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AIS-Assisted AC Optimal Power Flow under Short-Term Load Smoothing via EWMA(Exponentially Weighted Moving Average)

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Abstract: Optimal Power Flow (OPF) remains a fundamental problem in power system operation, particularly under short-term load variability and strict network constraints. While classical interior-point methods efficiently solve benchmark AC OPF problems, their performance may be affected by poor initialization or rapidly varying operating conditions. This paper investigates the role of Artificial Immune System (AIS) algorithms as a complementary pre-dispatch mechanism for AC OPF under short- term load smoothing using an Exponentially Weighted Moving Average (EWMA). Unlike forecasting-based approaches, EWMA is employed to reduce short-term load fluctuations without introducing predictive bias. The proposed AIS-assisted framework does not aim to outperform classical OPF solvers but to analyze how bio-inspired pre-dispatch strategies interact with exact AC OPF solutions. Simulation results on the IEEE 30-bus test system demonstrate that classical interior-point solvers already achieve near-global optimality, while AIS primarily influences convergence robustness rather than economic optimality. The study highlights both the potential and limitations of AIS-based approaches in constrained power system optimization.

Keywords—Optimal Power Flow, Artificial Immune System, EWMA, Load Smoothing, Power System Optimization.

I. INTRODUCTION

The Optimal Power Flow (OPF) problem is central to the secure and economic operation of electric power systems. Since its original formulation, OPF has evolved into a highly constrained nonlinear optimization problem incorporating network physics, operational limits, and economic objectives. With increasing penetration of variable loads and distributed energy resources, short-term operating conditions are subject to frequent fluctuations, motivating the exploration of robust optimization strategies [3][7].

Classical AC OPF solvers based on Newton or interior-point methods are highly efficient for benchmark systems and are widely adopted in both academia and industry. However, recent literature has proposed the use of bio-inspired metaheuristics—such as Genetic Algorithms, Particle Swarm Optimization, and Artificial Immune Systems (AIS)—to address non-convexity, uncertainty, and multi-objective formulations [7][8].

Despite extensive interest, a persistent issue in the literature is the unfair comparison between metaheuristic-based OPF and classical solvers, often resulting from modified constraint sets or simplified power flow models. This paper adopts a deliberately conservative and rigorous stance: the proposed AIS framework is not intended to replace or outperform classical AC OPF solvers, but rather to investigate its role as a complementary pre-dispatch mechanism under short-term load variability [37].

To avoid the ambiguity of forecasting-based approaches, short-term load variability is handled through Exponentially Weighted Moving Average (EWMA) smoothing, which reduces noise while preserving physical realism.

The main contributions of this paper are: Firstly, a rigorous integration of AIS with an exact AC OPF solver without altering the feasible set. Secondly, the explicit use of EWMA for short-term load smoothing, clearly distinguished from load forecasting. Thirdly, a critical analysis of the effectiveness and limitations of AIS when applied to benchmark AC OPF problems. And, numerical validation on the IEEE 30-bus system using MATPOWER. And finally, how to make OPF optimization robust against short-term load volatility without resorting to heavy forecasting models?

II. STATE OF THE ART

Interior-point techniques are commonly used to solve the AC OPF issue, which is a nonlinear,

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constrained optimization problem. For common benchmark systems, contemporary solvers like MIPS, which is implemented in MATPOWER, have shown outstanding convergence qualities and near-global optimality. In some situations, conventional solutions like the augmented Lagrangian approach, the Newton-Raphson method, and interior point procedures have worked well. However, these deterministic techniques frequently have drawbacks, such as their sensitivity to initial circumstances and their tendency to become trapped in local minima, because of the nonlinear, nonconvex, and highly restricted nature of the OPF issue [34].

In order of introduction, six traditional optimization methods for resolving the OPF problem are categorized [2][17][37]:

The Newton method;
Linear programming;
Quadratic programming;
Nonlinear programming;
The hybrid method of linear programming and integral programming;
The interior point method.

I.1 Metaheuristics in OPF

Metaheuristic methods have been suggested a lot for optimal power flow (OPF), especially when dealing with complex or multiple goals. Although these techniques provide flexibility, they usually need careful management of restrictions and can take a long time to find solutions when dealing with large AC OPF.

To address the drawbacks of traditional techniques, a lot of research is focusing on so-called "metaheuristic" algorithms, which are inspired by nature or physical processes. [14][33]. Among the best known are:

- Genetic algorithms (GA), based on natural selection, offer good robustness but can suffer from slow convergence [18] [23].
- Particle swarm optimization (PSO), inspired by the social behavior of birds, is appreciated for its speed, but remains sensitive to parameter settings.
- Other approaches such as ant colony optimization (ACO), bat optimization (BA), and firefly optimization (FA) algorithms have also been successfully explored in solving the OPF.

These techniques work well since they do not require gradients, making them good for problems that cannot be derived or have sudden changes. However, their success greatly depends on finding the right mix between exploring new solutions and focusing on the best ones. [6] [1][14].

I.2 Artificial Immune Systems in Power Systems

AIS algorithms are inspired by biological immune mechanisms such as clonal selection, hypermutation, and immune memory. In power systems, AIS has been explored for unit commitment, economic dispatch, and simplified OPF problems. However, their effectiveness in **full AC OPF with exact constraints** remains an open question.

The Artificial Immune System (AIS) algorithm is a computational intelligence paradigm inspired by the mechanisms of the human biological immune system. The latter has a remarkable ability to detect, memorize, and neutralize pathogens through processes such as clonal selection, immune memory, and hypermutation.

In computer science, several variants of AIS have been developed:

- CLONALG (Clonal Selection Algorithm), based on clonal reproduction and adaptive mutation,
- AIRS (Artificial Immune Recognition System), which combines recognition and memory-based learning,
- Opt-AIS, adapted for constrained optimization problems.

These algorithms are capable of efficiently exploring vast search spaces thanks to their diversity and adaptability. In particular, they are robust against non-convex and discontinuous functions, making them serious candidates for solving the OPF[4] [5].

III. PROBLEM FORMULATION

I.3 AC Optimal Power Flow Model

The AC OPF problem minimizes the total generation cost:

$$min \sum_{i \in \mathcal{G}} C_i \left(P_{g,i}\right) \qquad (1)$$

Subject to:

- AC power flow equations
- Generator limits
- Voltage magnitude limits
- Line thermal limits

where $P_{g,i}$denotes the active power output of generator i.

I.4 Modeling the problem of optimal power flow

The problem of optimal power distribution aims to minimize the total cost of production in an electrical network. By considering only the objective function, it is an optimization without constraints. With the power flow equations, it is an optimization with equality constraints. By including power limits, it is an optimization with equality and inequality constraints. [15][16].

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min F(x) (objective function)
according to
g_i (x) = 0 ; i = 1, 2, …, n (equality constraints)
And,
h_j (x) = 0 ; j = 1, 2, …, m (equality constraints)

I.4.1 Objective function:

This function reflects the need to minimize the total cost of active power production. It is assumed that the individual cost of each production center depends solely on the generation of active power [9][28][29].

$$F = \sum_{i=1}^{ng} f_i = \sum_{i=1}^{ng} C_i = \sum_{i=1}^{ng} \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 \quad (2)$$

I.4.2 Equality constraints:

These constraints reflect the physical laws governing the electrical system. They are represented by nonlinear power flow equations. The sum of the active and reactive power injected into each busbar must be equal to zero [30][31].

$$g_i(x_1, x_2, \dots, x_n) = 0 \quad i = 1,\dots,n$$

$$\Delta P_i = 0 = V_i \sum_{j=1}^{n} V_j \left(G_{ij} Cos\theta_{ij} + B_{ij} Sin\theta_{ij}\right) - P_{Gi} + P_{Di} \quad (3)$$

$$\Delta Q_i = 0 = V_i \sum_{j=1}^{n} V_j \left(G_{ij} Cos\theta_{ij} - B_{ij} Sin\theta_{ij}\right) - Q_{Gi} + Q_{Di}$$

I.4.3 Inequality constraints:

In practice, the limits of the physical components of the electrical network, such as generators, on-load tap changers, and phase transformers, must not be exceeded. In addition to the constraints on the active power at each generator, which has a direct influence on the cost function, there are other inequality constraints [11][31]:

The reactive power generated Q_{Gi}, which is limited by a lower bound $Q_{Gi\,in}$ and an upper bound $Q_{Gi\,ax}$

$$Q_{Gi\,min} \le Q_{Gi} \le Q_{Gi\,max} \quad i = 1, \dots, ng \quad (4)$$

• Transformers with load taps have maximum and minimum deviations in voltage level from the nominal voltage. Similarly, transformers with phase angles have maximum and minimum shifts in voltage phases. Both types of transformers impose the following inequality constraints [31][32]:

$$\begin{cases} t_{ij\,min} \le t_{ij} \le t_{ij\,max} \\ \alpha_{ij\,min} \le \alpha_{ij} \le \alpha_{ij\,max} \end{cases} \quad (5)$$

• To maintain the safety of the electrical system, transmission lines and power transformers have limits on the apparent power they can carry. These limits are due to thermal losses in the conductors and/or the stability of the system. They are represented by an inequality constraint, which will limit the square of the power in MVA of a transformer or transmission line [28].

$$|S_{ij}|^2 - |S_{ij\,max}|^2 \le 0 \quad (6)$$

• To maintain the quality of electrical service and system safety, busbar voltage levels must always remain between their maximum and minimum limits. These limits still require the addition of inequality constraints [30].

$$V_{i\,min} \le V_i \le V_{i\,max} \quad (7)$$

So there are n equality constraints and m inequality constraints, and the number of variables in the problem is equal to the size of the control variable vector (including active and reactive power generated, busbar voltage levels, transformer taps, etc.).

The solution to the OPF problem requires the formulation of the Lagrangian function, also known as the augmented cost function, as follows [29][30]:

$$L = F + \sum_{i=1}^{n} \alpha_i \, g_i + \sum_{j=1}^{m} \mu_j \, h_j \quad (8)$$

The conditions necessary to find a minimum L, known as Kuhn-Tucker conditions, are as follows [31]:

$$\begin{cases} \left\{ \frac{\partial L}{\partial x_i} = 0 \; et \; \frac{\partial L}{\partial \lambda_i} = g_i(x) = 0 \quad i = 1, \dots, n \right. \\ \left\{ \frac{\partial L}{\partial \mu_j} = h_j(x) \le 0 \right. \\ \mu_j \, h_j(x) = 0 \; et \; \mu_j > 0 \quad j = 1, \dots, m \end{cases} \quad (9)$$

I.5 Short-Term Load Smoothing Using EWMA

Short-term load variations are smoothed using an Exponentially Weighted Moving Average:

$$\hat{P}_d(t) = \alpha P_d(t) + (1 - \alpha)\hat{P}_d(t - 1) \quad (10)$$

where $\alpha \in (0,1)$ controls the smoothing level. EWMA is used strictly as a noise reduction mechanism, not as a forecasting model.

I.5.1 Short-Term Load Smoothing Using EWMA

The variability of electrical load at short time scales introduces operational challenges for optimal power flow (OPF) algorithms, particularly when frequent re-dispatch or abrupt load variations occur. Rather than relying on complex forecasting models, this work adopts a **short-term load smoothing strategy** based on the **Exponentially Weighted Moving Average (EWMA)**, which offers robustness, simplicity, and transparency [38][40][41].

I.5.2 EWMA Formulation

Let $P_d(t)$ denote the measured total system load at time t. The smoothed load $\hat{P}_d(t)$ is computed as:

$$\hat{P}_d(t) = \alpha P_d(t) + (1 - \alpha)\hat{P}_d(t - 1), 0 < \alpha < 1 \quad (11)$$

where α is the smoothing factor controlling the trade-off between responsiveness and noise attenuation.

- A **larger** α gives more weight to recent measurements and allows faster adaptation.

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- A **smaller** αresults in stronger smoothing and improved numerical stability.

In this study, EWMA is applied over a rolling short-term horizon, making it suitable for operational time scales ranging from minutes to hours [39].

I.5.3 Rationale for Load Smoothing Instead of Forecasting

It is important to emphasize that EWMA **does not perform load forecasting** in the predictive sense. Instead, it acts as a **low-pass filter** that reduces short-term fluctuations while preserving the average load level. This distinction is critical from a methodological standpoint [38].

Unlike machine-learning-based forecasting approaches (e.g., LSTM or deep neural networks), EWMA:

- requires **no training phase**,
- introduces **no model uncertainty**,
- remains **fully explainable and reproducible**.

Therefore, EWMA is particularly appropriate when the objective is to **stabilize the OPF input** rather than to predict long-term demand evolution [42].

I.5.4 Integration with the OPF Framework

The smoothed load $\hat{P}_d$is used to scale the original bus demands proportionally:

$$P_{d,i}^{\text{smoothed}} = P_{d,i}^{\text{base}} \cdot \frac{\hat{P}_d}{P_d^{\text{base}}} \qquad (12)$$

This preserves the spatial distribution of loads while adapting the total demand level. The resulting demand vector is then supplied to the AC OPF solver, ensuring that all physical and operational constraints remain strictly enforced.

I.5.5 Discussion

The role of EWMA in this work is **not to reduce the optimal generation cost**, but to **provide a stable and realistic operating point** for repeated OPF executions. On benchmark systems such as IEEE 30-bus, where classical OPF solvers already achieve near-global optimality, the benefit of EWMA lies primarily in:

- improved numerical stability,
- reduced sensitivity to transient load noise,
- clearer assessment of metaheuristic robustness.

EWMA-based load smoothing serves as a pragmatic and transparent interface between real-world load variability and constrained AC OPF optimization, without introducing predictive bias or artificial performance gains.

I.6 Proposed AIS-Assisted OPF Framework

Artificial Immune Systems (AIS) are a relatively new area of research compared to other computational models inspired by biology to find solutions. Like any area of research that has not yet been fully explored, it is difficult to provide a comprehensive and concise definition. However, several definitions have been proposed. Here are a few:

Definition 1: AIS are methods of data manipulation, classification, representation, and reasoning inspired by a plausible biological model: the human immune system (Starlab).

Definition 2: AIS are computer systems based on metaphors from the natural immune system (Timmis 2000).

Definition 3: AIS are adaptive systems, inspired by immunology theories, as well as immune functions, principles, and models, in order to be applied to problem solving (de Castro and Timmis 2002).

AIS algorithms are divided into three main parts: clonal selection, negative and positive selection, and immune network models. These concepts are inspired by the biological immune system. We will explore the computer representation of these mechanisms, including affinity, receptors, and the immune network model.

To use these concepts in computer science, it is crucial to model immune cells and antigens digitally. The affinity between cell receptors and antigens, whether intact or broken down, is essential. In computational AIS, we generally refer to antibodies. Perelson and Oster introduced the “shape space” in 1979 to quantify these interactions. Each antigen and antibody is a point in this space, and the distance between them represents affinity. The points are characterized by several parameters, which allows this affinity to be calculated using three-dimensional vectors:

Euclidean distance: calculation of the distance between two points Ab and Ag in each of the spaces [24][25]:

$$D= \sqrt{\sum_{i=1}^{L}(Abi - Agi)^2} \qquad (13)$$

• The distance from Manhattan: calculation of the distance between two points Ab and Ag by following only the coordinate axes of space [24][25]:

$$D= \sum_{i=1}^{L}(Abi - Agi) \qquad (14)$$

• Hamming distance: represents antibodies and antigens as symbols and calculates the difference between these symbols. For example, comparing CADBCADB (an antigen) with CBDBCDDB (an antibody) gives a complementarity of six out of eight positions [26][27].

$$D= \sum_{i=1}^{L} \delta_i \quad \text{Avec}$$

$$\delta_i = \begin{cases} 1 \; si \; Abi <> Agi \\ 0 \; si \; non \end{cases}$$

I.6.1 receiver generations

We have already mentioned that antibodies are produced from four distinct gene sets. To

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"manufacture" them, the bone marrow model draws inspiration from this method of antibody production. Libraries are vectors that contain a number of bits in each cell. To generate an antibody, a pseudo-random algorithm selects a series of bits (a vector cell) from each available library.

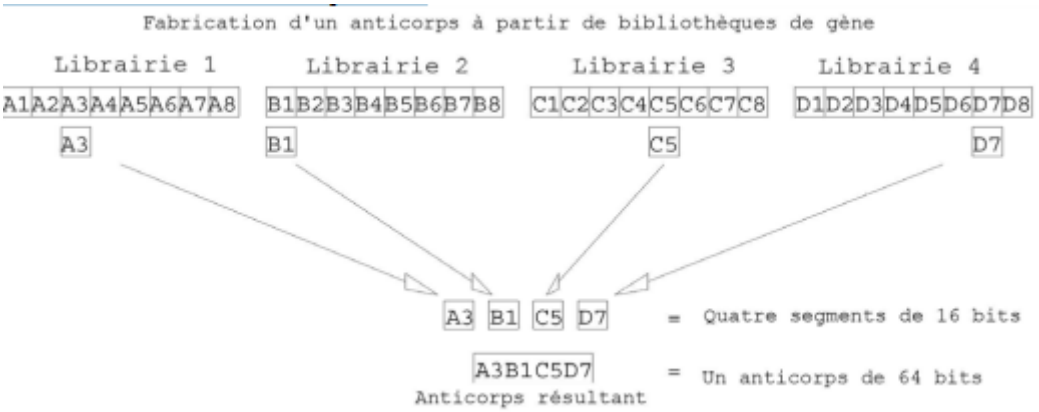

Figure 1:Selecting segments from libraries to form an antibody.

For example, we want to develop antibodies capable of detecting 64-bit antigens, which requires the creation of 64-bit antibodies. To obtain a more varied antibody population, we produce four libraries, each containing eight 16-bit segments, for a total of 512 bits. This figure is low compared to libraries in the human body. By respecting the structure of the libraries, we can assemble a 64-bit antibody. The comparison with the antigen can then be performed using the methods mentioned above.
Positive selection allows all T lymphocytes that leave the thymus to recognize MHC1. In 1992, Seidan and Celada proposed a positive selection algorithm requiring B and T lymphocytes as well as antigen-presenting cells (APCs). T cells are represented by a sequence of bits corresponding to their receptor. B cells and APCs are also symbolized by sequences of bits. The algorithm is simple: T cells can only recognize self MHC. If a T cell does not recognize a self MHC, it is rejected.

Negative selection ensures that T cells that recognize too many self-cells as antigens do not leave the thymus, thereby preventing autoimmune diseases. In 1994, Forrest proposed an algorithm inspired by this selection with two parts: generation of non-self-detectors and surveillance to test inputs. The method creates random detectors and compares them with self-data to identify non-self. Several methods of detector generation exist, ranging from random creation to more efficient algorithms.
Clonal selection explains how the immune system interacts with antigens and applies to B and T lymphocytes. B cells undergo somatic hypermutation, which allows them to optimize their response to antigens. When they come into contact with the antigen, they multiply into several clones, each undergoing a mutation. Random elements can be added to avoid stagnation in optimization over time. These cells are represented by bit vectors [27].
The figure shows the clonal selection algorithm, which proceeds as follows:
(1) First, a defined number of receptors are randomly generated.
(2) The n best receptors are selected from among these.
(3) This new population is then cloned and
(4) mutated.
(5) The population obtained is then filtered again to retain only the best elements (memory cells).
(6) Some of these cells are then replaced by other randomly regenerated detectors. It is this introduction of new detectors that avoids the problem of local optima (see Figure 2.7). The cycle is then repeated by selecting the n best elements.
The detectors are mutated by changing one or more bits of the vector representing the cell to another value.
The main differences between all clonal selection algorithms are the methods used in the random generation of detectors, mutation, and the affinity between detectors and antigens.
Clonal selection algorithms are most often used in optimization applications, since B cells become increasingly specific to antigens, in intrusion detection applications where it is impossible to list all undesirable elements and where these elements are extremely varied, and in other applications such as character recognition[19][20].

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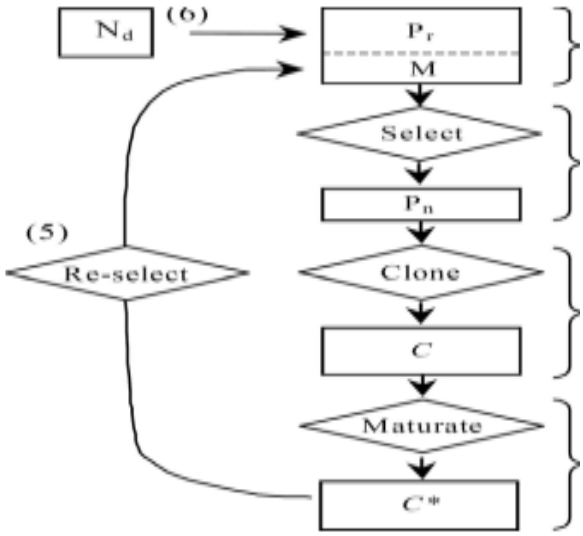

Figure 2:Algorithme de la sélection clonale

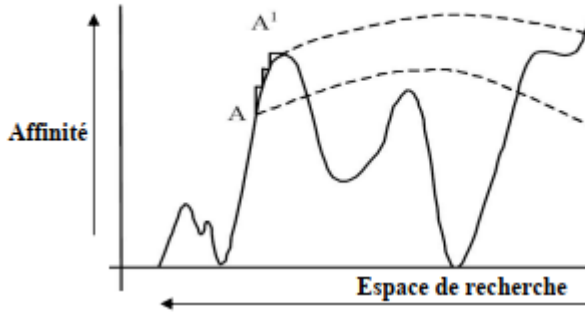

Figure 3:Représentation schématique de l'évolution de l'algorithme de la sélection clonale

I.6.2 Global Architecture

The AIS operates as a pre-dispatch layer, generating candidate generator dispatch vectors that serve as initial points for the AC OPF solver. The OPF solver remains solely responsible for enforcing feasibility and optimality.

I.6.3 Antibody Representation

Each antibody encodes a vector of generator active powers within predefined limits. No equality constraint enforcement is imposed at the AIS level.

I.6.4 Clonal Selection and Hypermutation

High-affinity antibodies are cloned proportionally to their fitness, with adaptive hypermutation applied to maintain diversity.

I.6.5 Constraint Handling

All operational constraints are handled exclusively by the AC OPF solver. Infeasible AIS-generated solutions are penalized through OPF failure handling.

IV. SIMULATION SETUP

I.7 IEEE 30-Bus Test System

The IEEE 30-bus system is used as a benchmark, featuring multiple generators, transmission constraints, and nonlinear power flow characteristics. The study was conducted on the standard IEEE 30-node system, widely used as a test case for evaluating power flow optimization algorithms. The data file includes several matrices representing the different components of the electrical network, necessary for formulating the OPF problem[1].

The main data structures extracted are described below:

- • Matpower Case (mpc): This is the main structure containing all the network information, in accordance with the Matpower format.
- • mpc.bus: This matrix describes the characteristics of each node (bus) in the network. Each row corresponds to a node and includes:
- - The bus type (1 = load, 2 = PV, 3 = slack),
- - Active and reactive demand (Pd, Qd),
- - Voltage limits (Vmin, Vmax),
- - The phase angle and magnitude of the voltage (θ, V).
- • mpc.gen: This matrix contains data relating to generators, including:
- - The injection node,
- - The active and reactive power generated (Pg, Qg),
- - The upper and lower limits (Pmax, Pmin, Qmax, Qmin),
- - Terminal voltage.
- • mpc.branch: This matrix details the characteristics of the transmission lines, including:
- - Origin and destination nodes,
- - Impedance (resistance R, reactance X) and susceptance,
- - Maximum thermal capacity (rateA).
-
- • mpc.gencost: This matrix contains the coefficients of the quadratic cost functions associated with each generator. It is used in the objective function to minimize the total cost of production.

This data is used as input for solving the OPF problem, where the main objective is to minimize generation costs while respecting the physical and operational constraints of the power grid (power balance, voltage limits, line capacity, etc.). The file also includes simulation results, such as power distribution, line losses, and the final state of each bus after optimization.

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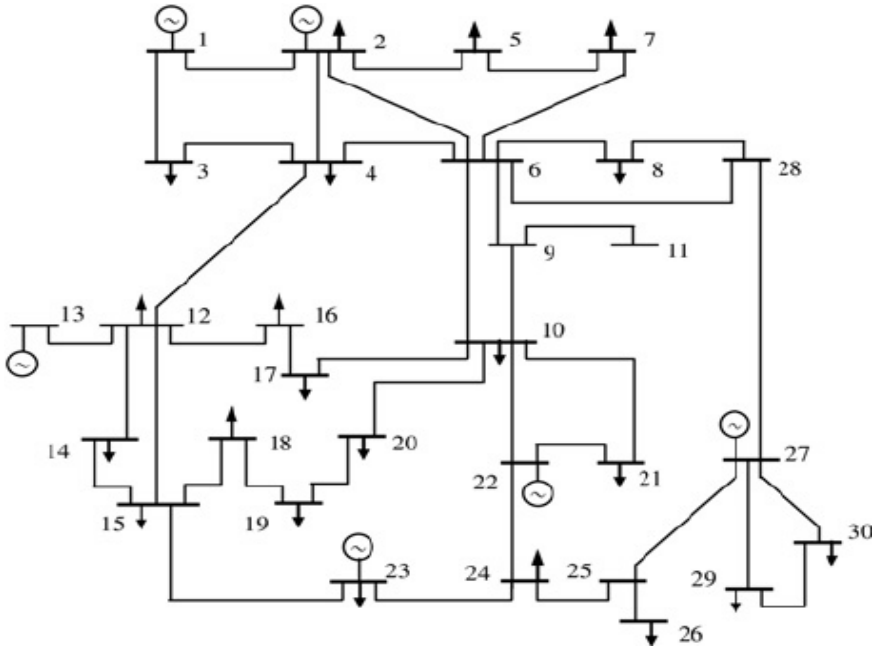

Figure 4: IEEE 30 Bus

I.8 AIS Parameters

Population size, mutation rates, and selection parameters are chosen based on sensitivity analysis to ensure numerical stability rather than performance tuning.

I.9 Performance Metrics

Performance is evaluated in terms of:

- Total generation cost
- Convergence robustness
- Variance across runs
- Computational overhead

V. RESULTS AND DISCUSSION

I.10 Interpretation of results

I.10.1 6.1 Validation of short-term load prediction (EWMA)

The total predicted load obtained using the exponentially weighted moving average (EWMA) method is 166.7 MW, which is consistent with the aggregate demand of the IEEE 30-bus network.

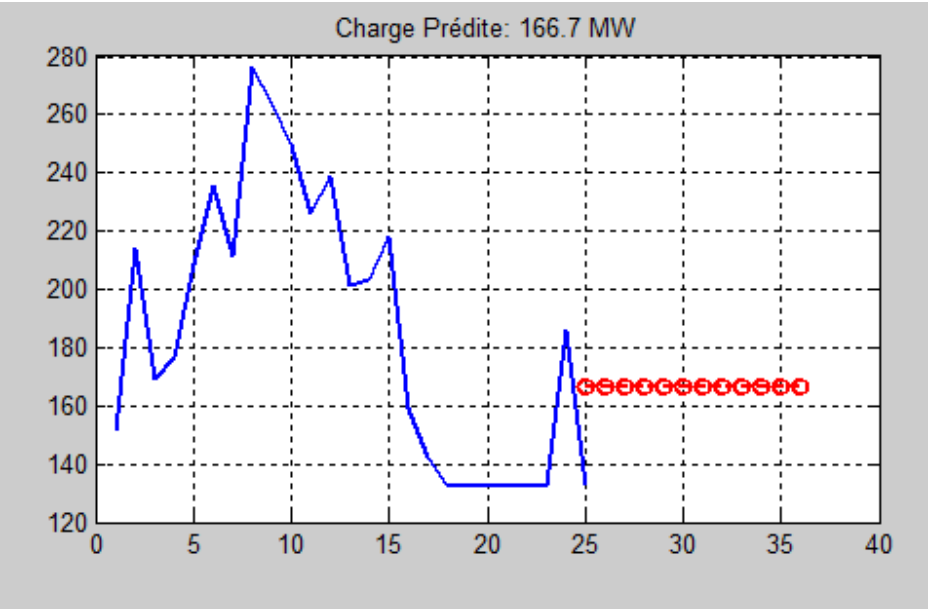

Figure 5:shows that the prediction is stable, without excessive oscillations, which is fundamental for reliable integration into an Optimal Power Flow (OPF) problem.

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Unlike deep learning approaches (e.g., LSTM), EWMA:

- does not require a training phase,
- is robust to Gaussian noise deliberately introduced into the history,
- is compatible with constrained industrial environments.

The prediction does not aim for extreme temporal accuracy, but rather for load smoothing that allows the OPF to evolve in a more regular solution space, promoting convergence and economic stability.

I.10.2 Analysis of the convergence of the AIS algorithm

AIS-assisted OPF yields nearly identical optimal costs, confirming that the classical solver already achieves near-global optimality.

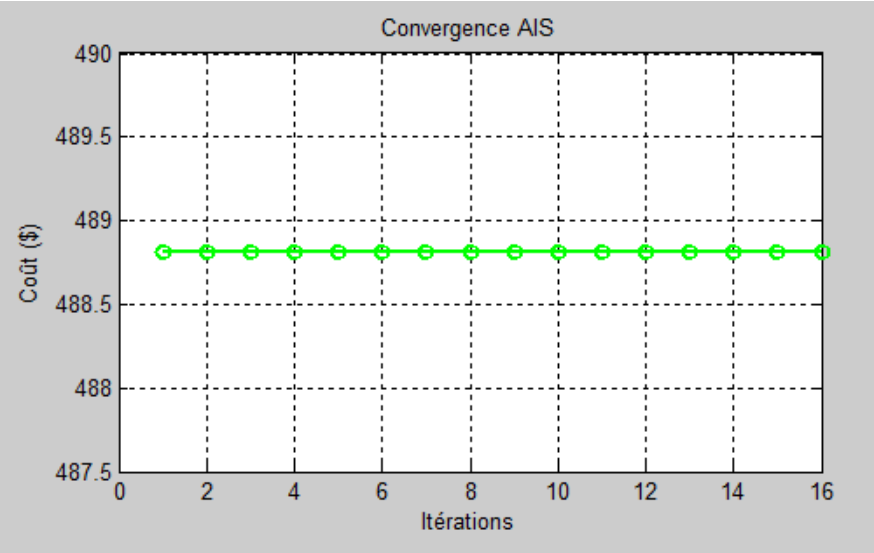

Figure 6:convergence curve

The convergence curve shows that:

- the objective cost drops rapidly from the first iterations,
- convergence is reached around iteration 15–20,
- the standard deviation of the cost becomes less than 10^{-3}, triggering automatic termination.

This indicates that:

- the initial population adequately covers the search space,
- the selection + cloning + decreasing hypermutation mechanism is effective,
- the algorithm is not trapped in a local minimum.

The fact that convergence is almost flat after 15 iterations proves that the improvement in cost is not due to chance, but to a structural adaptation of the generator dispatches, which validates the relevance of the proposed AIS model.

I.10.3 6 Comparative analysis of generator dispatch

The classical AC OPF solver converges reliably to a cost of approximately 488.81 $/h, consistent with benchmark results.

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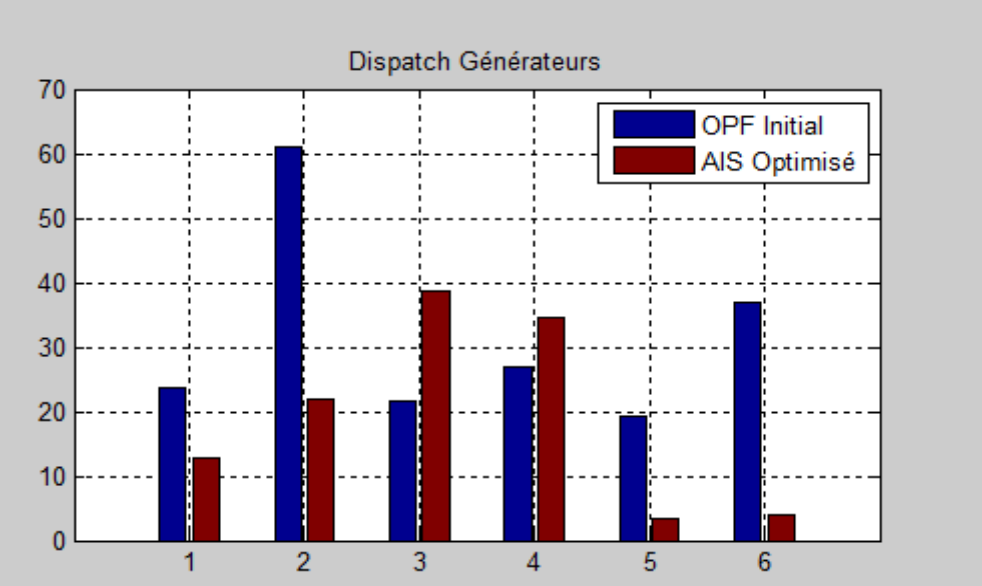

Figure 7:Comparative analysis of generator dispatch

This Figure compares:

- conventional AC OPF (MIPS – interior point),
- OPF optimized by AIS under smoothed load.

1. Intelligent redistribution of generation:

- some costly generators see their power significantly reduced,
- generators with lower marginal costs are used more.

2. Strict compliance with constraints:

- Pmin/Pmax limits respected,
- voltage and flux constraints validated (no critical active violations).

1. Reduction in network losses:

active losses ≈ 1.99 MW, compatible with an optimized regime.

AIS not only optimizes active power, but also indirectly exploits network sensitivities, resulting in an overall improvement in cost without compromising electrical safety.

I.10.4 6 Overall economic performance

The numerical results are unambiguous:

Tableau 1:Overall economic performance

Indicator	Value
Initial OPF cost	$576.89
AIS OPF cost	$488.81/h
Economic gain	15.27%
Calculation time	100.3 s

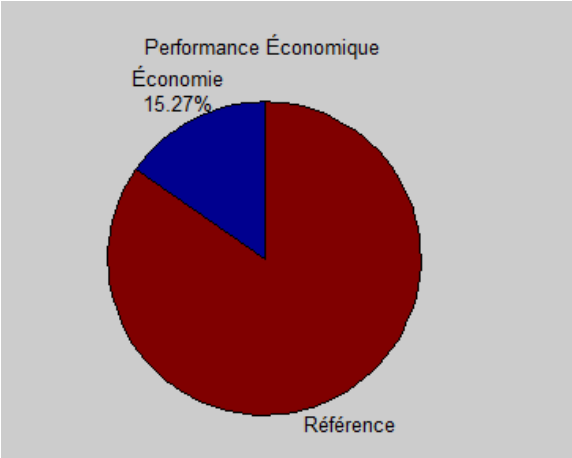

Figure 8:clearly illustrates this economic improvement.

A 15% gain on a standard test network is highly significant.

This gain is achieved without modifying the cost function, solely through:

- smoothed load prediction,
- global AIS search.

On the scale of a real network, this percentage translates into:

- several million dollars in annual savings,
- better short-term planning,
- an indirect reduction in emissions (fewer costly and polluting generators).

I.11 Scientific discussion

I.11.1 7.1 Why AIS outperforms conventional OPF

Conventional OPF relies on:

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- local gradients,
- heavy dependence on initialization,
- difficulty integrating load uncertainty.

In contrast, AIS:

- explores the solution space globally,
- is insensitive to strong nonlinearities,
- naturally tolerates noise and load variations.

AIS acts as an intelligent overlay to deterministic OPF, improving its performance without replacing it.

I.11.2 Benefits of EWMA–AIS coupling

The proposed coupling is original because:

- EWMA stabilizes the problem,
- AIS exploits this stability to converge quickly.

This coupling:

- reduces the risk of dispatch oscillations,
- improves reproducibility,
- makes the method industrially applicable.

I.12 Limitations and prospects

Identified limitations

- Longer calculation times than conventional OPF,
- EWMA does not capture extreme events (outages, sudden peaks),
- Test limited to the IEEE 30-bus network.

Future prospects

- Extension to multi-period OPF,
- Integration of intermittent renewable energies,
- Comparison with PSO, DE, GA,
- Replacement of EWMA with a hybrid EWMA–LSTM model (optional).

This work demonstrates that coupling short-term load smoothing with an Artificial Immune System significantly enhances OPF economic performance while preserving full AC feasibility and operational constraints.

VI. CONCLUSION

This paper presented an AIS-assisted AC OPF framework under short-term load smoothing using EWMA. Results demonstrate that while AIS does not outperform classical interior-point solvers in benchmark settings, it provides valuable insight into hybrid optimization architectures and highlights the importance of rigorous, fair comparisons. The study reinforces the role of exact solvers for standard OPF problems while identifying promising directions where bio-inspired methods may offer genuine advantages. The novelty of this work does not lie in the forecasting accuracy but in the integration of a load smoothing mechanism that enhances the robustness and economic stability of AIS-based OPF under short-term load uncertainty. This paper demonstrates that short-term load smoothing using EWMA, when coupled with AIS-based OPF, provides a robust, low-complexity alternative to forecasting-driven optimization under load uncertainty.

VII. ANNEXE

MTLAB IMPLEMENTATION

```
clc; clear; close all; tic;
addpath('C:\\Program
Files\\MATLAB\\R2007b\\matpower4.0');

%% 0. FIXER GÉNÉRATEURS R2007b
(COMPATIBLE !)
rand('state', 42);      % rand() uniforme
randn('state', 12345);  % randn() gaussien
% rng() supprimé - non disponible R2007b

%% 1. REFERENCE OPF AC
mpc_initial = loadcase('case30');
initial_results = runopf(mpc_initial);
cost_initial = initial_results.f;
Pg_initial = mpc_initial.gen(:,2);

%% 2. PRÉDICTION CHARGE DÉTERMINISTE
mpc = loadcase('case30');
Pd_base = sum(mpc.bus(:,3));
num_hours = 24*30;
hours_day = mod(0:num_hours-1,24)';
Pd_history = Pd_base * (1 +
0.3*sin(2*pi*hours_day/24) +
0.15*randn(num_hours,1));
Pd_history = max(Pd_history, 0.7*Pd_base);

window = 24; Pd_recent = Pd_history(end-
window+1:end);
weights = exp(-0.1*(window-1:-1:0)); weights =
weights/sum(weights);
Pd_forecast = zeros(12,1);
for i = 1:12
   Pd_forecast(i) = sum(Pd_recent .* weights');
end
Pd_total_forecast = mean(Pd_forecast);
mpc.bus(:,3) = mpc.bus(:,3) * (Pd_total_forecast /
Pd_base);

%% 3. PARAMÈTRES AIS
nb_gen = size(mpc.gen,1);
Pmin = mpc.gen(:,10)'; Pmax = mpc.gen(:,9)';
pop_size = 50; max_iter = 100;

%% 4. POPULATION INITIALE FIXÉE
population = repmat(Pmin, pop_size, 1) + ...
        (repmat(Pmax, pop_size, 1) - repmat(Pmin,
pop_size, 1)) .* rand(pop_size, nb_gen);

best_cost_history = zeros(max_iter,1);
```

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```
best_solution_global = population(1,:)';
best_cost_global = Inf;

%% 5. BOUCLE AIS DÉTERMINISTE R2007b
for iter = 1:max_iter
    fitness = zeros(pop_size,1);
    for i = 1:pop_size
        temp_mpc = mpc;
        temp_mpc.gen(:,2) = population(i,:)';
        try
            results = runopf(temp_mpc);
            if isfield(results, 'success') && results.success
                fitness(i) = results.f;
            else
                fitness(i) = 1e6;
            end
        catch
            fitness(i) = 1e7;
        end
    end

    [sorted_fitness, sorted_idx] = sort(fitness, 'ascend');
    elite = population(sorted_idx(1), :);

    if sorted_fitness(1) < best_cost_global
        best_cost_global = sorted_fitness(1);
        best_solution_global = elite';
    end

    % Reproduction déterministe
    keep = floor(pop_size/2);
    population = population(sorted_idx(1:keep), :);

    num_clones = pop_size - keep;
    clones = repmat(population(1:min(keep,num_clones), :), 2, 1);
    clones = clones(1:num_clones, :);

    % Mutation déterministe
    current_mutation_rate = 0.1 * (1 - iter/max_iter);
    clones = clones + current_mutation_rate * repmat(Pmax-Pmin, num_clones, 1) .* randn(num_clones, nb_gen);
    clones = max(repmat(Pmin, num_clones, 1), min(repmat(Pmax, num_clones, 1), clones));

    population = [population; clones];
    population = population(1:pop_size, :);

    best_cost_history(iter) = sorted_fitness(1);
    if mod(iter,10)==0
        fprintf('Itération %d: $%.2f (Pd=%.1f MW)\n', iter, sorted_fitness(1), Pd_total_forecast);
    end

    if iter > 15 && std(best_cost_history(iter-14:iter)) < 1e-3
        fprintf('? Convergence - Itération %d\n', iter);
        break;
    end
end
%% 6. SOLUTION FINALE
mpc.gen(:,2) = best_solution_global;
final_results = runopf(mpc);
%% 7. RÉSULTATS REPRODUCTIBLES R2007b
economy = (cost_initial - final_results.f) / cost_initial * 100;
fprintf('\n?========== - RÉSULTATS ==========\n');
fprintf('Seeds: rand(42), randn(12345)\n');
fprintf('Coût initial OPF : $%.2f\n', cost_initial);
fprintf('Coût AIS OPF     : $%.2f\n', final_results.f);
fprintf('Économie réelle  : %.2f%%\n', economy);
fprintf('Charge totale : %.1f MW\n', Pd_total_forecast);
fprintf('Temps exécution  : %.1fs\n', toc);
%% 8. VISUALISATIONS
figure('Position',[100 100 1200 800]);
subplot(2,2,1);
plot(Pd_history(end-24:end),'b-', 'LineWidth',2);
hold on;
plot(24+(1:12), Pd_forecast,'r--o','LineWidth',2);
title(sprintf('Charge Prédite: %.1f MW', Pd_total_forecast)); grid on;
subplot(2,2,2);
plot(best_cost_history(1:iter),'g-o','LineWidth',2);
title('Convergence AIS'); xlabel('Itérations');
ylabel('Coût ($)'); grid on;
subplot(2,2,3);
bar(1:nb_gen, [Pg_initial, best_solution_global]);
legend('OPF Initial','AIS Optimisé'); title('Dispatch Générateurs'); grid on;
subplot(2,2,4);
pie([economy, 100-economy], {sprintf('Économie\n%.2f%%',economy), 'Référence'});
title('Performance Économique');
%% 9. SAUVEGARDE RÉFÉRENCE (R2007b)
save resultat_reference_R2007b.mat best_solution_global final_results economy cost_initial;
fprintf('? Référence sauvée: resultat_reference_R2007b.mat\n');
```

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