Optimal Chiller Loading Using Improved Particle Swarm Optimization

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Abstract Reducing energy consumption is one of the most important for optimal electric-driven chiller operation. Therefore, even small reduction in power consumption will achieve significant energy savings. This paper adopts improved particle swarm optimization (IPSO), which is aiming to reduce energy consumption, and improve the performance of chillers. The method has been validated by real case study, and the results have demonstrated the effectiveness for saving energy and kept the cooling demand at satisfactory level.

Keywords Chillers · Energy consumption · IPSO

1 Introduction

According to the estimation of UN International Panel on Climate Change (IPCC) for increasing the air temperature [1], Heating Ventilating Air-Conditioning (HVAC) will act as source of pollutants and may contribute to increase in carbon dioxide (CO_2), if not maintained properly. Therefore, CO_2 increases atmosphere temperature and global warming.

The HVAC is used to provide air at a comfortable temperature for human being. These equipment's are major consumers for electrical energy. They reach up to 50 % of the overall energy consumption in buildings as reported by International

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Energy Agency (IEA) [2]. The electric-driven chillers are one of HVAC for facility cooling in buildings.

A better way to save the electrical energy in a cooling plant is by optimizing the chillers. The optimization is to enhance its performance that significantly keeps the cooling demand satisfied [3]. Several techniques have been proposed, which use searching algorithms inspired by the concepts of artificial intelligence.

In relation to optimal chiller loading (OCL) problem using swarm intelligence (SI), Ardakani and Lee et al. [4, 5] proposed particle swarm optimization (PSO) to solve a continuous problem of optimization parameters. The findings proved that the PSO algorithm has the capability to execute convergence at low loads. Also, simulated annealing (SA) has applied to chiller model, in order to adjust the operation setting points under partial load. This method overcomes the deficiencies of Lagrangian Multiplier (LM) for the convergence [6, 7]. SA is employed to optimize variable control parameters, in order to reduce consumption of the chilled-water plant by [8]. Lee et al. and Sulaiman et al. [9, 10] have utilized the differential evolution (DE) and differential search (DS) algorithms to optimize and solve the problem of optimal chiller loading. Also, an improved Firefly (IFF) algorithm based on Gaussian distribution function has been suggested dos Santos Coelho and Mariani [11]. This IFF can be used to accelerate the optimum in the search solutions. In [12], an artificial cooperative search (ACS), this algorithm is applied to solve the OCL problem.

For chiller efficiency, several control strategies have been suggested to maximize its performance based on the probability distribution of PLR [13, 14]. Alessandro Beghi et al. [15] employed PSO for efficient energy management to solve the OCL problems based on two steps to estimate the cooling load by PSO, and to determine which chiller to be ON or OFF according to the predicted and estimated load. Moreover, Wei et al. [16] has utilized modified PSO to solve multi-optimization objectives for HVAC. The objectives are used to minimize energy consumption, room temperature, humidity, and CO_2 concentration.

For reducing energy consumption (EC), Hamid et al. [17, 18] developed optimal and control strategy to set-points of cooling demand. These are based on 2 Fuzzy inference systems (FIS) for 24 h. This period was partitioned into four time zones, with 6 h each. Insufficient operation is the one of the chillers problems, which consumes more power. To overcome this problem and deficiencies of convergence at low load, this work employs IPSO to solve the problem of OCL, to minimize EC, and maximize efficiency.

2 Objective Function Formulation

In chiller-plant, the best performance can occur, when the chillers can be set under Part Load Ratio (PLR) as in Eq. (1),

$$\begin{aligned}\mathrm{F_i} = & \,(a_1 + \cdots + a_N) + (b_1 + \cdots + b_N).PLR_i + (c_1 + \cdots + c_5).PLR_i^2 + (d_1 + \cdots + d_N).PLR_i^3 \\ & + (e_1 + \cdots + e_N).PLR_i^4\end{aligned} \tag{1}$$

For reducing energy consumption, the objective function can be expressed in Eq. (2),

$$J_i = Minimize\,(F_1, F_2, \ldots, F_N) \tag{2}$$

where, F_i is a single objective, a_N, b_N, c_N, d_N, e_N are the power curve coefficients of ith chiller, and PLR_i is Part Load Ratio of ith chiller. The cooling load capacity (Q_i) should be equal to the total cooling demand as expressed in Eq. (3) [19],

$$Q_i = \sum_{i=1}^{N} PLR_i * RT_i,\ s.t.PLR_i^{Lower} \leq PLR_i \leq PLR_i^{Upper} \tag{3}$$

RT_i is the capacity of ith chiller in (ton), and PLR_i^{Lower} and PLR_i^{Upper} to be between (0.5–1.0) for cooling machines stability [9, 20]. The best performance for the chiller when operates under PLR, where its coefficient of performance (COP) is expressed in Eq. (4)

$$COP = J_i(kW)/Q_i(ton) \tag{4}$$

The efficiency of the chiller at peak load at Air-Conditioning, Heating and Refrigeration Institute (AHRI) standard, measured in kilowatts kW/ton. The power input per capacity kW/ton also called the coefficient of performance (COP), which can be measured at any given set of rating conditions. A lower COP rating indicates higher efficiency and performance [21].

3 Particle Swarm Optimization

PSO is an optimization technique proposed by Kennedy and Eberhart in 1995 [22]. Basically, PSO simulates the food searching of a swarm of birds and fishes (particles), and each particle has location and velocity. These particles move around the search space looking for the optimal solution. Each particle tries to modify its velocity and position based on its own previous experience, and the other neighboring particles of the swarm. For example; the particle i is randomly placed in two dimensional search space at the point X_i^K, this particle flies through the problem search space with a random velocity Vi^k. The particle remembers the best position achieved so far and stores it as $Pbest_i^k$. Then, each particle shares the information with the neighboring particles. In other words, each particle compares its best position with those attained by other particles. Finally, each particle stores the best position achieved in the whole swarm called $Gbest_i^k$ [23]. PSO depends on the movement behavior of birds and fish according to,

Table 1 PSO parameters

C1	C2	W_{min}	W_{max}	Swarm	iter	$iter_{max}$
1.2	0.4	0.25	0.85	25	100	200

$$V_i^{k+1} = W^* V_i^k + c_1 r_1^* \left(Pbest_i^k - X_i^k\right) + c_2 r_2^* \left(Gbest_i^k - X_i^k\right), \tag{5}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} i \; 1,\; 2,\; \ldots,\; M_{swarm} \tag{6}$$

where, V_i^{k+1} is the particle's updated velocity at (k + 1)th iteration, W is the inertia weight factor, c_1 and c_2 are the weighting factors which are used to accelerate PSO performance to find P$best_{\mathrm{i}}^k$ and G$best_{\mathrm{i}}^k$, also r_1 and r_2 are the random numbers (0–1), and X_i^{k+1} is the updated particle's current position [23–25]. The Eqs. (5) and (6) do not rightly reflect the process search to find out the optimum best local and global values [26]. Accordingly, the velocity can be modified by a constriction factor (K) as $\mathrm{V}^{k+1} = K\mathrm{V}^k$ [27]. This factor (K) improves PSO performance, where it selects between (0 and 1), which can be calculated from,

$$K = \frac{2}{2 - 2\varphi - \sqrt{4\varphi - \varphi^2}} \tag{7}$$

where, $\varphi = C_1 + C_2 <= 4$, in order to ensure the algorithm convergence, the velocity cannot exceed the set of specific range as can be expressed in,

$$V_i^{k+1} = K\left(W^* V_i^k + c_1 r_1^* \left(Pbest_i^k - X_i^k\right) + c_2 r_2^* \left(Gbest_i^k - X_i^k\right)\right) \tag{8}$$

Based on the experiments, a large inertia weight is facilitating the global search and does not rightly reflect the process search to find out the optimum best local and global values [26]. While a small inertia weight facilitates the local research for the particles swarm. The inertia weight can be expressed,

$$W = W_{max} - \left[\left(W_{max} - W_{min}\right)/\mathrm{iter}_{max}\right]^* \mathrm{iter} \tag{9}$$

where W is the inertia weight factor, W_{max} is the inertia weight initial value, W_{min} is the inertia weight final value, $iter_{max}$ is the maximum iteration and $iter$ is the current iteration number. The PSO parameters and its values as shown in Table 1.

4 Fuzzy Inference System

Fuzzy Inference System (FIS) can be used to adjust and evaluate C1 and C2. Among many trails, it was found that the membership function with the values of C1 = 1.2, C2 = 0.4 (if K = 0.632 and W = 0.55). Therefore, PSO calls these

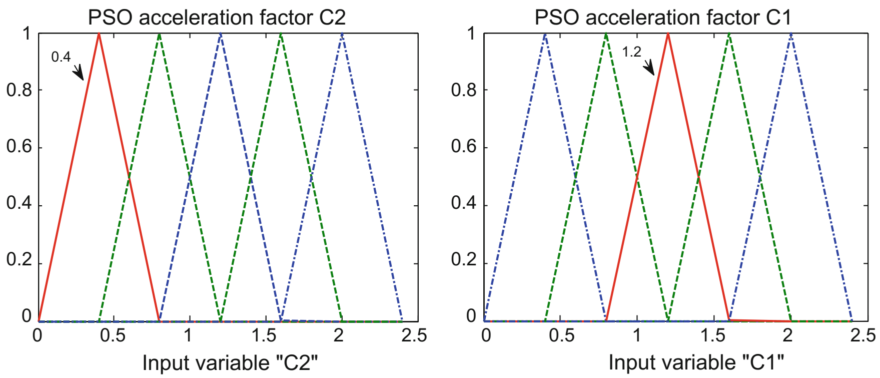

Fig. 1 Acceleration factors membership

weighting factors based on K and W to accelerate and improve its performance, among 10 evaluator's Fuzzy rules as seen its membership in Fig. 1.

The steps of the implementation of IPSO on OCL problem are given below.

Step. 1 initialize the swarm (S) from solution space
Step. 2 generate a variable decision of PLR*i*
Step. 3 evaluate the fitness of each particle, *i*, Eq. (2)
Step. 4 adjust constriction factor (K) using Fuzzy inference system
Step. 5 update individual and global bests (Pbest *i* and Gbest *i*),
Step. 6 update the inertia according to Eq. (9)
Step. 7 update velocity and position of each particle (V*i* and X*i*), Eqs. (6) and (8)
Step. 8 go to step 3 and repeat until the termination occurs.

To explain the algorithm steps in the above mentioned, Fig. 2 shows the flow chart of all steps for the proposed method implementation.

5 Case Study

The industry selected in this paper is a Glove factory with five electric-driven chillers. Each of them with a capacity 200 Refrigerant tonnage (RT). These chillers have been operating at full load condition, with the total power consumption of 690 kW and produce 5 × 180 ton of the chilled-water so that, the chilled-water supply temperatures (T_{CHWS}) are same for chillers (10 °C) and chilled-water return temperature (T_{CHWR}) between (16.8–18.7 °C). Table 2 shows the model and operating conditions of the existing system for chillers plant.

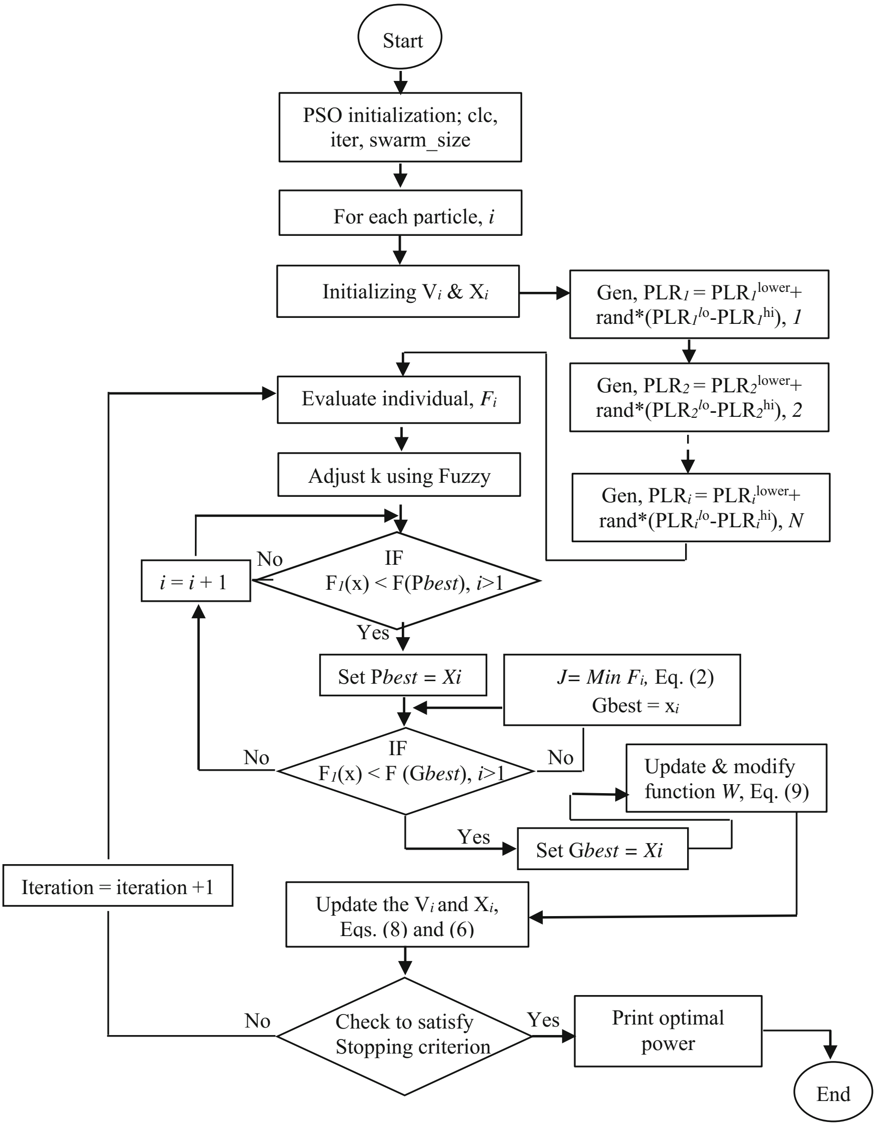

Fig. 2 Flow chart of improved PSO algorithm

6 Results and Discussion

The power consumption of electric-driven chillers is about 690 kW for normal operation for the existing system when all chillers operate at full and partial load. Figure 3 shows the power consumption for the normal operation at 100 % and the

Table 2 The quadratic model and operating conditions and of chillers

Chillers	1	2	3	4	5
a_i	2.3232	75.802	58.958	22.424	72.414
b_i	128.58	−462.57	−239.97	−0.341	−346
c_i	−55.603	1612.5	835.35	257.43	1100.3
d_i	144.88	−1851.8	−811.55	−213.58	−1068.7
e_i	−90.651	762.04	288.03	64.381	373.38
R2	0.9998	0.9985	0.9992	0.9999	0.9993
Stand. error	0.5324 %	1.0764 %	0.6533 %	0.2949 %	0.5885 %
RT_i (ton)	180	180	180	180	180
T_{CHWS} (°C)	10	10	10	10	10
T_{CHWR} (°C)	16.8	18.7	17.3	17	18

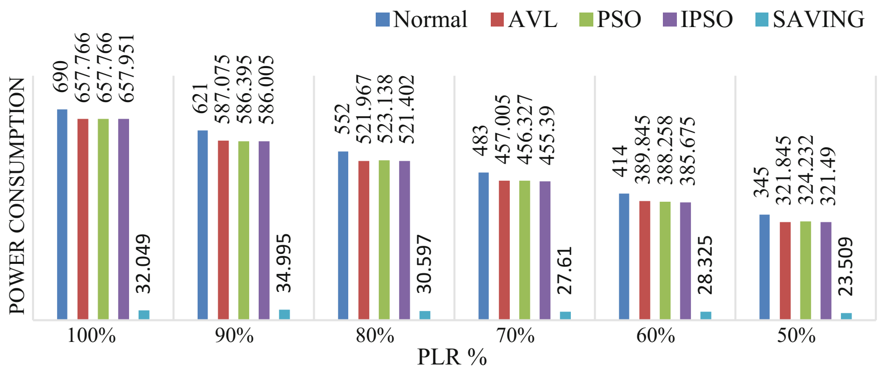

Fig. 3 The comparison of power consumption using different methods

consumption at partial load (50–90) % for three methods which are AVL, PSO, and IPSO.

From results, the existing system, the proposed method saves power at 100 % 32.049 which is (690–657.951) kW, at 90 % saves 34.995 kW, at 80 % saves 30.597 kW, at 70 % saves 27.61 kW, at 60 % saves 28.325 kW, and at 50 % saves 23.509 kW. The average percentage of saving (IPSO) is 35.18 %. Similarly, PSO saves 33.23 % and AVL saves 33.59 %.

Table 3 shows the results of AVL, PSO, and the proposed method (IPSO). For comparison, the cooling load demands are used to simulate which are 900 RT (a total capacity of 5 chillers at full load), 810 RT for 90 %, 720 RT for 80 %, 630 RT for 70 %, 540 RT for 60 %, and 450 RT for 50 %. In 900 RT the input power is same 657.766 kW for AVL and PSO, whilst, 657.9507 kW for IPSO. In 810 RT, the input power is 587.075 kW for AVL, 586.395 kW for PSO, whilst 586.005 kW for IPSO. In 720 RT, the input power is 521.967 kW for AVL, 523.138 kW for PSO, whilst 521.4025 kW for IPSO. In 630 RT, the input power is 457.005 kW for

Table 3 Methods comparison for the power consumption

Q_i RT%	Normal operation system (A)					Average loading AVL (B)			
	Chiller	PLR_i	RT_i	kW_i	COP_i	PLR_i	RT_i	kW_i	A–B
900 100 %	1	1	180	690	0.7667	1	180	657.766	32.234
	2	1	180			1	180		
	3	1	180			1	180		
	4	1	180			1	180		
	5	1	180			1	180		
810 90 %	1	0.9	162	621	0.7667	0.9	162	587.075	33.925
	2	0.9	162			0.9	162		
	3	0.9	162			0.9	162		
	4	0.9	162			0.9	162		
	5	0.9	162			0.9	162		
720 80 %	1	0.8	144	552	0.7667	0.8	144	521.967	30.033
	2	0.8	144			0.8	144		
	3	0.8	144			0.8	144		
	4	0.8	144			0.8	144		
	5	0.8	144			0.8	144		
630 70 %	1	0.7	126	483	0.7667	0.7	126	457.005	25.995
	2	0.7	126			0.7	126		
	3	0.7	126			0.7	126		
	4	0.7	126			0.7	126		
	5	0.7	126			0.7	126		
540 60 %	1	0.6	108	414	0.7667	0.6	108	389.845	24.155
	2	0.6	108			0.6	108		
	3	0.6	108			0.6	108		
	4	0.6	108			0.6	108		
	5	0.6	108			0.6	108		
450 50 %	1	0.5	90	345	0.7667	0.5	90	321.495	23.505
	2	0.5	90			0.5	90		
	3	0.5	90			0.5	90		
	4	0.5	90			0.5	90		
	5	0.5	90			0.5	90		
Q_i RT %	PSO (C)						IPSO (D)		
	Chiller	PLR_i	RT_i	kW_i	PLR_i	RT_i	kW_i	COP_i	A–D
899.64 100 %	1	1	180	657.766	1	180	657.9507	0.7311	32.05
	2	0.9999	179.82		0.9997	179.94			
	3	1	180		1	180			
	4	1	180		1	180			
	5	0.9999	179.82		1	180			
809.98 (90 %)	1	1	180	586.395	1	180	586.005	0.7234	34.99
	2	0.6182	111.28		0.5453	98.154			
	3	1	180		1	180			
	4	1	180		1	180			
	5	0.8817	158.71		0.9546	171.83			

(continued)

Table 3 (continued)

Q_i RT %	PSO (C)						IPSO (D)		
	Chiller	PLR_i	RT_i	kW_i	PLR_i	RT_i	kW_i	COP_i	A–D
719.98 (80 %)	1	0.9101	163.82	523.138	0.9684	174.31	521.4025	0.7242	30.60
	2	0.5651	101.72		0.6101	109.82			
	3	0.9711	174.79		0.8842	159.15			
	4	0.8880	159.84		0.8787	158.16			
	5	0.6656	119.81		0.6585	118.53			
630.04 (70 %)	1	0.7241	130.34	456.327	0.9255	166.59	455.3899	0.7230	27.61
	2	0.6402	115.23		0.3202	57.636			
	3	0.8732	157.17		0.9165	164.97			
	4	0.6823	122.81		0.7345	132.21			
	5	0.5804	104.47		0.6023	108.41			
540.18 (60 %)	1	0.6	108	388.258	0.9979	179.62	385.6747	0.7143	28.33
	2	0.4052	72.936		0.4613	83.034			
	3	0.8	144		0.4485	80.730			
	4	0.6272	112.89		0.5918	106.52			
	5	0.5686	102.35		0.5	90			
449.98 (50 %)	1	0.8905	160.29	324.232	0.6304	113.47	321.4905	0.7144	23.509
	2	0.3101	55.818		0.4122	74.196			
	3	0.4989	89.802		0.5206	93.708			
	4	0.3999	71.982		0.5171	93.078			
	5	0.4005	72.090		0.4196	75.528			

Table 4 Comparison of methods for saving, efficiency and computational time

	AVL	PSO	IPSO
Percentage saving (%)	33.59	33.23	35.18
Average of COP	0.76667	0.72423	0.72171
Computational time (s)	2.97243	1.68045	2.28563

AVL, 456.327 kW for PSO, whilst 455.3899 kW for IPSO. In 540 RT, the input power is 389.845 kW for AVL, 388.258 for PSO, whilst 385.6747 kW for IPSO. And in 450 RT, the input power is 321.495 kW for AVL, 324.232 kW for PSO, whilst 321.4905 kW for IPSO. The proposed method (IPSO) has demonstrated the effectiveness for saving power of 35.19 % compared to other methods. This percentage of saving can be analyzed from these tables as in Eq. (9),

$$\text{Saving} = \frac{\text{Consumption of (Normal operation} - \text{Proposed method)}}{\text{Consumption of Normal operation}} * 100\,\% \qquad (9)$$

For instance, the percentage saving of IPSO with respect to the existing system

$$\text{Saving at } 100\,\% = \frac{(690 - 657.9507)}{690} * 100\,\% = 4.645\,\%$$
$$\text{Saving at } 90\,\% = \frac{(621 - 586.005)}{621} * 100\,\% = 5.635\,\%$$
$$\text{Saving at } 80\,\% = \frac{(552 - 521.4025)}{552} * 100\,\% = 5.543\,\%$$
$$\text{Saving at } 70\,\% = \frac{(483 - 321.4905)}{483} * 100\,\% = 5.716\,\%$$
$$\text{Saving at } 60\,\% = \frac{(414 - 385.6747)}{414} * 100\,\% = 6.842\,\%$$
$$\text{Saving at } 50\,\% = \frac{(345 - 321.4905)}{345} * 100\,\% = 6.814\,\%$$

Compared to existing system, energy has been saving a 35.19 % using IPSO (full load + partial load) The analysis also was done for AVL and PSO techniue. Table 4 the saving of AVL and PSO are 33.59 % and 33.23 %, respectively. It's shown that AVL achieved better results in terms of saving, but PSO has achieved better results in terms of efficiency (COP) and computational time compared to AVL. This calculation time (in second) is according to Intel (R) Core™ i5-3470 CPU@3.20 GHz 3.20 GHz.

7 Conclusion

This paper employs an improved particle swarm optimization (IPSO) to minimize energy consumption, and to improve chillers efficiency. A typical case study of optimal searching using 5 chillers is carried out. The findings have demonstrated that IPSO has achieved a lower consumption and higher performance according to COP which considered a better than existing operating system. Also, it has met the cooling demand and saved by 35.19 %.

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