gradually optimizing and compressing the quantum chromosome search space during the evolution process. The improved projection pursuit model was applied to maize cultivation. The results show that the optimization efficiency and global search capability improved substantially. Increased nitrogen splits promoted dry matter above ground and nitrogen uptake in the maize, and also improved the yield and the plumping of seeds. A management practice of 150–200 kg/hm^2 of nitrogen applied at three splits produced the highest production in integrative drip-irrigation and fertilizer schemes for the black soil in Northeast China.

Keywords: Real coding; Quantum computing; Quantum genetic algorithm; Integrative drip-irrigation; Fertilizer

1. Introduction

Integrative water and fertilizer technology was introduced into the agricultural industry to have synchronous control of irrigation and fertilization processes [1,2]. This largely involved mulched drip irrigation, which offered savings in water and fertilizers by combining plastic film mulching and drip irrigation techniques, and transported water and nutrients to the soil at the crop root level. Currently, mulched drip irrigation technology is used for crops such as maize [3], cotton [4], potato [5], tomato [6] and cucumber [7]. The planting area of grain crops reached 214 million mu in the Heilongjiang province in 2014, and the planting area of maize, the first grain crop, reached 106.15 million mu in the same year. Water shortages caused by a lack of precipitation and low reservoir levels, chill damage and less than optimal water and fertilizer use have directly influenced maize yields, and this trend is predicted to continue. To solve the imbalance between supply and demand of fertilizer resources, the development of integrative drip-irrigation and fertilizers for black soil has played an important role in achieving the objective of realizing a water-saving agricultural system.

Projection pursuit (PP) [8–10] is an emerging statistical method that is designed to treat high-dimensional non-normal data, which overcomes the so-called curse of dimensionality. PP models have been used to convert high-dimensional

*Corresponding author.

indices (e.g., Sample Evaluation Index) into low-dimensional space. This is done by projecting the data into a specific direction; the optimal direction will reduce the dimension of the data while retaining as much of the original information as possible. This optimization problem has been approached using artificial intelligence methods.

In this research, we optimized and compressed the search space of quantum chromosomes by changing the value range of argument θ, which is the quantum bit of such chromosomes in the unit circle. We also improved the population diversity by introducing an immunity operator. For the above, we used parallel searches in a quantum algorithm and serial searches in a simulated annealing algorithm. The result is the improved accelerating double chains quantum genetic algorithm (ADCQGA), which we employ in a projection pursuit classification (PPC) model to evaluate integrative drip-irrigation and fertilization. The improved ADCQGA was used to find the best projection direction. At the same time, many evaluation indexes values of each scheme could be synthesized projection value with one dimension which indicates advantage of each scheme. Finally, we demonstrated how the integrative drip-irrigation and fertilizer scheme could be classified and evaluated for the black soil in Northeast China.

2. Projection pursuit model based on the improved double chains quantum genetic algorithm

2.1. Double chains quantum genetic algorithm

The concept of quantum computing was proposed by Feynman while developing computer simulations of a physical system in 1982 [11]. Peter Shor presented the quantum algorithm for discrete logarithms and factoring in 1994 [12]. It wasn't until 1996, though, when Grover devised a fast quantum mechanical algorithm for database searches [13], that quantum computation with its high performance became an international research focus. A quantum genetic algorithm (QGA) [14–18] is a probability optimization algorithm based on the quantum unit calculation principle, which has the advantages of having small populations, rapid convergence, and good global search capabilities.

In the double chains quantum genetic algorithm, the initial value θ_{ij} of the probability amplitude of the quantum bit $[\cos\theta_{ij}, \sin\theta_{ij}]^T$ is randomly generated in the domain (0, 2π). In the current approach, the quantum bit phase has a quantum rotation gate, and a quantum not gate is used to effect quantum mutation [19]. The probability amplitudes of the quantum bits $[\cos\theta_{ij}, \sin\theta_{ij}]^T$ are given by the periodic function, argument θ_{ij} of the quantum chromosomes' phase, which is relocated in the unit circle during the process of evolution. This ensures that the quantum chromosome search space is large and converges rapidly. To enhance the above algorithm, we developed the improved ADCQGA, in which the initial value θ_{ij} of the probability amplitude of the quantum bit is randomly generated in (0, π/2), thereby ensuring a monotonic population fitness value. The corresponding argument sorting reduced the search space of quantum chromosomes. The improved ADCQGA calculates the selection probability and expected reproductive rate based on the similarity and the vector distances of quantum chromosomes in the search space [20–22]. From the Metropolis criterion [23,24], the quantum chromosomes are selected with certain probability, and updated with the simulated annealing operation, which optimizes and compresses the search space of quantum chromosomes.

2.2. Projection pursuit model of integrative drip-irrigation and fertilization

The projection index function in the PPC model was used as an optimized objective function for the ADCQGA, making the projection of each index an optimization variable. The optimum projection direction and the corresponding index function value (greatest or least) were calculated by optimizing the projection index function. The results were classified and sorted. A comprehensive evaluation of integrative drip-irrigation and fertilization was performed using the PP model implementing the improved ADCQGA, as follows.

Step 1. Normalization of the sample index set. For sample set $\{x(I, j) \mid 1 \sim n, j = 1 \sim m\}$, $x(i, j)$ is the index value j of sample i, which corresponds to quantum bit j of quantum chromosome i, where n is the population size, m is the number of qubits of the quantum chromosome and the number of the evaluation index. To reduce the dimension of each index value, the sample index set is normalized as follows.

The bigger the index, the better the index,

$$X_{ij}^{'} = \frac{X_{ij} - \min X_j}{\max X_j - \min X_j} \tag{1}$$

The smaller the index, the better the index,

$$X_{ij}^{'} = \frac{\max X_j - X_{ij}}{\max X_j - \min X_j} \tag{2}$$

where X_{ij} was variable with before normalization processing, X_{ij} was variable with after normalization processing, $\max X_j$ was the maximum of the index j, $\min X_j$ was the minimum of the index j.

Step 2. Establishment of the projection index function *F(a)*. Dimension m in $\{x(I, j) \mid 1 \sim n, j = 1 \sim m\}$ gives the one-dimensional projection value $z(i)$, with $a = \{a(1), a(2), a(3), L, a(m)\}$ being the projection direction,

$$z(i) = \sum_{j=1}^{m} a(j) x(i,j) (i = 1 \sim n) \tag{3}$$

The a is the unit vector. $F(a) = S_v D_v$ is the projection index function, in which S_v and D_v are the standard deviation and the local density of projection value $z(i)$.

Step 3. Optimization of the projection index function. The optimum projection direction can be estimated by solving the maximization problem of the projection index function.

$$\max F(a) = S_v D_v \tag{4}$$

The constraint condition is

$$s.t. \sum_{j=1}^{m} a^2(j) = 1 \tag{5}$$

The optimization of the projection index function is a nonlinear optimization problem with the projection direction $\{a(j) \mid j = 1, 2, L, m\}$ as the optimization variable. We used the improved ADCQGA to solve the high-dimensional global optimization problem. The optimum projection direction was obtained when the objective function reached its extreme points.

Step 4. The improved Accelerating Double Chains Quantum Genetic Algorithm.

1) Population initialization. The initial chromosome population $Q(t) = \{q_1, q_2, \ldots, q_m\}$ was generated randomly in $(0, 2\pi)$ by the DCQCA coding method; $i = (1,2,\Lambda,m)$, m is population size, n is quantum digit capacity, θ_0 is the initial step value of the angle θ, and P_m is mutation probability. The fitness value of the quantum chromosome is the projection index function value.
2) Solution space transformation. Each chromosome in the population has a $2n$ probability amplitude in the quantum bit. The $2n$ probability amplitudes are mapped to the solution space of the continuous optimization problem max$F(a)$ using a linear transform. The ith quantum bit of chromosome q_j is $[\alpha_i^j, \beta_i^j]^T$, and the variables of the corresponding solution space are:

$$X_{ic}^j = a_i + \alpha_i^j \left(b_i - a_i\right) \tag{6}$$

$$X_{is}^j = a_i + \beta_i^j \left(b_i - a_i\right) \tag{7}$$

X_{ic}^j is the cosine solution of quantum bit i of chromosome j, X_{is}^j is the corresponding sine solution, $i = 1,2,\Lambda,m$ and $j = 1,2,\Lambda,n$.
3) The expected reproductive rate and selection probability are calculated from the vector distance of chromosomes in the population $Q(t)m$, in which chromosomes constitute a nonempty immune system X. The vector distance of chromosomes $f(x_i)$ in set X is regulated as

$$\rho(x_i) = \sum_{j=1}^{m} \left| f(x_i) - f(x_j) \right| \tag{8}$$

For quantum chromosomes, their density is given by

$$\text{Density}(x_i) = \frac{1}{\rho(x_i)} = \frac{1}{\sum_{j=1}^{m} \left| f(x_i) - f(x_j) \right|} \tag{9}$$

the selection probability is

$$P(x_i) = \frac{\rho(x_i)}{\sum_{i=1}^{m} \rho(x_i)} = \frac{\sum_{j=1}^{m} \left| f(x_i) - f(x_j) \right|}{\sum_{i=1}^{m} \sum_{j=1}^{m} \left| f(x_i) - f(x_j) \right|} \tag{10}$$

and their expected reproductive rate $e(x_i)$ is

$$e(x_i) = \frac{f(x_i)}{C(x_i)} = \sum_{k=1}^{m} f(x_i) \left| f(x_i) - f(x_k) \right| \tag{11}$$

In the above, $i,j,k = 1,2,\Lambda,m$.

4) According to the expected reproductive rate of quantum chromosomes, $P(t)$ the algorithm makes u higher expected reproductive rate of quantum chromosomes of population $Q(t)$ into the new population $P(t)$.
5) In the selection probability evaluation, the quantum bit of v quantum chromosomes is executed by rotation gate updating and by the mutation operation of DCQCA. These chromosomes are selected with a large selection probability in population $Q(t)$ and are entered into the new population $P(t)$. The quantitative relation of quantum chromosomes should meet the requirement $u + v = m$.
6) Each quantum chromosome of X_{new} is updated by using a quantum-rotating gate from DCQGA, implemented by the Hadamard mutation operation with mutation probability.
7) The new individual becomes the initial solution for the simulated annealing algorithm. The Metropolis criterion is used in this process, which uses a rate of 90% in X_{new}.
8) The fitness values of population $P(t)$ are determined by an evaluation function. The best quantum chromosomes and their corresponding quantum bit coding are recorded.
9) Optimize and compress the search space of quantum bit argument θ. The quantum chromosomes in population $P(t)$ are sorted by their quantum bit arguments θ_{ij}, recording the maximums θ_{ijmax} and minimums θ_{ijmin}. To improve the flexibility and robustness of the algorithm, the search space of argument θ_{ij} is repeatedly reevaluated according to the condition $|\theta_{ijmin} - \theta_{ijmax}| < \varepsilon$, where ε is an error tolerance.
10) Accelerated running and evolutionary iterations. If the convergence condition is not met within the maximum number of iterations, the interval $(\theta_{ijmin}, \theta_{ijmax})$ of the optimized argument θ_{ij} of the quantum bit is used as the new initial variable interval, the new population $Q(t)$ is randomly produced with a size m having n quantum bits, and the algorithm returns to step (2).

Step 5. The index contribution rate was determined by computing the optimum projection directions a^*, sorting them in descending order, calculating the projection value $z^*(i)$ of each sample point to determine its preferential ordering, and substituting a^* into Eq. (3).

3. Application example of ADCQGA-PPC

3.1. Experimental setup

The integrative drip-irrigation and fertilization experiments for maize were carried out at the test center of Heilongjiang Water Conservancy Institute in 2011. The perennial mean temperature was 3.1°C, the frostless period was 130–140 d, and the long-term average annual precipitation was 400–650 mm. The soil was loam with an average dry density of 1.34 g/cm^3, a field water-holding rate of 0.36 cm^3/cm^3, an organic matter content of 25.07 g/kg, and an average initial nitrate content of 67.79 mg/kg.

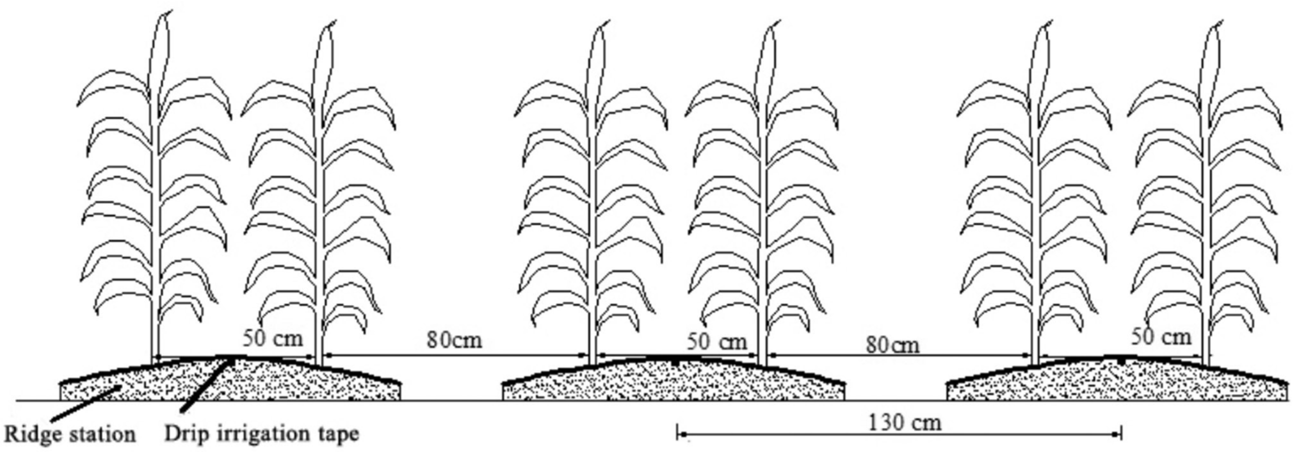

Fig. 1. Planting patterns of mulched and drip-irrigated maize.

Table 1
Experimental parameters for irrigation–fertilization optimization of mulched drip irrigation

Experimental treatment	Content of nitrogen fertilizer (kg/hm^2)	Nitrogen fertilizer application frequency	Irrigation and fertilization modes
T1N50	50	1	Mulched drip irrigation, integrative water and fertilizer
T1N100	100	1	
T1N150	150	1	
T1N200	200	1	
T3N50	50	3	
T3N100	100	3	
T3N150	150	3	
T3N200	200	3	

The maize was sowed on May 5th and harvested in September. Using planting of one big ridge two rows with plastic film mulching. The distance between two adjacent ridges was 130 cm, the row spacing of maize above ridge was 50 cm, width of ridge was 100 cm, the bottom width of ridge and furrow 30 cm, the height of ridge was 15 cm, the width of film was 120 cm, the thickness of film was 0.008 mm. Each experimental district had four ridges, which comprised two rows of maize. The plant spacing was 33 cm and the planting density was 46,620 $strains/hm^2$.

The nitrogen content of the fertilizer and the fertilizing frequency were experimental variables. The base fertilizer did not contain nitrogen. For each nitrogen split, four nitrogen levels were used: 50, 100, 150 and 200 kg N hm^2. The fertilizing consisted of a single nitrogen application at the jointing stage and three nitrogen splits, corresponding to the jointing, heading and filling stages. There were eight experimental treatments that were each repeated three times. Each experimental treatment covered an area of 40 m × 5.2 m of random arrangement. The effective rainfall was 308.9 mm in the growth stage. The irrigation system delivered 15 mm, 10 mm and 10 mm of precipitation at the jointing (July 16th), heading (August 2nd) and filling stages (August 15th), respectively.

3.2. Application of the ADCQGA-PPC model

As in this heading, they should be Times New Roman 11-point boldface, initially capitalized, flush left, with one blank line before, and one after.

Table 2
Evaluation indexes of different treatments

Experimental treatment	Leaf area index	Dry matter above ground/(t/hm^2)	Nitrogen uptake of maize/(kg/hm^2)	Barren ear tip/cm	The 100-seed weight/g	Yield /(t/hm^2)
T1N50	3.57	19.45	247.8	2.24	38.55	10.36
T1N100	3.65	18.93	242.5	2.31	36.73	10.17
T1N150	3.67	20.57	258.6	2.48	38.26	10.37
T1N200	3.79	21.41	269.7	2.4	39.75	10.7
T3N50	3.74	21.06	248	2.4	40.7	10.55
T3N100	3.85	22.43	272.5	2.51	39.2	10.87
T3N150	3.69	22.67	276.2	2.03	39.28	10.97
T3N200	3.78	23.27	284.9	2.28	39.84	11.4

In the comprehensive evaluation of the integrative drip-irrigation and fertilization schemes, leaf area index and the quantity of dry matter above ground were important in the physiological and biochemical crop processes. The nitrogen uptake of maize indicates the fertilizer utilization. Barren ear tip and 100-seed weight indicate the plumpness of the grain. Yield is the water saving as well as the maize harvest. Leaf area index, dry matter above ground, nitrogen uptake of maize, barren ear tip, 100-seed weight and yield were chosen and sorted as metrics of the eight mulched drip-irrigation treatments (Table 2). Besides barren ear tip, other index were that the bigger the index, the better the index.

The parameters for ADCQGA and DCQGA were: population size $m = 50$, quantum bit $n = 91$, selection probability $P_r = 0.009$, mutation probability $P_m = 0.05$, initial angle step $\theta_0 = 0.05\pi$, initial temperature $T_0 = 1000$, termination $T_e = 1$, maximum number of iterations $L_{\max} = 20$, and limiting factor $\varepsilon = 10^{-4}$. A comparison of the optimization results from 10 experiments is summarized in Table 3.

ADCQGA-PPC and DCQGA-PPC were optimized within 20 iterations. The optimal and average function values of ADCQGA-PPC were 0.3120 and 0.3070, respectively, and those for DCQGA-PPC were 0.3120 and 0.3070. ADCQGA-PPC produced a better quality result than did DCQGA-PPC. The average computing time of ADCQGA-PPC was 5.91 s, 15% faster than DCQGA-PPC (6.96 s). ADCQGA-PPC had a maximum projection index value of 0.3120 and optimum projection directions a^* = (0.3757, 0.5751, 0.5089, 0.0919, 0.3504, and 0.4877); see Table 4. The projection value $z^*(i)$ is shown in Table 5.

3.3. Analysis of the simulation results

The preferential order of the integrative drip-irrigation water and fertilizer schemes was T3N200 > T3N150 > T3N100 > T1N200 > T3N50 > T1N150 > T1N50 > T1N100.

The magnitude of the components of the optimum projection vector reflect the contributions of the evaluation indices on the integrative drip-irrigation water and fertilizer scheme. The a^* calculated from the ADCQGA-PPC model in Table 4 shows that dry matter above the ground in which the maize was planted had the most influence on the model predictions, followed by nitrogen uptake of maize, yield, leaf area index, 100-seed weight and barren ear tip. The results suggest that dry matter accumulation of water and fertilizer will lead to efficient use of nitrogen, thereby improving yield and quality, which has practical importance.

In single nitrogen applications, increasing the amount of nitrogen applied resulted in a higher leaf area index. When there were three nitrogen splits, however, the nitrogen applied had no obvious effect on leaf area index, although it might satisfy the reproductive growth of plants in the late growth stage. When the durations of the nitrogen splits were equal, the dry matter and nitrogen uptake in each growing stage increased when the nitrogen was applied. The nitrogen uptake was greatest when nitrogen was applied in three splits; increasing the nitrogen treatment from 50 kg N/hm^2 to 200 kg N/hm^2 improved the uptake by 15%. For a single nitrogen application, increasing the nitrogen treatment from 50 kg N/hm^2 to 200 kg N/hm^2 caused a 10% greater uptake, which is associated with dry matter accumulation of the plant. The barren ear tip after a single nitrogen application was, on average, 2% higher than for three nitrogen splits. In contrast, the 100-seed weight and the yield after three nitrogen splits were, on average, 4% and 5% higher, respectively, than after a single nitrogen application. For example, increasing the applied nitrogen from 50 to 100, 150, and then 200 kg N/hm^2 for three nitrogen splits improved the yield by 4%, 5% and 8%. From the above analysis, we recommend a management practice of 150–200 kg N/hm^2 of nitrogen applied in three splits and

Table 3
Comparison of optimization results (10 experiments)

Model	Optimization times	Optimal function value	Poorest function value	Average function value	Average time (s)
DCQGA-PPC	20	0.2931	0.2755	0.2845	6.96
ADCQGA-PPC	20	0.3120	0.2887	0.3070	5.91

Table 4
Optimal projection direction

Projection index	Leaf area index	Dry matter above ground	Nitrogen uptake of maize	Barren ear tip	The 100-seed weight	Yield
Component of projection direction	0.3757	0.5751	0.5089	0.0919	0.3504	0.4877

Table 5
Projection values of different deficit irrigation treatments

The preferential order	1	2	3	4	5	6	7	8
Treatment	T1N50	T1N100	T1N150	T1N200	T3N50	T3N100	T3N150	T3N200
Projection value	0.5751	0.3555	0.8508	1.3974	1.1178	1.5950	1.5952	1.9766

to employ a drip-irrigation integrative water and fertilizer scheme for the black soil in Northeast China.

4. Conclusion

In this research we developed the project pursuit model using the improved double chains quantum genetic algorithm. This ADCQGA-PPC model could meet the value range and mapping relation of both adaptive value and corresponding argument of adaptive value. The global optimal solution was reached rapidly with the introduction of the immunity operator, the simulated annealing operator, and gradually optimizing and compressing the quantum chromosome search space during the evolution process. The ADCQGA-PPC outperformed the DCQGA-PPC in terms of quality and efficiency.

Comprehensive evaluation of integrative drip-irrigation and fertilizer using ADCQGA-PPC had contained the weight of each evaluation index, given the projective direction and magnitude of each evaluation index, which had made an objective analysis on the contribution rate and directivity of each evaluation index. The yield with three nitrogen splits was on average 5% higher than for a single nitrogen application; 150–200 kg/hm^2 of nitrogen applied at three splits produced the optimum integrative drip-irrigation and fertilizer scheme. We submit that the ADCQGA-PPC provides a novel solution to the scheduling and optimization of integrative drip-irrigation and fertilization.

Acknowledgment

Funds for this research was provided by the National Science and Technology Plan Projects (2014BAD12B01), Heilongjiang provincial Science Fund for Young Scholars (QC2015052), Heilongjiang Postdoctoral Fund to pursue scientific research (LBH-Z14193).

References

[1] H.L. Liang, X.Y. Wu, M.L. Nong, F.S. Li, Effects of partial rootzone irrigation on yield and water use efficiency of sticky maize under the integrated management of water and fertilize. Agric. Res. Arid Areas., 5 (2012) 109–114.
[2] N. Wu, J.L. Liui, Existing problems and solutions of water and fertilizer integration in Ningxia. Ningxia J. Agric. Forestry Sci. Technol., 10 (2012) 124–126.
[3] T.N. Li , Y.T. Liu, Y. Li, Popularization effect and trend analysis of corn membrane drip irrigation technology in Heilongjiang Province. Modern Agric. Sci. Technol., 21 (2011) 105–107.
[4] S.M. Zai, F. Wu, J. Wen, Q.B Han, Effect of drip fertigation on soil salinity of cotton field in Northwest China. J. Hydr. Eng., 12 (2011) 1496–1502.
[5] D.L. Song, C.L. Lin, C.L. Zhang, E. Zeng, D.Q. Zheng, Integrated management of irrigation water and fertilizers for potato planting, Guangdong Agric. Sci., 15 (2011) 46–48.
[6] W.B. Du. Effects of drip fertigation on tomato in the solar greenhouse, J. Shanxi Agric. Sci., 1 (2009) 58–60.
[7] S.Z. Yu, Application of drip irrigation of integral control of water and fertilization for cucumber under protected cultivation in Shandong Province, J. Water Resour. Water Eng., 6 (2009) 173–176.
[8] J.J. Yuan Junjing, H.W. Li., Benefit evaluation of conservation tillage based on projection pursuit, Trans. Chinese Soc. Agric. Eng., 4 (2010) 175–176.
[9] Z.M. Feng, H.X. Zheng, B.Q. Liu., Comprehensive evaluation of agricultural water use efficiency based on genetic projection pursuit model, Trans. Chinese Soc. Agric. Eng., 3 (2005) 66–68.
[10] Q.X. Jiang, Q. Fu, Z.L. Wang, Comprehensive evaluation of regional land resources carrying capacity based on projection pursuit model optimized by particle swarm optimization, Trans. Chinese Soc. Agric. Eng., 11 (2011) 319–324.
[11] Simulating physics with computers, Int. J. Theor. Phys., 6(7) (1982) 467–488.
[12] P.W. Shor, Algorithms for quantum computation: Discrete logarithms and factoring. Proc of the 35th Annual Symp on Foundations of Computer Science, (1994), New York, USA, pp. 124–134.
[13] L.K. Grover, A fast quantum mechanical algorithm for database search. Proc of the 28th Annual ACM Symp on Theory of Computation, (1996), New York, USA, pp. 212–215.
[14] K.H. Han, J.H. Kim, Quantum-inspired evolutionary algorithm for a class of combinational optimization, IEEE Trans. Evol. Comp., 6 (2002) 580–593.
[15] X. Li, C.T. Cheng, Y. Zeng, Training of process neural networks based on improved quantum genetic algorithm, Control Decision, 3 (2009) 347–349.
[16] G.X. Zhang, N. Li, W.D. Jin, L.Z. Hu, A novel quantum genetic algorithm and its application, Acta Electron. Sinica., 3 (2004) 476–479.
[17] P.C. Li, K.P. Song, E.L. Yang, Phase encoded-based quantum ant optimization, Syst. Eng. Theory Practice, 8 (2011) 1565–1570.
[18] H.Y. Gao, J.L. Cao, Quantum-inspired bee colony optimization algorithm and its application for cognitive radio spectrum allocation, J. Central South University (Sci. Technol.), 43(12) (2012) 4743–4749.
[19] S.Y. Li, P.C. Li., Quantum Computation and Quantum Optimization Algorithms, Harbin Institute of Technology Press, Harbin 2009.
[20] M.X. Sun, X.P. Chen, An immune algorithm based on the vector distance applied to function optimization, J. Suzhou Univ.(Eng. Sci. Ed., 3 (2010) 56–57.
[21] Y.B. Duan, W.J. Ren, F.C. Huo, A kind of new immune genetic algorithm and its application, Control Decision., 10 (2005) 1185–1186.
[22] H. Ge, Z.Y. Mao, Realization of immune algorithm, Comp. Eng., 5 (2003) 62–63.
[23] S.H. Xiao, H.Y. Lu, A.D. Fan, H. Song, Applied Research of Simulated Annealing algorithm on solving combinatoria1 optimization problems, J. Sichuan Univ. Sci. Eng. (Nat. Sci. Ed.)., 1 (2010) 116–118.
[24] H.D. Zhu, Y. Zhong., A kind of renewed simulated annealing algorithm, Comp. Technol. Develop., 6 (2009) 32–35.