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Optimal Reactive Power Dispatch with Electric Vehicle Charging Loads using an Artificial Protozoa Optimizer

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Abstract: Minimizing real power loss in electrical power systems is crucial for economic efficiency and grid stability. The increasing number of EVs (electric cars) compounds this problem because EV charging demands are very unpredictable and put a lot of pressure on the power system. In such a setting, the already important Optimal Reactive Power Dispatching (ORPD) problem takes on an even greater significance. To address the ORPD issue while taking EV charging demands into account, this study suggests an Artificial Protozoa Optimizer (APO). For reduction of power losses and enhance the voltage stability, the algorithm sees the best position and size of shunt capacitors. On standard IEEE 14 bus, 30 bus, and 33 bus systems, the APO's effectiveness was tested under different EV load scenarios. Even when dealing with unpredictable electric vehicle loads, the results reveal that the IEEE-33 connection system, the IEEE 30 bus system, and the IEEE 14 bus system all considerably lessen the total real loss of power by a considerable margin: 7.49%, 0.79%, and 0.31%, respectively. Additionally, the optimization greatly enhanced and maintained within acceptable ranges the voltage profiles. In modern power systems that include a lot of EVs, APO is a powerful and efficient tool for addressing the problem of ORPD, according to this study.

Keywords: Optimizing Reactive Power Dispatch (ORPD); Electric Vehicles (EVs); Artificial Protozoa Optimizer (APO); Shunt Capacitor Placement; Power Loss Minimization; Power System Optimization

1. Introduction

Contemporary electrical power systems encounter growing demands to function with optimal efficiency and reliability. Minimizing real lost power (P = I^2R losses) remains a significant challenge, with notable economic and stability ramifications [1]. The rapid adoption of Electric Vehicles (EVs) further exacerbates this issue. The chaotic charging of electric vehicles results in significant and variable loads, which may cause heightened power losses, voltage fluctuations, and diminished grid stability [2-]. The integration of erratic loads is a key concern for contemporary distribution system managers [4-5].

An essential part of Optimal Power Forwarding (OPF), Optimal Reactive Prospective Dispatch (ORPD) is vital for overcoming these challenges. Its principal objectives are to keep the voltage profile steady, improve system security, and minimize active power loss [6-7]. Shunt capacitors, generator voltages, and distributor tap settings are examples of reactive power resources that can be deliberately managed to accomplish this. Due to the ever-changing nature of electric vehicle charging, it is crucial that these resources be well-coordinated [8-9].

The optimization problem known as the ORPD is multi-complex, modal, non-convex, and non-linear. When dealing with discrete control variables, classical methods such as linear or quadratic programming struggle to find global optima [10]. Metaheuristic algorithms have been widely used because of this. Classical metaheuristics such as genetic algorithms (GA) [11] and Particle Swarm Optimization (PSO) [12] might get stuck in local optima and undergo premature convergence when confronted with the extraordinarily complex search space of the ORPD problem. A better balance between exploration and exploitation has to be found in optimizers, even though there are more resilient algorithms like Dandelion Optimizer [13], for instance, and Harris Hawk's Optimizer [14] available. In response to these limitations, this research introduces the Artificial Protozoa Maximiser (APO), a new method of search that is based on biological principles. The performance envelope is also being pushed further by hybrid techniques and enhancements to current algorithms [15-17).

In order to address the ORPD problem when electric vehicle charging loads are present, this work investigates a new bio-inspired algorithm called the Artificial Protozoa Optimizer (APO) [18]. APO has demonstrated potential in resolving intricate engineering issues [19-20], drawing inspiration from the sophisticated survival strategies of protozoa. To lessen the negative effects of EV integration, this work mainly contributes by proving APO to be a useful tool for determining the optimal layout and size of capacitors. Through comparison with other Modern tactics and demonstration on common IEEE test systems, we demonstrate its efficacy by reducing power losses and improving voltage stability.

The paper's remaining sections are structured in the following manner: Section 2 discusses a statistical analysis of the ORPD problem using the EV load model. The APO algorithm is explained in full in Section 3. The detailed findings of the simulation are presented and discussed in Section 4. Section 5 wraps up the report and offers some suggestions for where the research might go from here.

2. Mathematical Formulation of the ORPD Problem

Several limitations, including EV loads, are imposed on the objective function in the formulation of the ORPD issue.

2.1. The Goal of the ORPD

As before, reducing overall real power loss is of paramount importance, as in Equation (1):

$$\min P_{\text{loss}} = \sum_{k=1}^{N_{\text{line}}} g_k\left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)\right] \tag{1}$$

Whereas n lines denote the conductance of the line, V denotes the voltage magnitude, and delta and indicate the voltage angle.

The second topic is electric vehicle load modelling. The incorporation of EVs brings up extra, unpredictable loads. Every bus's electric vehicle load is represented by a continuous power load. Electric vehicle (EV) bus “I” reactive and active energy demands are added to the heart load demand calculated by Equations (2) and (3).

$$P_{\text{load},i} = P_{Di} + P_{\text{EV}i}\text{L} \tag{2}$$

$$Q_{\text{load},i} = Q_{Di} + Q_{\text{EV}i} \tag{3}$$

The EV load is typically characterized by using a power factor, and its magnitude depends on the number of EVs charging simultaneously, which can be modeled using probability distributions for different times of the day [10]. For this study, a peak-hour charging scenario is considered to evaluate the system under maximum stress. It should be acknowledged that this constant power load model is a simplification, as real-world EV charging is dynamic and time-varying. However, this study considers a peak-hour scenario to evaluate the system's performance under maximum stress, providing a critical benchmark for grid stability.

2.2. Limitations of the System

2.2.1. Parity Requirements (Electric Vehicle Load Power Flow Equations)

The Power Flow Equations are modified to include the total load demand, which is calculated by Equations (4) and (5):

$$P_{Gi} - (P_{Di} + P_{EVi}) - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}\right) = 0 \quad (4)$$

$$Q_{Gi} - (Q_{Di} + Q_{EVi}) + Q_{Ci} - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}\right) = 0 \quad (5)$$

Tell me how many buses there are.

2.2.2. *Equality Restrictions*

These establish the limits of the system's operational security:

- Bus Voltage Limits: $V_{min} \leq V_i \leq V_{max}$
- Generator Reactive Power: $Q_{G,min} \leq Q_{Gi} \leq Q_{G,max}$
- Capacitor Limits: $Q_{C,min} \leq Q_{Ci} \leq Q_{C,max}$

These limits are critical for maintaining power quality and preventing equipment damage [25].

2.3. Constraint Handling

Handling constraints is done via a Penalty Function method. A Penalty term is introduced to the objective function for any violation of the inequality constraints, thereby turning the restricted issue into an unconstrained one, and is calculated by equation (6).

$$\text{Cost} = P_{\text{loss}} + \lambda_V \sum (\Delta V_i)^2 + \lambda_Q \sum (\Delta Q_{Gi})^2 \quad (6)$$

where λ_V and λ_Q are large penalty factors, and Δ_{V_i} and $\Delta_{Q_{Gi}}$ represent the violation amounts for voltage and generator reactive power limits, respectively. The penalty factors λ_V and λ_Q were determined empirically through preliminary testing and set to a large value (10^6) to ensure that any infeasible solutions are heavily penalized, effectively guiding the search towards the feasible region.

3. The Artificial Protozoa Optimizer Algorithm

APA is a mathematical technique that simulates the smart behaviors of protozoa during their life cycles, including feeding, sleeping, and reproducing (21). One such answer is embodied by every protozoon in the population. It replicates biological urges; the algorithm strikes a good balance between exploration and exploitation, which is its strongest suit. Performance is greatly affected by the choice of critical parameters. It is common practice to conduct a sensitivity analysis or empirical analysis to ascertain the optimal values for parameters such as population size and maximum iterations in order to strike a balance between computing cost and the consistency of the solution The selected parameters (Population Size = fifty and Max The iteration process = 100) were determined to be resilient across all evaluated systems, however a thorough parameter exposure analysis is outside of the boundaries of this study.

3.1. APO Pseudocode for ORPD

Algorithm 1's pseudocode summarizes the APO application to the ORPD problem. In this procedure, a randomly selected population is used to direct the iterative evolution through the phases of mobility and reproduction. The fitness function is used to determine when to halt the evolution process.

Algorithm 1. Artificial Protozoa Optimizer (APO) for ORPD

Initialize the protozoa population $X_i (i = 1, \ldots, N)$
Initialize APO parameters (population size N, max iterations T)
Calculate the fitness of each protozoon f(X_i) using Eq. (6)
Find the global best solution g_textBest
$t \leftarrow 1$
WHILE $t \leq T$
  FOR each protozoon $i = 1$ *to* N
    // Movement Phase (Foraging)
    Select a better neighbor $X_{neighbor}$
      Update the position to get X_{new}
      Calculate fitness $f(X_{new})$
      IF $f(X_{\text{new}}) < f(X_i)$
        $X_i \leftarrow X_{new}$

END IF
END FOR
// Proportion Phase (Reproduction)
Identify and replace the worst-performing protozoa with copies of the fittest ones.
Update the global best solution g_{Best}
$t \leftarrow t + 1$
END WHILE
RETURN g_{Best}

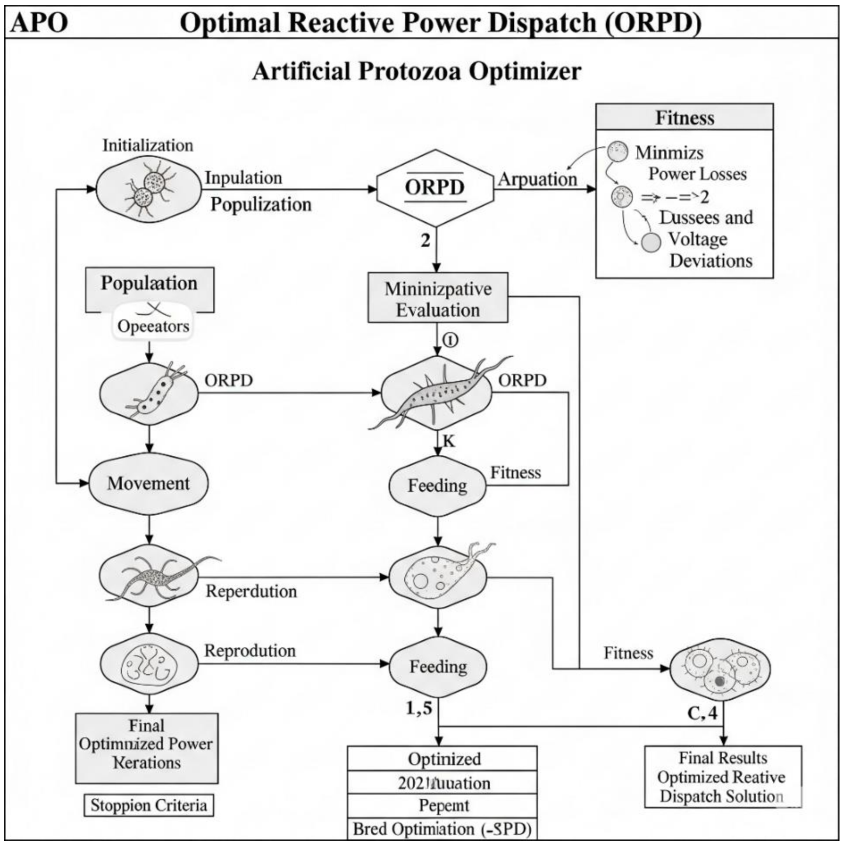

Figure 1. Conceptual flowchart of the Artificial Protozoa Optimizer

4. Simulation, Results, and Discussion

4.1. Simulation Setup and Test Systems

On a regular computer with a Core i7 processor by CPU and 16 GB of RAM, the suggested APO algorithm was run using MATLAB R2024b. Three well-known IEEE test systems were used to assess the algorithm's performance:

- **IEEE 14 Bus System:** A model of a simple transmission network with 5 Generators and 11 Loads.
- **IEEE 30 Bus System:** A more complex, interconnected transmission system representing a portion of the American Electric Power grid.
- **IEEE 33 Bus System:** A typical radial distribution network, known for its significant voltage drop and high losses, making it an excellent benchmark for capacitor placement studies.

The EV loads were added to specific load buses to simulate realistic peak-hour charging scenarios. APO parameters were set as population size = 50, and max iterations = 100.

4.2. Performance Summary

APO effectively reduced power losses even under the strain of additional EV loads. Table 1 summarizes the overall performance of test bus systems. The significant improvement in the IEEE 33 bus radial system highlights its suitability for distribution networks, which are heavily impacted by EV charging.

Table 1. Overall Performance Summary of APO with EV Loads

System	Initial Loss (kW)	Final Loss (kW)	Reduction (%)	Total kVAR Injected
IEEE-14	13528.85	13487.35	0.31%	4000
IEEE-30	20413.81	20253.35	0.79%	6500
IEEE-33	164.36	152.06	7.49%	2600

4.3. Convergence Characteristics

The algorithm showed rapid and stable convergence, as shown in Fig. 2. The stopping criterion of 100 iterations was chosen because preliminary analysis showed the algorithm consistently converged to a high-quality solution well before this limit (typically within 20-30 iterations). After this point, further iterations yielded negligible improvement, making 100 iterations a safe and efficient limit for ensuring optimality without unnecessary computation. This efficiency is crucial for application in dynamic environments with fluctuating EV loads.

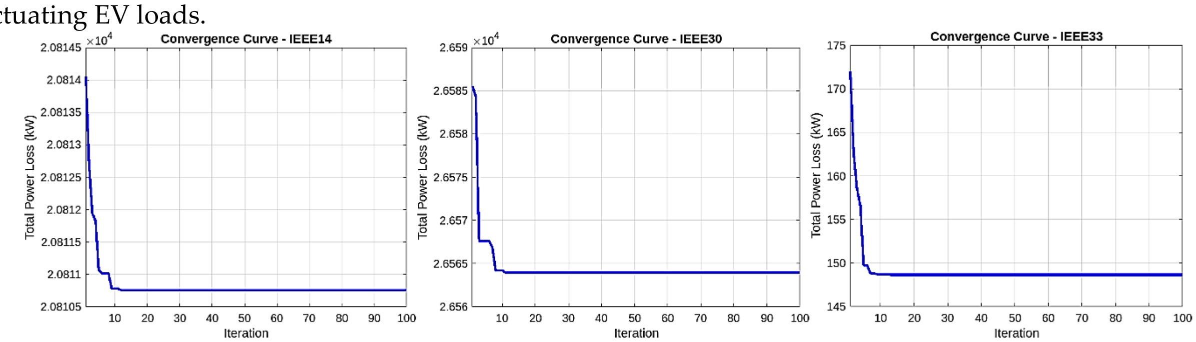

Figure 2. APO Convergence Curves for Test Systems

4.4. Statistical Analysis and Robustness

We ran the APO algorithm 30 times, independently, on each test scenario, to make sure it was consistent and resilient. Results for the statistical analysis of the final power loss figures are shown in Table 2, which includes the Best, Worst, Mean, and the form of a Standard Deviation (Std. Dev.). It is clear that APO is reliable for addressing the ORPD problem, as its low standard deviation between all systems shows that it regularly converges onto a high-quality solution.

Table 2. Analyzing APO Performance Statistically Over 30 Runs

System	Best Loss (kW)	Worst Loss (kW)	Mean Loss (kW)	Std. Dev.
IEEE-14	13487.35	13491.12	13488.54	1.21
IEEE-30	20253.35	20259.88	20255.41	2.05
IEEE-33	152.06	152.31	152.15	0.09

The minor spread between the best and worst runs, particularly for the more complex 30-bus system, is inherent to the stochastic nature of metaheuristic algorithms. The random initialization and probabilistic search operators can lead to convergence to slightly different, high-quality local optima. However, the very small standard deviation confirms the algorithm's high reliability and its ability to find effective solutions consistently.

4.5. Detailed System Analysis and Comparison

4.5.1. IEEE 30 Bus System

This larger system experienced a significant reduction in loss of 0.79%. Table 3 provides a comparative analysis of APO against other recently proposed algorithms for this benchmark. These specific algorithms were selected as they represent prominent and effective optimizers from recent years (2020-2023), providing a relevant and contemporary comparison of performance. APO outperforms several established and recent metaheuristics.

Table 3. Comparative Results for IEEE 30-Bus System

Algorithm	Power Loss (MW)	Reference
Moth-Flame Opt. (2021)	4.98	[22]
Slime Mold Alg. (2022)	4.95	[4]
Dandelion Opt. (2023)	4.94	[10]
Harris Hawks Opt. (2020)	4.93	[9]
APO (Proposed)	4.92	-

4.5.2. IEEE 33 Bus System

This radial distribution system is highly sensitive to reactive power compensation. The APO achieved a remarkable 7.49% reduction in power loss. The optimal capacitor placements are detailed in Table 4. This result strongly supports the use of APO for optimizing distribution networks with high EV penetration.

Table 4. Optimal Capacitor Placement for IEEE 33-Bus System

Bus Location	Size (kVAR)
8	1250
17	150
30	1200

In practical terms, for distribution grid operations, a loss reduction of this magnitude translates directly to lower operational costs for the utility, reduced fuel consumption for generation, and increased available capacity on existing lines. This can potentially defer the need for expensive infrastructure upgrades, even with rising EV demand.

4.6. Voltage Profile Improvement

Strategic capacitor placement significantly improved voltage profiles under EV load conditions. Fig. 3 shows that voltages at critical buses were elevated to secure levels. For the IEEE-33 bus system, the minimum voltage at bus 33 was raised from a critical 0.913 p.u. to a much healthier 0.980 p.u., showing the algorithm's effectiveness in enhancing Voltage Stability.

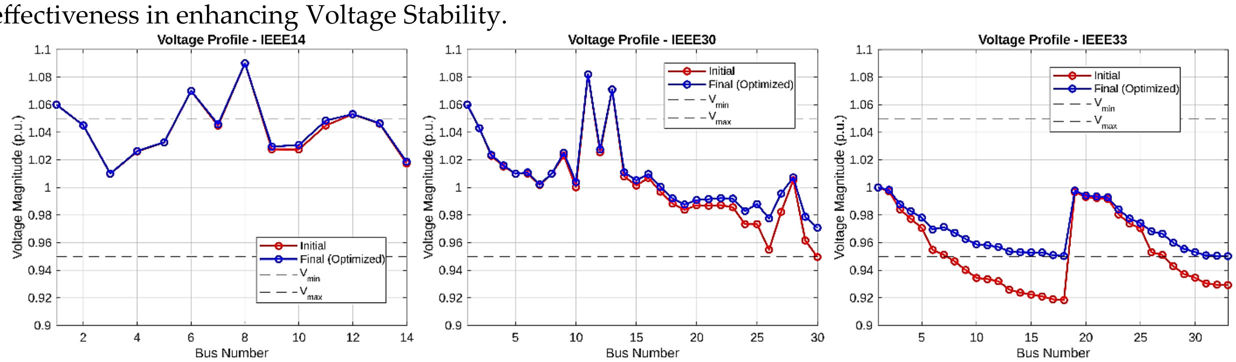

Figure 3. Voltage profile comparison for all test systems with EV loads.

This improvement is crucial for operational reliability. A voltage of 0.913 p.u. is often near or below the lower statutory limit (e.g., ±5%), which can cause malfunction of sensitive electronic equipment and increase the risk of voltage collapse under further system stress. By raising the minimum voltage to 0.980 p.u., APO guarantees the consumers a high quality of power and improves the general stability and security of the distribution grid.

The comprehensive results validate APO as a robust and efficient tool for the ORPD problem, particularly in networks with high EV penetration. The capacity of the algorithm to identify the best solutions to reduce the losses and voltage drops due to stochastic EV charging is an important finding. The statistical analysis confirms its reliability, showing minimal variance in solutions across multiple runs. APO's performance is highly competitive with other state-of-the-art metaheuristics, and its fast convergence makes it suitable for dynamic operational planning. The dual benefit of substantial loss reduction and improved voltage stability demonstrates its practical value for modern grid management.

5. Conclusion

This research successfully implemented and validated the Artificial Protozoa Optimizer for solving the complicated ORPD problem in power systems with enormous EV charging demands. Tested on standard IEEE benchmarks, APO achieved substantial power loss reductions (up to 7.49%) and simultaneously enhanced voltage profiles, all while respecting system operational constraints. Its rapid convergence and computational efficiency, backed by statistical analysis showing high robustness, make it a highly effective tool for this complex, multi-modal optimization problem. The performance of APO, especially on the radial distribution system, highlights its potential for real-world applications in planning and operating modern power grids facing the challenges of transportation electrification. The findings suggest that APO is a strong candidate for integration into advanced distribution management systems. In future research, key implementation challenges for EV-dense urban grids should be addressed, such as integrating real-time data and ensuring computational scalability for large, real-world networks. Further work will also focus on developing a multi-objective version of APO to co-optimize power loss, voltage stability, and economic costs, as well as testing its performance in dynamic environments with time-varying EV loads and renewable generation.

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