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Hybrid Artificial Cooperative Search – Crow Search Algorithm for Optimization of a Counter Flow Wet Cooling Tower

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Abstract: In this paper, an improved version of Artificial Cooperative Search (ACS) algorithm is applied on a counter flow wet-cooling tower design problem. The Merkel's method is used to determine the characteristic dimensions of cooling tower, along with empirical correlations for the loss and overall mass transfer coefficients in the packing region of the tower. Basic perturbation schemes of the Crow Search Algorithm, a recent developed metaheuristic algorithm inspired by the food searching behaviors intelligent crows, are incorporated into ACS to enhance the convergence speed and increase the solution diversity of the algorithm. In order to assess the solution performance of the proposed method, fourteen widely known optimization test function have been solved and corresponding convergence graphs has been reported. .Then the improved ACS algorithm (IACS) is applied on six different examples of counter flow wet-cooling tower optimization problem. The results obtained by applying the proposed algorithm are compared with the results of some other algorithms in the literature. Optimization results show that IACS is an effective algorithm with rapid convergence performance for the optimization of counter flow wet-cooling towers.

Keywords:*Artificial Cooperative Search, Cooling Tower, Crow Search Algorithm, Merkel's Method.*

1. Introduction

A cooling tower is a device that cools the incoming hot water by means of heat and mass transfer between air and water, which are in direct contact with each other during heat and mass transfer process. Cooling towers have large applications in chemical and petrochemical industries, electric-power generating stations, refrigeration and air conditioning plants [1,2]. The water, utilized to maintain large contact area with atmospheric air, can be distributed through the cooling tower by spray nozzles, splash bars, fills, etc. and the air circulation in the tower can be realized by mechanical drafts, natural drafts or the induction effect from water sprays [3,4]. Type of packing (distribution) constitutes an important part of cooling tower design since it controls the heat and mass transfer between the fluids [5].

In the cooling towers, warm water enters the cooling plant from the top and flows downward through labyrinth-like packings while air may flow upward (counter-flow) or horizontally (cross flow). Afterwards, the water is distributed uniformly in the packaging area; as a result, a large direct contact area occurs between the air and the water. Since the humidity of saturated air is less than the humidity of water at the temperature of the water, the air absorbs moist from the water and a portion of the water begins to evaporate. Evaporation draws energy from the water, therefore, the water is cooled. After the heat and mass transfer process completed, the cooled water is collected in a basin below the fills and returned to the cooling cycle. The water lost in the evaporation and drift processes is replaced with fresh make-up water [6]. Induction effect cooling towers use natural buoyancy property of air to circulate it across the tower; on the other hand, mechanical draft types use an electrically driven fan to circulate the air in the tower. There are two types of mechanical draft towers in the market. These types include forced draft tower, in which fan located at the bottom of the tower, and induced draft, in which fan located at the top of the tower.

In the literature, one of the first studies regarding cooling towers is made by Walker et al. [7]. Walker et al. proposed a mathematical framework to design cooling towers however, one of the first practical usages of the mathematical framework is proposed by Merkel [8], which combined the governing equations of heat and mass transfer between air and water droplets in the tower. Mohiuddin & Kant [9,10] expanded the previously mentioned mathematical models and proposed a more detailed procedure to mathematically model the cooling towers. El-Dessouky et al. [11], described a theoretical investigation for the steady-state counter flow cooling towers with modified definitions for both the number of transfer units and the tower thermal effectiveness. The model described in El-Dessouky et al. can be easily compared with conventional methods such as effectiveness-NTU and Logarithmic Mean Enthalpy Method (LMED). Lemouari et al. [12] experimentally investigated thermal performance of a forced draft counter flow wet cooling tower filled with a "VGA" (Vertical Grid Apparatus) type packing.

Other researchers conducted plenty of studies on optimization of cooling towers considering different objective functions and different optimization algorithms. Zou et al. [13] proposed an optimization method for solar enhanced natural draft dry cooling tower design. Proposed objective function included capital, labour, maintenance, and operation costs of each component in the cooling tower. Results showed that optimized cooling tower has better performance and cost effective compared to the currently used cooling towers. Serna-Gonzalez et al. [1] developed an objective function considering the annual operating

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costs and the required capital cost for a cooling tower to operate efficiently. The objective function along with the constraints were modelled as a mixed-integer nonlinear programming (MINLP) problem and solved with an appropriate optimization algorithm. Rao & Patel [2] considered a mechanical draft counter flow wet-cooling tower and formulated an objective function representing operating costs for this particular type of cooling tower. Artificial Bee Colony (ABC) algorithm was employed to solve this optimization problem and results were compared with the solutions given in [1]. Results showed that more preferable solutions could be obtained with the ABC algorithm. Castro et al. [14] investigated a cooling water system, which supplies a heat exchanger network. The authors considered the total operating costs as the objective function to be optimized. Soylemez [15] utilized the effectiveness-NTU method to model a cooling tower and benefited from P_1-P_2 method for thermo-economic optimization of the cooling tower. Kintner-Meyer & Emery [16,17] proposed an optimization method for optimum sizing and cost of the cooling towers. Kloppers & Kröger [18] described a counterflow natural draft wet-cooling tower and optimized the geometrical dimension of the cooling tower with Leap-frog Optimization Method with Operating Constraints (LFOPC) to obtain minimum operating and capital costs. Smrekar et al. [19] examined how efficiency of a natural draft cooling tower can be improved by optimizing the heat transfer taking place in the cooling tower, packing type and plane area. Ponce-Ortega et al. [20] described an optimization model for the simultaneous synthesis and design of re-circulating cooling water systems. The objective function is modelled as mixed-integer nonlinear programming problem and considers the annual cost of the cooling tower.

In the present work, a counter flow cooling tower with different possible types of packing and air circulating systems is considered. An objective function is comprised of the annual, operating and capital costs of the cooling tower. Selecting the most convenient type of packing and air circulating system makes the objective function a mixed-integer nonlinear programming problem. Solving this problem requires an effective and robust global optimization algorithm since the objective function consists of many local minimums. Artificial Cooperative Search (ACS) [21] algorithm is selected as an optimization algorithm to thermodynamically design and model this optimization problem. ACS is a swarm-intelligence based nature-inspired metaheuristic algorithm good at exploring large solution spaces and finding the optimum point of any optimization problem, however, it may be trapped in local optimum points in the search space. Therefore, this study proposes an enhancement on the basic perturbation schemes of the ACS by employing the fundamentals of Crow Search Algorithm [22]. By this integration, it is aimed to improve the solution accuracy and the convergence rate of the simple ACS optimizer.

The paper is organized into four sections. Section.2 gives proposed methodology. Section.3 describes results and discussion. Section.4 gives conclusion of the work.

2. Problem Formulation

When the inlet and outlet temperature of water, the dry- and wet-bulb temperatures of the entering air, the mass flow rate of air, the heat rejection load and the packing type are provided, a standard design of a cooling tower, which includes finding of the necessary size and cost of the tower can be accomplished. However, design of a cooling tower not only requires a detailed modelling of the constructional equations but also selection of optimum operating conditions such as inlet and outlet temperatures of water, mass flow rate of air and packing type [23]. Therefore, all of these variables can be regarded as independent design variables subjected to given constraints of the optimization problem.

Following assumptions are made to derive the modeling equations [24,25]:

1. The Lewis number related with the simultaneous heat and mass transfer is taken as one.
2. The cooling tower operates under adiabatic conditions.
3. The tower has a uniform cross-sectional area.
4. Thermodynamic properties of air and water do not change across horizontal cross-sections of the cooling tower.
5. The air leaving the tower is saturated with water vapor.
6. The mass flow rate of water through the tower remains constant.
7. The temperature of the air at the interface is equal to the local bulk temperature of the water at any intersection of the tower.
8. Water waste due to evaporation, drift and blow-down is insignificant compared to the total water load.

The main objective of this present work is to minimize the total annual cost of the cooling tower with the proposed improved ACS algorithm. Total annual cost can be formulized as follows,

$$\text{Minimize } TAC = K_f C_c + C_{op} \tag{1}$$

where K_f is the annualized factor for investment, C_{op} is the annual operating cost and C_c is the installed capital cost of the cooling tower. Annual operating cost can be mathematically described as,

$$C_{op} = H_Y C_{wat} m_{mw} + H_Y C_{el} P \tag{2}$$

where C_{el} is the unit cost of electricity, C_{wat} is the unit cost of make-up water, H_Y is the yearly operating time, m_{mw} is the mass flow rate of the make-up water and P is the power needed to operate the cooling tower.

The capital cost of cooling tower can be calculated according to the formula given in [17],

$$C_c = C_{FC} + C_{CTV} a_{fr} L_{fi} + C_{CM} m_a \tag{3}$$

where C_{CM} is the incremental cooling tower cost based on air mass flow rate, C_{CTV} is the incremental cooling tower cost based on tower fill volume and C_{FC} is the fixed cooling tower cost. C_{CTV} values varies depending on type of packing. The values it could take are 2006.6, 1812.25 and 1606.15 for splash fill, trickle fill and film fill respectively [1]. Following constraints are considered for the evaluation of the cooling tower optimization problem. Theoretically, the lowest temperature water can be cooled is the wet-bulb temperature of entering air. However, in practice, it is difficult to achieve such level of cooling. Therefore, water outlet temperature should be at least 2.8°C above wet-bulb temperature of the air [26].

$$TW_{out} - TWB_{in} \geq 2.8 \tag{4}$$

In order to avoid fouling, scaling and corrosion effects, an upper temperature limit is set on inlet cooling water. Generally, this maximum inlet temperature of inlet cooling water is set to above 50°C [27].

$$TW_{in} \leq 50°C \tag{5}$$

The outlet water temperature of the cooling tower should be lower than the outlet temperature of hot process stream,

$$TMPO - TW_{out} \geq \Delta T_{min} \tag{6}$$

Likewise, the inlet water temperature of the cooling tower should be lower than the inlet temperature of hot process stream,

$$TMPI - TW_{in} \geq \Delta T_{min} \tag{7}$$

From a thermodynamic point of view, the water stream must be cooled and the air stream must be heated,

$$TW_{in} > TW_{out} \tag{8}$$

$$TA_{out} > TA_{in} \tag{9}$$

Merkel number must be a positive non-infinite real number in order to identify the cooling tower correctly,

$$Me > 0 \tag{10}$$

In most of the applications, water to air mass flow rate is limited in a certain range [4]. In this paper, air to water mass flow rate operating range is taken as,

$$0.5 \leq \frac{m_w}{m_a} \leq 2.5 \tag{11}$$

The maximum and minimum water and air loads are reported in [28,29],

$$2.90 \leq \frac{m_w}{a_{fr}} \leq 5.96 \tag{12}$$

$$1.20 \leq \frac{m_a}{a_{fr}} \leq 4.25 \tag{13}$$

Finally, from a physical point of view, air and water mass flow rate must be positive,

$$m_a > 0 \tag{14}$$

$$m_w > 0 \tag{15}$$

Mathematical model of the cooling tower is presented in the next section.

3. Cooling Tower Model

Fig. 1 shows the general representation of a counter flow cooling tower. In Fig. 1, subscripts *in* and *out* represent the inlet and outlet flows, *TW* stands for the water temperature, *TA* symbolize the dry-bulb temperature of the air, *TWB* is the wet-bulb temperature of the air, *ha* represents the enthalpy of bulk air-water vapor mixture passing through the packing, L_{fi}refers to tower fill height, a_{fr} represents the cross-sectional area of the tower, and m_w and m_a show the water and dry air mass flow rates, respectively. The amount of heat transferred from the water to the air stream can be calculated from energy balance equation given below, which contains range of the tower, i.e. $\left(TW_{in} - TW_{out}\right)$.

$$Q = c_{pw} m_w \left(TW_{in} - TW_{out}\right) = m_a \left(ha_{out} - ha_{in}\right) \tag{16}$$

Merkel number is an important factor in designing of a cooling tower. Merkel number indicates the level of difficulty to cool the process water. A higher Merkel number value means a greater difficulty to cool the water but at the same time it means a more economic tower. Merkel number can be calculated as [28-30],

$$Me = \int_{TW_{out}}^{TW_{in}} \frac{c_p dTW}{hsa - ha} \tag{17}$$

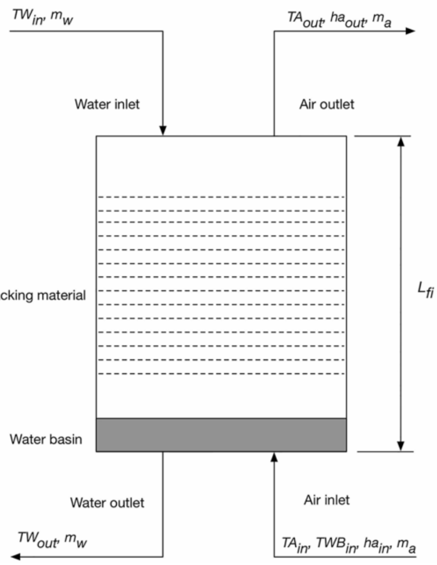

Figure 1. Cooling tower control volume

where $\left(hsa - ha\right)$ is the local enthalpy difference between the air and the saturated air in any section of the tower. Integration of this term along the cooling tower gives the required Merkel number. A more preferred way to calculate Eq. (17) is turning the equation to an algebraic form by applying Chebyshev's four point integration technique [31,32]. Application of this procedure on the cooling towers is presented and shown that Chebyshev procedure is an accurate technique compared to some other numerical integration techniques in the literature [9,33]. The application of four-point Chebyshev procedure on Merkel's equation can be mathematically described as,

$$Me = \int_{TW_{out}}^{TW_{in}} \frac{c_{pw} dTW}{\left(hsa - ha\right)} = 0.25 c_{pw} \left(TW_{in} - TW_{out}\right) \sum_{j=1}^{4} \frac{1}{\Delta h_j} \tag{18}$$

where j is the temperature increment index, which denotes the four points in the Chebyshev's method and Δh_j is the local enthalpy difference given by,

$$\Delta h_j = hsa_j - ha_j \quad \text{j} = 1, 2, ..., 4 \tag{19}$$

The water temperatures and air enthalpies for each Chebyshev point can be calculated as,

$$TW_j = TW_{out} + TCH_j \left(TW_{in} - TW_{out}\right) \quad \text{j} = 1, 2, ..., 4 \tag{20}$$

$$ha_j = ha_{in} + \frac{c_{pw} m_w}{m_a} \left(TW_{in} - TW_{out}\right) \quad j = 1, 2, ..., 4 \tag{21}$$

where TCH_j represents the four points used in Chebyshev's technique. Values of TCH_j for each point are $TCH_1 = 0.1$, $TCH_2 = 0.4$, $TCH_3 = 0.6$ and $TCH_4 = 0.9$. The saturated air enthalpy can be computed by the correlation given in [1],

$$\begin{aligned} hsa_j &= -6.38887667 + 0.86581791 TW_j + \\ &15.7153617 \, exp\left(0.0543977 TW_j\right) \quad \text{j} = 1, 2, ..., 4 \end{aligned} \tag{22}$$

Calculating the value of the Merkel number without prior knowledge of the properties of the air and water at the inlet and the exit from the cooling tower is called available Merkel number. The available Merkel number can be formulated by the following equation [3],

$$Me = \frac{h_d a_{fi} a_{fr} L_{fi}}{m_w} = \frac{h_d a_{fi} L_{fi}}{G_w} \tag{23}$$

where a_{fi} is the surface fill area of the per unit volume of fill, a_{fr} is the tower fill area, h_d is the coefficient of mass transfer, and G_w is the mass velocity of water. In the above equation, values of surface fill area of the per unit volume of fill, a_{fi}, and coefficient of mass transfer, h_d, must be known to calculate the cross sectional area and height of the fill by equating the "available Merkel" and "required Merkel" equations. However, due to the modelling of the two-phase flow in tower fills is quite difficult, it is hard to theoretically calculate or empirically obtain the exact value of a_{fi}. Thus, available Merkel number is an indication of packing quality and quantity. In this paper, filling types are limited to splash, trickle and film and the correlation to determine the available Merkel number is obtained from [29] in which splash, trickle and film type of fills are tested for counter flow wet cooling towers and the following correlation is given for the determination of available Merkel number,

$$Me = C_1\left(\frac{m_w}{a_{fr}}\right)^{C_2}\left(\frac{m_a}{a_{fr}}\right)^{C_3}\left(L_{fi}\right)^{1+C_4}\left(TW_{in}\right)^{C_5} \tag{24}$$

Compared with the traditional Merkel number equation, this correlation gives a much better fit to experimental data. The values of correlation coefficients C_1 to C_5 for each type of fills are given in Table 1.

Table 1. The values of correlation coefficients for available Merkel number [29].

j	C_j		
	Splash fill	Trickle fill	Film fill
1	0.249013	1.930306	1.019766
2	-0.464089	-0.568230	-0.432896
3	0.653578	0.641400	0.782744
4	0	-0.352377	-0.292870
5	0	-0.178670	0

Another important parameter to describe the tower fill performance is loss coefficient per meter depth of fill, K_{fi}. The correlation to calculate this parameter for each type of filling types is given in [28] as,

$$K_{fi} = \left[D_1\left(\frac{m_w}{a_{fr}}\right)^{D_2}\left(\frac{m_a}{a_{fr}}\right)^{D_3} + D_4\left(\frac{m_w}{a_{fr}}\right)^{D_5}\left(\frac{m_a}{a_{fr}}\right)^{D_6}\right] \tag{25}$$

The values of correlation coefficients D_1 to D_6 for each type of fills are given in Table 2. Another important factor in the modelling of cooling tower is pressure drop. The pressure drop through the fill matrix can be determined by,

$$\Delta p_f = K_{fi}L_{fi}\frac{mav_m^2}{2\rho_{mean}a_{fr}^2} \tag{26}$$

where mav_m represents the arithmetic mean air-vapor flow rate through the fill,

$$mav_m = \frac{mav_{in} + mav_{out}}{2} \tag{27}$$

Table 2 Correlation coefficients for K_{fi} [28].

l	D_l		
	Splash fill	Trickle fill	Film fill
1	3.179688	7.047319	3.897830
2	1.083916	0.812454	0.777271
3	-1.965418	-1.143846	-2.114727
4	0.639088	2.677231	15.327472
5	0.684936	0.294827	0.215975
6	0.642767	1.018498	0.079696

and ρ_{mean} is the moist air harmonic mean density through the fill,

$$\rho_{mean} = 1/\left(\frac{1}{\rho_i} + \frac{1}{\rho_o}\right) \tag{28}$$

Following equations are used to calculate the air-vapor flow at the fill inlet and outlet mav_{in} and mav_{out} in Eq. (27),

$$mav_{in} = m_a + w_{in}m_a \tag{29}$$

$$mav_{out} = m_a + w_{out}m_a \tag{30}$$

where w_{in} and w_{out} are the inlet and outlet air humidity, respectively and m_a is the air mass flow rate. w_{in} and w_{out} can be calculated by using the following equations,

$$w_{in} = \left(\frac{2501.6 - 2.3263\left(TWB_{in}\right)}{2506 + 1.8577\left(TA_{in}\right) - 4.184\left(TWB_{in}\right)}\right) \\ \left(\frac{0.62509\left(PV_{wbin}\right)}{P_{tot} - 1.005\left(PV_{wbin}\right)}\right) - \left(\frac{1.00416\left(TA_{in} - TWB_{in}\right)}{2506 + 1.8577\left(TA_{in}\right) - 4.184\left(TWB_{in}\right)}\right) \tag{31}$$

$$w_{out} = \frac{0.62509PV_{out}}{P_{tot} - 1.005PV_{out}} \tag{32}$$

where PV_{out} is the vapor pressure of water evaluated at $T = TA_{out}$ and P_{tot} is the total pressure of the ambient moist air in Pa. The vapor pressure of water can be calculated from the correlation given in [34],

$$ln\left(PV\right) = \sum_{n=-1}^{3} c_nT^n + 6.5459673\,ln\left(T\right) \tag{33}$$

where PV is the vapor pressure in Pa, T is the absolute temperature in K, and the values of the constants are: $c_{-1} = 5.8002206 \text{ x } 10^3$, $c_0 = 1.3914993$, $c_1 = -4.8640293 \text{ x } 10^{-3}$, $c_2 = 4.1764768 \text{ x } 10^{-5}$ and $c_3 = -1.4452093 \text{ x } 10^{-7}$.

The inlet and outlet density of air-water vapor mixtures in Eq. (28) can be calculated from the ideal gas law as,

$$\rho_i = \frac{P_{tot}}{287.08TA_{in}}\left[1 - \frac{w_{in}}{w_{in} + 0.62198}\right]\left[1 + w_{in}\right] \tag{34}$$

$$\rho_o = \frac{P_{tot}}{287.08TA_{out}}\left[1 - \frac{w_{out}}{w_{out} + 0.62198}\right]\left[1 + w_{out}\right] \tag{35}$$

The miscellaneous pressure losses in some components such as drift eliminators, column supports can be calculated as [35],

$$\Delta p_{ms} = K_{ms} \frac{\rho_{ms} v_{ms}^2}{2} \tag{36}$$

where K_{ms} is the component-loss coefficient, v_{ms} is the air-vapor velocity and ρ_{ms} is the air -vapor density. In the absence of component loss coefficient data, miscellaneous pressure losses can be described in terms of a miscellaneous component loss coefficient K_{misc}, which can also be expressed as $K_{misc} = K_{drift} + K_{air\ inlet} + K_{supports} + \ldots$. For mechanical draft cooling towers, K_{misc} can be taken as 6.5 [35]. Also, another approximation can be made for the velocity of air-vapor flow v_{ms} defined as,

$$\Delta p_{miscl} = 6.5 \frac{\rho_{ms} v_{ms}^2}{2} = 6.5 \frac{m a v_m^2}{2 \rho_{ms} a_{fr}^2} \tag{37}$$

The velocity pressure Δp_{vel} is another source of pressure loss that occurs in cooling towers, which should not be higher than 2/3 of total static pressure drop. In this work, upper limit of the permitted velocity pressure is considered as

$$\Delta p_{vel} = \frac{2}{3}\left(\Delta p_f + \Delta p_{miscl}\right) \tag{38}$$

The total pressure drop of air stream occurring in the cooling tower can be expressed as follows,

$$\Delta P_t = 1.667\left(\Delta p_f + \Delta p_{miscl}\right) \tag{39}$$

The required power to overcome the pressure drop is dependent on which draft type is used. Following equations can be used for the calculation of required power for mechanical forced and mechanical induced draft type cooling towers [26],

$$P = \frac{m a v_{in} \Delta p_{tot}}{\rho_i \eta_{eff}} \quad \text{(mechanical forced draft)} \tag{40}$$

$$P = \frac{m a v_{out} \Delta p_{tot}}{\rho_o \eta_{eff}} \quad \text{(mechanical induced draft)} \tag{41}$$

where η_{eff} is the mechanical efficiency of the fan. In the absence of manufacturer data, approximately it can be taken as 75% [26]. Due to the evaporative, drift and blowdown effects in the cooling towers, make-up water is constantly added into the basin to compensate the water losses. The rate of water evaporated into the air stream can be calculated from the conservation of mass,

$$m_{wev} = m_a\left(w_{out} - w_{in}\right) \tag{42}$$

Dissolved solids and other impurities accumulate in the cooling water as the water evaporates. In order to prevent the surplus of these solids and impurities, a certain amount of water is withdrawn from the system, which is called blow out and can be calculated as,

$$m_{bw} = \frac{m_{mw}}{\eta_{cyc}} - m_{wd} \tag{43}$$

where η_{cyc} is the number of cycles of concentration required to limit scale formation in cooling equipment. Generally, this value is taken between 2 and 4 [26]. An amount of water loss occurs in the form of suspended droplets at the exit air stream, which is known as drift loss. The drift loss should not be more than 0.2 percent of the total circulating water [36],

$$m_{wd} = 0.002 m_w \tag{44}$$

To compensate the water losses, the make-up water added to system must be total of all losses, that is $m_{mw} = m_{wev} + m_{bw} + m_{wd}$. Amount of make-up water can be calculated by combining the equations of above-mentioned losses,

$$m_{mw} = \frac{\eta_{cyc} m_{wev}}{\eta_{cyc} - 1} \tag{45}$$

4. Artificial Cooperative Search

Artificial Cooperative Search (ACS) is swarm-intelligence based metaheuristic algorithm developed for solving numerical optimization problems [21]. The algorithm is based on two artificial superorganisms biologically interacting with each other to find the global minimum of the optimization problem at hand. In nature, amount of food can be found in an area is very sensitive to climate changes. Therefore, many of the species in the nature develop migration behavior to find and migrate to more productive feeding zones. Additionally, prior to migration, many species in the nature form a superorganism. After some time, superorganism starts to move to more productive zones. However, it is not known that how the members of the superorganism make decisions or when or where to move information is known by all members. Also, prior to migration, many superorganisms can divide into smaller groups called sub-superorganisms. In this case, coordination between the sub-superorganisms determines the overall behavior of the superorganism.

Many living species in nature use explorers to find and explore new possible zones rich in food and suitable for nesting. After a new place is discovered by the explorer, the explorer informs the superorganism about the properties of the newly discovered area such as suitability for nesting and amount of food it contains. If the social decision making mechanism of the superorganism considers this area as a suitable place for migration, then the superorganism starts to move towards the area, meanwhile the explorers continue to search for possible migration zones and if it is considered suitable, the superorganism migrates again. In nature, different species develop different kinds of interaction with each other to satisfy their feeding and production needs. On the other hand, many species may also develop different interaction models in different stages of their lives. The superorganisms in interaction with each other may develop different relationships such as alturation, coevolution, coextinction or cooperation.

In ACS algorithm, two superorganisms, namely *α* and *β*, consisting of random solutions of the problem at hand migrate to more productive feeding areas corresponds to the candidate solutions of the problem. Each superorganism consists of artificial sub-superorganism, which equals to the dimension of the population (*N*) and each sub-superorganism contains a number of individuals, which is equal to the dimension of the problem (*D*). These two superorganisms are used to choose the Prey and Predator sub-superorganisms. The Predator sub-superorganism traces the Prey sub-superorganism for a timeframe while they migrate together towards the global minimum of the problem.

The initial values of the individuals of i^{th} sub-superorganism $\alpha_{i,j}$ and $\beta_{i,j}$ can be determined by using the following equations,

$$\begin{aligned} \alpha_{i,j:g=0} &= rnd.\left(up_j - low_j\right) + low_j \\ \beta_{i,j:g=0} &= rnd.\left(up_j - low_j\right) + low_j \end{aligned} \tag{46}$$

where $i = 1,2,3,\ldots,N$, $j = 1,2,3,\ldots,D$ and $g = 0,1,2,3,\ldots,maxcycle$. g shows the generation number or iteration number, rnd denotes to a random number chosen from a uniform distribution $U \sim [0,1]$ and up_j and low_j represents the upper and lower limits of search space for jth dimension of the problem.

Fitness values of the related sub-superorganisms are determined by using the following equations,

$$y_{i;\alpha} = f(\alpha_i) \qquad y_{i;\beta} = f(\beta_i) \tag{47}$$

Detailed description of Artificial Cooperative Search Algorithm is explicitly given in Table 3.

Table 3. Pseudocode of Artificial Cooperative Search algorithm

```
Input data: Population size (N), Problem Dimension (D),
 Maximum iteration number
(maxiter), objective function f(.), probability of biological interaction (p),
 upper and lower bounds (up and low)
Set Globalminimum to 1e20 and initialize Superorganisms ($\alpha$, $\beta$)
for i = 1 toN
   for j = 1 toD
        $\alpha_{i,j}=low_j + (up_j - low_j)$ x $rand_1(0,1)$
        $\beta_{i,j}=low_j + (up_j - low_j)$ x $rand_2(0,1)$
   end
   fitness-$\alpha_i = f(\alpha_i)$
   fitness-$\beta_i = f(\beta_i)$
end
for   iter = 1 to maxiter
     // Selection phase
      if $rand_3(0,1)<rand_4(0,1)$then
           Predator = $\alpha$, fitness-Predator = fitness-$\alpha$, key = 1
      else
           Predator = $\beta$, fitness-Predator = fitness-$\beta$, key = 2
      end
      if$rand_5(0,1)<rand_6(0,1)$then Prey = $\alpha$  else  Prey = $\beta$  end
      Prey = permute (Prey)
      if$rand_7(0,1)<rand_8(0,1)$then
            R=4x $rand_9(0,1)$x($rand_{10}(0,1)$- $rand_{11}(0,1)$ )
       else
R ~ Γ( 4x $rand_{12}(0,1)$, 1)
       end
       $M_{1:N,1:D}$= 1.0
       for i =1 toN
          for j = 1 toD
               if $rand_{13}(0,1)$ < ( p x  $rand_{14}(0,1)$) then
                   $M_{rndint(N),rndint(D)}$= 0
               end
         end
       end
       if$rand_{15}(0,1)$ <( p x $rand_{16}(0,1)$ )then
            for  i = 1 toN
                for j = 1 toD
                    if$rand_{17}(0,1)$ <( p x $rand_{18}(0,1)$ )then
                        $M_{i,j}$= 1.0
                    else
                        $M_{i,j}$= 0.0
                    end
                end
            end
       end
       for  i = 1 toN
           if Σ $M_i$ = Dthen  $M_{i,rndint(D)}$ = 0 end
       end
       // Mutation
       X = Predator + R x (Prey - Predator )
       for  i = 1 toN
           for  j = 1 to D
              // Crossover
              if $M_{i,j}$> 0 then $X_{i,j}$= $Predator_{i,j}$end
           end
       end
       // Boundary control
       for   i = 1 to N
           for  j = 1 to D
                if  ($X_{i,j}$<$low_j$)   ||  ($X_{i,j}$ >$up_j$)
                     $X_{i,j}$ = $low_j$ + ($up_j$ - $low_j$) x $rand_{19}(0,1)$
                end
            end
       end
       // Selection (Update)
       for i = 1 toN
                  if$f(X_i)$< fitness-$Predator_i$ then $Predator_i$ = $X_i$ ,fitness-
                         $Predator_i$ = $f(X_i)$end
end
 if   key = 1  then
           α = Predator,  fitness-α = fitness-Predator
       else
           β = Predator,  fitness- β = fitness-Predator
       end
      fitness-best = argmin (fitness - Predator)  $best \in \{1,2,3,..,N\}$
       if  fitness-best < Globalminimum  then
           Globalminimum = fitness-best
           Globalminimizer = Predator-best
       end
   end
   Output data : Globalminimum = f (Globalminimizer)
```

5. Improvements on Artificial Cooperative Search Algorithm

In this section global search capabilities of Artificial Cooperative Search algorithm is enhanced with some of perturbation schemes adopted from Crow Search Algorithm (CSA). Proposed by Askerzadeh [22], CSA mimics the food searching behaviors of the intelligent crows and tries to find the global optimum point through the search equations defined to simulate the subsistence characteristics of crows. CSA works under the basic principles of the given procedure as the following. When a crow is on its hunt or food search, they observe the movements and the manoeuvers of other birds and, eventually chase them to find where the flocks of the birds the crow chase hide their food. If the crow has the chance to find the hiding place of the food resource, it attempts to steal it when the keeper (owner) of the food leaves from the area. The crow committed a thievery secure itself such as moving hiding places of the food resources to avoid a future victim. The crow as its nature has the ability of using its own past experiences of being a thief to foresee the behaviors of the pilferer, and able to decide the safest way to secure its catched foods from the other pilferer birds. CSA has one fundamental perturbation scheme used in the iterations to simulate these aforementioned intelligent crow characteristics. In this context, assume that at the iteration iter crow j is intended to visit its food resource place. On this current iteration, crow i decides the follow crow j to reach the food hiding place of crow j. For this situation, two alternative cases may happen that could occur as given below:

Case 1: Crow *j* is not aware of the state that crow *i*is on the pursuit of it. As a result of this, crow *i* has the chance to visit the food hiding place of crow *j*. For this case, crow *i* is positioned as the equation given in the following

$$x^{iter+1} = x^{iter} + rand(0,1) \times fl^{iter} \times \left(m^{i,iter} - x^{i,iter} \right) \tag{48}$$

Where *rand*(0,1) is a Gaussian random number generated between 0 and 1, and fl^{iter} stands for the flight length of the crow *i* at the iteration iter. This value is generally set to 2.0 following the suggestion given in [22]. The term $m^{i,iter}$ represents the food hiding place of crow *i*. The parameter flight characteristic plays an important role in designing the search capabilities of the algorithm. Small values of *fl* improve the local search mechanism while the corresponding large values give rise to local search capacity of the algorithm.

Case 2: Crow *j* is conscious of being chased by crow *i*. Therefore, it misdirects the crow *i* in order to protect the food it possesses to avoid being pilfered by crow *i*. As a result, the crow *i* finds itself another place in the solution space. If it is to combine the both cases in a simple mathematical expression

$$x^{iter+1} = \begin{cases} x^{iter} + rand(0,1) \times fl^{iter} \\ \times \left(m^{i,iter} - x^{i,iter} \right) \quad rand(0,1) \geq AP^{i,iter} \\ \text{random position between the} \\ \text{specified bounds otherwise} \end{cases} \qquad (49)$$

Where *rand*(0,1) is uniform number defined between 0 and 1, and the awareness probability (AP) decides the tendencies of intensification and diversification phases of the algorithm, While lower values of AP leads algorithm to conduct searches in local areas, higher values of AP maintains an effective global search mechanism. As it was previously mentioned before, the scheme given in Eq.(49), is efficient in balancing the exploration and exploitation phase. Therefore, this perturbation scheme is incorporated into the fundamentals of ACS algorithm with a bit modification. Modified equation can be defined as

$$X^{iter+1} = X^{iter} + rnd(0.1, 0.5) \times \left(\Pr edator_{\text{rnd int}(N)} - X^{iter} \right) \qquad \mathbf{(50)}$$

Where *rnd*(0.1,0.5) generates random real numbers between 0.1 and 0.5, Predator denotes the predator individuals in ACS algorithm, and *rndint*(*N*) generates random integers between 1 and *N* those of which are different from each other. By this equation, algorithm randomly accesses the unvisited paths of the promising areas of the solution space and maintains solution diversity. The whole hybrid algorithm, thereinafter named as IACS algorithm, is summarized in a nutshell in a pseudo-code form given in Table 4. Optimization performance of the algorithm has been assessed with fourteen widely reputed 30 dimensional benchmark test function, which are explicitly formulated in Table 5. Dimension size is set to 30 for all benchmark problems and maximum numbers of function evolutions are fixed to 40000. 30 consecutive algorithm runs have been completed due to the stochastic nature of metaheuristic algorithms. All algorithms mentioned in Table 5 have been programmed in Java and run on Intel Core^{TM} with 2.50 GHz CPU with 6.0 GB RAM. Table 6 shows the optimization results of ACS and IACS algorithms with respect to statistical analysis obtained after 30 algorithm evaluations. Table 6 reveals that IACS algorithm surpasses ACS algorithm for each optimization case in terms of the statistical results it attains. Fig 2 to Fig 6 correspondingly shows the convergence behaviors of ACS and IACS algorithms for Ackley, Levy, Rastrigin, Salomon, and Schfewel 2.22 optimization test functions. As seen from the figures, IACS algorithm reaches its optimum point faster than ACS algorithm for each optimization test case.

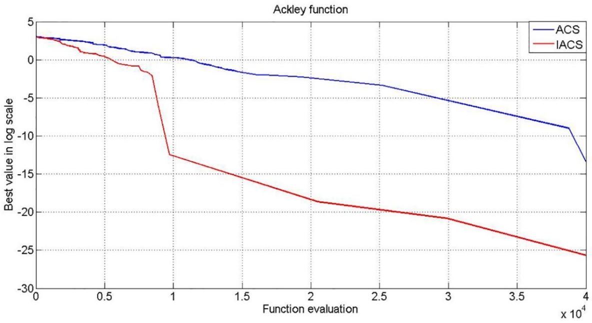

Figure 2. Convergence graphs of ACS and IACS algorithms for Ackley test function

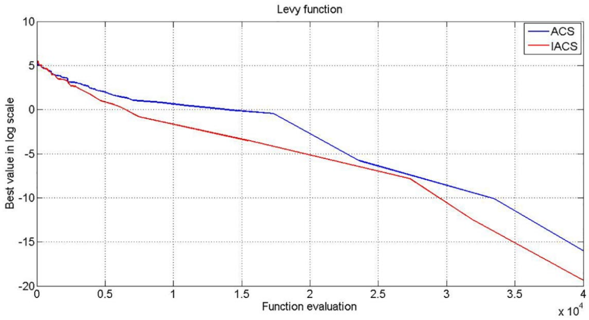

Figure 3. Evolution graphs of ACS and IACS algorithms for Levy test function

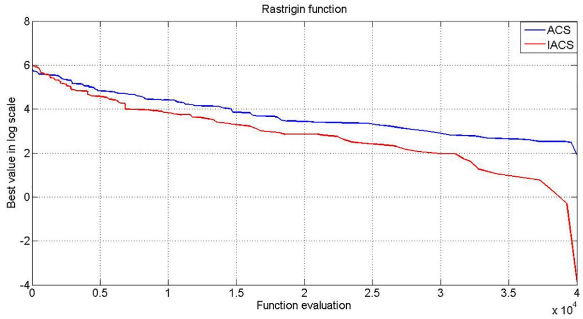

Figure 4. Convergence process of ACS and IACS algorithms for Rastrigin test function

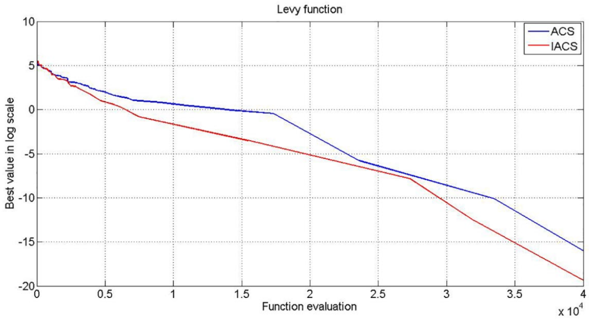

Figure 3. Evolution graphs of ACS and IACS algorithms for Levy test function

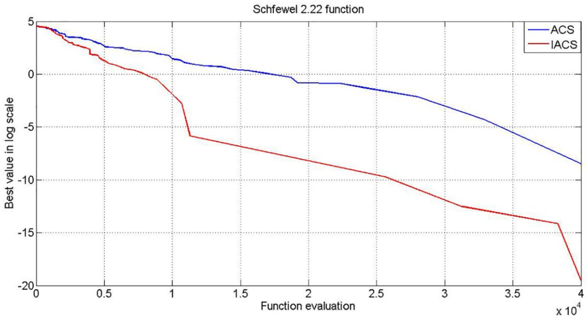

Figure 6. Evolution process of ACS and IACS algorithms for Schfewel 2.22 test function

Table 4. Pseudo-code of the hybrid IACS algorithm

```
Initialize algorithm parameters: Population size ($N$), problem dimension ($D$), Upper ($up$) and lower ($low$) bounds of the search space, probabili
of biological interaction ($p$), the objective function ($f$), and maximum number of iteration ($maxiter$)
Initialize the sub-superorganism of $\alpha$ and $\beta$ randomly with Eq.(46)
Determine respective fitness values of $\alpha$ and $\beta$ with Eq.(47)
While (iter < maxiter)
    Determine Predator individuals with the procedure given in the lines between 12 and 16 in Table 3
    Determine Prey individuals with the methodology given in the lines between 17 and 18 in Table 3
    Calculate scale factor according to the perturbation equations defined in the lines between 19 and 22 in Table 3
    Determine M passive individuals in accordance with the equations expressed in the lines between 24 and 45 in Table 3
    Decide the biological interaction location ($X$) with the mutation equation expressed in the line 47 in Table 3
    Generate integers those are different from each other defined between 1 and N (rndint(N))
    Increase the population diversity with applying Eq.(50)
    Determine the population individuals that have violated predefined search space and restrict them within the extreme bounds
    Update the current population by means of active individuals using the procedure defined in the lines between 48 and 53 in Table 3
    Apply boundary check on the current population individuals through the mechanism given in the lines between 55 and 61 in Table 3
    Update the Predator sub-superorganism with the procedure given in the lines between 63 and 65 in Table 3
    Determine the new sub organisms for next generations with using the selection scheme detailed in the lines 66 and 70 in Table 3
    Determine the best solution among the Predator individuals
    Update the current best solution
end
Output the global best vector
```

Table 5. Formulations of the optimization test functions

	Function	***D***	***Range***	f_{opt}
Ackley	$f_1(x) = -20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right) + 20 + \exp(1)$	30	$[-100,100]^D$	0
Alpine	$f_2(x) = \sum_{i=1}^{D}\lvert x_i\rvert + \prod_{i=1}^{D}\lvert x_i\rvert$	30	$[-10,10]^D$	0
Griewank	$f_3(x) = \sum_{i=1}^{D-1}\left(100\left(x_{i+1} - x_i^2\right)^2 + \left(x_i - 1\right)^2\right)$	30	$[-30,30]^D$	0
Levy	$f_4(x) = \sum_{i=1}^{D}\left(\lfloor x_i + 0.5\rfloor\right)^2$	30	$[-100,100]^D$	0
Pathological	$f_5(x) = \sum_{i=1}^{D} ix_i^4 + random(0,1)$	30	$[-1.28,1.28]^D$	0
Penalized	$f_6(x) = \frac{\pi}{D}\left\{10\sin^2(\pi y_1) + \sum_{i=1}^{D-1}(y_i - 1)^2\left[1 + 10\sin^2(\pi y_{i+1})\right] + (y_D - 1)^2\right\}$ $+ \sum_{i=1}^{D} u(x_i, 10, 100, 4)$	30	$[-50.0,50.0]^D$	0
Rastrigin	$f_7(x) = \sum_{i=1}^{D}\left(x_i^2 - 10\cos\left(2.0\pi x_i\right)\right) + 10D$	30	$[-5.12,5.12]^D$	0
Rosenbrock	$f_8(x) = \sum_{i=1}^{D-1}\left(100\left(x_{i+1} - x_i^2\right)^2 + \left(x_i - 1\right)^2\right)$	30	$[-2.048, 2.048]^D$	0

Salomon	$f_9(x) = 1.0 - \cos\left(2\pi\sqrt{\sum_{i=1}^{D} x_i^2}\right) + 0.1\sqrt{\sum_{i=1}^{D} x_i^2}$	30	$[-100.0,100.0]^D$	0
Schaffer	$f_{10}(x) = 0.5 + \frac{\sin^2\left(\sum_{i=1}^{D} x_i^2\right) - 0.5}{\left[1 + 0.001\sum_{i=1}^{D} x_i^2\right]^2}$	30	$[-100.0,100.0]^D$	0
Schfewel 2.22	$f_{11}(x) = \sum_{i=1}^{D} \lvert x_i \rvert + \prod_{i=1}^{D} \lvert x_i \rvert$	30	$[-10.0,10.0]^D$	0
Sphere	$f_{12}(x) = \sum_{i=1}^{D} x_i^2$	30	$[-100,100]^D$	0
Step	$f_{13}(x) = \sum_{i=1}^{D} \left(\lfloor x_i + 0.5 \rfloor\right)^2$	30	$[-100,100]^D$	0
Zakharov	$f_{14}(x) = \sum_{i=1}^{D} x_i^2 + \left(\sum_{i=1}^{D} 0.5ix_i\right)^2 + \left(\sum_{i=1}^{D} 0.5ix_i\right)^4$	30	$[-5.0,10.0]^D$	0

Table 6. Statistical results obtained after 30 algorithm runs for ACS and IACS algorithms

	Ackley			**Alpine**			**Griewank**		
	Min.	Max.	Std. dev.	Min.	Max.	Std.dev	Min.	Max.	Std.dev.
ACS	5.05E-06	3.35E-05	7.10E-06	1.05E-02	4.03E-02	6.97E-03	4.23E-09	6.04E-07	1.51E-07
IACS	**7.93E-12**	6.72E-11	1.48E-11	**2.23E-04**	1.87E-03	3.31E-04	**0.00E+00**	2.62E-13	5.71E-14
	Levy			**Pathological**			**Penalized**		
	Min.	Max.	Std. dev.	Min.	Max.	Std. dev.	Min.	Max.	Std. dev.
ACS	1.11E-07	1.71E-06	3.61E-07	5.11E-02	9.67E-02	1.24E-02	1.91E-10	1.91E-09	3.59E-10
IACS	**3.86E-09**	3.86E-09	1.51E-15	**3.40E-02**	8.20E-02	1.32E-02	**9.01E-11**	9.01E-11	3.91E-18
	Rastrigin			**Rosenbrock**			**Salomon**		
	Min.	Max.	Std. dev.	Min.	Max.	Std. dev.	Min.	Max.	Std. dev.
ACS	6.78E+00	1.46E+01	1.83E+00	2.49E+01	2.65E+01	8.82E-01	2.99E-01	4.99E-01	5.18E-02
IACS	**2.15E-02**	9.12E-01	2.32E-01	**2.26E+01**	2.59E+01	7.14E-01	**1.99E-01**	2.99E-01	4.63E-02
	Schaffer			**Schfewel 2.22**			**Sphere**		
	Min.	Max.	Std. dev.	Min.	Max.	Std. dev.	Min.	Max.	Std. dev.
ACS	6.02E-03	1.96E-02	2.34E-03	2.01E-04	1.38E-03	2.78E-04	1.78E-09	1.41E-07	3.01E-08
IACS	**3.12E-03**	1.04E-02	1.35E-03	**3.32E-09**	4.31E-08	6.38E-09	**1.53E-16**	1.78E-15	3.79E-16
	Step			**Zakharov**					
	Min.	Max.	Std. dev.	Min.	Max.	Std. dev.			
ACS	3.74E-09	1.41E-07	2.32E-08	2.02E-01	3.26E+00	5.46E-01			
IACS	**2.18E-17**	4.63E-16	1.11E-16	**1.03E-03**	2.45E-01	2.33E-02			

6. Results and discussion

Effectiveness of the proposed algorithm is tested by evaluating six different examples presented in [1]. Design specifications and constraints for the examples are given in Table 7. Example 1 is treated as the main example. Other examples are variations of the first example with different design specifications and constraint values. The dry bulb temperature of air, process inlet and outlet temperatures, minimum allowable temperature difference, wet-bulb temperature of air and heat load of the cooling tower are considered as design specifications. Whereas, mass velocity of water, mass velocity of air, water-to-air mass ratio, type of packing and type of draft is handled as design variables. Values of some parameters used in the modelling of the cooling tower are taken as accordingly for all examples, the total air pressure P_{tot} as 101325 Pa., c_{pw} value of the water as 4.187 kJ/kg°C, annualizing factor for the capital cost K_f as 0.2983/year and the values of H_Y, C_{wat}, C_{el}, C_{FC}, C_{CM}, η_{eff}, η_{cyc} are taken as 2.934 x 10^7 s/year, US\$5.283 x 10^{-4}/kg, US\$0.085/kWh, US\$31.185, US\$1097.5/(kg of dry air/s), 0.75 and 4, respectively. In the present work, improved ACS and ACS algorithms are implemented on the six different examples of the cooling tower design problem. Solutions obtained with the proposed and ACS algorithms are given and compared with other results in the literature in Table 8 to Table 10. Maximum iteration number and population size are taken as 10,000 and 50 respectively. The algorithm is implemented in Java programming language and all experiments are done on a 2.8 GHz Core 2 Duo machine.

In the base example, results of the proposed algorithm given in Table 8 show that around 6.32% increase in mass flow rate of air with significant reduction in dry bulb temperature of the air at outlet lead to fewer mass of mass of blow-down water and mass of evaporated water, thus, less mass of make-up water compared to ABC [2] results. Lesser mass of make-up water reduces the cost of make-up water greatly. Higher loss coefficient per meter depth of fill (K_{fi}) increases the pressure drop through fill matrix. Therefore, greater total pressure drop is obtained. To compensate the higher pressure drop, around 81% greater power cost is required. However reduction in the make-up water cost is greater than the increase in power costs, therefore, lower total cost is obtained compared to other results. Lower Merkel number compared to [2] results in reduced tower size, thus, reduces the total cost. The effect of the dry bulb temperature of air at inlet to the total cost is studied in example 2. As can be seen from Table 8, 5°C drop in TA_{in} resulted 4.1% increase of total annualized cost comparing to the main example.

Therefore, it can be said that total annualized cost is sensitive to the dry bulb temperature of air at inlet of the cooling tower.

In example 3, wet bulb temperature of air at the inlet is reduced by 5°C while other design specifications and constraints are held constant. As can be seen from the results of the proposed algorithm in Table 9, drop in TWB_{in} resulted 8.1% decrease in total annualized cost compared to the base example. Also, the proposed algorithm found more desirable results than other algorithms. The effect of minimum process inlet temperature (*TMPI*) is studied in example 4. 10°C decrease in *TMPI* results in 2.6% increase in total annualized cost compared to the preliminary design. Higher Merkel number caused greater tower length; therefore, higher total annualized cost is obtained compared to the main example. It can be seen that the proposed algorithm gave better results than other algorithms. The results obtained by different algorithms for cooling water design concerning example 5 and example 6 are given in Table 10. Example 5 demonstrates effect of the minimum outlet temperature (*TMPO*) decrement to the cooling tower system. 5°C decrement in *TMPO* resulted in sharp increase of total annualized cost. Compared to the total cost result obtained by ABC [2], the proposed algorithm gave more desirable results. Also, it should be noted that, reduction of the value of *TMPO,* decreases the value of optimal tower approach. And it can be said that reduction of the value of tower approach is responsible for sharp increase in total annualized cost. Additionally, larger value of Merkel number results in greater tower size. Example 6 demonstrates the effect of minimum allowable temperature difference (ΔT_{min}) decrement to the cooling tower system. It can be seen that approach increases and cooling range decreases as the value of ΔT_{min} drops. It was found that as the cooling range decreases, water temperature at outlet increases and Merkel number, thus tower size, becomes smaller. Smaller tower size results in lower total cost. Out of all examples, most desirable total cost is obtained in this example. Therefore, it can be said that total tower cost is very sensitive to cooling range.

Table 7. Design specification and constraints for the examples [1]

	Example 1	Example 2	Example 3	Example 4	Example 5	Example 6
Q (kW)	3400	3400	3400	3400	3400	3400
TWB_{in} (°C)	12	12	7	12	12	12
TA_{in} (°C)	22	17	22	22	22	22
TMPI (°C)	65	65	65	55	65	65
TMPO (°C)	30	30	30	30	25	30
ΔT_{min} (°C)	10	10	10	10	10	5

Table 8. Comparison of the best results obtained from different algorithms for examples 1 and 2

	Example 1				Example 2			
	GAMS [1]	ABC [2]	ACS	IACS	GAMS [1]	ABC [2]	ACS	IACS
m_w/m_a	0.829	0.987	0.976	0.927	0.82	0.9798	0.976	0.927
m_a (kg/s)	31.014	26.07	27.729	27.72	31.443	26.252	27.729	27.729
m_w (kg/s)	25.72	25.72	25.72	25.72	25.72	25.72	25.72	25.72
m_{mw} (kg/s)	1.541	1.512	1.067	0.900	1.456	1.439	1.067	1.067
m_{wev} (kg/s)	1.156	1.078	0.800	0.675	1.092	1.025	0.800	0.800
m_{bw} (kg/s)	0.334	0.327	0.212	0.170	0.312	0.308	0.214	0.212
m_{wd} (kg/s)	0.051	0.051	0.054	0.054	0.052	0.051	0.054	0.054
TW_{in} (°C)	50	50	50	50	50	50	50	50
TW_{out} (°C)	20	20	20	20	20	20	20	20
TA_{out} (°C)	37.077	39.000	37.000	37.000	36.871	38.900	37.000	37.587
Range (°C)	30	30	30	30	30	30	30	30
Approach(°C)	8	8	8	8	8	8	8	8
L_{fi} (m)	2.239	2.418	2.403	2.300	2.239	2.397	2.395	2.385
a_{fr} (m^2)	8.869	8.869	7.394	7.419	8.894	8.869	7.320	7.345
K_{fi}	21.95	22.07	23.19	23.17	21.95	22.07	23.24	23.23
Δp_f(Pa)	280.331	211.350	360.984	348.116	277.727	211.200	369.206	351.149
ΔP_{misc}(Pa)	36.19	25.75	42.15	42.45	36.74	25.96	43.00	42.71
ΔP_t(Pa)	527.64	395.26	672.03	651.08	524.22	395.36	687.16	656.57
P (hp)	24.637	15.500	21.098	20.941	24.474	15.400	21.573	20.613
Type of packing	Film	Film	Film	Film	Film	Film	Film	Film
Type of draft	Forced	Forced	Forced	Forced	Forced	Forced	Forced	Forced
Me	3.083	3.72	3.75	3.905	3.055	3.703	3.786	3.872
C_{mw}	23885.19	23449.11	16551.96	13955.48	22566.366	22302.01	16551.96	16551.96
C_{power}	12737.54	8013.02	14616.00	14507.33	12653.677	7960.02	14945.00	14279.84
C_{op}	36622.73	31462.13	31167.96	28462.82	35220.043	30262.03	31496.96	30831.81
K_fC_{cap}	29442.66	28110.04	26883.52	26557.01	29384.60	28081.90	26798.84	26475.32
TAC	66065.39	59572.17	58051.49	55019.83	64604.64	58343.93	58295.80	57307.13

Table 9. Comparison of the best results obtained from different algorithms for examples 3 and 4

	Example 3				Example 4			
	GAMS [1]	ABC [2]	ACS	IACS	GAMS [1]	ABC [2]	ACS	IACS
m_w/m_a	0.911	1.096	1.072	1.019	0.838	0.9924	1.024	1.091
m_a (kg/s)	28.199	23.465	25.23	25.23	36.95	31.10	28.72	28.37
m_w (kg/s)	25.72	25.72	25.72	25.72	30.975	30.975	30.975	30.975
m_{mw} (kg/s)	1.564	1.535	1.140	0.819	1.547	1.514	1.088	0.918
m_{wev} (kg/s)	1.173	1.100	0.855	0.614	1.16	1.079	0.816	0.688
m_{bw} (kg/s)	0.34	0.335	0.231	0.15	0.325	0.316	0.218	0.164
m_{wd} (kg/s)	0.051	0.051	0.054	0.054	0.062	0.062	0.064	0.064
TW_{in} (°C)	50	50	50	50	45	45	45	45
TW_{out} (°C)	20	20	20	20	20	20	20	20
TA_{out} (°C)	36.998	40.700	39.126	37.549	34.511	36.400	36.654	36.730
Range (°C)	30	30	30	30	25	25	25	25
Approach(°C)	13	13	13	13	8	8	8	8
L_{fi} (m)	1.858	1.793	1.895	1.812	2.154	2.242	2.178	2.145
a_{fr} (m^2)	8.862	8.869	6.94	6.836	10.68	10.644	7.521	7.546
K_{fi}	21.93	22.07	23.51	23.61	21.94	22.07	24.10	24.08
Δp_f(Pa)	186.621	126.470	281.555	346.026	254.540	191.400	382.368	363.62
ΔP_{misc}(Pa)	29.78	20.79	39.90	41.41	35.01	25.14	42.96	42.67
ΔP_t(Pa)	360.74	245.47	535.87	645.86	482.68	360.99	709.03	677.29
P (hp)	14.205	8.600	15.310	18.904	26.852	16.890	23.255	22.214
Type of packing	Film	Film	Film	Film	Film	Film	Film	Film
Type of draft	Forced	Forced	Forced	Forced	Forced	Forced	Forced	Forced
Me	2.466	3.016	3.142	3.253	2.923	3.533	3.743	3.852
C_{mw}	24239.785	23798.27	17683.69	12699.98	23983.449	23478.40	14230.77	14230.77
C_{power}	7861.037	4447.80	10606.21	13096.27	13882.754	8727.42	16110.16	15389.09
C_{op}	32100.822	28246.07	28289.90	25796.26	37866.203	32205.80	30340.93	29619.86
K_fC_{cap}	26616.00	24602.10	24057.04	25097.76	32667.71	30919.10	27208.02	26876.15
TAC	58716.817	52848.17	52346.94	50894.03	70533.909	63123.9	57548.95	56496.02

Table 10 Comparison of the best results obtained from different algorithms for examples 5 and 6

	Example 5				Example 6			
	GAMS [1]	ABC [2]	ACS	IACS	GAMS [1]	ABC [2]	ACS	IACS
m_w/m_a	0.682	0.704	0.627	0.599	1.13	1.343	1.171	1.513
m_a (kg/s)	32.428	31.31	36.96	36.91	27.205	22.984	27.729	20.317
m_w (kg/s)	22.127	22.127	22.127	22.127	30.749	30.749	30.749	30.749
m_{mw} (kg/s)	1.542	1.514	1.142	1.085	1.54	1.514	1.086	0.795
m_{wev} (kg/s)	1.157	1.079	0.856	0.814	1.155	1.079	0.814	0.596
m_{bw} (kg/s)	0.341	0.335	0.239	0.225	0.323	0.317	0.206	0.133
m_{wd} (kg/s)	0.044	0.044	0.046	0.046	0.061	0.0617	0.064	0.064
TW_{in} (°C)	50	50	50	50	50	50	50	50
TW_{out} (°C)	15	15	15	15	25	25	25	25
TA_{out} (°C)	36.411	36.980	39.501	36.467	39.083	41.000	39.000	39.134
Range (°C)	35	35	35	35	25	25	25	25
Approach(°C)	3	3	3	3	13	13	13	13
L_{fi} (m)	6.299	6.722	6.723	6.541	1.48	1.174	1.154	1.163
a_{fr} (m^2)	7.63	7.6	8.869	8.869	9.296	10.644	8.019	6.109
K_{fi}	22.07	22.07	21.54	21.54	22.64	22.07	23.72	25.32
Δp_f(Pa)	1139.529	1139.000	1001.733	1009.927	131.908	55.970	154.046	145.454
ΔP_{misc}(Pa)	53.29	49.91	52.66	52.54	25.60	14.05	36.69	33.94
ΔP_t(Pa)	1988.43	1982.10	1757.67	1771.14	262.56	116.70	317.96	299.05
P (hp)	97.077	93.400	75.356	75.933	10.754	4.040	10.227	7.047
Type of packing	Film	Film	Film	Film	Film	Film	Film	Film
Type of draft	Forced	Forced	Forced	Forced	Forced	Forced	Forced	Forced
Me	7.335	7.679	7.712	7.856	1.858	2.235	2.431	2.854
C_{mw}	23901.657	23481.2	17705.44	16833.11	23865.877	23474.16	16835.40	12335.053
C_{power}	50190.495	48265.1	52203.28	52603.11	5559.875	2086.32	7084.88	4882.18
C_{op}	74092.153	71746.3	69908.730	69436.23	29425.752	25560.48	23920.28	17217.23
K_fC_{cap}	43186.53	44040.40	45796.39	46051.21	25030.27	22810.40	22799.23	19173.82
TAC	117278.68	115786.7	115705.121	115487.44	54456.026	48370.88	46719.52	36391.06

7. Conclusion

In this study, an improved version of ACS algorithm is applied on the optimization of counter flow wet-cooling tower problem. ACS algorithm is a swarm-intelligence based metaheuristic algorithm effective at global search. Four design variables are optimized to reach the minimum total annualized cost under given set of constraints. Perturbation scheme of ACS algorithm is incorporated with the CSA's to improve the solution accuracy of the whole hybrid optimizer. Efficiency of the hybrid algorithm is tested with fourteen optimization test problem available in literature. Following this, effectivity of the proposed algorithm is benchmarked against six different examples of counter flow wet cooling tower optimization problem. Each example is based on demonstrating the effects of design specification and constraints on the total cost. The results obtained by implementing the proposed algorithm on this design problem are compared with the results of GAMS [1] and ABC algorithm [2]. The outcomes of the optimization results show that the proposed algorithm gives more desirable results with rapid solution convergence and proves the suitability of the hybrid method for the optimization of thermal systems.

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