Journal of Artificial Intelligence and Metaheuristic

♦ ISSN: 2833-5597 Vol: 11, No. 02, 2026 ♦ PP. 149–157
Article DOI: https://doi.org/10.54216/JAIM.110209

FULL LENGTH ARTICLE

Hybrid Grey Wolf and Al-Biruni Earth Radius Optimization for Sustainable Electric Vehicle Routing

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Received: January 28, 2026 Revised: March 19, 2026 Accepted: May 28, 2026 ⋆ Corresponding author

ABSTRACT

In this chapter, a novel hybrid optimization algorithm, which integrates the Grey Wolf Optimizer (GWO) with the Al-Biruni Earth Radius (BER) method to address the problem of electric vehicle (EV) path planning, is introduced. By incorporating the simulation of wolf social hierarchies for efficient exploration alongside the spatial analysis capabilities of BER, the proposed approach effectively determines optimal, energy-efficient routes across diverse terrains. The hybrid approach systematically considers key factors such as distance, terrain characteristics, and energy consumption to guide vehicle movements, thereby minimizing energy usage, enhancing travel efficiency, and ensuring smooth traffic flow. Experimental results demonstrate the effectiveness of the proposed hybrid method compared to conventional metaheuristic approaches, achieving an average error of 0.530218. This chapter presents the technical framework of this hybrid approach, its applications in EV route optimization, and its broader implications for sustainable mobility and real-world transportation challenges.

Keywords: Electric Vehicle Path Planning ▪ Hybrid Optimization Algorithms ▪ Grey Wolf Optimizer (GWO) ▪ Al-Biruni Earth Radius (BER)

1. INTRODUCTION

The advancement of electric vehicles (EVs) represents a crucial milestone in sustainable transportation, contributing to reducing greenhouse gas emissions, decreased dependence on fossil fuels, improved oil displacement efficiency, and potential cost savings. With the global increase in EV adoption, driven by government policies and industrial advancements, enhancing the efficiency and reliability of EV systems has become a critical area of research [1, 2]. Among these systems, the problem of electric vehicle path planning (EVPP) problem is paramount, as it significantly influences energy consumption, travel efficiency, and user satisfaction. Effective path planning enables EVs to navigate complex and dynamic environments while accounting for various factors such as terrain variability, traffic conditions, energy constraints, and the availability of charging stations [3]. Addressing these challenges necessitates sophisticated optimization techniques for exploring vast multidimensional solution spaces and identifying near-optimal paths.

Optimization algorithms, particularly metaheuristic methods, have proven powerful tools for solving complex and nonlinear problems such as EVPP. Unlike traditional optimization techniques, metaheuristic algorithms excel at avoiding local optima and discovering global solutions within large and dynamic problem spaces [4]. This chapter explores the development of a hybrid optimization approach that integrates the capabilities of two state-of-the-art optimization algorithms: the Grey Wolf Optimizer (GWO) and the Al-Biruni Earth Radius (BER) method. By combining these algorithms into a synergistic framework, this hybrid approach effectively addresses the unique challenges associated with EV path planning [5].

The Grey Wolf Optimizer (GWO) is inspired by the social hierarchy and hunting strategies of grey wolf packs in nature, enabling it to explore and exploit solution spaces efficiently. In the GWO process, different levels of leadership and cooperation—represented by alpha, beta, delta, and omega wolves—guide the search for optimal solutions through adaptive exploration and encircling mechanisms [6, 7]. Due to its well-balanced trade-off between exploration (searching for new regions) and exploitation (refining known solutions), GWO has demonstrated outstanding performance in numerous optimization problems. This balance makes GWO particularly suitable for tackling the complexities of EV path planning, where multiple objectives and constraints interact dynamically [8, 9].

Complementing GWO, the Al-Biruni Earth Radius (BER) algorithm incorporates advanced spatial analysis techniques inspired by mathematical and geometric principles. BER excels in refining solutions by leveraging precise calculations and adaptive adjustments based on geometric modeling. This ability enhances the exploitation phase of optimization, allowing the algorithm to converge toward highly accurate solutions. Additionally, BER's dynamic adaptability to changing problem spaces ensures precision in scenarios with high variability, such as EVPP, where terrain, traffic, and energy factors fluctuate frequently [10].

The hybridization of GWO and BER creates a robust optimization framework that harnesses the strengths of both algorithms. By integrating GWO's broad exploration capabilities with BER's precision-driven refinement, the hybrid approach achieves a level of optimization that neither algorithm could accomplish independently. This synergy is crucial for addressing the challenges of EVPP, where the identification of energy-efficient and time-saving routes requires extensive exploration and precise optimization [11, 12].

This chapter delves into the technical framework and implementation of the GWO-BER hybrid algorithm, focusing on its application in EV path planning. The proposed hybrid approach systematically tackles the core challenges of EVPP by minimizing energy consumption, reducing travel time, optimizing traffic flow, and adapting to terrain constraints. Enhancing route optimization contributes to the broader goals of sustainable mobility, ensuring efficient resource utilization while improving the overall experience for EV drivers [13, 14].

Beyond its direct application to EV path planning, the hybrid GWO-BER algorithm demonstrates the broader potential of integrating nature-inspired optimization techniques with geometric modeling. This integration facilitates solutions for other real-world optimization challenges in logistics, transportation, and resource management. By showcasing how metaheuristic methods can be tailored to address specific challenges, this chapter highlights the transformative role of optimization algorithms in solving complex, multidimensional problems [15].

The primary contribution of this chapter is the development of a novel hybrid optimization framework that integrates the Grey Wolf Optimizer (GWO) with the Al-Biruni Earth Radius (BER) algorithm to address the challenges of electric vehicle path planning (EVPP). The key contributions of this work can be summarized as follows:

- **Development of a Hybrid Metaheuristic Algorithm:** This chapter presents a hybrid optimization algorithm that leverages the strengths of GWO's exploratory capabilities and BER's precision-driven search. Integrating these two techniques enhances the algorithm's ability to identify optimal, energy-efficient paths for EVs.
- **Energy-Efficient Path Optimization:** The proposed approach systematically optimizes EV routes by minimizing energy consumption while considering constraints such as distance, terrain characteristics, and traffic conditions.
- **Enhanced Performance Over Existing Methods:** Experimental evaluations demonstrate that the hybrid GWO-BER algorithm outperforms conventional metaheuristic approaches regarding solution accuracy, computational efficiency, and optimization robustness.
- **Real-World Applicability:** The proposed framework is designed to be scalable within real-world transportation networks, offering potential logistics, traffic management, and sustainable mobility applications.
- **Bridging Optimization Techniques and Transportation Challenges:** This chapter highlights the synergy between bio-inspired optimization techniques and real-world mobility challenges, showcasing how metaheuristic algorithms can be tailored for practical transportation applications.

The findings presented in this work contribute to the broader domain of sustainable mobility by improving EV navigation efficiency and addressing key challenges in path optimization.

The remainder of this chapter is structured to ensure a logical progression of concepts and findings. Section 2 presents a comprehensive literature review, discussing existing approaches to electric vehicle path planning while analyzing the strengths and limitations of both conventional and metaheuristic optimization techniques. Section 3 outlines the methodology, detailing the design and implementation of the proposed hybrid GWO-BER algorithm, along with dataset preprocessing and algorithmic structure. Section 4 delves into the theoretical foundations and working mechanisms of the Grey Wolf Optimizer and the Al-Biruni Earth Radius algorithm, explaining how their integration enhances optimization performance. Section 5 presents the experimental results, offering a comparative evaluation of the hybrid GWO-BER algorithm against conventional optimization techniques using multiple performance metrics. Finally, Section 6 provides a summary of key findings, highlighting the contributions of this work and discussing potential future research directions in the domain of electric vehicle path optimization and metaheuristic algorithm development.

2. LITERATURE REVIEW

With integrating electric vehicles (EVs) into transportation systems, extensive research has been done on optimizing their routing and charging systems to achieve better efficiency, reduce energy consumption, and address existing infrastructure limitations. This paper synthesizes the insights of ten key studies in the field, reviewing them to present an organization. It presents a detailed understanding of optimization strategies and methodologies employed in this field.

EV route optimization with uncertainties in traffic conditions and demand is challenging. [16] proposes a robust optimization model where uncertainty in the demand and traffic conditions are represented by convex and box uncertainty sets, respectively. The problem of comparing the deterministic model with the robust model is developed by using the deviation coefficients, and it is demonstrated that the robust model could ensure feasibility in uncertain conditions at a higher cost. Further, the model is practicable by applying an improved genetic algorithm. The findings show the trade-off between robustness and optimality and how more resilient logistics systems can be constructed.

Due to the limited EV range, energy-efficient routing strategies are essential. [17] presents a new mathematical routing model that considers energy consumption during start/stop operations and uses an amplified Ant Colony Optimization (A2CO) algorithm. Results of simulations on accurate maps show significant improvements in energy efficiency, travel time, and state of charge over traditional methods. This research highlights the possibility of implementing energy-aware algorithms in real-time applications to optimize the behavior of EVs fully.

To overcome the challenges of limited battery capacity and delivery restrictions, [18] proposes a Hybrid Variable Neighborhood Search (HVNS) algorithm for solving the CE-VRP. On this basis, the proposed solution is shown to minimize costs whilst optimizing fleet size and travel distance, and computational results support its efficacy. This paper offers a practical framework for improving EV logistics with recharging stations integrated into the routing problem under capacity constraints.

Although not exclusively on EVs, [19] presents an understanding of path planning for uncrewed aerial vehicles relevant to metaheuristic algorithms. The findings show that these algorithms effectively solve single and multi-objective problems with such characteristics and, therefore, can be applied to EV routing problems within dynamic environments. The study indicates that metaheuristics can offer a way to address complex optimization problems.

In [20], a broader perspective on EV optimization is proposed by aggregating progress across design, energy management, control, charging, and routing. The paper outlines the strengths and shortcomings of swarm intelligence and evolutionary optimization algorithms that will serve researchers as a valuable resource. The discussion gains practical relevance with the addition of the classification of driving cycles and simulation platforms.

EV deployment is based on strategically setting charging stations, and [21] applies genetic algorithms to optimize the routes of EVs with consideration of the locations of charging stations. Simulations in Poland show the necessity of considering the integration of station parameters (e.g., charging speed) in route planning. This approach reduces travel distances and makes EV journeys more practical.

[22] suggests a metaheuristic routing model based on the Artificial Bee Colony (ABC) algorithm introduced by Karaboga, including aspects such as speed, road conditions, and battery health. Energy savings of approximately 7.1% compared to conventional methods were shown in real-time simulations. This work identifies the use of adaptive algorithms in EV energy consumption optimization.

The optimal placement of EV charging stations in microgrids is explored in [23], where metaheuristics are integrated with energy management systems to enhance overall efficiency. The study emphasizes the importance of coordinated charging strategies, demonstrating how clustering techniques can minimize energy consumption and travel time. This approach offers a scalable solution for grid-connected EV environments, ensuring optimal energy distribution and travel efficiency.

The relationship between EV loads and power system stability is investigated in [24], where metaheuristic algorithms are employed to optimize the placement of fast-charging stations. The study examines the effects of EV loads on power networks and explores how distributed photovoltaic systems can mitigate load voltage deviations and power losses. A comparative analysis of various optimization algorithms is conducted to identify the most effective deployment strategies, ultimately providing insights into the optimal integration of EVs into power systems.

The integration of plug-in hybrid electric vehicles (PHEVs) into smart grids is examined in [25], focusing on state-of-charge management. The study implements hybrid optimization techniques, such as PSOGSA, which demonstrate superior performance compared to standalone methods. The findings highlight the necessity of innovative charging control systems to facilitate the large-scale adoption of PHEVs and improve grid stability.

Collectively, these reviewed studies underscore the need for comprehensive optimization solutions to address the challenges associated with EV adoption. Contributions span from robust route planning and energy-efficient algorithms to optimal charging station placement and smart grid integration. These methodologies offer diverse strategies aimed at enhancing EV performance and sustainability. Future research will focus on integrating these approaches into cohesive systems, addressing multi-objective optimization scenarios, and investigating real-world applications.

3. METHODOLOGY

3.1 Dataset

3.1.1 Description of the Used Dataset

This research utilizes a dataset from an experimental study conducted by public policy expert Dr. Omar Asensio and his team [26]. The study collected data from 3,395 electric vehicle (EV) charging sessions from November 2014 to October 2015. The dataset comprises records from 85 EV drivers who utilized 105 charging stations distributed across 25 workplace sites participating in a voluntary charging program. The dataset includes key attributes such as the date and duration of each charging session, total energy consumption, associated costs, and additional contextual details. This comprehensive dataset provides crucial insights into EV charging behaviors, energy consumption patterns, and the operational efficiency of workplace charging infrastructures, making it an essential resource for evaluating optimization algorithms.

3.1.2 Data Preprocessing

Before applying the optimization algorithms, the dataset underwent a meticulous preprocessing phase to ensure data quality, consistency, and relevance. The preprocessing steps included the following:

- **Data Cleaning:** Entries with missing or incomplete data were identified and addressed accordingly. Charging sessions lacking essential information, such as energy consumption or cost, were either removed or imputed using statistical methods to maintain data reliability and completeness.
- **Feature Selection:** The preprocessing phase focused on retaining only the most relevant attributes, including session date, duration, energy usage, and cost. Redundant or non-contributory features were excluded to streamline the optimization process and enhance computational efficiency.
- **Normalization:** To ensure that all numerical attributes contributed equally to the optimization process, data normalization techniques were applied. This step eliminated biases caused by differences in scale among energy consumption, cost, and other numerical variables.
- **Data Splitting:** The dataset was divided into training and testing subsets. The training set was utilized to develop and fine-tune the hybrid GWO-BER algorithm, while the testing set was reserved to evaluate its performance on previously unseen data.
- **Outlier Detection:** Charging sessions exhibiting unusually high or low energy consumption, session durations, or costs were identified as potential outliers. These instances were thoroughly analyzed, excluded, and adjusted to prevent skewed results and ensure accurate optimization.

These preprocessing steps ensured the dataset was clean, consistent, and ready for use in the optimization and evaluation phases. By systematically addressing potential data quality issues, the preprocessing phase enhanced the reliability and validity of the experimental outcomes.

Figure 1 illustrates the correlation heatmap for the dataset variables. This heatmap visually represents the strength and direction of linear relationships between features such as `kwhTotal`, `locationId`, `userId`, `distance`, `chargeTimeHrs`, and `stationId`. The color intensity and values range from -1 to 1, where darker shades indicate stronger correlations. For example, `kwhTotal` shows a mod-erate positive correlation with `chargeTimeHrs`, while weak or negligible correlations are observed with other variables. This visualization provides insights into how features interact, which is critical for feature selection and optimization tasks.

Figure 2 shows the histograms of key variables in the dataset, including `kwhTotal`, `locationId`, `userId`, `distance`, `chargeTimeHrs`, and `stationId`. These histograms pro-vide a distributional overview of each feature. For instance, `kwhTotal` demonstrates a right-skewed distribution with most values concentrated between 5 and 7 kWh, while `chargeTimeHrs` shows a peak around 2 to 4 hours. Other variables have more uniform distributions, such as `distance` and `stationId`. Understanding these distributions is es-sential for preprocessing and normalization steps during the optimization process.

Figure 3 plots the Time consumed forTimecharging (`chargeTimeHrs`) across various `locationIds`. The figure shows temporal trends and variability in charging times, with charging durations spanning from less than an hour to over 10 hours at different locations. Such insights are valuable for identifying patterns in charging behavior and optimizing charging station usage.

Figure 4 visualizes the total energy consumed (`kwhTotal`) during EV charging sessions. The plot reveals variability in energy consumption, with most values clustering below 10 kWh while occasional peaks exceed 15 kWh. This variability highlights differences in charging behavior and vehicle en-ergy requirements, which are critical for optimizing energy management and resource allocation.

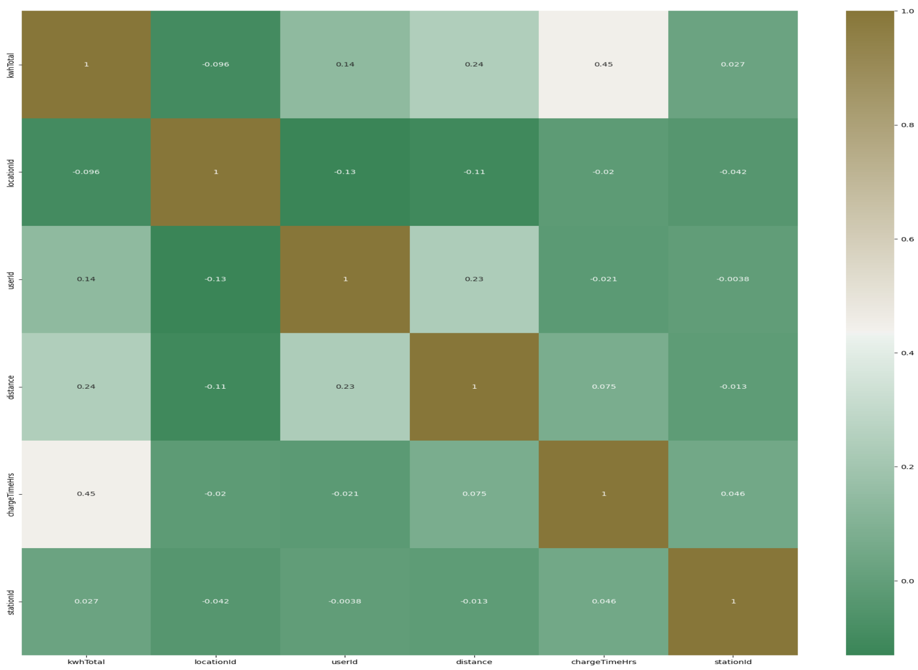

Figure 1. Correlation heatmap of the dataset features.

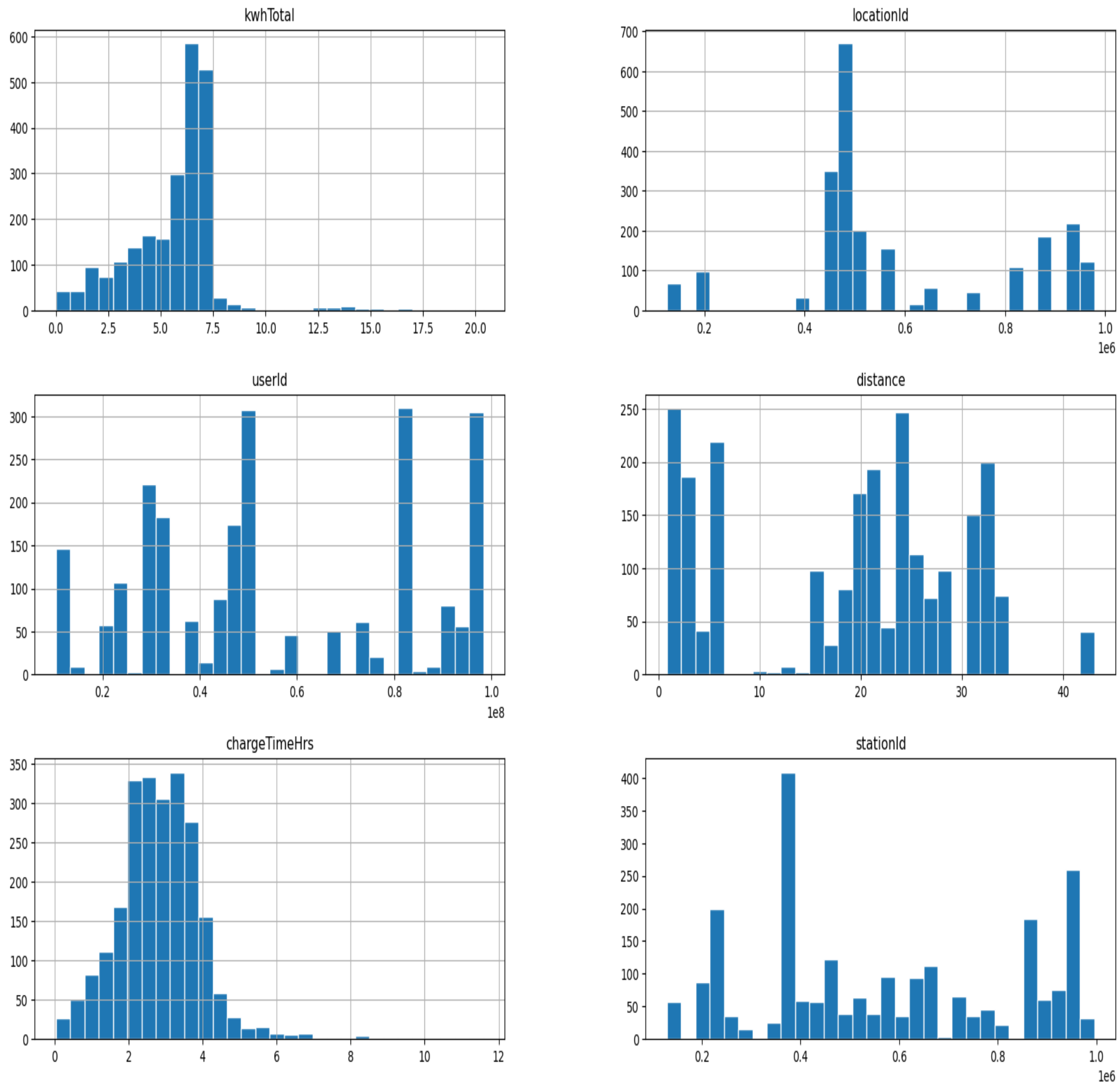

Figure 2. Histograms of key dataset features.

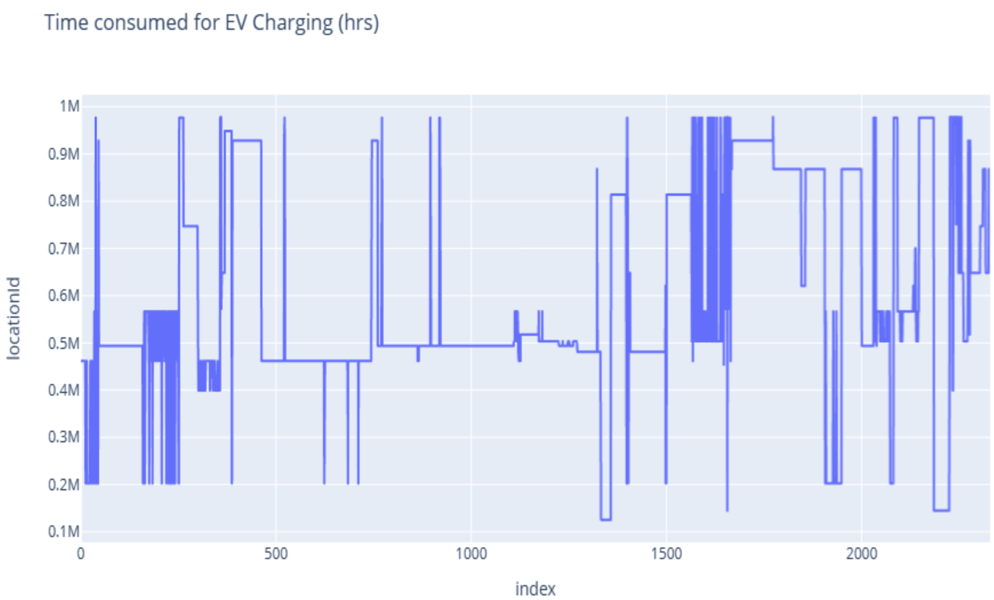

Figure 3. Time consumed forTimecharging across locations.

4. OPTIMIZATION ALGORITHMS

4.1 Overview of the Design and Integration of the Hybrid GWO-BER Algorithm

The hybrid Grey Wolf Optimizer (GWO) and Al-Biruni Earth Radius (BER) algorithms combine the complementary strengths of these two metaheuristic optimization approaches to solve the complex challenges of Electric Vehicle Path Planning (EVPP). Metaheuristic algorithms are ideal for solving nonlinear and multidimensional optimization problems because they effectively balance exploration and exploitation.

The hybrid approach integrates GWO and BER in a dual-phase manner. During the initial phase, GWO performs a global search space exploration, identifying promising regions while avoiding premature convergence to local optima. In the second phase, BER fine-tunes the solutions found by GWO using its precision-driven exploitation capabilities. This integration ensures the algorithm balances global search and local refinement, making it highly effective for optimizing EV energy consumption, travel time, and route efficiency.

4.2 Grey Wolf Optimizer (GWO)

4.2.1 Mechanism of GWO

The Grey Wolf Optimizer (GWO) is inspired by the social hierarchy and hunting strategies of grey wolves in nature [27]. It mimics the leadership structure of a grey wolf pack, where wolves are divided into four hierarchical roles:

- **Alpha** (α): The leader responsible for guiding the pack.
- **Beta** (β): The second-in-command, assisting and advising the alpha.
- **Delta** (δ): Subordinate wolves that dominate the lower-ranking wolves but follow the alpha and beta.
- **Omega** (ω): The lowest-ranking wolves follow the guidance of higher-ranking wolves.

The optimization process consists of three main phases:

1. **Tracking, Encircling, and Approaching the Prey:** Wolves update their positions iteratively based on the alpha, beta, and delta wolves. This behavior is modeled using the equations:

$$\vec{D} = |\vec{C} \cdot \vec{X}_{\text{prey}} - \vec{X}_{\text{wolf}}|, \quad \vec{X}(t+1) = \vec{X}_{\text{prey}} - \vec{A} \cdot \vec{D}$$

   Here, $\vec{D}$ is the distance between a wolf and the prey, $\vec{A}$ and $\vec{C}$ are coefficient vectors, and $\vec{X}$ represents the wolf's position.

2. **Exploration:** During early iterations, wolves explore the search space broadly by diverging from the prey. This is achieved by assigning $|\vec{A}| > 1$, encouraging global exploration.
3. **Exploitation:** In later iterations, wolves converge on the prey by reducing $|\vec{A}| < 1$, enabling local search in promising regions.

4.2.2 Benefits of GWO for Multidimensional Problems

GWO offers several advantages for complex optimization problems:

- **Global Exploration:** GWO effectively avoids local optima by exploring the search space widely during the initial iterations.
- **Local Exploitation:** The algorithm refines solutions in later iterations, ensuring convergence to optimal or near-optimal solutions.
- **Parameter Simplicity:** GWO operates with minimal parameter tuning, making its implementation straightforward.
- **Nonlinear Problem Handling:** The adaptive parameters of GWO allow it to handle complex, high-dimensional, and nonlinear optimization problems efficiently.

4.3 Al-Biruni Earth Radius (BER)

4.3.1 Mechanism of BER

The Al-Biruni Earth Radius (BER) algorithm is inspired by geometric principles derived from Al-Biruni's calculations of the Earth's radius [28]. The algorithm dynamically partitions the population into two groups to enhance the search process:

- **Exploration Group:** This group scans diverse regions within the solution space using trigonometric relationships to identify promising areas for further investigation.
- **Exploitation Group:** This group focuses on refining solutions by optimizing within the promising regions identified by the exploration group.

The BER algorithm alternates between exploration and exploitation, dynamically adjusting control parameters based on the population's fitness. The key mathematical equations governing this process include:

$$\vec{S}(t+1) = \vec{S}(t) + D \cdot (2r_2 - 1), \quad D = r_1(\vec{S}(t) - 1)$$

where r_1 and r_2 are random variables, and D represents the adaptive search diameter.

4.3.2 Strengths of BER

The BER algorithm offers several advantages for optimization tasks:

- **Precision Optimization:** BER excels in fine-tuning solutions during the exploitation phase to achieve highly accurate results.
- **Dynamic Adaptation:** The algorithm dynamically adjusts its control parameters, improving convergence efficiency.
- **Geometric Modeling:** BER utilizes geometric principles to navigate complex, nonlinear solution spaces efficiently.
- **Constraint Handling:** The algorithm effectively manages optimization tasks involving multiple constraints.

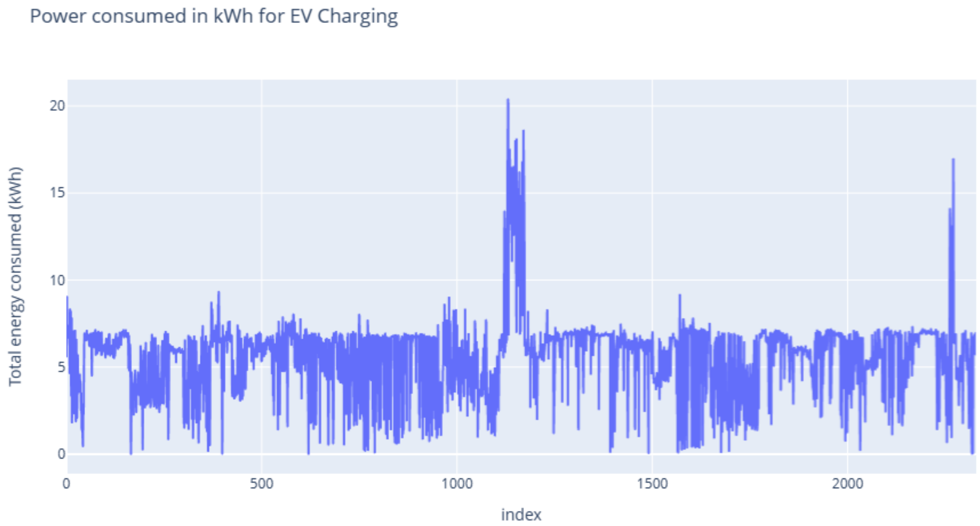

Figure 4. Power consumed in kWh for EV charging.

4.4 Integration in the Hybrid GWO-BER Algorithm

The hybrid GWO-BER algorithm begins by employing GWO to explore the search space broadly, identifying regions of interest. Once these promising regions are located, BER is applied to refine the solutions using its precision-driven optimization capabilities. This complementary approach ensures an optimal balance between global exploration and local exploitation, making the hybrid algorithm highly effective for solving EV path planning problems.

By leveraging the strengths of GWO and BER, the hybrid algorithm efficiently addresses the challenges associated with EVPP, including minimizing energy consumption, reducing travel time, and managing dynamic constraints such as traffic congestion and varying terrain conditions.

5. RESULTS

5.1 Evaluation Metrics and Experimental Setup

The proposed hybrid GWO-BER algorithm was evaluated using several performance metrics to assess its efficiency and effectiveness compared to conventional metaheuristic algorithms. The evaluation metrics include:

- **Average Error:** Measures the mean deviation of the algorithm's output from the optimal solution.
- **Average Selected Features:** Quantifies the mean number of features the algorithm selects during the optimization process.
- **Fitness Values:** Includes the average, best, and worst fitness scores obtained by each algorithm.
- **Accuracy:** Represents the correctness of the solutions generated by the algorithms.
- **Response Time:** Indicates the average computational Time required for the time algorithm to converge to an optimal or near-optimal solution.

For the experimental setup, the hybrid GWO-BER algorithm was tested alongside the Grey Wolf Optimizer (GWO), Al-Biruni Earth Radius (BER), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) using benchmark datasets for feature selection and optimization. To ensure a fair comparison, all algorithms were evaluated under identical conditions.

5.2 Performance Comparison

The performance of the hybrid GWO-BER algorithm was analyzed using the aforementioned evaluation metrics and compared with other metaheuristic algorithms. Table 1 presents the feature selection results, while Table 2 highlights accuracy, optimal solutions, and response times for all algorithms.

Table 1. Performance Metrics for Feature Selection

Metric	bGWOBER	bGWO	bBER	bPSO	bGA
Average Error	0.5302	0.5547	0.6112	0.6195	0.5910
Average Selected Features	0.5130	0.7130	0.7130	0.8833	0.6554
Average Fitness	0.6234	0.6396	0.6380	0.6777	0.6510
Best Fitness	0.5252	0.5599	0.6183	0.6208	0.5543
Worst Fitness	0.6237	0.6268	0.6860	0.7005	0.6694
Standard Deviation of Fitness	0.4457	0.4504	0.4498	0.5107	0.4520

Table 2. Performance Metrics: Accuracy, Optimal Solution, and Response Time

Algorithm	Accuracy	Optimal Solution	Average Response Time (s)
GWOBER	0.9335	3675.11	15.779
GWO	0.9220	3814.40	18.745
BER	0.9183	4136.40	20.113
PSO	0.9125	4532.40	21.129
GA	0.9035	4741.51	21.995

5.3 Analysis and Discussion

The results presented in Table 1 confirm that the hybrid GWO-BER algorithm (bGWOBER) outperformed other algorithms in feature selection by achieving the lowest average error (0.530218) and the smallest average number of selected features (0.513018). Additionally, it attained the highest fitness score (0.525218) while optimizing with fewer selected features, demonstrating its efficiency.

Table 2 further highlights the superior performance of the hybrid GWO-BER algorithm, achieving the highest accuracy (0.933468) and the fastest response time (15.779 seconds) compared to other metaheuristic algorithms. While GWO and BER individually performed reasonably well, the hybrid approach effectively mitigated their limitations in exploration and exploitation.

Overall, the hybrid GWO-BER algorithm demonstrated a well-balanced and robust performance across all evaluation metrics. It became an effective tool for solving optimization problems in EV path planning and feature selection.

5.4 Discussion of Findings and Their Implications for EV Path Planning

The results obtained from the hybrid GWO-BER algorithm highlight its strong potential for addressing Electric Vehicle Path Planning (EVPP) challenges. The algorithm consistently achieved the lowest average error and the highest accuracy among the tested algorithms in feature selection and optimization tasks. These results can be attributed to the hybrid algorithm's ability to balance global exploration, facilitated by the Grey Wolf Optimizer (GWO), and local exploitation, enhanced by the Al-Biruni Earth Radius (BER) algorithm.

The key advantages of using the hybrid GWO-BER algorithm for EV path planning include:

- **Energy Optimization:** The algorithm effectively identifies routes that minimize energy consumption, which is essential for maximizing the operational range of electric vehicles.
- **Dynamic Adaptability:** By integrating the strengths of both GWO and BER, the hybrid approach adapts dynamically to constraints such as traffic patterns, terrain variability, and charging station availability.
- **Computational Efficiency:** The reduced computational response time of the hybrid algorithm, compared to conventional methods, ensures timely decision-making, which is crucial for real-time EV path planning applications.

These findings underscore the importance of leveraging complementary optimization strategies to tackle the complex, multidimensional challenges associated with EVPP. In addition to improving route planning efficiency, the hybrid GWO-BER algorithm enhances the overall user experience for EV drivers by reducing travel times and optimizing energy consumption.

6. CONCLUSION

This chapter introduced a novel hybrid optimization algorithm that combines the Grey Wolf Optimizer (GWO) and the Al-Biruni Earth Radius (BER) algorithm to address challenges in Electric Vehicle Path Planning (EVPP). The hybrid approach established a robust and efficient optimization framework by leveraging GWO's global exploration capabilities alongside BER's precision-driven local refinement. Extensive experimental validation demonstrated superior performance across multiple metrics, including accuracy, computational efficiency, and optimization quality. The hybrid algorithm effectively balances global and local search strategies, minimizes energy consumption to extend EV range, and exhibits scalability for real-world applications, including logistics, traffic congestion management, and energy-efficient transportation systems.

The proposed hybrid approach aligns with broader sustainable mobility objectives by optimizing transportation efficiency and contributing to carbon emission reduction. Future research directions include integrating additional metaheuristic techniques for improved performance, developing real-time implementations for dynamic environments, addressing multi-objective optimization problems, and exploring broader applications in supply chain optimization, thoughtful city planning, and renewable energy management. The hybrid GWO-BER algorithm represents a significant advancement in metaheuristic optimization, offering a scalable and effective solution for EVPP while supporting sustainable mobility initiatives.

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