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LOAD RATIO OPTIMIZATION OF CHILLERS BASED ON IMPROVED GOLDEN EAGLE OPTIMIZER

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Abstract: Under the requirement of ensuring the cold load at the end, the load ratio of the chiller units is optimized to achieve the purpose of energy saving and consumption reduction. To achieve this goal, an improved Golden Eagle Optimizer (IGEO) is proposed by adding three strategies to the Golden Eagle Optimizer (GEO). The performance of the IGEO is tested on the CEC2022 test set, and the results show that the IGEO has good solution accuracy. Finally, the chiller load ratio is optimized using IGEO and the remaining seven algorithms. The experimental simulation results in the best optimization results for IGEO with the lowest total energy consumption of the chiller. Compared to the original GEO, the total energy consumption of the solutions solved by IGEO are lower by202.42 KW (9.8%), 54.38 KW (3.6%), and 49.39 KW (4%), saving power consumption.
Keywords: Chiller; Load ratio; Golden Eagle Optimizer; GEO; IGEO; Power consumption

1 INTRODUCTION

A centralized air-conditioning system with cold water supply is generally used in large buildings. The cold source comes from multiple chiller units connected in parallel. The energy consumption of chiller units is huge, about 25-40% of the energy consumption of the whole building[1]. Due to its enormous energy-saving potential, researching energy-saving issues related to central air conditioning has become a hot topic, among which optimizing the load ratio of chiller units has a very good energy-saving prospect.

The load ratio optimization of chiller units is essentially a complex multivariate optimization problem, and meta-heuristic algorithms have good accuracy in solving such optimization problem. The Golden Eagle Optimizer (GEO) is a relatively novel meta-heuristic optimization algorithm proposed in 2021[2]. However, according to the NFL theorem[3], when facing special problems, GEO still has the characteristics of insufficient accuracy and slow convergence. Therefore, some scholars have improved GEO and applied it to related fields. IVA et al.[4] proposed an adaptive GEO algorithm and applied it to software defect detection, achieving good results. PAN et al.[5] proposed a dual learning strategy applied to the GEO algorithm, named GEO-DLS. And apply the improved algorithm to path planning for power inspection. PONNIAH et al.[6] proposed the Fisher's Yates Adapted Golden Eagle Optimizer (FY-GEO) and applied it to the field of the internet of things. VIJH et al.[7] improved the original golden eagle optimization algorithm and applied it to the medical field to classify pathological images. PANNEERSELVAM et al.[8]combined Convolutional Neural Network (CNN) and Adaptive Golden Eagle Optimization (IGEO) to improve the accuracy of skin image segmentation for psoriasis.

In summary, the original GEO algorithm may not be well suited for specific problems, so further improvements are needed to better optimize the load ratio of chillers. Therefore, this article proposes an improved GEO (IGEO) by combining three strategies, and applies the IGEO algorithm to the standard CEC2022 test set for simulation testing. Finally, it is applied to the load ratio optimization model of the chiller units to test its performance.

2 MATHEMATICAL MODEL FOR LOAD RATIO OPTIMIZATION OF PARALLEL CHILLER UNITS

Parallel chillers are composed of two or more chillers. This combination mode can serve as a backup for each other, making it easy to maintain and highly flexible. As shown in Figure 1, it is a simplified cold source system diagram of parallel chiller units in a certain building.

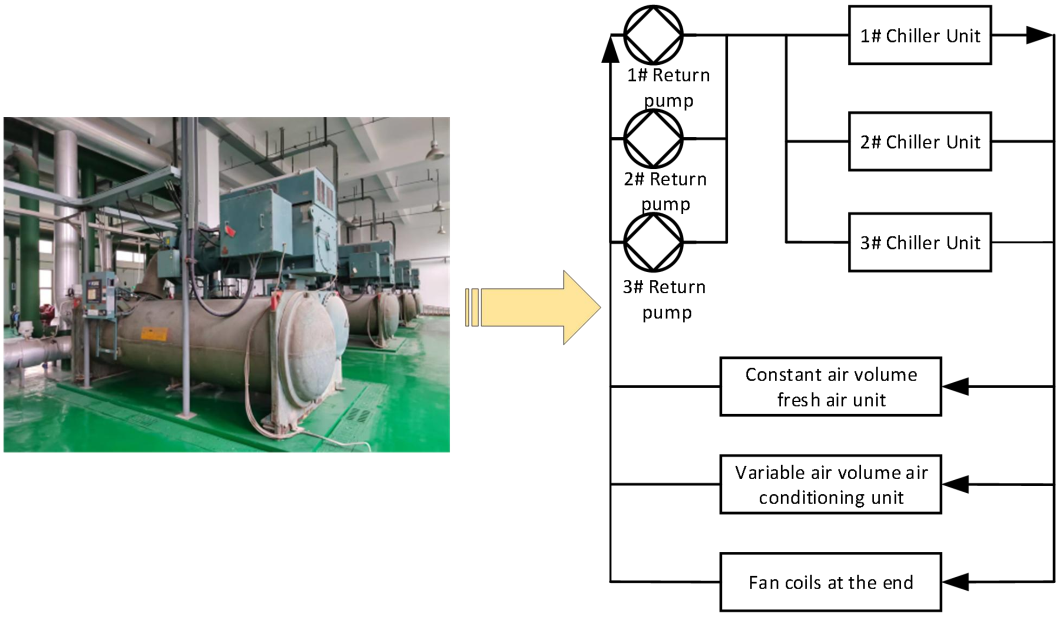


Figure 1 Simplified Cold Source System Diagram of a Parallel Chiller Unit in a Certain Building

The energy consumption model for a single chiller unit can be expressed as follows[1]:

$$P_{chiller,i} = m_{1,i} + m_{2,i}\ PLR_i + m_{3,i}\ PLR_i^2 + m_{4,i}\ PLR_i^3 \tag{1}$$

where $P_{chiller,i}$ is the power of the i^{th} chiller, $m_{1,i}$, $m_{2,i}$, $m_{3,i}$ and $m_{4,i}$ represent the parameter coefficients of the energy model of the i^{th} chiller, and PLR_i represents the load ratio of the i^{th} chiller.

According to the performance requirements of the chiller unit, its load ratio PLR_i must be greater than or equal to 0.3 and less than or equal to 1[1]. During operation, the total cooling load provided by all chillers should be equivalent to the end using cooling load CL.

Therefore, based on the above analysis, in order to optimize the load ratio of parallel chillers and achieve energy-saving goal, the mathematical model can be simplified as follows:

$$\begin{cases} P_{min} = P_{chiller,1} + P_{chiller,2} + \cdots P_{chiller,n} \\ 0.3 \le PLR_i \le 1 \\ \sum_{i=1}^{n} PLR_i * Q_i = CL \end{cases} \tag{2}$$

Among them, Q_i represents the rated cooling capacity of i^{th} chiller unit.

3 IMPROVED GOLDEN EAGLE OPTIMIZER (IGEO)

The GEO algorithm is a simulation of the different behaviors of the golden eagle based on actual hunting situations. In the early stages of the hunt they are more inclined to cruise and search for prey, and in the final stages they are more inclined to attack. In order to be able to enhance the optimization seeking ability of GEO and better solve the chiller load ratio optimization problem, three strategies are therefore introduced in this paper.

3.1 Cauchy Factor Combined with NM Strategy（Cauchy-NM）

During the iterative process of the algorithm, the optimal solution of each current iteration will guide the next round of population optimization, so further fine-tuning of the current optimal solution is required. The NM strategy is a relatively new strategy that essentially adjusts each dimension of the current solution space along the search space[9]. Therefore, the NM strategy can be utilized to improve the quality of the optimal solution by adjusting the dimensionality of the optimal solution in each round in the GEO algorithm. In order to better enhance the NM effect, the original NM strategy is perturbed using the Cauchy factor to improve the solution accuracy. The key formula for the Cauchy-NM strategy is as follows:

$$p_{new}(j) = p_{best}(j) - \left(p_{best}(RS) \times rand\right) \times eps - Cauchy \times \left(p_{best}(j) - NO\right) \tag{3}$$

where $p_{best}(j)$ represents the j th dimension of the optimal solution under the current iteration, eps represents a very small value, and RS represents a random dimension.

3.2 Dynamic Factor Combined with FDB Strategy (D-FDB)

The Fitness Distance Balancing (FDB) mechanism achieves efficient exploration in the search space by integrating the fitness values of individuals and the spatial distances between them[10]. In order to be able to increase the diversity of the search as well as to avoid falling into local optimal solutions, this paper adds dynamic factor to the FDB mechanism. This strategy enables the algorithm to adjust the weight of the fitness distance at each iteration, which is helpful to improve the optimization performance, and the key formula is as follows:

3.3 Trap Jumping Strategy (TJ)

Like other meta-heuristic algorithms, the GEO population is inevitably prone to fall into local optimal solutions during the iterative search process, and the key is how to improve its ability to jump out of the local traps. In this paper, we propose a TJ strategy. This strategy can effectively help golden eagle jump over existing traps and improve the accuracy of the search. The key formula is as follows:

$$p_i^{T+1} = \begin{cases} p_i^T + UB, r \le D \\ p_i^T + \left(p_{r1}^T - p_{r2}^T\right), r > D \end{cases} \tag{4}$$

where p_i^T represents the new location of the golden eagle and UB represents the search on-line area. p_{r2}^T and p_{r2}^T represent random individuals in the golden eagle population.

4 CEC2022 TEST SET ANALYSIS

In this section, a total of six algorithms, ARO[11], KOA[12], WOA[13], SABO[14], COA[15], and GOOSE[16], are used as the comparison algorithms for IGEO, plus the original GEO, making a total of eight algorithms. To test the effectiveness, CEC2022 with higher complexity is chosen as the test set to evaluate the effect . Also for fair comparison, the same number of iterations and population size are set, i.e., $T_{const} = 500$, $pop\_size = 50$. To avoid chance in the experiment, the number of runs is fixed, i.e., $R = 51$.

Twelve functions in CEC2022 are used as the objective functions of the comparison algorithms, and the dimensions are chosen to operate in 10 and 20 dimensions. The average of eight algorithms is chosen as the comparison result. The results are shown in Tables 1-2 below.

Table 1 Numerical Results of IGEO and Seven Comparison Algorithms in the CEC2022-10D

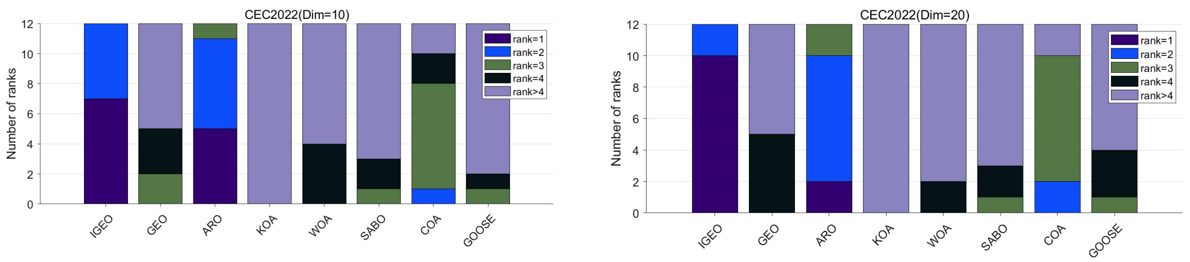
Function	IGEO	GEO	ARO	KOA	WOA	SABO	COA	GOOSE
F1	3.0000E+02	2.3260E+03	3.6315E+02	3.1537E+04	2.1918E+04	4.6854E+03	2.5120E+03	2.4638E+03
F2	4.0414E+02	4.2084E+02	4.0315E+02	1.7061E+03	4.4871E+02	4.5322E+02	4.1847E+02	4.3444E+02
F3	6.0001E+02	6.4610E+02	6.0001E+02	6.7680E+02	6.3498E+02	6.1778E+02	6.0409E+02	6.5814E+02
F4	8.1272E+02	8.2326E+02	8.1412E+02	8.9856E+02	8.3950E+02	8.4438E+02	8.3048E+02	8.5120E+02
F5	9.0220E+02	1.2791E+03	9.0110E+02	3.2553E+03	1.5565E+03	9.4740E+02	9.9738E+02	1.9906E+03
F6	1.8117E+03	8.3156E+03	2.1202E+03	3.2668E+08	4.0665E+03	3.5260E+04	4.4520E+03	3.8736E+03
F7	2.0053E+03	2.0932E+03	2.0106E+03	2.1739E+03	2.0762E+03	2.0795E+03	2.0230E+03	2.1376E+03

F8	2.2037E+03	2.2842E+03	2.2181E+03	2.3640E+03	2.2369E+03	2.2537E+03	2.2257E+03	2.3610E+03
F9	2.5293E+03	2.5721E+03	2.5293E+03	2.8376E+03	2.5885E+03	2.6269E+03	2.5379E+03	2.6191E+03
F10	2.5094E+03	2.5745E+03	2.5051E+03	2.7833E+03	2.5558E+03	2.6201E+03	2.5423E+03	2.7972E+03
F11	2.7356E+03	2.9074E+03	2.6590E+03	5.2217E+04	2.9629E+03	3.2526E+03	2.8221E+03	2.3826E+04
F12	2.8634E+03	2.9610E+03	2.8663E+03	3.0496E+03	2.8911E+03	2.8730E+03	2.8660E+03	2.9917E+03

Table 2 Numerical Results of IGEO and Seven Comparison Algorithms in the CEC2022-20D

Function	IGEO	GEO	ARO	KOA	WOA	SABO	COA	GOOSE
F1	3.0025E+02	2.2890E+04	1.0868E+04	6.4380E+05	2.8560E+04	2.8315E+04	3.4722E+04	1.8020E+04
F2	4.4953E+02	5.9967E+02	4.7063E+02	5.3678E+03	5.9451E+02	6.6936E+02	4.6791E+02	4.9312E+02
F3	6.0010E+02	6.6460E+02	6.0126E+02	7.0941E+02	6.6508E+02	6.4045E+02	6.2804E+02	6.6900E+02
F4	8.5968E+02	8.8421E+02	8.4802E+02	1.0732E+03	9.2454E+02	9.4681E+02	8.8081E+02	9.2697E+02
F5	1.3439E+03	2.3524E+03	1.0007E+03	1.0797E+04	3.9705E+03	2.0201E+03	2.5762E+03	3.9378E+03
F6	2.5614E+03	6.6518E+05	3.7216E+03	4.6716E+09	1.1030E+06	7.8917E+06	6.3599E+03	6.4688E+03
F7	2.0310E+03	2.1422E+03	2.0457E+03	2.4012E+03	2.2199E+03	2.1959E+03	2.1017E+03	2.2986E+03
F8	2.2212E+03	2.4365E+03	2.2232E+03	3.1838E+03	2.2964E+03	2.3840E+03	2.2711E+03	2.6473E+03
F9	2.4808E+03	2.5882E+03	2.4846E+03	3.4843E+03	2.5918E+03	2.7044E+03	2.4810E+03	2.5876E+03
F10	2.5185E+03	4.4938E+03	2.5603E+03	6.9420E+03	4.6913E+03	6.3132E+03	3.8112E+03	4.6946E+03
F11	2.9032E+03	4.1259E+03	2.9323E+03	1.5859E+05	3.5199E+03	5.2213E+03	2.9538E+03	7.9473E+04
F12	2.9554E+03	3.6605E+03	2.9683E+03	3.8860E+03	3.0809E+03	3.0714E+03	2.9836E+03	3.6569E+03

In order to clearly reflect the excellence of the IGEO algorithm, the data in the Tables 1-2 is organized to draw a ranking tree diagram as shown in Figure 2 below:



（A）Ranking Results for CEC2022-10D Test Set （B）Ranking Results for CEC2022-20D Test Set

Figure 2 Ranking Results of IGEO and Seven Comparison Algorithms in the CEC2022 Test Set

From Fig. 3, it can be observed that the number of IGEO ranked first is the highest, the second ranked is ARO, and KOA is the worst performer among all the algorithms, no matter whether it is 10 or 20 dimensions of CEC2022.

5 CASE ANALYSIS

5.1 Data Sources and Related Settings

In order to verify the optimization ability of IGEO on the load ratio of chillers, relevant information of chillers in a typical building is selected for analysis[1]. The specific relevant data and energy consumption model parameters are shown in the following Table 3:

Table 3 Energy Consumption Model and Related Data of Chiller Unit

Number	m_1	m_2	m_3	m_4	Customized cooling capacity（RT）
1# Chiller	100.95	818.61	-973.43	788.55	800
2# Chiller	66.598	606.34	-380.58	275.95	800
3# Chiller	130.09	304.5	-14.377	99.8	800

For the sake of experimental fairness, the seven comparison algorithms in Chapter 4 are still selected for this case, and the value of population size is uniformly set to 50 as well as the maximum number of iterations to 100.

5.2 Presentation and Analysis of Results

The operating results of IGEO and its seven comparison algorithms for the three cases of terminal cooling loads of 2610RT, 2320RT, and 2030RT are shown in Tables 4 - 6 below:

Table 4 Results of IGEO and Comparison Algorithms for Load Ratio Optimization of Chillers (CL=2610RT)

Algorithm	Terminal cooling load ratio (%)	CL(RT)	Load ratio				Total power P(KW)	Ranking
			1# Chiller	2# Chiller	3# Chiller	4# Chiller		
IGEO	90%	2610	0.9012	0.8533	0.9873	0.8527	1865.777330	1
GEO			0.9149	0.9609	0.8709	0.8950	2068.196461	5
ARO			0.9627	0.9350	0.9056	0.8504	1970.133742	4
KOA			0.9558	0.7664	0.8788	0.9614	276696.915483	8
WOA			1	0.9937	1	0.7129	1882.269377	2
SABO			1	0.3555	1	1	2556.520362	7
COA			0.7415	0.9344	0.9680	0.8877	2081.692804	6
GOOSE			0.9740	0.7593	0.9975	0.8325	1928.074705	3

Table 5 Results of IGEO and Comparison Algorithms for Load Ratio Optimization of Chillers (CL=2320RT)

Algorithm	Terminal cooling load ratio (%)	CL(RT)	Load ratio				Total power P(KW)	Ranking
			1# Chiller	2# Chiller	3# Chiller	4# Chiller		
IGEO	80%	2320	1	0.3	1	0.8221	1456.721345	1
GEO			0.8069	0.8147	0.8207	0.7697	1511.097362	3
ARO			0.8541	0.7823	0.8530	0.7307	1485.574640	2
KOA			0.8905	0.5889	0.8575	0.8143	3065044.405875	8
WOA			0.7761	0.7860	0.7922	0.8248	1567.096611	4
SABO			0.5457	0.7067	0.7564	1	2159.992935	5
COA			1	0.4632	0.9898	0.6715	2370.769936	7
GOOSE			0.3044	0.4067	1	1	2323.375286	6

Table 6 Results of IGEO and Comparison Algorithms for Load Ratio Optimization of Chillers (CL=2030RT)

Load ratio

Algorithm	Terminal cooling load ratio (%)	CL(RT)	1# Chiller	2# Chiller	3# Chiller	4# Chiller	Total power P(KW)	Ranking
IGEO	70%	2030	0.6006	0.7375	0.7978	0.6769	1179.418876	1
GEO			0.6757	0.6577	0.6866	0.7434	1228.804358	3
ARO			0.5813	0.6335	0.7610	0.7223	1228.786342	2
KOA			0.3186	0.5019	0.9588	0.7027	6366.686922	8
WOA			0.3999	1	1	0.4	1605.239406	6
SABO			0.8786	0.7363	0.4379	0.8653	1519.289079	5
COA			0.8441	0.4608	0.7583	0.6847	1639.131324	7
GOOSE			0.4922	0.8276	0.9589	0.4772	1391.333444	4

The following conclusions can be drawn from Tables 4 - 6:
(1) From the ranking of total power P in Table 4, it can be seen that the load ratio that has been optimized by IGEO is ranked first with a total power P of about 1865.78 KW. Compared to the total power P calculated by the original GEO algorithm, it saves about 202.42 KW (9.8%). The total power P calculated by the KOA algorithm is ranked last, and its total power value is abnormal, with a huge difference from the results of other algorithms, which may be for falling into the local optimal solution and unable to jump out.
(2) From the ranking of total power P in Table 5, it can be seen that the load ratio that has been optimized by IGEO is ranked first with a total power P of about 1456.72KW. Compared to the total power P calculated by the original GEO algorithm, it saves about 54.38KW (3.6%). The total power P calculated by the KOA algorithm is ranked last, and its total power value is abnormal, with a huge difference from the results of other algorithms, which may be for falling into the local optimal solution and unable to jump out.
(3) From the ranking of total power P in Table 6, it can be seen that the load ratio that has been optimized by IGEO is ranked first with a total power P of about 1179.42KW. Compared to the total power P calculated by the original GEO algorithm, it saves about 49.39KW (4%). The total power P calculated by the KOA algorithm is ranked last, and its total power consumes 5,187.27 KW more energy than IGEO.
In summary, compared to the original GEO, the proposed IGEO for optimization of the total power of the parallel chillers has a significant improvement effect and can save the energy consumption of the whole unit. Compared to the remaining six algorithms compared, IGEO also has the highest solution accuracy.

6 SUMMARY

In this paper, three enhancement strategies are utilized to improve the original GEO and the IGEO algorithm is proposed. The accuracy of the IGEO algorithm's optimization search is verified by the CEC2022 standard test set. IGEO is also used to optimize the load ratio of parallel chillers to minimize energy consumption. The experimental results show that the calculated energy consumption of IGEO saves 202.42 KW (9.8%), 54.38 KW (3.6%), and 49.39 KW (4%) compared to the original GEO under the three types of end-load demands. It has obvious energy saving effect.

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COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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