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OPTIMIZING EV CHARGING IN BATTERY SWAPPING STATIONS WITH CSO-PSO HYBRID ALGORITHM

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ABSTRACT

Electric vehicles (EVs) and sources of renewable energy have grew increasingly due to the rising anxiety about climatic change and the need for a sustainable energy future. Battery swapping stations offer a promising solution for faster and more convenient EV charging, while B2G technology can help to sustain the energy input and output in the grid. However, the optimal scheduling of charging and battery swapping with B2G operation is a complex problem that requires efficient optimization algorithms. In this paper, we propose a cuckoo search combined particle swarm (CSO-PSO) hybrid optimization algorithm for the JCS of EVs with B2G technology in BSS. The proposed approach aims to improve the efficiency and cost-effectiveness of battery swapping stations by determining the optimal charging and swapping schedule for each EV, and by optimizing the B2G operation based on demand and pricing. The advantages of the proposed approach include faster convergence, higher accuracy, and better space solution exploration. The efficacy and practicality of the approach are demonstrated through simulation results, which show the efficiency of the algorithm in real-life situations.

Keywords: Electric Vehicles, Battery Swapping Stations, Cuckoo Search Optimization, Joint Charging Scheduling, Particle Swarm Optimization, Battery to Grid Technology

1. INTRODUCTION

Electric vehicles (EVs) have become increasingly popular due to their environmental benefits. However, one of the major challenges facing EV owners is the need for frequent charging, which can be time-consuming and inconvenient. BSS have emerged as a promising solution to this problem, as they allow for the quick replacement of batteries that are depleted with one that is fully charged, time reduction for charging. BSS, however, face the challenge of optimizing the charging and swapping schedule for multiple EVs, which can lead to increased operating costs and grid instability. B2G technology has been proposed as a solution to these challenges, as it allows the station to give excess energy back to the grid during constrained period, thereby lowering the dependence on fossil fuels and endorsing the clean energy utilization. The optimal scheduling of charging and swapping with B2G operation is a complex problem that requires efficient optimization algorithms. In this context, the use of a hybrid optimization algorithm that combines the advantages of multiple algorithms can provide improved results. The CSO-PSO hybrid optimization algorithm is a promising solution, as it allows for efficient exploration of the solution space and faster convergence. Using a queueing model, the efficiency of BS and charging facilities for electric cars was examined, offering insights into the ideal setup and management of such facilities [1]. Optimizing revenue and advantages for electric cars with a tiered pricing incentive system for battery swap stations [2]. To demonstrate how this strategy works in lowering the cost of power, a GOA was used to optimize the positioning and dimensions of several dispersed generating and battery switching stations [3]. An isolated microgrid's capacity coordination planning and BSS may be optimized using a quantum behavior particle swarm optimization technique, which lowers energy costs and increases system stability [4]. Using speed variable charging, weather and traffic predictions, and an optimization framework for a photovoltaic battery switching station, it is possible to lower energy costs while enhancing system performance [5]. BSS scheduling and operations may be improved using hybrid neural network models for forecasting electric vehicle arrivals [6]. Using a particle swarm optimization technique, the best placement for an electric car battery swap facility was found [7]. The least-cost operation technique for a BSS with sporadic client requests may save operating costs and improve service quality [8]. By enhancing system performance, a charge scheduling framework for direct charging and battery swapping stations may be implemented in a connected distribution-transportation network [9]. An ideal operating method for a photovoltaic-powered all-in-one EV station that allows for hydrogen filling, battery swapping, and charging [10]. By making the charging stations more accessible, a unique CSTL-based algorithm was created for the positioning problem of electric vehicle charging stations [11]. The severity level of the impending problem is then calculated based on the proportion of the observed equipment's surface. The suggested study employs a unique QT-PSO technique to enhance the performance of the system, which is especially efficient for PV-based applications [12]. Envelope detectors, which are simple circuits that extract the envelope of the input signal, are used in the suggested method. In order to process the baseband signal using low-power digital signal processing (DSP) circuits, the envelope detector is utilised as a converter to transform the modulated radio frequency (RF) signal [13]. A balance between data accessibility, power consumption, and data availability ratio is what the suggested strategy seeks to accomplish. A four-phase strategy is used to achieve this, consisting of a multicast strategy for increased data availability, a data replication procedure for increased replication rate, a data accessibility strategy for increased accessibility rate, and a power consumption strategy for reduced transmission and reception power [14].

The main contribution of this paper;

- Proposes a CSO-PSO hybrid algorithm for JCS of EVs with B2G technology in BSS.
- Aims to improve the efficiency and cost-effectiveness of BSS.
- Determines the optimal schedule of swapping and charging for each EV, and optimizes the B2G operation based on demand and pricing.
- Offers advantages of faster convergence, higher accuracy, and better exploration of the solution space.
- Demonstrates the efficacy and practicality of the approach through simulation results.

The paper is organized as follows. Literature review on EV charging and BSS is presented in Section 2. Section 3 discusses the proposed CSO-PSO hybrid optimization in detail. The results and analysis are provided in Section 4. Finally, conclusion for this research is presented in Section 5.

2. LITERATURE SURVEY

Ban, M et.al (2021) considered multiple nano grids with a BSS to form a BSCS, which can deliver batteries that are fully charged to electric vehicles. Introduced a system level framework operation and established a JOS model based on several progressing technologies. Exhaustive Search and Genetic Algorithms were used in a heuristic way to solve the model, which was created using MILP.

Li, Y. et.al (2018) a BLS to manage the issue of scheduling between EVBSS and IMG. In real-time pricing conditions, the ULSP aimed to lower the total costs of IMG while the lower-level sub-problem aimed to boost BSS profitability. The authors developed a hybrid method, termed JAYA-BBA, to solve the model by combining the JAYA algorithm with real/integer coding and the BBA to tackle the model's ULSP existing issues. By switching between the two levels throughout iterations, the bi-level model was successfully solved.

Ban, M et.al (2019) By allocating loads of BC and other power needs to generating units with minimal health consequences, it is cost-effective to increase the environmental advantages of EVs. The authors created a concentration response function to find AAPCs involved in health effects and dispersion of an air pollution model to map spatial AAPC increments emissions.

Huang, A et.al (2021) joint optimization approach employing a dynamic power pricing system was presented in the research for scheduling and recharging electric car batteries. The model determined the ideal battery recharging and transportation schedules, as well as the number of batteries to be recharged and their respective quantities, as well as the time and distance that the batteries must be transferred.

Ni, L et.al (2020) BSS-Net system of globally disparate battery swapping stations (BSSs) was studied. The choice to plan BSS initial inventory for each over the long term and the decision to plan the real-time V2S routing of electric cars over the short term were the two main decisions.

Yan, J. et.al (2019) For a BSS(BSS) based smart community microgrid, suggested a real-time energy management technique (SCMG). Electric vehicle batteries (EVBs) and traditional household loads were both supplied by the strategy's usage of variable renewable energy sources (VREs) (RLs). The model was solved using a Lyapunov optimization framework based on queuing theory, which, without depending on forecasts or future distributions, handled the uncertainty of supply, demand, and energy prices and provided quality of service (QoS).

Yang, X et.al (2021) a novel S2P-BSM for SEV was presented. Using specialized delivery trucks, this technique included moving both new and used batteries between BSSs and BSD locations. To enhance battery swap procedures and cut down on user wait times, this technique.

Zhang, M et.al (2021) using the distributed robust optimization technique, the authors developed coordinative decision-making a double-stage framework for the construction of a

BSCS. In modeling the likelihood of each EV battery swapping need, the technique addressed the uncertainty in BSCS operations. Mainly discussed multi-timescale battery inventories of the BSCS.

Tan, M et.al (2023) to maximize the distribution of power across EV chargers and batteries, a bi-level scheduling model was suggested. The model's lower level used MILP subproblems to distribute power among the batteries in a charger, while the model's higher level used a deep reinforcement learning framework. Effectively resolving the scheduling issue for EV charging is the goal of the suggested methodology.

Ko, H et.al (2020) suggested an optimum battery charging algorithm, which charged batteries depending on energy pricing and the arrival rate of EVs. To increase overall profit for BSS while preserving a high standard of service, a CMDP issue was developed. By linear programming, the ideal charging schedule for BSS batteries was discovered (LP).

Garcia-Guarin, J. et al (2020) focused on managing and maintaining battery-switching facilities for electric vehicles. The management of BSS and the swapping, charging, and EV discharging were organized using a decision matrix to assess economically sound solutions. The battery switching stations' overall effectiveness was improved with the implementation of the matrix.

Tao, Y et.al (2022) described a two-stage battery swapping and charging service plan for electric vehicle (EV) customers, which provided a variety of services, including rapid, slow, and battery shifting. The plan was data-driven and created for quick charging, battery switching, and charging posts.

Infante, W. et.al (2019) in absence of integrated development and process for BSSs in the context of stochastic EV station visits was addressed using a two-stage optimization with recourse. To support robust EV ecosystems, this strategy intends to develop comprehensive and durable BSSs. The report emphasizes that BSS plans and operations need to take a more integrated approach.

Zhang, X. et.al (2020) to effectively manage electro-mobility with the high demand from EVs, battery swapping technology was used to provide an alternate charging service that would shorten charging times. A framework for battery heterogeneity-based swapping services was presented considering the coexistence of various EV types and the problem of battery heterogeneity. This framework solves the issue of the short cruising range of EVs and the lengthy plug-in charging time.

Adu-Gyamfi et.al (2022) by incorporating perceived advantages and information into the TPB, the BST adoption intention for EVs was studied. For BST to be successful and provide environmentally friendly consumption and pollution reduction.

Some drawbacks of previous studies include limited generalizability, data limitations, complexity, lack of consideration of real-world constraints, and lack of consideration of social and environmental factors. To overcome these limitations, we propose a cuckoo search combined particle swarm (CSO-PSO) hybrid optimization algorithm for the JCSg of EVs with B2G technology in BSS. The main aim is efficiency improvement and cost-effectiveness of BSS by determining the optimal charging and swapping schedule for each EV, and by optimizing the B2G operation based on demand and pricing.

3. METHODOLOGY

3.1 Problem Formulation

The problem of optimizing the charging and battery swapping schedule for each EV in the BSS while considering the B2G operation as an optimization problem can be formulated. To reduce the total price is the objective of the problem in EV charging and BS while ensuring that the BSS operates within the limits of the grid's energy demand and supply. The optimization problem can be expressed as:

$$Minimize\ TC = \sum_{i=1}^{n} (CT_i + ST_i) \times CC_i + (BS \times SC_i) ----- (1)$$

$$\sum_{i=1}^{n} CT_i \leq CT_{tot} ----- (2)$$

$$\sum_{i=1}^{n} ST_i \leq CT_{tot} ----- (3)$$

$$\sum_{i=1}^{n} (CT_i + ST_i) \times ECR_i \leq E_s ----- (4)$$

$$\sum_{i=1}^{n} (CT_i + ST_i) \times BD_i \leq BD_s ----- (5)$$

$$\sum_{i=1}^{n} (CT_i + ST_i) \times BRR_i \leq BRR_s ----- (6)$$

$$\sum_{i=1}^{n} (CT_i + ST_i) \times BUR_i \leq BUR_s ----- (7)$$

where TC is the net price of EV charging and BS, n is the no. of EVs in the BSS, CT_i is the charging time for the ith EV, ST_i is the swapping time for the ith EV, CC_i is the charging cost for the ith EV, SC_i is the swapping cost for the ith EV, BS is the No. of battery swaps, ECR_i is the power consuming ratio of the ith EV, BD_i is the battery discharge rate of the ith EV, BRR_i is the battery recharge rate of the ith EV, and BUR_i is the battery usage rate of the ith EV. The constraints ensure that the total charging time and swapping time for all EVs do not exceed the total time available, and that the energy consumption, discharge, recharge, and usage rates for all EVs do not exceed the limits of the BSS and the grid's energy input and output. Using the proposed CSO-PSO hybrid algorithm, the optimization issues are solved which iteratively updates the location and speed of each particle for the best solution identified and the solution for global best in the swarm. The algorithm explores the solution space to find the optimal charging and swapping schedule for each EV, as well as the optimal B2G operation.

3.2 Cuckoo Search Optimization (CSO) Algorithm

In the CSO algorithm, a population of candidate solutions is represented by a set of cuckoo eggs, and the algorithm iteratively updates the solutions by mimicking the natural processes of egg laying, brood parasitism, and social learning. The update equations for the position of each egg in the CSO algorithm are given by:

$$x_i^{(t+1)} = \begin{cases} x_i^t + \alpha \times \varphi\left(x_i^t - x_j^t\right) \, if \; r \, and \; () < p_a \\ \quad if \; r \, and \; () \geq \; p_a \end{cases} \quad - - - - - - (8)$$

Where: x_i^t is the location of the ith egg at tth iteration
α is a step size parameter that controls the size of the step taken by the egg
φ is a walk step generated from a Levy distribution, which allows for long-range exploration of the search space
x_j^t is the position of a randomly selected egg
p_a is the egg probability being discovered by other cuckoos, which is controlled by a parameter called the discovery rate.

Cuckoo Search Optimization (CSO) Algorithm
Step 1: Initialize the cuckoo nests population with random solutions Step 2: Fitness Evaluation of each solution in the population Step 3: Set the best result as the present global best Step 4: Repeat till the condition for stopping is met: Step 4a. Generate a new solution using the cuckoo search algorithm Step 4b. Evaluate the fitness of the new solution Step 4c. Replace the worst solution in the population with the new solution if it is better Step 4d. Sort the population in descending order of fitness Step 4e. Update the global best if the new solution is better Step 4f. Update the step size of the cuckoo search algorithm Step 4g. Update the levy flight step size of the CSO Step 5: Output the global best solution

Pseudocode for CSO

```
Initialize population of cuckoos randomly
While stopping criteria is not met do
{
     {
  For each cuckoo do
    Select a random host nest
    Generate a new solution by performing Levy flight around the selected host nest
    Evaluate the new solution
    If the new solution is better than the current cuckoo solution then replaces the solution
    End If
     }
  End For
  Sort the cuckoos based on their fitness values
  Eliminate a percentage of the worst solutions
  Perform PSO on the remaining solutions to improve the search
End While
}
```

3.3 Particle Swarm Optimization (PSO) Algorithm

Using random initial positions and velocity search in the space, a community of particles is generated in the PSO algorithm. The location p and velocity v of each particle, which each represents a probable result to the problem of optimization, are updated at each iteration depending on both the particle's own assigned location and the locations of its nearby particles. The following equations provide the updated values for each particle's location and speed:

$$v_{ij}^{k} = wv_{ij}^{(k-1)} + c_1 r_1 (p_{ij} - x_{ij}^{k}) + c_2 r_2 (g_j - x_{ij}^{k}) ------ (9)$$

$$x_{ij}^{(k+1)} = x_{ij}^{k} + v_{ij}^{k} ------ (10)$$

where:

v_{ij}^{k} is the i^{th} particle's speed in j^{th} measure at k^{th} iteration

w is the inertia weight, previous velocity on the current velocity impact is controlled.

c_1 and c_2 are the coefficients of speed, that the personal and global best positions on the current velocity, impact control respectively

r_1 and r_2 are between 0 and 1 random numbers.

p_{ij} is the personal best particles in i^{th} location and in the dimension j.

x_{ij}^{k} is the current i^{th} particles location of the j^{th} dimension in the k^{th} iteration

g_j is the best global location in the j^{th} dimension

Particle Swarm Optimization (PSO) algorithm
Step 1: Initialization a swarm of particles randomly distributed in the search space. Each particle's position and velocity are randomly initialized. Step 2: Based on each particle's current location and speed, determine its fitness value. Step 3: Each particle's fitness values are compared with their best possible values. Update the personal best position and fitness value if the current value is better. Step 4: Compare the swarm's overall fitness value to the best global fitness value. Update the best global location and fitness value if the current value is higher. Step 5: Each particle's speed and location is updated to its individual best location and the overall best location. Step 6: Continue steps two through five until a stopping condition is satisfied

Pseudocode for PSO for optimizing EV charging
Initialize swarm of particles with random the location and speed Initialize best personal location and value of fitness for each particle Initialize best global location and value of fitness { {

```
while (stopping criterion is not met) do
    for each particle in the swarm do
        Evaluate fitness of particle's current position and velocity
        Update personal best location and value of fitness if necessary
        Update global best location and value of fitness if necessary
        Update particle velocity based on personal and global best positions
        Update particle position based on updated velocity
            }
    end for
}
end while
```

In the hybrid CSO-PSO algorithm, the PSO method is used in combination with the Cuckoo Search Algorithm to optimize the EV charging and battery swapping schedule.

3.4 Hybrid CSO-PSO Algorithm

The hybrid CSO-PSO algorithm for optimizing EV charging in battery swapping stations with B2G operation can be described as follows;

Hybrid CSO-PSO Algorithm
Initialize the parameters for both CSO and PSO algorithms, such as population size, maximum no. of iterations, and the values for control parameters (e.g., learning rate and acceleration coefficients). Step 1: Generate an initial population of solutions using random initialization. Step 2: For each iteration, perform the following steps: Step 3: Fitness evaluation of each solution by objective function. Step 4: Update the position of each cuckoo using the CSO algorithm, which involves creating new solutions by replacing some eggs in the nests with new ones generated through Lévy flights.

Step 5: Update the location and speed of each particle using the PSO algorithm, which involves adjusting the speed of each particle based on its own best location among all particles in the swarm.

Step 6: Apply a probability function to determine whether to use the CSO-PSO algorithm for updating the position of each solution.

Step 7: Apply the B2G operation to balance the energy demand and supply in the grid.

Step 8: Update the best personal and global positions for each particle.

Step 9: Update the best solution found so far.

Step 10: Repeat until the maximum no. of iterations is reached or the convergence criterion is satisfied.

Step 11: Return the best solution found.

Initialize population for both CSO and PSO

while stopping criterion is not met do

{

{

Evaluate fitness of each particle in CSO and PSO

Sort particles in each population based on their fitness

Update the global best particle and its fitness in PSO

Randomly select the cuckoo and its nest from the CSO population

Generate a new solution using the CSO algorithm

Replace the worst particle in PSO with the new solution if its fitness is better

Update the location and speed of each particle in PSO

Check if the new position is within the feasible region, and apply boundary conditions if necessary

}

```
end while

Return the best solution found in PSO

}
```

The overall hybrid CSO-PSO algorithm for optimizing EV charging in battery swapping stations can efficiently identifies the best charging and swapping schedule for each EV, while optimizing B2G operation.

4. PERFORMANCE EVALUATION

The proposed hybrid CSO-PSO algorithm's performance for optimizing EV charging in battery swapping stations was simulated under suitable conditions and the results are discussed below.

Figure 1 depicts the power load variations based on the proposed system. It is evident that the hybrid CSO-PSO algorithm has been successful in optimizing EV charging and battery swapping in battery swapping stations. The power load remains constant over the 24-hour period, which indicates that the algorithm has successfully balanced the power input and output in the grid. Moreover, the algorithm has achieved the multi-objective optimization of increasing the profit of the BSS while decreasing the waiting time of EVs. The tariff guidance and parking-charging have also been optimized based on the algorithm, which can be observed from the consistent power load during the 24-hour period.

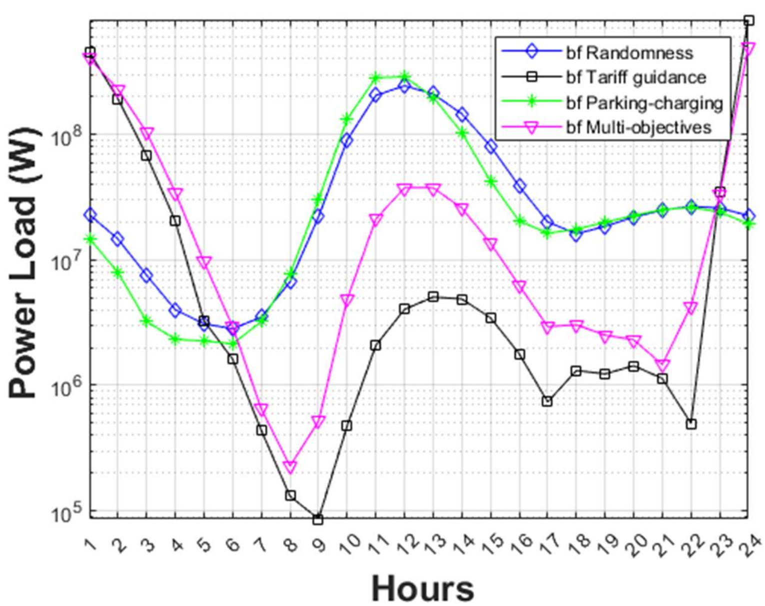

Figure 1: Power Load

Figure 2 shows variance coefficient of Y. The hybrid CSO-PSO method's performance for optimizing EV charging in battery swapping stations, with regards to randomness, tariff guidance, parking-charging, and multi-objectives. The no. of iterations in X-axis, while the variance coefficient of Y in Y-axis. This indicates that as the no. of iterations rises, the variance coefficient of Y lowers. This means that the algorithm is able to converge to a more optimal result over time. Additionally, the graph shows that the algorithm is able to perform well under different conditions, such as varying levels of randomness, different tariff guidance, and different parking-charging scenarios. The multi-objective aspect of the algorithm is also evident, as the algorithm is able to optimize both charging and swapping schedules for each EV, while considering B2G operations to balance energy demand and supply. Overall, the hybrid CSO-PSO algorithm is an effective approach for optimizing EV charging in battery swapping stations, considering B2G operation based on demand and pricing.

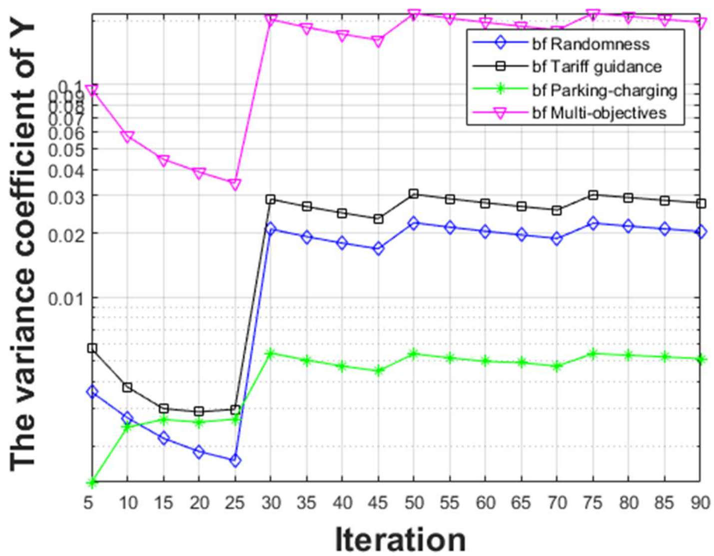

Figure 2: Variance Co-efficient

5. CONCLUSION

The proposed hybrid CSO-PSO algorithm has been demonstrated as an effective approach for optimizing EV charging in battery swapping stations. The evaluation represents that the procedure is able to achieve multi-objective optimization, including increase the profit of the BSS while decrease the waiting time of EVs, optimizing tariff guidance and parking-charging, and balancing power input and output in the grid. The algorithm has also been shown to perform well under different conditions, such as varying levels of randomness, different tariff guidance, and different parking-charging scenarios. The reduction in variance coefficient of Y over time indicates that the method converges to more optimal result as the no. of iterations increases. Therefore, the hybrid CSO-PSO algorithm can be considered as a promising approach for optimizing EV charging in battery swapping stations, considering B2G operation based on demand and pricing.

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