Envisage Computer Modelling and Statistics for Agriculture

Forecast of agricultural water resources demand based on particle swarm algorithm

Wenzhou Yi
Information Engineering College, Guangdong Polytechnic of Engineering, Guangzhou, People’s Republic of China

ABSTRACT
The planning and management of water resources are becoming more and more important, and the forecast of water demand as the prerequisite and foundation of the entire planning has become a very important task in agricultural development. This paper combines the particle swarm algorithm to construct the agricultural water resource demand forecasting model, analyzes the shortcomings of the traditional particle swarm algorithm, and makes appropriate improvements to the quantum particle swarm algorithm. Moreover, this paper constructs the functional structure of the agricultural water resource demand forecast model based on the forecast demand of water resources, and analyzes the application process of the particle swarm algorithm in the system of this paper. After the model is constructed, the performance of the model is verified, and the simulation test is designed to evaluate the effect of system forecast with actual data. At the same time, this paper uses the model constructed in this paper to analyze the factors affecting water resources forecast demand. From the results of the experimental analysis, it can be seen that the model constructed in this paper is more effective in the forecast of water resources demand.

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Introduction
Water is the source of life, a controlling element of ecology and environment, and an important resource that cannot be substituted for human survival and development. As a basic natural resource and strategic economic resource, water is an extremely important guarantee for rapid, stable and sustainable economic and social development. However, with the growth of population and economy, the demand for water resources continues to increase. Moreover, many problems have emerged one after another, such as inefficient use of water resources, prominent contradiction between supply and demand, and continuous deterioration of the water environment. At present, the problem of water has become an important bottleneck restricting economic development and sustainable social development, and mankind has entered an era of water resources and environmental constraints (Boretti and Rosa 2019). Enhanced supplies of water, as well as better management of water resources, boosts a country’s economic development and improves to eliminate poverty. Global economies are much more tolerant to rain fluctuation, and increased water storage space improves productivity. Greater provision of basic water and sanitation benefits the impoverished immediately by improving their health, reducing health-care expenditures, and saving time. Water resource management improves productivity across economic sectors by increasing predictability and effectiveness, as well as contributing to the ecological system sustainability.

The forecast of agricultural water demand is the basis of the comprehensive utilisation of water resources. The comprehensive utilisation of water supplies in small watersheds should emphasise the thorough management and application of numerous types of water assets, and maintain an ideal and acceptable aquifer depletion developing system, resulting in a positive macroeconomic, cultural, and environmental advantage, and enhance the financial, cultural, and environmental climate, so that the liminal zone is reduced. As a result, the full utilisation of water supplies in limited watersheds is important in some ways (Ahilan et al. 2019). In order to meet the demand for water resources for sustainable development, a scientific long-term supply and demand plan for water resources needs to be formulated, and a reasonable forecast of water demand needs to be made (Nayak et al. 2018). The forecast of agricultural water demand can be divided into
medium and long-term forecasts and short-term forecasts according to the length of the forecast period. They are effective means for agricultural management departments to plan and manage water resources, are an important part of the optimal dispatch management of water supply systems, and are the main content of water supply and demand research. At the same time, they also provide a reference for strengthening water demand management and formulating social development plans, which is of extremely important significance (Sheffield et al. 2018).

Through water demand forecasting, the amount of water shortage can be estimated, which helps to adopt some methods and measures in advance to reduce the loss caused by water shortage to a minimum. At the same time, it also helps the country or region to formulate medium and long-term water resources development and utilisation master plans and water supply. The plan provides a more reliable reference basis for the stable and rapid development of the national economy, realises stable water supply, and effectively improves the economic and social benefits of water resources. At the same time, in the process of water demand research, by analyzing the structure and characteristics of the water system, the factors affecting water demand can be found, and the main driving factors can be identified through certain mathematical methods, and the most important factors affecting water use can be found. Provide guidance for specific water supply, water use planning and management and other practical work, and maximise the benefits and eliminate the disadvantages (Quilty et al. 2019).

At present, my country’s economy is showing a trend of rapid development, and a series of resource and environmental problems have followed one after another. That is to say, our social environment does not have the ability to withstand such rapid economic development. Some regions ignore the objective conditions of natural resources and ecological environment for the sake of current economic benefits. The speed of their development has exceeded the limit that resources and the environment can withstand, leading to resource shortages and environmental degradation, which then form a chain reaction and destroy A model of sustainable development.

With the rapid development of social economy and the increase of population, the continuous growth of water consumption, coupled with the increasingly serious water pollution problem, has exacerbated the shortage of water resources. The improper utilisation non-conventional freshwater resources in agricultural production particularly sewage treatment can result in the production of physicochemical and microbiological contaminants in crop production, livestock, water and soil assets, and, as a result, catastrophic results for uncovered processed foods and farm labourers (Meza et al. 2017). But as a basic resource, water is the basic guarantee for people’s life and production, and it is also the basic need for economic development. Therefore, it is a very important research topic to study the water demand problem in depth and use appropriate methods to scientifically and accurately predict the water demand in a certain forecast year (Myronidis et al. 2018). Machine learning is a popular technique these days, and it can be used to modern agriculture. The application of machine learning in agriculture aids in the development of healthier seeds. Machine learning is a popular technique these days, and can also be used to intensive farming. The application of machine learning in agriculture aids in the development of healthier seeds. The ML model’s effectiveness grows over time as it gathers knowledge. Various computational and scientific methods are being used to verify the profitability of ML algorithms and machine learning techniques in farming (Rodriguez et al. 2018).

This paper combines particle algorithm to predict the demand of agricultural water resources, constructs the corresponding demand forecast model, and constructs the functional structure of the model in combination with the actual situation.

**Related work**

(Zubaidi et al. 2020) proposed the BP algorithm on the basis of multi-layer neural network, which solved the learning problem of multi-layer forward neural network. BP network is currently the most commonly used neural network. Because tiny learning speeds are required for sustained learning, the gradient descent technique is typically quite sluggish. Because it enables for higher education rates while preserving stable, velocity variability is probably quicker than standard linear regression, though it’s still too sluggish for so many practical uses. (Javadinejad et al. 2019) established logarithmic and semi-logarithmic regression models of water demand prediction based on the correlation between precipitation, water price, population, income and other influencing factors and water demand. (Srivastava 2017) proposed a non-linear regression model, which took into account climate factors such as temperature and precipitation, and fully considered the characteristics of changes in water consumption. (Ashofteh et al. 2017) established the WaterGAP2 water consumption model to predict the water demand of domestic, agricultural, and industrial respectively.
WaterGAP is a worldwide hydrologic system that calculates human underground and groundwater usage, and also water fluxes and retention, and consequently water supplies, across all land masses. It is now being used to analyses water supplies and soil moisture in the past and in the prospective, particularly in context of climate change. It has enhanced our knowledge of regional rainwater harvesting variations, with a special emphasis on water management overfishing and degradation (Cotterman et al. 2018; Mi et al. 2010). The model takes into account factors such as national income, water use efficiency, and rainfall days. The domestic water process is represented by a Sigmoid curve, and the industrial water process is represented by a hyperbola.

(Bolandnazar et al. 2020) used analytic hierarchy and autoregressive model to predict the urban domestic water demand, and applies it to the domestic water demand forecast in Chengdu. The accuracy of the model is high. The model first processes the original data sequence into a white noise sequence. Therefore, any water use process can be simulated, and the prediction speed is fast and the accuracy is high. However, the forecast period is short, the data used is single, and it can only give the forecast value of the water demand in the next period, and cannot make a reasonable error estimation. For judgments, AHP employs precise attributes. i.e. in practical instances, emotional responses are hazy, and the commanders are often unable to match the assessment evaluations to the meticulous feature vectors. AHP isn’t relevant in this circumstance. It can only resolve straightforward equations. To evaluate the likelihood of another signal, conventional autoregressive based methods use just polynomial-time processing. Because this is appealing, it implies they are unable to represent distributed with difficult-to-compute next-symbol probabilities. At present, the improved model of this model has ARMA (p, d, q) model and ARMA (P, D, Q) 8 model. Because the model uses computer dynamic modeling, the prediction speed is fast, and it is suitable for time prediction, daily prediction, and annual prediction, as well as for simulating the water use process. Du Guoming uses an improved fast second-order BP neural network method to predict water consumption (Guzman et al. 2017). (Fu et al. 2018) uses trigonometric function method to predict water demand. The precision of the observations will influence the quality conclusion, which is an apparent constraint of trigonometric functions. Objects aren’t always accurately measured in actual situations. (Karbasi 2018) used the RBF network prediction model to predict urban water demand, and uses radial basis functions to establish a dynamic prediction model for daily water consumption. The model takes into account the effects of temperature, cloudy and sunny conditions, and holidays in the city’s water consumption. (Yaseen et al. 2018) established the water resources agricultural production function, industrial production function, and urban residents’ living water storage function. Aiming at the problem that in the medium and long-term urban water demand forecasting, the farther the prediction year of the conventional GM (1,1) model is, the weaker the prediction significance, (Gu et al. 2017) established the gray metabolism GM (1,1) model. On the one hand, this model inherits the advantages of the conventional GM (1, 1) model, on the other hand, it can take the disturbance factors into the system into consideration in time. At the same time, according to the principles of gray theory, it can also establish a gray index model that is applied to changes in the growth rate, a gray topology model that is used to process seasonal change data or noise data, and a GM (1, N) model that can include multiple factors affecting water consumption (Gao et al. 2020). Aiming at the problem of slow convergence of BP network and easy to fall into local minima, (Tiwari and Adamowski 2017) proposed an improved urban water demand prediction model based on genetic neural network. (Peng et al. 2018) uses a system dynamics model to predict urban water demand. The system dynamics model is a mathematical model established in accordance with the principles of system dynamics, and it is simulated by a computer to deal with system problems that change over time. Its essence is a kind of conditional prediction, a kind of feedback, which can make predictions in the absence of basic data and difficulty in establishing expressions. Moreover, it establishes a model by analyzing the effect of the system feedback mechanism. The analysis process of this model is complex, the workload is huge, and the forecaster’s professional knowledge, practical experience, and systematic analysis and modeling capabilities are all required. However, the model has strong system city, high prediction accuracy, and high application value.

Water demand forecasting methods can be divided into two types, mathematical model method and quota method. Estimating existing per-capita water usage, commonly observed in gallons per capita each day, and multiplying this by predicted population increase seems to be the easiest and perhaps most conventional method of estimating prospective water requirements. The designed flow patterns for water-supply system components are commonly estimated by forecasting the populace of the served building at the end of the life span, which will then be compounded by per capita water requirements to obtain
the designed water flow rate. The mathematical model methods are divided into three categories according to different data processing methods: time series method, structural analysis method and system method. The time series method is based on the statistical data of the predicted object, finds out the law of its change over time, and establishes a time series model to infer future values. It is divided into two types: deterministic and random. Among them, the deterministic methods include moving average method, exponential smoothing method, trend extrapolation method, and seasonal change method (Archibald and Marshall 2018). The random type has Markov method and Box–Jenkins method (B-J). Markov models are frequently used to predict the likelihood of numerous states and the speeds at which they shift. Modeling systems is a common application of the approach. Pattern recognition, forecasting, and learning the statistical of sequential data can all be done with Markov models. The Box–Jenkins technique uses autoregressive moving average methods to determine the best fitting of a time operation to previous data of a time – series data in analysis. The structural analysis method is based on the study of various influencing factors and their relationships, and establishes a model of the relationship between the predicted objects and the influencing factors. Moreover, it indirectly reflects the change rule of the forecast object by analyzing the change rule of influencing factors, including regression analysis method, industrial water elasticity coefficient method, and index analysis method. A series of statistical techniques for estimating relationship among variables and one or even more control variables is known as regression analysis. The water resources elasticity factor approach can be used to explore and quantify temperature fluctuations in radioactive groundwater concentrations in the environment. It also represents the frequency of water supplies and the productivity of secondary industries. As soon as the inquiry is conducted from inside the Plan Explorer experience, Index Information gives a simulated scenario in which you can test an indexes technique for a particular subject in a request. The system method uses the viewpoint of system science to regard the change of the predicted object as a dynamic system behaviour. After that, by studying the structure of the system, a system model is constructed to predict future values, including gray methods, artificial neural network methods and system dynamics methods (Jia et al. 2017). In addition, there is a quota method widely used in water resources planning, which is a microscopic forecasting method for forecasting water consumption based on comprehensive water quotas.

Basic evolution equation of water resources forecast demand

Under the one-dimensional δ potential well, the stationary wave function of a single particle can be calculated, that is, the probability density of particles appearing in a one-dimensional situation and its distribution function. In each and every detectable sense, a stationary line is represented as the system remaining in the same condition as time passes. For a single-particle, this indicates that the subatomic particle location, speed, and rotation that have a uniform confidence interval. In practice, we need to know or predict where the particles appear through the probability density distribution function. Only if the sampling distribution of an allocation is certainly consistent, it has a density function. Chance distributions aid in the modelling of our world by allowing us to predict the probability of a given event occurring or the variation of occurrences. They’re a frequent means of describing and possibly predicting an event’s possibility. For example, when point p is taken as the centre, in the motion of a one-dimensional δ potential well, it can be concluded that the position equation after inverse transformation (Monte Carlo method) has the following form:

\[ X = p \pm \frac{1}{2} \ln(1/u) \]  \hspace{1cm} (1)

Monte Carlo simulations are being used to represent the possibility of different scenarios in a procedure that is difficult to anticipate down to random factors’ involvement. It’s a method for figuring out how uncertainties affect prediction models.

In the formula, L represents the feature length of the δ potential well, and the specific derivation process is as follows (Sundarasekar et al. 2019):

Setting: u obeys (0, 1) and satisfies a uniform distribution, and is random at (0, 1), which can be expressed as:

\[ u \sim U(0, 1) \]  \hspace{1cm} (2)

When it is replaced with u,

\[ u = F(Y) \]  \hspace{1cm} (3)

The following results can be obtained:

\[ u = e^{-2|Y|/L} \]  \hspace{1cm} (4)

Using the inverse transformation, the expression of Y can be calculated as:

\[ Y = \pm \frac{L}{2} \ln(1/u) \]  \hspace{1cm} (5)
and
\[
Y = X - p
\]
(6)

Therefore, the random equation of the specific position of a single particle p can be calculated:
\[
X = p + \frac{L}{2} \ln(1/u)
\]
(7)

Through the one-dimensional results, it is possible to deduce the multi-dimensional or high-dimensional situation, so it is considered that the change of the particle’s position in each dimension changes with the number of iterations. If it is assumed that a centre of attraction is \( p_i = (p_{i1}, p_{i2}, \ldots, p_{iN}) \), the evolution equation of the particle i at the j-dimensional position is expressed as:
\[
X_{ij}(t + 1) = p_{ij}(t) + \frac{L}{2} \ln(1/u(t))
\]
(8)

In the formula, \( u(t) \sim U(0, 1) \).

Now, we discuss \( L_{ij}(t) \). We first introduce the mean best position (mbest), denoted as \( C(t) \), which represents the average of the best positions of all particles:
\[
C(t) = (c_1(t), c_2(t), \ldots, c_N(t)) = \frac{1}{M} \sum_{i=1}^{M} p_i(t)
\]
(9)

In the formula, \( M \) represents the size of the population, and \( N \) is the dimension of the problem.

\( L_{ij}(t) \) is evaluated using the following formula:
\[
L_{ij}(t) = 2a|C(t) - X_{ij}(t)|
\]
(10)

The evolution equation of the particles of the standard QPSO algorithm can be obtained as:
\[
X_{ij}(t + 1) = p_{ij}(t) + a(C(t) - X_{ij}(t)) \cdot \ln(1/u(t))
\]
(11)

The formula (10) obtained above is called the quantum particle swarm optimisation algorithm. Similarly, \( u(t) \sim U(0, 1) \). The \( a \) mentioned in the above derivation process is called the shrinkage-expansion coefficient. The variation of the estimated coefficients is greatly reduced when they are shrunk. Whenever we lower the coefficient estimates, you are effectively bringing them nearer to 0. The difficulty of ridge regression or overfitting the data necessitates the use of a shrinkage procedure. It can be seen from the above formula that in addition to the size of the population and the number of iterations of the problem, it is the only parameter to be controlled. Moreover, the evolution equation of QPSO only includes the position to describe the particle, and does not include the term of speed. In the QPSO algorithm, \( L_{ij}(t) \) is judged by the average best position, and the collaboration ability is enhanced, which makes the global search stronger. At the same time, the state in the algorithm is also different.

The QPSO algorithm flow is as follows:

Step 1: Initialise the spatial position information, maximum number of iterations and various parameters of each particle in the space.

Step 2: According to the fitness function, calculate the current fitness value of the particle, and compare the fitness value with the iteration result of the previous iteration. If the current fitness value is relatively small, replace the previous value with it, otherwise continue to retain the smaller fitness value last time.

Step 3: Calculate the current optimal position of the entire group, record the current global optimal position of each particle and compare it with the previous value, if the current value is better, the current fitness value will replace the original value, get the new global optimal value, otherwise it will remain unchanged.

Step 4: Calculate the average optimal position of all particles.

Step 5: Get the location of a random point.

Step 6: Update the new position of the particle.

Step 7: Repeat steps 2–6 until the required loop conditions are met to terminate the loop.

The QPSO algorithm flow is shown in Figure 1:

The quantum particle swarm algorithm not only inherits the advantages of the particle swarm algorithm, but also has its own more concise calculation model, fewer control parameters and other more prominent advantages, but it still has certain limitations. For example, there will also be the problem of premature convergence. The control parameters in QPSO are fewer and easier to settle into a locally optimal. The sample is subjected to a random optimum, while the parental person is subjected to an interleaved procedure. In the situation of infinite scanning repetitions, QPSO’s global convergence ensures that the globally global optimum is determined. This circumstance, nevertheless, is unreasonable in exercise since any optimisation process means allowing only a finite iteration to figure out a solution (Moon et al. 2018). As the number of iterations increases, after reaching a certain value, the optimal position of a single particle will get closer and closer to the optimal position of the population, which reduces the diversity of the population and leads to poor local optimisation capabilities. For the selection and determination of the parameter \( a \), the smaller the value of \( a \), the more conducive to the local search, but the convergence speed will be affected. The larger the value of \( a \), the faster the global convergence speed, but it will affect the accuracy of the model to a large extent.

In the early stage of the algorithm, a relatively large search speed is needed to quickly approach the global extremum, so at this time the value of \( a \) needs to be
larger and better. However, in the later stage of the algorithm, the local search capability needs to be appropriately strengthened, so the search speed needs to be reduced, and a smaller $a$ value can be appropriately selected.

According to people’s analysis, the value of $a$ is generally controlled by a linear reduction method. The specific formula is as follows:

$$a = a_{\text{min}} + (a_{\text{max}} - a_{\text{min}}) \frac{t_{\text{max}} - t}{t_{\text{max}}}$$ \hspace{1cm} (12)

In the formula, $a_{\text{max}}$ is the initial value of contraction-expansion coefficient, $a_{\text{max}}$ is the final value, and is generally taken as $a_{\text{max}} = 1$, $a_{\text{min}} = 0.5$ based on experience, $t_{\text{max}}$ is the maximum number of iterations, and $t$ is the current number of iterations. It can be seen from the above formula that the value of $a$ is monotonically decreasing, and it is difficult to meet the dynamic changes of actual production needs. In unstable flow, compression and expansions effects are typically doesn’t use, hence the standard values are 0. Pressure force variations are used in the numerical solution to manage forces caused by contraction and expansions.

In order to obtain better suitable parameters for particles in the optimisation process, this paper will propose an improvement to the quantum particle swarm algorithm, which is called Improved Quantum Particle Swarm Optimisation (IQPSO). During the operation of the QPSO algorithm, the population is evolving, so the differences between the particles become smaller and smaller, and the size of the particle fitness is determined by the position of the particle. Therefore, there will be an overall change in the fitness of the particles in the population. Based on this, the status of the population can be judged.

We assume that the fitness of particle $i$ is $f_i$. In the current state, the average fitness of the population is $\bar{f}$, and the variance of fitness is $s^2$ and its expression is:

$$s^2 = \frac{1}{M} \sum_{i=1}^{M} (f_i - \bar{f})^2$$ \hspace{1cm} (13)

In the formula, $M$ represents the number of particles in the population. At this time, the fitness variance of the population can reflect the degree of aggregation of particles in the entire population. The weighted aggregate based on a revised resemblance is utilised to explain the degree of community variety in addition to increasing PSO’s global seeking capabilities. With an adaptable judgement, it also modifies the particles computational complexity. When $s^2$ is smaller, it indicates that all particles are gathered together more compactly. On the contrary, the less compact the collection of all particles. With the iteration of the algorithm, the particle aggregation degree of the later population will become tighter and tighter, and $s^2$ will become smaller. When $s^2$ is smaller than a threshold $s$ that we assume, the algorithm comes to the later iterative search. At this time, premature occurs. In order to prevent the algorithm from being restricted by the local optimum and avoid falling into the above situation and enable it to continue to expand the search area, this paper increases the evolution factor $\lambda_t$ when obtaining the average optimal position.

$$\lambda_t = \mu_1 K_t(0, 1) + \mu_2 N_t(0, 1)$$ \hspace{1cm} (14)

In the formula, $K_t(0, 1)$ is a random number in the interval $(0, 1)$ generated by the standard Cauchy distribution, $N_t(0, 1)$ is a random number in the interval $(0, 1)$ generated by the standard Gaussian distribution,
and $\mu_1$ and $\mu_2$ are interference coefficients. The Cauchy distribution is a continual probability that describes resonant activity when the denominator distributions have norm 0 and the proportion of multiple individuals uniformly distributed random elements is equal. It has also been used to simulate the striking sites of a constant single direction of pollutants emitted by a single point. The expression is:

$$\left\{ \begin{array}{l}
\mu_1 = \mu_{1\text{min}} + (\mu_{1\text{max}} - \mu_{1\text{min}}) \frac{t}{t_{\text{max}}} \\
\mu_2 = \mu_{2\text{max}} + (\mu_{2\text{max}} - \mu_{2\text{min}}) \frac{t}{t_{\text{max}}} 
\end{array} \right. \quad (15)$$

In the formula, $\mu_{1\text{min}}$ is the minimum value of $\mu_1$, $\mu_{1\text{max}}$ is the maximum value of $\mu_1$, $\mu_{2\text{min}}$ is the minimum value of $\mu_2$, and $\mu_{2\text{max}}$ is the maximum value of $\mu_2$. $t$ represents the current number of iterations, and $t_{\text{max}}$ represents the maximum number of iterations. After increasing the evolution factor, the average optimal position $C(t)$ of the particle is expressed as:

$$C(t) = \lambda t \cdot C(t) \quad (16)$$

$\mu_1$ can be a linearly increasing process. At the initial stage of the iteration, a smaller value of $\mu_1$ can be beneficial to local convergence, and as the number of iterations increases, a larger value of $\mu_1$ is beneficial to global search. The change of $\mu_2$ can make the search range wider, so that the algorithm can be improved to a certain extent.

The traditional contraction-expansion coefficient update formula is a linearly decreasing straight line, which is difficult to fully satisfy the dynamic change process of the actual production and life model. Therefore, according to the idea of parameter dynamic change in the PSO algorithm, a non-linear change adaptive method is used to control the parameter for actual problems. Non-linear change adaptive methods, like wavelet, provide time–frequency-energy interpretation of information without utilising an a preexisting premise. However, improving global search functions while also speeding up converging is a challenging task. Moreover, the contraction-expansion coefficient $\alpha$ adopts a new dynamic reduction method to improve the optimisation effect of the model parameters, and the improvement is recorded as AQPSO. Massive linear and non-linear simulation behaviour is reduced using model reduction approaches that are defined by divergent and algebraic equations that are extensively employed in linear programming. In some situations, the performance of an independent distributed system, that is, one that is driven by no exogenous variables, is of importance. The specific update method is as follows:

$$\alpha_2 = \alpha_{\text{max}} - (\alpha_{\text{max}} - \alpha_{\text{min}}) \tan \left( \frac{t}{t_{\text{max}}} \cdot \frac{\pi}{4} \right) \quad (17)$$

Similarly, in the above formula, $a_{\text{max}}$, $a_{\text{min}}$ represents the initial value and final value of the shrinkage–expansion coefficient, and generally takes the value $a_{\text{max}} = 1$, $a_{\text{min}} = 0.5$ according to experience, $t_{\text{max}}$ represents the maximum number of iterations, and $t$ represents the number of current iterations.

Figure 2 shows the comparison of the change of the contraction-expansion coefficient $\alpha$ using the traditional linear decreasing strategy and the improved decreasing strategy. We assume that the maximum number of this iteration is 100, and the other parameters and conditions set by the two methods are the same without any difference.

It can be seen from the figure that in the initial stage of particle evolution iteration, the value of the contraction-expansion coefficient $\alpha$ of the improved decreasing strategy is obviously larger than that of the traditional updating strategy, which is more helpful for the global search of the algorithm. At the later stage of the iteration, the value of $\alpha$ of the improved decrement strategy algorithm is smaller than the value of the traditional formula, and the decline speed of the former is obviously better than the latter, which can strengthen the local search and strengthen the accuracy requirements of the search. It can be seen that the improved more progressive update strategy has improved the global search of the algorithm and the local search ability of the algorithm no matter which stage it is in the first, middle and later stages.

The specific algorithm steps of the improved quantum particle swarm algorithm are as follows:

The first step: the algorithm initialises the parameters of the particle swarm, and obtains the position information of the particle in a random manner;

![Figure 2. Comparison of the change of the contraction-expansion coefficient $\alpha$.](image-url)
Step 2: the algorithm resets the contraction-expansion coefficient;

The third step: According to the fitness function, the algorithm calculates the fitness value $f(p)$ of each particle and compares it with the previous individual optimal $p_i$. If the current value $f(p)$ is smaller than $p_i$, the algorithm is updated, otherwise the last fitness value will be retained;

Step 4: The algorithm calculates the current optimal position $f(g)$ of the entire group and compares it with the previous global optimal position $g_i$. If $f(g)$ is smaller, the algorithm replaces $g_i$ with $f(g)$ to get the new value, otherwise, it remains unchanged;

Step 5: The algorithm calculates the average optimal position of all particles;

When $s^2$ is less than $\sigma$, the algorithm increases the evolution factor, re-evolves the population, and then returns to the third step. When the termination condition is met, the algorithm terminates the loop.

Particles should be started by projecting a chaotic sequence. Calculate every particle’s fitness function value. Retrieve each subatomic particle early engineering ideal position and global best, as well as their respective fitness function results, and change the present iteration’s value to zero. Examine whether the programme is meeting one of its two access conditions listed below. Calculate the average optimum position using the recession coefficient. Create a local attraction location and modify all the particle orientations. If any starting role surpasses the computational complexity, make it fair to the searching structure’s top or the bottom boundary and assess all particles locations and calculate the fitness function. (Figure 3).

In order to verify that the improved algorithm proposed in this paper has a better effect than the traditional particle swarm algorithm and quantum particle swarm algorithm mentioned in this paper, four functions will be selected for the comparison and analysis of the verification test of the algorithm. The expressions of the selected 4 functions are as follows:

(1) **Sphere function**

Many clearly outlining are used for the research, including the sphere feature. Such test functions, sometimes known as fake sceneries, are used in applied maths to monitor the effectiveness of algorithms.

$$f_1(x) = \sum_{i=1}^{N} x_i^2$$  \hspace{1cm} \text{(18)}

The range of the value of the argument $x_i$ of the Sphere function is $-100 < x_i < 100$. This function has a unique global minimum, and when $x^* = (0, 0, \cdots, 0)$, the function obtains the global minimum $f_1(x) = 0$. This function is to test the accuracy of the algorithm optimisation.

(1) **Griewank function**

The Griewank function is a non-convex, bimodal distribution, n-dimensional scientific function that is...
commonly used to evaluate optimisation techniques.

\[ f_2(x) = \frac{1}{4000} \sum_{i=1}^{N} x_i^2 - \prod_{i=1}^{N} \cos \left( \frac{x_i}{\sqrt{i}} \right) + 1 \]  

(19)

The range of the value of the argument \( x_i \) of the Griewank function is \(-600 < x_i < 600\). This function contains a large number of local extrema in the entire data distribution, but there is a global minimum \( f_2(0) = 0 \), and it is a more complex multi-modal complexity problem. Therefore, the purpose of choosing this function is to test whether the algorithm jumps out of the local area and can continue to search.

(1) Rastrigin function

There are multiple local minima in the Rastrigin component. Although it is very heterogeneous, the minima are equitably spread.

\[ f_3(x) = \sum_{i=1}^{N} \left[ x_i^2 - 10 \cos (2\pi x_i) + 10 \right] \]  

(20)

The range of the independent variable of the Rastrigin function is \(-60.12 < x_i < 60.12\), and there is a global minimum at \( x = (0, 0, \ldots, 0) \). This function is a non-linear multi-peak function with a large number of local minima, and it is difficult to find the global minima. Therefore, this function can be used to test the global optimisation ability of the algorithm.

(1) Rosenbrock function

Rosenbrock’s banana function is a well-known optimisation software testing ground. Along with its curved shape, it’s known as the bananas effect. The regular expression global minimal is set to \((1, 1)\).

\[ f_4(x) = \sum_{i=1}^{N-1} \left[ 100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2 \right] \]  

(21)

The value range of the argument \( m \) of the Rosenbrock function is \(-2 < x_i < 2\). This function is a unimodal function with a global minimum, which is located at

\[(1, 1, \ldots, 1, 1)\].

\[ -2 < x_i < 2 \]

Figure 4. Calculation framework of water footprint.
the lowest point of a parabola that resembles an opening upward. Although it is relatively easy to find, it is difficult to converge to the lowest point. Therefore, it is possible to test the ability of global optimisation.

**Forecast of agricultural water resources demand based on particle swarm optimisation**

Particle swarm optimisation (PSO) is an analytical tool for optimising a topic by continuously finding the most effective answer in terms of a specific quality indicator in scientific computing. It’s doesn’t involve the optimised variables divergence, derivatives, or continuum; it has a quick convergence speed, and the method is easy and basic to construct. There are many factors that affect the per capita water footprint. People’s consumption, consumption habits, climate factors, agricultural practices, etc. are closely related to the water footprint. Through the calculation of the internal and external water footprint of the region, the per capita water footprint of the region is calculated. The calculation process is shown in **Figure 4**. Through some kind of series of rounds, the algorithm finds the specific problem for optima. The particles explore for viable solutions during the rounds and improve over time depending according to their own and other particle encounters. Each particle’s mobility is governed by its fitness function posture, which is referred to as previous best. The optimally place of the entire population, referred to as global best, also affects the overall value for money of all particle. The speed and position of the particle are changed throughout each repetition, and the work is carried out by predicting a new velocity component for each component in proportion to its proximity.

The specific process of forecast of agricultural water demand based on particle swarm algorithm is shown in **Figure 5**.

This paper analyzes the particle swarm algorithm process of the system model in combination with the model, and the results are shown in **Figure 6**.

After constructing the above model, the effectiveness of the algorithm in this paper is analyzed through experimental research. According to the actual situation, this paper uses the agricultural water resources in a certain area to make a forecast analysis. This paper uses the basis of the past 6 years as input to predict the monthly agricultural water demand for the next 6
years, and compares the forecast results with the actual agricultural water demand, and calculates the accuracy of the forecast, as shown in Table 1 and Figure 7.

Judging from the results of the above chart analysis, the particle swarm algorithm constructed in this paper has a good performance in the forecast of agricultural water resources demand. On this basis, this paper uses the algorithm proposed in this paper to analyze the factors affecting agricultural water resources, and compares it with the standard situation. The results are shown in the following table and Figure 8. (Table 2).

From the above analysis, it can be seen that the agricultural water resource demand forecast model based on particle swarm algorithm proposed in this paper can more accurately analyze the factors that affect agricultural water resource demand, and facilitate the subsequent timely formulation of effective response strategies.

**Conclusion**

With the intensification of human activities, the spatial mismatch between water resources and productivity distribution in the river basin has become more prominent. The development of water resources has exceeded the safety limit, and the uncertainty of water resources is increasing. Convergence speed and search precision are enhanced, and a subsequent search method reduces the likelihood of a local optimal while increase the reliability of the later searching. Under the background of increasing demand for water resources due to population growth and economic and social development, the problem of water scarcity has become a ‘bottleneck’ restricting regional economic and social development. The rational development and utilisation of limited water resources and the balancing of water use by various departments are urgent tasks. China is a large

| Num | Accuracy(%) | Num | Accuracy(%) | Num | Accuracy(%) |
|-----|-------------|-----|-------------|-----|-------------|
| 1   | 75.32       | 25  | 71.63       | 49  | 66.65       |
| 2   | 70.24       | 26  | 72.96       | 50  | 71.84       |
| 3   | 61.71       | 27  | 64.07       | 51  | 69.34       |
| 4   | 67.81       | 28  | 66.21       | 52  | 74.08       |
| 5   | 63.25       | 29  | 73.64       | 53  | 64.33       |
| 6   | 67.59       | 30  | 70.04       | 54  | 72.88       |
| 7   | 72.91       | 31  | 69.67       | 55  | 69.01       |
| 8   | 70.82       | 32  | 61.63       | 56  | 69.47       |
| 9   | 65.05       | 33  | 67.80       | 57  | 64.80       |
| 10  | 75.02       | 34  | 63.32       | 58  | 61.37       |
| 11  | 61.29       | 35  | 64.89       | 59  | 64.32       |
| 12  | 71.70       | 36  | 71.64       | 60  | 75.00       |
| 13  | 67.54       | 37  | 68.51       | 61  | 70.57       |
| 14  | 68.97       | 38  | 62.72       | 62  | 62.18       |
| 15  | 70.63       | 39  | 75.16       | 63  | 62.41       |
| 16  | 75.17       | 40  | 67.92       | 64  | 64.84       |
| 17  | 66.96       | 41  | 67.83       | 65  | 75.11       |
| 18  | 67.51       | 42  | 63.38       | 66  | 68.00       |
| 19  | 61.80       | 43  | 70.58       | 67  | 75.56       |
| 20  | 72.71       | 44  | 66.86       | 68  | 73.91       |
| 21  | 61.56       | 45  | 75.21       | 69  | 66.18       |
| 22  | 61.34       | 46  | 65.24       | 70  | 65.90       |
| 23  | 70.05       | 47  | 61.54       | 71  | 74.56       |
| 24  | 75.20       | 48  | 62.88       | 72  | 74.21       |

![Figure 7](image-url) Statistical diagram of accuracy of the forecast of agricultural water resources demand.
As an important crop in our country, rice requires a lot of water resources during the planting process. Therefore, it is of great significance to predict the demand for agricultural water resources. This paper combines particle swarm algorithm to predict and analyze the demand of agricultural water resources, and verifies the system performance through experiments. The research results show that the model proposed in this paper has a certain effect.

**Disclosure statement**

No potential conflict of interest was reported by the author(s).

**Notes on contributor**

Wenzhou Yi is an associate professor of Information Engineering College of Guangdong Polytechnic of Engineering, China. He graduated from Guangxi Normal University. His research interests include swarm intelligence algorithm. He has published more than ten papers.

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