Reducing Operational Costs in Sulselbar's 150 kV System with Electromagnetic Field and Sine-Cosine Optimization

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***Abstract*—Dynamic economic dispatch (DED) is a crucial task in modern power systems, requiring efficient optimization to minimize generation costs while satisfying operational constraints. This study introduces a Hybrid Electromagnetic Field Optimization with Sine-Cosine Algorithm (EMFO-SCA) tailored to address the unique challenges of the Sulselbar 150 kV power system. Specifically, the algorithm is designed to handle non-linear cost functions, complex constraints, and dynamic load variations across a 24-hour scheduling period. EMFO-SCA achieves a balanced integration of global exploration (via Electromagnetic Field Optimization) and local exploitation (via the Sine-Cosine Algorithm), resulting in robust optimization performance. Applied to a system with seven active generator buses, EMFO-SCA demonstrates an average operational cost reduction of 0.27% compared to the Kho-Kho Algorithm (KKA). This improvement translates to measurable cost savings while maintaining strict adherence to generation limits, ramp rate constraints, and power balance at all intervals. For instance, during peak demand at 521.52 MW (hour 12), the method effectively minimizes costs without compromising operational reliability. The dual-phase design of EMFO-SCA enables faster convergence and higher accuracy than conventional methods, making it a scalable solution for real-world DED challenges. By optimizing power generation schedules dynamically and reliably, this study establishes EMFO-SCA as a significant advancement in energy system optimization, with clear potential for practical deployment in similar power systems.**

Keywords*—*economic dispatch, electromagnetic field optimization, power system, python, sine-cosine algorithm

I. INTRODUCTION

In Sulawesi, the electricity infrastructure is divided into two systems: the Northern Sulawesi System and the Southern Sulawesi System [1]. The transmission networks, which include 150 kV and 275 kV lines. Among these, the Southern System is the larger of the two, with a generation capacity of 1,977 MW and a peak load of 1413 MW. In comparison, the Northern System has a smaller scale, with a generation capacity of 573 MW and a peak load of 421 MW [1].

The Sulselbar power system in Sulawesi, Indonesia, is a critical element of the region's energy infrastructure, delivering reliable electricity to diverse consumers, including industrial, commercial, and residential sector[2]. This interconnected system operates at a 150 kV voltage level, with generation units spread across geographically distinct locations, predominantly powered by thermal plants relying on fossil fuels. However, the system faces significant challenges, including dynamic load variations, transmission losses, and operational constraints such as ramp rate limits and generation capacities. These factors demand advanced optimization methods to ensure cost-efficient and reliable electricity distribution [3].

Economic Dispatch (ED) [4], a cornerstone of power system optimization, aims to determine the optimal power outputs of generation units to meet load demands at the lowest operational cost while adhering to environmental and operational constraints [5]. However, as electricity systems increasingly face dynamic load patterns, classical ED methods, often referred to as Static Economic Dispatch (SED) [6], prove inadequate. SED fails to account for temporal complexities and operational constraints, necessitating the development of Dynamic Economic Dispatch (DED) [7], [8]. Unlike its static counterpart, DED incorporates the variability of load demand and generation units' temporal response capabilities, ensuring efficient power management over time.

Traditional optimization approaches for the Sulselbar system, such as the Lagrange method [9], have been utilized extensively but struggle with non-linear, multi-dimensional problem spaces. Metaheuristic techniques, such as the Artificial Bee Colony (ABC) algorithm [10], have shown promise in addressing some of these limitations by effectively reducing fuel costs and stabilizing power generation under static and dynamic conditions. Similarly, Modified Improved Particle Swarm Optimization (MIPSO) has demonstrated significant potential in enhancing convergence speed and improving solution quality by introducing modifications to the standard PSO framework, such as dynamic weight

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adjustments and enhanced position updates [11]. These modifications allow MIPSO to better balance global exploration and local exploitation, addressing certain complexities in economic dispatch problems. However, even robust methods like ABC and MIPSO have inherent limitations in fully achieving this balance, particularly in highly complex and dynamic scenarios. This necessitates further advancements in optimization techniques to address these challenges more comprehensively and ensure scalability and adaptability to real-world applications. In addition, methods like MFOA-ABC [12], FFA-ABC [13], and PSOHIC [14] have been proposed for optimization tasks. Compared to EMFO-SCA, which combines the attraction-repulsion dynamics of Electromagnetic Field Optimization (EMFO) with the periodic behavior of the Sine-Cosine Algorithm (SCA) to balance exploration and exploitation, these methods employ different hybridization strategies. For instance, MFOA-ABC integrates the Multifactorial Optimization Algorithm (MFOA) with Artificial Bee Colony (ABC) to enhance search efficiency, while FFA-ABC combines Firefly Algorithm (FFA) with ABC for improved convergence. PSOHIC leverages a hybrid of Particle Swarm Optimization (PSO) and Harmony Inspired Crossover (HIC) for solution refinement. Each approach offers unique strengths, but EMFO-SCA stands out for its adaptability and precision in navigating complex search spaces.

The Artificial Bee Colony (ABC) algorithm and Modified Improved Particle Swarm Optimization (MIPSO) are metaheuristic techniques that have demonstrated capabilities in reducing fuel costs and improving power generation stability. ABC effectively balances exploration and exploitation but struggles in highly complex and dynamic scenarios, while MIPSO enhances convergence speed and solution quality through dynamic weight adjustments and refined position updates, though it remains sensitive to parameter tuning. In contrast, EMFO-SCA surpasses these methods by integrating EMFO's strong global exploration with SCA's precise local exploitation, achieving a superior balance that enhances adaptability, scalability, and solution robustness, particularly in highly dynamic and complex economic dispatch problems.

The proposed hybrid EMFO-SCA method effectively addresses key challenges in Dynamic Economic Dispatch (DED) optimization. The goal of the dynamic economic dispatch (DED) program is to optimize the output of the generators over a period of time in an optimized economic manner . By enhancing exploration capabilities, thorough search of the solution space and avoiding suboptimal results. Simultaneously, it improves local search precision, enabling fine-tuning of solutions to achieve optimal cost efficiency and adherence to constraints. This hybrid approach dynamically schedules power generation outputs over a 24-hour period, accommodating hourly variations in load demand with high adaptability. Additionally, the method applies stringent penalties for power mismatches, ensuring that load demands are met accurately while maintaining operational feasibility. Together, these features make the EMFO-SCA method a robust and efficient solution for addressing the complexities of modern power systems.

Using real-world load data from the Sulselbar power system, the hybrid EMFO-SCA algorithm demonstrates its capability to dynamically optimize power generation schedules. It surpasses the performance of traditional methods, such as the Lagrange technique and ABC algorithm, achieving significant cost savings, reducing computational time, and improving compliance with ramp rate and generation limit constraints. By incorporating penalties for mismatches and ensuring normalized power balance at each step, the approach ensures both feasibility and cost-effectiveness.

This research significantly contributes to advancing the optimization methodologies for the Sulselbar power system, aligning with Indonesia's broader goals of sustainable and efficient energy management. The study underscores the potential of hybrid metaheuristics in addressing the complexities of modern power systems, providing a scalable and adaptable framework for dynamic power generation scheduling in regions with similar challenges.

II. PROBLEM FORMULATION

The dynamic economic dispatch problem is formulated to optimize power generation schedules over a specified period, such as 24 hours, by minimizing operational costs while adhering to system constraints. The key elements of this formulation include the objective function, power balance, generation limits, and ramp rate constraints.

1. Objective Function

The primary goal is to minimize the total fuel cost associated with power generation across all units. The fuel cost for each generator is represented as a quadratic function of its power output [8]:

$$F(P) = \sum_{i=1}^{N} (a_i P_i^2 + b_i P_i + c_i) \tag{1}$$

Where:

P_i	:	Power output of the i -th generator (MW).
a_i, b_i, c_i	:	Fuel cost coefficients for the i -th generator.
N	:	Total number of generators.

This cost function captures both the fixed and variable costs of generation. The objective is to minimize $F(P)$ while maintaining operational feasibility.

2. Power Balance Constraint

To ensure system reliability, the total power generated must match the load demand at each time step, accounting for transmission losses if necessary. This is expressed as [8]:

$$\sum_{i=1}^{N} P_i = P_D + P_{Loss} \tag{2}$$

Where:

P_D	:	Total power demand (MW).
P_{Loss}	:	The total transmission losses in the network (MW).
$\sum_{i=1}^{N} P_i$	:	Total power generated by all units (MW).

This equality constraint ensures that the power supply meets the load requirement at all times, avoiding surplus or deficit conditions.

3. Generation Limits Constraint

Each generator operates within its specified capacity range, defined by its minimum and maximum generation limits. This constraint is represented as [8]:

$$P_{min,i} \leq P_i \leq P_{max,i} \ \forall_i \in [1, N] \tag{3}$$

Where:

$P_{min,i}$	:	Minimum generation capacity of the i-th generator (MW).
$P_{max,i}$	:	Maximum generation capacity of the i-th generator (MW).

This ensures that generators do not operate beyond their physical or economic capabilities.

4. Ramp Rate Constraint

To account for the dynamic nature of generation, the rate at which a generator's output can increase or decrease between time steps is limited by its ramp-up and ramp-down capabilities. This constraint is defined as [8]:

$$-\Delta P_{down,i} \leq P_i^{(t)} - P_i^{(t-1)} \leq \Delta P_{up,i} \ \forall_t \in [2, T] \tag{4}$$

Where:

$\Delta P_{down,i}$	:	Maximum ramp-down rate for the i-th generator (MW/time step).
$\Delta P_{up,i}$	:	Maximum ramp-up rate for the i-th generator (MW/time step).
$P_i^{(t)}$	:	Power output of the i-th generator at time t.

This constraint ensures smooth transitions in generator output, preventing rapid changes that could destabilize the system or damage equipment.

III. Methodology

The optimization of Dynamic Economic Dispatch (DED) is crucial for modern power systems, particularly in managing the Sulselbar power system in Sulawesi, Indonesia. This study introduces a hybrid metaheuristic approach that combines Electromagnetic Field Optimization (EMFO) and the Sine-Cosine Algorithm (SCA) to address the non-linear, multi-dimensional challenges of DED. Below, the methodology is detailed step-by-step to illustrate the design and execution of the hybrid EMFO-SCA optimization.

A. Datasets

The test data used in this study was derived from real generation data of the 150 kV Sulselbar power system, which comprises nine generator buses. However, the testing was conducted using only seven generator buses: Tello, Balusu, Tallasa, Punagaya, Pare-Pare, Sengkang, and Palopo. The other two buses, Sungguminasa and Bakaru, were not operational during the testing period. The analysis also incorporated the fuel cost functions and generator power constraints specific to the thermal power system of the 150 kV Sulselbar network, as detailed in Table 1 [10].

Table 1. Characteristics of Thermal Power Plants

Unit	a (Rp/MW^2)	b (Rp/MW)	c (Rp)	Pmin (MW)	Pmax (MW)	Ramp Up (MW/h)	Ramp Down (MW/h)
1	1.3736E-12	2240.9	7.1332E-11	2	8	480	480
2	-2.4144E-14	427.4	-1.1182E-11	9.68	38.73	180	180
3	-3.6365E-14	1917.8	-4.5984E-11	5	8	480	480
4	6.346E-15	432.75	1.9212E-10	55.59	222.35	180	180
5	-2.5302E-14	1908.44	1.8497E-11	15	60	480	480
6	-4.7539E-15	427.78	-1.0608E-10	54.88	219.5	600	600
7	1.587E-13	2634.3	1.3227E-11	1.25	5	480	480

In this study, the load data used to evaluate the effectiveness of the proposed method over a 24-hour period was randomized to represent typical daily load patterns observed in real-world power systems. This approach was employed to simulate varying demand conditions across peak and off-peak periods, enabling a robust evaluation of the algorithm's adaptability and efficiency.

While the dataset used in this study was not directly obtained from actual measurements, it was designed to reflect realistic load variations typically encountered in systems like Sulselbar's 150 kV network. The randomized data ensures diversity in demand patterns, including gradual load increases during morning hours, peak demands around midday, and reduced demands during nighttime, thereby capturing the dynamic nature of power system operations.

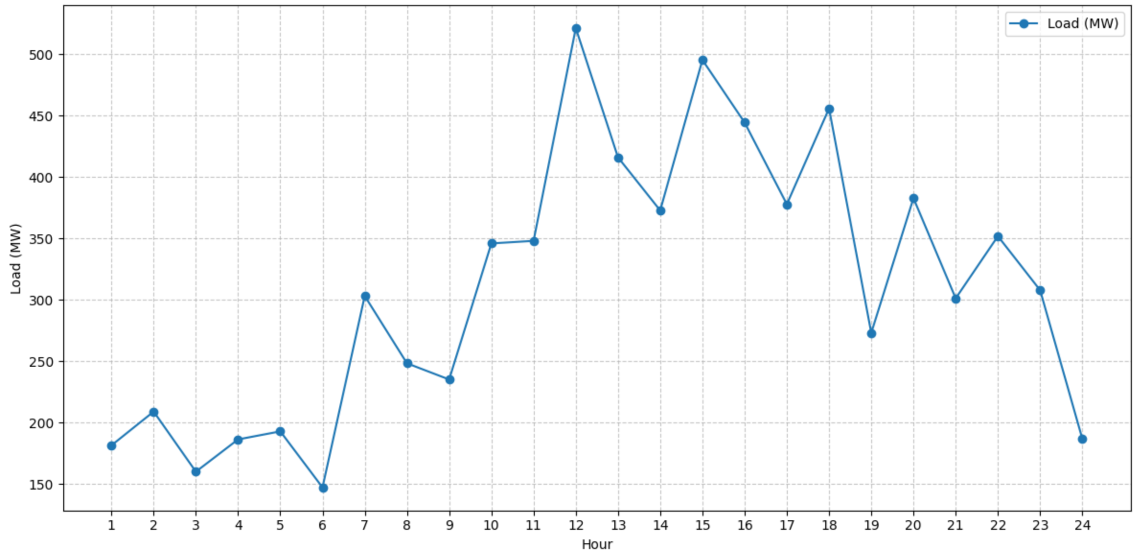

Fig. 1. 24-hours power demand

B. EMFO-SCA

The Hybrid Electromagnetic Field Optimization with Sine-Cosine Algorithm (EMFO-SCA) is a metaheuristic optimization technique designed to address complex, multi-dimensional, and constrained problems, such as the dynamic economic dispatch in power systems. This hybrid approach integrates the strengths of Electromagnetic Field Optimization (EMFO) and the Sine-Cosine Algorithm (SCA) to achieve an efficient balance between global exploration and local exploitation.

Electromagnetic Field Optimization (EMFO) is a metaheuristic optimization algorithm inspired by the attraction and repulsion dynamics of electromagnetic fields. This algorithm was first introduced by H. Abedinpourshotorban et al. (2016) [15], utilizing electromagnetic forces to balance exploration and exploitation in the solution search space. The approach was further refined by S. Song et al. (2019) [16], who incorporated chaotic maps and fuzzy entropy to enhance EMFO's performance in color image segmentation, and by S. Ahmad (2022) [17], who applied it to selective harmonic elimination in power systems. The attraction and repulsion interactions in EMFO are based on Coulomb's law, with forces calculated using the equation $F = k \cdot \frac{q_1 \cdot q_2}{r^2} \cdot \hat{r}$, where k is a constant, q_1 and q_2 represent the fitness values of solutions, r is the distance between particles, and $\hat{r}$ is the direction vector. This dynamic ensures that particles are attracted toward promising solutions (global optima) while avoiding suboptimal areas, enabling a broader search and reducing the risk of premature convergence, as demonstrated in [16] and [17].

Sine-Cosine Algorithm (SCA), on the other hand, leverages the natural oscillatory properties of sine and cosine functions to guide particles in exploring and exploiting the solution space. The algorithm has been comprehensively reviewed by A. B. Gabis et al. (2021) [18], highlighting its adaptability to various optimization problems, and further developed by J. Tang and L. Wang (2023) [19], who proposed a collaborative approach based on elite solutions. Additionally, J. C. Bansal et al. (2023) [20] elaborated on the mathematical foundation of SCA, demonstrating how it generates controlled periodic movements to refine solutions around promising regions. In SCA, particle positions are updated using the equations $X_{new} = X_{current} + r \cdot \sin(\omega)$ or $X_{new} = X_{current} + r \cdot \cos(\omega)$, where r determines the step size and ω controls the oscillatory frequency. This approach balances exploration of new areas and exploitation of promising solutions, with dynamic adaptability highlighted in [18] and [19]. By combining these oscillatory mechanisms, the algorithm ensures efficient convergence to the global optimum with high precision. SCA complements this by refining the search process through sine-cosine-based adjustments [20], [21], which are applied to the particle positions during the exploitation phase. This mechanism focuses on fine-tuning the solutions around promising regions by leveraging periodic mathematical functions, which provide controlled randomness and precision. SCA's adaptability allows it to dynamically adjust solutions based on their proximity to the global best, ensuring efficient convergence.

The Hybrid EMFO-SCA algorithm is designed to dynamically schedule power generation over a 24-hour period for dynamic economic dispatch. It aims to minimize generation costs while adhering to key operational constraints, such as ramp rate limits and generation capacities. To ensure the demand is accurately met, the algorithm imposes penalties for power mismatches, making it highly effective in balancing generation and load. Its capacity to handle non-linear cost functions and intricate constraints establishes it as a reliable and versatile solution for addressing modern optimization challenges in power systems.

This hybrid optimization approach seamlessly integrates global exploration with local exploitation to tackle complex problems efficiently. The algorithm begins with particle initialization, followed by two complementary phases: the Electromagnetic Field Optimization (EMFO) phase, which emphasizes comprehensive exploration of the solution space, and the Sine-Cosine Algorithm (SCA) phase, which refines potential solutions to achieve precise convergence. By combining these phases, the Hybrid EMFO-SCA method ensures a robust and flexible framework for finding optimal solutions.

1. Initialization

The process begins with the initialization of number of particles in the search space. Each particle represents a candidate solution and is randomly positioned within the generation limits:

$$P_j(0) \sim U\left(P_{min,i}, P_{max,i}\right) \quad (5)$$

The initial global best position P_{Best} is set to a neutral state (zeros), and the global best score is initialized to infinity.

2. EMFO Update (Exploration Phase)

In the exploration phase, particles move under the influence of attraction-repulsion dynamics and sinusoidal oscillations. Each particle position $P_j^{(t)}$ is updated as follows:

$$P_j^{(t+1)} = P_j^{(t)} + A \cdot \left(P_{Best} - P_j^{(t)}\right) + B \cdot C \quad (6)$$

Where:

A: Attraction force, promoting convergence towards promising solutions:

$$A = \alpha \cdot exp\left(-\frac{\sigma \cdot t}{T_{max}}\right) \cdot (2r_1 - 1) \quad (7)$$

B: Repulsion force, encouraging diversity in the search:

$$B = \alpha \cdot exp\left(-\frac{\sigma \cdot t}{T_{max}}\right) \cdot (2r_2 - 1) \quad (8)$$

C: Sinusoidal oscillation, enhancing randomness and preventing stagnation:

$$C = exp\left(-\frac{\sigma \cdot t}{T_{max}}\right) \cdot (2\pi r_1) \quad (9)$$

3. SCA update (Exploitation Phase)

In the exploitation phase [22], particles refine their positions using the sine-cosine adjustment rule, which emphasizes local search near the global best:

$$P_j^{(t+1)} = \begin{cases} P_j^{(t)} + \beta \cdot \sin(2\pi r_3) \cdot \left(P_{Best} - P_j^{(t)}\right) \cdot r_2, & r_1 < 0.5 \\ P_j^{(t)} + \beta \cdot \cos(2\pi r_3)\left(P_{Best} - P_j^{(t)}\right) \cdot r_2, & r_1 \geq 0.5 \end{cases} \quad (10)$$

Where:

β	:	Sine-Cosine scaling factor
r_1, r_2, r_3	:	Random value in [0,1]

Presented below is the pseudocode for the EMFO-SCA algorithm, which is developed to deliver efficient and precise optimization results while addressing the technical limitations of power generation systems. By integrating the capabilities of Enhanced Moth Flame Optimization (EMFO) and the Sine Cosine Algorithm (SCA), this algorithm effectively tackles the Economic Dispatch problem by reducing fuel costs and ensuring compliance with power demand, generation capacity, and ramp rate constraints.

Initialize parameters and data
Read unit parameters $\{a_i, b_i, c_i, P_{min,i}, P_{max,i}, \Delta P_{up,i}, \Delta P_{down,i}\}$
Read power demand data $\{P_D\}$
Set Hybrid EMFO-SCA parameters $\{n_{Particles}, n_{Iterations}, \alpha, \beta, \sigma\}$
outputs ← ∅
ramp_violations ← ∅

for demand $\in P_D$ **do**
  Initialize particle_positions randomly within $[P_{min,i}, P_{max,i}]$
  global_best_position ← ∅
  global_best_score ← ∞

  repeat
    for particle ∈ particle_positions **do**
      Enforce generation limits $[P_{min,i}, P_{max,i}]$
      Calculate fuel cost and mismatch penalty
      Update global_best_position if score improves
    end for

    for particle ∈ particle_positions **do** // EMFO update
      Update position using EMFO equations:

$$P_j^{(t+1)} = P_j^{(t)} + A \cdot \left(P_{Best} - P_j^{(t)}\right) + B \cdot C$$

      Enforce generation limits $[P_{min,i}, P_{max,i}]$
    end for

    for particle ∈ particle_positions **do** // SCA update
      Update position using SCA equations:

$$P_j^{(t+1)} = \begin{cases} P_j^{(t)} + \beta \cdot \sin(2\pi r_3) \cdot \left(P_{Best} - P_j^{(t)}\right) \cdot r_2, & r_1 < 0.5 \\ P_j^{(t)} + \beta \cdot \cos(2\pi r_3)\left(P_{Best} - P_j^{(t)}\right) \cdot r_2, & r_1 \geq 0.5 \end{cases}$$

      Enforce generation limits $[P_{min,i}, P_{max,i}]$
    end for

    Normalize global_best_position to match demand
    if $|P_D - \sum P_{Best}| < 0.0001$ **then** // Termination condition for power balance
      break
    end if
  until Convergence or max_iterations

  Calculate total power and fuel cost
  Store output for demand in outputs
  if previous_output exists **then**
    Compute ramp rate violations
    Append violations to ramp_violations
  end if
end for

Save outputs and violations to Excel
return outputs

IV. Results and Discussion

The optimization testing scenario involves dynamic load optimization over a 24-hour period using the Sulselbar 150 kV power system dataset. The proposed method, Hybrid EMFO-SCA, is benchmarked against a comparator algorithm, the KKA (Kho-Kho Algorithm), to evaluate its effectiveness. This comparative analysis aims to assess the performance of the optimization techniques in terms of minimizing generation costs, adhering to operational constraints such as ramp rates and generation limits, and ensuring accurate load balancing. By applying realistic load data from the Sulselbar 150 kV system, this study provides a comprehensive evaluation of the methodologies in a practical context, highlighting the strengths and weaknesses of each approach in addressing the challenges of dynamic economic dispatch.

The implementation of EMFO-SCA for the Dynamic Economic Dispatch (DED) problem was tailored to align with the specific characteristics of the Sulselbar 150 kV system. Adjustments included incorporating Sulselbar's generator parameters, such as cost functions, generation limits, and ramp rate constraints, to ensure accurate modeling of operational behavior. The 24-hour load profile was designed to simulate typical demand patterns in Sulselbar, including peak and off-peak periods. Key algorithm parameters, such as the attraction-repulsion forces in the EMFO phase and sine-cosine scaling factors in the SCA phase, were fine-tuned to optimize performance for Sulselbar-specific conditions.

The algorithm emphasized strict adherence to operational constraints, such as power balance, ramp rates, and generation limits, ensuring practical and feasible solutions. While these adjustments were based on generalized load profiles, future enhancements will incorporate real-world Sulselbar data to further improve accuracy and applicability. These tailored implementations highlight the relevance and effectiveness of EMFO-SCA in addressing the DED challenges specific to Sulselbar's network.

Table 2 presents the scheduling details for each generator across all hours of the 24-hour period. The results indicate that the generation limits for all units have been adhered to throughout the scheduling process, ensuring that no violations occurred. This demonstrates the effectiveness of the optimization method in maintaining operational feasibility while meeting the dynamic load requirements.

Table 2. EMFO-SCA's Scheduling

Time	Demand	Power Generated by Unit-*i* (MW)							Run Time (s)
		1	2	3	4	5	6	7	
00.00	181.5439	4.392955	25.61519	6.035240	64.69397	18.54628	60.44110	1.819130	0.001618
01.00	209.069	2.490025	25.05817	6.041138	72.75305	35.85042	65.30625	1.569927	0.001503
02.00	160.0999	4.422348	12.20728	5.000000	59.72122	15.24484	61.91818	1.586115	0.045805
03.00	186.4085	5.925943	16.16410	5.930043	80.75238	19.11571	56.35514	2.165195	0.004503
04.00	192.9472	4.861556	26.72637	6.322347	60.59422	20.52073	68.92194	5.000000	0.004421
05.00	147.2849	2.679443	11.17109	5.147685	55.61266	16.61142	54.88000	1.295781	0.088429
06.00	303.2549	6.716982	38.10799	7.855788	71.60349	31.58655	142.7771	4.607040	0.000912
07.00	248.4289	3.261861	25.49845	7.620106	93.57927	34.45501	79.64583	4.368409	0.000899
08.00	235.197	4.254816	18.53946	7.639776	56.00831	20.13945	123.6152	5.000000	0.002653
09.00	346.0775	4.073603	38.17110	5.049118	137.7293	22.66553	136.5341	1.854773	0.000905
10.00	348.1784	7.595427	21.38117	7.261662	196.8526	38.54608	73.16069	3.380770	0.000914
11.00	521.5178	7.087102	18.90458	7.932186	213.3069	52.98169	218.9400	2.365336	0.000897
12.00	416.1817	3.298991	14.37251	5.186468	166.2373	25.98317	199.4374	1.665774	0.00092
13.00	372.9123	6.290236	34.53292	5.525458	155.2424	34.56605	131.7833	4.971871	0.000911
14.00	495.5563	2.105513	28.02969	7.732779	203.5828	56.83939	194.5894	2.676742	0.000907
15.00	444.5215	5.452056	33.06777	6.003347	215.6743	59.31857	122.0049	3.000468	0.000892
16.00	378.007	6.214540	25.79269	7.729737	207.9952	50.07035	78.59948	1.605017	0.000911
17.00	456.0265	4.800869	30.18902	7.494073	185.0703	38.34128	188.2856	1.845400	0.000913
18.00	273.1682	5.583877	33.08319	7.010995	59.04435	19.52409	145.1550	3.766643	0.000937
19.00	382.9319	6.911094	17.45810	6.430431	134.8907	16.06922	198.6163	2.555970	0.000982
20.00	301.319	2.604629	32.36035	7.151877	133.8691	26.75970	93.78161	4.791670	0.000921
21.00	351.9701	5.720538	38.07112	5.648320	205.7339	21.59463	72.16349	3.038120	0.000911
22.00	307.9594	4.312440	24.22118	6.611432	123.0270	23.05266	124.2800	2.454721	0.000914
23.00	186.8964	3.188615	14.45840	5.000000	84.15503	22.19548	56.02142	1.877515	0.002683
Average		4.76022746	25.1325788	6.47333358	126.572073	30.0240958	114.467226	2.88593279	0.00692754

In addition to ensuring that the generation limits were not violated, the scheduling also adhered strictly to the ramp rate constraints for all generators. Throughout the 24-hour period, no ramp rate violations were observed, as detailed in Table 3. This highlights the robustness of the optimization approach in managing both static and dynamic operational constraints, ensuring smooth transitions in power output while meeting load demands efficiently.

The EMFO-SCA program effectively handles dynamic and fluctuating load conditions through a series of adaptive mechanisms. It optimizes power distribution iteratively for each load, enabling the algorithm to adjust the power output of each generating unit individually without disrupting prior optimizations. The global best position is updated dynamically based on fuel cost evaluation and mismatch penalties, ensuring that the solution aligns with changing load demands. After each iteration, the total power output is normalized to meet the required load while adhering to generation constraints, maintaining a balance between global exploration and local exploitation. To address rapid load changes, ramp rate constraints are enforced, preventing violations and ensuring smooth power transitions between intervals. The hybrid nature of EMFO and SCA enhances the algorithm's robustness, with EMFO offering strong global exploration for significant load fluctuations and SCA providing precise local adjustments for minor variations. Additionally, the algorithm uses a maximum iteration limit and a convergence criterion based on power mismatch, halting computations early when the generated power closely matches the required demand (error < 0.0001 MW). These strategies enable EMFO-SCA to effectively manage dynamic load

fluctuations, minimize operational costs, and fulfill power requirements while adhering to technical constraints.

Table 3. EMFO-SCA's Ramp Rate

From	To	Ramp Rate (MW) 1	2	3	4	5	6	7
00.00	01.00	-1.90293	-0.55702	0.005898	8.059074	17.30414	4.865147	-0.2492
01.00	02.00	1.932322	-12.8509	-1.04114	-13.0318	-20.6056	-3.38807	0.016188
02.00	03.00	1.503595	3.956821	0.930043	21.03115	3.870871	-5.56303	0.579079
03.00	04.00	-1.06439	10.56227	0.392304	-20.1582	1.405019	12.5668	2.834805
04.00	05.00	-2.18211	-15.5553	-1.17466	-4.98156	-3.90932	-14.0419	-3.70422
05.00	06.00	4.037539	26.9369	2.708103	15.99083	14.97513	87.8971	3.311259
06.00	07.00	-3.45512	-12.6095	-0.23568	21.97578	2.868464	-63.1313	-0.23863
07.00	08.00	0.992955	-6.95899	0.01967	-37.571	-14.3156	43.96933	0.631591
08.00	09.00	-0.18121	19.63164	-2.59066	81.72097	2.52608	12.91892	-3.14523
09.00	10.00	3.521824	-16.7899	2.212544	59.12332	15.88056	-63.3734	1.525997
10.00	11.00	-0.50832	-2.47659	0.670525	16.45429	14.43561	145.7793	-1.01543
11.00	12.00	-3.78811	-4.53206	-2.74572	-47.0696	-26.9985	-19.5026	-0.69956
12.00	13.00	2.991245	20.16041	0.338991	-10.995	8.582879	-67.6541	3.306098
13.00	14.00	-4.18472	-6.50324	2.207321	48.34044	22.27335	62.806	-2.29513
14.00	15.00	3.346542	5.038086	-1.72943	12.09153	2.479178	-72.5844	0.323726
15.00	16.00	0.762485	-7.27508	1.72639	-7.67918	-9.24823	-43.4054	-1.39545
16.00	17.00	-1.41367	4.396327	-0.23566	-22.9249	-11.7291	109.6861	0.240382
17.00	18.00	0.783007	2.894168	-0.48308	-126.026	-18.8172	-43.1306	1.921244
18.00	19.00	1.327217	-15.6251	-0.58056	75.84637	-3.45487	53.46131	-1.21067
19.00	20.00	-4.30646	14.90225	0.721446	-1.02157	10.69047	-104.835	2.2357
20.00	21.00	3.115909	5.710773	-1.50356	71.86471	-5.16507	-21.6181	-1.75355
21.00	22.00	-1.40810	-13.8499	0.963113	-82.7069	1.458031	52.11651	-0.5834
22.00	23.00	-1.12382	-9.76277	-1.61143	-38.8719	-0.85718	-68.2586	-0.57721
23.00	00.00	-1.90293	-0.55702	0.005898	8.059074	17.30414	4.865147	-0.2492
Ramp Rate		480	180	480	180	480	600	480

*(-) represents a decrease in the generator's power output between two consecutive time steps (ramp down).

Table 4 presents a comparison between the Hybrid EMFO-SCA method and the Kho-Kho Algorithm (KKA), focusing on the reduction of operational costs over a 24-hour period. The results demonstrate that the EMFO-SCA method effectively reduces daily operational costs, achieving an average cost reduction of 0.27% compared to KKA. Furthermore, the EMFO-SCA method maintains an exceptionally accurate power balance, ensuring that the total power generated matches the demand precisely, without surplus or deficit. This underscores the efficiency and reliability of the proposed hybrid method in optimizing power generation while minimizing costs, offering a clear advantage over the comparator algorithm in both accuracy and practical applications.

The analysis of operational costs reveals that the EMFO-SCA method consistently outperforms the KKA method in terms of cost efficiency, particularly when applied to the Sulselbar 150 kV power system. Over a 24-hour period, the total operational cost using EMFO-SCA is Rp 4,859,180.93, compared to Rp 4,872,095.04 for KKA. This represents an average hourly cost reduction of approximately Rp 538.09 per hour, translating to a 0.27% reduction in daily operational costs. For a critical system like Sulselbar, which supports diverse consumer demands including industrial, commercial, and residential sectors, this efficiency improvement directly reduces operational expenses and enhances the system's reliability. When extended to a yearly calculation, assuming similar demand patterns and operational consistency across Sulselbar's 150 kV system, the daily savings of Rp 12,914.11 accumulate to an annual savings of approximately Rp 4,712,649.15. Given Sulselbar's strategic importance as a backbone for electricity distribution in South Sulawesi and surrounding regions, these savings represent a significant economic advantage. They underscore the practicality of EMFO-SCA in optimizing power generation scheduling, reducing costs, and ensuring operational feasibility. This highlights the method's scalability and value in managing dynamic power demands while maintaining the stability and efficiency of Sulselbar's 150 kV system.

Table 4. Performance Comparison

Time	Demand	EMFO-SCA Operational Cost (Rp)	EMFO-SCA Computation Time (s)	KKA Operational Cost (Rp)	KKA Computation Time (s)
00.00	181.5439	126,404.89	0.001618	151,642.75	0.001091
01.00	209.069	159,850.08	0.001503	140,635.85	0.009438
02.00	160.0999	110,320.32	0.045805	111,020.86	0.016314
03.00	186.4085	132,798.78	0.004503	167,906.52	0.000472
04.00	192.9472	142,481.77	0.004421	135,820.85	0.000464
05.00	147.2849	103,309.43	0.088429	106,770.01	0.011210
06.00	303.2549	210,886.22	0.000912	199,683.88	0.001212
07.00	248.4289	184,651.72	0.000899	182,211.27	0.000425
08.00	235.197	160,834.06	0.002653	190,202.66	0.000419
09.00	346.0775	201,276.79	0.000905	203,040.15	0.000433
10.00	348.1784	239,038.81	0.000914	198,982.30	0.000418
11.00	521.5178	332,483.75	0.000897	309,694.01	0.003922
12.00	416.1817	234,712.15	0.000920	260,342.60	0.000420
13.00	372.9123	242,071.93	0.000911	218,768.28	0.000414
14.00	495.5563	318,395.87	0.000907	305,636.89	0.000418
15.00	444.5215	304,498.30	0.000892	249,559.82	0.000402
16.00	378.007	263,191.59	0.000911	230,476.76	0.000402
17.00	456.0265	276,700.54	0.000913	267,398.47	0.000421
18.00	273.1682	174,927.24	0.000937	200,498.09	0.000416
19.00	382.9319	216,019.34	0.000982	246,932.88	0.000458
20.00	301.319	195,125.14	0.000921	198,661.32	0.000411
21.00	351.9701	209,039.90	0.000911	229,103.72	0.000402
22.00	307.9594	189,560.79	0.000914	202,850.79	0.000411
23.00	186.8964	130,601.50	0.002683	164,254.30	0.000404
Total		4,859,180.93	0.166261	4,872,095.04	0.050798
Average		202,465.87	0.013301	203,003.96	0.002117

The Hybrid EMFO-SCA (Electromagnetic Field Optimization with Sine-Cosine Algorithm) demonstrates significant advantages over the Kho-Kho Algorithm (KKA) in addressing dynamic economic dispatch optimization problems. These advantages stem from its superior design, which balances global exploration and local exploitation while efficiently handling operational constraints.

The EMFO-SCA method excels in maintaining a robust exploration-exploitation balance through its dual-phase mechanism. The EMFO phase employs attraction-repulsion dynamics inspired by electromagnetic fields to explore the solution space thoroughly and avoid premature convergence to local optima. The SCA phase complements this by refining solutions using sine-cosine adjustments, enabling precise convergence toward the global best solution. In contrast, KKA relies on tagging-inspired movements for exploration and exploitation, which, while effective in general, lacks the precision and adaptability needed to handle highly constrained, multi-dimensional problems.

One of EMFO-SCA's key strengths lies in its ability to manage constraints effectively. By integrating constraint handling directly into its update equations, the method ensures that generation limits and ramp rate constraints are consistently met. Additionally, its normalization step guarantees an exact match between generated power and demand, minimizing power mismatches. On the other hand, KKA, which uses penalty-based approaches for constraint handling, is less adaptive and more prone to violations, particularly under dynamic conditions.

EMFO-SCA also outperforms KKA in convergence speed. The dynamic adjustment of forces in the EMFO phase accelerates global search, while the SCA phase expedites local refinement, reducing the number of iterations needed to achieve optimal solutions. In contrast, KKA's more stochastic exploration phase often requires additional iterations, increasing computational time and limiting its efficiency in real-time applications.

Moreover, EMFO-SCA is particularly robust in tackling the complexities of non-linear, constrained optimization problems. Its hybrid design is well-suited for navigating non-convex cost landscapes and adapting to operational constraints. Conversely, KKA's simpler movement and refinement mechanisms make it more prone to getting trapped in local optima and struggling with the intricacies of non-linear cost functions. The practical results further underscore EMFO-SCA's superiority, with the method achieving consistent operational cost reductions over 24-hour periods. Its ability to achieve an average cost reduction of 0.27% compared to KKA highlights its effectiveness in minimizing expenses while maintaining reliable power scheduling.

V. Conclusion

The Hybrid Electromagnetic Field Optimization with Sine-Cosine Algorithm (EMFO-SCA) represents a significant advancement in solving the dynamic economic dispatch problem, especially for the Sulselbar 150 kV power system. This study validates its capability to achieve superior performance by minimizing operational costs, maintaining strict compliance with operational constraints, and ensuring robust power balance over a 24-hour period.

The EMFO-SCA method achieved an average operational cost reduction of 0.27% compared to the Kho-Kho Algorithm (KKA), translating into measurable financial savings across the entire scheduling horizon. For instance, during the peak demand at hour 12 (521.52 MW), the method dynamically allocated generation resources to minimize fuel costs while maintaining precise power balance. Since the power balance was exact, with no surplus or deficit, the system operated without any losses. Additionally, the method ensured strict adherence to generation limits and ramp rate constraints, highlighting its efficiency and reliability in optimizing power generation under dynamic conditions. Similar efficiency was observed at off-peak periods, such as hour 3 (160.10 MW), demonstrating the algorithm's adaptability across varying load conditions. When projected over a year, assuming consistent demand patterns across Sulselbar's 150 kV system, the daily savings of Rp 12,914.11 translate into annual savings of approximately Rp 4,712,649.15. As the backbone for electricity distribution in South Sulawesi and surrounding regions, these savings represent a significant economic advantage for the Sulselbar system. The results highlight the practicality and scalability of EMFO-SCA in optimizing power generation schedules, reducing costs, and ensuring operational feasibility while maintaining the stability and efficiency of Sulselbar's 150 kV system in meeting dynamic power demands. From a computational perspective, the EMFO-SCA method demonstrated higher efficiency, requiring fewer iterations to achieve optimal results while maintaining computational feasibility. This makes it well-suited for real-time applications in modern power systems.

The algorithm ensures that no generation limits were exceeded, as the power output for each generator consistently stayed within the permissible range. Furthermore, the ramp rate constraints, critical for system stability, were strictly adhered to, with zero violations recorded over all scheduling intervals. The dynamic normalization of the global best solution at each iteration allowed EMFO-SCA to meet demand accurately, ensuring an exact match between power supply and load without surplus or deficit.

The dual-phase design of EMFO-SCA—combining the exploration capabilities of Electromagnetic Field Optimization (EMFO) with the refinement precision of the Sine-Cosine Algorithm (SCA)—contributed to faster convergence and more accurate solutions. The EMFO phase explored the solution space effectively by simulating attraction-repulsion dynamics, avoiding local optima. The SCA phase refined these solutions through sine-cosine adjustments, enabling precise optimization. In comparison, the KKA's simpler exploration-exploitation mechanism resulted in slower convergence and less optimal solutions.

In summary, the findings confirm that the Hybrid EMFO-SCA method is not only robust and reliable but also capable of delivering substantial operational cost savings and enhanced performance in dynamic economic dispatch scenarios. Its adaptability to varying load demands, strict adherence to constraints, and superior cost minimization highlight its potential as a scalable and practical solution for optimizing power generation in real-world energy systems. By outperforming traditional methods such as KKA, EMFO-SCA establishes itself as a powerful tool for addressing the complexities of modern power systems, paving the way for more efficient and reliable energy management.

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