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A Novel Horse Herd Optimization Algorithm for Optimal Economic Dispatch in Sulbagsel Electricity System

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Abstract: This study investigates the optimization of generation costs for thermal power plants in the South Sulawesi (Sulbagsel) electricity system in Indonesia. The novel swarm intelligence method, the horse herding optimization algorithm (HHOA), is inspired by the social behavior of horses within herds across different age groups. HHOA is a new metaheuristic algorithm recognized for its high efficiency in exploration and exploitation. The primary objective of the HHOA method is to minimize generation costs. To evaluate the effectiveness of the proposed method, similar swarm intelligence techniques, namely particle swarm optimization (PSO) and whale optimization algorithm (WOA), are also employed. Statistical analysis demonstrates that HHOA offers superior exploration and exploitation capabilities, along with strong consistency and accuracy. The optimization results for thermal generation costs during mid-day peak loads indicate that the PSO method reduces costs by 23.78%, the WOA method by 23.02%, while the HHOA-based method achieves a reduction of 24.23%.

Keywords: Economic dispatch, Sulbagsel electricity system, HHOA, Generator, Cost.

1. Introduction

At a power generation facility, efficient management is essential for controlling both the load and the power output that generators must supply to the system [1]. Effective operational management is particularly crucial in thermal power plants, which use fuel to drive turbines [2]. Economic Dispatch (ED) involves calculating the generation levels required to minimize the total cost of power production for a given load demand. Finding the optimal solution for ED is vital for ensuring sustainability in the power system. It focuses on minimizing delivery costs, balancing demand and supply, and adhering to constraints such as generation capacity limits [3].

Several methods were initially developed for ED solutions, including iterative techniques [4], gradient-based methods [5], and projection methods [6]. Traditional methods require continuously differentiable and convex cost functions. However, these approaches cannot handle functions involving ramp rate limits (RRL), prohibited operating zones (POZ), and valve point loading (VPL), as these constraints make the functions non-convex [7]. This limitation underscores the need for developing intelligent methods to address ED more effectively.

Over the past two years, researchers have developed several advanced swarm intelligence techniques to address ED problems. Study [8] proposes a strategy using power and load forecasting models based on the Salp Swarm Algorithm (SSA). The case study involves a test scenario with 40 thermal generator units, energy storage systems, and photovoltaic (PV) systems. The experimental results highlight the effectiveness of the proposed framework across various levels of PV penetration. In study [9], the optimal measurement of Distributed Energy Resources (DER) in an isolated microgrid test system was conducted to reduce generation costs. The Hybrid Modified Grey Wolf Optimizer and Crow Search Algorithm (MGWOCSA) was used for optimization, showing superior performance by effectively minimizing both costs and emissions while consuming minimal computational time. Study [10] presents a new method based on Termite Colony Optimization (TCO) to solve ED problems in test cases with 5, 10, and 30 units. TCO proves highly effective and advantageous for addressing both small-scale (5 and 10 units) and medium-scale (30 units) ED problems. Paper [11] introduces a recent metaheuristic called the Stochastic Shaking Algorithm (SSA) for addressing ED problems in a test case with 13 generators of various energy resources. Paper [12] develops a new technique known as Cohesive Swarm Intelligence Bat Optimization (CSIBO) to tackle economic load dispatch (ELD) problems in power systems. This study investigates various power generation sources, including fuel cells, wind turbines, and PV systems. The results indicate that the proposed CSIBO outperforms alternative methods, delivering superior outcomes for each renewable energy source (RES). Overall, these studies highlight the significant results achieved through the application of swarm intelligence methods to solve ED problems. However, most evaluations are conducted using test cases, which may not fully represent real-world conditions.

The South Sulawesi system (Sulbagsel), formerly known as Sulselrabar, is part of the Sulawesi province in Indonesia [13]. Operating at 150 kV, this system includes 57 transmission networks connecting various load centers such as Makassar, Maros, Pangkep, Barru, and others. It consists of 46 buses and several thermal power plants. Several studies have explored ED optimization in the Sulbagsel system. Study [14] proposed using the Particle Swarm Optimization (PSO) method, which successfully reduced thermal generation costs by 7.9%. Study [15] applied the Modified Improved Particle Swarm Optimization (MIPSO) algorithm, achieving a 13.73% reduction in generation costs. Study [16] employed the Ant Colony Optimization (ACO) method, which demonstrated a reduction of 6.62% in generation costs. Given the increasing complexity of the Sulbagsel system, there is a clear need for ongoing analysis to evaluate its performance. This motivates our review of the optimal ED of thermal generation in the real Sulbagsel system using the most recent data.

Swarm Intelligence (SI) studies the collective behavior of natural systems where numerous agents work together. Recently, a new SI technique, the Horse Herd Optimization Algorithm (HHOA), was developed by Farid MiarNaeimi [17]. HHOA is inspired by the social behavior of horses of different ages and incorporates six key traits: grazing, pecking order, sociability, imitation, protection mechanisms, and roaming. It is recognized as a fast and robust optimization algorithm [18, 19] and has been explored in power system optimization, particularly for ED. In study [20], HHOA was applied to various ED test cases, including systems with 40, 10, and 280 units, with multiple fuels and valve-point effects, as well as a 140-unit Korean system. Comparative and statistical analyses showed that HHOA achieved superior results compared to several Differential Evolution (DE) algorithms. Study [21] recommended HHOA for solving ED problems involving demand-side management, integrating wind turbine generators, photovoltaic solar power plants, and pumped hydro storage plants across three different scenarios. In study [22], HHOA was developed to address dynamic multi-area ED problems. The three-region test system, which included Wind Turbine Generators (WTGs), solar PV plants, and Pumped Hydro Storage (PHS) plants, demonstrated that HHOA delivered better solutions compared to other methods. Based on the research into HHOA's application for ED problems, there is a need for a comprehensive study on real systems to ensure optimal implementation. This motivates our exploration of HHOA's performance in solving ED problems to achieve the lowest generation costs for the Sulbagsel system.

The main contributions of this research are:

1) Assessing optimal ED for thermal generation in the Sulbagsel system, while considering generation limits and ensuring that load demands are met, with both equality and inequality constraints.
2) Exploring the performance of HHOA in optimizing ED for the Sulbagsel system.

The organization of this paper is as follows: Section II provides an overview of ED and the Sulbagsel system; Section III outlines the research method; Section IV presents the results; and Section V concludes the study.

2. Economic dispatch problem

This section discusses the formulation of ED theory and the test systems used in this research.

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2.1. Economic dispatch

An electrical power system consists of multiple generating units. While transmission losses can be disregarded in distribution among nearby generators, it is crucial to recognize that actual transmission losses do occur. If these losses are ignored, the cost of fuel consumption and electricity generation can be represented by Eqs. (1) to (3) [23].

$$F_T = F_a P_a + F_b P_b + F_c P_c \tag{1}$$

$$P_R = P_r \tag{2}$$

$$P_T = P_a + P_b + P_c \tag{3}$$

F_T represents the fuel consumption (Rp/hr), P_T is the total output power of the generators (MW), and P_R is the system load (MW).

Economic Characteristics

The input-output characteristics of thermal generators indicate that fuel costs increase with higher output power. These characteristics are represented by Eq. (4).

$$H_n = \alpha_n + \beta_n P_n + \gamma_n P_n^2 \tag{4}$$

H_n is the fuel input of the generator (L/hr) and P_n is the output of the generator (MW). α_n, β_n, and γ_n are the input-output constants for the n-th unit generator. To determine the values of $\alpha_n, \beta_n, \gamma_n$, fuel cost parameters and output power data for a specific generator must be used. The data were analyzed using the least squares regression method to derive a specific function based on the observed data.

Optimal Economic Dispatch

The solution to ED considers the capacity of each generator. Optimal operation must address both equality and inequality constraints [24], [25]. The equality constraint ensures that the total power generated by all generators meets the load demand plus transmission losses, as shown in Eq. (5). Loss coefficients can be considered constant despite variations in the output power of each generator within the system [26].

$$\sum_{i=1}^{N} P_i = P_R + P_L \tag{5}$$

P_i is the output power of the generator (MW), P_R is the total load (MW), and P_L is the transmission losses (MW).

The inequality constraint ensures that the generator's output power remains within specified limits, meaning it is not less than the minimum permitted power and does not exceed the maximum permitted power. This is represented by Eqs. (6) and (7).

$$P_{i\,min} \leq P_i \leq P_{i\,max} \tag{6}$$

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{i0} P_j + B_{00} \tag{7}$$

B_{ij} represents the loss coefficients, B_{i0} and B_{00} are constants related to the losses. The loss coefficients were assumed to be constant for changes in output power.

2.2. Sulbagsel electricity system

This study utilizes the most recent data from the Sulbagsel electricity system, which includes 15 generators, 57 transmission lines connecting major

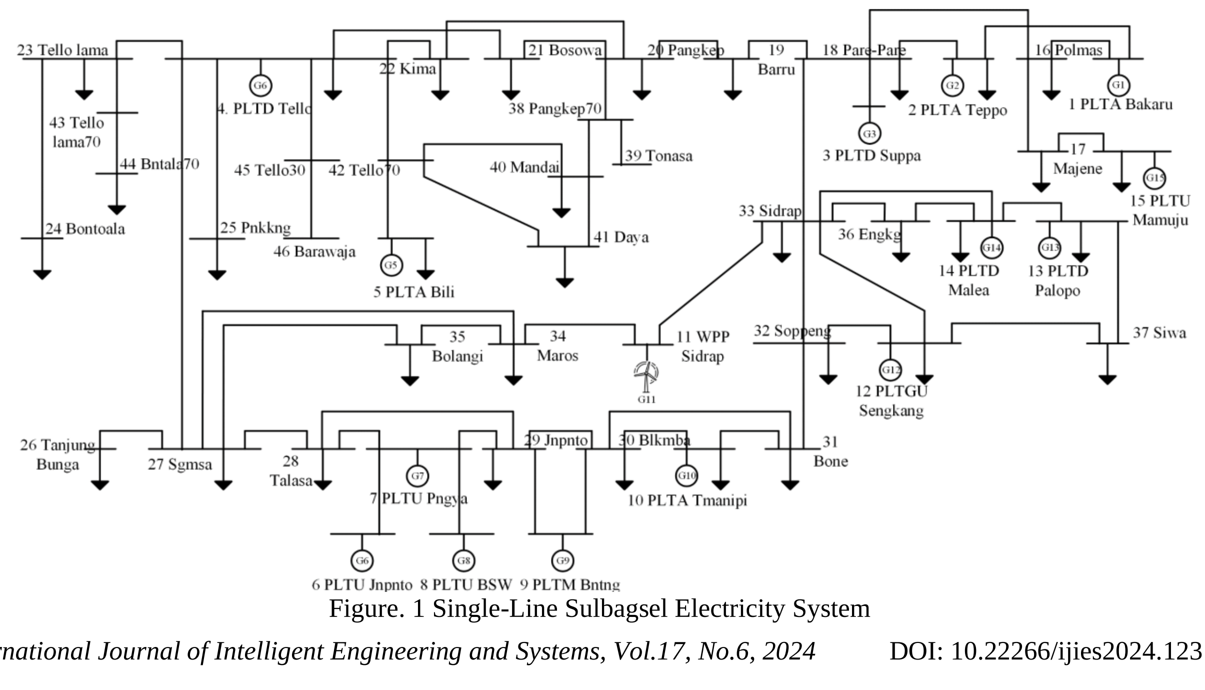

Figure. 1 Single-Line Sulbagsel Electricity System

load centers, and current daily operational data. The system operates at a voltage of 150 kV and includes 46 buses [27]. Fig. 1 presents a single-line diagram of the Sulbagsel electricity system [28].

3. Research method

This section outlines the formulation of the proposed method and the objective function used.

3.1. Horse Herd Optimization Algorithm (HHOA)

HHOA mimics the behavior of horse herds of different ages. Horse behavior is categorized into six general types: Grazing, Hierarchy, Sociability, Imitation, Defense Mechanism, and Roaming [17]. To update the position and speed of the horses, Eq. 8 is used.

$$X_i^{Iter,Age} = V_i^{Iter,Age} + X_I^{(Iter-1),Age} \tag{8}$$

Age = α,β,γ,δ

where, signifies the position of the *k* th horse, *Age* and $\overline{V}_k^{Age,Itr}$ denote the age range and velocity vector of the horse in question, and *Itr* indicates the current iteration.

In the model, $X_i^{Iter,Age}$ represents the position of the *i*-th horse, $V_i^{Iter,Age}$ denotes its velocity vector, and Age indicates the horse's age range. Horses are classified into four age groups: Alfa (α), Beta (β), Gamma (γ), and Delta (δ). The classification is as follows: Delta for horses aged 0 to 5 years, Gamma for those aged 5 to 10 years, Beta for horses aged 10 to 15 years, and Alpha for horses older than 15 years. For each iteration, a comprehensive response matrix must be generated to select the age of the horses. This matrix is then sorted based on the appropriate response. The top 10% in the sorted matrix are classified as Alpha horses, the next 20% as Beta horses, with the remaining horses distributed as approximately 30% Gamma and 40% Delta. The velocity vector is determined by mathematically simulating the six behaviors of horses.

Eq. (9) can be expressed as a motion vector in the HHOA, incorporating the behavioral patterns of horses with different ages as described above.

$$\begin{aligned} V_i^{Iter,\alpha} &= G_i^{Iter,\alpha} + D_i^{Iter,\alpha} \\ V_i^{Iter,\beta} &= G_i^{Iter,\beta} + H_i^{Iter,\beta} + S_i^{Iter,\beta} + D_i^{Iter,\beta} \\ V_i^{Iter,\gamma} &= G_i^{Iter,\gamma} + H_i^{Iter,\gamma} + S_i^{Iter,\gamma} + I_i^{Iter,\gamma} + D_i^{Iter,\gamma} + R_i^{Iter,\gamma} \\ V_i^{Iter,\delta} &= G_i^{Iter,\delta} + I_i^{Iter,\delta} + R_i^{Iter,\delta} \end{aligned} \tag{9}$$

3.1.1. Grazing (G)

One of the most common horse behaviors is grazing, which occurs at any age throughout their lives. Eqs. (10) and (11) provide the mathematical framework for describing grazing.

$$G_i^{Iter,Age} = g_{iter}\left(\breve{u} + p\breve{l}\right)\left[X_i^{(Iter-1)}\right] \tag{10}$$

Age = α,β,γ,δ

$$g_i^{Iter,Age} = g_i^{(Iter-1),Age} x\omega_g \tag{11}$$

Where $G_i^{Iter,Age}$ represents the movement of the i_{th} shows their tendency to graze.

3.1.2. Hierarchy (H)

In the wild, horses form herds to protect themselves from predators. Within these herds, they exhibit hierarchical behavior, with an adult stallion typically serving as the leader. The parameter *h* represents the inclination of all horses in the herd to follow the strongest and oldest horse. This hierarchical behavior is observed in horses aged between 5 and 15 years, as outlined in Eqs. (12) and (13).

$$H_i^{Iter,Age} = h_i^{Iter,Age}\left[X_*^{(Iter-1)} - X_i^{(Iter-1)}\right] \tag{12}$$

Age = α,β, γ

$$h_i^{Iter,Age} = h_i^{(Iter-1),Age} x\omega_h \tag{13}$$

Where, $H_k^{Age,Itr}$ represents the best horse position, $X_*^{(Itr-1)}$ shows how the best horse position affects the velocity vector.

3.1.3. Hierarchy (H)

Horses are social animals and can learn habits, such as finding good grazing areas, by observing other horses. This behavior is more common among younger horses and can be described by Eqs. (14) and (15).

$$I_i^{Iter,Age} = i_i^{Iter,Age}\left[\left(\frac{1}{pN}\sum_{j=1}^{pN}\hat{X}_j^{(Iter-1)}\right) - X^{(Iter-1)}\right] \tag{14}$$

Age = γ

$$i_i^{Iter,Age} = i_i^{(Iter-1),Age} x\omega_i \tag{15}$$

Where $I_i^{Iter,Age}$ denotes the movement vector of horse i towards the average position of the best horses located in *X*. pN represents the number of horses with the best location. It has been suggested that 10% of the horses should be designated as *p*.

3.1.4. Hierarchy (H)

For social mammals, group behavior is crucial for survival. Since horses are preyed upon by predators, living in groups enhances their safety. The survival rate increases with group living because the plurality makes it easier for them to escape. Sociability in horses can be explained by Eqs. (16) and (17).

$$S_i^{Iter,Age} = s_i^{Iter,Age}\left[\left(\frac{1}{N}\sum_{j=1}^{N} X_j^{(Iter-1)}\right) - X_i^{(Iter-1)}\right] \quad (16)$$

Age = β, γ

$$s_i^{Iter,Age} = s_i^{(Iter-1),Age} x\omega_s \quad (17)$$

Here, $S_i^{Iter,Age}$ represents the social movement vector of horse *i* and decreases by a factor ω_s, with each iteration, while *N* denotes the total number of horses. Friendliness is more pronounced in the age ranges Beta (β) dan Gamma (γ).

3.1.5. Defense mechanism (D)

In response to perceived threats or danger, horses primarily use running as their defense mechanism, with fighting being a secondary option. Horses will instinctively flee from danger, avoiding inappropriate and suboptimal responses. Their defense mechanism is illustrated by their tendency to move away from unsuitable positions, as depicted by Eqs. (18) and (19), which include negative coefficients.

$$D_i^{Iter,Age} = -d_i^{Iter,Age}\left[\left(\frac{1}{qN}\sum_{j=1}^{qN} \hat{X}_j^{(Iter-1)}\right) - X^{(Iter-1)}\right] \quad (18)$$

Age = α,β, γ

$$d_i^{Iter,Age} = d_i^{(Iter-1),Age} x\omega_d \quad (19)$$

$D_i^{Iter,Age}$ is the escape vector of the i_{th} horse, based on the average of the worst locations, indicated by the vector *X*. Additionally, *qN* represents the horse with the worst possible location. It is conjectured that *q* represents twenty percent of the total number of horses.

3.1.6. Roam (R)

Horses are very curious animals and often wander in search of new pastures and to explore their surroundings. The factor *r* is used to simulate this behavior as random movement. Young horses, in particular, tend to wander, but this behavior gradually diminishes as they mature. Wandering is described by Eqs. (20) and (21), which represent $R_i^{Iter,Age}$ as a random velocity vector for local search and avoidance of local minima.

$$R_i^{Iter,Age} = r_i^{Iter,Age} pX^{(Iter-1)} \quad (20)$$

Age = γ,δ

$$r_i^{Iter,Age} = r_i^{(Iter-1),Age} x\omega_r \quad (21)$$

Table 1. Pseudo Code of HHOA

HHOA
Start Enter the specific system data, associated constraints, and the parameters for the algorithm. [Initialize generator constraints] Set Iter = 1. **Initialization:** Set the positions of the horses randomly and uniformly within their limits or feasible spaces. **Fitness Evaluation:** Using the current positions of the horses, calculate the fitness value for each horse according to the problem's objective function. **while** Iter< Iter max Sort the horses' fitness values in ascending order and rearrange their positions accordingly. Categorize the horses into Alpha (α), Beta (β), Gamma (γ), and Delta (δ) groups based on their age ranges. **Velocity/Motion Vector Calculation:** Compute the motion vector for horses in each category. **Position update:** Determine the new positions of the horses by applying the corresponding motion vectors to all age groups. **Fitness Evaluation:** Using the updated positions of the horses, calculate the fitness value for each horse according to the problem's objective function. Iter = Iter + 1; **end** while Return the best solution. **end** Post process results and visualization (Optimal generation costs)

The core framework of the HHOA for performing the optimization process is summarized in the pseudocode presented in Table 1.

3.2. Objective function

In this study, the ED problem for the Sulbagsel electricity system was tackled using various swarm intelligence methods, including PSO and the proposed HHOA. The objective is to optimize the configuration of thermal generators to find the most cost-effective generation combination, as determined by Eq. (22). The process starts with calculating the input-output characteristics of the generators [29].

$$C_t = \sum_{i=1}^{n_g} \alpha_i + \beta_i P_i + \gamma_i P_i^2 \quad (22)$$

To ensure stable generator performance, the operation of each generator must remain within its capacity limits [30]. Thus, the generator's power production is constrained by the equality constraint, as shown in Eq. (23). Additionally, it must comply with the limits specified by the inequality constraint, as outlined in Eq. (24) [31].

$$\sum_{i=1}^{n_g} P_i = P_D \quad (23)$$

$$Pi_{i_{max}\, i_{min}} \quad (24)$$

Input-Output & Cost Function Characteristics

The computational process begins by determining the input-output characteristics of the thermal generators. Next, the fuel cost equation is derived by multiplying the input-output equation by the fuel price. The results, including the input-output characteristics and cost functions for each thermal generator in the Sulbagsel electricity system, are detailed in Table 2 [16]. The fuel cost equation for each generator is obtained by applying the fuel price to its respective input-output equation.

Table 2. Cost function of thermal power plant

No	Unit	Input-Output Equation (L/Hr)
1	PLTD Suppa	$42642000 + 3679160P + 8240P^2$
2	PLTD Agrekko/T.Lama	$15902685 + 3296000P + 56437.82P^2$
3	PLTU Jeneponto	$57795360 + 5182960P - 2467.056P^2$
4	PLTU PNGYA	$11494800 + 3594700P + 28325P^2$
5	PLTU BSW	$68319900 + 444960P + 233671.98P^2$
6	PLTD Bantaeng	$12723075 + 9831350P - 85834.02P^2$
7	PLTGU Sengkang	$14708400 + 11688440P - 67858.46P^2$
8	PLTD Palopo	$2132100 + 2315440P + 1030000P^2$
9	PLTU Mamuju	$12967185 + 3631780P + 98987.12P^2$

4. Results and discussion

This section discusses the application of the HHOA method for optimizing thermal generation costs in the Sulbagsel system. A case study focusing on the mid-day peak load in the Sulbagsel system is used to test the effectiveness of the HHOA method.

4.1. Analysis benchmarking

Before implementing the HHOA method for optimization, a benchmark analysis was conducted using the PSO and WOA methods for comparison. This analysis aimed to evaluate the exploration and exploitation capabilities of each method. The parameters for the algorithms are outlined in Table 3.

Five benchmark test functions, comprising both unimodal and multimodal types, are presented in Table 4. The unimodal benchmark functions are designed to evaluate the algorithm's exploitation ability, while the multimodal benchmark functions assess its exploration capability. This dual approach provides a comprehensive evaluation of the algorithms' performance across different optimization challenges. The fixed-dimension multimodal benchmark functions specifically test the algorithm's ability to handle low-dimensional optimization cases. The HHOA was executed 30 times, and the results, including the best values and standard deviations, are shown in Table 5. These statistical tests highlight the significant differences, consistency, and accuracy of the proposed algorithm. Based on the outcomes, it is evident that HHOA outperforms the PSO and WOA method, demonstrating superior exploration and exploitation

Table 3. The parameters of algorithms

Algorithm	Parameter	Value
PSO	Particles	30
	The quantity of variables	8
	C_1, C_2 Constants	2
	W Moment Inersia	0.9
WOA	Number of search agents	30
	Number of variables	15
	Max iteration	100
HHOA	Number of horses	35
	Max iteration	100
	Problem dimension	No.of genes
	Search domain	15
	No. Repetition of runs	30
	α, β	0.99, 0.01

Table 4. Benchmark functions

Name	Test Function	Range	Dim	f_{min}
Unimodal Functions				
Sphere	$f_1(x) = \sum_{i=1}^{D} x_i^2$	(-100, 100)	30	0
Rosenbrock's	$f_2(x) = \sum_{i=1}^{D-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	(-30, 30)	30	0
Quartic	$f_3(x) = \sum_{i=1}^{n} i x_i^4 + rand(0,1)$	(-1.28, 1.28)	30	0
Multimodal Functions				
Rastrigin	$f_4(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	(-5.12, 5.12)	30	0
Ackley	$f_5(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n} \cos(2\pi x_i)\right) + 20 + e$	(-32, 32)	30	0
Penalized 2	$f_6(x) = 0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{n} (x_i - 1)^2[1 + \sin^2(3\pi x_1 + 1)] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n} u(x_i, 5,100,4)$	(-50, 50)	30	0

Table 5. Benchmarking results

Func.	Statistical Parameter	Algorithm		
		PSO	WOA	HHOA
f_1	Best	4.13E-05	2.45E-15	3.49E-72
	Std.	8.01E+02	9.94E+03	6.92E-03
f_2	Best	7.99E-01	7.26E-04	4.92E-01
	Std.	1.17E+03	1.03E+07	7.14E+00
f_3	Best	1.78E-02	1.12E-02	1.05E-02
	Std.	2.26E+00	2.52E+01	2.70E-02
f_4	Best	1.06E+00	1.35E+00	4.98E-01
	Std.	4.56E+00	1.26E+02	4.07E-01
f_5	Best	2.40E-05	1.85E-06	1.86E-07
	Std.	2.39E+00	5.50E+00	4.90E-01
f_6	Best	3.17E-02	3.19E-01	1.57E-03
	Std.	1.61E+07	1.41E+08	7.49E-02

capabilities, along with enhanced consistency and accuracy.

The process of finding the optimal solution using the algorithm is depicted through convergence curves, which track the progression of the best solution at each iteration. Fig. 2 shows the normalized average convergence curves of the evaluated algorithms over 30 runs for both unimodal and multimodal benchmark functions. These curves provide insights into the performance and effectiveness of each algorithm in reaching optimal solutions. It is evident that HHOA demonstrates a superior convergence curve compared to PSO and WOA, converging more quickly to the optimal solution and showing a better ability to avoid local optima. These results highlight the advantages of the HHOA-based approach for solving optimization problems, particularly in the context of ED.

4.2. Economic dispatch optimization

The peak load for the Sulbagsel system during the day is 774.8 MW. Before optimizing generation costs, the actual costs of thermal generation for the Sulbagsel system were calculated, as shown in Table 6. The total real generation cost is Rp. 687.967.542,42 per hour, with a power demand on thermal generators amounting to 704.7 MW and

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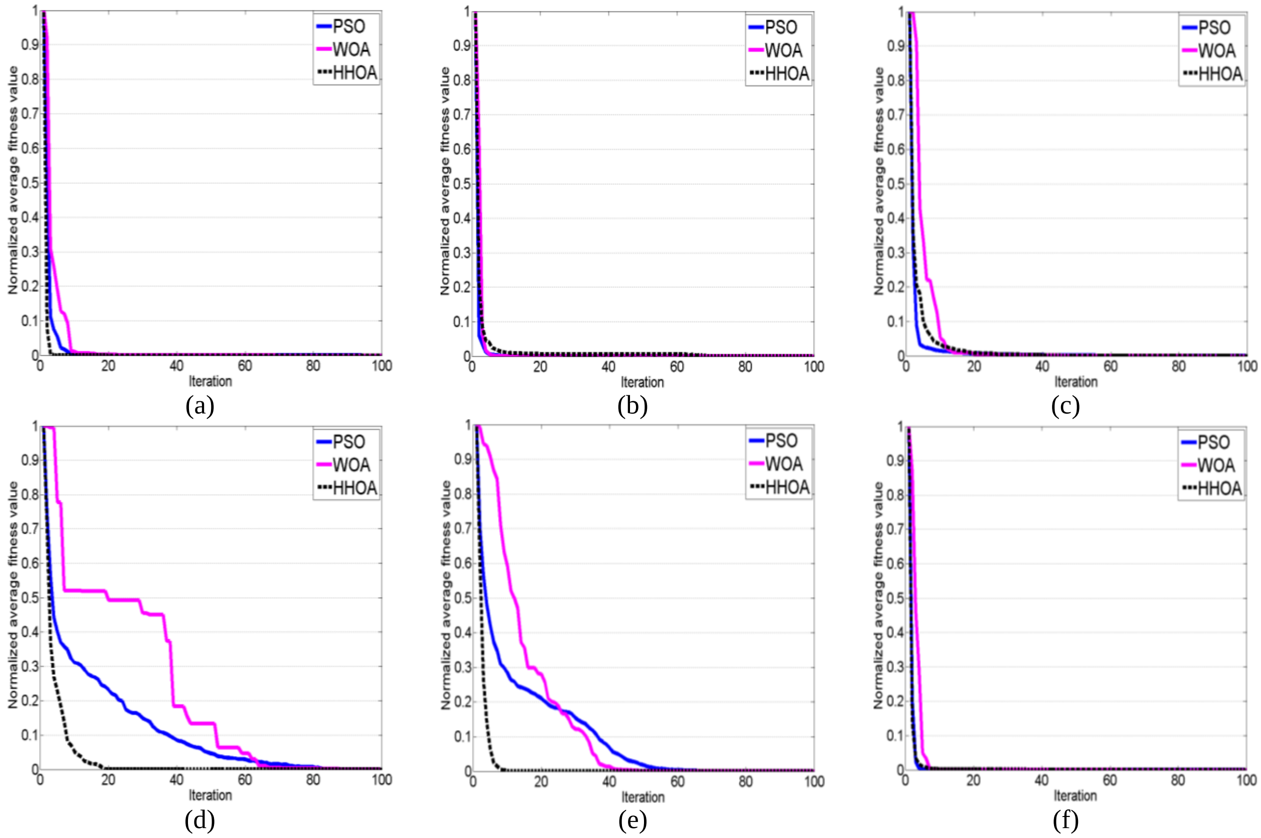

Figure.2 The comparison of the convergence curve of the algorithms in unimodal and multimodal benchmark functions (a) f_1, (b) f_2, (c) f_3, (d) f_4, (e) f_5, and (f) f_6

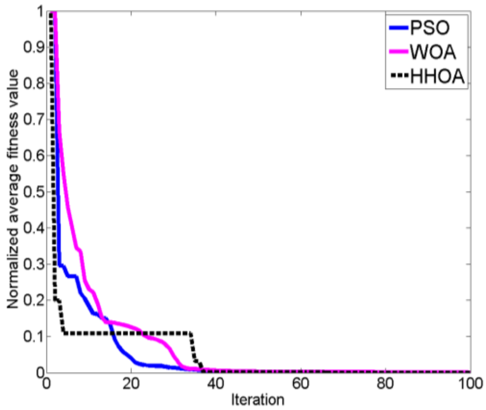

Figure.3 Optimization convergence graph

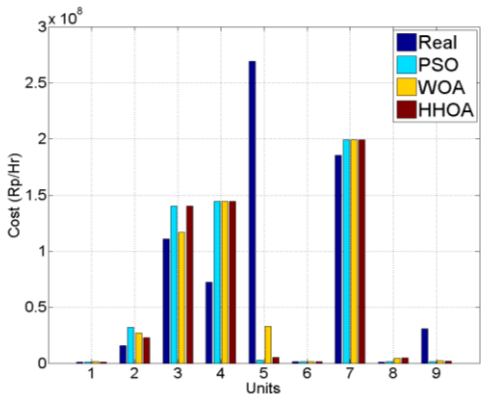

Figure.4 Comparison of the generation cost

losses totaling 55.93 MW under the N-1 contingency condition for the SIDRAP-MAROS middle line.

The computation results are shown in Fig. 3, which depicts the convergence of generation costs over 100 iterations. Fig. 4 illustrates the generation cost optimization results using various methods, including PSO, WOA, and HHOA. The PSO method achieved convergence at iteration 44, resulting in a generation cost of Rp. 524.351.561,00 per hour, representing a 23.78% reduction. The WOA method converged at iteration 46, with a generation cost of Rp. 529.597.560,64 per hour, representing a 23.02% reduction. The proposed HHOA method converged more quickly, achieving optimal results at iteration 37, with the lowest generation cost of Rp. 521.258.590,50 per hour, representing a 24.23% reduction. The total power demand on thermal generators using PSO and HHOA is 657.099 MW, reflecting a 6.7547% decrease, while WOA shows a decrease of 6.3545%.

Fig. 4 provides a visual comparison of generation cost optimization for each thermal power plant at peak daytime load. For non-thermal generators, the power contributions are as follows: Bakaru MHPP 123.138 MW, Pinrang MHPP 1 MW, Borongloe/Bili-Bili MHPP 12.1 MW, Sinjai MHPP 2

MW, WPP Sidrap 34.3 MW, and Makale MHPP 1 MW. The economic dispatch achieved optimal load flow, as evidenced by the reduction in line losses following optimization. Initially, real losses were 55.93 MW, but optimization led to a reduction. With the PSO method, losses decreased to 53.533 MW, representing a 4.28% reduction. The WOA method reduced losses to 54.420 MW, representing a 2.69% reduction. In contrast, the proposed HHOA method resulted in losses of 55.845 MW, reflecting a 0.15% reduction. Although the losses with the HHOA method are slightly higher compared to PSO and WOA, the generation costs achieved with HHOA are more optimal. This aligns with the study's objective of minimizing generation costs.

5. Conclusion

This paper introduces a novel Swarm Intelligence technique, the Horse Herding Optimization Algorithm (HHOA), inspired by the social behavior of horses of different ages. The algorithm employs six significant traits: grazing, hierarchy, sociability, imitation, defense mechanisms, and roaming, all aimed at achieving the lowest generation cost. To evaluate HHOA's performance, five benchmark functions were used to assess exploration, exploitation, local optima avoidance, and convergence. The results demonstrate that HHOA is highly competitive compared to similar swarm intelligence methods, such as Particle Swarm Optimization (PSO) and the Whale Optimization Algorithm (WOA). Specifically, HHOA excels in exploitation on unimodal functions and exploration on multimodal functions.

The performance of the HHOA in optimizing the Economic Dispatch (ED) of the Sulbagsel electricity system shows promising results for mid-day peak loads. The optimization results for thermal generation costs indicate that the PSO method achieved a cost reduction of 23.78%, while the WOA method achieved a reduction of 23.02%. In contrast, the HHOA-based method achieved a slightly higher reduction of 24.23%. In terms of losses, the PSO method resulted in a 4.28% reduction, the WOA method yielded a 2.69% reduction, and the HHOA method achieved a 0.15% reduction. For future work, this research could be extended to develop binary and multi-objective versions of the HHOA algorithm.

Table 6. Comparison of generation cost optimization results

No Bus	Real		PSO		WOA		HHOA	
	P (MW)	Cost (Rp/hr)	P (MW)	Cost (Rp/hr)	P (MW)	Cost (Rp/hr)	P (MW)	Cost (Rp/hr)
3	1	1.196.899,55	1	1.196.899,55	1.040461	1.259.221,23	0.998959503	1.195.311,65
4	28.4	15.502.957,31	50	32.179.723,50	44.25799	27.232.573,28	38.95895253	22.997.271,47
6	156.1	110.619.564,35	200	140.118.609,20	164.8724	116.551.834,25	199.8365219	140.009.629,67
7	90.3	72.424.871,29	200	144.367.551,33	199.9818	144.356.928,45	199.8369602	144.272.473,29
8	202.4	269.373.905,44	1	2.563.783,52	36.46708	32.779.033,14	4.578064558	5.286.872,15
9	1	1.511.782,50	1	1.511.782,50	1.037698	1.525.551,56	0.990303088	1.508.242,08
12	184.1	185.329.742,27	200	199.244.375,00	199.7522	199.030.069,00	199.9380329	199.190.787,22
13	1	1.052.042	3.09899	1.559.834,70	9.328929	4.403.119,12	9.987984882	4.820.817,41
15	40.4	30.955.777,71	1	1.609.001,70	3.180996	2.459.230,61	1.973220393	1.977.185,60
Total	**704.7**	**687.967.542,42**	**657.099**	**524.351.561,00**	**659.9195**	**529.597.560,64**	**657.099**	**521.258.590,5**
%			**6.7547**	**23.78**	**6.3545**	**23.02**	**6.7547**	**24.23**

Notation List

Parameters	Notation
$\boldsymbol{F_T}$	Fuel consumption (Rp/hr),
$\boldsymbol{P_T}$	Output power of the generators (MW)
$\boldsymbol{P_R}$	Load (MW)
H_n	Fuel input of the generator (L/hr)
α_n, β_n, γ_n	Input-output constants of generator.
P_L	Transmission losses (MW).
B_{ij}	Loss coefficients
B_{i0} and B_{00}	Constants related to the losses.
Delta (δ)	Horses aged 0 to 5 years
Gamma (γ)	Horses aged 5 to 10 years
Beta (β)	Horses aged 10 to 15 years
Alpha (α)	Horses older than 15 years
$\overline{V}_k^{Age,Itr}$	Age range and velocity vector of the horse
Itr	Iteration
X	Average position of the best horses
pN	Number of horses with the best locatio
$S_i^{Iter,Age}$	Social movement vector of horse *i*
N	Total number of horses
$D_i^{Iter,Age}$	Escape vector of the i_{th} horse
qN	Horse with the worst possible location
q	Total number of horses.
$R_i^{Iter,Age}$	Random velocity vector
Ct	cost-effective generation combination

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, RNH, MRD; Methodology, HRG, VL; Software, MRD, MAP, WH; Validation, IR, S, RNH; Formal Analysis, MRD, MAP; Investigation, S, MRD; Resources: HLG, VL, WH; Writing Original Draft Preparation, MRD; Writing Review and Editing, MAP; Visualization, MRD.

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