Quantum and Condor-Based Brainstorming Optimization Algorithm for NOx Prediction

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Abstract. This paper proposed a quantum bald eagle brainstorm (QBBSO) based on quantum initialization and combined with the bald eagle optimization algorithm in light of the original Brain Storm Optimization (BSO) algorithm's strong local search ability, which would result in local optimization, a poor optimization effect, and difficult development. To accomplish the randomness of the number and increase the randomness of the population, we first modified the initialization method of the original brainstorming population, introduced the idea of quantum code, and then translated the binary numbers 0 and 1 to the decimal number. To achieve the best outcome, the original step size formula was employed for global selection, local search, and final selection using the vulture search method. The original BSO was then optimized to attract more global individuals. The algorithm versions were compared using the common benchmark function test. The findings demonstrated that QBBSO had a greater capacity for global search and a faster convergence speed. This research also applied the QBBSO algorithm to the long-term and short-term memory network (LSTM) to forecast the NOx concentration in the boiler, further demonstrating the algorithm's superiority in real-world settings.

1. Introduction

With the iterative updating of intelligent algorithms in recent years, a limitless number of new algorithms have emerged. Through collaboration, competition, and other team activities, the swarm intelligent optimization algorithm can identify a superior solution. Particle swarm optimization (PSO) is currently a well-known swarm-intelligent optimization algorithm [1]. Optimization of ant colonies (ACO) [2]. Humans are the world's greatest social organism, and their peculiar thinking can be utilized as a novel swarm intelligence optimization algorithm. By enhancing the population initialization method, clustering method, selection and variation, etc. of BSO, academics and specialists domestically and internationally have created a large number of variants of BSO. The concept of differential variation was first introduced to BSO by Chen et al. [3]. Based on the discussion mechanism, Zhou et al. modified BSO, created the DMBSO optimization algorithm, and increased algorithm accuracy [4]. A multi-branch chaotic mutation operator was created by Yi et al. to improve the algorithm's capacity for global search [5]. To enhance the capability of global search, Zhao et al. created a reinforcement learning brainstorming algorithm featuring a learning mechanism and four mutation techniques [6]. The brainstorming algorithm should be studied in further detail to increase its precision and search capability. This will help optimize the neural network so that it can be used to tackle real-world engineering challenges. In 1997, Schmidhuber and Hochreiter made the suggestion. It is widely employed in a variety of industries, including the detection of coke quality, short-term orbit prediction, AC motor failure detection, stock price prediction, and missile trajectory prediction [7, 8]. The revised brainstorming approach is utilized in conjunction with the LSTM network to estimate the NOx concentration in the boiler.

2. Quantum Condor Brainstorming Algorithm

2.1 Original Brainstorming Optimization Algorith

The k means clustering approach was used in the original brainstorming process to partition the initial population into m classes. Let's say there are 5 clusters and m = 5. One or two clusters were randomly chosen rather than utilizing all five of these clusters simultaneously. There are two methods for updating the n individuals: one involves randomly selecting a cluster and then selecting the cluster center within that cluster. The alternative is to arbitrarily choose two clusters and choose the clustering center using the corresponding weight value. The target individual X is obtained following the aforementioned selection, and the following Formula (1) is applied for X new updates.

$$X\_new = X\_select + \varepsilon * normrnd(\mu, \sigma, 1, D) \tag{1}$$

$$\varepsilon = logsig((0.5 * max\_iternation - current\_iteration)/k) * rand(1, D) \tag{2}$$

where D stands for the dimension of data, which in Matlab corresponds to the logistic regression's sigmoid function as well as the function for generating random integers with a positive distribution.

$$logsig(n) = \frac{1}{1+e^{-n}} \tag{3}$$

The brainstorming optimization algorithm has a straightforward structure and some competitiveness with swarm intelligence optimization algorithms. However, the original BSO algorithm has some drawbacks, including a strong affinity for local searches, a propensity towards local optimal, and difficulty in developing. This research suggests a brainstorming optimization method (QBBSO) based on the quantum and Condor algorithms to address these issues. The algorithm flowchart is shown in Figure 1.

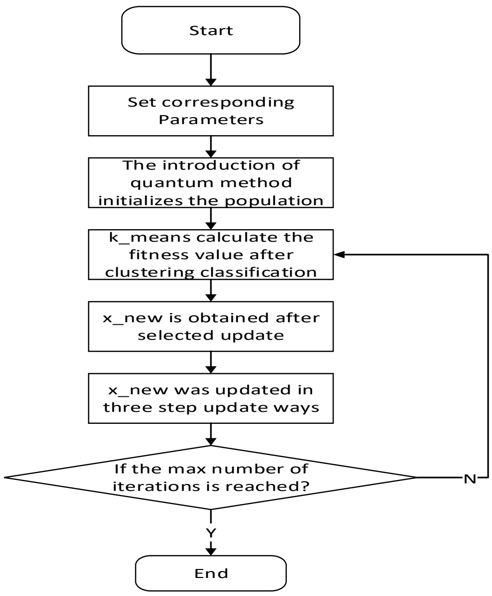

Figure 1. QBBSO flow chart

2.2 Quantum Initialization Population

The early population distribution of a swarm intelligence optimization algorithm greatly affects the program's accuracy and speed of convergence. The original brainstorming algorithm used a random method, which causes an uneven starting population distribution and low levels of unpredictability, slowing down the optimization process. To address these issues, the idea of quantum is proposed in this study as a means of encoding and measuring the population. This method not only solves the issue of initial population regularity but also enhances the population's randomness and ergodicity. To broaden the search area and improve population randomness, the parallel search of many universes is used in this research to include the idea of quantum multi-universes in the brainstorming method. Each dimension of the population is defined as 20 bits, and the population is coded and measured during initialization. Assume that the binary population is initialized, that each encoding length is $1/\sqrt{2}$, and that each binary encoding site is represented by the linear superposition of two orthogonal base vectors (4).

$$|\varphi k>= \alpha k|0> +\alpha k|1> \tag{4}$$

$$|\alpha k|^2+|\beta k|^2=1 \tag{5}$$

We measure the probability of operating results for |0>,|1> respectively$|\alpha k|^2$ ， $|\beta k|^2 =1- |\alpha k|^2$.

We create a random number, compare it to $|\alpha k|^2$ random generation 0 and 1, which produce binary code; shift the binary number to produce a decimal number; and then, receive the population initialization.

Stormy weather allows condors to fly higher. An increase in wind speed triggers soaring, so the eagle spends a lot of time in the air. Eagles have been seen gliding beautifully and motionless for extended periods.

2.3 Condor Changes Step Length

In the original brainstorming algorithm, the step size updating formula makes it simple for the population to settle into a locally optimal state, and the search space is limited with a sluggish convergence rate. The condor search strategy is introduced in this paper.

2.3.1 Selection Phase

First, during the selection phase, condors decide where in the chosen search region is the optimum place to look for prey, depending on the availability of food. This behavior is expressed quantitatively in Formula (6).

$$Pi,new = Pbest + \alpha \ * r(Pmean - Pi) \tag{6}$$

where α is a random number between 0 and 1, is a parameter used to govern the change in position, and its value is between 1.5 and 2. represents the search space chosen once the line mode has been selected based on the best position discovered in the previous search. represents the typical position, while the current search is calculated by dividing the prior information from a random search by alpha. All search points are changed at random by this method.

2.3.2 Search Phase

The second phase is the search phase when the condor glides quickly through the spiral space while looking for prey inside the chosen search zone. The formula is a mathematical representation of the dive's ideal location (7).

$$Pi,new = Pi + y(i) * (Pi - Pi + 1) + x(i) * (Pi - Pmean) \tag{7}$$

$$x(i) = \frac{xr(i)}{max(|xr|)} \quad y(i) = \frac{yr(i)}{max(|yr|)} \tag{8}$$

$$xr(i) = r(i) * \sin(\theta\ (i)) \quad yr(i) = r(i) * \cos(\theta\ (i)) \tag{9}$$

where represents the average position, and represents different angles and moves to different directions, which can be obtained through setting and calculation.

2.3.3 Selection Phase

Condors swing from sweet spots in the search space to their target prey. All the points will move toward the sweet spot. Formula (3) illustrates this behavior mathematically.

$$Pi,new = rand * Pbest + x1(i) * (Pi - c1 * Pmean) + y1(i) * (Pi - c2 * Pbest) \tag{10}$$

$$x1(i) = \frac{xr(i)}{max(|xr|)} \quad y1(i) = \frac{yr(i)}{max(|yr|)} \tag{11}$$

$$xr(i) = r(i) * \sin h(\theta\ (i)) \quad yr(i) = r(i) * \cos h(\theta\ (i)) \tag{12}$$

where x1(i) and y1(i) are obtained by the swoo_p function, the same as in 2.2.2, and represent the movement from the X and Y axes, respectively. Pbest is the current optimal individual, Pi is the individual of the current iteration times, c1 and c2 are both taken as 2.

To achieve global selection, local selection, and ultimately optimal individual selection, this paper introduces the concept of quantum mechanics and the influence of the condor optimization algorithm, applies the gliding, graceful, and static flight of the eagle into brainstorming, changes the step size of BSO, and updates the formula.

3. Simulation Test

3.1 Standard Test Functions

In this paper, six commonly used standard functions are chosen for optimization testing, of which f1–f3 is a single-peak standard reference function and f3–f6 is a multi-mode standard reference function. Single-peak functions can be used to test the local optimization capabilities of the algorithm, while multi-peak functions can be used to test its global search capabilities. The test findings are therefore instructive.

3.2 Experimental Analysis

F1 through F3 are single peak standard reference functions for the aforementioned 6 standard functions, and F3 through F6 are multi-mode standard reference functions. The effectiveness of the algorithm optimization may be thoroughly tested. The exam results serve as a guide in several ways. to confirm the QBBSO algorithm's superiority. The function convergence diagram is shown in Figure 2. Two brainstorming algorithm versions, IBSO and TBSO, as well as the original BSO method, were compared to the QBBSO algorithm.

The following parameter unification of the BSO, IBSO, TBSO, and QBBSO algorithms for comparison is chosen to assure fairness and eliminate the randomness of results: The maximum number of iterations was 100, the dimension was 30, and the initial population size was 40. The findings of 30 independent tests were conducted, and the evaluation was based on the mean value and standard deviation of the outcomes of the function optimization. The test results were displayed in Table 1.

Table 1. Comparison of Experimental Results

		BSO	IBSO	TBSO	QBBSO
f1	MEAN	1.11E+01	2.78E+01	4.94E-118	**0.00E+00**
	STD	4.30E+01	1.52E+02	1.13E-117	**0.00E+00**
	VAR	1.85E+03	2.32E+04	1.27E-234	**0.00E+00**
f2	MEAN	1.06E+12	9.99E-02	8.59E-60	**1.08E-217**
	STD	5.82E+12	5.47E-01	5.38E-60	**0.00E+00**
	VAR	3.38E+25	2.99E-01	2.90E-119	**0.00E+00**
f3	MEAN	2.53E+04	2.70E-108	9.91E-118	**8.85E-226**
	STD	1.11E+05	1.48E-107	1.38E-117	**0.00E+00**
	VAR	1.23E+10	2.18E-214	1.89E-234	**0.00E+00**
F4	MEAN	-4.24E+02	-1.94E+03	-1.76E+02	**6.87E+01**
	STD	3.45E+03	4.86E+03	1.93E+03	**6.39E+02**
	VAR	1.19E+07	2.36E+07	3.73E+06	**4.09E+05**
F5	MEAN	2.98E+01	1.03E+02	2.49E+01	**0.00E+00**
	STD	1.13E+02	1.37E+02	7.81E+01	**0.00E+00**
	VAR	1.29E+04	1.88E+04	6.10E+03	**0.00E+00**
F6	MEAN	1.62E-05	1.00E+00	4.44E-15	**8.88E-16**
	STD	4.63E-06	3.39E+00	**0.00E+00**	**0.00E+00**
	VAR	2.14E-11	1.15E+01	**0.00E+00**	**0.00E+00**

As observed in Table 1, QBBSO has the best accuracy for unimodal functions, whereas BSO has the worst accuracy, with the exception that f6's variance and standard deviation are the same as TBSO.

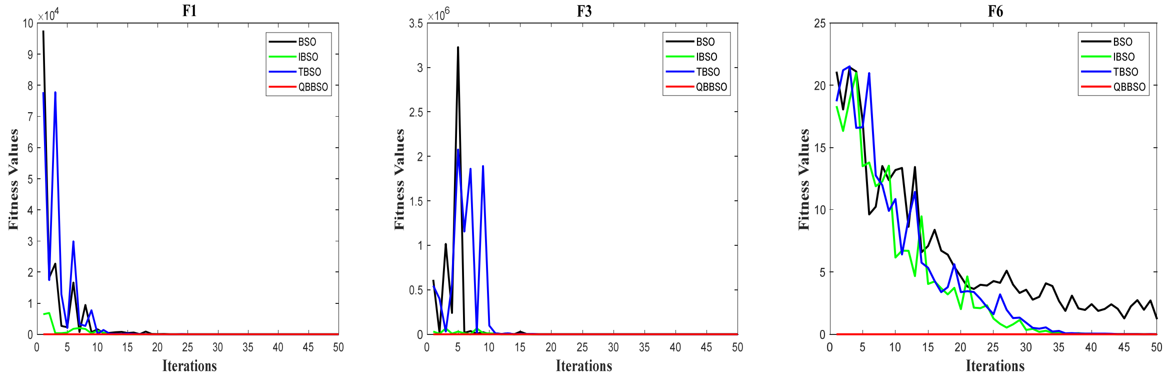

Figure 2. The convergence diagram is analyzed experimentally

4. Application of Optimization Algorithm in Boiler NOx Prediction

Air pollution is a major contributor to the environmental issues facing our nation, and because NOx emissions from boilers have a significant impact on this problem, it is crucial to predict NOx emission concentrations to produce more accurate predictions. This is why developing accurate and reliable NOx content prediction models is crucial to reducing emissions. Unit load, total air volume, total coal volume, feed water flow, main steam pressure, main steam temperature, water to coal ratio, boiler tail flue temperature, flue gas oxygen content, the aforementioned parameters as input data, NOx concentration as an output, and training a model to predict are the variables that affect NOx emission in the boiler.

In this study, the super-parametric learning efficiency of LSTM is optimized using the QBBSO optimization technique, and an LSTM prediction model based on QBBSO is created. For training and prediction, the already-existing public data set— which predicts the production of NOx in a boiler under the impact of environmental factors— is employed. The usefulness of the QBBSO algorithm is confirmed, as is the original BSO's and LSTM's supremacy.

When performing data training, LSTM selects an open data set with the following inputs: boiler flue temperature, water-to-coal ratio, unit load, total air volume, total coal volume, feed water flow, main steam pressure, main steam temperature, secondary air valve position of Layers A through F, secondary air valve position of Layers B through D, secondary air valve position of Layers E through F, and secondary air valve position of Layers C through D. The oxygen content of flue gas, the prior NOx concentration, and the present NOx concentration are output along with upper burnout air B, lower burnout air B, lower burnout air C, and lower burnout air D.

The mean absolute error, mean absolute percentage error, and root mean square error were chosen as the decision data after the LSTM trained the data and picked 1000 groups of data, the first 800 groups for training, and the last 200 groups for prediction. The accuracy is described using root mean square error (RMSE), which can properly indicate the magnitude of the real prediction error. The more accurate the prediction model, the lower the MAPE number should be. Table 2 presents the experimental outcomes.

Table 2. Comparison of Experimental Results

	MAE	MAPE	RMSE
LSTM	20.6297	0.0809	26.8307
BSO_LSTM	18.9040	0.0746	24.2201
QBBSO_LSTM	16.6132	0.0659	21.5738

Table 2 demonstrates that, when compared to the LSTM model, the QBBSO LSTM prediction model grows by 19.4% in MAE, 18.5% in MAPE, and 19.5% in RMSE, respectively. This suggests that the model has higher accuracy because the RMSE of the prediction model is the highest. In comparison to

LSTM, the original BSO, or BSO LSTM prediction model, showed gains in MAE of 8.3%, MAPE of 7.7%, and RMSE of 9.7%. Tests demonstrate that the LSTM prediction network model based on QBBSO described in this paper is more accurate than the original LSTM and that the projected outcomes are more in line with the general trend of the actual walking trajectory and have fewer relative errors. In conclusion, the QBBSO algorithm has some benefits when solving issues of this nature. But it has to be improved upon and validated by actual research when faced with other difficult engineering issues.

5. Conclusion

The Quantum Condor Brainstorming Method is a revolutionary brainstorming technique that is proposed in this paper (QBBSO). This algorithm expands the search space, successfully avoids local optimization, and enhances algorithm convergence speed and accuracy by introducing the quantum notion into the starting population and incorporating the condor-hunting technique into the step update mode. When compared to previous BSO variations, the QBBSO method has a significant optimization effect in terms of accuracy, convergence speed, stability, and other factors. Additionally, a prediction network model of QBBSO LSTM is created by applying the QBBSO algorithm to LSTM, further demonstrating the algorithm's exceptional performance and fierce rivalry.

Acknowledgments

This work is supported by the project of the Jilin Provincial Science and Technology Department (20210402081GH), the Jilin Provincial Development and Reform Commission (2023C042-4), and the Innovation and Entrepreneurship Talent Funding Project of Jilin Province (2023RY17).

References

[1] Zhang Y, Xie C, Peterson B S, et al. An MR Brain Image Classifier System via Particle Swarm Optimization and Kernel Support Vector Machine[C]// 20th Annual Meeting of International Society of Magnetic Resonance in Medicine. 2013.
[2] Ma Zhaoxiang, Zhu Qingwei, Zhang Jun, et al. Indoor Flight path Planning of UAV based on Ant Colony Optimization Algorithm [J]. *Journal of Xi'an University of Science and Technology*, 2022(002):042.
[3] Chen Junfeng, Wang Yuhao, Zhang Xuewu, et al. Dam deformation prediction based on Wavelet transform and Difference Variation BSO-BP algorithm [J]. *Control and Decision*, 2021, 36(7):8.
[4] Zhou Shuangniu, Li Zhi, Wang Zhe. Garbage collection and transportation path optimization based on improved DMBSO algorithm from low-carbon perspective [J]. *Science Technology and Engineering*, 2021, 21(23):8.
[5] Yi Junyan, Shi Xiaodong, Yang Gang. Multi-branch chaotic mutation of brainstorming optimization algorithm [J]. *Computer Engineering and Applications*, 2022, 58(16):10.
[6] Zhao, Fuqing; Hu, Xiaotong; Wang, Ling; Zhao, Jinlong; Tang, Jianxin; Jonrinaldi.A reinforcement learning brain storm optimization algorithm (BSO) with learning mechanism. [J]. *Knowledge-Based Systems*,2022,Vol.235
[7] Zhang Xinyu, Liu Yuan, Song Jialing. Short-term orbit prediction based on LSTM neural network [J]. *Systems Engineering and Electronics*,2022, Vol. 44 (3): 939-947
[8] Ji Ruiping, Zhang Chengyi, Liang Yan, Wang Yuedong. Trajectory prediction of ballistic missile active phase based on LSTM [J]. *Systems Engineering and Electronics*,2022, Vol. 44 (6): 1968-1976