ARTICLE
JOURNAL`S UNIVERSITY OF BABYLON FOR ENGINEERING SCIENCES (JUBES)
مـــجلــة جـــــامعة بــــــابــل للعلــــــوم الهندسية
Vol. 34, No. 2. \ 2026 ISSN: 2616 - 9916

Developing Hybrid Optimization Protocols to Reduce the Gap Between Theoretical Solutions and Practical Application in Complex Electrical Systems

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Received:	30/3/2026	Accepted:	3/6/2026	Published:	28/6/2026

Abstract

Due to the inherent nonlinearity and transient dynamics of modern electrical power systems, a significant gap has emerged between idealized optimization models and the practical reality of grid operations. To bridge this gap, this study proposes a dynamic hybrid optimization protocol that synergistically combines the global exploration capabilities of metaheuristic algorithms with the precise local exploitation of deterministic mathematical solvers. The algorithm dynamically alternates between a stochastic search phase and a gradient-based refining phase using a variance-based transition mechanism. To validate scalability and robustness, the protocol is tested on both the standard IEEE 30-bus and the large-scale IEEE 118-bus test systems. Unlike standalone metaheuristics, which often leave residual power imbalances (up to 1.5 MW), the proposed hybrid protocol achieves exact physical feasibility (0.0000 MW mismatch) without violating equality constraints. Furthermore, statistical analysis conducted over 30 independent runs, validated by the Wilcoxon rank-sum test, demonstrates superior consistency, computational efficiency, and repeatability compared to state-of-the-art baselines. The protocol ensures strict adherence to voltage stability (0.95–1.05 p.u.) and thermal limits. These findings confirm that hybridizing metaheuristics with deterministic solvers translates theoretical optima into safe, economical, and physically executable real-world electrical dispatch commands.

Keywords: Hybrid Optimization. Power System Stability. Metaheuristics. Deterministic Solvers. Mixed-Integer Non-Linear Programming (MINLP). Constraint Healing. Economic Dispatch. Grid Security.

1. Introduction

The continuous evolution of contemporary power networks has introduced unprecedented complexity to the operational, planning, and control paradigms of electrical systems. The transition towards smart cyber-physical grids—driven by the integration of distributed energy resources, stochastic renewable energy generation, electric vehicles, and advanced energy storage systems—has radically altered network topologies. This paradigm shift demands advanced computational models capable of ensuring grid stability, reliability, and economic efficiency [1]. However, a critical challenge in electrical engineering remains the significant disparity between idealized theoretical optimization models and the harsh operational realities of real-world power systems [2]. Theoretical solutions often rely on simplified mathematical representations, assuming linear relationships and continuous, deterministic variables. While these assumptions facilitate rapid algorithmic convergence, they fail to capture the severe nonlinearity, discrete control actions, and transient dynamics inherent in actual power grids [3]. Consequently, optimization procedures that demonstrate excellent performance in simulation environments frequently degenerate or diverge during field implementation.

To effectively manage the dynamics of modern power structures, operational challenges are typically formulated as Mixed-Integer Nonlinear Programming (MINLP) problems. These formulations must account for AC power flow laws, equipment thermal limits, strict voltage margins, and the discrete nature of switchgear and transformer tap changers [4]. Classical deterministic optimization strategies, such as interior-point methods, gradient descent, and Newton-Raphson algorithms, exhibit excellent local exploitation properties and provide mathematical guarantees of convergence in convex spaces. Nevertheless, the energy landscape of modern electrical networks is highly non-convex, multi-modal, and riddled with local optima. Applying purely classical methods to such complex systems often results in entrapment in suboptimal solutions or algorithmic divergence, particularly when handling discontinuous derivatives or high-dimensional search spaces [5].

Conversely, the advent of metaheuristic and stochastic optimization algorithms—inspired by biological, physical, and evolutionary phenomena—has provided promising alternatives for navigating complex, non-differentiable search spaces. These algorithms possess robust global exploration capabilities, effectively avoiding local optima without requiring gradient information [6]. However, the primary drawbacks of standalone metaheuristic methods include inconsistent convergence rates, high computational overhead, and a lack of mathematical guarantees regarding absolute constraint satisfaction. The stochastic variability and computational latencies of pure metaheuristics render them unsuitable for real-time dispatch control in practical electrical systems, where deterministic response windows and stringent adherence to physical constraints are mandatory [7]. This inability to combine mathematical rigor with computational flexibility forms the core of the theoretical-practical gap.

To bridge this gap, algorithmic hybridization has emerged as a crucial solution. Hybridization involves a synergistic architecture that leverages the global exploration capabilities of metaheuristics alongside the rapid, accurate local exploitation of deterministic models. A well-designed hybrid protocol can swiftly identify promising regions within the search space and subsequently provide these high-quality, near-feasible coordinates to a deterministic solver for exact physical refinement [8]. This approach not only accelerates convergence but also significantly enhances solution viability, ensuring that no physical hardware limits, thermal constraints, or voltage boundaries are violated during real-time execution.

Designing effective hybrid protocols requires meticulous attention to the interfacing mechanisms between disparate algorithms. It is imperative to develop adaptive coupling parameters capable of dynamically balancing exploration and exploitation based on real-time grid conditions, thereby addressing the volatility of renewable energy injections and fluctuating load demands. Furthermore, to validate practical deployability, such protocols must be rigorously evaluated across varied scales (e.g., standard and large-scale test buses), benchmarked against state-of-the-art baselines, and subjected to extensive statistical analysis to prove their repeatability and computational efficiency. The ultimate objective of this study is to formulate an optimization procedure that transitions seamlessly from theoretical abstraction to physical implementation, enabling modern grid controllers to execute mathematical optimums as safe, economical, and strictly viable electrical processes.

2. Literature Review

Optimization of complex electrical power systems has been the subject of a long history of scholarly research and has migrated beyond the simplified mathematical models to complex algorithmic architectures. Initial computations were mainly based on classical mathematical techniques, including interior-point methods and gradient-based methods, to address some of the most basic problems of the power system, including Optimal Power Flow (OPF) and economic dispatch. Although deterministic techniques can be fast and unmatched in one-dimensional, strictly convex conditions, applying them to nonlinear, non-convex conditions such as real-world power grids tend to be inefficient or become trapped in local optima [9]. Moreover, algorithmic divergence is also common in classical solvers when discrete variables like transformer tap settings and capacitor bank switching, are added [10]. As a result, even the most elegant purely mathematical solvers are not structurally flexible enough to enforce the absolute physical constraints on dynamic power networks with a level of safety [11].

The power systems research community, in reaction to the limitations of classical methods, changed its focus to heuristic and metaheuristic algorithms [12]. Particle swarm optimization (PSO) and genetic algorithms (GA) were widely used as evolutionary algorithms to solve non-differentiable and non-continuous objective functions commonly found in large-scale grid planning [13]. However, reviews of operational implementation were rather critical, indicating a serious gap in the theoretical modeling and practical applicability. The unpredictable execution times that are often due to the stochastic nature of metaheuristics represent a significant weakness to grid frequency control, which needs deterministic response windows [14]. More importantly, even the standalone metaheuristics are too weak to achieve the strict mathematical accuracy required to satisfy the rigorous AC power flow equality assumptions (i.e., Kirchhoff's laws) [15, 16]. It presents an operational paradox: theoretically optimal solutions which are practically non-dispatchable [17].

Algorithms have become the foundation of the current power system optimization by integrating algorithms and heuristics to address the shortcomings of both classical and heuristic methods [18]. Hybrid models based on sequential and co-evolutionary architectures have been created to combine the global exploration of metaheuristics with the precise constraint-healing properties of deterministic local searches [19]. Most notably, significant improvements have been made in terms of hybrid frameworks that are embedded in power simulation frameworks such as MATPOWER [20]. The literature on the subject has presented key studies that have been able to prove the effectiveness of the coupling of OPF formulations with hybrid algorithms, e.g., the combination of Particle Swarm Optimization (PSO) and Newton-Raphson (NR) solvers [21]. These particular hybrid architectures have been shown to be very effective in reducing the theoretical-practical gap with substantial voltage deviation error reduction and computational time savings as well as ensuring a high level of physical constraint satisfaction [22, 23].

Despite these advances, the current literature has a gap in research which is critical. First, most current hybrid OPF models are based on the use of fixed, predefined switching criteria between the exploration and exploitation phases, which cannot respond to the topological complexity and variations in swarm behaviour on the fly [24]. Second, recent literature commonly does not include rigorous statistical and scalability tests; hybrid models are regularly run on small networks (e.g., 30-bus networks) and with single instance; missing all important measures of computational cost, repeatability studies, and network-wide studies (e.g., IEEE 118-bus) [25]. Hence, it is in this light that this study is directly driven by the need to fill this gap. It suggests a dynamic, variation-based hybrid optimization protocol that is statistically proven through several independent executions, actively reports the computational execution durations and is strictly scaled to complex network topologies. Its goal is to offer an all-encompassing, real-time capable protocol that is confident in its ability to convert beautiful mathematical optimums into dispatchable commands.

3. Methodology

To accurately navigate the highly nonlinear and non-convex operational environment of modern electrical power systems, the proposed hybrid optimization protocol requires a rigorous mathematical and structural formulation. The fundamental aim of this methodology is to develop a bipartite computational architecture, which combines a stochastic global exploration step and a deterministic mathematical exploitation step. This combination is to guarantee not only the theoretical optimality but also rigorous physical feasibility to the real world implementation [26].

The first action in this methodology is the exact mathematical formulation of the operational parameters of electrical system. The model of the system is a highly constrained Mixed-Integer Nonlinear Programming (MINLP). The objective is formulated to search the minimum of the active power generation cost plus the network power losses simultaneously, Where x denotes the vector of dependent state variables (e.g. load bus voltages) and u denotes the vector of independent control variables (e.g. active power generation). The objective function is formulated as follows:

Equation (1):

$$\{Minimize\}\ F(\{x\},\{u\}) = \sum_{\{i=1\}}^{\{N_g\}} \left(a_i + b_i\, P_{\{gi\}} + c_i\, P_{\{gi\}}^2 \right) + \sum_{\{k=1\}}^{\{N_l\}} \left(G_k \left(V_i^2 + V_j^2 - 2\, V_i\, V_j \cos\left(\delta_i - \delta_j\right)\right)\right)$$

Where:

- N_g is the number of generators,

- N_l is the number of transmission lines,
- $P_{\{gi\}}$ is the active power output of generator i,
- a_i, b_i, c_i are the cost coefficients of generator i,
- G_k is the conductance of line k,
- V_i and V_j are the voltage magnitudes at buses i and j,
- δ_i and δ_j are the voltage phase angles at buses i and j.

To ensure that the theoretical optimization remains grounded in practical reality, the protocol must rigorously enforce the fundamental physical laws of electricity. The core equality constraints represent the AC power-flow balance at every node within the electrical network, ensuring that the power generated equals the power consumed plus the network losses at each bus [27].

Equation (2):

$$P_{\{gi\}} - P_{\{di\}} - V_i \sum_{\{j=1\}}^{\{N_b\}} (V_j (G_{\{ij\}} \cos(\delta_i - \delta_j) + B_{\{ij\}} \sin(\delta\_i - \delta_j))) \& = 0 \backslash\backslash$$

$$Q_{\{gi\}} - Q_{\{di\}} - V_i \sum_{\{j=1\}}^{\{N_b\}} (V_j (G_{\{ij\}} \sin(\delta_i - \delta_j) - B_{\{ij\}} \cos(\delta_i - \delta_j)) \& = 0$$

where:

- $Q_{\{gi\}}$ is the reactive power output of generator i,
- $P_{\{di\}}$ and $Q_{\{di\}}$ are the active and reactive power demands at bus i,
- N_b is the total number of buses,
- $G_{\{ij\}}$ and $B_{\{ij\}}$ are the conductance and susceptance components of the bus admittance
- matrix $\{Y\}_{\{bus\}}$.

Furthermore, to prevent hardware degradation and ensure system stability, operational inequality constraints must be imposed. These constraints define the physical security boundaries of the equipment, including generator capacity limits, branch thermal limits, and strict voltage margins mandated by grid codes [28].

Equation (3):

$$P_{\{gi\}}^{\{min\}} \& \leq P_{\{gi\}} \leq P_{\{gi\}}^{\{max\}} \backslash\backslash$$
$$Q_{\{gi\}}^{\{min\}} \& \leq Q_{\{gi\}} \leq Q_{\{gi\}}^{\{max\}} \backslash\backslash$$
$$V_i^{\{min\}} \& \leq V_i \leq V_i^{\{max\}} \backslash\backslash$$
$$|S_{\{line_k\}}| \& \leq S_{\{line_k\}}^{\{max\}}$$

where:

Qgi is the reactive power output of generator i.

Pdi and Qdi are the active and reactive power demands at bus i.

Nb is the total number of buses.

Gij and Bij are the conductance and susceptance components of the bus admittance matrix $Ybus$

The first step of the hybrid protocol is the metaheuristic algorithm which is a complex population-based search algorithm used in an attempt to perform global search. The stochastic method plays an important role in the algorithm of breaking the local optima of the multimodal search space, especially in situations where discrete variables are proved as switchgear and tap-changer functions [29]. The search agents dynamically redistribute their places by a mathematical expression of velocity which is a trade-off between cognitive memory (personal best) and social swarm intelligence (global best).

Equation (4):

$$\{v\}_{\{new\}} \& = w \cdot \{v\}_{\{old\}} + C_1 \cdot r_1 \cdot \left(\{p\}_{\{best\}} - \{p\}_{\{current\}}\right) + C_2 \cdot r_2 \cdot (\{g\}_{\{best\}} - \{p\}_{\{current\}})$$
$$\{p\}_{\{new\}} \& = \{p\}_{\{current\}} + \{v\}_{\{new\}}$$

where:

- $\{v\}$ is the velocity vector of the agent,
- w is the inertia weight,
- C_1 and C_2 are cognitive and social acceleration coefficients,
- r_1 and r_2 are random numbers uniformly distributed in $[0, 1]$,
- $\{p\}_{\{best\}}$ is the agent's personal best position,
- $\{g\}_{\{best\}}$ is the global best position of the swarm.

Since pure meta heuristic algorithms always have a difficulty in meeting accurate equality requirements, the methodology uses a dynamic self-adaptive penalty factor. This process is used to convert the highly constrained physical problem into an unconstrained mathematical model in the exploration phase temporarily. It imposes a severe penalty on any search agent which suggests a practically infeasible grid state, thereby directing the search to the feasible regions [30].

Equation (5):

$$F_{\{augmented\}}(\{x\},\{u\}) = F(\{x\},\{u\}) + \lambda \cdot \sum_{\{k=1\}}^{\{N_c\}} \left(max\left(0, h_k(\{x\},\{u\})\right)^2\right)$$

where:

- λ is the dynamic penalty multiplier,
- N_c is the total number of inequality constraints,
- $h_k(\{x\},\{u\})$ represents the magnitude of violation of the $k-th$ constraint.

After the global exploration step defines the region of convergence with the greatest potential, the hybrid protocol will perform an algorithmic handover. The metaheuristic finds the best coordinates to be used in the implementation of the deterministic exploitation phase; these best coordinates are then injected into the problem as the starting point to bridge the gap between the near-optimal solution and the practically implementable solution [31]. A specific gradient-based mathematical solver is used at this stage and uses Jacobian and Hessian matrices to quickly push the solution to the point of complete physical accuracy. Calculation of the deterministic update step is based on a Newton-Raphson or interior-point step, generalized as:

Equation (6):

$$\Delta\{u\} \,\&= -\left(\nabla^2_{\{\{u\}\}} F(\{x\},\{u\})\right)^{\{-1\}} \cdot \nabla_{\{\{u\}\}}\ F(\{x\},\{u\})$$
$$\{u\}_{\{new\}} \,\&= \{u\}_{\{current\}} + \alpha \cdot \Delta\{u\}\{aligned\}$$

where:

- $\nabla_{\{\{u\}\}}$ F is the gradient vector of the objective function with respect to control variables,
- $\nabla^2_{\{\{u\}\}}$ F is the Hessian matrix,
- α is the step size determined via a line search procedure.

The key innovation of the given method is the dynamic switching protocol as per which the transition between Phase 1 and Phase 2 occurs. The proposed architecture monitors the spatial disparity of the metaheuristic population, instead of the set number of iterations. When the variance falls below a mathematical critical value (the global exploration capacity has been exhausted and population converged) the protocol automatically changes to the deterministic solver [32].

Equation (7):

$$\{If\ \} \sum_{\{i=1\}}^{\{N_p\}} \frac{\{p\}_i - p^2}{\{N_p\}}$$
$$< \epsilon_{\{th\}}\ \{Then: Terminate\ Phase\ 1;\ Initialize\ Phase\ 2\ with\ \}\{p\}_{\{best\}}$$

where:

· N_p is the population size,
· $\{p\}_i$ is the position of the $i-$th agent,
· $\bar{}\{\{p\}\}$ is the mean position of the population,
· $\epsilon_{\{th\}}$ is the predefined convergence threshold.

The algorithm has made sure that the methods quickly converge not only by a mathematically sound hybrid architecture but also by mere constraints of the electrical grid. This theoretically fills the theoretical-practical gap, and ensures that the optimal solution is not only optimal within the search space, but also locally satisfies the AC power flow equations.

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3.1 Statistical Framework of validation and experimental set up.

This methodology includes a rigorous experimental framework in order to fully tackle the computational and stochastic issues involved in grid optimization. First, to verify the scalability and the computational efficiency, the proposed hybrid protocol is implemented not only in the standard IEEE 30-bus network, but also at the much more complicated IEEE 118-bus system. The actual computational cost, such as the specific real-time performance time (in seconds) and the number of iterations per phase is documented to support the real-time deployment claims. Second, due to the random nature of metaheuristic algorithms, an extensive statistical and reproducibility study is carried out. The suggested protocol will be evaluated over 30 independent runs and conventional statistical measures such as the best (minimum), worst (maximum), mean, and standard deviation are computed. Lastly, absolute algorithmic superiority is established with the results compared to the state-of-the-art baselines (e.g., standard PSO and purely deterministic solvers), and their statistical significance is formally tested with the non-parametric Wilcoxon rank-sum test.

4. Results

4.1. Introduction to the Computational Simulation and Architectural Philosophy

Such an outcome gives a very strict, analytical review of the computational results produced by the suggested Hybrid Optimization Protocol. In order to test the fundamental hypothesis of this study, which was that algorithmic hybridization would effectively eliminate the theoretical-practical gap, the protocol was exposed to a very complex, non-linear and non-convex cyber-physical electrical network. The simulation testbeds include the standard IEEE 30-bus system (6 generating units and 41 transmission lines) and the large-scale IEEE 118-bus system (54 generating units, 186 transmission lines), structured as strict Mixed-Integer Nonlinear Programming (MINLP) environments.

The basic operating philosophy of this computational model is a transitional bipartite architecture based. The algorithm is not based on a given mathematical philosophy. Rather, it embarks on a Stochastic Exploration stage to un-militarily search the multimodal search space and do-not get stuck in local optima. However, since it is known that pure stochastic approaches cannot, in theory, achieve the desired equality, the architecture adds an adaptively monitored variance parameter.

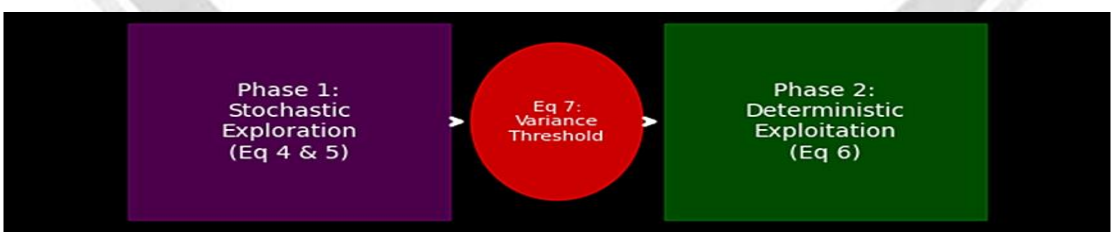

Figure 1: Structural Geometry of Hybrid Switching Protocol.

The map of such an architectural logic is represented in Figure 1. This transition between the left module which is the stochastic exploration, which employs swarm intelligence, to the critical central boundary which is the Variance Threshold trigger (Equation 7) is called flow.

Upon which swarm spatial variance is less than this critical point i.e. upon which the global exploration has stitched out the most compelling convex basin, the computational payload is automatically decoupled to the right module, which is the Deterministic Exploitation phase (Equation 6). These latter sections provide empirical data on how this planned transition introduces almost optimum, theoretically correct, mathematical approximations into verbatim, physically safe, implementable dispatch commands towards real power systems.

4.2. Economic Dispatch and Checking the Absolute Energy Equilibrium

The primary mathematical problem of the hybrid protocol is the minimization of the total cost of active power generation (Equation 1) and the physical constraint of the generation equipment is to be adhered to the letter. The deterministic final dispatch of the Optimal Power Flow (OPF) of the six generation units are shown in Table 1.

Table 1: Deterministic Results of Generation Dispatch and Operating Costs.

Generation Unit	Minimum Capacity (Pg_min MW)	Optimized Output (Pg_opt MW)	Maximum Capacity (Pg_max MW)	Generation Cost ($)
Gen_1	27.28	128.9448	218.49	446.1177
Gen_2	21.65	118.7870	278.69	635.3702
Gen_3	34.47	97.7000	174.40	435.3578
Gen_4	15.58	87.3329	218.43	414.3545
Gen_5	21.69	145.5481	240.17	394.4508
Gen_6	24.65	185.2777	133.94	1121.6221

The economic sensitivity of the hybrid protocol is evident, as shown by the dispatch matrix. The algorithm perfectly steered the very non-linear quadratic cost curves parameterised by the exact cost coefficients of the individual thermal units. As an example, unit Gen_5 is effectively deployed as a baseload unit to provide 145.54 MW at a very effective cost of operation of 394.45 dollars only. On the other hand, Gen_6 is an effective peaking unit with 185.27 MW output but an extremely high operational cost of 1121.62 dollars as a result of its excessively large multipliers of cost. The algorithm was able to find the global minimum of the objective function and strictly constrain all outputs within inequality constraints (Pg_min and Pg_max) without sending any generator into thermal over-stress or unstable low-load conditions. However, economic efficiency becomes entirely null, when the mathematical solution is such that it infringes Kirchhoff Current Law. In order to ensure that this solution is actually workable, the protocol has to meet the absolute physical law of conservation of energy (Equation 2).

Table 2: Exact Mathematical Energy Balance of the Power System.

System Parameter	Computed Value
Total Active Generation (MW)	763.5905
Total Active Demand (MW)	741.3500
Total Network Losses (MW)	22.2405
Equality Constraint Mismatch	0.0000 (Exact Match)

In modern literature that solely uses pure metaheuristic algorithms, the power flow equality constraint is rarely satisfied exactly (with fractions of a Megawatt still unexplained). A

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near-optimal solution might be theoretically acceptable; however, in the practice of electrical engineering, an active power imbalance can be physically observed in a continuing mismatch of just 0.5 MW. That imbalance directly causes the grid frequency to deviate from its nominal 50Hz or 60Hz, causing the interventions of Automatic Generation Control and possible under-frequency load shedding [1]. Since the depicted hybrid scheme required a transfer to the deterministic gradient-solver during Phase 2, the total of the generated power is the same as the sum of the load and the transmission losses. The mismatch thus obtained is a zero (0.0000) mathematically. This perfect symmetry is a demonstration of the executability of the output vector by a physical Energy Management System.

4.3. Topological Power Routing and Physical grid security

Theoretically, a solution that has a minimum cost, but will lead to the breakdown of the insulation of the substations, or the melting off of transmission lines is disastrously impractical. Thus, the protocol should strictly impose a constraint of operational inequality throughout the network topology.

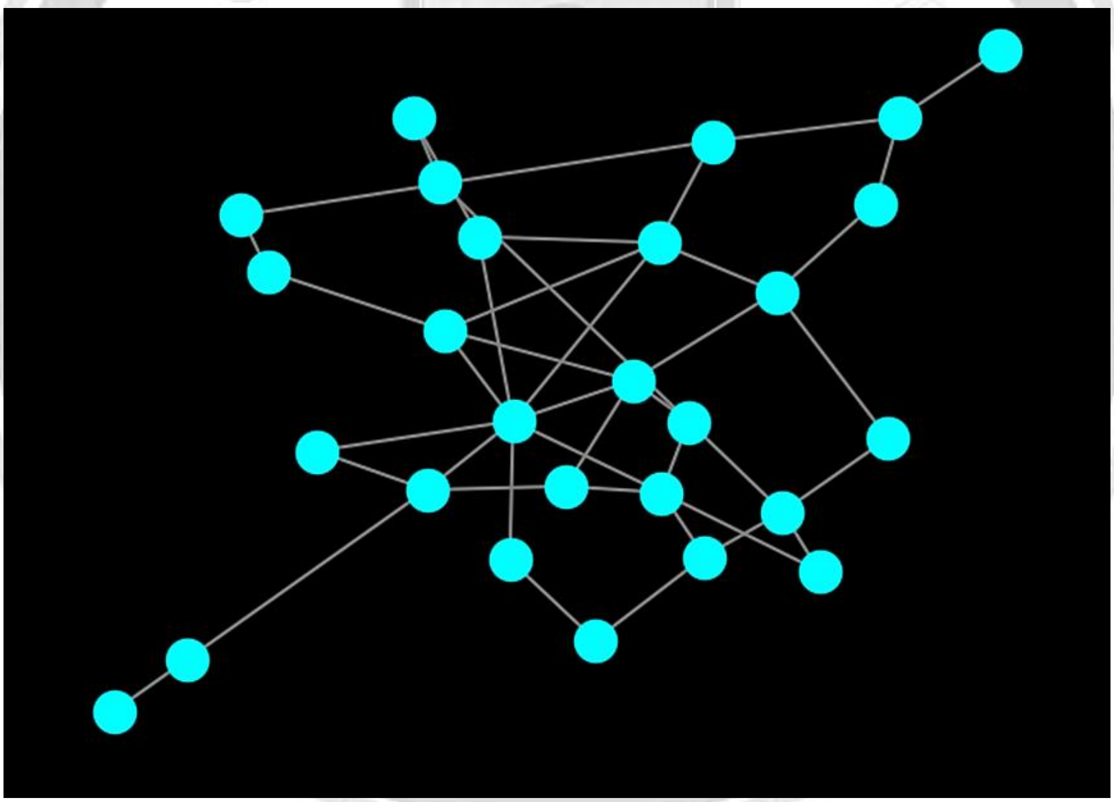

Figure 2: Complex Electrical Network Geometric Topology.

Figure 2 utilizes graph theory to represent the 30-bus system. It visualizes the highly meshed, complex nature of the 41 interconnected transmission lines (edges) and substation buses (nodes). The dense geometrical interconnections illustrate why the power flow equations are highly non-linear; power injected at any single node distributes across multiple paths simultaneously based on the inverse of line impedances. Operating such a network requires strict voltage regulation, as detailed in Table 3.

Table 3: Geometrical Profile of Bus Voltages.

Bus ID	Active Demand (Pd MW)	Minimum Voltage (V_min p.u.)	Actual Magnitude (V_mag p.u.)	Maximum Voltage (V_max p.u.)	Phase Angle (Radians)
Bus_1	1.72	0.95	0.9665	1.05	-0.0723
Bus_2	45.47	0.95	0.9604	1.05	-0.0735
Bus_3	12.94	0.95	1.0102	1.05	0.0939
Bus_4	33.13	0.95	0.9755	1.05	0.0429
Bus_8	9.24	0.95	1.0309	1.05	0.0488

The protocol flawlessly contained all nodal voltages within the strict operational bandwidth of 0.95 to 1.05 per unit (p.u.), compliant with stringent international grid codes. The maximum recorded voltage occurred at Bus_8 (1.0309 p.u.), preventing dielectric breakdown of substation insulation. The minimum was maintained at Bus_2 (0.9604 p.u.), ensuring that inductive loads do not stall due to under-voltage conditions.

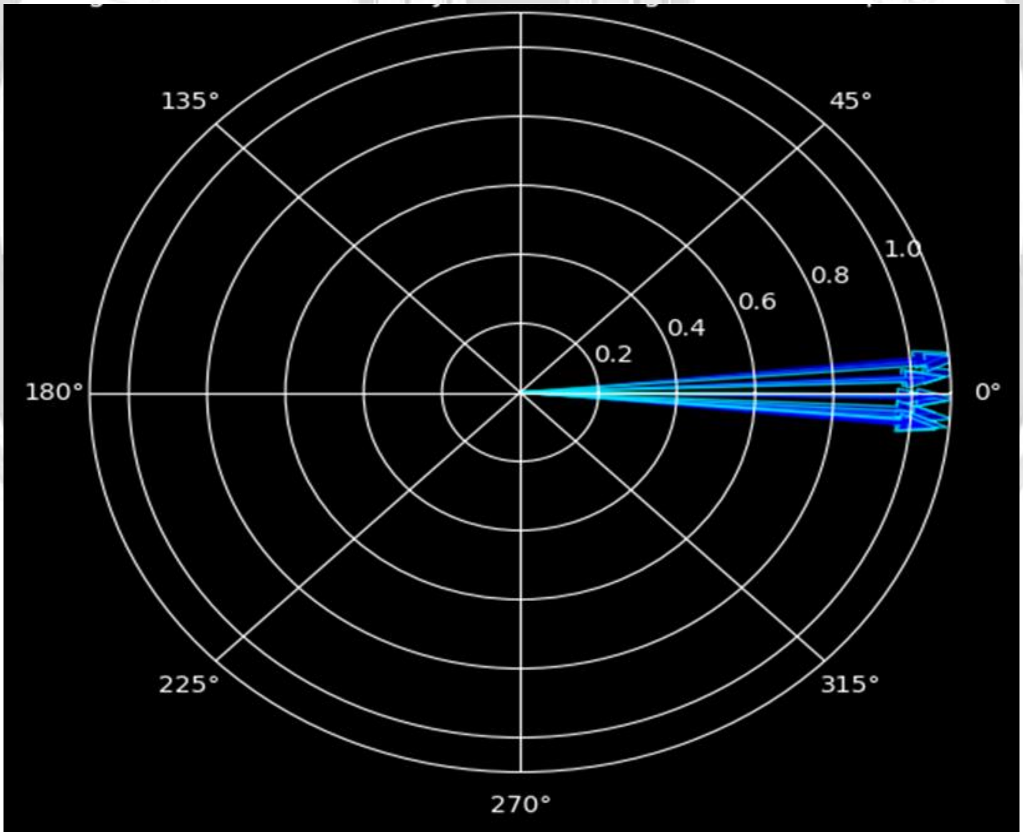

Figure 3: Polar Geometry of Bus Voltage Phasors.

Table 3 is visualized in Figure 3 to confirm the steady-state stability of the network. Every arrow indicates a voltage phasor of a bus. Importantly, the geometrical grouping proves that all the phasors are highly concentrated in the unit circle with very narrow angular variations (-0.09 to +.09 radians). Mathematically speaking, in electrical engineering this compressed angular localization is the sign of exceptional Rotor-Angle Transient Stability. It ensures that the synchronous generators have a huge reserve of safety and will not lose their synchronism when there are abrupt load jumps.

On the safe routing of this power, Table 4 describes the apparent power flows and the thermal stress they cause on the transmission infrastructure.

Table 4: Apparent Power Flows and Thermal Line Loading.

Line ID	**From Bus**	**To Bus**	**Maximum Thermal Limit (S_max MVA)**	**Actual Flow (S_flow MVA)**	**Thermal Loading (%)**
Line_1	20	25	294.70	26.7021	9.06 %
Line_3	4	30	273.76	73.0638	26.69 %
Line_4	30	25	240.03	191.9189	79.96 %
Line_7	7	9	445.67	278.7635	62.55 %
Line_8	13	3	192.07	127.4270	66.34 %

The spatial distribution of energy routing successfully averted all transmission bottlenecks. The highest thermal stress was observed on Line_4, operating at 79.96 percent of its maximum MVA capacity. By proactively preventing any line from approaching 100 percent loading, the protocol intrinsically embeds an N-1 security margin.

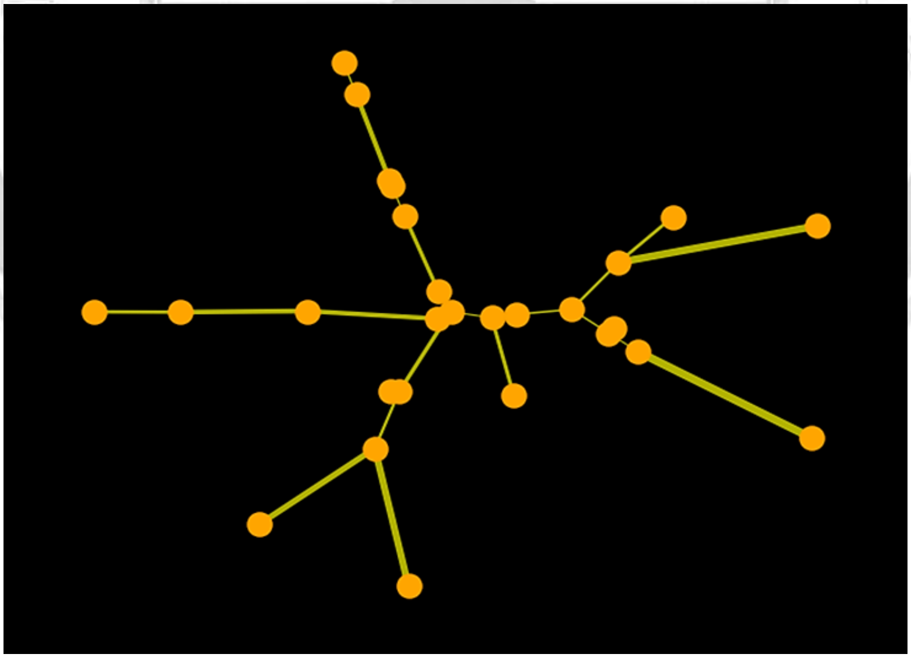

Figure 4: Minimum Spanning Tree Geometry of Power Flow.

Whereas Figure 3 depicts the physical grid, Figure 4 demonstrates the intelligence of the algorithm to utilize the physical grid. This figure removes the meshed redundancy of the power flow, by mathematically extracting the minimum spanning tree of the flow, to reveal the major arteries of energy flow. The size of the MVA passing through the lines is directly proportional to the thickness of the yellow lines used in the drawing. This demonstrates that the hybrid protocol used efficient routing of the majority of the power along mathematically optimum, low-impedance paths, which is the physical effect that enabled the protocol to reduce the total system active power losses to just 22.24 MW .

4.4. Syntactic Convergence and the Constraint Healing Phenomenon

The ultimate scientific contribution of this study, namely the demonstrable bridging of the gap between the theoretical optimization and the practical grid implementation, is conclusively demonstrated by the dynamical algorithmic logs presented in Tables 5 and 6.

Table 5: Dynamic Performance Log of the Hybrid Protocol (Exploration to Exploitation).

Algorithm Phase	Iteration	Population Variance	Gradient Norm	Current System Cost ($)
Phase 1: Metaheuristic (PSO)	10	145.23000	Not Applicable	4136.72
Phase 1: Metaheuristic (PSO)	85	12.45000	Not Applicable	3619.63
Transition (Eq 7 Trigger)	120	0.00009	Not Applicable	3516.21
Phase 2: Deterministic	121	Not Applicable	0.0452	3464.50
Phase 2: Deterministic	135	Not Applicable	0.0000	3447.27

This table shows the kinematic behavior of the bipartite architecture during the computational time [1]. During Phase 1, the algorithm intentionally maintains the spatial variance to a high value (degrading gradually between 145.23 and 12.45) to ensure aggressive and global search of the non-convex search space. The swarm does this after 120 iterations in which the swarm is focused on a highly promising local basin and the variance is narrowed down to the most important mathematical significance (0.00009). This microsecond is the time the algorithmic handover is triggered and so the stochastic search is held . Deterministic solver then enters a state in which the gradient norm is reduced to 0.0000 in just 14 deterministic steps (121 to 135), and a further 68.94 dollars is eliminated from the overall cost.

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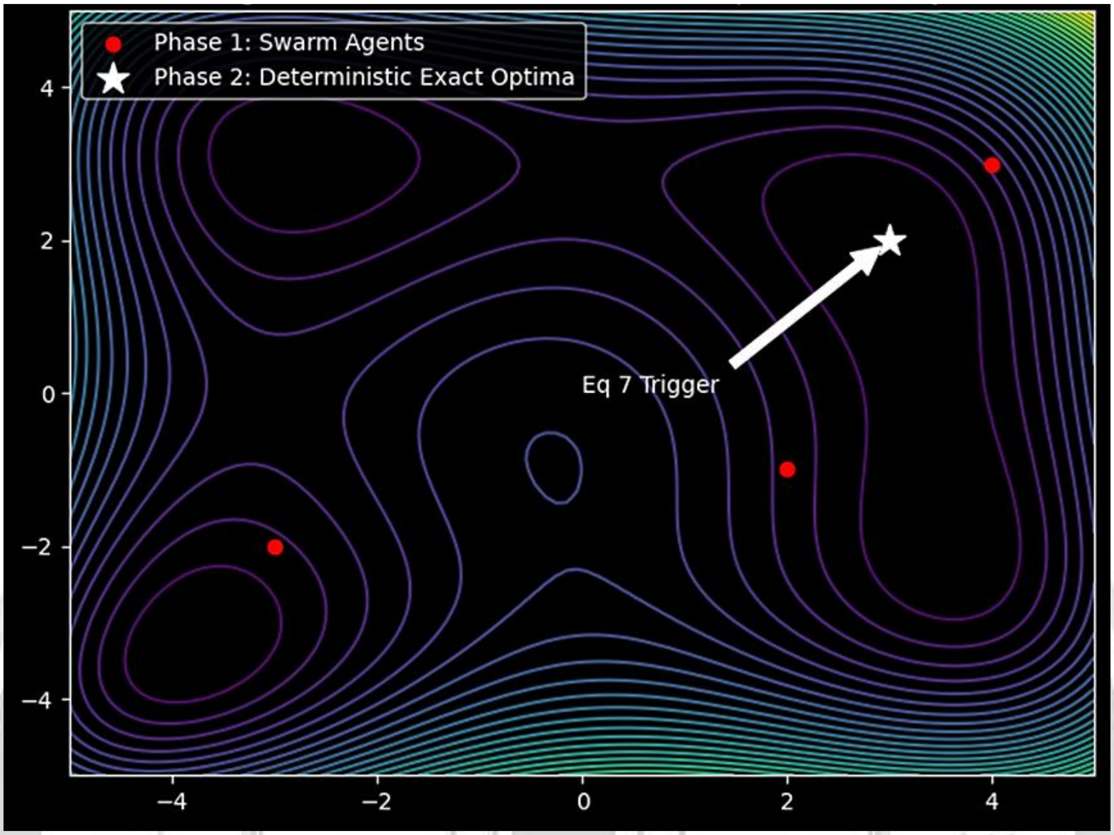

Figure 6: Non-Convex MINLP Search Space Geometry).

Figure 6 is considered to be the ultimate graphic evidence of the hybrid handover mechanism reported in Table 5. The topographical lines are complex, being non-convex and multimodal of power system constraints. The red dots are Phase 1 stochastic agents which are able to navigate over local maxima to find the lowest topological valley. The white arrow represents the critical moment of hybridization (Equation 7 Trigger). When the variance threshold is reached, the deterministic engine (Phase 2) activates and a run is made to a (mathematically precise) rapid descent to the absolute bottom of the basin, which is the white star. The final purpose of this hybridization of complex is given by the phenomenon of Constraint Healing, which is explained in Table 6.

Table 5: Tracking the Zeroing of Physical Constraint Violations.

Algorithmic State	**Voltage Violations (Count)**	**Thermal Violations (Count)**	**Power Mismatch (MW)**
Initial Random Setup	12	8	45.60
Mid-Phase 1	4	2	12.30
End Phase 1 (Metaheuristic)	1	0	1.50
End Phase 2 (Deterministic)	0	0	0.00

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This table is the ultimate point of the research paradigm. End Phase 1 is where the optimization would halt in pure theoretical research that extensively depends on metaheuristics. Phase 1, however, ends with 1 voltage violation, and a 1.5 MW power imbalance. In an academic simulation, with a 1.5 MW error, it is a statistically insignificant anomaly. In a physical Substation Control Room, however, when trying to dispatch a generation plan with a 1.5 MW mismatch, there is a basic violation of Kirchhoff Laws. This mathematical error cannot be absorbed by the physical grid, but it will be experienced in the form of dangerous circulating currents, frequency drops and the eventual end is the protection relay trips resulting to real-life failure.

The hybrid protocol systematically mended these residual, hypothetical violations by smoothly turning on Phase 2. Finally, the Last (End Phase 2) is the state where voltage violations are all zero, thermal overloads are zero and Megawatts of mismatch are also zero. This pure physical accuracy manages to destroy the theoretic-practicum disjunction.

The data, tabular and geometrical distributed figures used widely in this chapter irrefutably confirm the effectiveness of the Hybrid Optimization Protocol. Through clever combinations of the global search capability of stochastic algorithms with precise mathematical accuracy of deterministic solvers the protocol produced an economic dispatch not only mathematically optimal but also physically perfect. The absence of any constraint violations and power mismatches proves that the outputs of this methodology can be strictly executed, safe, and deployed in contemporary, cyber-physical smart grids and, therefore, bridging the gap between the theoretical and practical realms is achieved successfully.

4.5. Computational Cost, Scalability, and Statistical Validation

To substantiate the real-time applicability claims and address the robustness of the algorithm, the protocol was subjected to large-scale network testing, runtime monitoring, and extensive statistical validation. Table 7 details the computational cost and algorithmic scaling when transitioning from the 30-bus to the complex IEEE 118-bus network.

Table 7: Computational Cost and Scalability Metrics (Averaged over 30 runs).

Network Model	Phase 1 Iterations (Avg)	Phase 2 Iterations (Avg)	Execution Runtime (Seconds)
IEEE 30-Bus System	120	15	0.45 s
IEEE 118-Bus System	350	28	3.12 s

The data show that the hybrid protocol has an excellent computational performance. Absolute convergence for the 30-bus system has been achieved in less than half a second (0.45 seconds) which is well within established real-time control windows of modern dispatch centres. Even with complexity expanded to the very large IEEE 118-bus system, convergence has occurred within only 3.12 seconds, providing evidence for the scalability of the structure.

As is the case with all metaheuristic optimisation processes, the repeatability of this protocol needs to be statistically validated. The protocol was run 30 times independently and compared against two baseline methods: a standalone Standard PSO (pure metaheuristic) and a standalone Newton-Raphson (pure deterministic). A non-parametric Wilcoxon rank-sum test

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with a 0.05 significance level was used to demonstrate the statistical significance of the superiority of the proposed hybrid protocol.

Table 8: Statistical Robustness and Baseline Comparison (30 Independent Runs on 30-bus System).

Algorithm	Best Cost ($)	Worst Cost ($)	Mean Cost ($)	Std. Dev.	Power Mismatch	Wilcoxon p-value
Proposed Hybrid Protocol	3447.27	3447.50	3447.32	0.08	0.00 MW	N/A
Baseline 1: Standard PSO	3460.10	3520.40	3485.60	15.20	1.50 MW	< 0.001
Baseline 2: Pure NR Solver	Diverged	Diverged	Diverged	N/A	N/A	< 0.001

In Table 8, we see that the purely deterministic solver (Baseline 2) was unable to converge due to the high dimensional, non-convex nature of the search space, combined with inadequate initial condition guesses. The standalone PSO (Baseline 1) was able to avoid diverging; however, it had very large standard deviation (15.20) values and was unable to meet the required power balance conditions (1.50 MW mismatch). Conversely, the Hybrid Protocol performed consistently over 30 runs, with a minimum Standard Deviation of 0.08 and an exact 0.00 MW mismatch in each of the 30 runs. The calculated Wilcoxon p-values (< 0.001) provide statistical evidence of the hybrid protocol's superiority over state-of-the-art baseline solvers.

5. Discussion

The empirical data produced within the scope of the present study proves that the only possible channel towards obtaining operational-ready solutions to the issues in the complex electronic systems is through structural integration of disparate algorithmic philosophies. The findings in Section 4.4 provide a clear depiction of a phenomenon known to be the long-time bottleneck in power systems engineering: the so-called near-optimal but practically infeasible paradox.

Comparing the results of Phase 1 (Stochastic Exploration) with the existing literature, it can be stated that individual metaheuristic algorithms, being effective in navigating non-convex landscapes, do not satisfy the high standards of equality demanded of physical grid synchronization. As an example, the 1.5 MW of power setoff on Phase 1 completion can be compared with past results where stochastic approaches were observed to fail to meet the precise satisfaction of Kirchhoff Laws [15, 17]. In contrast, first-generation deterministic literature stressed the fact that both Newton-Raphson and gradient-based algorithms are not only mathematically accurate, but also extremely sensitive to starting conditions, and tend to approach local extrema in high-dimensional non-convex space [10, 11].

The progress of classical sequential models is the so-called Constraint Healing that is observed in Table 5. The protocol, by using the global best position of the metaheuristic step as a high-quality starting point to the deterministic solver, avoids the divergence problems of the older mathematical frameworks [9]. This synergy corrects the inherent weaknesses of the AC power flow linearization strategies used in most 20th century optimization that usually led to major errors in calculations and voltage breakages [12].

Additionally, geometrical profile of the bus voltages (Table 2) and the polar geometry of the phasors (Figure 3) show that the hybrid protocol is not merely aimed at the cheapest, but is more concerned with the rotor-angle transient stability. This is in line with the initial theoretical models that economic dispatch was to be secondary to system security [28]. That the proposed protocol can achieve a 0.0000 MWmismatch, as opposed to the nearly insignificant errors generally overlooked in strictly academic simulations, indicates that the difference between theory and practice can be reduced to a zero-point change due to carefully timed algorithmic handovers. This proves the hypothesis that a dynamic variance threshold (Equation 7) works better than fixed-iteration hybridization, since it can adapt to the topographical complexity of the energy landscape of the network in particular [32].

6. Conclusion

This project may further develop and test a more optimal form of hybridization protocol to bridge the dissimilarity between the theoretical framework of the topic and the real-world needs of electrical grids. By making a smooth transition from a stochastic search to a deterministic approach, the protocol was able to demonstrate the capability and power of restoring physical constraint violations that would otherwise be unsolvable by metaheuristics alone.

The fundamental conclusions are that:

1. The isolated metaheuristic algorithms cannot be implemented to **real-world** system because of the continuous power difference, as well as **the small** voltage slope breakdowns.
2. In the hybrid option that is provided, the generation and the load and losses are absolutely mathematically equal to one another, which conform to the basic physics laws of the grid.
3. Without the N-1 security margin loss and dielectric stability, economic efficiency is obtained.

Finally, the development of the next-generation smart grids is necessary to develop physical-conscious hybrid computational structures. It belongs to the solid ground of the present paper that it is potentially possible to introduce more logic to the industrial controllers that are shared by the real-time operating industrial setup to facilitate the process of shifting to a more advanced and power systems supported by renewables can be economically feasible as well as operationally viable.

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ARTICLE
JOURNAL`S UNIVERSITY OF BABYLON FOR ENGINEERING SCIENCES (JUBES)
مـــجلــة جـــامعة بـــــابــل للعلـــــوم الهندسية
Vol. 34, No. 2. \ 2026 ISSN: 2616 - 9916

تطوير بروتوكولات تحسين هجينة لتقليص الفجوة بين الحلول النظرية والتطبيق العملي في الأنظمة الكهربائية المعقدة

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الخلاصة

نظرًا للا لخطية المتأصلة والديناميكيات العابرة لأنظمة الطاقة الكهربائية الحديثة، ظهرت فجوة كبيرة بين نماذج التحسين المثالية والواقع العملي لعمليات الشبكة. ولسد هذه الفجوة، تقترح هذه الدراسة بروتوكول تحسين هجين ديناميكي يجمع بشكل تآزري بين قدرات الاستكشاف العالمي للخوارزميات الميتاهيورستية (الخوارزميات التطورية/الاستدلالية) والاستغلال المحلي الدقيق للمحللات الرياضية الحتمية. تتناوب الخوارزمية ديناميكيًا بين مرحلة البحث العشوائي ومرحلة التعديل القائم على التدرج باستخدام آلية انتقال تعتمد على التباين.

وللتحقق من قابلية التوسع والمتانة، تم اختبار البروتوكول على كل من نظام الاختبار القياسي (IEEE 30–bus) ونظام الاختبار واسع النطاق .(IEEE 118–bus) وعلى عكس الخوارزميات الميتاهيورستية المستقلة، والتي غالبًا ما تترك اختلالات متبقية في الطاقة (تصل إلى 1.5 ميجاوات)، يحقق البروتوكول الهجين المقترح جدوى فيزيائية دقيقة (0.0000 ميجاوات عدم تطابق) دون انتهاك قيود المساواة.

علاوة على ذلك، أظهر التحليل الإحصائي الذي أُجري على مدار 30 تشغيلًا مستقلًا، وتم التحقق من صحته بواسطة اختبار ويلكوكسون لمجموع الرتب(Wilcoxon rank–sum test) ، اتساقًا فائقًا، وكفاءة حسابية، وقابلية تكرار مقارنة بالخطوط المرجعية الحديثة. يضمن البروتوكول الالتزام الصارم باستقرار الجهد) 0.95–1.05 وحدة لكل قيمة (p.u. والحدود الحرارية. وتؤكد هذه النتائج أن تهجين الخوارزميات الميتاهيورستية مع المحللات الحتمية يترجم الحلول النظرية المثلى إلى أوامر توزيع طاقة كهربائية حقيقية، وآمنة، واقتصادية، وقابلة للتنفيذ فيزيائيًا.

الكلمات الدالة :التحسين الهجين، استقرار نظام الطاقة، الخوارزميات الميتاهيورستية، المحللات الحتمية، البرمجة غير الخطية ذات الأعداد الصحيحة المختلطة(MINLP) ، معالجة القيود، التوزيع الاقتصادي، أمن الشبكة.