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# A Comparative Analysis of Meta-heuristic Algorithms for Energy Management in Smart Grids

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*Abstract*—**Motivated by the ever-increasing demand for energy and guided by economic and environmental considerations, the smart grid represents a future of tremendous opportunities. It must evolve to seamlessly incorporate the intermittent and decentralized production of renewable energies. This paper conducts a comprehensive analysis of four well-known meta-heuristic algorithms utilized for addressing energy management challenges in smart grids: Particle Swarm Optimization (PSO), Gorilla Troop Optimizer (GTO), Manta Ray Foraging Optimization (MRFO), and Bald Eagle Search (BES). The study evaluates the performance of each algorithm in terms of solution quality, convergence speed, and efficiency. The experiments specifically examine the adaptability of the algorithms to dynamic changes and their ability to optimize energy utilization within a real-world smart grid scenario.**

*Index Terms*—**Smart Grid, renewable energy resources, optimization technique, energy management system, intelligent control of power systems**

## I. Introduction

The electricity sector holds a considerable share of the responsibility for global carbon emissions. Under the pressure of policies aimed at reducing these emissions, Renewable Energy Sources (RES) are rapidly being integrated into the electrical grid [4]. However, this transition to RES presents a major challenge to electrical grid operators, namely, maintaining the balance between production and demand [11], while evolving towards Smart Grids [8].

A Smart Grid is a power grid that can intelligently integrate the actions of all users connected to it, including generators, consumers, and those who do both, in order to efficiently deliver sustainable, affordable, and secure electricity supplies [18]. It is also known as an intelligent grid or futuregrid. It makes use of cutting-edge goods and services as well as clever technology for communication, control, monitoring, and self-healing [17].

The integration of an energy management system proves crucial in addressing the challenges associated with managing a smart grid, particularly when dealing with the inherent variability and unpredictability of RES such as solar and wind power [7], [9]. This system can efficiently coordinate energy sharing and trading among all available resources, ensuring reliable, secure, and economically optimal power system operation under diverse conditions [15]. Furthermore, the energy management system uses optimal control approaches to dynamically modify different components operations in real time. With the use of these strategies, the system is able to make well-informed choices about energy production, distribution, and storage while taking system limitations, costs, and demand into account [16], [20].

Several research has focused on the development of optimal control methods for the energy management and control of microgrids [10], [13]. In [5], an optimal management approach based on reducing the electricity cost for a residential customer in the Smart Grid is developed. The proposed cost minimization problem is solved by a Lyapunov optimization technique; however, uncertainties related to the solar forecasting data are present since the sunshine is highly variable and cannot be taken into account. An incremental welfare consensus algorithm is presented in [14] relating to coordination between distributed generation and load. The proposed algorithm was evaluated through numerical case studies.

The performance and operating costs of Smart Grid are significantly influenced by the uncertainties and variabilities of the weather, grid, and load. Constant deregulation of the modern power system poses a unique challenge for the Smart Grid to assess and compute optimal time for the energy exchange. The limitations of existing objective functions and constraints in addressing these conditions have a direct impact on the performance of microgrids. Consequently, it is imperative to devise a novel optimization algorithm that takes into account the mentioned challenges to effectively ascertain the optimal performance of Smart Grids.

In this paper, we aim to extend the study of Optimal Control-Based Energy Management in a Real Smart Grid using a Genetic Algorithm (GA) as presented in [2] to the utilization of four other well-known metaheuristic algorithms. The innovations in our work lie in the comprehensive analysis and comparison of these four widely recognized metaheuristic algorithms commonly employed to address energy management challenges in smart grids. Unlike previous studies, our research offers a systematic evaluation of the performance and efficiency of these algorithms in real smart grid scenarios

The structure of the paper is given as follows: The optimal control strategy for Smart Grid is proposed in section II. Section III presents the different metaheuristic methods applied in this research work. The results of the proposed model, in comparison with different techniques, are discussed in Section IV. Finally, conclusions are drawn and future works of research are outlined in Section V.

## II. PROPOSED STRATEGY FOR SMART GRID CONTROL

The engagement profile approach to designing an ideal controller is described in this section. Subsection II-A introduces the general hierarchical control architecture of the smart grid as well as the coordination model between the grid supplier and the smart grid. The optimization problem is then developed in subsection II-B.
In the following, $t$ denotes the current time and $N \in \mathcal{N}$ the optimal control horizon.

### A. General Architecture of Smart Grid Control System

The smart grid typical architecture is described in Fig.1. It contains a public distribution power grid (G), a Photovoltaic array (PV), an Energy Storage System (ESS) and a load (L). Furthermore, it is equipped with inverters and transformers.

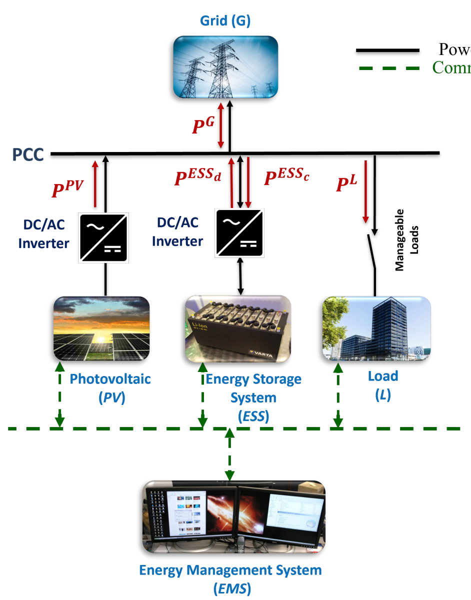


Fig. 1. Smart grid typical architecture.

Where $P^{PV}$, $P^{ESS_d}$, $P^{ESS_c}$ and $P^L$ represent respectively the power supplied by the PV array, the power supplied by the battery, the power received by the battery and the power received by the load ($t = 1, ..., N$). The smart grid can, at any time, either inject (i.e. supply) power to the grid, or withdraw power from it.

The coordination model between the smart grid and the grid supplier is defined by (1).

$$\eta_{PV}^{trans}\eta_{PV}^{inv}P^{PV}(t) + \eta_{ESS}^{trans}(P^{ESS_d}(t) - P^{ESS_c}(t))... \\ - P^{los}(t) - P^L(t) = P^G(t) \;\; \forall t = 1, ..., T \quad (1)$$

with $\eta_{PV}^{trans}$, $\eta_{PV}^{inv}$ and $\eta_{ESS}^{trans}$ are the efficiencies (values between 0 and 1) of the PV array converter, the PV array output transformer and the battery output transformer, respectively. This model also considers power losses $P^{los}$ due to the cooling of components (converters, transformers, etc.).

As they are often neglected in the literature, we do not consider in this model the efficiencies of converters and transformers ($\eta_{PV}^{trans} = \eta_{PV}^{inv}P^{PV}(t) = \eta_{ESS}^{trans} = 1$). Thus, $P^{los}(t) = 0$. Therefore, the model balance of the grid given by (1) becomes:

$$P^{PV}(t) + (P^{ESS_d}(t) - P^{ESS_c}(t)) - P^L(t) = P^G(t) \quad (2)$$

### B. Objective Function

The control objective involves tracking a power profile mandated by the grid supplier, EDF (Electricité De France), to enhance the efficiency of smart grids. The aim is to minimize the cost associated with the exchanged energy between the smart grid and the EDF supplier, as indicated by the criterion detailed in [12].

$$J = \sum_{t=1}^{N} \alpha\rho(t)P^G(t) \quad (3)$$

Where:

- $\alpha$ is the duration of a time step in hours;
- $\rho(t)$ represents the price of exchanged electricity between the grid supplier and the smart grid. It is given in €$\backslash$Kwh by (4).

$$\rho(t) = \begin{cases} 0,38 & \text{if} \quad 1140 \leq t \leq 1259 \\ 0,18 & \text{if not} \end{cases} \quad (4)$$

Note that an increase in this price is planned for the evening peak period (from 7pm to 9pm).

When the smart grid operator does not respect its commitment, i.e. at each moment of the horizon, it supplies a quantity of electricity greater (overproduction) or less (underproduction), with tolerance margin $e$ around the engaged power $P^{G_D(t)}$, it is penalized [12]. These penalties are given by (5).

$$C(P^G, P^{G_D}) = \begin{cases} 0 \quad \text{if} \quad d^-(t) \leq P^G(t) \leq d^+(t) \\ P^G(t) \quad \text{if} \quad d^+(t) \leq P^G(t) \leq 0,8P_{Max} \\ P_{bis}(t) \quad \text{if} - 0,7P_{Max} \leq P^G(t) \leq d^-(t) \end{cases} \quad (5)$$

where

- $P_{Max}$ the maximum power of the smart grid test bench.
- $d_t^+$ and $d_t^-$ are given respectively by (6) ($\forall t = 1, ..., T$).

$$\begin{cases} d^+(t) = P^{G_D}(t) + e \\ d^-(t) = P^{G_D}(t) - e \end{cases} \quad (6)$$

- $P_{bis}(t)$ is a power given by the following equation:

$$P_{bis}(t) = \frac{\left(P^G(t) - d^+(t)\right)^2 - \left(d^-(t) - d^+(t)\right)^2}{P_{Max}} \quad (7)$$

Using (5), the criterion $J$ given by (3) becomes:

$$J = \sum_{t=1}^{T} \alpha\rho(t) \left[P^G(t) - C(P_t^G, P^{G_D}(t))\right] \quad (8)$$

To maximize the usefulness of smart grids, the optimization problem that gives the optimal exchanged cost $\hat{\rho}_{exch}$, can thus be formulated as:

$$\hat{\rho}_{exch} = \max \sum_{t=1}^{T} \alpha\rho(t) \left[P^G(t) - C(P^G(t), P^{G_D}(t))\right] \quad (9)$$

### C. Constraints

The power exchanged between the smart grid and the grid is given by equation (2) The State of Charge (SOC) of the ESS expresses its capacity to provide/receive energy at the beginning of time step t. The dynamics of this variable are expressed by equation (10)

$$SOC(t) = SOC(t-1) - \frac{\sigma}{B_{nom}} \left(\eta_c P^{ESS_c}(t) - \frac{P^{ESS_d}(t)}{\eta_d}\right) \quad (10)$$

where $B_{nom}$ represents the nominal capacity of the ESS, respectively. The state initial ESS charge $SOC_0$ is known, as well as the minimum $SOC_{Min}$ and maximum $SOC_{Max}$. The SOC at the terminals of the battery at each moment:

$$SOC_{Min} \leq SOC(t) \leq SOC_{Max} \quad (11)$$

The ESS cannot be charged and discharged at the same time. The limits during charging or discharging of a battery are given by the equations (12) and (13).

$$0 \leq P^{ESS_c}(t) \leq P_{Max}^{ESS_c} \quad (12)$$

$$0 \leq P^{ESS_d}(t) \leq P_{Max}^{ESS_d} \quad (13)$$

where the parameters $P_{Max}^{ESS_d}$ and $P_{Max}^{ESS_c}$ are the maximum power that the ESS can supply or receive at each instant.
The Constraint (14) represents the exchanged power on a time step $t = 1, ..., N$. It is symbolized in our model by the variable $P^G(t)$. It has fixed limits proportional to the maximum power $P_{Max}$ of the smart grid test bench.

$$-0,7P_{Max} \leq P^G(t) \leq 0,8P_{Max} \quad (14)$$

## III. METAHEURISTIC ALGORITHM

The metaheuristic methods applied in this research work are Particle Swarm Optimization (PSO), Manta Ray Foraging Optimization (MRFO), Gorilla Troop Optimizer (GTO) and Bald Eagle Search (BES). Table I gives the references from which these meta-heuristic algorithms were referred and implemented.

TABLE I
META-HEURISTIC TECHNIQUES

| Sr. No. | Name | Reference |
|---|---|---|
| 1 | PSO | [6] |
| 2 | MRFO | [19] |
| 3 | GTO | [1] |
| 4 | BES | [3] |

PSO is a robust and well-researched metaheuristic algorithm. It has been widely applied to solve different optimization problems. PSO is based on the collective behavior of fishes and birds. It also indirectly mimics the human brain. The movement of the particles is affected by their previous movements and collective social behavior. Each iteration is used to change the position of the particle and evaluate its objective function value.

MRFO is derived from the foraging behavior of the Manta Rays. Manta Rays forage for food in a collective and individualistic manner. This behavior leads to explorative and exploitative search. There are three foraging steps implemented in MRFO. In the first step, the mantas form a chain from head to tail and follow the manta preceding it. In the second step, the mantas form a chain as in the previous step but also follow the optimal solution in the population. In the last step, the manta shall pivot around the solution and will enter an exploitative search.

GTO is derived from the behavior of gorillas in a troop. The basic search process is divided into exploitation and exploration. Exploitation of the search space is further classified under two processes i.e., following the silverback and competing for females. On the other hand, the exploration phase is classified into three parts i.e., migration to known places, migration to unknown places, and move to other gorillas.

BES optimization is based on the foraging behavior of bald eagles. The search process is divided into three parts i.e., select space, search space, and swoop. In the first part, the bald eagles identify and enter into the search space. In the second step, the bald eagles accelerate the search by moving spirally. It also gets into a position to swoop onto its prey. In the last step, the bald eagles swoop on the prey i.e., the optimal solution.

## IV. RESULTS AND DISCUSSION

This section presents the results of the research study, providing an in-depth analysis of the effectiveness of the four meta-heuristic methods applied to energy optimization within the smart grid.
The designed optimal controller was implemented on the real smart grid system available at ESTP Paris, France (see Fig.2). All specifications of this system have been taken into consideration while implementing the metaheuristic methods.

It is a micro-grid connected to the grid. The components are:

- **Renewable Energy Source:** A photovoltaic (PV) emulator installed on the test bench allows genuine electrical powers ($10\mathrm{kW}$ maximum, or $400\mathrm{m}^2$ of PV array) to be implemented.

Fig. 2. The test bench smart grid at ESTP Paris.

- **Energy Storage System:** A lithium-ion battery bank ($B$) for storing the generated renewable energy is part of the test bench. It is made up of an assembly of 14 battery modules connected in series.
- **Energy Load:** There is a Regatron load emulator on the test bench. It is a 4 quadrant 3-phase AC programmable power source that is totally digital (50kW maximum).
- **Electric Vehicle Charging Station:** A Schneider EVlink Electric Vehicle (EV) charging station with a maximum capacity of 14kW is also included in the testbed. The electric vehicle that is compatible with the ESTP is linked to this EV charging station.

Furthermore, a hypervisor is used to monitor the smart grid test bench. It serves as the main component that connects the operator, the Energy Management System (EMS), and the programmable logic controller (PLC). It is also possible to control this test bench in real-time with MATLAB Real-Time Workshop.
The profiles of PV production and consumption are shown in Fig.3.

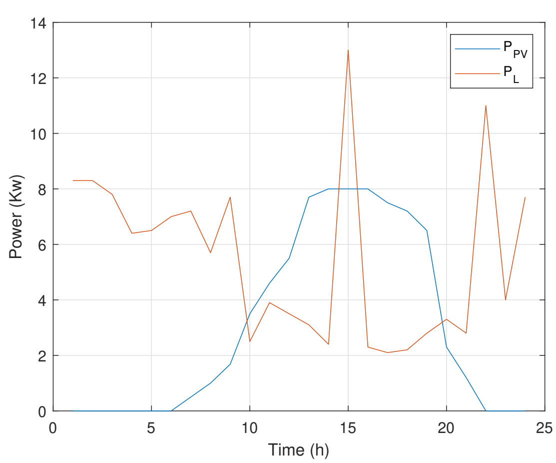


Fig. 3. PV production power profile (blue curve) and load profile (red curve).
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The convergence curves generated for each method revealed interesting trends in the optimization process (see Fig.4). It is clear from analyzing each method's performance that some of these methods work better than others in certain optimization scenarios.

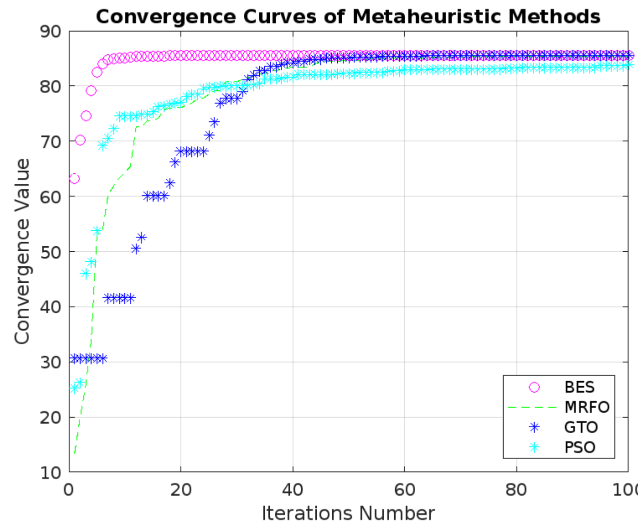


Fig. 4. Convergence Curves of Meta-heuristic Methods.

In Fig. 5, a comparison between the optimal power obtained using different metaheuristic techniques and the engaged power is shown. Each algorithm produces varying results in terms of the best solution and objective function value. However, the MRFO tends to deviate slightly from the target, while the PSO struggles to reach the optimal solution.

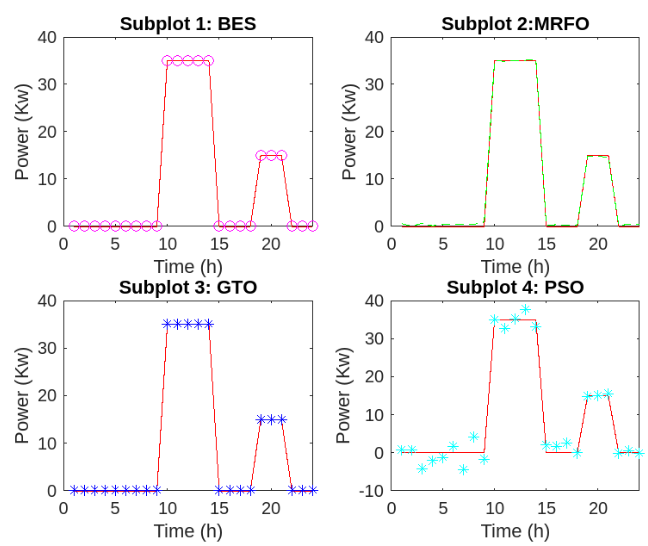


Fig. 5. Comparison between the obtained power for each algorithm and the engaged power (red curve).

To further evaluate the efficiency of each proposed algorithm, Table II gives the optimal cost associated with the exchanged energy between the smart grid and the grid supplier. GTO and BES are found to obtain optimal costs. BES showed more consistency in obtaining the best results.

TABLE II
COST OBTAINED FOR EACH META-HEURISTIC TECHNIQUE

| Meta-heuristic Technique | Cost |
|---|---|
| BES | $85,5$ |
| MRFO | $85,4272$ |
| GTO | $85,5$ |
| PSO | $83,7815$ |

## V. CONCLUSION

The increased efficiency and reliability of the smart grid is expected to save consumers money. The study's findings in this paper provide an invaluable overview of the effectiveness of metaheuristic methods for energy optimization within smart grids. The ESTP Paris test bed is used in this research work. BES and GTO were found to obtain optimal results. These findings also pave the way for further research aimed at refining and adapting these techniques, such as integrating different energy markets into the optimization problem, to meet the evolving needs of this technology. Furthermore, the algorithms studied could be applied to other areas of energy management, such as energy storage optimization, and the coordination of electric vehicles. The proposed framework could also be extended to include considerations of cybersecurity, fault resilience, and critical load management in emergency scenarios.

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