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The Research Status and Prospect of Particle Swarm Optimization Algorithm for Water Environment Quality Assessment

Haonan Liu[a,*] Xiaofei Lv[a] Jun Xiao[a]

a. Heibei Provincial Institute of Environmental Protection Products Quality Supervision and Inspection Shi jiazhuang, CHINA

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ABSTRACT

The paper introduced the basic thoughts and principles of particle swarm optimization algorithm (PSO), and discussed the application status of particle swarm optimization algorithm for water environment quality assessment including that the improvement of PSO and the special applying in water environment quality assessment. Finally, it introduced the prospect of particle swarm optimization algorithm for water environment quality assessment.

1. Summary of Water Quality Evaluation Methods

Water quality evaluation is the premise of ensuring the safe and rational use of water. The main evaluation methods of water quality evaluation are described below.

1.1 Single factor pollution index method

The single factor pollution index method is to compare the evaluation factor with the evaluation criterion. Determining the water quality category of each evaluation factor. The worst water quality category is selected as the water quality category for all water quality categories in all projects. This method can be used to determine the main pollutants in water. The method is able to examine the main water pollution factors, which is the most widely used water quality evaluation at present. This approach is commonly used in environmental impact assessment of construction projects. The eigenvalues of this method include the rate of each standard, the rate of over standard and the standard multiple.

1.2 Horton's water quality index method

Horton's water quality index method was first proposed by Horton et al. in 1965. Horton's water quality index method is a kind of integrated pollution index method, including 10 parameters. The formula is shown in equation (1). Pan Feng et al. Applied Horton's water quality index method to evaluate the water quality of Guanting Reservoir and achieved good results.

$$\mathrm{WQI} = [\frac{\sum_{i=1}^{m} C_i W_i}{\sum_{i=1}^{m} W_i}] M_1 M_2 \qquad (1)$$

In the formula:
$\boldsymbol{C_i}$ is based on the measured concentration of the water quality score
$\boldsymbol{W_i}$ is the weight of each parameter
$\boldsymbol{M_1}$ is the temperature coefficient
$\boldsymbol{M_2}$ is the sensory apparent pollution coefficient

1.3 Brown water quality index method

Brown water quality index was proposed by Brown in 1970. It selects 11 parameters, including dissolved oxygen, BOD5, turbidity, nitrate, total solid, phosphate, temperature, pH value, coliforms, insecticides and toxic elements. The quality score and weight of each parameter were determined. The formulas are shown in equation (2) and (3).

$$\mathrm{WQI} = \sum_{i=1}^{n} W_i P_i \qquad (2)$$

where, W_i is the parameter weight; P_i is the quality score of the parameter.

* Corresponding author.
E-mail addresses: lhnhby@163.com (H. Liu)

$$\sum_{i=1}^{n} \mathbf{W_i} = \mathbf{1} \text{..................}(3)$$

where, n is the number of parameters.

1.4 The nemrow water pollution index method

The nemrow water pollution index was proposed by Nemrow and it is a widely used evaluation method. The Nemrow Index focuses on the most polluting factors. The formula is shown in formula (4).

$$PI = \sqrt{\frac{(\frac{C_i}{L_{i,j}})^2_{MAX} + \frac{(C_i)^2}{L_{i,j}}_{AVG}}{2}} \text{..................}(4)$$

Here, $\mathbf{PI}$ is the water quality index for a certain purpose, $\boldsymbol{C_i}$ is the measured concentration of some pollutant in water, $\boldsymbol{L_{i,j}}$ is the standard of the water quality in a pollutant. The nemrow water pollution index method was also widely used in water quality evaluation. For example the underground water quality was evaluated by endomelo method.

1.5 Scoring method

Scoring method is an essential evaluation model with convenient and simple application. It is widely used for eutrophication. The expression is shown in figure (5).

$$\mathrm{M} = \frac{1}{n}\sum_{i=1}^{n} M_i \text{...............}(5)$$

Where: $\mathbf{M}$ is the lake eutrophication score, $\boldsymbol{M_i}$ is the score of the ith index, $\boldsymbol{n}$ is the number of the evaluation index.

According to the corresponding standards, the corresponding scores of each evaluation parameter are respectively given in the range of 0-100. The higher the total score indicates the higher eutrophication of the lake.

2 The overview of particle swarm optimization algorithm

2.1 The background of particle swarm optimization algorithm

The main body of the bird flock movement is discrete and its arrangement appears to be random in nature. But they maintain a surprisingly synchronized in the overall movement, and the form of the overall movement is very smooth and very beautiful. The distribution of the population was exhibited seems to be conscious of centralized control, which has been the subject of interest to many researchers. Researchers have conducted computer simulations of the movement of the bird flock , They mimic the complex behavior of birds by setting simple rules of movement for individuals. For instance, Craig Reynols proposed Boid model in 1986, which Used to simulate the behavior of birds flying together. Through the observation of the movements of these groups in the real world, copying and recreating these trajectories in a computer and modeling these movements to discover new patterns of movement. Later A new flock model is proposed by Frank Heppner, who added the simulation of habitat attraction to birds.

The key to the above model is the operation between the individuals; the synchronization of group behavior depends on Individuals which strived to maintain the optimal distance between themselves and their neighbors. Therefore each individual's location and the location of their neighbors must be known. E. O. Wilson thinks that In the process of searching for food, Individual members of the group can be predicted scattered , The advantages of collaboration are greater than those of food competition at least in in theory. The above two examples show that social sharing of information among individuals in a group contributes to the evolution of a group.

James Kennedy and Russell proposed particle swarm optimization Influenced by the above bird flock movement model in 1995[1-5]. Particle swarm optimization is actually an evolutionary computation technique. The algorithm compares the habitat in the bird flock movement model with the possible solutions in space. Through the information transmission between individuals, the whole group can be moved in the direction of possible solutions, and the possibility of finding a better solution is gradually increased in the solution process. The birds in the group are abstracted as "particles" without mass or volume, through the mutual cooperation and information sharing between these "particles", the movement speed is influenced by the information of the historical motion of the self and the group. The current motion direction and motion speed of the particle are influenced by the historical optimal position of self and group. The relationship between the particles themselves and the group is coordinated better in order to facilitate the group in the complex solution space optimization operation. James Kennedy published an article called Particle swarm optimization in IEEE International Conference on Neural Networks in 1995,which marks the birth of particle swarm algorithm.

Since 1990s, the research for swarm intelligence has aroused the interest of many scholars. PSO is a kind of optimization algorithm based on swarm intelligence. It came of the simulation research on bird flock preying behavior and was first proposed by Kennedy & Eberhart. As a parallelism global optimum algorithm, PSO is widely used in field of function optimization, model systematization, fuzzy system controlling and neural network, because it has the advantages of easy implementation, less parameters modification and higher intelligence level, etc.

2.2 Researching on improving performance

The performance improvement of the algorithm is mainly to improve the accuracy of the algorithm to solve the optimal solution. But , the algorithm has the disadvantage of being vulnerable to local optimal solution. At present, the algorithm is mainly improved from the following aspects: 1) improving the value of the parameter weight， 2) increasing the diversity of the PSO algorithm， 3） mixing other intelligent optimization algorithms.

1） Improving the value of the parameter weight

The balance of the global search ability and local search ability of the algorithm can be adjusted by the function of the weight. The inertial weight of the standard algorithm is linear reduction, which makes the algorithm better at the early stage of the iteration, which can also enhances the local search capability of the algorithm in the later. However, the search process is a non-linear complex process; the method of inertia weight linear transition cannot correctly reflect the real search process. The systematic experiments on the inertial weight of the important parameters in the algorithm were carried out by Wang junwei, who also analyzes the selection of fixed weight and time-varying weights, and analyzes the influence of inertia weight on the performance of the algorithm from the aspects of problem dependency, population size and topology structure. The results show that the problem of inertia weight is less dependent, and the value of inertia weight should be reduced appropriately as the population increases. In local version, the choice of inertia weight has more freedom. Y.Shi gives a method to dynamically adjust the inertia weight by using fuzzy rules. Through the evaluation of the best performance at present, the corresponding membership functions and fuzzy inference rules are formulated for the inertia weights to determine the increment of inertia weight. The experiment shows that the fuzzy adaptive method has similar or better results than the linear reduction of inertia weight. Li Ning gives a method to reduce the cosine of the moment of the inertia by the iterative algebra method, The result is good. Chatterjee A and Siarry P proposed a non-linear weighted decreasing method. The main idea is to add an exponential parameter to the linear decreasing method of the weight of the standard algorithm to change the weight non-linearly. Jiao B. proposes a method of weight dynamic change, whose idea is to make the weight change dynamically according to the algorithm in each step. As the number of iteration steps increases, the weight may increase or decrease. R. Bberhart and Y. Shi proposed a particle swarm optimization algorithm with a convergence factor. Experiments show that the particle swarm optimization algorithm using the convergence factor has a faster convergence rate than the particle swarm optimization algorithm using inertia weight. As long as the appropriate choice of parameter values, the two algorithms are the same. Particle swarm optimization with convergence factor can be considered as a special case of PSO with inertia weight.

2） Increasing the diversity of the PSO algorithm

The standard algorithm mainly has the shortcoming of precocious convergence, and the optimal solution of the algorithm may not converge to the global optimal solution. In order to avoid premature convergence, some researchers have proposed a method of improving the performance of the algorithm by controlling the diversity of the population. Diversity is the extent, to which a population is scattered in search space, and the more diverse it is, the stronger it is. The literature suggests that by increasing the diversity of the population when the particles start to gather, the conflict and aggregation of the particles can be resolved. The algorithm assigns a radius value to each particle to detect whether the two particles collide or not, and if there is a collision, take the method of bouncing off. For multi-peak functions, this method significantly improves the performance of the algorithm and maintains the diversity of the population. X.Hu and R.Eberhart propose the idea of population stochastic multigenerational initialization, and give different strategies to enhance the diversity of population so that the algorithm cannot get into local minima too earl. On the other hand, it is a very effective way to enhance the global search performance by introducing "variation" operation of genetic algorithm

It is a common way to improve the performance of the algorithm by increasing the diversity of groups. There is a lot of literature on this area, and there are many kinds of techniques used in the research literature. In addition to the methods described above, there are also ideas such as quantum and Gaussian variation. The purpose of these ideas is to increase diversity, improve global search capabilities, and thus enhance the ability to search for the best. Although these research efforts have given ways to improve the global search capability of algorithms, but it is difficult for them to strike a balance between increasing search speed and keeping the diversity of the population.

3）Mixing other intelligent optimization algorithms

The essential goal of PSO algorithm and evolutionary algorithm is the same, but there are differences in the principle of thought between them, and the technical methods are different, and each has its advantages and disadvantages. Mixing with evolutionary algorithms to get new algorithms tends to produce some good results. Gao Haibing proposed a generalized particle swarm optimization model to make it suitable for solving discrete combinatorial optimization problems. The essence of the model still conforms to the particle swarm optimization mechanism, but its particle update strategy can be designed according to the characteristics of the optimization problem, and also can realize the integration with the method. Some documents have proposed the introduction of simulated annealing into parallel algorithms. This algorithm preserves population diversity and thus avoids population degradation, however, there also exists the idea of mixing with the differential evolution algorithm and other evolutionary algorithms.

2.3 Basic Thought

The basic thought of PSO would be draw inspiration from hypothesis as below: During bird block preying, the most simple and effective strategy is that seek around the nearest bird to food. The potential solutions of PSO are the bird (called 'particle') in seeking domain. At the moment, every particle has respective flight direction, velocity and the adaptive value to objective function, and all particles were seek in solution domain following the optimal particle[6-10]. In each iteration, particle will be updated itself by tracking the individual extreme and the global extreme.

2.4 Basic Principle

In D-dimensional space, there is a particle swarm which the group size is 'm', and the position of i-th is shown as x (x_{i1}, x_{i2}, …, x_{id}), where i=1,2,…,m, that is, every particle is one potential solution of objective function and the adaptive value can be obtained by plugging it into objective function. The optimal position of i-th particle will be recorded as history optimal position, p_i, and the velocity of this particle is recorded as v_i, the optimal position of all particles is recorded as global history optimal position, p_g, and then, according to equation (1) and (2), the i-th particle can be updated to t-th generation:

$$\begin{aligned} \mathrm{v}_{id}(t+1) = u\mathrm{v}_{id}(t) + c_1\mathrm{r}_1(p_{id} - x_{id}(t)) \\ + c_2\mathrm{r}_2(p_{gd} - x_{id}(t)) \end{aligned} \tag{6}$$

$$x_{id}(t+1) = x_{id}(t) + \mathrm{v}_{id}(t+1) \tag{7}$$

where, u, c_1, c_2, r_1, r_2, is inertia weight, two acceleration coefficients and 2 random numbers between 0 and 1, respectively.

2.5 Basic Principle

The overall process of PSO works as blow:

a) Initialization; the initial particle's position and velocity were generated, and then some parameters were pre-defined, such as group size, inertia weight, acceleration coefficient and maximum iterations, etc.

b) Calculated the initial adaptive value of each particle based on objective function.

c) Updated the position and velocity of initial particle based on function (1) and (2), meanwhile, it conducts the new position and velocity amplitude limit.

d) Re-calculated the adaptive value.

e) Re-selected the individual optimal adaptive value and the global optimal adaptive value.

f) Terminated on meeting the accuracy requirements or reaching the maximum iterations, if not, back to 3) and continue to search.

3. The research status of PSO

3.1 The research status of PSO for water environment quality assessment

The reliability of the results of water environment quality assessment depends on the accuracy of monitoring data. On the other hand, it depends on effective assessment method including technology selection. Recently, the increasing number of researchers began to liven up on seeking the method of water quality assessment.

The method of water quality assessment falls into two categories: single-parameter assessment and multi-parameters comprehensive assessment. The single-parameter assessment is relatively easy to evaluate limit exceeding or not, based on national standard limit or exceeding index method; multi-parameters comprehensive assessment is evaluated by the synthetic effect of all pollutants, and then confirm the comprehensive level of water quality[11-15].

In China, the method based on mathematical model has been advocated to apply to evaluate the water quality in 1974. Up to now, dozens kind of methods for water quality and index assessment have developed for nearly 30 years. Many kinds of assessment methods were depend on PSO, and have the following kinds.

3.1.1 Index assessment method based on PSO for water environment quality assessment

Index assessment method is the criterion of environment quality mathematical synthesizing by sub-index which is the ratio of the statistic of original monitoring data to evaluation criterion.

On the assessment of eutrophication, PSO is widely used in optimizing relevant parameter of algorithms to evaluate Lake Eutrophication indexes and predict the development tendency of eutrophic state. The results indicate the optimized index formula has distinct advantages for accurate, convenient and practical calculating and more comparable, objective, universal.

For example, PSO is used to calculate a 'reference' value for universal index formula of eutrophic state, and replace the index value in the Carson's index formula by a new 'relative index' that correspond to the 'reference' value of eutrophic state, in the new formula, the parameter could be considered as irrelevant to index properties, so the parameters of universal index formula for eutrophic state is optimized by PSO. And then the optimized index formula is applied to 20 examples of different territories and types of lakes in China, it offers an efficient path to evaluate eutrophication and the result are consistent with the reality [2][3].

3.1.2 Combination operators method based on PSO for water environment quality assessment

Because water environment quality assessment is a fuzzy problem, it could set up a kind of assessment model for fuzzy evaluation method by assessment model of parametric combination operators. The results have proven the feasibility and validity of this assessment model for eutrophic sea water, underground water and surface water quality assessment [4].

3.1.3 Projection pursuit method based on PSO for water environment quality assessment

Projection pursuit method is used in handling and analyzing high dimensional data, especially used for analyzing non-normal distribution high dimensional data. The principle is that high dimensional data is projected on lower dimensional subspace by computer, and sought for the projection which could be reflected high dimensional data structure feature [1].

Projection pursuit method could be used for evaluating water quality[5]. In the process, PSO is applied to seek the optimal projection direction and solve optimal function. Facts proved that the optimizing projection pursuit method has advantages of high efficient and rate of convergence for solving complex problem of water quality comprehensive assessment in the optimization process.

For instance, in the grade evaluation model of Fuhe River, 11 monitoring sections and 7 monitoring indexes were substituted into comprehensive assessment model functions which is optimizing by the PSO projection pursuit. The result was reliable and high comparability, and it indicated that it could intuitively reflect water environment condition of each section while show each monitoring point's pollution level [6].

3.1.4 Support vector machine based on PSO for water environment quality assessment

The principle of Support vector machine is that it finds out an optimal classification hyperplane and maximizes the blank on either side of hyperplane while meeting the requirement of classification.

Because traditional assessment method was obviously affected by human factors, it could be built support vector machine which lies on chaos PSO optimization and 3-a-3 multi-classification method. In fact, it has been applied in evaluating monthly water quality condition based on the date from 7 automatic monitoring stations in Tai Lake, and proves that the result meets the reality [7].

3.2 At present, the study on PSO improvement

As PSO research continues, it is found that the inherent disadvantages, such as low local search capability, lost in local optimal easily, search capability relies on indexes and so on. Therefore, improving and refining PSO is a vital research direction. The existing strategies were Chaos optimization, adjusting parameters choice, combining various algorithms, maintaining population diversity.

3.2.1 Chaos optimization strategy

The basic thought of chaos optimization is that optimization variables map to the domain of chaotic variable space by chaotic mapping rule, thereby increasing particles' diversification. Although it cannot overcome premature convergence and would even increase the computation, the strategy which the particle swarm distribution is initialized by chaos sequence characters could expand the search scope and distinct enhance the search diversification[16-20].

For instance, through modified Tent chaos sequence, the particle could increase particle's path and may jump out of local extreme point, and then evenly map to the domain of definition. At the initial search stage, the particles were enhanced the search performance and randomness by modified Tent chaos sequence instead of random number to update the velocity and position of particles. In order to increase the rate of convergence and the efficiency of search at the later stage, the particle farthest from optimal solution is removed in some step iterations and the system will be re-searched by new particle position which set up by the average value of all particles position. Because of decreasing of hunting zone, the system search will be enhanced.

3.2.2 Adjusting parameters choice strategy

3.2.2.1 Adjusting acceleration coefficient strategy

In PSO, there are 2 acceleration coefficients, c_1 and c_2, representing the capacity of individual to self-cognitive and other individuals to its guidance, respectively. The ideal strategy is good to enhance the search rate of convergence and precise, that is, the system has bigger c1 and smaller c2 for searching in whole space at the initial stage of evolution. And there are smaller c1 and bigger c2 for algorithm convergence to global optimal solution at the last stage[21-25].

3.2.2.2 Adjusting inertia weight strategy

The particle could be kept the motion inertia and enhanced search capacity for new space by inertia weight. During the period of bigger inertia weight, the particle has better capacity for global search. On the contrary, the particle has better capacity for local search during the period of smaller inertia weight. Therefore, the ideal strategy is that it has bigger inertia weight at the initial stage for better global search, and gradually decreases inertia weight for better local search at the later stage[26-30].

3.2.3 Combining various algorithms strategy

The target of combining algorithms strategy is used of other intelligence algorithms to offset the deficiency of basic PSO algorithm. Specifically, basic PSO is hard to jump out of it when entire colony is caught in local optimizing. Thus, through drawing into valid local optimized algorithm, every particle has possibility to be found out local optimal solution as new position from local scope, and confirmed the global convergence [8].

3.2.4 Maintaining population diversity strategy

There are many kinds of methods to maintain population diversity, and common strategy is used of mutation operator to increase diversity. It could be avoid algorithm premature by enhancing particle's search capacity around global optimal solution. The key issue of this strategy is mutation probability selection, that is, the algorithm convergence will be decreased by overlarge mutation probability leads to search scope expanding. However, the particle will be limited in a small search scope if the mutation probability is too small, and will weaken the capacity of jumping out of local optimizing and have negative impact on maintaining population diversity.

3. An example of a simple PSO algorithm

Finding the maximum value of $y = 1 - \csc(3x) \times \exp(-x)$ in [0,4].

In order to get the maximum of this function, we place two points between [0,4], and then Calculate the function value of these two points, and then set both of these points to a speed between [0,4]. The following points will change their location according to a certain formula until they find the maximum position. This process is compared with Particle Swarm Optimization as follows:

(1) These two points are particles in the particle swarm algorithm

(2) The maximum value of this function is the food in the flock

(3) To compute two point function values is the adaptive value in the particle swarm algorithm

(4) The function of calculation is the fitness function of particle swarm algorithm

The function of the graph was shown in Figure 1.

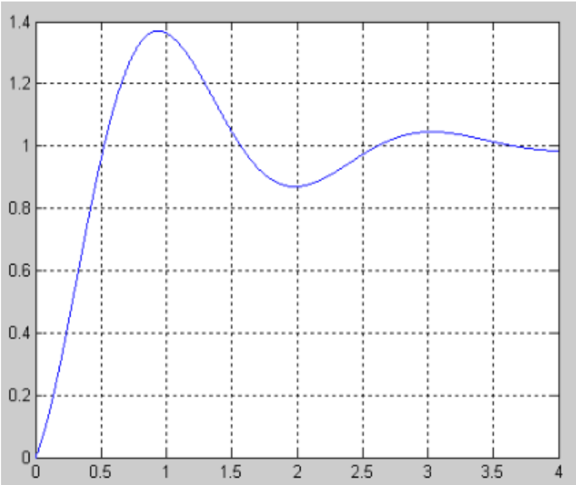

Figure .1. When x =0.9350-0.9450, the maximum y=1.3706 is reached.

The first initialization was shown in Figure 2

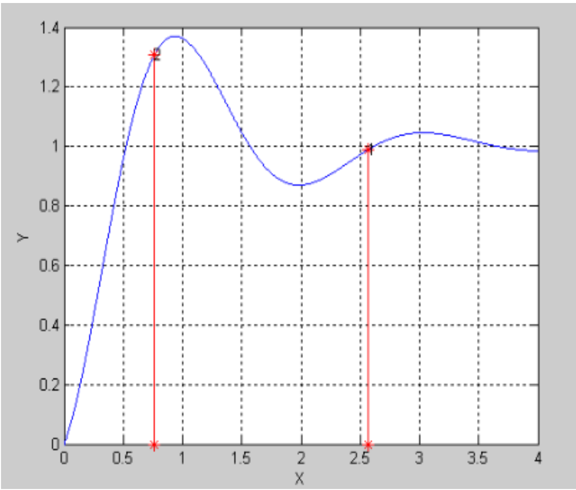

Figure .2. Take two points, where x1 = 0.7512, x2 = 2.6 and y1 = 1.3654, y2 = 0.9989

The first update location was shown in Figure 3

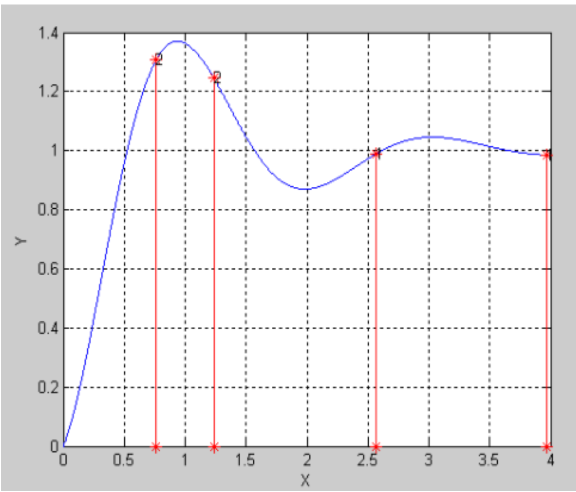

Figure .3. The other two positions are compared to the original position

The second update location was shown in Figure 4

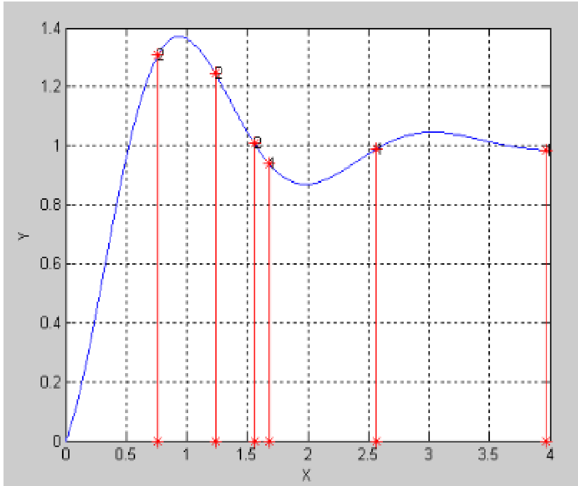

Figure .4. Keep looking for the maximum, Two values are calculated to compare with the original value.

The 21st location update was shown in Figure 5

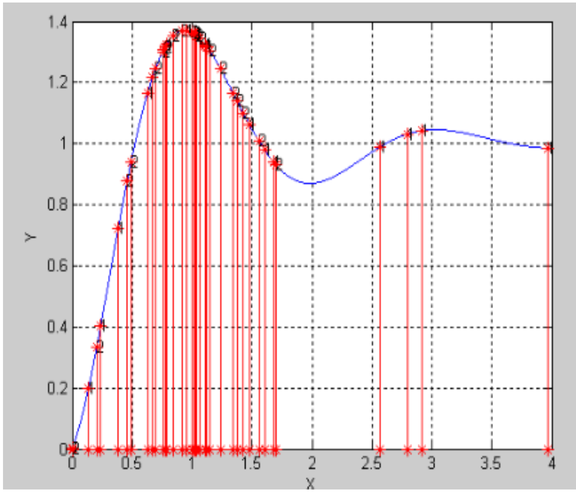

Figure .5. It's getting closer and closer to the maximum

The results of 30 iterations are shown in Figure 6

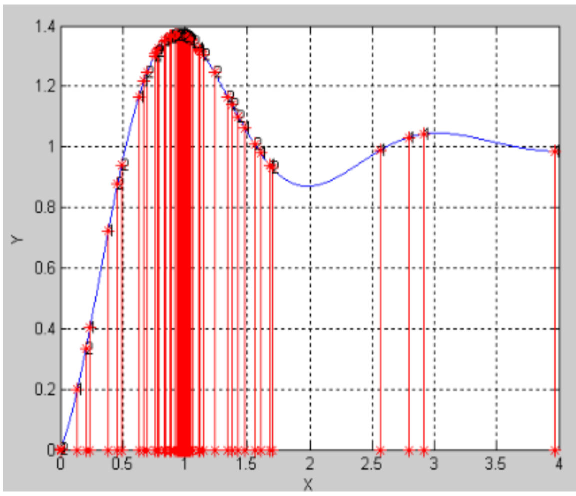

Figure .6. The resulut y=1.3706 is to be found

4. The prospect of PSO for water environment quality assessment

As a kind of efficient swarm intelligence optimization algorithm, PSO will be further applied in water environment assessment. The prospect of PSO for water environment quality assessment is as below.

The PSO has some inherent shortcoming, such as low capacity for global search, falling into local extremum easily, etc.. It is difficult to adapt the requirement of water environment assessment, so PSO further optimizing is a crucial research direction. Moreover, PSO has been used in different assessment method - Support vector machine, Projection pursuit method, et cetera. It has potential for using in other assessment method in future.

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HaoNan LIU is currently pursuing his master's degree study at the School of Electrical Engineering, HeBei University of science and technology, Shijiazhuang, China.

XiaoFei LV is the associate dean of the Heibei Provincial Institute of Environmental Protection Products Quality Supervision and Inspection, Shijiazhuang, China.

Jun XIAO is currently pursuing his master's degree study at the School of material science and Engineering, HeBei University of science and technology, Shijiazhuang, China.