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Parameter Estimation of Standard and PV Diode Models for Electric Vehicle Charging Using Arctic Puffin Optimization.

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INTRODUCTION

For PV systems to operate as effectively as possible in applications like EV charging infrastructure, parameter estimation of Standard PV diode models, such as the well-known Single Diode Model (SDM), is essential. The current-voltage (I-V) and power-voltage (P-V) characteristics of PV modules under various environmental conditions can be accurately modeled by estimating a number of parameters, including reverse saturation current, photocurrent, diode ideality factor, series resistance, and shunt resistance. This accuracy ensures effective PV-EV system operation by enhancing maximum power point tracking (MPPT), energy forecasting, and fault diagnostics.

Conventional analytical and curve-fitting techniques are frequently inconsistent and unreliable due to the nonlinear and multi-modal nature of the PV parameter estimate problem, particularly in the presence of partial shade or variable irradiance. The ability of metaheuristic optimization algorithms to adapt to complex objective functions and search globally has made them popular for this task. One of these is Arctic Puffin Optimization (APO), a brand-new bio-inspired metaheuristic algorithm that draws inspiration from the migratory and social feeding habits of Arctic puffins. Using Levy flights and adaptive synergy factors, APO's airborne exploration and submarine exploitation phases collaborate to efficiently refine solutions and search the search space globally.

In addition to preventing premature convergence, this dynamic balancing of exploration and exploitation increases the speed and precision of parameter estimation in APO.

Although APO has shown competitive performance in several challenging real-world optimization problems, its use in PV parameter estimation is still in its early stages, especially for intelligent, decentralized PV-powered EV charging systems. APO has the ability to improve the accuracy and resilience of PV model parameters in a variety of climatic conditions due to its benefits in speeding convergence and avoiding local optima, which will make it easier to plan and operate sustainable EV charging infrastructure.

This method improves scalability and reliability for embedded or real-time PV-EV system applications by building upon well-known metaheuristics like Particle Swarm Optimization, Genetic Algorithms, and Differential Evolution. The significance of PV parameter estimation, the difficulty of nonlinear optimization, and the special function of APO in enhancing parameter estimation in PV diode models for EV charging systems are all covered in this introduction.

OBJECTIVE:

The Arctic Puffin Optimization technique is used to model PV modules in EV charging systems by accurately estimating the essential parameters of the Single Diode Model: photocurrent, diode ideality factor, reverse saturation current, series resistance, and shunt resistance. to assess how well APO overcomes the difficulties of nonlinear and multi-modal PV parameter estimation problems, such as avoiding local optima and speeding up convergence speed, when compared to conventional optimization techniques.

to illustrate how, in a variety of environmental circumstances, APO-based parameter estimation can improve energy forecasts, fault diagnostics, and maximum power point tracking (MPPT) for PV-powered EV charging infrastructures. to evaluate the viability and computational efficiency of applying APO to embedded PV-EV systems or real-time applications that support intelligent, decentralized, and sustainable EV charging solutions.

Single Diode:

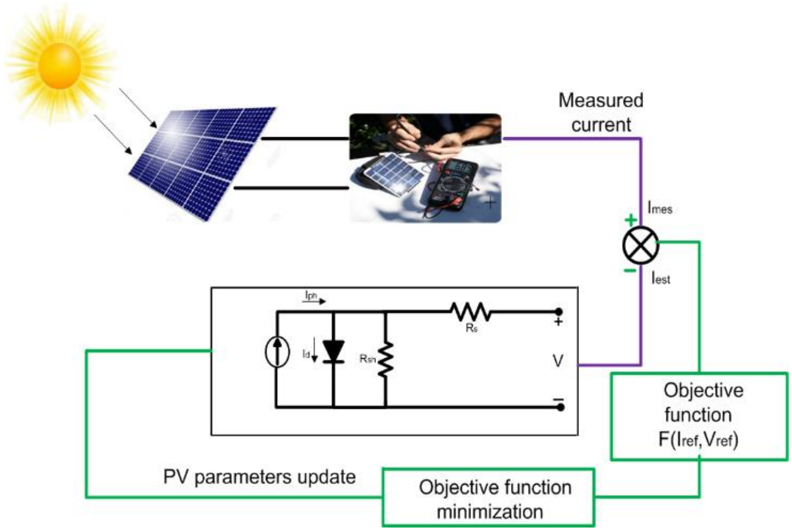
Output current equation:

$$I = I_L - I_0\left[exp\left(\frac{V+IR_S}{nV_T}\right) - 1\right] - \frac{V+IR_S}{R_{sh}}$$

Parameters:

I: Output current (A)

I_{ph}: Photocurrent (light-generated current) (A)
I_0: Reverse saturation current of the diode (A)
q: Electron charge (1.602×10^{-19} C)
V: Terminal voltage (V)
R_s: Series resistance (Ω)
R_{sh}: Shunt resistance (Ω)
n: Diode ideality factor



About APO
An innovative bio-inspired metaheuristic optimization method called Arctic Puffin Optimization (APO) was developed to tackle difficult technical and real-world optimization issues. It is based on the hunting and survival strategies of the Arctic puffin, a seabird known for its remarkable ability to combine flying through the air with diving underwater for food. In order to achieve a strong balance between exploration and exploitation—two key behaviors for solving optimization problems—the algorithm imitates these two behaviors: underwater foraging and aerial flying. While exploitation concentrates on honing solutions in those regions to reach the global optimum, exploration in optimization refers to the process of searching widely across the solution space to find promising locations.

Due to their propensity to become trapped in local optima, traditional optimization techniques like gradient descent frequently have trouble solving non-linear, multi-modal, or high-dimensional problems. To overcome these obstacles, metaheuristic algorithms such as APO employ stochastic and adaptive techniques that are modeled after nature. In order to achieve faster convergence and higher accuracy, the APO algorithm employs an adaptive behavioral mechanism that dynamically switches between exploration and exploitation depending on the iteration stage.

Each puffin is a potential solution to the issue, and the APO algorithm begins with population initialization. Within the specified upper and lower bounds of the search space, the initial population is created at random. After initialization, the algorithm moves through two primary behavioral stages that are based on puffin activities: the aerial flight stage and the submerged foraging stage. Together, these two stages mimic how puffins scour vast regions for food before utilizing nearby areas once they locate suitable feeding grounds.

In search of possible food sources, puffins fly in coordinated groups at low altitudes during the aerial flight stage, which is symbolic of exploration. Levy flights and velocity factors are used to mathematically simulate this behavior, enabling the algorithm to randomly jump across the search space of varying sizes. Sometimes puffins with levy flight travel long distances to escape local optima and explore a wider area. The algorithm uses a swooping predation behavior, where puffins swiftly dive towards their prey after identifying favorable locations. By simulating rapid movement toward the optimal solutions with a velocity coefficient, this procedure enhances the algorithm's exploration capabilities and prevents premature convergence.

Puffins use three primary strategies to focus their search on the best solutions discovered thus far during the underwater foraging stage, which stands for exploitation: gathering forage, intensifying their search, and avoiding predators. By using the gathering foraging method, puffins move in groups toward areas that show promise based on a synergy factor that regulates how much each individual is influenced by others. The accuracy of local searches and convergence speed are enhanced by this partnership. Using a changing factor that varies with the number of iterations, puffins adaptively modify their positions during the intensifying search phase, enabling them to concentrate more precisely on potential locations as the algorithm advances.

Puffins mimic the algorithm's strategy for avoiding local optima during the predator avoidance phase, when they identify possible threats and abruptly or randomly shift their locations to avoid danger. These behaviors work together to give the APO the ability to combine local optimization with broad global search.
The behavioral conversion factor, represented by the letter B, is a significant advancement in the APO algorithm. The switch between the two primary stages—underwater foraging and aerial flight—is automatically managed by this setting. The algorithm gives global exploration priority at the start of the process when B surpasses a threshold value C (set at 0.5), enabling puffins to search over sizable areas of the solution space.

The algorithm turns to local exploitation as iterations increase and B falls, exploring areas with superior solutions in greater detail. Throughout the optimization process, the APO algorithm is guaranteed to maintain an appropriate balance between exploration and exploitation thanks to this adaptive switching mechanism. Early convergence is prevented and the population's diversity is maintained by incorporating randomization into the behavioral component. The synergy factor F and the comparison parameter C are the two main control parameters of the APO algorithm.

According to sensitivity studies, the ideal value of the synergy factor, which controls how cooperative puffins are during foraging, is 0.5. While a lower number might impede progress, a higher value might cause premature convergence. The ideal trade-off between local refinement and global search was found to be 0.5 for the comparison parameter C, which establishes the boundary between exploration and exploitation. Because of these parameter selections, APO is stable, robust, and effective for a wide range of problem types. The number of iterations, problem dimension, and population size are multiplied to determine the algorithm's temporal complexity. Despite this, APO's parallel population-based operations and adaptive techniques make it computationally efficient.

The CEC2017, CEC2019, and CEC2022 test suites were used to thoroughly evaluate it on common benchmark functions, such as unimodal, multimodal, hybrid, and composite functions.

According to the findings, APO performed better than nine novel optimization algorithms, such as Harris Hawks Optimization, Grey Wolf Optimization, Arithmetic Optimization, and Particle Swarm Optimization. It produced better results in 70–75% of test scenarios and showed enhanced performance in both local convergence and global search.

One of the advantages of the APO algorithm is its capacity to dynamically modify its search pattern based on the complexity of the problem and the stage of iteration. It converges more quickly than most algorithms, employs fewer control parameters, and successfully avoids local optima. Furthermore, it has demonstrated remarkable applicability to practical engineering optimization issues like structural analysis, energy system modeling, and mechanical design. APO can precisely handle non-linear and multi-constraint problems by combining adaptive behavioral transitions, velocity management, and Levy flight.

In conclusion, the Arctic Puffin Optimization algorithm is a clever and effective method of global optimization that draws inspiration from Arctic puffins' adaptive and cooperative behaviors. By using mathematical modeling that considers the principles of natural survival, APO successfully strikes a balance between exploration and exploitation. It is a promising approach to challenging optimization problems in a variety of scientific and technical fields because of its enhanced convergence, resilience, and adaptability.

Arctic Puffin Optimization (APO)

The Arctic Puffin Optimization (APO) algorithm is a newly developed bio-inspired metaheuristic optimization technique that emulates the unique survival tactics of Arctic puffins in the wild. These seabirds demonstrate remarkable adaptability by balancing aerial flight (exploration) and underwater foraging (exploitation) to locate and capture prey. APO uses this dual-behavior approach to solve optimization problems by dynamically alternating between the global exploration and local exploitation phases, ensuring high search diversity and faster convergence to the global optimum.

In optimization, exploration helps identify new regions of the search space, while exploitation enhances solutions discovered in promising regions. Many evolutionary and conventional algorithms often converge too soon and lose this equilibrium. Through the introduction of an adaptive behavioral conversion mechanism that emulates the transition of puffins from flying to diving, APO automatically adjusts the global to local search ratio as the algorithm evolves.

In the wild, Arctic puffins employ a variety of ingenious strategies, including flying in groups to identify potential feeding areas, diving rapidly after spotting prey, foraging together to maximize hunting efficiency, and changing positions when food supplies run low or predators appear.

These behaviors are used to develop mathematical models that govern puffins' movements in the search space. Large areas are searched during the exploration phase (aerial flight) using Levy flights, which generate both small and large random steps to increase diversity. Swooping predation, a rapid and focused search around promising areas, is what puffins do when they find a good solution. The exploitation phase, or underwater foraging, models three primary behaviors: gathering foraging, where puffins work together to intensify search around optimal regions; intensifying search, where adaptive factors refine solutions based on iteration progress; and predator avoidance, where puffins quickly shift positions to avoid danger, preventing the algorithm from becoming stuck in local minima.

One of APO's most important innovations is the behavioral conversion factor (B), which dynamically controls whether puffins explore or exploit. Early in the search, B gives priority to flight (broad exploration), and later on, foraging (local refinement). This adaptive switching improves the convergence efficiency and robustness. Low parameter dependence and an excellent trade-off between global search capability, accuracy, and convergence speed are guaranteed by the algorithm's architecture. Benchmark and engineering tests show that APO consistently outperforms several modern algorithms, making it a powerful tool for solving highly nonlinear and constrained optimization problems.

Single Diode Modulation:

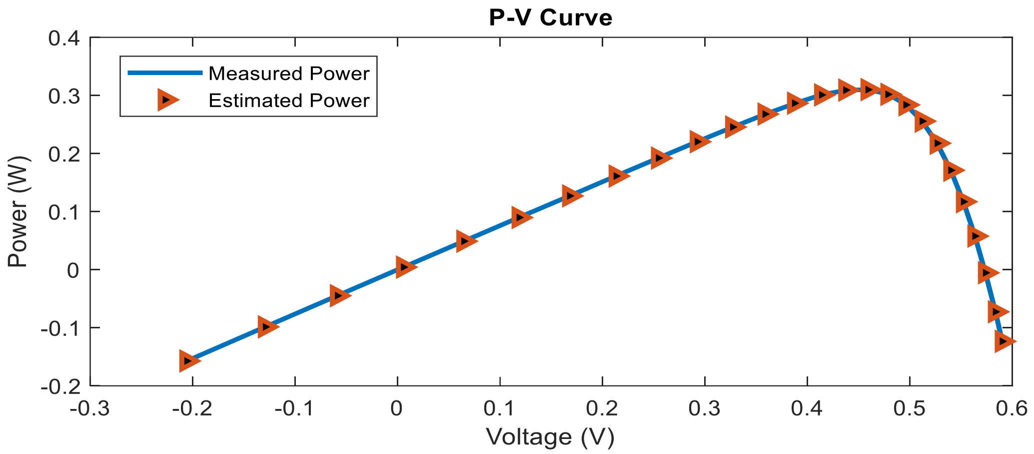
When compared to other algorithms, the optimization (APO) algorithm performed the best for the R.T.C. France PV module. With Iph = 0.760788, I0 = 0.310691, Rsh = 52.88991 Ω, Rs = 0.036547 Ω, and n = 1.477272, it obtained precise parameter values. Additionally, APO demonstrated high accuracy and stability by producing the lowest error values (Best Score = 7.73×10^{-4}) with very little variation (Std = 1.289388×10^{-17}). All things considered, APO was the most dependable and successful technique for estimating photovoltaic parameters.

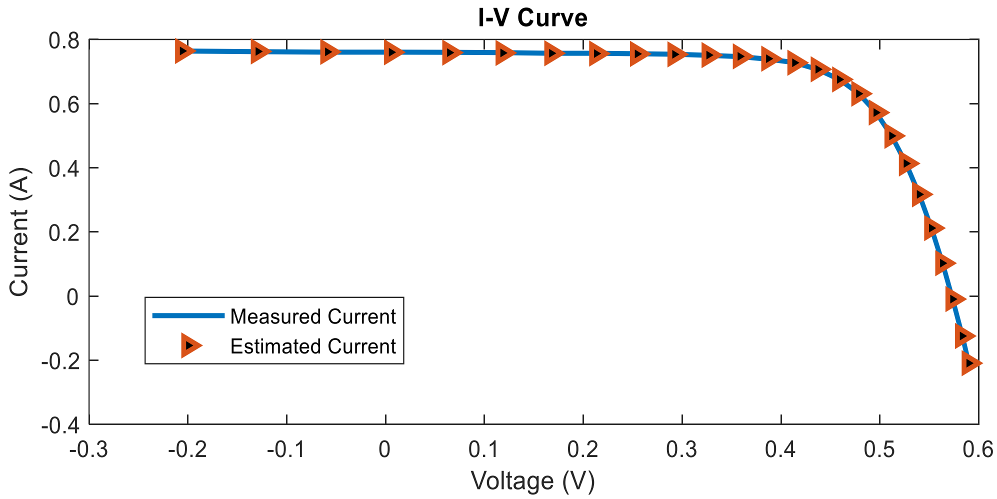
Table. Acquired parameters for the R.T.C. France PV module (SDM) using APO compared to the other algorithms.

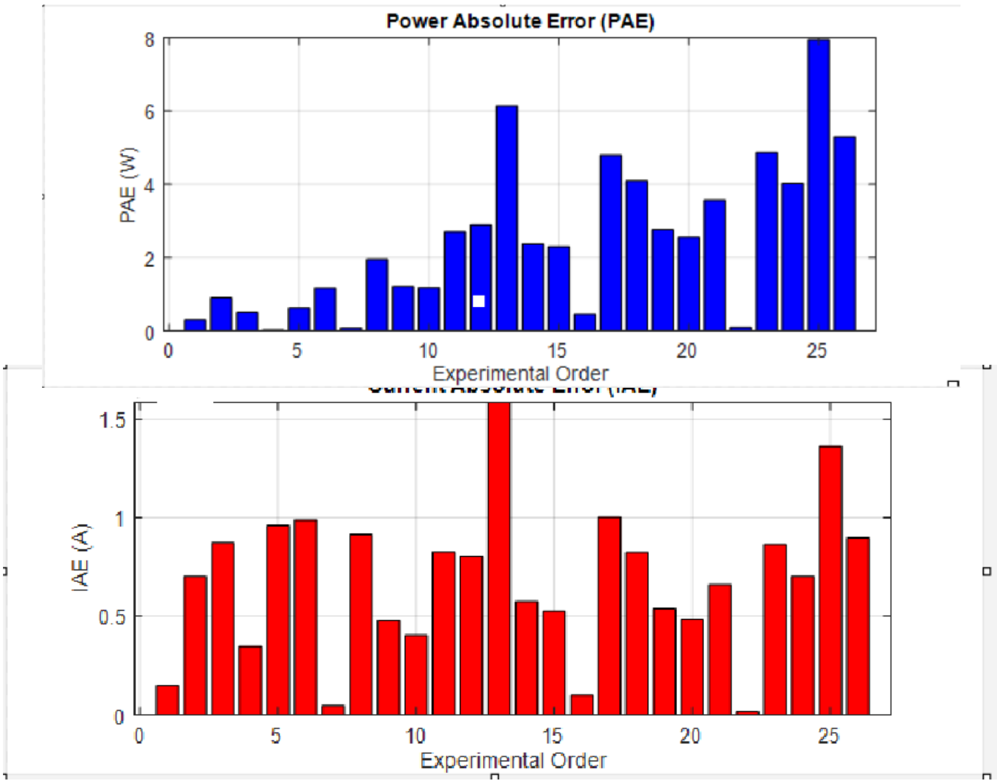
Algorithm	Min	Max	Mean	Std	Best Score
APO	7.729857×10^{-4}	7.712857×10^{-4}	7.72857×10^{-4}	1.289388×10^{-17}	7.73×10^{-4}
GSA	1.334236×10^{-3}	5.510722×10^{-3}	2.149118×10^{-3}	1.211429×10^{-3}	0.00182
GTO	1.457797×10^{-3}	2.878898×10^{-2}	5.095100×10^{-3}	5.941538×10^{-3}	0.00355
SSA	9.421958×10^{-4}	5.3354550×10^{-3}	2.269107×10^{-3}	1.377649×10^{-3}	0.00186
GWO	1.206915×10^{-3}	4.665430×10^{-3}	2.348018×10^{-3}	1.256511×10^{-3}	0.00143
ACO	5.378158×10^{-3}	2.666122×10^{-2}	1.575325×10^{-2}	5.708099×10^{-3}	0.01985

Table. Statistics for the R.T.C. France PV module (SDM) using APO compared to the other algorithms.

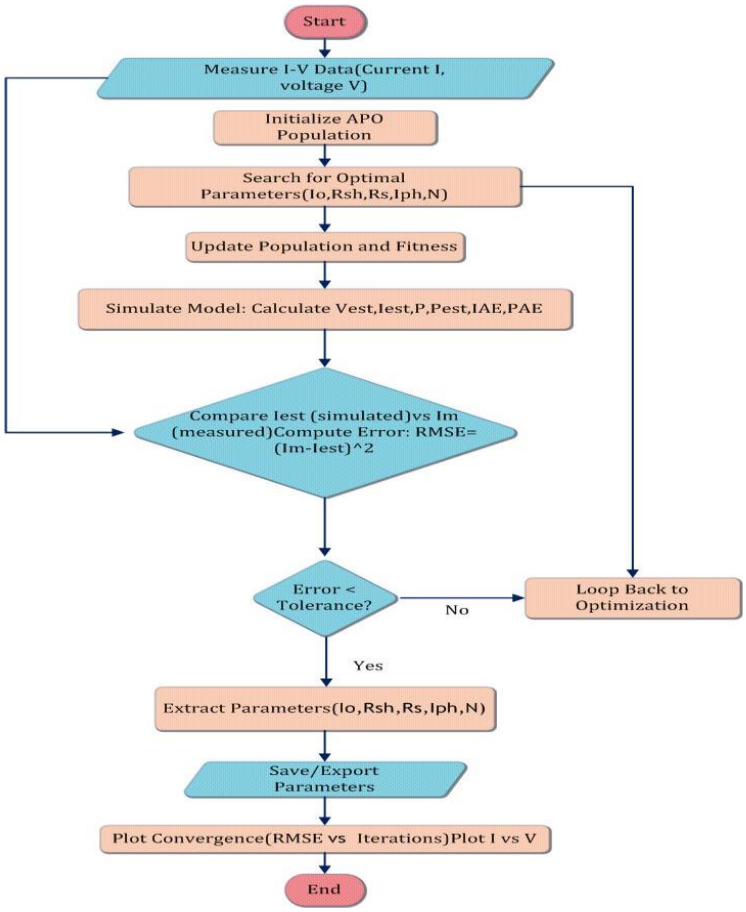
Algorithm	Iph	I0	Rsh	Rs	n
APO	0.760788	0.310691	52.88991	0.036547	1.477272
GSA	0.761031	0.824068	73.28785	0.031890	1.582145
GTO	0.757258	0.125198	42.39581	0.040867	1.391497
SSA	0.762212	0.628527	46.42206	0.032833	1.551964
GWO	0.759804	0.609331	91.475	0.033376	1.547937
ACO	0.784458	0.445017	76.79768	0.038856	1.506401






Power Absolute Error (PAE)
PAE (W)
Experimental Order
IAE (A)
Experimental Order

Flow Chart:


Start
Measure I-V Data(Current I, voltage V)
Initialize APO Population
Search for Optimal Parameters(Io,Rsh,Rs,Iph,N)
Update Population and Fitness
Simulate Model: Calculate Vest,Iest,P,Pest,IAE,PAE
Compare Iest (simulated)vs Im (measured)Compute Error: RMSE= (Im-Iest)^2
Error < Tolerance?
No
Loop Back to Optimization
Yes
Extract Parameters(Io,Rsh,Rs,Iph,N)
Save/Export Parameters
Plot Convergence(RMSE vs Iterations)Plot I vs V
End

Conclusion:

This research explored the effectiveness of the Arctic Puffin Optimization (APO) algorithm for estimating the parameters of standard photovoltaic (PV) diode models used in electric vehicle (EV) charging applications. Inspired by the natural flight and diving behaviors of Arctic puffins, APO maintains a strong balance between exploration and exploitation, leading to precise and rapid convergence toward the optimal solution. Experimental evaluation using RTC France PV module data confirmed that APO achieved the smallest errors and highest consistency compared to other metaheuristic algorithms such as GSA, GWO, SSA, GTO, and ACO. For both single and double diode configurations, the APO method delivered accurate current and power estimations, demonstrating excellent performance in modeling nonlinear PV characteristics under diverse conditions.

The overall findings indicate that APO is an efficient and dependable optimization technique for enhancing the accuracy and reliability of PV-based EV charging systems. Its fast convergence, stability, and computational simplicity make it ideal for real-time renewable energy applications. Future studies can focus on extending the APO approach to multi-diode and hybrid PV models, integrating it with AI-driven control mechanisms, and testing its adaptability under varying environmental scenarios to further improve the performance of smart and sustainable energy systems.

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