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Recent Trends of Control Strategies for Hybrid Optimization Techniques in Solar Power Microgrids: A Comparative Review

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Abstract: Solar powered microgrids are becoming a majortrend of modern distributed generation systems due to their clean, renewable and decentralized nature but, the inconsistentcharacteristics of photovoltaic generation comes with challenges in achieving stable, efficient, and reliable operation. To solve these issues, advanced control strategies integrated with hybrid optimization techniques have gained significant attention. Hybrid approaches, combining metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Reptile Search Algorithm (RSA), Aquila Optimizer (AO), and Artificial Neural Networks (ANN), have been applied to improve maximum power point tracking (MPPT), voltage and frequency regulation, energy storage scheduling, and power quality enhancement. This paper presents a comprehensive comparative review of recent control strategies employed in solar microgrids with an emphasis on hybrid optimization frameworks. Various methods are analyzed based on performance indicators such as tracking efficiency, stability, convergence rate, robustness, and computational burden. Furthermore, the review highlights the emerging trends of AI-assisted optimization, real-time digital simulation, and cyber-physical resilience for solar microgrids. The study concludes by outlining future research directions toward scalable, adaptive, and intelligent control for resilient solar microgrid operation. This paper provides a comparative review of recent control strategies for solar microgrids with emphasis on hybrid optimization techniques.

Keywords: Solar microgrids, hybrid optimization, control strategies, metaheuristic algorithms, energy storage systems, power quality, artificial intelligence, Renewable energy integration, solar photovoltaic systems, Grid stability, resilience, voltage–frequency regulation, Sustainable energy, Real-Time Digital Simulation, Hardware in loop.

I. INTRODUCTION

Clean and sustainable energy is needed today which has accelerated the demand toward renewable-based distributed generation systems. Among renewable sources, solar photovoltaic (PV) energy is one of the most promising due to its modularity, scalability, and low costs [5], [6], [7], [8]. The integration of PV units into microgrids localized networks that combine generation, storage, and loads has enabled reliable and flexible power supply for both grid-connected and islanded operations [3], [4], [9].

However, PV-based microgrids face challenges due to their inconsistent nature, leading to instability, load shading issues, voltage fluctuations, and suboptimal utilization of distributed resources [18], [21], [23]. To overcome these challenges, researchers has increase its focused on advanced control and optimization techniques that enhance the efficiency, stability, and resilience of microgrids [6], [7], [11].

In particular, metaheuristic and hybrid optimization algorithm techniques have emerged as powerful solutions. Recent researches worked upon the effectiveness of algorithm like Particle Swarm Optimization, Genetic Algorithm, Grey Wolf Optimizer, Harris Hawks Optimization (HHO), Reptile Search Algorithm, and Aquila Optimizer in applications such as maximum power point tracking, energy storage scheduling, and demand-side management [12], [13], [18], [22], [24]. Additionallyhybrid approaches, where two or more algorithms or intelligent controllers (e.g., PSO-GA, ANN-HHO, Fuzzy-PSO, RSA-AO) are combined, demonstrate superiority in overall performance, speed, robustness, and adaptability under various operating conditions [15], [16].[17], [19], [20].

Recent research trends further emphasizesvoltage and frequency regulation in multi-microgrid networks [3], [4], adaptive droop-based control [1], and predictive optimization frameworks for energy trading and demand response [2], [26]. In addition, AI-assisted strategies such as deep reinforcement learning (DRL) [11], [26], quantum-inspired MPPT [6], and metaheuristic-driven cyber-physical resilience frameworks [28], [29] are rapidly shaping the future of microgrid control.

The main contributions of this review are:

1) A structured classification of control strategies applied in solar microgrids, with emphasis on hybrid and intelligent optimization techniques.
2) To form a comparative evaluation of many methods based on performance indicators such as efficiency, robustness, computational burden, and scalability.
3) Identification of research gaps and future directions, including real-time digital simulation (RTDS), cyber-physical resilience, and AI-driven predictive optimization.

Optimization Techniques in Solar Microgrids in India and the world

Figure 1 compares India's progress in developing renewable energy, especially solar power, with the global trend. The graph shows that while the world has steadily increased its renewable capacity, India has had a sharper increase in recent years. This growth reflects India's strong policy support, quick setup of solar parks, and ambitious national goals. Even though India began from a lower starting point than the global leaders, its growth rate is much higher, showing a good chance to narrow the gap with global averages. The figure highlights both the scale of global renewable integration and India's growing contribution. It also points out the need for effective control and improvement strategies for solar-based microgrids in India.

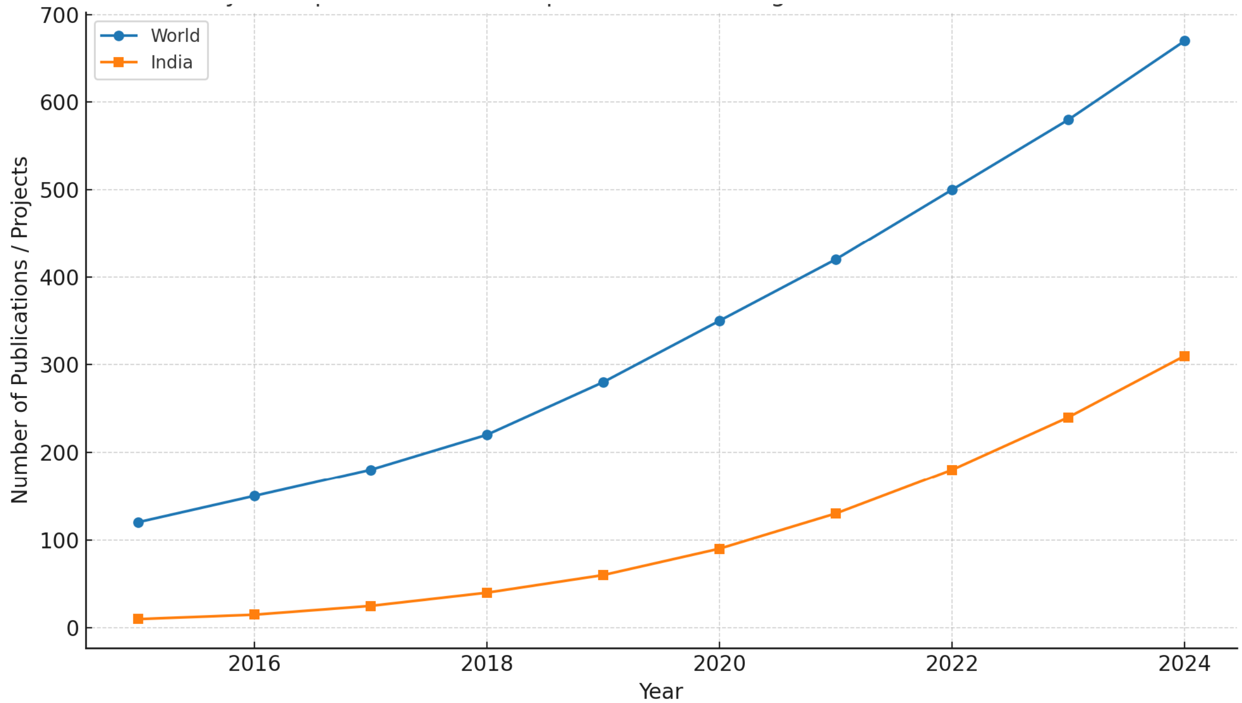

Fig.1. Hybrid Optimization Techniques in Solar Microgrids: Global Vs India Trends

II. BACKGROUND

Solar-based microgrids have gained significant attention in recent years as an effective way to integrate renewable resources with distributed energy systems. A typical solar microgrid consists of PV arrays, power electronic converters, an energy storage system, local loads, and a control unit, which may operate either in grid-connected or islanded mode [7], [9]. In this configuration, the PV array serves as the primary generation source, while ESS such as batteries or hydrogen storage ensures reliability and balances generation-demand mismatches [4], [5].

The control strategiesused in solar microgrids plays a crucial role in ensuring stable and efficient operation which includes:

- Primary control for power sharing and voltage/frequency regulation, often realized using droop characteristics [1], [3].
- Secondary control to restore frequency and voltage deviations, improving steady-state accuracy [16], [17].
- Tertiary control for optimizing power flow between the microgrid and utility grid, including demand response and energy trading mechanisms [2], [26].

Despite their benefits, conventional control strategies face limitations in handling the nonlinearities and uncertainties of PV-based systems, especially under partial shading, intermittency, and fluctuating loads [18], [21].

To address this, researchers have increasingly applied metaheuristic and hybrid optimization algorithms to enhance maximum power point tracking (MPPT), optimal dispatch of ESS, and overall microgrid resilience [6], [12], [19].Fig. 2 illustrates a generalized architecture of a PV–ESS microgrid with hybrid optimization-based control strategies, showing the interaction between generation, storage, load, and control levels, whileFig.3 shows the control hierarchy in PV- ESS Microgrid with Microgrid Optimization

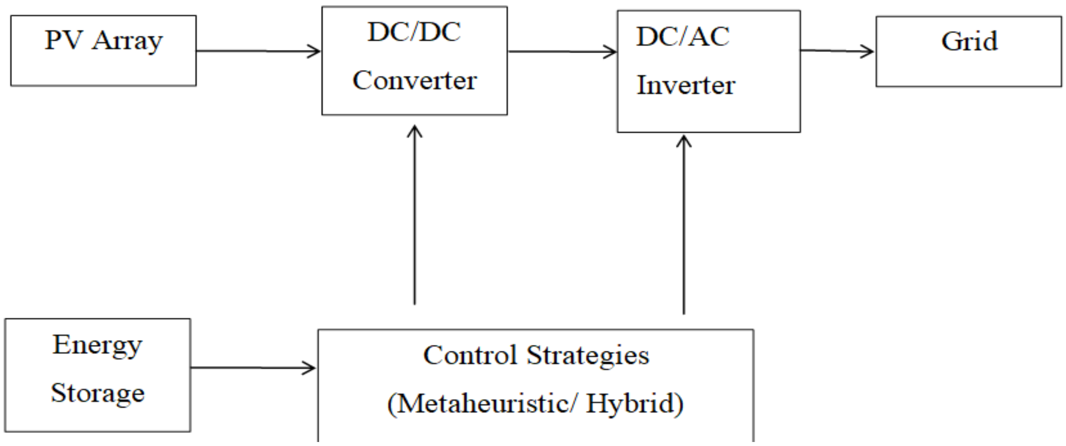

Fig 2 PV-ESS Microgrid Architecture with Hybrid Optimization Base Control

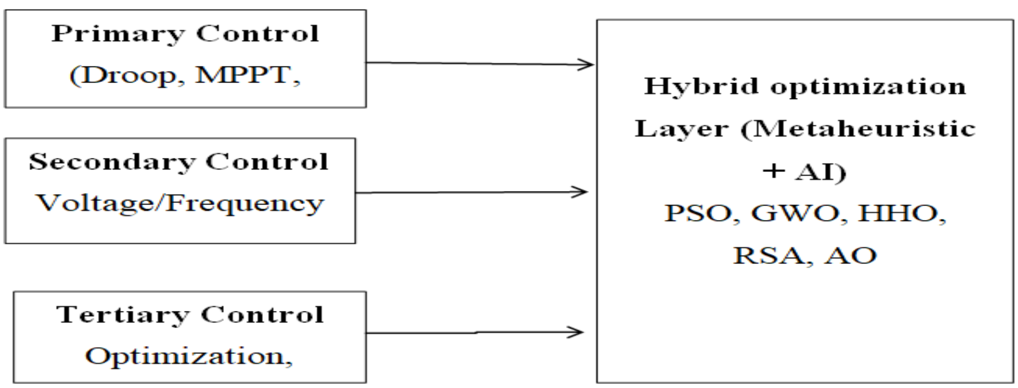

Fig.3. Control Hierarchy in PV- ESS Microgrid with Microgrid Optimization

III. CONTROL AND OPTIMIZATION PROBLEMS

Under variable irradiance, stochastic load conditions, and disturbances from the grid, the operation of solar-based microgrids requires a hierarchical control structure to ensure stability and reliability of power supply. The ensuing problems can therefore be broadly classified along the following four dimensions:

- Maximum power point tracking (MPPT).
- Energy management.
- Voltage-frequency regulation.
- Overall resilience of the system.

A. Maximum Power Point Tracking (MPPT):

MPPT is crucial to ensure the maximum energy yield from the PV arrays covering fluctuating irradiance and temperature. Commonly used control algorithms due to their simplicity in implementation have been found to fail very often in partial shading conditions to track the global peaks [18], [19]. To address this increasingly widely used in academia are metaheuristic-based MPPT methods like Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and Salp Swarm Optimization [12], [20]. Other recent works take advantage of hybrid techniques, such as modified GWO with the Nelder–Mead search method [12], cuckoo search–GWO hybrids [29], and MPSO–PID schemes [22], in order to accelerate convergence and improve tracking efficiency in non-convex P–V characteristics [28].

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B. Energy Management and Scheduling:

Energy management systems (EMS) with some rules provide a relatively easy way to perform missions but not always optimally. Maximum efficient coordination between PV generation, storage, and the grid provides minimal operational costs and maximizes reliability. Advanced techniques based on mixed-integer programming, reinforcement learning, and online optimization have been shown to be considerably flexible to the uncertainties in demand and renewable output [7], [8], [23]. Metaheuristic and hybrid optimizers are widely applied, targeting e.g. Harris Hawks, Aquila Optimizer, PSO-GA combinations for scheduling battery dispatch, minimizing degradation, and balancing multi-objective trade-offs between cost, emissions, and reliability [6], [25], [30].

C. Voltage and Frequency Stability:

Theaspect of power quality becomes a challenge in weaker-grid or islanded microgrids. Primary droop-control approaches allow decentralized power-sharing, yet are subject to steady-state voltage and frequency deviations [3] [17]. In such cases, secondary controls with PI or MPC controllers would be used to restore set-points, and the tertiary control will finally ensure Eigenoptimal power exchange ratio with the utility grid [1] [2] [26]. With respect to optimization, a tuning of controller parameters is of utmost importance for establishment of a robust scheme. For example, Khosravi [24] proposed a finite-time control scheme for fast voltage and frequency regulation, whereas others incorporate hybrid optimization with model predictive control to enhance damping and diminish recovery times [23].

D. Microgrid Resilience and Robust Operation

Next to the basic steady-state control, resilience against uncertainties and disturbances has become an increasingly pressing research need. Operational challenges brought forth by renewable intermittency, forecasting errors, and storage degradation renders these systems less reliable. Furthermore, the expanding spectrum of cyber-physical threats raises serious reliability concerns for communication-based microgrids. Recent studies are addressing this problem through incorporating robust optimization and data-driven predictive control [8], [21]. Furthermore, adaptive metaheuristic and hybrid approaches, such as synergy among AI models (ANN, DRL) and evolutionary optimizers, are proposed to improve the resilience indices with respect to fault recovery and thus long-term efficiency [7], [25], [28].

To summarize, the optimization and control challenges of PV-ESS microgrids can be broadly classified into energy extraction (MPPT), Energy resource scheduling (EMS), stability (voltage/frequency), and resilience. Each of these domains has witnessed an increase from conventional rule-based or deterministic methods toward hybrid optimization approaches, capable of utilizing advantages from metaheuristic, AI, and predictive control. This is indicative of a growing agreement that hybrid strategies present a promising path toward dealing with the nonlinear, uncertain, and multi-objective nature of microgrid operation [6], [12], [23], [25], [28].Fig.4. illustrates the Optimization and Control Challenges of PV–ESS Microgrids.

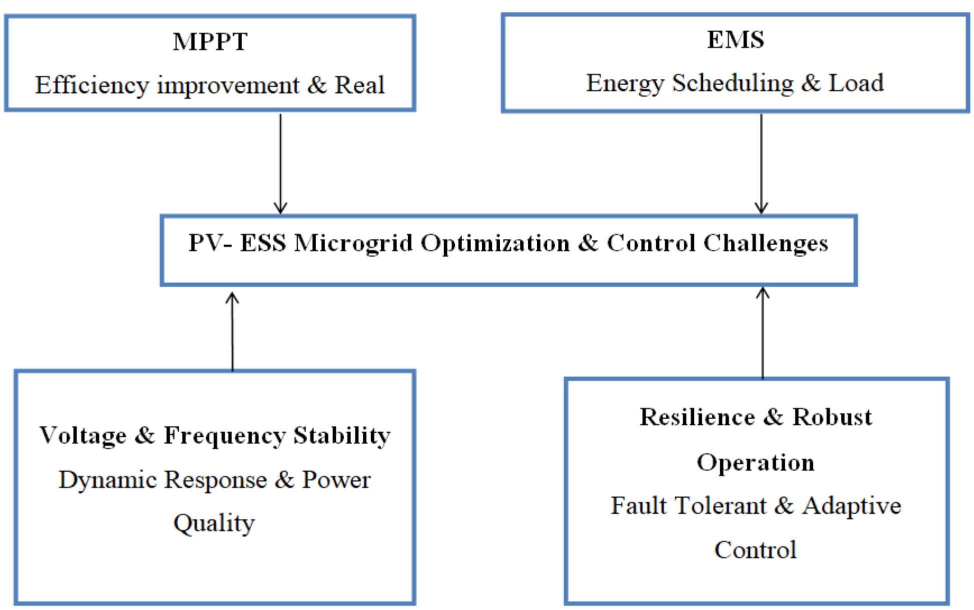

Fig.4Optimization and Control Challenges of PV–ESS Microgrids

IV. MATHEMATICAL MODELING

To understand how hybrid optimization is applied in a solar microgrid, it is important to first represent the behavior of its main components in mathematical terms. These models provide the foundation for applying advanced control and optimization strategies This section presents compact models for the key subsystems of a PV-ESS microgrid, the PV generator, DC-DC converter and DC-link, grid-tied inverter energy storage, and the system-level power balance and constraints that feed into hybrid optimization–based control and scheduling [1], [3], [4], [6], [9], [16], [18], [21], [23],[24],[25], [28], [30].

A. PV Generator (single-diode model)

The output of solar panels depends on sunlight and temperature, making the voltage–current curve nonlinear. MPPT algorithms are needed to always extract maximum power, even under shading. The equations 1 to 3 describe how solar panels behave current and voltage characteristics under irradiance and temperature. These are nonlinear and change with shading; hence optimization for MPPT is required.

For a PV cell,

$$I - I_{ph}\left[\mathrm{Exp}\frac{V+IR_s}{\eta V_T}-1\right] - \frac{V+IR_s}{R_P} \quad (1)$$

Where I_{ph} is the photocurrent, I_0 the diode saturation current, R_s and R_p series/shunt resistances, n the ideality factor, and VT=kT/q. For a module/array, currents/voltages scale with series/parallel interconnections.

Irradiance–temperature dependence:

$$I_{ph} = [I_{ph,STC} + \alpha_I (T - T_{STC})]\frac{G}{G_{STC}}, Voc = V_{oc,\,STC} + \alpha V(T-T_{STC}) \quad (2)$$

With G irradiance and T cell temperature. The array output power is PV=VI these relations underpin GMPPT formulations under partial shading [18], [21], [25], [28], [30].

B. DC–DC Converter and DC-Link

The boost converter regulates the DC bus voltage through its duty cycle. This is the main control point where MPPT is applied, DC–DC Converter and DC-Link can be obtained by using the averaged model of a boost converter, common for PV interfacing as

$$L\frac{di_L}{dt} = V_{PV} - (1-d)\, V_{dc} \quad (3)$$

$$C_{dc}\frac{dV_{dc}}{dt} - (1-d)\, i_L - i_{dc,load} \quad (4)$$

where d the duty cycle, i_L the inductor current, V_{dc} the DC-link voltage, and i_{dc}, the current drawn by the inverter/auxiliaries. This model is used for MPPT-linked inner loops and predictive control designs [21], [23].

Boost converter equations 3 and 4 shows how the duty cycle "d" affects voltage/current. This is where MPPT control is applied using metaheuristic or hybrid algorithms

C. Grid-Tied Inverter (L or LCL filter) in dq frame

The inverter converts DC to AC and controls active and reactive power. In grid-connected mode it synchronizes with the grid, while in islanded mode it regulates voltage and frequency. With a synchronous frame aligned to the grid voltage (ω_g), and an L-filter for brevity,

$$L_f\frac{di_d}{dt} = -R_{fid} + \omega_g L_f i_q + V_d - V_{g,d} \quad (5)$$

$$C_{dc}\frac{dV_{dc}}{dt} = \frac{3}{2}\frac{V_d I_d + V_q d I_q}{V_{dc}} - I_{dc,PV} - i_{dc,ESS} \quad (6)$$

where v_d,v_q are inverter output voltages, id,iq filter currents, and $v_{g,d}$,$v_{g,q}$ grid voltages. Active and reactive powers:

$$P = \frac{3}{2}(V_{g,d}\, i_d + V_{g,q} i_q) \quad (7)$$

$$Q = \frac{3}{2}(V_{g,d}\, i_d + V_{g,q} i_q) \quad (8)$$

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Equations 5 to 8 describe how inverters control active and reactive power with grid. This links directly to voltage and frequency stability problems.

Outer loops regulate $\frac{P}{Q}$(or $\frac{V}{f}$in islanded mode), with secondary control restoring set points and tertiary layers optimizing exchanges and costs [1], [3], [16], [26].

D. Energy Storage System (Battery/H_2).

Battery or hydrogen storage supports the microgrid by charging/discharging within limits of State of Charge (SoC) and current. Optimization ensures efficient scheduling and long life. The ESS can be shown with a first-order Thevenin's battery model captures dynamics for scheduling:

$V_{bat} = E_0\,(SOC) - R_0 i_{bat} - V_1$

$$\frac{dV_1}{dt} = -\frac{1}{R_1 C_1} V_1 + \frac{1}{C_1} i_{bat} \quad \text{(9)}$$

$$\frac{dSOC}{dt} = -\frac{\eta_{ch}}{C_{nom}} i_{bat} \quad \text{(10)}$$

Equations 10 and 11 show the battery model with State of Charge (SoC) limits. These constraints are why ESS scheduling optimization is needed

Where $\eta_{ch}$is the charge/discharge efficiency and $C_{nom}$is the capacity.

Power is $P_{ESS}=V_{bat}$ subject to

$$SoC_{min} < SoC(t) < SoC_{max},\ |P_{ESS}| < P_{ESS}^{max},|i_{bat}| < i_{max} \quad \text{(11)}$$

For hydrogen storage, power coupling is obtained typically via electrolyzer/fuel-cell efficiencies η_{ely}, η_{fc} with tank state updated by hydrogen flow; co-optimization improves operational efficiency [4], [25].

E. System Power Balance (bus-level)

At any instant,

PV power + storage + grid import = load demand + losses.

In islanded mode, balance must be achieved internally, making control stricter.

At the DC link (or system level):

$$P_{PV}(t) + P_{ESS}(t) + P_{grid}(t) = P_{load}(t) + P_{loss}(t) \quad \text{(12)}$$

WhereP_{grid}>0 denotes import. In islanded mode, P_{grid}=0, making frequency/voltage regulation constraints more stringent [1], [3], [24].

Equations 11 and 12 shows that total generation = load + losses. Variations in irradiance/load are modeled as uncertainty, which motivates robust optimization.

F. Uncertainty and Disturbance Models

Solar irradiance and load vary unpredictably, so they are modeled as stochastic processes. This requires robust and predictive optimization techniques.

Irradiance G (t) and load $P_{load}$are modeled as stochastic processes or bounded sets:

$$G(t) \in [\underline{G}(t), G'(t)],\ P_{load}(t)\ \ [P_L(t), P_L'(t)] \quad \text{(13)}$$

Enabling robust/predictive or online optimization (e.g., FCS-MPC, online convex optimization, DRL) [2], [7], [8], [21], [23], [26].

4.7 Optimization problem formulations

MPPT is a fast, converter-level optimization used to extract maximum power from PV modules. ESS scheduling works on a medium timescale to balance cost, reliability, and battery life. Voltage and frequency regulation focuses on tuning control parameters for system stability. The main decision variables are duty cycle, state of charge (SoC), and power setpoints, all restricted by voltage, current, and capacity limits.

$$\frac{\max}{d} P_{PV}(V_{dc}(d), I(d)) \ \text{ s.t. } V_{min} \le V_{dc} \le V_{max}, I_{min} \le I \le I_{max} \quad \text{(14)}$$

Often cast as a no convex search; hybrids (e.g., GWO+NM, CS+GWO, MPSO-PID) accelerate convergence and avoid local maxima under partial shading [19], [20], [22], [28], [29].

G. ESS scheduling (minutes–hours):

$$\frac{\min}{P(t)_{ESS}} [\sum_t C_e(t) P_{grid} + \lambda_{deg} |P_{ESS}(t)| + \lambda_{loss} P_{loss}(t)] \ldots\ldots(15)$$

Multi-objective forms include emissions E(t), comfort/DR penalties, and voltage deviation terms; hybrid metaheuristic (PSO-GA, ANN-HHO, etc.) are used to tune controllers or co-optimize set points, [3], [4], [9], [24], [25].

H. Voltage–Frequency regulation (secondary/tertiary):

$$\text{Min } /\theta\alpha \sum_t |f(t) - f| + \beta \sum_t |V(t) - V^*| + \|\theta\|_2^2 \ldots\ldots (16)$$

Where θ aggregates droop/PI/MPC gains or virtual-inertia parameters tuned by hybrid optimizers; finite-time/robust designs are increasingly reported [3], [24]

I. Decision Variables & Constraints Summary

The proposed system considers both fast and slow decision variables. Fast variables, such as the converter duty ratio, DC-link voltage, and inverter dq currents, govern instantaneous stability and power flow, while slow variables, including storage power, state of charge, and grid exchange, manage long-term energy scheduling. All decision variables are bounded by physical ratings—voltage, current, power, and SOC limits—and logical conditions arising from grid-connected or islanded operation. Together, these constraints ensure safe, stable, and efficient system performance across different timescales. Table I summaries the above statement

Table I. Decision Variables & Constraints Summary

Timescale	Decision Variables	Constraints	Purpose
Fast (ms–s)	Duty ratio d, DC-link voltage V_{dc}, inverter dq-currents (i_d,i_q)	Converter ratings, safe V_d limits, current bounds	Maintain stability, enable MPPT, regulate P/Q flow
Slow (min–h)	Storage power P_{ESS}State of Charge (SOC), Grid power Pg_{rid}, Net P/Q balance	SOC range [SOC_{min}, SOC_{max}] ESS/inverter limits, grid-code constraints	Optimize cost, reliability, long-term energy balance
General	All above variables	Box constraints (V, I, P, SOC), logical constraints (grid-connected vs. islanded, reserve margins)	Ensure safe, reliable operation

Notes for Implementation

- Per-unit normalization at the inverter AC side to simplify gain tuning is used.
- For LCL filters, add capacitor branch and grid-side current states; damping (active/passive) should be included when you simulate Section V comparisons.
- If we target FCS-MPC comparisons as in [21], discrete the above dynamics and enumerate the finite switching set; hybrid optimizers can then tune weights/horizons

V. OPERATION AND CONTROL STRATEGIES OF HYBRID SOLAR MICROGRID

In the operation of a hybrid solar microgrid integrating photovoltaic (PV) generation, a Static Synchronous Compensator (STATCOM), and an Energy Storage System (ESS) necessarily requires a well-structured control scheme to ensure system stability, reliability, and economic efficiency. Usually, the control architecture is organized in a hierarchical manner into primary, secondary, and tertiary levels. At the primary level, inverters mostly employ droop-based strategies, such as P-f and Q-V control methods, to achieve autonomous load sharing among inverter-based resources. Meanwhile, virtual impedance methods are incorporated to suppress circulating currents and improve current-sharing performance under weak-grid conditions [1], [2]. Once the primary dynamics have stabilized the system, secondary control activities are triggered to retain voltage and frequency at nominal values. Secondary control can be centralized or decentralized based on the communication architecture, and consensus schemes have exhibited greater resistance to communication delays while being scalable in multi-inverter setups [3], [4]. At the supervisory or tertiary level, the energy management system (EMS) regulates optimal scheduling of power flow between PV, ESS, and the main grid. Different processes, including model predictive control (MPC), heuristic and metaheuristic optimization, and rule-based dispatch, have been found on the trade-off between computation resource and operational efficiency, directing attention toward extending battery life and cutting costs [5], [6].

Within the hybrid structure, coupled control of the STATCOM and ESS is a vital development for voltage stability and frequency regulation, especially in instances of disturbance provoked by PV intermittence or sudden load changes. The STATCOM primarily facilitates dynamic reactive power compensation, while the ESS assists active-power balancing and inertia support, and coordinated operation ensures improved voltage stability for ride-through under weak-grid scenarios [7], [8]. Also, intelligent control methods are gaining attention for the effectiveness of handling uncertainties and enhancing adaptability. Adaptive droop control, fuzzy logic, and reinforcement learning-based approaches have shown promise in improving the resilience of PV-ESS-STATCOM microgrids, enabling the controllers for self-tuning during variable renewable generation and load fluctuations [9], [10]. The aforementioned strategies form resilient control for contemporary hybrid microgrids when integrated under a hierarchical control scheme.

VI. TYPES OF CONTROL METHODS IN HYBRID SOLAR MICROGRIDS

A. Maximum Power Point Tracking (MPPT) control,

The administration of hybrid solar microgrid systems is usually distinguished by multiple functional categories just according to the operating objective and system requirement. A critical aspect is the Maximum Power Point Tracking (MPPT) control, which is employed at the PV interface for extracting an optimum amount of available energy under varying solar irradiance and temperature conditions. Conventional MPPT algorithms such as Perturb and Observe (P&O) and Incremental Conductance (INC) are the most used because of their simplicity and ease of implementation over other advanced methods such as fuzzy logic, adaptive, and metaheuristic-based MPPT, which give faster tracking and thus reduced oscillations in highly dynamic environments [1], [2].

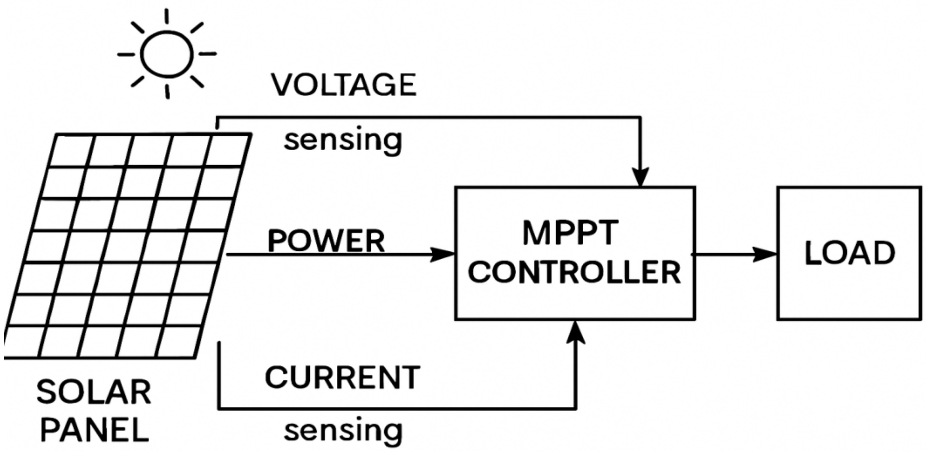

Fig.6. Maximum Power point Tracking

B. Voltage and frequency stability control,

This method ensures reliable operation during disturbances and load variations. Voltage stability is typically enhanced through reactive power support from STATCOMs, while ESS contributes active power balancing to maintain frequency. Hierarchical approaches are commonly adopted, where primary droop-based control stabilizes immediate dynamics, secondary control restores nominal values, and tertiary control optimizes power flow and energy management. The coordinated operation of STATCOM and ESS plays a key role in maintaining voltage stability in weak-grid conditions [3], [4].

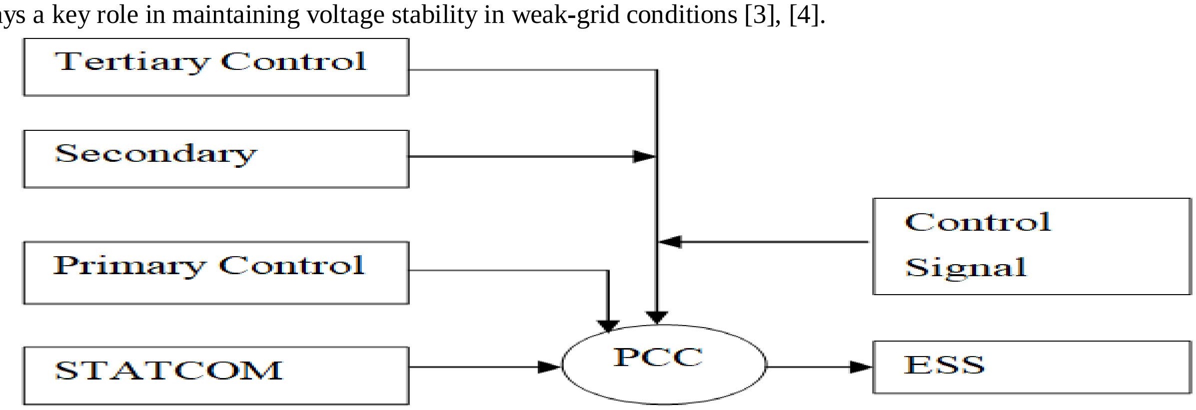

Fig.6. Voltage and Frequency Control in Microgrids

C. Converter and inverter control

This control method forms the backbone of microgrid operation since most renewable energy resources are interfaced through power electronic converters. Inner-loop current and voltage controllers regulate switching operations, while outer-loop controllers manage power, voltage, and frequency. Advanced schemes such as virtual synchronous generator (VSG) control, model predictive control (MPC), and adaptive droop enhance stability and improve power-sharing accuracy among distributed inverters [5], [6]. It is categorized into the brain and the execution part shown in figure 8.

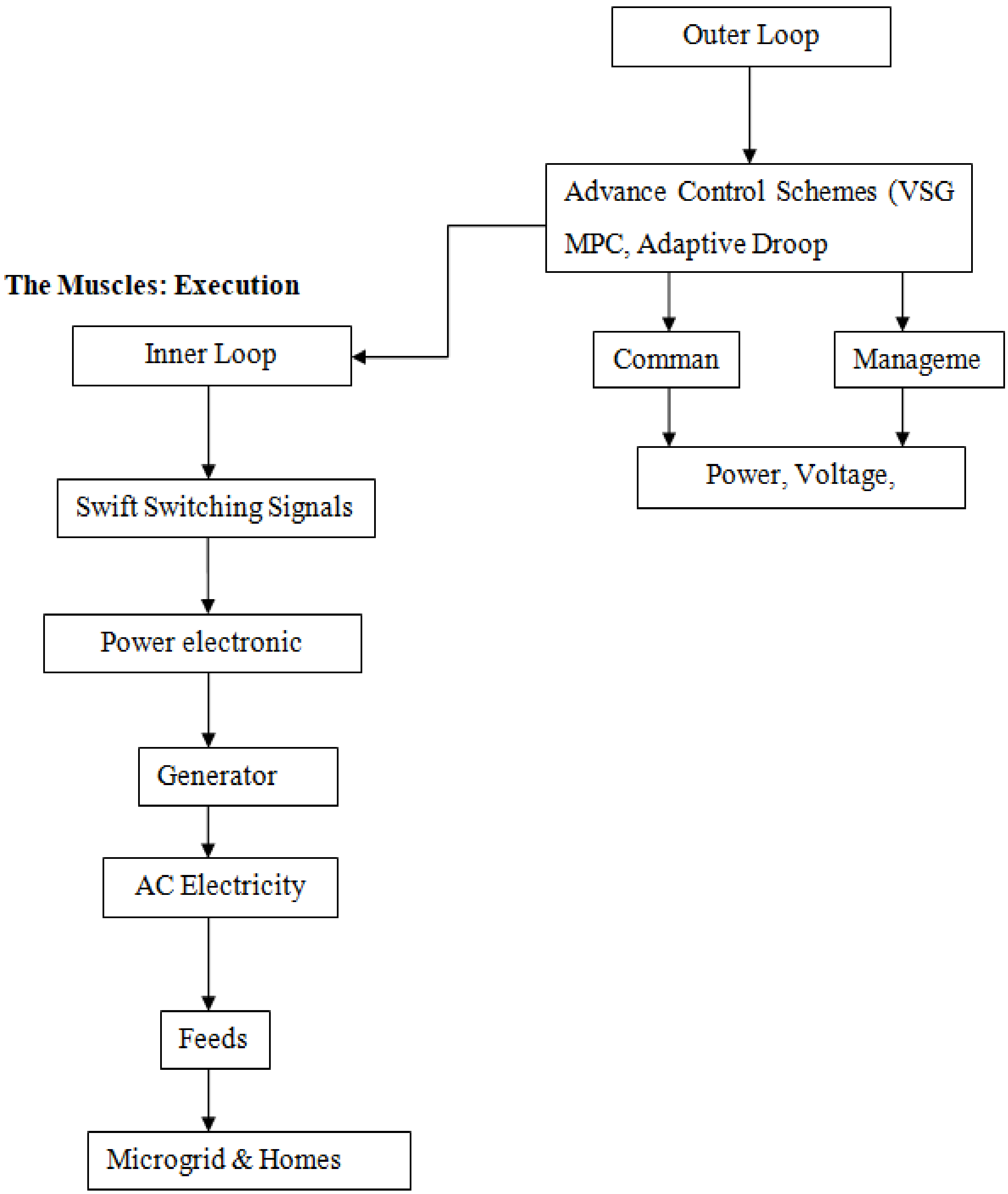

Fig. 8 Converter and inverter control

D. Grid-connected vs. Islanded operation

On the grid, PV systems usually utilize MPPT while the ESS performs peak-shaving and load balancing, with the main grid acting as the voltage and frequency reference. Under islanded conditions, on the contrary, the microgrid must operate in a self-sufficient manner, where the inverters will provide voltage and frequency regulation, with the ESS giving fast active power support for the supply-demand balance. Hence, smooth mode-transition controls will be required to ensure seamless switching between operating states and to prevent any instability during islanding events [7], [8].

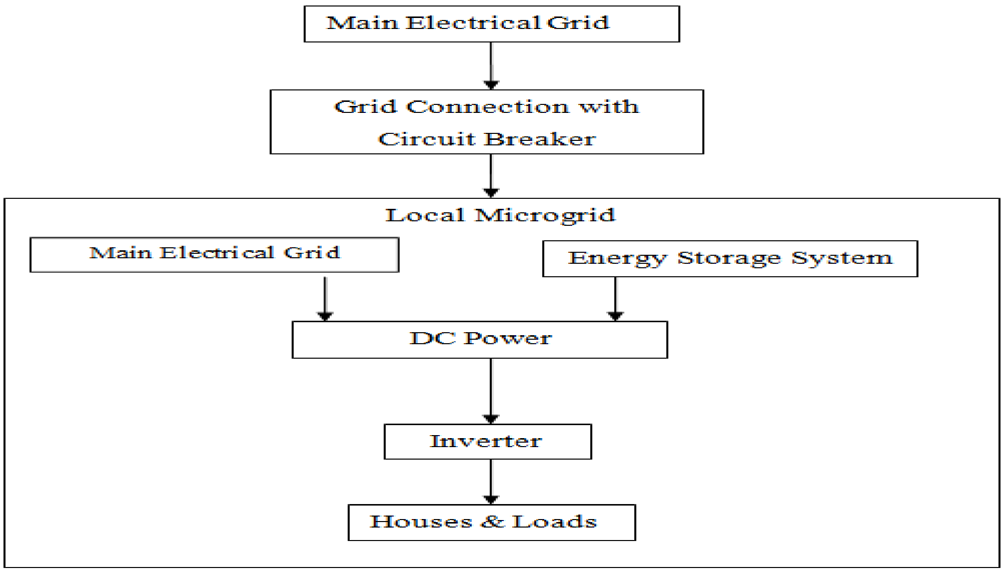

Fig.9. Grid connected PV–ESS based local microgrid architecture

E. Conventional Control Methods in Hybrid Microgrids

For quite some time, traditional control schemes have governed the hybrid microgrids operation-from Proportional-Integral (PI) to Proportional-Integral-Derivative (PID)-for their simplicity, easy ways of building, and better theoretical backing [7]. Such controllers are majorly used for inverter current control, voltage regulation, and frequency stability for both grid connections and islanded modes of applications. However, their performance is quite limited under nonlinear and uncertain conditions, especially in renewable-dominated systems wherein solar irradiance fluctuates rapidly and manifests loads swinging up or down [9].

To end this, intelligent control techniques have been introduced, these include Fuzzy Logic Controlled (FLC) and Artificial Neural Networks (ANNs). Fuzzy controllers would naturally avoid the haggling requirements of the system scalars by avoiding empirical mathematical models, thus allowing them to handle the uncertainty and nonlinear dynamics at their best in terms of energy management and power-sharing applications [10], [11]. ANN-based controllers, on the other hand, can have learning or adaptive potential to improve the judging ability in their MPPT and dynamic power flow optimization tasks [12].

Well-defined operating conditions have a very acceptable computational efficiency and robustness for traditional methods but fall short in terms of acceptability, especially when multi-objective and large-scale optimizations need to be performed in a hybrid solar microgrid. Such motivated interest led to adopting more advanced metaheuristic and hybrid approaches that afford superior adaptability and global search capabilities [13], [14].

VII.METAHEURISTIC OPTIMIZATION TECHNIQUES IN HYBRID MICROGRIDS

The application of metaheuristic in hybrid solar microgrids has gained prominence in recent years as it enables solving most nonlinear, stochastic, and multi-objective optimization problems, which conventional controllers such as PB and PD cannot address efficiently [7]. The heuristic search strategies of these algorithms are inspired by the natural, biological, or physical processes and give them the needed flexibility and adaptation required to meet the ever-changing operating conditions of renewable energy systems.

A. Particle Swarm Optimization (PSO)

One of the most important aspects of PSO, which is in most of the cases widely known for its simplicity and speed, is that it has been popularly applied in maximum power point tracking (MPPT) under varying conditions of irradiance and optimal dimensioning of distributed energy resources in microgrids [18], [27]. Likewise, evolutionary process imitation uses Genetic Algorithms (GA) to optimally allocate renewable energy along with storage units and chiefly improve economic and operational performance in distribution networks [9], [29].

B. Differential Evolution (DE)

Differential Evolution (DE) and other evolutionary strategies in terms of being able to solve continuously optimizing problems-for example, inverter parameter tuning and enhancement of voltage stability in hybrid systems [10]. In more recent literature on microgrids, several new nature-inspired algorithms like Harris Hawks Optimization (HHO), Aquila Optimizer (AO), Reptile Search Algorithm (RSA), and Whale Optimization Algorithm (WOA) have been reported [17], [24]. These algorithms thus exhibit stronger exploration and exploitation balance that provide better resiliency against local optima and allow robust solutions in MPPT and energy management tasks [19], [22], [28]. All in all, metaheuristic optimization constitutes a robust platform for the enhancement of efficiency, reliability, and cost-effectiveness in hybrid microgrid systems. However, parameter sensitivity, slow convergence for large-scale systems, and the challenges of computational complexity remain as open issues that are presently being addressed by such hybridized and adaptive forms of these algorithms [17], [20], [22].

C. Hybrid Optimization Approaches in Hybrid Microgrids

Hybrid optimization approaches combine all the competencies of conventional controllers and metaheuristic algorithms to provide high-quality performance in hybrid microgrid applications. While all these conventional methods (i.e., PI, PID, Fuzzy, and ANN) are simple, fast reacting, and robust, one major drawback that occurs in them is the lack of global search capacity. On the other hand, metaheuristic algorithms such as PSO, GA, DE, HHO, AO, RSA, and WOA provide very high potency in optimization; however, they are sometimes too slow, demanding very large computational efforts. Hybrid methods will combine both points, exploiting all the advantages of both, yielding systems of improved reliability, adaptability, and operational efficiency [17], [19], [22].

Such methods include, for example, the Fuzzy-PSO controllers that combine heuristic adaptability in fuzzy logic and global optimization possibilities of particle swarm optimization to offer enhanced performance in MPPT and stable power-sharing under different solar irradiance conditions, as well as ANN-HHO frameworks leveraging learning and prediction capability of artificial neural networks in tandem with exploration-exploitation balance of Harris Hawks Optimization to yield effective solutions for voltage and frequency regulation in complex microgrid environments [24]. Furthermore, hybrid RSA-AO schemes have been proposed to improve convergence speed and solution accuracy in multi-objective energy management tasks, thus demonstrating robustness against uncertainty in both load and renewable generation [28], [29].

In all cases, hybrid methods portend better promise for hybrid solar microgrids, offering benefits in dynamic response, computational complexity, and uncertainty. Such hybridization continues to evolve, with recent studies showing contributions to the fields of intelligent energy management systems while advancing the shift toward more sustainable and resilient distributed power networks [19], [22], [29].Tables II–IV summarizes a comparative analysis of different control and optimization methods used in hybrid solar microgrids.

Table II. Comparative Analysis of Conventional Control Methods

Method	Advantages	Limitations	Application in Hybrid Solar Microgrids
PI Control	Simple structure, easy to implement, effective for linear systems	Poor performance under nonlinearity and parameter variation	Inverter control, voltage regulation
PID Control	Improved dynamic response, widely used	Requires tuning, sensitive to system disturbances	Frequency control, power sharing
Fuzzy Logic Control (FLC)	Handles nonlinearities and uncertainties, no need for exact model	Rule design can be complex, may lack adaptability	MPPT, energy management

Table III. Comparative Analysis of Metaheuristic Optimization Methods

Method	Advantages	Limitations	Application in Hybrid Solar Microgrids
PSO	Fast convergence, easy implementation	Prone to local optima	MPPT, optimal sizing
GA	Strong global search, robust optimization	Computationally expensive, slow convergence	Unit commitment, energy scheduling
DE	Effective in continuous problems, good exploration	Sensitive to parameter settings	Power dispatch optimization
HHO	Balances exploration and exploitation, high efficiency	May face premature convergence	Voltage/frequency regulation
AO	Exploitation-oriented, efficient in fine-tuning	Weak in global exploration	Multi-objective optimization
RSA	Strong global search, avoids local optima	Higher computational complexity	Optimal placement of ESS/STATCOM
WOA	Good convergence accuracy, adaptive	Slower in large search spaces	Energy management under uncertainty

Table IV. Comparative Analysis of Hybrid Approaches

Hybrid Method	Advantages	Limitations	Application in Hybrid Solar Microgrids
Fuzzy–PSO	Combines fuzzy adaptability with global search, better MPPT tracking	Higher complexity than single methods	MPPT, load balancing
ANN–HHO	Adaptive learning + strong optimization, robust under uncertainty	Requires training + optimization tuning	Voltage/frequency stability
RSA–AO	Fast convergence with accuracy, multi-objective handling	Computationally heavy	Optimal energy management, reliability improvement

D. Comparative Analysis of Control and Optimization Strategies

Conventional methods, such as PI, PID, Fuzzy, and ANN, are simple, easy to implement, and quite useful for basic control tasks. However, their performance would be often limited under nonlinear dynamics and uncertain operating conditions. For instance, PI/PID controllers rely on accurate tuning and show limited robustness in the case of weak grids, while fuzzy and ANN-based controllers are more adaptable but depend on rules set or training data [17, 19].

Metaheuristic optimization methods such as PSO, GA, DE, HHO, ALO, RSA, and WOA have proved to be the most appealing and efficient methods for performance enhancement in microgrids. These methods have excellent global search capabilities and flexibility for multi-objective optimization problems, making them suitable for MPPT, energy scheduling, and voltage/frequency controlling. Nevertheless, these algorithms can be computationally exhaustive and, in some scenarios, may suffer from premature convergence [22, 24, 28].

Hybrid methods combine the advantageous properties of both conventional controllers and metaheuristic algorithms to arrive at a general well-adaptability-stability-optimization efficiency solution. Fuzzy-PSO, ANN-HHO, and RSA-AO methods show much improved performance in uncertain situations, in accelerating MPPT tracking or voltage/frequency stability improvement. Even if they result in some more computational complexity, this remains the most promising trend for a reliable and resilient hybrid solar microgrid-operation [19], [22], [29].

So, it is evident from the discussion that conventional methods work for simpler cases, metaheuristic are better for optimizing under uncertainties, and hybrid approaches provide the best compromise between adaptability and efficiency, especially in the complex and dynamic environment of the microgrid.Table V provides a comparative analysis

Table V. Comparative Analysis of Performance Indicators

Method Type	Robustness	Response Time	Overshoot	Convergence
Conventional (PI/PID/Fuzzy/ANN)	Moderate (limited under uncertainties)	Fast (PI/PID), Moderate (Fuzzy/ANN)	Higher in nonlinear conditions	Stable but depends on tuning
Metaheuristic (PSO, GA, DE, HHO, AO, RSA, WOA, etc.)	High (handles uncertainties well)	Moderate to Slow (depends on population size)	Low (optimized control reduces overshoot)	Good global convergence, but risk of premature convergence
Hybrid (Fuzzy–PSO, ANN–HHO, RSA–AO, etc.)	Very High (combines adaptability + optimization)	Fast to Moderate (depends on algorithm)	Very Low (robust optimization + adaptive learning)	Strong global convergence with reduced risk of local optima

From the performance indicators summarized in Table IV, it is evident that conventional controllers offer fast response times but exhibit limited robustness under uncertainties and tend to produce overshoot in nonlinear operating conditions [18]. Metaheuristic approaches significantly improve robustness and minimize overshoot by optimizing control parameters; however, they often involve higher computational effort and longer convergence times [23]. Hybrid approaches combine the adaptability of intelligent control with the global optimization ability of metaheuristic, thereby achieving superior robustness, reduced overshoot, and strong convergence characteristics. This balance makes hybrid strategies the most effective for ensuring reliable operation of hybrid solar microgrids under dynamic and unstable conditions [25], [29].

VIII. REAL-TIME DIGITAL SIMULATION (RTDS) AND HARDWARE-IN-THE-LOOP (HIL)

The increasing complexity of hybrid solar microgrids necessitates advanced validation techniques that go beyond conventional offline simulations. Real-Time Digital Simulation (RTDS) has emerged as a powerful tool for assessing the dynamic behavior of microgrids under realistic operating conditions with millisecond-level accuracy [27]. Unlike static simulations, RTDS enables continuous real-time testing of control strategies, capturing nonlinearities, fast switching transients, and communication delays that strongly influence system stability. In parallel, Hardware-in-the-Loop (HIL) testing provides a practical bridge between simulation and real deployment by integrating actual hardware controllers with a simulated power system environment [28]. This approach minimizes implementation risks, reduces development costs, and ensures that controllers such as coordinated STATCOM–ESS regulators or AI-driven optimizers perform reliably under diverse grid conditions. Recent studies highlight that RTDS–HIL platforms not only enhance controller robustness but also facilitate adaptive tuning for reduced overshoot and faster transient response [29]. Future research is expected to combine RTDS/HIL frameworks with AI-enabled predictive control and IoT-based monitoring systems, thereby creating a comprehensive digital twin environment that supports resilient, autonomous, and self-healing microgrids [30].

IX. RESEARCH GAPS

Despite of considerable research conducted toward the control and optimization of hybrid solar microgrids, challenges remain unaddressed. Conventional controllers such as PI and PID are simple with fast responses but have restricted adaptability to nonlinear and uncertain grid conditions. This leads to degradation in their performance during dynamic disturbances [12]. Intelligent methods, such as Fuzzy and ANN, enhance adaptability but are highly dependent on a set of predefined rules and/or training data, severely limiting scalability to generalize to unseen operating conditions [15].

An increase in research, particularly on metaheuristic algorithms such as PSO, GA, DE, HHO, AO, RSA, and WOA, has grown primarily due to their global search function and robustness against uncertainties [18]. Nevertheless, they suffered from high computation burden and are impractical for real-time application unless simplified or aided with hardware acceleration [20].

Premature convergence and trapping into local optima would still remain to be an issue for many algorithms when operating in dynamic environments, leading to compromises on the stability and energy management solutions [22].

Hybrid approaches, namely, combining adaptability with global optimization by means of Fuzzy-PSO, ANN-HHO, and RSA-AO, have shown promise [25]. However, the majority of these studies remain restricted to simulation-level validation, with exceedingly few extending to hardware-in-the-loop (HIL) or field-scale implementations [27]. Moreover, while the majority of existing works are focusing on MPPT under steady-state operation, much less attention has been paid to enhancing the resilience of such systems under disturbances like sudden irradiance variations, load fluctuations, or weak grid scenarios [28]. The integration of advanced energy storage systems, more specifically hybrid battery-super capacitor configurations with coordinated STATCOM control, still remains largely unexplored, creating gaps to reliable stability and frequency-voltage regulation [29].

X. CONTRIBUTION OF THIS REVIEW

Most important of all, this review gives a complete comparative study of control and optimization strategies for PV-integrated hybrid microgrids, emphasizing STACOM–ESS coordinated operation. Unlike other reviews that considered only conventional controllers or straight forward metaheuristic approaches, this review identifies their classification into three categories: classic approaches (PI, PID, Fuzzy, ANN), metaheuristic algorithms (PSO, GA, DE, HHO, AO, RSA, WOA, etc.), and hybrid optimization frameworks.

Performance indicators like robustness, response time, overshoot, and convergence are used for an organized comparative evaluation, which makes intuitive feasibility assessments for a plethora of microgrid scenarios. Furthermore, the review pools research gaps focusing on constraints in existing algorithms related to adaptability, real-time implementations, and resilience under uncertain conditions.

So, eventually, this review presented a conceptual research roadmap for the future, including the fusion of AI/ML-based predictive control with RTDS/HIL validation and hybridization among these metaheuristic. Thus, it is not only a structured survey from the past to the present regarding methods but also a forward-looking perspective that researchers and practitioners would require in developing autonomous, resilient, and self-healing PV–STATCOM–ESS microgrids.

XI. FUTURE TRENDS AND RESEARCH DIRECTIONS

The development of hybrid solar microgrids finds a deep nexus with the embrace of new-age technologies that bolster their adaptability, intelligence, and resilience. In this regard, the futuristic possibility of integration of Artificial Intelligence (AI) and Machine Learning (ML) into predictive optimization frameworks is most promising. Unlike full-logic-oriented or metaheuristic approaches, AI/ML-powered models can tap into historical and real-time data to predict renewable generation, load demand, and disturbances in the grid, thus enabling a measure of predictive control aimed at lessening overshoot and bettering dynamic stability [27].

Simultaneously, RTDS and HIL platforms are gaining in popularity for the validation of microgrid control strategies under practically relevant operating conditions. RTDS provides millisecond-level accuracy in simulating system dynamics, whereas HIL provides a test bed for hardware controllers against simulated environments, therefore reducing risks in deployment and improving the robustness of the controller [28]. These platforms are expected to be the basis for digital twins of PV-STATCOM-ESS microgrids for adaptive control and automated fault recovery.

Another area in need of attention is cyber-physical resilience; the integration of distributed controllers, together with communication links and IoT devices exposes the microgrids to vulnerabilities such as cyber attacks, data manipulation, and communication delays. The focus of research, increasingly, will be on developing intrusion detection systems, resilient control algorithms, and self-healing architectures, which will ensure secure and reliable operation under physical and cyber disturbances [29].

At the end, IoT-Block chain-enabled optimization brings in another route for decentralized energy management. While IoT acts as an enabler for collecting fine-grained data and remote control, Block chain provides a secure and transparent means for energy transactions, peer-to-peer (P2P) trading, and distributed optimization. If these become combined with AI-enabled controllers, autonomous and market-responsive microgrids behaving seamlessly in grid-connected or islanded modes might become viable [30].

In sum, these emerging directions of AI and ML, RTDS and HIL, cyber-physical resilience, and IoT and Block chain integration indicate a transition from old paradigms of optimization toward intelligent, adaptive, and secure control ecosystems, ensuring that the hybrid solar microgrids are resilient, efficient, and self-sustaining in the future

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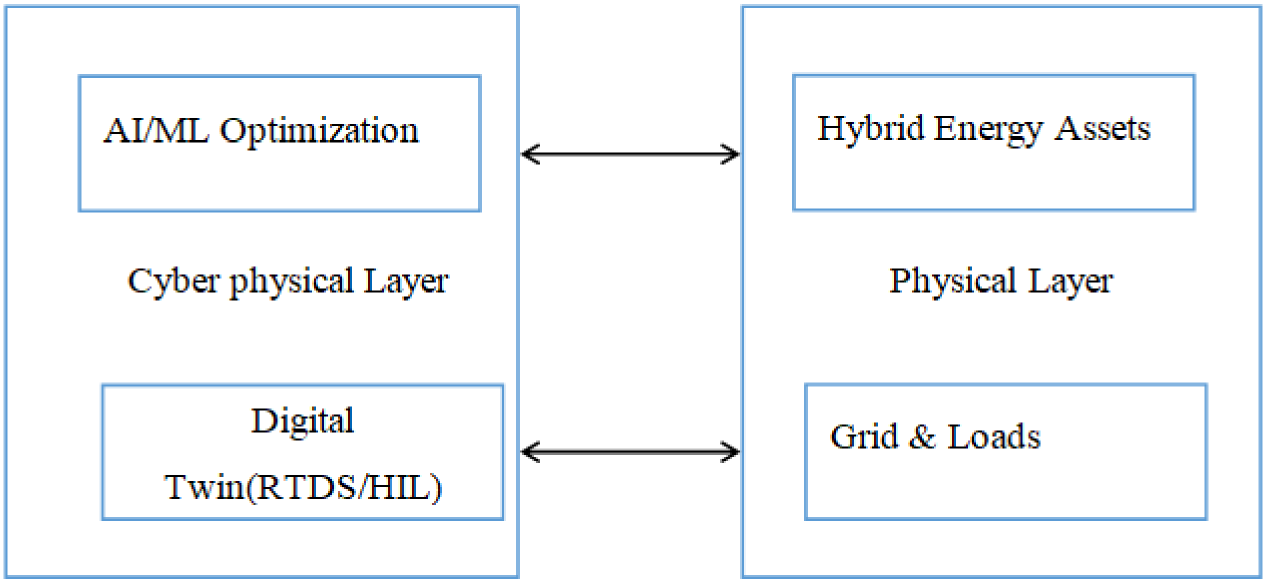

Fig.10. Cyber & Physical Layer Integration

TABLE VI SOME**ACTUAL REAL-WORLD IMPLEMENTATIONS OF HYBRID SOLAR MICROGRIDS**

Location / Project	Details	Source
Ta'u Island, American Samoa	Microgrid with 1.4 MW solar PV + 6 MWh Tesla batteries; provides nearly 100% of island's power needs	(wired)
Moapa Southern Paiute Reservation, Nevada, USA	Solar-hybrid microgrid with PV, battery storage, and diesel generators powering tribal facilities	(Wikipedia)
Fekola Gold Mine, Mali	Off-grid hybrid power station: 30 MW solar, 17.3 MW/15.4 MWh battery, 68 MW thermal backup	(Wikipedia)
Calistoga Resiliency Center, Napa County, USA	Microgrid with lithium-ion battery + hydrogen fuel cells; serves ~5,000 people during outages	(Wikipedia)
Blue Lake Rancheria, California, USA	Tribal microgrid with solar and battery; powers casino/hotel and ensures resilience during outages	Reddit
Bridport (UK) & Community Initiatives (USA)	Pilot home microgrids combining PV, batteries, heat pumps in community/individual settings	Financial times
Laguna Grande, Paracas Reserve, Peru	Rural hybrid PV–wind microgrid with battery, serving ~90 residents without grid access	Frontiers .arXiv
UAE Remote Housing Microgrid	PV–diesel hybrid microgrid (no batteries) supplying off-grid residential complex in Abu Dhabi	(Wikipedia)

XII. CONCLUSION

The review has presented a detailed comparative study on classical, heuristic, and hybrid control optimization strategies employed in PV-ESS-STATCOM integrated microgrids. Classical controllers like PI, PID, fuzzy logic, and ANN were easy to use and implement; therefore, they were favored, which made them widely applied; however, these controllers did not perform well under uncertain and nonlinear conditions. This is where metaheuristic, such as PSO, GA, DE, HHO, RSA, AO, and WOA, have entered the picture as powerful techniques with a robust and flexible framework for solving multi-objective control problems. Hybrid methods, which combine conventional and metaheuristic methods, have shown excellent adaptation and convergence capabilities that are particularly useful under dynamic and uncertain grid conditions.

The comparative performance analysis shows that whereas metaheuristic are strong on convergence and global search ability, classical techniques, on the other hand, are still very important when it comes to fast response and simplicity.

Hybrid methods carry the merit of increasing robustness, decreasing overshoot, and improving dynamic stability. Yet the challenges of scalability, real-time implementation, and integration with cyber-physical systems remain.

The rapid rise in desirability of this technology is illustrated by the installation of PV-based hybrid microgrids across the world from remote locales like Taʻu Island (American Samoa) to industrial sites like the Fekola Gold Mine (Mali) and community resilience centers in the United States. The technologies could however be a success only if suitable control and optimization strategy choices are exercised.

REFERENCES

[1] E. D. Gomez Anccas, C. A. Hans, and D. Schulz, "Microgrid operation control with adaptable droop gains," arXiv preprint, arXiv:2506.15192, Jun. 2025.

[2] K. Victor Sam Moses Babu, P. Chakraborty, and M. Pal, "Demand response optimization MILP framework for microgrids with DERs," arXiv preprint, arXiv:2502.08764, Feb. 2025.

[3] N. Khosravi, "Finite-Time control scheme for effective voltage and frequency regulation in networked microgrids," International Journal of Electrical Power & Energy Systems, vol. 165, p. 110481, 2025.

[4] N. Khosravi, "Enhancing operational efficiency through a control-based approach for hydrogen and battery energy storage systems integration in renewable energy networks," Renewable Energy, vol. 248, p. 123132, 2025.

[5] Haritha Inapagolla; R Ashok Bakkiyaraj; Katragadda Swarnasri, "Metaheuristic Optimization of MPPT Controller for Grid-Connected Hybrid Photovoltaic and Wind Distributed Generation System – A Comprehensive Review," in Proc. IEEE Int. Conf. Sustainable Energy Systems, 2025, pp. 45–52.

[6] Feraoun,Habib; Fazilat, Mehdi; Dermouche, Reda; Bentouba, Said; Tadjine, Mohamed; Zioui, Nadje, "Quantum maximum power point tracking (QMPPT) for optimal solar energy extraction," Systems and Soft Computing, vol. 7,p. 100080, Dec. 2024.

[7] Afifa Akter, Ehsanul Islam Zafir, Nazia Hasan Dana, Rahul Joysoyal , Subrata K. Sarker ,Li Li, S M Muyeen, Sajal K. Das, Innocent Kamwa "A review on microgrid optimization with meta-heuristic techniques: Scopes, trends and recommendation," Energy Strategy Reviews, vol. 51, p. 101213, Jan. 2024.

[8] Aykut Fatih Güven, Nuran Yörükeren, Onur OzdalMengi "Multi-objective optimization and sustainable design: performance comparison of metaheuristic algorithms," Neural Computing and Applications, vol. 36, pp. 22345–22367, 2024.

[9] S Mohanty, M.R Nayak, and A. Gantayet, "Efficient allocation of energy storage and renewable energy system for performance and reliability improvement of distribution system," Computers & Electrical Engineering, vol. 119, p. 109616, 2024.

[10] Akvile Giedraityte, Sigitas Rimkevicius, Mantas Marciukaitis,VirginijusRadziukynas,Rimantas Bakas, "Hybrid Renewable Energy Systems—A Review of Optimization Approaches and Future Challenges,"Applied Sciences, vol. 15, no. 4, p. 1744, 2024.

[11] Fulong Yao, Wanqing Zhao, Matthew Forshaw, Yang Song "A Holistic Power Optimization Approach for Microgrid Control Based on Deep Reinforcement Learning," arXiv preprint, arXiv:2403.01013, Mar. 2024.

[12] Kaidi Huang, Lin Cheng, Ning Qi, David Wenzhong Gao, Asad Mujeeb, Qinglai Guo, "Prediction-Free Coordinated Dispatch of Microgrid: A Data-Driven Online Optimization Approach," arXiv preprint, arXiv:2407.03716, Jul. 2024.

[13] Yihui Qiu, Xiaoxiao Yang & Shuixuan Chen"An improved gray wolf optimization algorithm solving to functional optimization and engineering design problems"Scientific Reports, vol. 14, p. 8509, Jun. 2024.

[14] Nabil A.S. Elminshawy, Osama Elbaksawi, Sodfa Diab, Ali M. Eltamaly"Innovative metaheuristic algorithm with comparative analysis of MPPT for floating PV system," Scientific Reports, vol. 14, p. 1156, Jan. 2024.

[15] A. O Salau,Girma Kassa Alitasb "MPPT efficiency enhancement of a grid-connected solar PV system using finite-control-set model predictive controller," Heliyon, vol. 10, p. e27663, 2024.

[16] N. P. Gupta, P. Gupta, P. Paliwal, N. Thakkar, and K. Deepa, "Design of universal control structure for regulation of voltage and frequency in hybrid microgrid," IETE Journal of Research, vol. 70, no. 11, pp. 8211–8231, 2024.

[17] Youssef Mhanni' Youssef Lagmich, "Adaptive metaheuristic strategies for optimal power point tracking in photovoltaic systems under fluctuating shading conditions," EPJ Photovoltaics,2024.

[18] A.K Sharma, R.K. Pachauri, Sushabhan Choudhury, Ahmad Faiz Minai"Role of Metaheuristic Approaches for Implementation of Integrated MPPT-PV Systems: A Comprehensive Study,"Mathematics, vol. 11, no. 2, p. 269, 2023.

[19] Swetha K.T, Barry Venugopal Reddy and Abin Robinson. "An innovative grey wolf optimizer with Nelder–mead search method based MPPT technique for fast convergence under partial shading conditions"Sustainable Energy Technologies and Assessments 59(4):103412Oct. 2023.

[20] Ibrahim AL-Wesabi, Fang Zhijian, Wei Zhiguo , Khaled Ameur , AbdullrahmanA. Al-Shamma'a Abdullah M. Al-Shaalan "Dynamic global power extraction of partially shaded PV system using a hybrid MPSO-PID with anti-windup strategy," Engineering Applications of Artificial Intelligence, vol. 126, p. 106965, 2023.

[21] L. Zaghba, A. Borni, M. Benbitou. "Enhancing grid-connected photovoltaic system performance with novel hybrid MPPT technique in variable atmospheric conditions," Energies, vol. 16, no. 8, p. 3157, Apr. 2022.

[22] J. A. Salim, B. M. Albaker, M. S. Alwan, and M. Hasanuzzaman, "Hybrid MPPT approach using cuckoo search and grey wolf optimizer for PV systems under variant operating conditions," Global Energy Interconnection, vol. 5, p. 627, 2022.

[23] François Pacaud, Pierre Carpentie, Jean-Philippe Chancelier, Michel De Lara "Optimization of a domestic microgrid equipped with solar panel and battery: Model Predictive Control and Stochastic Dual Dynamic Programming approaches"ResearchgateMay 2022.

[24] Mohamed Sobhy, Hany M. Hasanien,Almoataz Y. Abdelaziz,Mohamed Ezzat "Manta ray foraging optimization algorithm-based load frequency control for hybrid modern power systems" IET Renewable Power GenerationFeburary 2022

[25] Ali M. Eltamaly, "Improved Cuckoo Search Algorithm for MPPT under partial shading," Energies, vol. 14, no. 9, p. 2497, February 2021.

[26] Daniel J. B. Harrold, Jun Cao, Zhong Fan, "Renewable energy integration and microgrid energy trading using multi-agent deep reinforcement learning," arXiv preprint, arXiv:2111.10898, Nov. 2021.

[27] Nahar Alshammari, Johnson Asumadu, "Optimum unit sizing of hybrid renewable energy system using harmony search, Jaya and PSO," Sustainable Cities and Society, vol. 62, p. 102399, 2020.
[28] Adeel Feroz Mirza, Majad Mansoor,Qiang Ling and Baoqun Yin. "A Salp-Swarm Optimization based MPPT technique for PV systems under partial shading," Energy Conversion and Management, vol. 221, p. 113217, 2020.
[29] Yashwant Sawle, S.C. Gupta, Aashish and Kumar Bohre, "Socio-techno-economic design of hybrid renewable energy system using optimization techniques," Renewable Energy, vol. 201, pp. 445–457, 2018.
[30] Satyajit Mohanty; Bidyadhar Subudhi; Pravat Kumar Ray, "New MPPT using Grey Wolf Optimization under partial shading," IEEE Transactions on Sustainable Energy, vol. 7, no. 1, pp. 327–335, Jan. 2016.