

Achievements of Generations Inheritance and Optimization in Reactive Power and Voltage Control

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Abstract: - This paper introduces a novel evolutionary optimization algorithm, AGIO (Achievements of Generations Inheritance and Optimization), inspired by the way human family trees evolve through inherited and improved achievements. AGIO simulates multiple family lineages, each producing one offspring per generation, with individuals aiming to enhance the accomplishments of their predecessors. Each individual's capability—shaped by creativity, character traits, environmental factors, and inherited performance—determines the quality of the solution. The method is well suited for complex engineering problems, where decision variables are treated as individual capabilities and objectives reflect accumulated achievements. AGIO is applied to reactive power and voltage control in the IEEE 30-bus test system. Its performance is evaluated against Particle Swarm Optimization (PSO) and the Grey Wolf Optimizer (GWO), demonstrating more consistent convergence and improved optimization results.

Key-Words: - Evolutionary algorithms, generation inheritance, planning, power systems, reactive power, voltage control.

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1 Introduction

Throughout the evolution of computational intelligence, numerous evolutionary algorithms (EAs) have been proposed, achieving varying degrees of success in addressing complex, nonlinear engineering optimization problems [1], [2], [3], [4]. Among them, the best, in our opinion, were the very popular particle swarm optimization (PSO) introduced by [5], the ant-colony systems (ACS) introduced by [6], and the cultural algorithm introduced by [7]. The effort was continued, generating more effective EA [8]. However, the main problem of the proposed EA remains the achievement of the global best solution, avoiding

local minima. Under this condition, we introduce a novel EA more effective and capable of solving nonlinear optimization problems faster with more accuracy. The main idea behind this approach is based on the fact that the achievements of generations are inherited and optimized during the evolution of human family trees.

From life's experience, it is well known that the achievement during the evolution of human family trees depends on the capabilities of their adjacent individuals. Each individual with good intentions tends to maximize the achievement of their family tree. The creativity and personality of an individual, as well as the normal (e.g., education, etc.) and other

random conditions of his generation, drastically affect his capability. More specifically, the achievement of each family tree is improved based on the capabilities of its adjacent individuals. The capabilities of individuals are affected by a) creativity, b) personal choices, c) normal and random conditions of the generations, and d) inherited achievements and infeasible creations of adjacent ancestors.

The proposed Achievements of Generations are Inherited and Optimized (AGIO) algorithm can solve nonlinear optimization problems, where the state variables are considered as capabilities of individuals and the objective values as achievements of family trees. Specifically, AGIO supposes a number of progressed family trees which have one offspring at each generation (single family trees). The main advantage of AGIO is that it faces the aspect of the dead-end of the family tree during its evolution. The dead-ended family tree results when its achievement is fixed at a specific value during the evolution of their offspring (they fall into a local minimum). In this case, the family tree is randomly reinitialized with a new individual who takes a random value of capability near the neighborhood of the last successful individual's capability. So the local minima of a nonlinear problem are successfully avoided.

In this paper, the AGIO algorithm is applied for the first time in the two nonlinear problems of reactive power and voltage control of the IEEE 30-bus test system. The results obtained by AGIO are compared with those given by a state-of-the-art PSO algorithm [9] and the EA of Grey-Wolf Optimizer (GWO) [10], demonstrating the superiority of the first.

2 AGIO Algorithm

This paper simulates how the Achievements of Generations are Inherited and Optimized (AGIO) among adjacent individuals during their family tree's evolution.

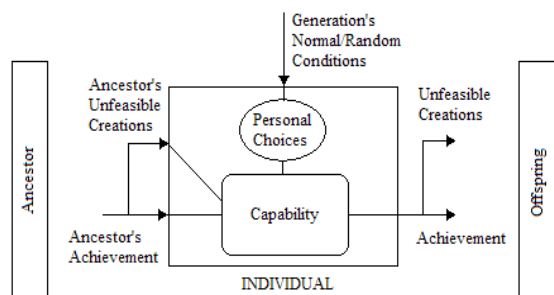


Fig. 1: AGIO by a single family tree
Source: created by the authors.

This first version of AGIO assumes single family trees (with one offspring in each generation), whose evolution is affected only by the best of the generation's achievements. Figure 1 depicts the inheritance and optimization of achievements during the evolution of generations.

The steps of the proposed AGIO algorithm are listed below:

A) Initialization: Create $2N$ individuals, namely N individuals as the grandparents' generation (gp) and N individuals as the parents' generation (p). For each individual -i choose randomly an initial capability, namely, a state vector $\bar{c}_{gp,i}$ when it belongs to generation-gp and $\bar{c}_{p,i}$ when it belongs to generation-p. For each individual-i in the grandparent's generation-gp calculate his initial achievement, namely objective value $A(\bar{c}_{gp,i})$ and among them find the maximum ($\max_i A(\bar{c}_{gp,i})$) called grandparent's generation-gp achievement. For each individual-i in the parent's generation-p, calculate his initial achievement $A(\bar{c}_{p,i})$ and among them find the parent's generation-p achievement ($\max_i A(\bar{c}_{p,i})$). Then, produce the offspring generations in accordance with the following procedure:

B) Family tree's evolution: The capability improvement achieved by the offspring-i (in relation to his parent-i) ($\bar{c}_{s,i} - \bar{c}_{p,i}$) is equal to the capability improvement that has been achieved by his parent-i (in relation to grandparent-i) ($\bar{c}_{p,i} - \bar{c}_{gp,i}$) multiplied by an expected creation gain of offspring-i, namely, an expected creation of offspring-i ($\Delta A_{exp,s,i}$) to the creation which has been achieved by his parent-i ($A(\bar{c}_{p,i}) - A(\bar{c}_{gp,i})$):

$$\bar{c}_{s,i} - \bar{c}_{p,i} = \frac{\Delta A_{exp,s,i}}{A(\bar{c}_{p,i}) - A(\bar{c}_{gp,i})} \cdot (\bar{c}_{p,i} - \bar{c}_{gp,i}) \quad (1)$$

If the creation of parent-i is equal to zero ($A(\bar{c}_{p,i}) - A(\bar{c}_{gp,i}) = 0$), then:

a) the capability of the offspring-i ($\bar{c}_{s,i}$) is randomly redefined and b) since the family tree's achievement was fixed at the value succeeded by grandparent-i, the capability of parent-i ($\bar{c}_{p,i}$) is randomly redefined, reinitializing the dead-end family tree.

The expected creation of offspring-i is defined as:

$$\Delta A_{exp,s,i} = \max A_{exp,s,i} - A(\bar{c}_{p,i}) \quad (2)$$

where: $\max A_{exp,s,i}$ represents the expected maximum achievement of the offspring-i, which is composed of the best of the generations' achievements until now

and a random variable of creation, denoted as $G(\mu, \sigma)$:

$$\max A_{\text{exp},s,i} = \max A(\bar{c}_g) + G(\mu, \sigma) \quad (3)$$

Rewriting (2) by means of (3), the following formula is concluded:

$$\Delta A_{\text{exp},s,i} = \max A(\bar{c}_g) - A(\bar{c}_{p,i}) + G(\mu, \sigma) \quad (4)$$

So, the expected creation of an offspring-i is equal to the infeasible creation of his parent-i plus a random creation which represents the influence of normal and random conditions of offspring generation-s, as well as the personal choices of offspring-i.

In accordance with one of the fundamental theorems of statistics, the central limit theorem, when the sample size, namely the number of individuals in a generation, is large enough ($N > 100$), then the random variables of creations with mean (μ) and standard deviation (σ^2/N) follow the Gaussian distribution. In this case, the mean and the standard deviation are calculated as:

$$\mu = \frac{\sum_{i=1}^N (A(\bar{c}_{p,i}) - A(\bar{c}_{gp,i}))}{N} \quad (5)$$

$$\sigma = \frac{\sum_{j=1}^N [\mu - (A(\bar{c}_{p,j}) - A(\bar{c}_{gp,j}))]^2}{N^2} \quad (6)$$

C) Generation update: Replace grandparent's generation-gp with parent's generation-p and replace parent's generation-p with offspring generation-s.

D) Stopping criteria: Repeat evolution of family trees, namely steps B)-C) until no more improvement in the best of the generations' achievements in the last 25 generations is observed or the maximum allowable number of generations is achieved (in this case study, 50 generations).

E) Global optimal solution: Choose as the global optimal solution the capability that reaches the best of the generations' achievements:

$$\bar{c}_g = \arg \max A(\bar{c}) \quad (7)$$

3 Reactive Power and Voltage Control

The proposed AGIO is tested on the reactive power control. The scope of reactive power control is to optimize the steady-state performance of a power system in terms of one or more objective functions while satisfying several equality and inequality constraints:

A) The first objective is to minimize the real power loss in transmission lines, which can be expressed as:

$$J_1 = P_{\text{Loss}}(\mathbf{x}, \mathbf{u}) = \sum_{l=1}^{NL} P_l \quad (8)$$

where: P_l is the real power losses at line-l, and NL is the number of transmission lines.

B) The second objective is to minimize the voltage magnitudes at load buses, which can be expressed as:

$$J_2 = VD(\mathbf{x}, \mathbf{u}) = \sum_{i=1}^{Nd} |V_i - V_i^{sp}| \quad (9)$$

where: V_i^{sp} is the pre-specified reference value at load bus-i, which is usually set to a value of 1.0 pu, and Nd is the number of load buses.

$\mathbf{x}$ is the vector of dependent variables consisting of load bus voltages V_L , generator reactive power outputs Q_G , and transmission line loadings S_L .

Hence, $\mathbf{x}$ can be expressed as:

$$\mathbf{x}^T = [V_{L_1}, V_{L_2} \dots V_{L_{Nd}}, Q_{G_1}, Q_{G_2} \dots Q_{G_{Ng}}, S_{L_1}, S_{L_2} \dots S_{L_{NL}}] \quad (10)$$

$\mathbf{u}$ is the vector of control variables consisting of generator voltages V_G , transformer tap settings T , and shunt VAR compensations QC . Hence, $\mathbf{u}$ can be expressed as:

$$\mathbf{u}^T = [V_{G_1}, V_{G_2} \dots V_{G_{Ng}}, Q_{C_1}, Q_{C_2} \dots Q_{C_{NC}}, T_1, T_2 \dots T_{NT}] \quad (11)$$

C) The equality constraints represent typical load flow equations as follows:

$$P_{G_i} - P_{D_i} - f_P(\mathbf{x}, \mathbf{u}) = 0 \quad (12)$$

$$Q_{G_i} - Q_{D_i} - f_Q(\mathbf{x}, \mathbf{u}) = 0 \quad (13)$$

where: P_G and Q_G are the generator real and reactive power, respectively, and P_D and Q_D are the load real and reactive power, respectively.

D) The inequality constraints represent the system operating constraints as follows:

Generation constraints: Generator voltages V_G and reactive power outputs Q_G are restricted by their limits as follows:

$$V_{G_i}^{\min} \leq V_{G_i} \leq V_{G_i}^{\max} \quad i=1,2,\dots,NG \quad (14)$$

$$Q_{G_i}^{\min} \leq Q_{G_i} \leq Q_{G_i}^{\max} \quad i=1,2,\dots,NG \quad (15)$$

where: NG is the number of generators.

Switchable VAR sources constraints: Switchable VAR compensations Q_C are restricted by their limits as follows:

$$Q_{C_i}^{\min} \leq Q_{C_i} \leq Q_{C_i}^{\max} \quad i=1,2,\dots,NC \quad (16)$$

where: NC is the number of switchable VAR sources.

Transformer constraints: Transformer tap settings T are bounded as follows:

$$T_i^{\min} \leq T_i \leq T_i^{\max} \quad i=1,2...NT \quad (17)$$

where NT is the number of transformers.

Security constraints: These include the constraints of load voltages at load buses V_L and transmission line loadings S_L as follows:

$$V_{L_i}^{\min} \leq V_{L_i} \leq V_{L_i}^{\max} \quad i=1,2...Nd \quad (18)$$

$$S_{L_i} \leq S_{L_i}^{\max} \quad i=1,2...Nl \quad (19)$$

In the case of AGIO's application to reactive power control, the achievements (objective functions) of family trees consider the J_1 (8), and in the case of application to voltage control, the achievement considers the J_2 (9). As capabilities (state variables) of individuals are chosen as the $\mathbf{x}$ (10) and $\mathbf{u}$ (11) vectors. The decision space in both AGIO's applications is constrained by (13)-(19).

4 Adaptation of AGIO to Reactive Power and Voltage Control

The AGIO algorithm can be applied to the reactive power and voltage control problem through the following steps:

Step 1: Initialization of the Population

A total of 2N candidate solutions (individuals) are created: N individuals forming the grandparent generation (GP) and N individuals forming the parent generation (P). For each individual-i, a random initial capability (state vector) is assigned: $\mathbf{u}_{GP}$ if it belongs to generation GP, or $\mathbf{u}_P$ if it belongs to generation P. In the context of reactive power and voltage control, these N individuals represent different possible configurations of generator voltages, reactive compensation devices, and transformer tap settings in the power system. Each individual is represented by a state vector (capability) composed of the key control variables of the problem (11). Each control variable is initialized randomly within its allowable range. This ensures that all initial individuals are feasible and cover diverse regions of the solution space.

Step 2: Evaluation and Optimization of the GP Generation

Each candidate solution is evaluated by computing its achievement—that is, the objective function value (e.g., power losses (8) or voltage deviation (9)). In this context, for each GP and P pair

(e.g., combining generator voltages, reactive settings from a GP individual and tap settings from the corresponding P individual), a power flow simulation is executed to calculate system losses (8) and bus voltages (9).

Once all individuals are evaluated, the best-performing configurations are identified (i.e., those with the lowest objective values that meet system constraints).

Next, the algorithm focuses on improving the GP generation while holding the P generation fixed. This means that while transformer tap settings are kept constant (from the P individuals), the reactive power capabilities of the GP individuals are optimized. For instance, the capacitor outputs in each GP individual may be adjusted—either randomly or via a local search method—to attempt improvement in the objective function.

One approach is to combine information from the best-performing P individuals with GP individuals (e.g., through guided mutation or interpolation), generating new reactive settings aimed at reducing losses or voltage deviation. As a result, an updated GP generation is formed, featuring refined reactive settings expected to enhance performance.

Step 3: Optimization of the P Generation (Sub-problem Switching)

After updating the GP generation, the algorithm turns its focus to the P generation. Now, the updated reactive settings of the GP individuals are held fixed, and the voltage control variables (i.e., transformer tap positions) in the P individuals are optimized. For each candidate solution in the P generation, the algorithm explores different transformer tap configurations while using the fixed capacitor settings from the corresponding GP individual.

The goal is to minimize the objective function further—either by reducing power losses or improving the voltage profile—through improved tap settings. This may involve random adjustments, guided modifications, or discrete searches (since tap settings often take values from a finite set). Once complete, the P generation is updated with these newly optimized voltage control settings.

This alternating optimization cycle (Steps 2 and 3) continues iteratively: in each generation, one family lineage (either GP or P) is optimized while the other remains fixed. This means that at any given iteration, the algorithm treats one subset of control variables (e.g., the reactive power compensation devices represented in the GP lineage) as the active search space, while keeping the complementary subset (such as transformer tap positions in the P lineage) constant. In the next generation, the roles are reversed. This strategy allows coordinated

refinement of both types of control variables—reactive power and voltage—over successive generations.

The iterative process (Figure 2) continues until a stopping criterion is met, such as no significant improvement in the best achievement over a fixed number of generations or a maximum number of generations is reached. At termination, the best individual encountered during the entire process is selected as the global optimal solution, representing the control setting that achieves the most favorable performance for the power system.

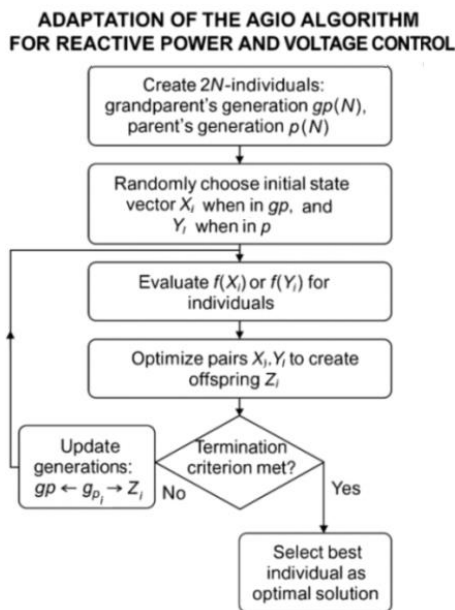


Fig. 2: AGIO procedure for reactive power and voltage control

Source: created by the authors.

5 Problem Solution

This section presents and analyzes the performance of the proposed AGIO algorithm in solving the two main objectives, J1 (8) and J2 (9), of the reactive power and voltage control problem in the IEEE 30-bus test system. The results are benchmarked against two state-of-the-art optimization algorithms: an adaptive Particle Swarm Optimization (PSO) [9] and the Grey-Wolf Optimizer (GWO) [10], a recent high-performing Evolutionary Algorithm (EA).

All three algorithms were applied under identical system conditions and control constraints, and the best results among repeated runs are reported. The number of individuals (or particles/wolves) was set to 30 for all methods to ensure a fair comparison. The convergence behavior and final optimized control settings are summarized in the following figures and tables.

5.1 Minimization of Active Power Losses

For the power loss minimization problem, AGIO converged rapidly, reaching its optimal value of 5.0920 MW in just 23 generations, while PSO and EA required 60 and 50 iterations, respectively, to reach nearly the same result (Table 1).

Table 1 presents the final optimized control variable settings (generator voltages, transformer tap ratios, and shunt compensations) obtained by each method along with the final power loss values. Despite all methods arriving at essentially the same optimal loss (with negligible differences in the fourth decimal), AGIO required significantly fewer evaluations and exhibited the most stable convergence behavior.

These results validate that AGIO achieves global optimality while requiring significantly fewer generations. Its inheritance-based search mechanism enables accelerated convergence without compromising solution quality.

Table 1. Optimized control settings, total active power loss, and converged characteristics for the IEEE 30-bus system – Loss Minimization (Best Case)

Control Variable	AGIO	PSO	GWO
VG ₁	0.9500	1.0408	1.0000
VG ₂	0.9500	1.1000	1.0000
VG ₅	0.9500	0.9500	0.9500
VG ₈	0.9622	0.9500	0.9600
VG ₁₁	0.9753	1.1000	1.1000
VG ₁₃	1.0930	1.0000	1.0700
T ₆₋₉	0.9966	1.0329	1.0200
T ₆₋₁₀	1.1000	1.0132	1.0500
T ₄₋₁₂	1.0006	1.0007	1.0000
T ₂₇₋₂₈	1.0073	1.0069	1.0000
QC ₁ (MVar)	25.110	18.938	22.000
QC ₂ (MVar)	6.2530	6.2810	6.3000
P_{Loss} (MW)	5.0920	5.0922	5.0921
Converged iteration	23	60	50

Source: created by the authors.

5.2 Minimization of Voltage Deviations

For the voltage deviation minimization objective (only best cases), AGIO again showed fast convergence, achieving a deviation value of 0.1221 pu in 24 generations. The GWO slightly outperformed AGIO with a final deviation of 0.1220 pu after 50 iterations, while PSO required 80 iterations to reach 0.1326 pu (Table 2).

In this case, AGIO and GWO produced nearly identical final performance with different adjustment strategies. Notably, both AGIO and GWO deactivated all reactive compensators ($Q_{C1}=Q_{C2}=0$), whereas PSO retained capacitor usage. AGIO achieved a high-quality voltage profile with minimal intervention. AGIO's solution strategy of aggressively tuning transformer taps (e.g., $T_{6-10}=0.9000$) while avoiding overcompensation with capacitors proved effective.

Table 2. Optimized control settings, voltage deviation, and converged characteristics for the IEEE 30-bus system – Voltage Control (Best Case)

Control Variable	AGIO	PSO	GWO
VG ₁	1.0890	1.0929	1.0900
VG ₂	0.9500	1.1000	1.0000
VG ₅	1.0860	0.9500	1.0500
VG ₈	1.1000	0.9500	1.0000
VG ₁₁	1.0021	1.1000	1.0500
VG ₁₃	1.0279	1.0156	1.0300
T ₆₋₉	1.0287	1.0335	1.0300
T ₆₋₁₀	0.9000	0.9532	0.9200
T ₄₋₁₂	0.9929	0.9941	0.9930
T ₂₇₋₂₈	1.0248	1.0222	1.0230
Q _{C1} (MVar)	0.0000	11.131	0.0000
Q _{C2} (MVar)	0.0000	0.0000	0.0000
VD (pu)	0.1221	0.1326	0.1220
Converged iteration	24	80	50

Source: created by the authors.

While the GWO achieved marginally better voltage uniformity, AGIO did so in significantly fewer generations and with cleaner control action. The above results corresponding to the best cases of achievements clearly demonstrate that AGIO achieves equally good or better performance with faster convergence and simpler algorithmic structure. Its ability to handle both reactive dispatch and voltage profile improvement with minimal tuning highlights its practical value for real-world power system optimization tasks.

5.3 Comparative Statistical Performance

This sub-section presents the comparative statistical performance of the AGIO against PSO and GWO on the IEEE 30-bus test system. The first experimental scenario addresses the minimization of active power losses, J_1 (8).

As summarized in Figure 3 (boxplot) and Figure 4 (convergence curves), the AGIO algorithm consistently achieved the lowest mean and best loss values, followed closely by PSO, whereas GWO exhibited higher residual losses on average.

From a convergence standpoint, AGIO revealed the most stable and rapid trajectory toward the

minimum loss level. Its single-offspring evolutionary scheme and adaptive step-size control contributed to fine local improvements after feasibility was attained.

The second optimization scenario focuses on minimizing the aggregate voltage deviation, J_2 (9), across load buses. As shown in Figure 5, the AGIO method achieved the lowest mean and best voltage-deviation values, confirming its superior capability in voltage profile regulation.

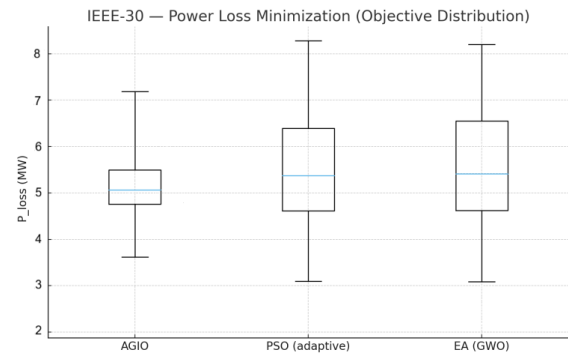


Fig. 3: Distribution of a ctive power loss values over 20 independent runs

Source: created by the authors.

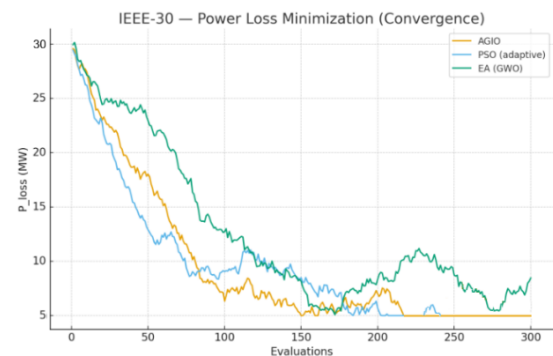


Fig. 4: Convergence behavior of a GIO, PSO and GWO in minimizing active power losses

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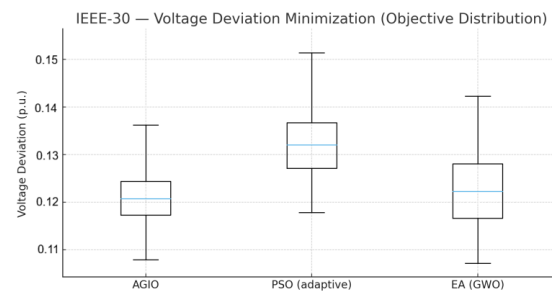


Fig. 5: Distribution of voltage deviation values over 20 independent runs

Source: created by the authors.

As depicted in Figure 6, all algorithms demonstrated smooth convergence behavior, characterized by monotonically decreasing voltage deviation values as the number of evaluations increased. Nevertheless, AGIO consistently converged to the lowest final deviation, highlighting its precision and robustness in maintaining voltages close to the nominal 1.0 p.u. reference.

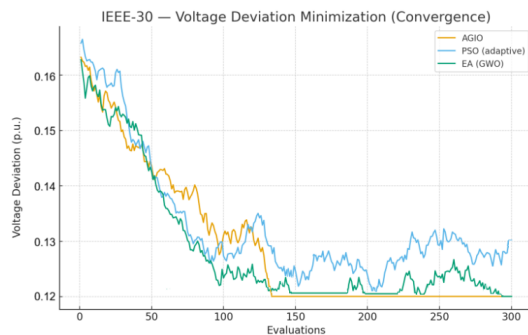


Fig. 6: Convergence behavior of a GIO, PSO, and GWO in minimizing voltage deviations
Source: created by the authors.

6 Conclusions

This study presented a novel evolutionary optimization framework named AGIO for solving reactive power and voltage control problems in power networks. By simulating the inheritance of performance achievements across successive generations, AGIO offers a biologically inspired mechanism for steady and adaptive improvement within a single family-tree structure. Comparative evaluations against an adaptive PSO and GWO—both strong contemporary meta-heuristics—demonstrated that AGIO consistently achieved global optima in significantly fewer iterations, requiring minimal parameter tuning. Its ability to self-correct stagnation through lineage re-initialization (i.e., when a family lineage exhibits stagnation, the AGIO detects this condition and selectively regenerates the stagnated lineage) ensures reliable global optimization without the tuning complexity typical of swarm or pack-based approaches.

References:

- [1] K.Y. Lee, and M.A. El-Sharkawi, Modern heuristics optimization techniques: Theory and applications to power systems, IEEE Press-Wiley, Hoboken, NJ, USA, 2008. ISBN: 978-0471-45711-4. doi: 10.1002/9780470225868.
- [2] Mircea Eremia, Abdel-Aty Edris, and Chen-Ching Liu, Advanced solutions in power systems: HVDC, FACTS and Artificial Intelligence, IEEE Press-Wiley, Hoboken, NJ, USA, 2016. ISBN: 978-1-119-03569-5. doi: 10.1002/9781119175391.
- [3] E. Cuevas, E. Barocio Espejo and A. Conde Enriquez, Metaheuristics algorithms in power systems, Springer, Cham, Switzerland, 2019. ISBN: 978-3-030-11592-0. doi: 10.1007/978-3-030-11593-7.
- [4] K.Y. Lee, and Zita A. Vale, Applications of modern heuristic optimization methods in power and energy systems, IEEE Press-Wiley, Hoboken, NJ, USA, 2020. ISBN: 978-1-119-60229-3. doi: 10.1002/9781119602286.
- [5] J. Kennedy, R. Eberhart, Particle Swarm Optimization, Proc. IEEE Int. Conf. Neural Networks, Perth, WA, Australia, Vol.IV, 1995, pp. 1942-1948. doi: 10.1109/ICNN.1995.488968.
- [6] M. Dorigo, Optimization, learning and natural algorithms, Unpublished PhD Thesis, Dipartimento di Elettronica, Politecnico de Milano, Italy, 1992, in Italian.
- [7] R.G. Reynolds, An Introduction to Cultural Algorithms, Proceedings of the Third Annual Conference on Evolutionary Programming, San Diego, California, USA, World Scientific 1994, pp. 131–139.
- [8] C.A. Coello Coello, R. Landa Becerra, Adding knowledge and efficient data structures to evolutionary programming: A cultural algorithm for constrained optimization, Proceedings of the Genetic and Evolutionary Computation Conference (GECCO' 2002), New York, USA, Morgan Kaufmann Publishers 2002, pp. 201–209.
- [9] D. Mourtzis, J. Angelopoulos, Reactive Power Optimization Based on the Application of an Improved Particle Swarm Optimization Algorithm, Machines, Vol.11 No.7, 2023, p.724. doi: 10.3390/machines11070724.
- [10] M. Varan, A. Erduman, F. Menevşeoğlu, A Grey Wolf Optimization Algorithm-Based Optimal Reactive Power Dispatch with Wind-Integrated Power Systems, Energies, Vol.16 No.13, 2023, p.5021. doi: 10.3390/en16135021.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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