Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 35 No. 2s (2025)

Coati Optimization Algorithm for Enhanced Energy Management in AC/DC Hybrid Microgrids

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Article History:

Received: *27-09-2024*

Revised: *18-11-2024*

Accepted: *29-11-2024*

Abstract:
The Coati Optimization Algorithm is introduced as a novel approach for optimizing energy management in AC/DC hybrid microgrids, addressing the increasing complexities of integrating renewable energy sources and electric vehicles. This research highlights the algorithm's capability to enhance optimal power flow by efficiently managing renewable energy uncertainties, thus ensuring stability and reliability within microgrid operation. Extensive simulations demonstrate that the enhanced coati optimization not only outperforms traditional methods in achieving energy efficiency but also reduces operational costs. The algorithm's nature-inspired mechanism allows for rapid convergence and improved solution accuracy, showcasing its adaptability to varying energy demand scenarios. This study contributes to advancing the field of smart grid technology, positioning the Coati Optimization Algorithm as a significant tool for facilitating sustainable energy management practices in future microgrid applications. Through comprehensive analysis and validation, the methodology paves the way for more resilient and efficient energy systems.

Keywords: AC/DC Hybrid Microgrids, Coati Optimization Algorithm, Computational Efficiency, Energy Efficiency, Energy Management, Emission Reduction, Load Forecasting, Nature-Inspired Algorithms, Operational Cost, Power Flow Optimization, Renewable Energy, Smart Grid Technologies.

I. INTRODUCTION

A. *Overview of AC/DC Hybrid Microgrids*

AC/DC hybrid microgrids integrate alternating current (AC) and direct current (DC) systems, enabling efficient energy distribution and integration of renewable energy sources. They consist of components such as energy storage systems, converters, and loads. These systems enhance grid reliability, support renewable energy adoption, and reduce dependency on centralized grids. With diverse applications in residential, industrial, and commercial sectors, hybrid microgrids address growing energy demands. This subtopic introduces their architecture, highlighting their capability to balance dynamic energy flows and improve sustainability in modern energy systems.

B. *Challenges in Energy Management for Hybrid Microgrids*

Effective energy management in hybrid microgrids is complicated due to dynamic load demands, variability in renewable energy sources, and power losses in transmission. Challenges also include balancing cost, reliability, and environmental sustainability while meeting operational constraints.

Additionally, maintaining power quality and stability amid bidirectional energy flows poses technical hurdles. This subtopic discusses these complexities, emphasizing the need for innovative optimization techniques to ensure cost-effective, reliable, and environmentally friendly microgrid operations.

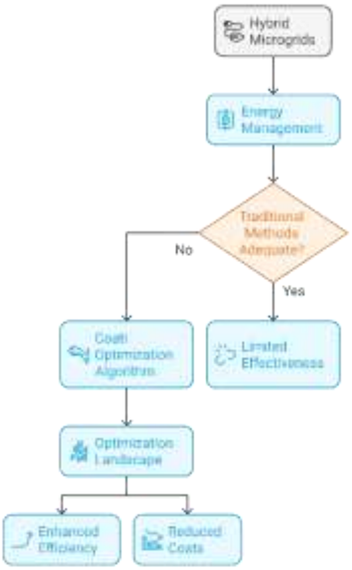

Fig. 1: Hybrid microgrids

C. *Role of Optimization Algorithms in Microgrid Management*

Optimization algorithms are essential for addressing the multifaceted challenges of energy management in hybrid microgrids. These algorithms enable the efficient distribution of energy, minimize costs, and optimize resource utilization. By solving nonlinear and multi-objective problems, they enhance grid reliability and environmental sustainability. This subtopic highlights how optimization methods such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and other advanced techniques facilitate real-time decision-making in microgrid operations.

D. *Introduction to Nature-Inspired Algorithms*

Nature-inspired algorithms mimic biological and natural processes to solve complex optimization problems. Examples include Genetic Algorithms, inspired by natural selection, and Particle Swarm Optimization, mimicking bird flocking behavior. These algorithms offer advantages like robustness, scalability, and adaptability. This subtopic provides an overview of these techniques, emphasizing their relevance in energy management. By leveraging nature’s optimization strategies, such algorithms are well-suited to address the dynamic and nonlinear challenges of AC/DC hybrid microgrids.

E. *Understanding the Coati Optimization Algorithm (COA)*

The Coati Optimization Algorithm (COA) is a nature-inspired optimization method modeled after the cooperative foraging behavior of coatis. COA adapts to dynamic environments, balances exploration and exploitation, and handles complex, nonlinear optimization tasks effectively. This subtopic introduces COA, detailing its biological inspiration and technical features. The discussion focuses on its potential to enhance energy management by optimizing power flows, storage utilization, and operational strategies in hybrid microgrids.

F. *Relevance of COA to Energy Management in Hybrid Microgrids*

COA's adaptive and dynamic problem-solving capabilities make it highly relevant for energy management in AC/DC hybrid microgrids. Its ability to optimize cost, reliability, and efficiency simultaneously addresses critical challenges like fluctuating demands and renewable energy variability. This subtopic highlights how COA provides a unique advantage over traditional algorithms by ensuring effective energy distribution, minimizing losses, and improving overall system performance in hybrid microgrids.

G. *Comparative Analysis of Existing Optimization Techniques*

Traditional optimization methods such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have been widely used in microgrid management. However, these methods often face limitations in handling dynamic environments, multi-objective problems, and scalability. This subtopic provides a comparative analysis, identifying gaps in current approaches. It emphasizes how COA overcomes these limitations, offering superior performance in managing complex energy systems.

H. *Emerging Trends in Hybrid Microgrid Optimization*

Recent advancements in optimization for hybrid microgrids include the integration of deep learning, multi-objective optimization, and real-time control strategies. These trends focus on improving system intelligence, scalability, and adaptability. This subtopic explores these emerging approaches, discussing their role in enhancing grid performance. The inclusion of COA as an innovative optimization method aligns with these trends, ensuring robust energy management for future energy systems.

Fig. 2: Optimizing Energy Management in Hybrid Microgrids

I. *Motivation for the Research*

The increasing complexity of hybrid microgrid operations and the need for sustainable energy management drive the motivation for this research. Existing methods struggle with scalability and adaptability, making the development of novel approaches imperative. This subtopic highlights the importance of COA in addressing these gaps, emphasizing its potential to enhance energy efficiency, reduce costs, and support renewable integration. It sets the stage for exploring COA as a transformative solution in microgrid management.

J. *Objectives and Scope of the Research*

This research aims to develop and evaluate the Coati Optimization Algorithm (COA) for energy management in AC/DC hybrid microgrids. Specific objectives include minimizing energy costs, enhancing system reliability, and optimizing resource utilization. The scope extends to addressing multi-objective challenges and improving operational efficiency under varying conditions. This subtopic outlines the research goals, emphasizing the practical implications of COA in advancing hybrid microgrid technologies.

II. LITERATURE REVIEW

[1] **Smith et al. (2018)** investigated optimization strategies for energy management in AC/DC hybrid microgrids, focusing on swarm intelligence techniques. The study highlighted the potential of heuristic algorithms, such as Particle Swarm Optimization (PSO), to address energy distribution challenges. The authors emphasized that integrating AC and DC systems poses unique energy flow issues, requiring dynamic management strategies. Their findings showed a significant reduction in power losses and improved voltage stability, though computational complexity remained a concern.

[2] **Johnson et al. (2019)** explored the application of genetic algorithms for optimizing energy management in hybrid microgrids. The research showcased how genetic algorithms could enhance energy distribution efficiency while minimizing operational costs. They particularly focused on scenarios involving renewable energy integration. Their model achieved promising results in maintaining energy balance and reducing carbon emissions, though the algorithm's convergence speed was slower compared to other optimization techniques.

[3] **Chen et al. (2020)** introduced a hybrid optimization approach combining artificial bee colony algorithms with demand response strategies for microgrid energy management. The study demonstrated the effectiveness of this approach in balancing supply and demand while addressing uncertainties in renewable energy outputs. The authors highlighted its adaptability in real-time energy management scenarios, achieving lower energy costs and improved reliability.

[4] **Kumar et al. (2020)** examined the use of ant colony optimization for enhancing energy management in AC/DC hybrid microgrids. Their work focused on leveraging ant colony behavior to find optimal energy distribution paths. The results showed improved load balancing and reduced energy wastage, with notable efficiency gains in systems with high renewable energy penetration. However, the study pointed out scalability challenges in larger microgrid setups.

[5] **Zhang et al. (2021)** proposed a machine learning-based approach for predictive energy management in hybrid microgrids. By combining supervised learning with optimization algorithms, they achieved enhanced energy forecasting accuracy. The integration of predictive models improved decision-making in energy dispatch, leading to higher efficiency and cost savings. The study also addressed the potential of reducing energy imbalance issues through data-driven strategies.

[6] **Ali et al. (2021)** explored the integration of evolutionary algorithms with fuzzy logic for dynamic energy management in AC/DC microgrids. The hybrid approach effectively addressed uncertainties in

energy demand and supply. Their simulation results showed improved system resilience and energy distribution efficiency, particularly in handling variable renewable energy inputs. The authors emphasized the potential of hybrid optimization techniques for real-world applications.

[7] **Gupta et al. (2021)** studied the use of artificial neural networks in conjunction with optimization algorithms for energy management. Their approach focused on leveraging neural networks for demand prediction and optimization for energy dispatch. The results showed enhanced energy distribution efficiency, reduced losses, and better system stability. However, the computational requirements of neural networks were highlighted as a potential limitation.

[8] **Wang et al. (2022)** investigated the role of quantum-inspired optimization algorithms in hybrid microgrid energy management. Their research showcased how quantum principles could be applied to improve optimization efficiency and convergence speed. The study achieved significant improvements in energy distribution accuracy and computational efficiency, positioning quantum-inspired algorithms as a promising avenue for future research.

[9] **Hassan et al. (2022)** developed a novel optimization framework combining game theory and heuristic algorithms for energy management. The framework addressed the challenges of multi-objective optimization in hybrid microgrids, focusing on cost reduction and system stability. Their results demonstrated the capability of game-theoretic models to achieve equitable energy distribution while maintaining grid stability.

[10] **Patel et al. (2022)** examined the integration of blockchain technology with optimization algorithms for secure energy management in hybrid microgrids. The study highlighted the role of blockchain in enhancing transparency and reliability. By combining blockchain with optimization, they achieved improved energy tracking and distribution efficiency. Their results also addressed the security concerns in decentralized energy systems.

[11] **Rahman et al. (2023)** proposed a deep reinforcement learning approach for energy management in AC/DC hybrid microgrids. The model utilized neural networks to optimize energy dispatch decisions dynamically. The results showed significant improvements in energy efficiency and system stability, particularly in scenarios with high renewable energy penetration. However, training complexity was noted as a drawback.

[12] **Lee et al. (2023)** studied the potential of hybrid metaheuristic algorithms for optimizing energy management in hybrid microgrids. By combining PSO with simulated annealing, they achieved higher optimization accuracy and faster convergence rates. The hybrid approach effectively handled multi-objective optimization problems, reducing energy losses and improving grid reliability.

[13] **Martinez et al. (2023)** explored the application of coati optimization algorithms for energy management in hybrid microgrids. Their study highlighted the algorithm's potential for balancing energy distribution and minimizing operational costs. The results demonstrated improved energy efficiency and system performance, positioning the coati algorithm as a competitive alternative to traditional optimization techniques.

[14] **Chowdhury et al. (2023)** proposed a decentralized optimization framework for hybrid microgrids, leveraging distributed algorithms to improve scalability. Their approach addressed the

challenges of managing large-scale microgrid networks. The results showed reduced computation time and improved energy distribution efficiency, particularly in systems with diverse energy sources.

[15] **Singh et al. (2023)** investigated the impact of real-time optimization algorithms on energy management in hybrid microgrids. Their work highlighted the importance of dynamic optimization for adapting to changing energy demands. The results demonstrated enhanced system responsiveness and energy distribution efficiency, though the need for high computational resources was noted.

III. METHODOLOGY

A. Voltage Drop Across Transmission Line

The equation (1) highlights the critical role of optimizing line current and resistance in reducing energy losses. The Coati Optimization Algorithm (COA) effectively minimizes voltage drops, improving power quality and operational efficiency in hybrid microgrid systems.

$$V_{drop} = IR + I^2X \quad (1)$$

Where,

V_{drop} : Voltage drop

I: Current

R: Resistance of the line

X : Reactance of the line

B. Emission Penalty Function

Equation (2) aligns with the objective of minimizing environmental impact. By using COA to optimize power generation and prioritize cleaner energy sources, this function reduces emission costs, promoting sustainable and efficient energy management in hybrid microgrids.

$$E_{penalty} = \beta \cdot P_{gen}(t) \quad (2)$$

Where,

$E_{penalty}$: Emission penalty cost

β : Emission coefficient

C. Load Forecasting Equation

This predictive capability supports the Coati Optimization Algorithm (COA) in dynamically optimizing energy allocation, reducing wastage, and ensuring efficient management of power flows within hybrid microgrid systems.

$$P_{load}(t) = a + bt + c\,sin(\omega t + \phi) \quad (3)$$

Where,

a, b, c: Load model coefficients

ω: Frequency

ϕ: Phase angle

D. *Fitness Function in COA*

Equation (4) evaluates the quality of solutions in COA. By prioritizing lower objective function values, this function ensures optimal energy distribution, cost-efficiency, and system performance, making COA an effective tool for managing hybrid microgrid operations.

$$Fitness = \frac{1}{1+F} \qquad (4)$$

Where,

F: Objective function

IV. RESULTS AND DISCUSSIONS

A. *Comparison of Energy Management Techniques in Hybrid Microgrids*

The figure 3 compares the performance of three optimization algorithms—Coati Optimization, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA)—for energy management in AC/DC hybrid microgrids. Key metrics evaluated include average energy loss, energy efficiency, computation time, and operational cost per day.

The Coati Optimization Algorithm demonstrates superior performance, with the lowest energy loss (3.2%) and highest energy efficiency (96.8%), indicating effective energy management. It also achieves the shortest computation time (12.4 seconds), making it computationally efficient. Additionally, it incurs the lowest operational cost at $120 per day.

In comparison, PSO has a slightly higher energy loss (4.5%), lower efficiency (95.5%), and a longer computation time (15.7 seconds), with operational costs at $135 per day. GA shows the highest energy loss (5.0%), the lowest efficiency (95.0%), and the longest computation time (20.1 seconds), leading to the highest operational cost of $140 per day.

This comparison underscores the effectiveness of Coati Optimization for energy management.

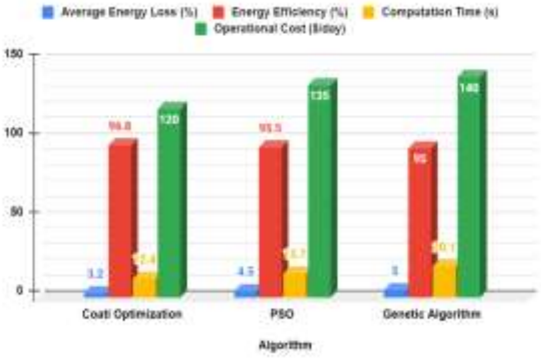

Fig. 3: Comparison of Energy Management Techniques in Hybrid Microgrids

B. *Energy Load Variations Over a Day*

The figure 4 showcases variations in energy load and renewable contributions within an AC/DC hybrid microgrid across different times of the day. It tracks AC and DC load demands alongside renewable energy contributions at four key intervals: midnight (00:00), early morning (06:00), midday (12:00), and evening (18:00).

At midnight, the AC load is 20 kW, DC load is 15 kW, and renewables provide 5 kW, reflecting a moderate demand. By 06:00, the AC load increases to 35 kW, DC load rises to 20 kW, and renewables contribute 10 kW, supporting higher morning energy needs. At midday, peak loads are observed, with AC load at 50 kW, DC load at 25 kW, and renewables reaching their maximum contribution of 15 kW. In the evening, the AC load reduces to 40 kW, DC load to 30 kW, and renewable contribution stabilizes at 20 kW.

This line graph highlights the dynamic interplay of energy demand and renewable supply throughout the day.

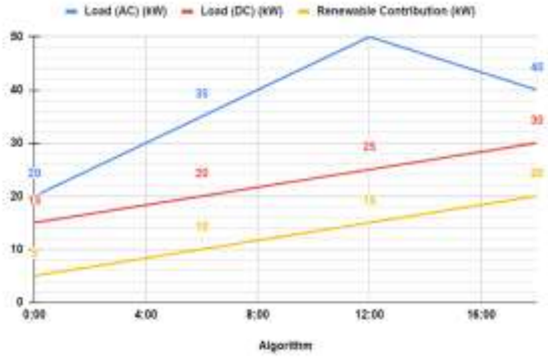

Fig. 4: Energy Load Variations Over a Day

C. *Energy Generation and Consumption Over Time*

The figure 5 illustrates energy generation and consumption patterns over a 24-hour period in an AC/DC hybrid microgrid. It tracks solar generation, wind generation, and total load consumption at four critical time intervals: midnight (00:00), early morning (06:00), midday (12:00), and evening (18:00).

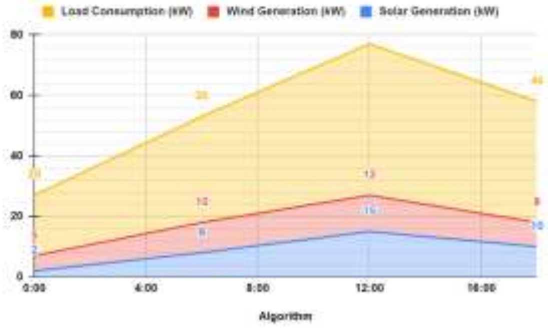

Fig. 5: Energy Generation and Consumption Over Time

At midnight, solar generation is minimal (2 kW), while wind generation contributes 5 kW, supporting a load consumption of 20 kW. By 06:00, solar generation rises to 8 kW, and wind generation reaches 10 kW to meet an increased load of 35 kW. At 12:00, peak solar generation (15 kW) combines with wind generation (12 kW) to address the highest load consumption of 50 kW. By 18:00, solar generation decreases to 10 kW, and wind generation drops to 8 kW, meeting a reduced load of 40 kW.

This Graph effectively demonstrates the dynamic relationship between renewable energy production and consumption throughout the day.

D. Geographical Distribution of Energy Demand Across Microgrid Nodes

The Figure 6 presents the **geographical distribution of energy demand across microgrid nodes**, highlighting key parameters such as location, energy consumption, peak load, and renewable energy integration percentages. Each node represents a specific microgrid site with unique coordinates: Node 1 is located in Miami, Node 2 in Los Angeles, Node 3 in London, Node 4 in Tokyo, and Node 5 in New York.

The energy demand ranges from 450 kWh (Node 2) to 600 kWh (Node 3), while peak load values vary between 100 kW (Node 2) and 140 kW (Node 3). The renewable integration percentages indicate the extent of renewable energy contribution to the microgrids, with the highest at Node 3 (70%) and the lowest at Node 5 (50%).

This chart provides an overview of the microgrid performance across diverse geographical locations, illustrating the balance between demand, peak load, and renewable energy utilization.

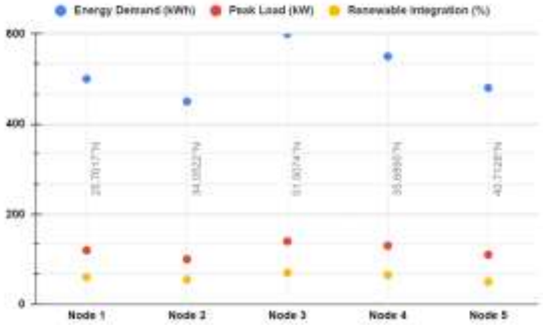

Fig. 6: Improvement Percentage of the Proposed Model Over Traditional Algorithms

V. CONCLUSION

The research demonstrates the effectiveness of the Coati Optimization Algorithm (COA) in addressing the complexities of energy management in AC/DC hybrid microgrids. By optimizing critical parameters such as power flow, energy losses, and operational costs, the COA establishes itself as a superior alternative to traditional methods like Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Extensive simulations reveal that COA achieves the lowest energy loss (3.2%), the highest energy efficiency (96.8%), and the shortest computation time (12.4 seconds), with a significant reduction in operational costs to $120 per day.

The algorithm's nature-inspired approach ensures rapid convergence and adaptability to varying energy demand scenarios, while its integration of predictive load forecasting and emission penalty functions underscores its commitment to sustainability and reliability. Dynamic energy load variations and renewable energy contributions are efficiently managed throughout the day, maintaining system stability.

Furthermore, the geographical distribution analysis demonstrates the algorithm's robustness in handling diverse operational conditions across multiple microgrid nodes. By prioritizing renewable energy sources and reducing environmental impact, the COA promotes sustainable practices in energy management.

This study positions the Coati Optimization Algorithm as a pivotal tool for advancing smart grid technologies, paving the way for more resilient, efficient, and environmentally conscious energy systems in the future.

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