Application of Spotted Hyena Optimizer in Cogeneration Power Plant on Single and Multiple-Objective

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Abstract— **In this paper, a Spotted Hyena Optimizer (SHO) is employed in the context of addressing a constrained optimization problem to solve a cogeneration power plant (CGPP) problem through a classical approach. The paper examines the CGPP system through consideration of the 3E aspects (energy, exergy, and economy) through thermodynamic analysis. The equipment used in the system included a condenser, a turbo-generators, and a boiler. Two design optimization approaches were used: single objective optimization (SOO) and multi-objective optimization (MOO), with a comparison conducted using the SHO algorithm. On the basis of the findings, one optimal solution was returned by SOO-SHO from a single run, while a set of optimal solutions was discovered using MOO-SHO. The use of a SOO-SHO model requires the researcher to determine the preferred settings prior to starting the run, whereas the MOO-SHO does not require such decisions to be taken until after the run is complete. Typically, the SOO approach generates the optimal solution when considering a particular objective, while the MOO uses a broader array of information to reach richer solutions that consider the broader perspective.**

Keywords*— *Spotted Hyena Optimizer, Cogeneration power plant, Single objective optimization, Multi-objectives optimization, Meta-heuristics

I. Introduction

Numerous external factors affect the operational aspects of energy systems, and therefore the environmental and economic factors must be considered by system designers if they are to optimize the system in practice. The combined cycle power plants (CCPP) offer a high level of energy efficiency. They have drawn considerable attention due to this advantage and the low levels of pollution generated, especially in terms of greenhouse gases, and the flexibility offered by their operation. One frequently used approach for CCPP is the gas-steam combined cycle, involving a gas turbine cycle, known as the topping cycle, and a steam turbine cycle, known as the bottoming cycle. These cycles are then combined via the heat recovery steam generator [1].

Energy analysis is the most widely applied approach to assess energy conversion system performance, but today there is growing attention focused on the combined issues of exergy and exergy destruction. It has been shown that the 3E (energy, exergy, and environment) analysis can be an effective means of evaluating thermal power plant performance from varying perspectives [2-4].

In order to achieve optimal operational efficiency while controlling costs and minimizing the environmental impact of a power plant, it is first necessary to establish the nature and whereabouts of the various aspects which require improvement, as well as to determine the scale of the problems. To do this, exergy analysis can be applied since it allows the various thermodynamic inefficiencies within the system to be quantified. Exergy can be defined as the work of a system as it achieves thermodynamic equilibrium with its surrounding environment in a process which can be reversed. Exergy analysis has been applied frequently over recent years in research into power plants [5-9].

In practice, the solutions to real-world problems must often address more than one objective. For instance, it may be necessary to minimize risk, cost, or variation from specific targets while maximizing reliability and efficiency. When applying single-objective optimization (SOO), the approach aims to find just one solution deemed to be the best by treating all of these objectives as a single goal. While this approach can help decision makers provide an overview of the problems, it does not provide a range of solutions that offer different advantages as the various objectives are balanced against each other. In contrast, multi-objective optimization (MOO) allows many solutions to be proposed since no single solution is optimal for all of the contrasting objectives. The solutions form a set of compromises described as the trade-off, non-inferior, non-dominated, or Pareto-optimal solutions [10].

Used in isolation, SOO will locate one optimal solution, but it can also be used as a MOO component. When this is done, the various objectives are not combined to form a single goal, but instead, the algorithm works to optimize one of the variables while the others are pre-set to act as constraints. Where objectives take the form of constraints, the levels are set in line with the desired objective function, minimizing cost, or maximizing reliability. The algorithm then performs multiple runs, aiming to determine solutions that satisfy the requirements of various constraint combinations. The problem is that typical real-life scenarios in design and planning have vast numbers of alternative solutions. Therefore, MOO techniques will be advantageous to discover a broader range of solutions, especially where it is not specified initially which of

2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC) | 978-1-6654-1490-6/21/$31.00 ©2021 IEEE | DOI: 10.1109/CCWC51732.2021.9376078

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the various objectives must be prioritized when seeking solutions since pre-specification of this preference is not required [10].

In recent years, the real world, along with its various problems, has become increasingly complex, and as a consequence, it is necessary to apply metaheuristic techniques that are better able to address these scenarios. Such algorithms are now routinely applied to find optimal solutions in situations involving engineering design. Their use has risen in popularity due to their ability to handle complex real-life scenarios efficiently in a manner superior to that of traditional classical approaches [11].

There are four main metaheuristic classes, based on the underlying form of inspiration taken by each type. These four types can be listed as follows: Swarm Intelligence (SI), Evolutionary Algorithm (EA), Physical Algorithms, and Human Algorithms [12-13].

The typical EA has its basis in natural Darwinian evolution, and it mimics the evolutionary biological processes of recombination, mutation, and selection. Examples of this type include the Genetic Algorithm (GA) [14] and Differential Evolution (DE) [15]. SI is based on how animal groups behave naturally, whether migrating, hunting, or seeking a mate. One widely applied example is Particle Swarm Optimization (PSO) [16], while the Spotted Hyena Optimizer (SHO) [17] is also gaining attention, along with the Jellyfish Sear

II. Methodology

A. Spotted Hyena Optimizer (SHO)

The SHO [17] is based on spotted hyena packs' activity as they converge upon their prey [17]. The animals operate in groups and work together to locate their prey, surround it, and launch their attack. The algorithm, therefore, models this behavior as it searches for optimal solutions, shown Fig.1 [17].

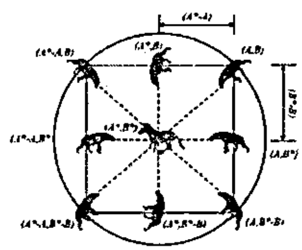

Fig. 1. The locational updates mechanism for the search agent, when (A, B) its initial position and (A^*, B^*) updates its position of prey [17].

In the course of the search process, the best candidate solution at any given point can take the role of the prey, which acts as a solution close to the optimum since there is no prior knowledge of the search space [24]. The SHO assumes that the elite search agent is aware of the prey's whereabouts, while the other individuals will seek to make positional updates by forming a cluster-based around the elite agent. Earlier studies have detailed the equations which govern the activity of the SHO [25–27]. The mathematical modeling of the phase where the prey is surrounded during the optimization follows the equations given below [17],[25]:

$$\vec{D}_h = \left|\vec{B}\cdot\vec{P}_p(t) - \vec{P}(t)\right| \tag{1}$$

$$\vec{P}(t+1) = \vec{P}_p(t) - \vec{E}\cdot\vec{D}_h \tag{2}$$

in which t indicates the present iteration, $\vec{B}$ and $\vec{E}$ acts as the coefficient vectors, $\vec{P}_p$ represents the prey position vector, $\vec{P}$ represents the spotted hyena position vector, $\vec{D}_h$ shows the distance between the hyena and the prey, and $|\ |$ indicates the absolute value and vector multiplication [17], [25].

The coefficient vectors given by $\vec{B}$, $\vec{E}$ can be determined as shown [17], [25].

$$\vec{B} = 2\cdot\Phi\vec{d}_1 \tag{3}$$

$$\vec{E} = 2\vec{h}\cdot\Phi\vec{d}_2 - \vec{h} \tag{4}$$

$$\vec{h} = 5 - \left(t*\left(\frac{5}{T}\right)\right) \tag{5}$$

in which $t = 1,2,3,\dots,T$ arranged to achieve a balance of exploration and exploitation, while $\vec{h}$ decreases in a linear fashion from 5 to 0 as the iterations progress, and $\Phi\vec{d}_1$, $\Phi\vec{d}_2$ serve as random vectors in $[0,1]$ [17], [25].

To replicate the hunting activity of the hyenas in mathematical form, it is assumed that the best search agent is the optimum, representing the prey location, while the other search agents undergo a process of position updating as they approach the best solution, which is then saved. Mathematically, the following equations convey this process [17], [25].

$$\vec{D}_h = \left|\vec{B}\cdot\vec{P}_h - \vec{P}_k\right| \tag{6}$$

$$\vec{P}_k = \vec{P}_h - \vec{E}\cdot\vec{D}_h \tag{7}$$

$$\vec{C}_h = \vec{P}_k + \vec{P}_{k+1} + \dots + \vec{P}_{k+N} \tag{8}$$

$$N = c_{nos}\left(\vec{P}_h, \vec{P}_{h+1}, \vec{P}_{h+2}, \dots, \left(\vec{P}_h + \vec{M}\right)\right) \tag{9}$$

Initially, $\vec{P}_h$ it shows the location of the best hyena, $\vec{P}_k$ shows the location of other hyenas, N reveals the total number of hyenas, $\vec{M}$ acts as a random vector $[0.5,1]$, nos indicates how many solutions there are, c_{nos} is the count of the candidate solutions, $\vec{C}_h$ indicates a cluster containing N optimal solutions [17],[25].

To formulate the mathematical model describing the attack upon the prey, the equation given below is applied [17], [25].

$$\vec{P}(t+1) = \frac{\vec{C}_h}{N} \tag{10}$$

$\vec{P}(t+1)$ indicates the current best solution while giving updates of the other search agent positions relative to that of the best agent, and as the hyena attack upon the prey takes place, the positions are updated continuously [17],[25].

Based on the various approximations, the steps required for the SHO can be simplified to create the SHO algorithm, for which the pseudo-code is indicated, as shown below [17],[25].

SHO algorithm [17],[25]

1. Determine the spotted hyena population P_i $(i=1,2,\ldots,n)$
2. Initialize h, B, E and N
3. Determine the fitness for each of the search agents
4. $\vec{P}_h$ = the best search agent
5. $\vec{C}_h$ =the group or cluster of all far optimal solutions
6. **While** (t < Max number of iterations) do
7. **for** each search agent, do
8. Update the position of the current search agent by Eq. (10)
9. **End for**
10. Update h, B, E and N
11. Assess whether any search agent extends beyond the search space and make the necessary alterations
12. Assess the fitness for each of the search agents
13. Assess $\vec{P}_h$ and determine whether a superior solution can be found using Eq. (6) and Eq. (7)
14. $t=t+1$
15. **end while**
16. Return $\vec{P}_h$

B. Optimization formulation

This study investigates the use of SHO with both SOO and MOO problems. The MOO process generates a set of solutions that are non-determined and known as a Pareto optimal set. Each of these sets is based on a compromise between the stated objectives and represents an option that the user can choose when considering the prioritization of different objectives based on the specific circumstances faced in any given project. In general, the MOO problem can be set out, as shown below [28]:

$$\left.\begin{array}{lll} \text{min/max:} & f_i(x) & i=1,2,\ldots,l \\ \text{Subject to:} & g_j(x)=0 & j=1,2,\ldots,m \\ & h_k(x)\geq 0 & k=1,2,\ldots,p \\ & X=(x_1,x_2,\ldots,x_n)^T & \end{array}\right\} \quad (11)$$

Where $f_i(x)$ indicates the k^{th} objective function, and min/max denotes the combination of object operations. Moreover, k it refers to the total number of functions of the criteria. It is the decision vector, while X it serves as the column vector representing the n independent variables. $g_j(x)=0$ indicate equality constraints while $h_k(x)\geq 0$ serving as inequality constraints. In the absence of friction arising objective functions, it is possible to reach a solution for which all of the stated objective function will be optimized. However, to eliminate trivial cases, there is the assumption that no single solution exists, which will be optimal for all objective functions. From this, it can be inferred that there must be a certain degree of conflict among the objective functions, which will also be expressed using different units.

In this research, the MOO-SHO, which can be solved through the weighted sum method (WSM), which changes MOO problems into aggregated scalar objective functions, which is achieved by multiplication of each of the objective functions by a weighting factor, followed by determining the sum of all the terms, as shown Eq. (12) [29-33]:

$$\min/\max_{x\in U} \quad z=\sum_{k=1}^{k} w_k f_k(x) \qquad (12)$$

This research has three fitness functions shown in Eq. (13-15), which can be expressed:

$$\max f_E\left(\eta_{E,condenser}, \eta_{E,turbogenerator}, \eta_{E,boiler}\right) \qquad (13)$$

$$\max f_\varepsilon\left(\eta_{\varepsilon,condenser}, \eta_{\varepsilon,turbogenerator}, \eta_{\varepsilon,boiler}\right) \qquad (14)$$

$$\min f_c\left(C_{condenser}, C_{turbogenerator}, C_{boiler}\right) \qquad (15)$$

In which the average enthalpy efficiency, average exergy efficiency, and the overall cost shown as a symbol f_E, f_ε, f_c, respectively.

C. Cogeneration power plant (CGPP) problem

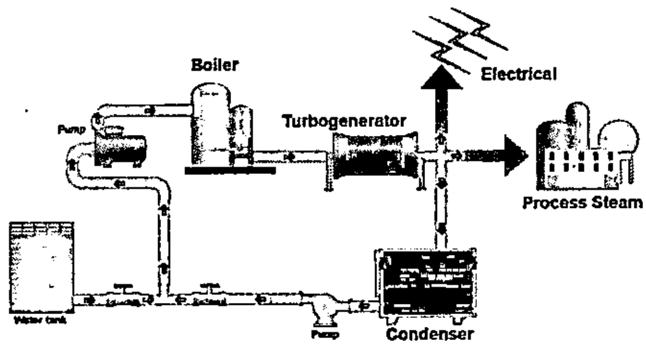

Fig. 2. CGPP configuration.

The configuration for the CGPP is presented in Fig. 2 and shows the various components, including the condenser, the turbogenerator, the boiler, and the transformer. As the operational process takes place, the water, and natural gas initially enter the boiler, proceeding to the turbine, connected to the generator to produce electricity. For each of these processes, the steady-state and steady-flow conditions must be taken into consideration.

- Energy analysis

Using the first law of thermodynamics, it is thus possible to calculate the enthalpy efficiency (η_E) for each of the key equipment items using the equation:

$$\eta_E=\left(\frac{\sum Enthalpy\ output}{\sum Enthalpy\ input}\right)\times 100 \qquad (16)$$

- Exergy analysis

Using the second law of thermodynamics, it is possible to calculate the enthalpy efficiency (η_ε) for each of the key equipment items through the application of:

$$\eta_{\varepsilon} = \left(\frac{\sum Exergy\ output}{\sum Exergy\ input} \right) \times 100 \tag{17}$$

- Economics Evaluation

1. Cost of condenser [33]

$$C_{condenser} = A_{condenser}^{1.01} \times 280 \tag{18}$$

Where $A_{condenser}$ is the heat transfer area on the condenser (m^2)

2. Cost of turbogenerator [34-35]

$$C_{turbogenerator} = \frac{\left(560 \times P_{ts}^{0.45}\right) + \left(c_0 \times \frac{w_{elec}}{w_{elec,0}}\right)^{0.67}}{1.18} \tag{19}$$

Where w_{elec} is power electrical (kW)

$w_{elec,0}$ is power electrical at reference (kW)

P_{ts} is the turbine shaft power output (kJ/h)

c_0 is the cost correlations at reference condition ($USD)

3. Cost of boiler [34]

$$C_{boiler} = 3 \times Q_b^{0.77} \times N_{FP} \times N_{FT} \tag{20}$$

Where Q_b is the boiler heat require (kJ/h)

N_{FP} is the operating pressure factor

N_{FT} is a superheat temperature factor

D. SHO algorithm Validation

Before applying the SHO algorithm, it must undergo validation, which can be carried out via MATLAB software V.2020a. The process used a population of 50, with 1000 iterations, while the SHO parameters can be found in [17].

Accordingly, two well-known functions of the benchmark function problem [36] underwent testing: unimodal (Function 1) and multimodal (Function 2).

Function 1: Step function is a unimodal function for which the minimum solution 0 is located $f_1(x^*) = [0,0,...,0]$ while the values lie within the range of $[-100,100]$.

$$f_1(x) = \sum_{i=1}^{n} \left(x_i + 0.5\right)^2 \tag{21}$$

in which the values of $n = 100$

Function 2: Penalized-1 function serves as a problematic multimodal function. The global optimum 0 has the location $f_2(x^*) = [1,1,...,1]$ within the domain of [-50,50]. The mathematical representation of the Penalized-1 function is shown as follows:

$$f_2(x) = \frac{\pi}{D}\left\{10\sin^2(\pi y_1) + \sum_{i=1}^{D-1}(y_i - 1)^2\left[1 + 10\sin^2(\pi y_{i+1})\right] + (y_D - 1)^2\right\} + \sum_{i=1}^{D} u_i \tag{22}$$

$$u_i = \begin{cases} k\left(x_i - a\right)^n & x_i > a \\ 0 & a \le x_i \le a \\ k\left(-x_i - a\right)^n & x_i < -a \end{cases} \tag{23}$$

$$y = 1 + \frac{(x_i + 1)}{4} \tag{24}$$

in which the parameter values are set to be $D = 20, k = 100$, $a = 10$, and $n = 4$.

III. Results and Discussion

A. Validation of the algorithm

The 30 reliability tests using the SHO algorithm conclude that the SHO algorithm can be applied to seek solutions and determine the global optima or near-global optima for all formula types. As indicated by the standard deviation, the test robustness may be summarized using the statistical findings shown in Table 1.

TABLE I. STATISTICAL DATA

Function	Mean	Best	Worst	St.dev.
Step	0.0088	0	0.2486	0.0454
Penalized	0.0001	0	0.0022	0.0004

B. Comparing the SOO and MOO options using SHO algorithm

To evaluate the running performance, the test would be run 30 times for each option using the same fitness for the first iteration according to the SHO algorithm. When the four options were examined, the SOO tests were η_E, η_{ε}, C_C options while the MOO test was performed to compare the performance. The resulting scatter plot for the correlation is shown in Fig. 3, using a bar for each option. The SOO test η_E appears in Fig.3(a) and the MOO value for enthalpy's average efficiency. Consequently, the SOO η_{ε} option and the MOO provide quite similar values at 79.05% to 83.16%. In contrast, the SOO C_C option provides the worst average efficiency of enthalpy value at 65.21% to 71.29%.

In Fig. 3(b), the MOO for average efficiency of exergy achieves a maximum value at 38.05%, while running the SOO η_{ε} provides the best outcome at 37.79%. It can thus be inferred that the MOO searching solution is preferable to that of the SOO η_{ε} option and the alternative SOO. Fig. 3(c) shows more excellent value in running the MOO for overall costs than the SOO for cost options. However, the SOO's enthalpy and exergy values and efficiencies are low, while overall cost value saves. The temperature used is also low, and therefore the values for energy consumption, enthalpy, and exergy efficiency are also low due to the relationship between these factors.

Data for the mean and st. dev. for the average efficiency of enthalpy, the average efficiency of exergy, and the overall cost for both MOO and SOO options can be observed in Table 2, from which it can be determined that the MOO testing approach provides an acceptable mean and robust st. dev.

The difference between the MOO and SOO options lies in the search solution capacity. Only one objective function will be suitable for solving the SOO problem because SOO can find only one function globally optimized, but the other two objective functions are local optima points. However, multiple objective functions will arise to meet MOO because MOO can find the global optima point or near-global point of all objective functions.

TABLE II. STATISTICAL DATA OF EACH OPTION

Option	$\eta_{E_{Average}}$,% (Mean/St.dev.)	$\eta_{\varepsilon_{Average}}$,% (Mean/St.dev.)	$Cost_{overall}$ (x10E7), $USD (Mean/St.dev.)
MOO	79.05-82.43 (81.54/0.75)	35.31-38.05 (37.03/0.56)	2.79-2.93 (2.87/0.0512)
SOO f_E	82.11-83.16 (82.79/0.29)	31.73-36.50 (33.82/1.46)	2.88-2.92 (2.90/0.00817)
SOO f_ε	80.78-82.59 (81.66/0.50)	36.47-37.79 (37.22/0.35)	2.80-2.93 (2.88/0.0318)
SOO f_c	65.21-71.29 (67.86/1.13)	30.04-35.89 (33.18/1.13)	1.68-1.80 (1.73/0.0248)

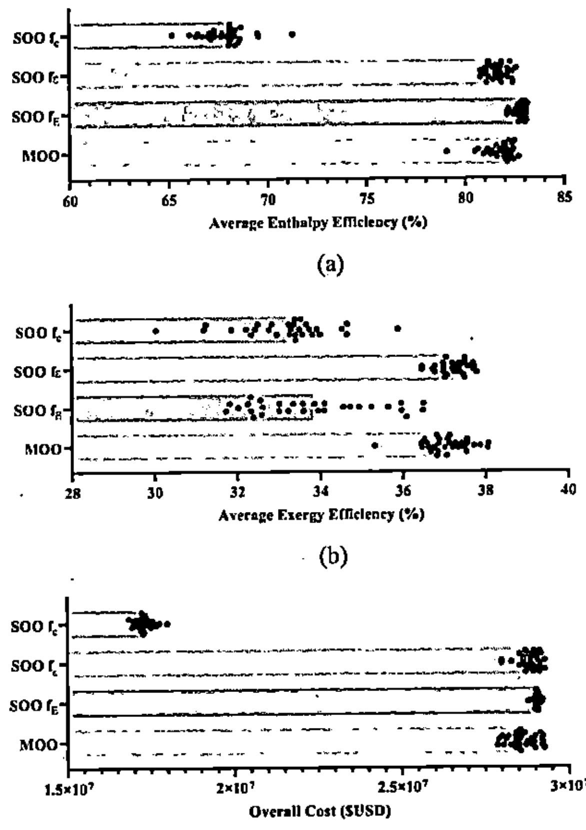

Fig. 3. The individual scatters plot values using column bars for each option via SHO (a) average enthalpy efficiency, (b) average exergy efficiency, (c) overall cost.

IV. CONCLUSION

In this paper, a CGPP system was evaluated using a single and multi-objective optimization structure to minimize cost, maximize energy efficiency, and simultaneously maximize exergy efficiency. A novel balanced model of the spotted Hyena Optimizer (SHO) algorithm was used to perform the optimization to achieve these aims.

The varying attributes and efficiencies of the proposed methods were assessed by comparing the algorithm performance when addressing SOO and MOO problems with the CGPP under specified constraints. For the optimal average energy and exergy efficiency, MOO-SHO achieved respective values of 82.43% and 38.05%, while the optimal overall equipment cost for the CGPP system was $USD 2.79 x 10E7. In comparison, the SOO-SHO achieved 83.16% and 37.79% values for energy and exergy efficiency, with a total cost of $USD 1.68 x 10E7. Therefore, it was concluded that when the SOO-SHO was used to optimize the CGPP system, there could not be a single optimal solution where the objectives were contradictory since no single value could simultaneously address all of these objectives. Where the MOO-SHO approach is used, sets of solutions will be generated, superior to other alternatives within a particular search space concerning the specified objectives. However, when only one of the objectives is examined, the solutions generated may not be optimal. This is also true when considering a small subset of the entire set of objectives overall. Thus, it can be demonstrated that when the constraints are relaxed, it is possible to generate an appropriate MOO function for the CGPP system.

ACKNOWLEDGMENT

This research was supported by the Rajamangala University of Technology Thanyaburi (RMUTT).

REFERENCES

[1] A. Pouria, I. Dincer, and M.A. Rosen, "Exergy, exergoeconomic and environmental analyses and evolutionary algorithm based multi-objective optimization of combined cycle power plants", Energy. vol.36, no.10,pp.5886-5898, 2011.

[2] K. Shoaib, A. R. Azimian, and S. Khanmohammadi, "Exergy and exergo–economic evaluation of Isfahan steam power plant", International Journal of Exergy. vol.12, no. 2, pp.249-272, 2013.

[3] K. Ravinder, "A critical review on energy, exergy, exergoeconomic and economic (4-E) analysis of thermal power plants", Engineering Science and Technology, an International Journal. vol.20, no. 1,pp. 283-292, 2017.

[4] A. Gholamreza, D. Toghraie, and O. Akbari, "Energy, exergy and environmental (3E) analysis of the existing CHP system in a petrochemical plant", Renewable and Sustainable Energy Reviews. vol.99, pp.234-242, 2019.

[5] K. Hüseyin, Z. Recebli, and E. Gedik, "Performance analysis of open cycle gas turbines", International Journal of Energy Research. vol.33, no. 3, pp.285-294, 2009.

[6] A. Mozafari, A. E. M. A. Ahmadi, and M. A. Ehyaei, "Optimisation of micro gas turbine by exergy, economic and environmental (3E) analysis", International Journal of Exergy. vol.7, no.1, pp.1-19, 2010.

[7] MJ. Ebadi, MB. Gorji, "Exergetic analysis of gas turbine plants", International Journal of Exergy.vol.2, no.1, pp.285-90, 2005.

[8] K. T. Jozef. The exergy method of thermal plant analysis. Elsevier, 2013.

[9] A. Pouria, I. Dincer, and M. A. Rosen. "Exergy, exergoeconomic and environmental analyses and evolutionary algorithm based multi-objective optimization of combined cycle power plants", Energy. vol.36, no.10, pp.5886-5898, 2011.

[10] S. Dragan, "Single-objective vs. multiobjective optimisation for integrated decision support", 2002.

[11] K. Vijay, J. K. Chhabra, and D. Kumar, "Parameter adaptive harmony search algorithm for unimodal and multimodal optimization problems", Journal of Computational Science. vol.5, no. 2, pp.144-155, 2014.

[12] M. Seyedali, S. M. Mirjalili, and A. Hatamlou, "Multi-verse optimizer: a nature-inspired algorithm for global optimization", Neural Computing and Applications. vol.27, no. 2, pp. 495-513, 2016.

[13] B. Esref, and S. Beyhan, "Adolescent Identity Search Algorithm (AISA): A novel metaheuristic approach for solving optimization problems" Applied Soft Computing. vol.95, 2020.

[14] H. J. Henry, Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. MIT press, 1992.

[15] S. Rainer, and K. Price, "Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces", Journal of global optimization. vol.11, no. 4, pp. 341-359, 1997.

[16] K. James, and R. Eberhart, "Particle swarm optimization", In Proceedings of ICNN'95-International Conference on Neural Networks. vol. 4, pp. 1942-1948. IEEE, 1995.

[17] D. Gaurav, and V. Kumar, "Spotted hyena optimizer: a novel bio-inspired based metaheuristic technique for engineering applications", Advances in Engineering Software. vol.114, pp. 48-70, 2017.

[18] C. Jui-Sheng, and D. Truong, "A novel metaheuristic optimizer inspired by behavior of jellyfish in ocean", Applied Mathematics and Computation. vol.389, pp.125535.

[19] K. Scott, C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing", vol.220, no. 4598, pp.671-680, 1983.

[20] F. A. Hashim, E. H. Houssein, M. S. Mabrouk, W. Al-Atabany, and S. Mirjalili, "Henry gas solubility optimization: A novel physics-based algorithm", Future Generation Computer Systems. vol.101, pp. 646-667, 2019.

[21] G. Fred, "Future paths for integer programming and links to artificial intelli- gence", Computers operations research. vol.13, no. 5, pp. 533-549, 1986.

[22] R. R. Venkata, V. J. Savsani, and D. P. Vakharia, "Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems", Computer-Aided Design. vol.43, no. 3, pp. 303-315, 2011.

[23] Z. Yiying, and Z. Jin, "Group teaching optimization algorithm: A novel metaheuristic method for solving global optimization problems", Expert Systems with Applications. vol.148, 2020.

[24] D. Gaurav, and V. Kumar, "Multi-objective spotted hyena optimizer: a multi-objective optimization algorithm for engineering problems", Knowledge-Based Systems. vol.150, pp.175-197, 2018.

[25] L. Qifang, J. Li, and Y. Zhou, "Spotted hyena optimizer with lateral inhibition for image matching", Multimedia Tools and Applications. vol.78, no. 24, pp. 34277-34296, 2019.

[26] J. Heming, J. Li, W. Song, X. Peng, C. Lang, and Y. Li, "Spotted hyena optimization algorithm with simulated annealing for feature selection", IEEE Access. vol.7, pp.71943-71962, 2019.

[27] K. Amandeep, S. Kaur, and G. Dhiman, "A quantum method for dynamic nonlinear programming technique using Schrödinger equation and Monte Carlo approach", Modern Physics Letters. vol.32, no. 30, 2018.

[28] D. Kalyanmoy, Multi-objective optimization using evolutionary algorithms. Vol. 16. John Wiley & Sons, 2001.

[29] E. Matthias, Multicriteria optimization. Vol. 491. Springer Science & Business Media, 2005.

[30] J. S. Dodgson, M. Spackman, A. Pearman, and L. D. Phillips. "Multi-criteria analysis: a manual", 2009.

[31] I. Y. Kim, O. L. De Weck, "Adaptive weighted-sum method for bi-objective optimization: Pareto front generation", Structural and multidisciplinary optimization. vol.29, no.2, pp.149-158, 2005.

[32] G. Nyoman, "A review of multi-objective optimization: Methods and its applications", Cogent Engineering. vol.5, no.1, 2018.

[33] A. Muammer, "Thermoeconomic Optimisation of Steam Condenser for Combined Cycle Power Plant", International Journal of Science and Engineering Applications. vol.6, no.3, pp. 70-75, 2017.

[34] H. S. Bamufleh, J. M. Ponce-Ortega, and M. M. El-Halwagi, "Multi-objective optimization of process cogeneration systems with economic, environmental, and social tradeoffs", Clean Technologies and Environmental Policy. vol.15, no. 1, pp.185-197, 2013.

[35] A. Marco, M. C. Romano, P. Bombarda, and E. Macchi, "Binary ORC (Organic Rankine Cycles) power plants for the exploitation of medium–low temperature geothermal sources–Part B: Techno-economic optimization", Energy. vol.66, pp. 435-446, 2014.

[36] H. Kashif, M. N. M. Salleh, S. Cheng, and R. Naseem, "Common benchmark functions for metaheuristic evaluation: A review", JOIV: International Journal on Informatics Visualization. vol.1, no. 4-2, pp. 218-223, 2017.

2021 IEEE 11th Annual Computing and Communication Workshop and Conference, CCWC 2021 • Pages 1 - 5 • 27 January 2021 • Article number 9376078 • 11th IEEE Annual Computing and Communication Workshop and Conference, CCWC 2021, Virtual, Las Vegas, 27 January 2021 - 30 January 2021, 167930

Document type
Conference Paper

Source type
Conference Proceedings

ISBN
978-073814394-1

DOI
10.1109/CCWC51732.2021.9376078

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Application of Spotted Hyena Optimizer in Cogeneration Power Plant on Single and Multiple-Objective

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Abstract

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In this paper, a Spotted Hyena Optimizer (SHO) is employed in the context of addressing a

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ISBN: 978-0-7381-4394-1

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