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Review

Optimization Techniques for Low-Level Control of DC–AC Converters in Renewable-Integrated Microgrids: A Brief Review

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Abstract: The optimization of low-level control for DC–AC power converters is crucial for enhancing efficiency, stability, and adaptability in modern power systems. With the increasing penetration of renewable energy sources and the shift toward decentralized grid architectures, advanced control strategies are needed to address challenges such as reduced system inertia and dynamic operating conditions. This paper provides a concise review of key optimization techniques for low-level control, highlighting their advantages, limitations, and applicability. Additionally, emerging trends, such as artificial intelligence (AI)-based real-time control algorithms and hybrid optimization approaches, are explored as potential enablers for the next generation of power conversion systems. Notably, no single optimized control technique universally outperforms others, as each involves trade-offs in mathematical complexity, robustness, computational burden, and implementation feasibility. Therefore, selecting the most appropriate control strategy requires a thorough understanding of the specific application and system constraints.

Keywords: applications of control; grid-forming converters; grid-following converters; LMIs; adaptive control; model predictive control; genetic algorithms; particle swarm optimization; AI based

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1. Introduction

Over the past decades, significant changes have occurred in how humanity generates and consumes energy. While the transition from fossil fuels to renewable energy sources (RESs) has not progressed as rapidly as some researchers and energy experts predicted, the global energy matrix is steadily shifting. Increasing efforts are being made to promote RES adoption, aiming for cleaner energy generation and mitigating climate change [1,2]. In this transition, microgrids and RESs play a crucial role, offering mutual benefits such as enhanced energy independence, improved reliability, reduced carbon footprint, and greater system flexibility [3,4].

Although microgrids are often considered a modern concept, their origins date back to Thomas Edison's Pearl Street Station in New York City (1882) [5], which functioned as an early microgrid before the centralized power grid existed [6]. However, substantial research into microgrids gained attention in the late 20th century, largely driven by advancements in RESs. While fossil fuels have dominated electricity generation since the adoption of electrical energy, the 1980s saw a rise in combined heat and power (CHP) systems and widespread adoption of nuclear power [7,8]. Hydropower, although extensively used, remained geographically constrained [9]. After the 2000s, interest in RESs such as solar, wind, geothermal, and biomass grew significantly, shifting focus toward islanded power systems (operating independently from the main grid) and early renewable-based microgrids [10,11]. Even though RESs generally have a lower environmental impact than conventional power generation, transitioning to an energy matrix entirely based on renewables remains a significant challenge due to geographic constraints, intermittency, and low system inertia [12,13]. Additionally, to establish a power system based on RESs, the load profiles, generation capacities, and energy storage requirements must be carefully evaluated to optimize the use of electrical energy. Nevertheless, the increasing penetration of RESs and the adoption of microgrids to at least support the main grid have been notable trends in recent years [14,15]. Figure 1 presents a simplified diagram of a microgrid.

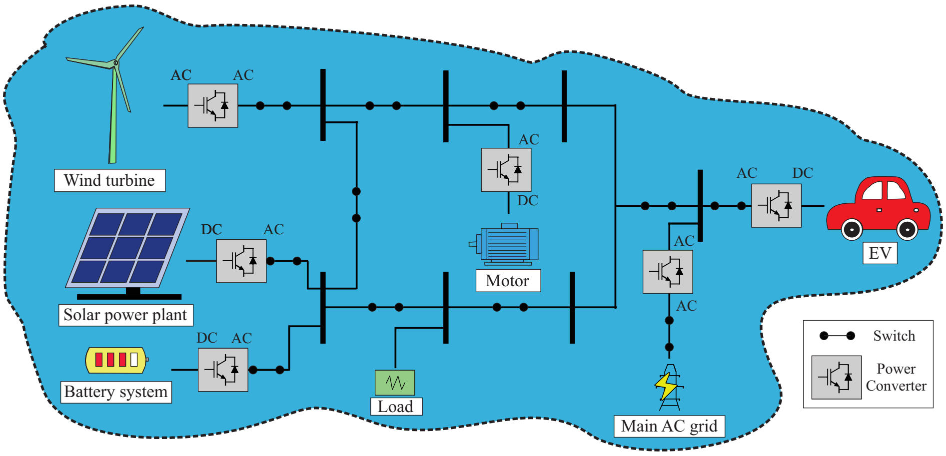
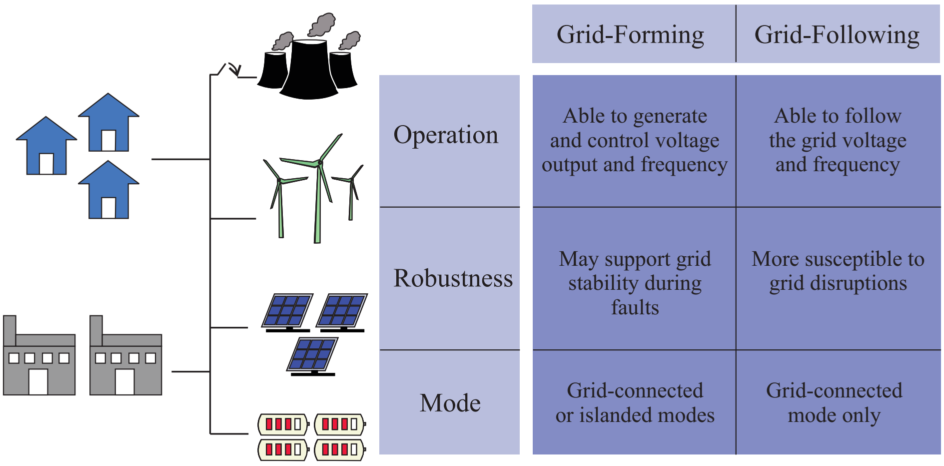


Figure 1. Microgrid simplified diagram.

Recently, several natural disasters have underscored the vulnerabilities of traditional power grids. One notable example is the failure of Texas's power grid in 2021, which resulted in one of the most severe energy crises in U.S. history, leaving millions without power for days in freezing temperatures [16]. Such events highlight the critical role of microgrids in providing reliable power during outages. As commented earlier, since microgrids can operate in island mode; this makes them ideal for integrating localized renewable energy sources such as solar, wind, and hydro, helping to provide power when the main grid suffers any kind of issue [17]. This capability enhances energy independence and reliability, particularly in the face of grid failures and extreme conditions. Additionally, microgrids can efficiently manage and balance energy from renewable sources by storing excess energy in batteries and releasing it when needed [18,19]. This optimizes renewable energy usage, reduces waste, and tends to enhance overall grid resilience. It is evident that when microgrids start to integrate different types of RESs together, with batteries, electrical vehicles (EVs), and techniques as Vehicle-to-grid (V2G) and Vehicle-to-vehicle (V2V), their design, control, and energy management become more complex [20,21].

In order to integrate RESs, battery energy storage systems (BESSs) to manage power generation and processing as well as power converters (able to change the form of electrical energy) are largely adopted. DC–DC converters play a crucial role in microgrids by managing voltage and current levels [22,23]. Since many renewable sources, such as photovoltaic (PV) panels and batteries, operate on DC voltage, DC–DC converters are needed to regulate and adapt their output to match the required voltage levels of the microgrid. These converters can be unidirectional, as in boost converters that step up solar panel voltage, or bidirectional, such as buck–boost converters used in BESSs to facilitate both charging and discharging. In DC microgrids, DC–DC converters are essential for maintaining stable voltage levels across different loads and sources, improving efficiency and reducing power losses. DC–AC converters, or inverters, on the other way, are responsible for converting DC power from sources like PV panels and batteries into AC power, which is required for most electrical loads and grid connections [24,25]. In microgrids, DC–AC converters often operate in either grid-following or grid-forming modes, ensuring synchronization with the main grid or establishing voltage and frequency in islanded operation. When operating as grid-following (GFL), as the name says, the power converters operate by synchronizing with the main grid voltage (reference) and injecting power accordingly [26,27]. They rely on a Phase-Locked Loop (PLL) to track the grid voltage phase and frequency to connect to the grid or even adjust the output current phase angle for changing the power factor [28,29]. On the other hand, when the power converters operate in grid-forming (GFM) mode, they do not rely on the main grid for synchronization. Instead, they actively regulate voltage and frequency, behaving like a traditional synchronous generator and providing a reference for other DC–AC converters. Additionally, these grid-tied inverters (GTIs) enable microgrids to export excess renewable energy to the main utility grid, enhancing energy efficiency and reliability. Figure 2 presents an overall comparison between grid-following converters and grid-forming converters.



	Grid-Forming	Grid-Following
Operation	Able to generate and control voltage output and frequency	Able to follow the grid voltage and frequency
Robustness	May support grid stability during faults	More susceptible to grid disruptions
Mode	Grid-connected or islanded modes	Grid-connected mode only

Figure 2. Overview comparison between grid-following and grid-forming power converters.

The coordination of DC–DC and DC–AC converters [30,31] is essential for optimizing energy distribution and ensuring the stability of modern microgrid systems [32,33]. However, since DC–AC converters tend to be more complex to design, control, and implement, their modulation and control strategies tend to sometimes require complex algorithms and advanced optimization techniques for keeping the regulated currents and voltages in good shape, with low harmonic content, respecting the standards and providing stable, reliable, and high-quality energy [34,35]. In recent advancements, high-frequency AC (HFAC) microgrids have emerged as a promising alternative to traditional microgrid architectures [36]. HFAC systems utilize HFAC-to-HFAC matrix converters and HFAC-to-low-frequency (LF) converters to reduce transformer size, improve power transfer efficiency, and lower system losses. These systems are especially advantageous for decentralized energy systems that aim to enhance energy efficiency while minimizing costs. However, the integration of multiple power conversion stages in HFAC systems demands advanced control strategies to ensure stability and reliable performance. The coordination of DC–DC, DC–AC, and HFAC power conversion technologies in modern microgrids is essential for optimizing energy distribution and maintaining system integrity.

In terms of control algorithms, a microgrid control system can be divided into two main types: low-level control, which comprises both primary and secondary control, focusing on real-time power conversion, voltage and current regulation, and local stability; and high-level control, also known as tertiary control or the energy management system (EMS), which focuses on energy dispatch, economic optimization, grid interaction, and overall coordination [37,38]. Both low-level and high-level control are essential for the proper operation of a microgrid, but they can be treated as two decoupled control loops due to their differences in dynamics—low-level control typically operates with microsecond (µs) sampling times, whereas high-level control works with millisecond (ms) or second (s) sampling times. From a control perspective, low-level control requires advanced techniques due to its real-time constraints, fast-changing dynamics, and low sampling times [39,40]. Nonlinear control strategies such as Model Predictive Control (MPC) [3,41,42], sliding-mode control [43–45], and adaptive control [46–48], along with their variations and extensions, are often employed. Additionally, a significant challenge for control algorithms lies in the accurate modeling of RESs, power converters, and filters, as well as their interactions. Disturbances, noise, and sensor inaccuracies further complicate low-level control implementation, requiring robust optimized solutions [49–51].

Due to the growing interest in this research area, numerous innovative solutions are being proposed, necessitating a systematic and critical review of existing methodologies. This paper presents a concise yet technically rigorous review of optimization techniques for the low-level control of DC–AC converters in renewable-integrated microgrids. Several research articles have been critically analyzed to provide a structured assessment of current advancements, highlighting their theoretical foundations, practical implementations, and comparative performance. This review addresses key challenges in power electronics and power systems, emphasizing optimization strategies that enhance efficiency, stability, and adaptability in modern microgrids. Selected techniques will be discussed in depth, with an evaluation of their advantages, limitations, and applicability to different operating scenarios. Rather than serving as an exhaustive comprehensive survey, this brief technical review aims to benefit researchers, academics, industry professionals, and newcomers by synthesizing recent developments, identifying research gaps, and offering insights into emerging trends that shape the future of microgrids and DC–AC converter control.

This review paper is structured as follows: Section 2 discusses the key challenges in the operation and control of DC–AC converters and the need for efficient and optimized control algorithms. Section 3 provides an overview of control optimization, including concepts of local and global minima, as well as optimal and optimized techniques. Section 4 presents a comprehensive literature review of optimization techniques for DC–AC converters, highlighting the advantages, disadvantages, and main characteristics of key optimization methods for low-level control. Section 5 explores future directions and offers predictions for emerging control algorithms and optimization techniques for GTIs in the context of microgrids and power systems. Finally, Section 6 concludes the paper by summarizing the findings and their implications for improving robustness, efficiency, and energy management in renewable-integrated microgrids.

2. Key Challenges in Operation and Control of DC–AC Converters

As discussed in the last section, power converters are the backbone of modern renewable energy systems, facilitating the seamless integration of RESs into the power grid. They not only convert DC and AC power as needed but also regulate voltage, current, and frequency to maintain system stability, enhance power quality, and optimize energy efficiency. Despite significant advancements in their modeling, design, and control over the past two to three decades, practical implementation continues to face critical challenges, particularly under dynamic grid conditions and high penetration of renewables [2,52–54]. Regarding DC–AC converters for renewable-integrated microgrids—the focus of this brief review—ongoing research efforts are addressing a range of unresolved technical challenges, particularly GFL and grid-forming GFM control strategies. As explored in this section, both GFL and GFM power converters share fundamental control challenges due to their similar operational principles, yet each presents unique stability and performance considerations that must be carefully considered.

2.1. Main Challenges in Grid-Following Converters

Basically, grid-following converters operate by synchronizing with the grid voltage (reference) and injecting or extracting power accordingly, depending on the power setpoint or reference current. For this task, they rely on PLL to track the grid voltage phase and frequency, being able to connect to the grid when it is suitable [25,55].

One remarkable challenge in the operation of GFL power converters is their synchronization with weak grids. The definition of a weak grid is widely discussed in the literature, and, to date, there is no single parameter that definitively determines whether a grid is strong or weak, nor a consensus among power systems and renewable energy researchers [40,56]. In an inverter-based resource, the injected power into the grid is seen by the grid side as both active and reactive power. So, in a weak grid, the active power of a GTI becomes coupled with reactive power seen by the grid operator. The reactive power tends to increase transmission losses, reducing the maximum transmission capacity and requiring the power sources to increase their injected power to supply more active power [57–59].

It is commonly agreed upon by many authors that a short circuit ratio (SCR), a metric that considers X/R ratio and grid impedance, of less than 5 (SCR < 5) indicates a weak grid, presenting significant challenges for grid-connected structures and their energy management [56,60]. Furthermore, some authors consider that when the system's SCR is between 2 and 3 ($2 < \text{SCR} < 3$), it is in a very weak grid state. Other SCR thresholds for weak, very weak, and even extreme cases such as mountain grids or remote grids exist in the literature, but they generally rely on the SCR value: the lower the SCR, the more challenging it becomes to maintain grid stability and ensure proper power converter operation [40,61,62]. Figure 3 presents a standard DC–AC converter operating under a weak grid. Notice that as the SCR increases, the reference voltage becomes highly distorted, affecting the control system's readings and, consequently, degrading the quality of the regulated current and overall power quality.

Additionally, a major challenge in designing power converters is that even if the SCR is calculated for the electrical grid where the converter is connected, the real output impedance remains uncertain, as its value fluctuates in real time based on the voltage and current characteristics of the loads. In weak grids and similarly challenging scenarios, PLL-based synchronization algorithms become unstable, leading to oscillations and poor power quality [40,63]. Similarly, challenges arise when power converters operate in low-inertia systems. Low-inertia grids are those with significantly reduced rotational mass compared to traditional power grids. Additionally, inverters do not inherently contribute to system inertia, and the high penetration of renewable energy sources can degrade frequency stability, making grid control operations more complex. This issue is particularly common in microgrids, especially when operating in islanded mode, disconnected from the main grid, which typically relies on thermal power plants, hydroelectric systems, and other energy sources that provide high rotational inertia [64,65].

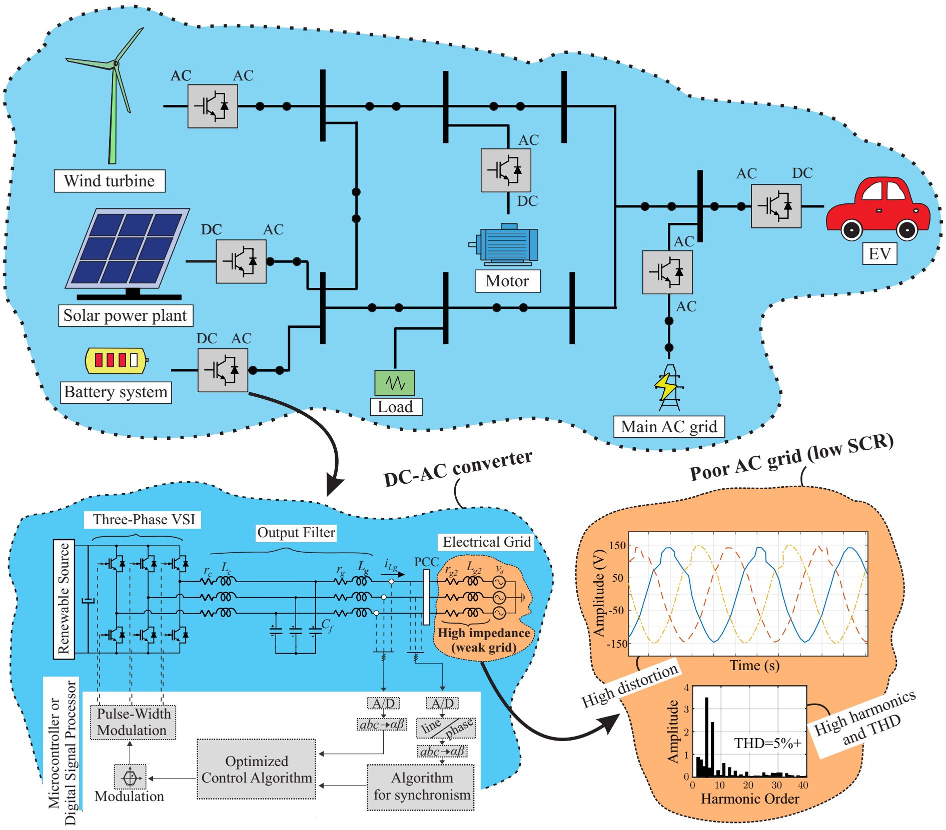


Figure 3. A general representation of a DC–AC converter operating in a weak grid scenario.

Another common issue in power converter operation is the problem of harmonics and resonance. When designing DC–AC converters for RES applications, an output filter is typically incorporated to attenuate the high-frequency switching waveform synthesized by the inverter stage, which is often generated using sinusoidal pulse-width modulation (SPWM)-based techniques [35,46]. One of the most widely used filters is the inductor–capacitor–inductor (LCL) filter, favored for its reduced weight, compact size, and superior filtering capability compared to standard L filters (−60 dB/dec attenuation in LCL vs. −20 dB/dec attenuation in L) [66,67]. Other filter configurations, such as LC, LCL-LC, T-LCL, and MLCL filters [67–71], are also possible, but the LCL filter is generally preferred to general applications due its advantages in weight, volume, and cost. While LCL-based filters provide a decent cost–benefit value, their resonance characteristics must be carefully managed to prevent instability. The primary drawback of these output filters, especially those of higher order, is their resonance. Interactions between these filters and the grid impedance can lead to harmonic amplification, necessitating active damping techniques and more precise control strategies [35]. As grid impedance increases, it adversely affects the designed filter, causing the filter's resonance—typically designed to be at least ten times higher than the grid frequency (50 or 60 Hz)—to shift toward lower frequencies [40]. If this resonance peak moves too close to lower frequencies, it creates significant control challenges, requiring highly robust control algorithms to maintain stability. Additionally, ensuring high-quality current injection into the grid, as well as accurately sampling reference voltages, is critical. Harmonics, missing samples, and quantization errors generated in these processes can be amplified and fed back into the control algorithm, further complicating system stability and regulation [35]. This makes it even more challenging to comply with stringent standards such as IEEE 1547 and IEC 61000 [72,73].

One inherent limitation of GFL converters is their reliance on the external grid voltage for synchronization, which makes their Fault Ride-Through (FRT) capability more challenging compared to GFM converters [74]. FRT is a critical feature that enables grid-connected converters to remain operational during grid disturbances, such as voltage sags or short circuits, thereby supporting grid reliability and stability. However, during such faults, GFL converters may lose synchronization, necessitating advanced control strategies, including adaptive-PLLs, to maintain power supply [74–76]. The issue extends beyond individual disconnections; it can trigger widespread disruptions. As GFL converters begin to disconnect, the overall generation capacity of the system decreases, potentially leading to a cascading failure where multiple converters shut down in succession, further destabilizing the grid and leading to possible system inertia issues and large-scale blackouts.

2.2. Main Challenges in Grid-Forming Converters

Unlike GFL converters, GFM converters do not rely on an external grid for synchronization. Instead, they actively regulate voltage and frequency, mimicking the behavior of traditional synchronous generators. This capability makes them inherently more complex than GFL converters, as they must not only generate the reference voltage for the system but also have the flexibility to operate in GFL mode when an external reference is available. Consequently, when GFM converters operate in GFL mode, they inherit all the challenges faced by conventional GFL converters [77].

A critical challenge exclusive to GFM converters is ensuring stable voltage and frequency regulation. To achieve this, they require precise droop control, virtual inertia emulation, or advanced nonlinear control techniques. The complexity of the low-level control algorithm increases because, in addition to regulating voltage and current, the system must also maintain frequency stability. If the voltage frequency, amplitude, or phase is not properly regulated, the entire microgrid can become unstable, as other GFL converters depend on GFM units for synchronization [78].

GFM converters play a crucial role in microgrid operation, particularly during transitions between grid-connected and islanded modes. Ensuring a seamless transition without large transients is a major control challenge [40,77]. When a microgrid is connected to the main grid, GFM converters synchronize with an external voltage reference. However, during islanding, they must instantaneously switch to generating their own voltage reference. If this transition is not smooth, other grid elements may disconnect, leading to potential inertia issues and overall system destabilization. From a control perspective, this is a significant challenge, as transitions should ideally occur with minimal energy disturbances to prevent overshoots, undershoots, and prolonged or unfeasible transient periods.

In multi-inverter systems, different GFM units must coordinate their frequency and voltage setpoints to prevent conflicts such as circulating currents or frequency mismatches. Usually, not all capable converters should operate in GFM mode simultaneously, as this could lead to phase discrepancies and further stability issues [79]. Typically, only a subset of converters is designated as GFM, while others operate in GFL mode. Additionally, GFM inverters must handle sudden load variations, requiring robust power-sharing mechanisms—such as droop control [80], consensus-based control [81], or secondary controllers—to maintain stability and regulation. In terms of high-level control complexity, GFM converters are significantly more demanding than GFL structures [79,82].

As discussed in the challenges faced by GFL converters, the transition from traditional synchronous generators to GFM inverters reduces overall system inertia. Implementing synthetic inertia and frequency damping techniques is essential to compensate for this loss. Like GFL converters, GFM units also face challenges in weak grids and low-inertia systems. However, their advantage lies in their ability to manage energy more effectively through advanced power-sharing and load-balancing algorithms, making them a key element in ensuring microgrid resilience and stability. Table 1 brings a summary of the discussed challenges for GFM and GFL converters.

Table 1. Comparison of challenges in GFM and GFL converters.

Challenge	GFM Converters	GFL Converters
Synchronization	Self-regulated; does not rely on an external reference	Requires external grid voltage for synchronization
Voltage and frequency regulation	Must generate and stabilize voltage and frequency	Follows grid voltage and frequency
Control complexity	Higher due to frequency control, droop control, virtual inertia, and power-sharing algorithms	Lower, as the reference is externally defined
Transition handling	Must ensure smooth transitions between grid-connected and islanded operation	Typically remains grid-connected; islanding can cause instability
Inertia and stability	Requires synthetic inertia and damping techniques to compensate for low system inertia	Contributes to inertia issues in weak grids but does not directly compensate
Load variation response	Directly responsible for stabilizing sudden load changes	Reacts to changes but relies on the grid for stability
Multi-inverter coordination	Requires precise coordination to avoid circulating currents and phase mismatches	Less critical since synchronization is externally dictated

In addition to these technical considerations, international standards play a crucial role in the successful integration of power converters in renewable-integrated microgrids. Table 2 presents an overview of key international standards relevant to the low-level control of DC–AC power converters. These standards ensure interoperability, power quality, and compliance with safety regulations. IEEE 1547 and UL 1741 define the interconnection criteria for distributed energy resources (DERs), establishing performance and testing requirements for inverters and converters. IEEE 519 sets harmonic limits, mitigating power quality issues that arise due to high-frequency switching in power electronics. For communication and system interoperability, IEC 61850 provides a standardized framework for automation and protection within microgrids. Furthermore, regional standards such as EN 50160 and EN 50549-1 specify voltage characteristics and grid connection requirements in European networks, ensuring the stable operation of renewable energy sources within distribution systems. NPR 9090, a Dutch guideline, emphasizes best practices for low-voltage DC installations, which are particularly relevant as DC microgrids gain prominence in renewable energy applications. These standards collectively establish a regulatory foundation that facilitates the reliable and efficient integration of power converters within modern microgrid infrastructures.

Table 2. Applicable international standards [83–88].

Standards	Description	Comments
IEEE 1547	Provides criteria and requirements for the interconnection of distributed energy resources with electric power systems.	Establishes uniform standards for performance, operation, testing, safety, and maintenance of interconnections. Ensures reliable integration of DERs into the grid.
IEEE 519	Defines recommended practices and requirements for harmonic control in power systems.	Specifies acceptable levels of voltage and current harmonics to maintain power quality and mitigate interference issues in microgrids.
UL 1741	Standard for inverters, converters, controllers, and interconnection system equipment for distributed energy resources.	Ensures compliance with safety and performance requirements for grid-tied inverters and converters. Often used in conjunction with IEEE 1547.
IEC 61850	Standard for communication networks and systems in substations.	Defines protocols and data models for substation automation, supporting seamless communication between protection and control devices in microgrids.
EN 50160	Specifies voltage characteristics of electricity supplied by public distribution networks in Europe.	Ensures consistency in voltage levels, waveform quality, and power frequency across different grid conditions.
EN 50549-1	Defines requirements for the connection of generating plants to distribution networks.	Focuses on grid connection of renewable energy systems up to and including Type B generation, ensuring compliance with grid stability criteria.
NPR 9090	Dutch practice guideline for low-voltage DC installations.	Provides design and safety considerations for DC microgrids, emphasizing proper isolation and protection mechanisms.

3. Overview of Control Optimization

Following the discussion on the main challenges associated with the control and operation of GFL and GFM converters, it becomes evident that control algorithms must not only be robust—capable of handling disturbances and unmodeled dynamics—but also efficient, ensuring operation as close to optimal conditions as possible. As the penetration of RESs continues to grow, the increasing reliance on DC–AC converters amplifies these challenges, requesting advanced control strategies that can address them effectively while maximizing system performance.

In control systems, the terms optimal and optimized have distinct yet closely related meanings. This section provides a brief discussion on local and global minima in optimization, followed by an overview of control optimization methodologies, distinguishing between optimal controllers and optimized controllers to clarify their respective roles in power electronics applications.

3.1. Minimizing a Function: Global Minimum and Local Minimum

In the context of optimization for control systems, understanding the difference between local and global optimization is crucial for selecting the appropriate technique when designing control algorithms. Consider the problem of finding the minimum value of a smooth function F, where $F : \mathbb{R}^n \to \mathbb{R}$. The objective is to determine a point $x^* \in \mathbb{R}^n$ such that

$$F(x^*) \leq F(x), \quad \forall x \in \mathbb{R}^n. \tag{1}$$

A necessary condition for x^* to be a minimum is that the gradient of the function vanishes at x^*, expressed as

$$\frac{\partial F}{\partial x}(x^*) = 0. \tag{2}$$

The function $F(x)$ is commonly referred to as the cost function, and x^* represents the optimal value for x, as it minimizes $F(x)$. However, minimizing a function is often challenging, especially when the cost function is complex and exhibits multiple minima. In such cases, finding the global minimum may be difficult, potentially leading to suboptimal control performance. This general concept is further detailed in [89]. In the context of power converters, optimization is frequently used to minimize the control effort (reducing computational complexity), minimize tracking errors (enhancing efficiency), or suppress harmonics in regulated signals, as previously discussed.

3.1.1. Local Optimization

Local optimization aims to find the best solution within a limited region of the search space. It does not guarantee a globally optimal solution but ensures that small variations in the solution space do not yield a better result [90,91]. In a simplified way, these algorithms' workflows are as follows: (1) a random hypothesis is generated; (2) a greedy algorithm is used to iteratively improve the hypothesis; (3) the algorithm makes small changes to the hypothesis and evaluates the change; (4) if the change improves the hypothesis, it becomes the new candidate solution. Several well-known local optimization techniques include Gradient Descent and Newton's Method. The key characteristics of these algorithms are as follows:

- Converges to a local minimum or maximum, depending on the problem.
- Performs well for convex functions where the local minimum is also the global minimum.
- Exhibits fast convergence but may become trapped in suboptimal solutions if multiple minima exist.

3.1.2. Global Optimization

Global optimization, in contrast to local optimization, aims to find the best possible solution across the entire search space rather than settling for a locally optimal one [90,91]. It is particularly crucial for non-convex, nonlinear, or complex control problems where multiple local minima exist. Unlike local optimization algorithms, which are generally simpler and faster to implement, global optimization techniques do not follow a single standardized workflow. Instead, they encompass a wide range of methodologies with diverse theoretical foundations and optimization strategies in order to increase the chance of finding the global minimum.

Examples of global optimization approaches include evolutionary-inspired algorithms such as Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO), as well as learning-based techniques like Reinforcement Learning (RL) and Bayesian Optimization. However, while these methods are designed to explore large search spaces and often provide near-optimal solutions, they do not inherently guarantee global optimality. Their performance is highly dependent on algorithm parameters, problem formulation, and convergence criteria, which can sometimes lead to suboptimal solutions in complex optimization problems. The main characteristics of these algorithms are as follows:

- Broadly explore the solution space to avoid becoming trapped in local minima.
- Typically require higher computational effort.
- Suitable for nonlinear, non-convex, or highly constrained problems.

As an illustrative example, the Ackley function is minimized using the Simulated Annealing (SA) technique, which is a well-known global optimization method. The Ackley function is a highly non-convex function commonly used as a benchmark for optimization algorithms due to its numerous local minima. It is defined according to

$$f(x) = -a \exp\left(-b\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(cx_i)\right) + a + \exp(1), \tag{3}$$

where a, b, and c are predefined constants and here were considered as $a = 20$, $b = 0.2$, and $c = 2\pi$.

The SA technique was configured with the following parameters: an initial temperature of 50, a cooling rate of 0.95, and a maximum of 1000 iterations. The search space was constrained between -10 and 10. Figure 4 presents the solution exploration and the fitness function. It can be observed that the system converged approximately after 75 iterations, with the algorithm consistently refining its result by minimizing $f(x)$. Eventually, the global minimum was found at $x^* = 0$, where $f(x^*) = 0$.

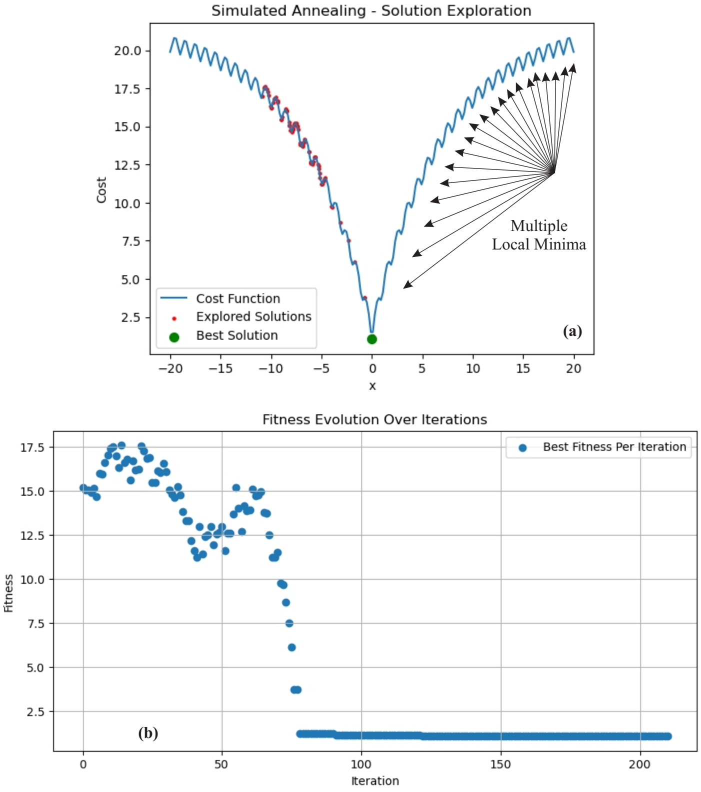


Figure 4. Minimization of Ackley function (3) using Simulated Annealing technique. (**a**) Optimization result; (**b**) fitness function.

3.1.3. Key Differences Between Local and Global Optimization

Table 3 summarizes the main differences between local and global optimization.

Table 3. Comparison of local and global optimization techniques.

Aspect	Local Optimization	Global Optimization
Search Scope	Limited to a local region	Searches the entire solution space
Convergence Speed	Fast for convex functions	Typically slower due to broader search
Risk of Becoming Stuck	High (in local minima)	Lower (designed to escape local minima)
Computational complexity	Lower	Higher
Suitable Problems	Convex and smooth functions	Nonlinear, non-convex, and complex problems
Example Methods	Gradient Descent, Newton's Method	Genetic Algorithms, Particle Swarm, Reinforcement Learning

3.2. Optimal Controllers

Optimal control refers to a control strategy designed to achieve the best possible performance according to specific criteria and the desired system behavior. It is typically obtained mathematically using techniques such as the Calculus of Variations, Pontryagin's Maximum Principle (PMP), or Dynamic Programming (Bellman's Principle of Optimality). Dynamic Programming is both a mathematical optimization method and an algorithmic paradigm. The method was developed by Richard Bellman in the 1950s and has been applied in various fields, including aerospace, control engineering, and even economics [92,93]. In mathematical optimization, Dynamic Programming typically involves simplifying a decision-making process by breaking it down into a sequence of decision steps over time and solving it recursively. Optimal control techniques also include the Linear Quadratic Regulator (LQR) and Model Predictive Control (MPC), where a cost function (e.g., minimizing tracking errors, control effort, or energy consumption) is explicitly optimized. In these cases, the controller's performance is optimal for the defined application. However, this does not mean it is the best possible controller in a broader sense, but rather that it performs optimally within the given scenario and constraints [89,94].

For clarification of the optimal control problem in a general way, consider

$$\min_{u(\cdot)} \int_0^T L(x,u)\,dt + V(x(T)), \tag{4}$$

where $u(\cdot)$ represents a control function, meaning u is not a single value but a function of time. The term $L(x,u)$ is commonly referred to as the integral cost, while $V(x(T))$ is the terminal cost. The integral cost is typically chosen to be non-negative and penalize certain undesirable states or specific conditions. Furthermore, (4) is subject to the following constraint:

$$\dot{x} = f(x,u), \quad x \in \mathbb{R}^n, \quad u \in \mathbb{R}^m. \tag{5}$$

In the field of mathematical optimization, a constrained optimization problem involves optimizing a specific objective function subject to given constraints. Thus, (4) and (5) characterize a constrained optimization problem, in which the objective is to find a feasible trajectory $(x(t), u(t))$ that minimizes the following cost function:

$$J(x,u) = \int_0^T L(x,u)\,dt + V(x(T)). \tag{6}$$

This optimization problem is equivalent to the general problem of minimizing a cost function $J(x, u)$, where $(x, u) \in L_2[0, T]$ and $h(z) = \dot{x}(t) - f(x(t), u(t)) = 0$ models the system dynamics. Several approaches have been proposed to solve this optimization problem, such as the infinite horizon (if $T = \infty$ and $V = 0$, optimizing a cost function over all time) and the finite horizon (when $T < \infty$) optimal controllers. These formulations have led to the development of MPC, which can be found in both finite [95] and infinite horizon forms [96]. Additionally, if the dynamical system is linear (or can be linearized) and the cost function is quadratic, the resulting controller is the linear quadratic optimal regulator, commonly known as the LQR [97].

The objective of this paper is not to delve deeply into the mathematical foundations of these controllers but to provide an overview of the most recent optimization techniques for low-level control of DC–AC power converters. For a more detailed discussion on these optimal controllers, including stability analysis and mathematical formulations, the reader is referred to [89,94].

3.3. Optimized Controllers

On the other hand, optimized control refers to a control strategy that has been improved through numerical or heuristic optimization techniques, though it may not necessarily be globally optimal. In other words, there is no mathematical assurance that the found solution is optimal. This approach includes techniques such as heuristic or metaheuristic algorithms, such as GA, PSO, and SA. Additionally, learning-based methods like RL, which fine-tune control parameters based on observed performance rather than solving an explicit optimal control problem, are also common choices for the fine-tuning of control algorithms [40,50,98]. In this sense, even classical PI or PID controllers—despite not being inherently optimal—can benefit from optimization techniques. A control structure often confused with optimal control is adaptive control, more specifically direct adaptive control, which often uses gradient-based algorithms to tune parameters. While these controllers minimize a cost function at each time step to regulate the system ($\boldsymbol{\theta}$ update in order to find $\boldsymbol{\theta}^*$), this does not imply that they find the globally optimal gains for a given application, since they perform local real-time optimization rather than global optimization, as they adjust parameters based on local gradient information rather than searching the entire parameter space.

4. Literature Review on Optimization Techniques for DC–AC Converters

After presenting the main differences between global and local optimization as well as optimal and optimized controllers, this section reviews recent advancements in optimization techniques for low-level control of DC–AC converters. While some of the selected studies are not directly applied to microgrid environments, their methodologies exhibit strong potential for RESs, as highlighted by their respective authors. This review provides insights into the latest optimization approaches, examining their applicability, complexity, benefits, and limitations in the context of power electronics and control systems.

4.1. Most Common Techniques for Low-Level Control of DC–AC Converters

Control optimization involves both optimal and optimized controllers, aiming to improve the performance, efficiency, and robustness of DC–AC converters. This process systematically adjusts control parameters or designs controllers to minimize steady-state error, reduce total harmonic distortion (THD), enhance dynamic response, and maintain stability across varying operating conditions (including weak and low-inertia power grids).

Traditional control techniques, such as PI and PID controllers, rely on predefined tuning rules or mathematical formulations. However, these methods may be suboptimal for highly nonlinear systems, as they may do not explicitly account for real-time system variations, constraints, or disturbances. To address these limitations, various new control structures and optimization methodologies have been employed to refine control performance (even for those PI and PID structures). These optimizations can be run offline or online, depending on each technique.

Broadly, control optimization techniques for DC–AC converters can be classified into three main categories: model-based optimization, heuristic and metaheuristic optimization, and data-driven and AI-based optimization, which will be discussed in the following sections.

4.1.1. Model-Based Optimization

These methods leverage mathematical models of the system to determine optimal control strategies. Examples include linear and nonlinear MPC, Linear Matrix Inequalities (LMIs), and extremum-seeking control. Convex optimization and mathematical programming techniques are often combined with these approaches. Additionally, special cases such as direct adaptive control algorithms, where the optimization is performed implicitly through adaptation laws to adjust control parameters, are also categorized here due to their model-based behavior. Some of the key techniques will be briefly discussed below.

Model Predictive Control

The objective of MPC is to minimize a cost function over a finite prediction horizon, subject to system dynamics and constraints. As discussed in Section 3.2, the general optimal control problem (given by Equations (4)–(6)) can be defined over an infinite or finite time horizon and may include constraints. MPC, in particular, applies finite-horizon optimization in a discrete-time setting, making real-time implementation feasible.

A general optimization formulation for MPC in discrete time is given by

$$\min_{u} \sum_{k=0}^{N-1} \left[\|y(k)) - y_{ref}(k)\|_Q^2 + \|u(k)\|_R^2 \right], \tag{7}$$

subject to system dynamics (in state-space form), as

$$x(k+1) = \boldsymbol{A}x(k) + \boldsymbol{B}u(k), y(k) = Cx(k), \tag{8}$$

and constraints on states and inputs, which leads to

$$x_{min} \le x(k) \le x_{max}, u_{min} \le u(k) \le u_{max}, \tag{9}$$

where the following are true:

- $u(k)$ is the control input and $y(k)$ is the system output;
- $y_{ref}(k)$ is the reference signal;
- Q and R are weighting matrices;
- N is the prediction horizon;
- x is the system state, and $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{C}$ define the system dynamics.

Note that the minimum and maximum values in (9) are the system constraints and define the boundaries of the control problem. By continuously solving this optimization problem in real time, MPC provides a flexible and robust control strategy, effectively handling constraints and optimizing system performance under uncertainty. Recently, new MPC-based controllers were proposed for dealing with DC–AC converters, such as in [99–101].

Linear Matrix Inequalities

LMIs play a fundamental role in modern control theory and the optimization of control, and LMI-based controllers are often applied in low-level control of DC–AC converters in renewable-integrated microgrids. An LMI is generally expressed as:

$$\mathbf{F}(\mathbf{x}) = \mathbf{F}_0 + \sum_{i=1}^{m} x_i \mathbf{F}_i \preceq 0, \tag{10}$$

where the following are true:

- $\mathbf{x} = [x_1, x_2, \ldots, x_m]^T$ is the decision variable vector;
- $\mathbf{F}_0, \mathbf{F}_i$, ..., $\mathbf{F}_m$ are symmetric matrices of appropriate dimensions;
- $\preceq 0$ denotes negative semi-definiteness, ensuring $\mathbf{F}(\mathbf{x})$ is negative semi-definite.

LMIs arise in control applications such as the following:

- Stability analysis: using the Lyapunov function approach, system stability can be formulated as an LMI feasibility problem;
- Robust control: designing controllers that guarantee stability and performance under uncertainties, e.g., H_∞ and H_2 control;
- State-feedback and observer design: finding gain matrices that satisfy performance and stability constraints.

The advantage of LMI-based methods is that they transform complex control problems into convex optimization problems, which can be efficiently solved using semi-definite programming (SDP). Due to their convex nature, LMIs provide globally optimal solutions, making them a powerful tool for applications of control in DC–AC power converters. Recently, H_∞- and H_2-based controllers for dealing with power converters under severe uncertain dynamics have emerged, such as in [74,102,103].

Adaptive Control

Direct adaptive controllers, which rely on a reference model to dictate the system dynamics, are implemented with an adaptive mechanism that adjusts the controller gains to reduce the regulation error. The adaptation algorithm is typically designed using either a gradient-based approach or recursive least squares. However, for implementation purposes, gradient-based algorithms are preferred, as they reduce computational burden by requiring fewer matrix multiplication operations, making adaptive controllers feasible for deployment on low-cost microcontrollers.

A common approach involves adjusting the adaptive parameters vector $\hat{\theta}(t)$ based on the error between the desired and actual system response. In a general and simplified way, for a single-input single-output (SISO) plant, it can be written as

$$\boldsymbol{\theta}^T(t)\boldsymbol{\omega}(t) + r(t) = 0, \tag{11}$$

and

$$\boldsymbol{\theta}(t+1) = \boldsymbol{\theta}(t) - \boldsymbol{\Gamma}\boldsymbol{\zeta}(t)(y_m(t) - y(t)), \tag{12}$$

with (11) being a general control law and (12) a general gradient-based adaptive parameters algorithm, where the following are true:

- $\boldsymbol{\theta}$ is the calculated parameter vector;
- $\boldsymbol{\omega}$ is the internal signals vector;
- r is the reference signal;
- $\boldsymbol{\Gamma}$ is the adaptation rate vector;
- $\boldsymbol{\zeta}$ is an auxiliary vector;
- y_m is the reference model output;

- y is the system output.

In some applications, the tracking error $e_1 = y_m - y$ can be replaced by an augmented error ϵ. Additionally, to enhance the robustness of the algorithm, a majorant m or m^2, as well as a modification function to prevent parameter drift, can be incorporated into the controller. Since this control algorithm adjusts its parameters in real time based on feedback from the regulated system, it serves as an excellent alternative for handling power converters operating under severe unmodeled dynamics and challenging conditions, such as weak, very weak, and low-inertia grids. Recently, several discrete-time robust model reference adaptive control (RMRAC)-based structures have been proposed for DC–AC converters, as seen in [104–106].

4.1.2. Heuristics and Metaheuristics

These techniques are largely applied for the optimization of controllers. These algorithms optimize control parameters without requiring an explicit mathematical model of the system and are generally run offline due to their elevated computational burden. Metaheuristics are often inspired by natural processes, and techniques such as GA and PSO have been successfully applied not only to optimize power converters' performance and robustness but also to assist in the design process.

Genetic Algorithms

GAs are computational methods for solving both constrained and unconstrained optimization problems, inspired by the principles of natural selection. In essence, a GA iteratively evolves a population of candidate solutions to approximate the optimal solution. The optimization process is guided by a fitness function, typically the cost function to be minimized or maximized, formulated as:

$$\min_x f(x), \tag{13}$$

where x represents the decision variables (e.g., control parameters or initialization values for power converters) and $f(x)$ is the objective function to be optimized. The GA employs key evolutionary operators—selection, crossover, and mutation—to refine solutions over successive generations. The crossover operation, responsible for generating new candidate solutions, can be expressed as:

$$x_{\text{new}} = \text{Crossover}(x_{parent1}, x_{parent2}), \tag{14}$$

where $x_{parent1}$ and $x_{parent2}$ are parent solutions selected based on their fitness and x_{new} is the offspring solution. Recently, GA-based approaches have been successfully applied for the optimization of low-level control algorithms in DC–AC power converters [107–109].

Particle Swarm Optimization

PSO is a population-based stochastic optimization technique inspired by the collective behavior of biological swarms. It is widely used for solving nonlinear and multidimensional optimization problems due to its simplicity and efficiency.

In PSO, a set of particles—each representing a candidate solution—explores the search space by iteratively updating their positions and velocities based on both individual and collective experiences. The position of particle i, denoted as $x_i(t)$, is adjusted at each iteration according to the velocity update equation, as follows:

$$v_i(t+1) = v_i(t)w + c_1 r_1 \left(x_{pbest,i} - x_i(t)\right) + c_2 r_2 \left(x_{gbest} - x_i(t)\right), \tag{15}$$

where the following are true:

- $v_i(t)$ is the velocity of particle i at time step t;
- w is the inertia weight, controlling the influence of the previous velocity;
- c_1 and c_2 are acceleration coefficients that balance exploration (searching new regions of the space) and exploitation (refining known good solutions);
- r_1 and r_2 are random numbers sampled from a uniform distribution in $[0, 1]$;
- $x_{pbest,i}$ is the personal best position of particle i, representing the best solution found by that particle;
- x_{gbest} is the global best position found by the entire swarm.

Each particle updates its position based on the new velocity, according to

$$x_i(t+1) = x_i(t) + v_i(t+1). \tag{16}$$

The algorithm iteratively refines the swarm's positions, promoting convergence toward an optimal solution by balancing exploration and exploitation. The inertia weight w plays a crucial role in this balance: a higher w encourages global exploration, while a lower w focuses on local search. PSO has been successfully applied in various fields, including power electronics, control systems, and artificial intelligence. Recent studies keep demonstrating its effectiveness in optimizing low-level control strategies for DC–AC converters [110,111]. However, as expected, since metaheuristic techniques tend to be computationally expensive, their applicability to real-time control is generally limited to offline use, where they assist in selecting or fine-tuning low-level control algorithms.

Simulated Annealing

SA is a probabilistic optimization algorithm inspired by the annealing process in metallurgy, where materials are heated and gradually cooled to achieve a low-energy crystalline structure. The algorithm is particularly useful for solving complex, non-convex optimization problems where gradient-based methods may struggle due to local minima, as discussed in Section 3.1.2. The SA algorithm minimizes the cost function $f(x)$ by iteratively exploring the solution space, accepting new solutions with a probability that decreases with time (temperature), reducing the chance of converging to a local minimum. In general form, it can be written as

$$P(\Delta E) = \exp\left(-\frac{\Delta E}{T}\right), \tag{17}$$

where ΔE is the change in the objective function and T is the temperature, which decreases over time. The solution is accepted if $\Delta E \leq 0$, or with probability $P(\Delta E)$ if $\Delta E > 0$. The solution transition follows these rules:

- If $\Delta E \leq 0$, the new solution x_{new} is always accepted.
- If $\Delta E > 0$, the solution is accepted with probability $P(\Delta E)$, allowing occasional uphill moves to escape local minima.

A well-designed cooling schedule is critical to SA's performance in order to minimize T but prioritize the finding of the global minima. Common cooling functions include

$$T(t) = \alpha T(t-1), \tag{18}$$

where α is a cooling rate factor (typically $0.8 \leq \alpha \leq 0.99$). Recently, some novel Simulated Annealing combined controllers were proposed for DC–AC converters [112,113], but not specifically for low-level control.

Hybrid GA–PSO and Evolutionary Algorithms

A hybrid approach combines the population-based search of the GA with the continuous velocity updates of PSO. The velocity update equation for a hybrid GA–PSO approach is as follows:

$$v_i(t+1) = v_i(t)w + c_1 r_1 \left(x_{pbest,i} - x_i(t) \right) + c_2 r_2 \left(x_{gbest} - x_i(t) \right) + \text{Crossover}(x_{parent1}, x_{parent2}). \quad (19)$$

Observe that the crossover operator integrates the strengths of the GA's global search with PSO's local search. As discussed before, evolutionary algorithms use operators like mutation, selection, and crossover to evolve a population of solutions. A general optimization problem can be formulated as

$$\min_x f(x) \quad \text{subject to} \quad x \in \mathbb{X}, \quad (20)$$

where x represents the optimization variables and $\mathbb{X}$ is the search space. This representation is similar to (13) and is common for most evolutionary algorithms. Recently, several combined metaheuristic-based optimization techniques applied to DC–AC converters have emerged. Some are applied to enhance offline parametrization of current controllers, while others aim to improve design and system performance indirectly [114–116]. It is important to highlight the growing interest in combining metaheuristics with multi-level optimization techniques. Although these methods are typically not intended for real-time control, they can play a crucial role in enhancing the robustness and performance of real-time algorithms through offline fine-tuning.

4.1.3. Data-Driven and AI-Based Optimization

Recent advancements in artificial intelligence (AI) and machine learning (ML) have enabled novel data-driven optimization approaches. Techniques such as Reinforcement Learning, deep learning-based controllers, and adaptive neural network-based optimization have shown promise in enhancing the adaptability of power converters. Similar to heuristic and metaheuristic methods, these approaches require significant computational effort and are generally applied offline when used for low-level control optimization. For real-time voltage or current regulation, these techniques present considerable challenges, as the required sampling frequency for controlling such signals is typically greater than 5 kHz [35]. In this context, control algorithms must run the calculations and compute and apply new control actions at each sampling instant, demanding extremely fast processing times.

Despite these challenges, AI-driven techniques have demonstrated significant potential, particularly for high-level control structures. Moreover, recent advancements suggest that, with further optimizations and hardware improvements, their feasibility for low-level control may also become more practical. However, real-time implementation remains constrained, as most studies in this domain are either simulation-based or limited to strict hardware-in-the-loop experiments. In this regard, these techniques will also be covered in this brief review. However, they are not yet as mature for low-level control as the previously discussed optimization-based control algorithms, though they offer significant potential for further research and improvements—either in combination with traditional approaches or as standalone solutions.

Reinforcement Learning

RL is an ML technique that enables algorithms to learn decision-making strategies to achieve optimal outcomes. It is a type of AI that mimics how individuals learn through trial and error. In RL, an agent learns to select actions that maximize cumulative reward R over time by optimizing a cost function. A general objective function for RL can be expressed as

$$\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t r_t\right], \tag{21}$$

where the following are true:

- π is the policy that maps states to actions;
- r_t is the reward at time step t;
- γ is the discount factor;
- T is the time horizon.

To train the system, an environment must be defined. The environment is typically modeled (but not limited to) as a Markov decision process, as many Reinforcement Learning algorithms rely on Dynamic Programming techniques. The vast majority of recent studies employing RL for DC–AC converters focus on improving maximum power point tracking (MPPT) or high-level control applications [117,118], once these applications have more flexibility with the sampling times and computational burden. Additionally, Reinforcement Learning can be implemented either with or without deep learning, as will be briefly addressed next.

Deep Learning (DL)

Unlike RL, deep learning is a subset of ML that uses artificial neural networks (ANNs) to enable algorithms to perform specific tasks in a manner similar to human intelligence. The term "deep" in deep learning refers to the multiple layers through which data are transformed, often involving numerous hidden layers. In DL-based techniques, the control system can be represented by a neural network that learns to approximate the control action $u(t)$. The optimization of network weights w is performed using a dedicated optimization algorithm, such as Gradient Descent, applied to a loss function $\mathcal{L}$.

The general optimization control problem can be written as

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}(y_i - f(x_i, w))^2, \tag{22}$$

where the following are true:

- y_i is the desired output;
- x_i, represents the input data;
- $f(x_i, w)$ is the neural network output;
- N is the number of training samples.

The network adjusts the weights of the connections between nodes to minimize errors through backpropagation. Similar to RL, once trained, the network can make predictions on new data. It is important to note that optimization techniques provide a systematic approach to enhancing control performance by addressing key challenges in power electronics, such as minimizing switching losses, compensating for control delays, improving voltage and current regulation, and ensuring stability in weak-grid conditions. Some of the recent papers applying DL-based techniques for DC–AC power converters are [119–121].

4.2. Stability Analysis of Optimization-Based Control Techniques

The stability of control algorithms is a critical aspect in the design and implementation of optimized controllers for DC–AC converters. However, providing a unified stability analysis (even in a simplified form) for all key optimization techniques discussed in this paper is unfeasible due to the diversity of control structures, algorithms, modifications, and their underlying methodologies. For instance, adaptive control encompasses direct and indirect approaches, each of which includes several variations such as MRAC, RMRAC, adaptive one sample ahead preview (AOSAP), among others. Similarly, MPC can be implemented in various forms, including linear and nonlinear formulations, finite or infinite horizons, and explicit or implicit implementations. The same complexity applies to other optimization-based controllers such as LMIs, heuristic/metaheuristic approaches (e.g., GA, PSO), and AI-driven techniques (e.g., RL and DL).

Given this diversity, a comprehensive stability analysis for each optimization technique would require an in-depth examination of multiple algorithms, making it impractical within the scope of this review. Instead, we focus on providing an overview of key optimization techniques, their advantages, limitations, and applicability in power converter control in a brief way. Readers interested in stability analysis for specific control structures are encouraged to refer to the specialized literature on each methodology.

4.3. Comparison of Key Optimization Techniques and Summary

Based on our extensive review of the literature, Table 4 provides a critical comparison of optimization techniques applied to the low-level control of DC–AC converters in renewable-integrated microgrids. The techniques were categorized into model-based, heuristic/metaheuristic, and AI-driven approaches, analyzing their key characteristics, advantages, limitations, and suitability for microgrid applications. Additionally, Table 5 summarizes the boundary conditions and limitations of key optimization techniques, offering insights into their applicability and constraints in low-level control of DC–AC power converters.

Model-based methods, such as MPCs, LMIs, and direct adaptive controllers, offer rigorous mathematical formulations and can be mathematically proven stable. However, they often require accurate system models (particularly for MPC-based structures) or, at the very least, a partial understanding of the system dynamics (as in direct adaptive control). Additionally, these methods typically demand substantial computational resources, which can pose challenges for real-time implementation, especially when compared to non-optimized classical approaches or when hardware limitations are severe (e.g., low-cost 8-bit microcontrollers). Among model-based approaches, adaptive control stands out for its adaptability, as it continuously adjusts control parameters in real time to maintain system stability and regulation (which can be excellent for weak or low-inertia grids' operation). However, this advantage comes at the cost of increased complexity in mathematical formulation, design, and implementation. Unlike MPCs and controllers based on LMIs, which aim for optimality within specific constraints, adaptive controllers focus on flexibility and adaptability in dynamic environments.

In contrast, heuristic and metaheuristic approaches, such as GAs and PSO, provide flexible, model-free optimization strategies that do not require explicit system modeling. While these methods can be highly effective for tuning control parameters, they often suffer from convergence issues and are typically implemented offline due to their high computational burden. Despite these limitations, metaheuristic techniques play a crucial role when integrated with model-based methods, as they can optimize the system or control parameters, refine controller performance, and reduce reliance on expert-driven tuning. By leveraging the strengths of both approaches, hybrid control strategies can achieve enhanced adaptability, robustness, and efficiency, making them a promising direction for advanced DC–AC converter low-level control.

Table 4. Comparison of key optimization techniques for low-level control of DC–AC converters.

Optimization Technique	Key Characteristics	Advantages	Limitations	Ref.	Comments
Model Predictive Control	Utilizes system models to predict future states and optimize control actions	Ensures optimal performance	Requires highly accurate models; stability, design, and implementation are challenging	[100,101]	Effective for systems with well-defined dynamics; may perform poorly when unmodeled dynamics are significant
Linear Matrix Inequalities	Employs convex optimization techniques for controller design	Provides robust control solutions with low computational burden; may achieve optimal performance	Limited to linear or linearized systems; may be conservative	[102,103]	Suitable for systems where linear approximations are valid
Adaptive control	May require a reference model (if direct-type); operates by estimating or measuring system states; can be designed with simplified reduced-order models	Robust to matched and unmatched dynamics; delivers satisfactory performance (may not be optimal); can stabilize unstable systems	Challenging to design initial gains; stability, design, and implementation are nontrivial	[104,106]	Suitable for various systems; non-minimum phase zeros and frequency-rich references may pose challenges
Genetic Algorithm	Mimics natural selection to find optimal solutions	Does not require explicit models; flexible and simple to implement	May converge to local optima; computationally demanding; usually implemented offline	[107,108]	Useful for complex optimization problems with large search spaces; easily combinable with other metaheuristics
Particle Swarm Optimization	Simulates the social behavior of swarms to explore optimal solutions	Simple implementation; efficient search capabilities; faster convergence compared to similar metaheuristics	May suffer from premature convergence; requires parameter tuning; computationally demanding; usually implemented offline	[110,111]	Effective for optimizing microgrid operations with multiple renewable sources; easily combinable with other metaheuristics
Reinforcement Learning	Learns optimal control policies through interaction with the environment	Handles complex, nonlinear dynamics; adaptable and potentially highly robust to uncertainties	Requires extensive, high-quality training data; usually implemented offline	[117,118]	Promising for systems with high uncertainty and variability; computationally intensive (especially for training)
Neural network-based control	Utilizes neural networks to model and control system behavior	Capable of approximating complex functions; adaptable and potentially highly robust to uncertainties	Prone to overfitting with deep architectures; requires extensive high-quality data; usually implemented offline	[119,120]	Promising for systems where traditional modeling is challenging; needs substantial computational resources (especially for training)

Table 5. Boundary conditions and challenges of key optimization techniques.

Optimization Technique	Boundary Conditions	Challenges
Model Predictive Control	Requires an accurate system model; works best with systems that have well-defined state-space representations	Computationally intensive for high-dimensional systems; stability and feasibility depend on tuning and constraints; may struggle with harsh unmodeled dynamics
Linear Matrix Inequalities	Limited to convex optimization problems; most effective for linear or linearized systems	May be conservative; not suitable for highly nonlinear systems; require accurate system characterization
Adaptive control	Can handle system uncertainties; typically assumes system dynamics are slowly time-varying or, at least, much slower than the adaptation rate	Requires appropriate parameter initialization; stability depends on adaptation laws; non-minimum phase systems pose challenges
Genetic Algorithm	Effective for global optimization in high-dimensional spaces; does not require explicit system models	High computational cost; convergence is not guaranteed to be globally optimal; often requires offline implementation
Particle Swarm Optimization	Works well for problems with large search spaces; requires a well-defined fitness function	Susceptible to premature convergence; requires parameter tuning; typically implemented offline due to computational demands
Reinforcement Learning	Suitable for highly nonlinear and uncertain environments; can adapt to dynamic conditions	Requires extensive training data; computationally expensive for real-time applications; stability and safety are difficult to guarantee
Neural network-based control	Can approximate complex nonlinear functions; does not require explicit system equations	Prone to overfitting; requires large datasets for training; computationally expensive, limiting real-time feasibility

More recently, data-driven and AI-based methods, such as RL and neural network-based control, have shown promising results in handling complex, nonlinear, and uncertain system dynamics. However, they are predominantly utilized for high-level control or, in a few cases, for low-level control, mostly in offline implementations. The recent studies exploring real-time AI-based low-level control are largely simulation-based, with practical implementation still posing significant challenges due to computational constraints and lack of interpretability. Given that low-level control typically requires extremely short sampling times and high processing frequencies, real-time deployment of these AI-driven techniques in real power converters (not only simulation) remains a challenge.

This review highlights the trade-offs among these techniques and provides insights into their applicability, paving the way for future advancements in optimizing power converter control within renewable-integrated microgrids. Additionally, as mentioned in the previous section, the optimization techniques covered in this paper span multiple categories, including model-based, heuristic/metaheuristic, and learning-based approaches. Each of these methodologies has numerous variations, each with its own advantages and limitations in different domains. Given this diversity, selecting a limited set of techniques for a case study would not only be impractical but could also lead to an unfair assessment, as different methods have distinct design objectives, constraints, and applicability conditions. For readers interested in performance evaluations, we encourage referring to specialized studies that directly compare optimized methods for specific applications.

5. Future Directions and Emerging Trends

As the demand for efficient and resilient power conversion continues to grow, the field of low-level controllers is evolving toward more adaptive, intelligent, and computationally efficient strategies. The increasing penetration of renewable energy sources, coupled with advancements in grid-forming converters, is driving a shift toward more decentralized power systems. Recent disruptions in conventional power systems, such as the 2021 Texas power crisis, have underscored the need for more robust and adaptive strategies to maintain stability under adverse conditions. As power systems transition toward lower inertia and weaker grids, control methodologies must evolve to ensure stability and efficiency in increasingly complex operational scenarios.

As discussed in the previous section, various optimization techniques have been applied to power electronics and low-level control, each with distinct advantages and limitations. No single technique universally outperforms the others, as their applicability depends on factors such as mathematical complexity, the necessity of global optimality, computational burden, and the feasibility of online implementation. A key research direction in this field is the integration of real-time AI-based controllers, such as Reinforcement Learning and neural networks, into embedded systems. While these techniques have demonstrated strong potential for low-level control in simulations, their real-time deployment remains challenging due to computational constraints and the requirement for high-frequency sampling. Depending on the DC–AC converter topology and design, sampling frequencies of at least 5 kHz are often necessary (depending on power levels, these values can reach up to 100–200 kHz), necessitating control algorithms that are not only robust and optimal but also feasible enough to be implemented on cost-effective commercial microcontrollers. Although advancements in quantum computing and specialized hardware, such as field-programmable gate arrays and neuromorphic processors, may help address these challenges, AI-driven techniques currently remain more suitable for high-level control, where execution time windows are in the range of hundreds of milliseconds or even seconds.

Another promising topic is the hybridization of optimization techniques. Instead of relying exclusively on model-based, heuristic, or AI-driven methods, researchers are increasingly exploring hybrid controllers that leverage the strengths of multiple approaches. For instance, integrating Model Predictive Control with evolutionary algorithms or deep learning-based algorithms can enhance robustness while mitigating computational complexity. Similarly, adaptive controllers incorporating data-driven elements can improve performance in systems with high uncertainties, overcoming the limitations of traditional model-based designs and the challenge of selecting appropriate initial parameters. While some studies have begun addressing these issues, the majority of optimization techniques employed thus far are metaheuristic-based, leaving an open research gap for the exploration of more advanced approaches, such as Bayesian and deep neural network-based optimization algorithms.

Furthermore, the widespread adoption of RESs and grid-forming inverters necessitates more sophisticated real-time optimization strategies for power converters. Future control methodologies will likely incorporate multi-objective optimization frameworks that simultaneously address stability, efficiency, and grid compliance under dynamic conditions. Advanced techniques, such as distributed optimization and cooperative control of multiple converters in microgrids, are expected to gain traction, enabling enhanced grid support functionalities, including adaptive droop control and virtual inertia emulation. Additionally, control co-design—though not a novel concept—has been gaining increasing attention from researchers in recent years. This approach integrates the design of both the system's plant and its controller to improve overall performance. By enabling systems to adapt to changing conditions, control co-design has the potential to enhance performance, reduce costs, and increase reliability, making it particularly well suited for addressing the uncertainties and unmodeled dynamics of complex power electronics and power systems.

Finally, due to strong advancements in hardware-in-the-loop techniques, the role of digital twins in power electronics is expected to expand significantly in the coming years. By leveraging high-fidelity models that operate in parallel with physical systems, digital twins can facilitate predictive control, real-time fault detection, and self-tuning optimization of power converters. When combined with novel robust and optimized controllers, this approach could enable highly autonomous and self-adaptive power conversion systems, paving the way for next-generation smart grids with increased reliability and efficiency. However, achieving these advancements will likely require increased computational resources and more complex mathematical and algorithmic frameworks. As is often the case in electrical and computer engineering, there are no purely "win–win" solutions; trade-offs between mathematical and computational complexity, cost, and implementation feasibility will continue to shape the development of future control strategies.

6. Conclusions

The continuous evolution of robust and high-performance low-level control strategies for DC–AC power converters is essential for ensuring stable, efficient, and adaptive power conversion in modern electrical grids. While a wide range of optimization techniques exist, no single approach universally outperforms others due to inherent trade-offs in mathematical complexity, robustness, computational burden, and implementation feasibility. Therefore, selecting the most appropriate control strategy requires a thorough assessment of system constraints, operational requirements, and performance trade-offs.

The integration of AI-driven methodologies, hybrid optimization frameworks, and multi-objective control strategies presents promising avenues for improving converter performance and resilience under dynamic grid conditions. The adoption of digital twins and control co-design methodologies is expected to play a transformative role in enabling real-time adaptability and predictive maintenance in power electronics-based resources.

As power systems become more decentralized and increasingly reliant on renewable energy, future advancements must prioritize the development of computationally efficient, scalable, and robust control solutions capable of ensuring high power quality, stability, and interoperability in next-generation power electronics and microgrid applications. Future research should continue prioritizing performance in low-level control algorithms to optimize the use of electrical energy while ensuring the control structures are as robust as possible. This includes addressing uncertainties, unmodeled dynamics, and the challenges of low-inertia grids inherent in scenarios with high penetration of inverter-based resources.

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