Al-Biruni Earth Radius Algorithm-Based Hybrid Metaheuristic for Efficient Electric Vehicle Path Planning

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Abstract. In this paper, 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.

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 reduced 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. Among these systems, the problem of electric vehicle path planning (EVPP) is paramount, as it significantly influences energy consumption, travel efficiency, and user satisfaction.

In this chapter, the authors discuss the concept of creating a hybrid optimization algorithm that combines the properties of two state-of-the-art optimization algorithms: the Al-Biruni Earth Radius (BER) and the Grey Wolf Optimizer (GWO) algorithm. As a supplement to GWO, the Al-Biruni Earth Radius (BER) algorithm employs sophisticated methods of spatial analysis, drawing on mathematical and geometrical concepts. The combination of GWO and BER yields a robust optimization framework that leverages the strengths of both algorithms [1], [2], [3].

2. LITERATURE REVIEW

Metaheuristic optimization algorithms have become essential tools for addressing a wide range of complex and computationally demanding problems. Recent advancements have introduced novel algorithms inspired by natural, physical, and mathematical principles, leading to improved performance in terms of convergence speed, solution quality, and robustness [4]. Hybrid algorithms, which combine the strengths of different metaheuristic techniques, have shown further enhancements in exploration and exploitation balance [5]. Multi-objective variants have been developed to effectively approximate Pareto fronts and handle trade-offs among conflicting objectives [6]. Binary adaptations have gained attention for solving discrete and combinatorial problems, particularly in feature selection and classification tasks [7]. Adaptive and dynamic strategies within metaheuristic frameworks have been employed to fine-tune algorithm behavior during the search process [8].

EV route optimization with uncertainties in traffic conditions and demand is challenging. [9] proposes a robust optimization model where uncertainty in demand and traffic conditions are represented by convex and box uncertainty sets, respectively. [10] presents a new mathematical routing model that considers energy consumption during start/stop operations and uses an amplified Ant Colony Optimization (A2CO) algorithm, showing significant improvements in energy efficiency. [11] proposes a Hybrid Variable Neighborhood Search (HVNS) algorithm for solving the CEVRP, minimizing costs whilst optimizing fleet size and travel distance. [12] presents path planning insights for uncrewed aerial vehicles using metaheuristic algorithms relevant to EV routing in dynamic environments.

3. DATASET

The dataset presented in this study is based on an experimental study conducted by Dr. Omar Asensio and his team members [13]. The researchers gathered 3,395 electric vehicle (EV) charging events between November 2014 and October 2015. The data includes the records of 85 EV drivers who used 105 charging stations at 25 workplace sites as part of a voluntary charging program. The data contains essential features, such as the date and time of each charging session, overall energy usage, costs, and other background information. Figure 1 is a histogram of some of the most critical variables in the data set, such as the number of kWh used, the location ID, the user ID, the distance covered, the charge time in hours, and the station ID. These histograms provide a visual representation of the distribution of each feature. Knowledge of these distributions is crucial in preprocessing and normalization steps in the optimization process.

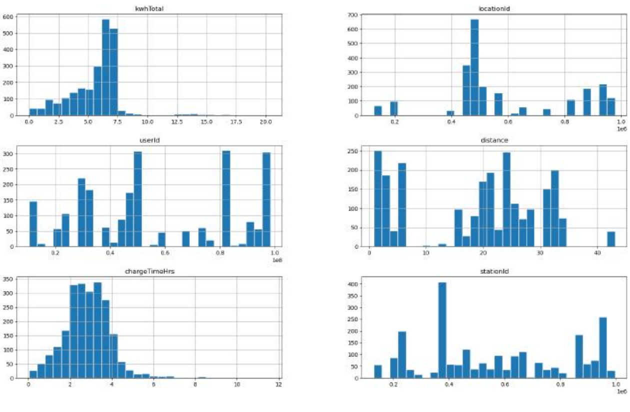

Fig. 1. Histograms of key dataset features.

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). 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)

The Grey Wolf Optimizer (GWO) is inspired by the social hierarchy and hunting strategies of grey wolves in nature [14]. 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 that 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, modeled using the equations:

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

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, 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.

4.3. Al-Biruni Earth Radius (BER)

The Al-Biruni Earth Radius (BER) algorithm is inspired by geometric principles derived from Al-Biruni's calculations of the Earth's radius [15]. The algorithm dynamically partitions the population into two groups: the Exploration Group, which scans diverse regions within the solution space using trigonometric relationships to identify promising areas; and the Exploitation Group, which focuses on refining solutions 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.

5. RESULTS

5.1. Evaluation Metrics and Experimental Setup

The proposed hybrid GWO-BER algorithm was evaluated using several performance metrics: Average Error (mean deviation from the optimal solution), Average Selected Features (mean number of features selected), Fitness Values (average, best, and worst fitness scores), Accuracy (correctness of generated solutions), and Response Time (average computational time to converge). For the experimental setup, the hybrid GWO-BER algorithm was tested alongside GWO, BER, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) using benchmark datasets for feature selection and optimization. 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 I presents the feature selection results, while Table II highlights accuracy, optimal solutions, and response times for all algorithms.

TABLE I. 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
Std. Dev. of Fitness	0.4457	0.4504	0.4498	0.5107	0.4520

TABLE II. Performance Metrics: Accuracy, Optimal Solution, and Response Time

Algorithm	Accuracy	Optimal Solution	Avg. Response Time (s)
GWOBER	0.9335	3675.11	15.779

Algorithm	Accuracy	Optimal Solution	Avg. Response Time (s)
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 I 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 II 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, making it an effective tool for solving optimization problems in EV path planning and feature selection.

6. CONCLUSION

This paper proposes a novel hybrid optimization algorithm that combines the Al-Biruni Earth Radius (BER) algorithm with the Grey Wolf Optimizer (GWO) to address problems in Electric Vehicle Path Planning (EVPP). The hybrid strategy developed a powerful and effective optimization system that leverages the global exploration potential of GWO and the local refinement capabilities of BER. Ample experimental validation has demonstrated improved performance on several key measures, including accuracy, computational efficiency, and optimization quality. The hybrid algorithm effectively balances local and global search strategies, reduces energy usage to increase EV range, and is scalable for practical applications, such as logistics, traffic congestion control, and energy-efficient transportation systems. The suggested hybrid solution aligns with the overall sustainable mobility goals, as it maximizes transportation efficiency and helps reduce carbon emissions. Future research directions include combining more metaheuristic methods to achieve better performance, building real-time implementations in dynamic environments, solving multi-objective optimization problems, and extending applications to supply chain optimization, smart city planning, and renewable energy management.

7. REFERENCES

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