



Review Virtual Inertia Control Methods in Islanded Microgrids

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Abstract: Although the deployment and integration of isolated microgrids is gaining widespread support, regulation of microgrid frequency under high penetration levels of renewable sources is still being researched. Among the numerous studies on frequency stability, one key approach is based on integrating an additional loop with virtual inertia control, designed to mimic the behavior of traditional synchronous machines. In this survey, recent works related to virtual inertia control methods in islanded microgrids are reviewed. Based on a contextual analysis of recent papers from the last decade, we attempt to better understand why certain control methods are suitable for different scenarios, the currently open theoretical and numerical challenges, and which control strategies will predominate in the following years. Some of the reviewed methods are the coefficient diagram method, H-infinity-based methods, reinforcement-learning-based methods, practical-swarm-based methods, fuzzy-logic-based methods, and model-predictive controllers.

Keywords: frequency control; islanded microgrid; renewable energy; virtual inertia control

1. Introduction

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Renewable energy sources (RESs) are frequently deployed in modern power grids to promote a myriad of environmental and economical benefits. However, the increasing integration of RESs significantly decreases the rotational inertia of the grid, which jeopardizes grid stability and its overall dynamic behavior [1–4]. A central challenge is regulating the grid's frequency under high penetration levels of renewable sources. One approach for addressing this problem is to install fast-reacting storage systems with virtual inertia controllers alongside low-inertia power sources; such controllers have been extensively studied in recent years [5–11]. Each control method has its own benefits and limitations. For instance, classical control paradigms are simple in general but are designed for specific scenarios, whereas data-driven algorithms are flexible and enable online learning. However, these algorithms are numerically complex and require adequate data to operate efficiently. Hybrid control strategies have low numeric complexity, but their convergence is hard to guarantee in most cases. Proposing suitable guidelines for choosing the best algorithm is currently an open question, and this question becomes more important when the microgrid is isolated [11–17].

Microgrids have received increasing attention as a means of integrating distributed generation into the electricity grid [18]. Usually described as confined clusters of loads, storage devices, and small generators, these autonomous networks connect as single entities to the public distribution grid through a point of common coupling (PCC). Figure 1 illustrates a typical microgrid network. Microgrids comprise a variety of technologies: renewable sources, such as photovoltaic and wind generators, are operated alongside



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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). traditional high-inertia synchronous generators, batteries, and fuel-cells. Thus, energy is generated near the loads, enabling the use of small-scale generators that increase reliability and reduce losses over long power lines. The locality of the microgrid network enables the improved management of energy. Generators (and possibly loads) may be controlled by a local energy management system to optimize power flow within the network. The objectives of energy management depend on the mode of operation: islanded or grid-connected [19]. In grid-connected mode, the typical objectives are to minimize the price of energy import at the PCC, to improve power factor at the PCC, and to optimize the voltage profile within the microgrid [20]. In islanded mode, which is addressed in this paper, the main goal of power management is to stabilize the system and preserve high reliability and resiliency in terms of frequency and voltage.



Figure 1. Schematic representation of a typical microgrid. PCC—point of common coupling.

Few recent survey papers describe different aspects in the context of virtual inertia within power grids with a high penetration of RESs. A comprehensive review of virtual inertia implementation techniques was provided in [12]. The reviewed works were classified and compared using virtual inertia topologies. Some selected topologies were simulated, showing that similar inertial responses can be achieved, relating the parameters of these topologies through time and inertia constants. A discussion of the challenges and research directions is presented, indicating future research needs for the integration of virtual inertia algorithm along with control strategies for general distributed generation. They also reviewed the optimal size and location of synthetic inertia in a power system. Other authors [22] presented a review focusing on the inertia values for power systems. The inertia values were estimated based on different regions in the last 20 years. The contribution of photovoltaic (PV) power plants as virtual inertia was discussed and the damping factor evolution was analyzed.

Contrary to these comprehensive reviews, which focused on virtual inertia topologies implementation [12], virtual inertia and frequency control for distributed energy sources [21], and inertia estimation evolution in power systems [22], we focused on the systematic comparison of virtual inertia control methods designed to solve the frequency regulation problem in islanded microgrids. In particular, we aimed to understand why certain control methods are more efficient in different circumstances, and which control strategies will gain popularity in the coming years. Toward this end, we considered different control techniques available in the literature for the period of 2010–2020, and then categorized them into three groups: classic, advanced, and hybrid methods. We provide a detailed analysis of each control and optimization paradigm through various quality criteria. Finally, we provide a contextual analysis and highlight the current developments and trends for various combinations of virtual inertia control methods and technologies with a focus on microgrid applications. The rest of this paper is organized as follows: Section 2 presents a model of a standard low-inertia microgrid and explains different control quality criteria. Section 3 summarizes the classical methods applied for virtual inertia control, followed by a discussion of the advanced control methods presented in Section 4. Hybrid control algorithms are described in Section 5. Section 6 provides an analysis of recent trends in low-inertia power systems and virtual inertia control.

2. Overview of Low-Inertia Microgrid System

The low-inertia microgrid encompasses participants with different power generation inertia and loads with complex dynamics [23–26]. Therefore, microgrids with high RES penetration pose various challenges for integration to the massive distribution networks such as (1) active/reactive power imbalance and voltage droop in transmission lines, (2) production/consumption imbalance in distribution loads, and (3) frequency mismatch with other microgrids and the rest of the power grid [3,27]. Hence, energy storage systems are considered the prime actuator in frequency stability control, which, in reality, have physical limitations such as (1) (dis)charge cycles, (2) restricted power reservation, (3) reserved power losses, and (4) individual speed of (dis)charge. Moreover, energy storage control performed by virtual inertia or a virtual synchronous generator (VSG) uses power-inverting electronics, which has delays in frequency measurement and power conversion [12,28–32].

2.1. Modeling of a Low-Inertia Microgrid

The considered microgrid was adopted from several recent publications [16,33–37] and is depicted in Figure 2. The addressed scenario includes simplified residential/industrial loads, energy sources (thermal power plant, wind farm, and solar power plant), and energy storage systems [11,38,39]. The thermal power plant is composed of a governor with a generator rate constraint (GRC) and a turbine with a frequency rate limiter, which restricts the valve opening/closing (V_{U} and V_{L} , respectively). The dynamic model of a microgrid uses a hierarchical architecture with primary and secondary control loops. The primary control loop has a droop coefficient 1/R, and the secondary loop has an area control error (ACE) system with a second frequency controller K_I and a first-order integrator. Frequency regulation is performed by a virtual inertia device with an additional controller. The balancing system is performed as the first-order transfer function with microgrid damping coefficient D and system inertia H, which are common for all generators. The power generation by variable energy sources is modeled as a random signal with a first-order holder. The hierarchical structure includes the reservation of the primary and secondary control loops. The modeling parameters of the microgrid are summarized in Table 1; Table 2 lists the typical simulation scenarios available in the recent literature.

Table 1. Nomenclature	: microgrid	parameters.
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Variable	Physical Meaning
ΔP_m	Generated power change from the distributed generator
T_t	Time constant of the turbine
ΔP_g	Governor valve-position change
T_g	Time constant of the governor
ΔP_{ACE}	Control signal change for secondary control
K_I	Integral control variable gain
ΔP_W	Change in generated power-based wind farm
ΔP_{wind}	Initial wind power variation
T_{WT}	Time constant of wind turbines
ΔP_{PV}	Change in generated power-based solar farm
ΔP_{solar}	Initial solar power variation
T_{PV}	Time constant of the solar system
ΔP_L	Load power change
ΔP_{RL}	Variations in residential loads
ΔP_{IL}	Variations in industrial loads



Figure 2. Schematic representation of an islanded microgrid with hierarchical control. GRC—generator rate constant; LFC—load-frequency control.

2.2. Frequency Regulation in Low-Inertia Power Systems

Frequency stability is important when low-inertia energy sources penetrate the grid in large amounts [1,40,41]. For example, the wind turbine rotor of a synchronous generator has natural inertia, which plays a key role in the power compensation for short periods (up to 5 s) [3]. Solar panels may be considered as zero-inertia generators, since they do not provide physical energy storage [42]. The response of frequency deviation is defined by the rate of change of frequency (RoCoF), which can be calculated as follows [43,44]:

$$\operatorname{RoCoF} = \frac{\mathrm{d}(\Delta f)}{\mathrm{d}t}.$$
(1)

The magnitude of the RoCoF reflects the balanced state in the dynamics of renewable power sources. The problem is generating an active power resembling that generated by traditional power plants.

Name	Uncertainty Parameter	Nominal Value	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
System inertia	H (p.u. MW	95–100%	80%	40–50%	25–30%	15%	10%
Droop characteristic	R (Hz/p.u. MW)	2.4	2.4	2.4	1.8–2.4	2.4	1.2
Time constant of governor	T_{q} (s)	0.1-0.12	0.1	0.1	0.1-0.15	0.1	0.175
Time constant of turbine	T_t (s)	0.4-0.975	0.4	0.4	0.4 - 0.7	0.4	0.7
Time constant of solar panel	T_{PV} (s)	1.8–1.85	1.85	1.8–1.85	1.8	1.85	1.85
Time constant of wind turbine	T_{WT} (s)	1.5	1.5	1.5	1.5	1.5	1.5
Integral control variable gain	K_i (s)	0.05	0.05	0.05	0.04–0.05	0.05	0.03
System damping coeffi- cient	D (p.u. MW/Hz)	0.015–0.0195	0.015	0.015	0.0135-0.015	0.015	0.003
Frequency bias	β (p.u. MW/Hz)	1.0	1.0	1.0	0.8–1.0	1.0	0.7

Table 2. Nomenclature: dynamic parameters of islanded microgrids in different scenarios.

Name	Uncertainty Parameter	Nominal Value	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Virtual inertia control gain	K_{VI}	0.5–0.8	1.0	1.0	0.8–1.0	1.0	0.4
Virtual inertia time constant	T_{VI} (s)	10	10	10	10	10	11
Virtual inertia control power limiter	$\Delta P_{inertia, \max}$ / r	_{nin} 0.25–0.3	0.25-0.3	0.25–0.3	0.3	0.3	0.25
Valve gate speed	$V_{U/L}$	0.3-0.5	0.5	0.1 - 0.5	0.1 - 0.5	0.3	0.5
Time constant phased locked-loop (PLL)	ω_n (s)	1.5	_	-	_	_	0.3
References		[16,33,35– 37,45]	[34,37]	[16,33,34, 37,45,46]	[16,34]	[33]	[35]

Table 2. Cont.

2.3. Virtual Inertia Control

The virtual synchronous generator (VSG) produces the power alternative to the real synchronous machine [47,48]. This generator can be applied in systems with a high level of fluctuating renewable power to enhance the frequency stability. Virtual inertia (VI) is a specific part of the VSG designed to compensate for the lack of inertia using a power injection mechanism [3]. The default operational limitations of the virtual inertia device cannot provide reliable frequency support. Therefore, an additional robust controller must be used to deal with nonlinearities in low-inertia environments. Traditionally, the virtual inertia control setup (Figure 3) consists of a derivative component, a designed controller K(s), virtual inertia control (energy storage system and virtual inertia variable gain), and a power limiter ($\Delta P_{inertia,max}$, $\Delta P_{inertia,min}$).



Figure 3. Typical structure of a virtual inertia control block.

2.4. Energy Storage System

The energy storage system (ESS) has been implemented in various physical realizations [38,49,50]. The technology can be directly incorporated into frequency-response services and support the RoCoF during a frequency event. For the last decade, ESSs became an essential component in renewable energy integration, since they may provide frequency smoothness and balance for further dispatch [5,51–57]. The simplified ESS model can be represented as follows:

$$G(s) = \frac{1}{T_{VI}s + 1}.$$
 (2)

2.5. Hierarchical Control

Hierarchical frequency control introduces a multilevel cascade system with three key layers: primary, secondary (load frequency control), and tertiary control, and two additional layers: internal generation control and high-level policy control. Primary control is responsible for regulation of individual elements: power sharing, frequency droop, and local voltage control. Secondary control is oriented toward the balancing of active and reactive power by determination of the set-points of the primary controller and secondary control, including grid synchronization, automatic generation control (AGC), secondary load-frequency control (LFC), and voltage-drop control. Tertiary control (i.e., reserved) is

2.6. Control Quality Criteria

In this section, we discuss typical control criteria. They are then used to examine the benefits and drawbacks of the presented algorithms.

- Online learning. Real-time optimization is used to adapt controllers to varying conditions [62,63], and usually requires a special computational device for additional tuning, validation, and verification.
- Robustness. Flexible reaction to disturbances is an important requirement in lowinertia power grids, since, in practice, frequency deviation is limited to the range of ±0.1–1.5 Hz [12,64–68], and Nadir requirements are ±0.024 Hz [12,69]. Using this criterion, we briefly describe testing scenarios and the performance of the considered virtual inertia controller.
- Implementation complexity. Complexity corresponds to the implementation efforts
 of an algorithm in real controlling hardware: size, number of inputs and outputs,
 mathematical complexity, etc.
- Optimization difficulty. This depends on the number of inputs and outputs, time for optimization procedure, and other requirements for the computational power to provide the maximum possible efficiency.

2.7. Description of the Virtual Inertia Control Algorithms

Several recent works [12,16,33–36,70,71] addressed the problem of optimal frequency support with high penetration of variable renewable energy sources. For example, Kerdphol et al. [35] designed a robust H_{∞} controller to provide stability support based on the rate of change of frequency. The proposed solution provides advantages over conventional virtual inertia control and optimally tuned proportional integral (PI) controllers in scenarios when the wind farm is connected, solar panels are disconnected, and the system inertia is 10% and 100%, respectively. Kerdphol et al. [34] further studied the problem by implementing a virtual inertia control scheme combined with a fuzzy-logic-based approach. The proposed algorithm performed robustly under different scenarios with additional uncertainties, including 80%, 40%, and 30% total system inertia and mismatches in the primary/secondary control loops. Kerdphol et al. [45] proposed a model predictive control scheme and compared it to a fuzzy-logic controller for the case of additional load connections. Unlike the previous works, the studied microgrid has conceptual differences: a closed-loop turbine system, RES power generation from two complex wind farms, and minor differences in the transfer function describing the turbine and system inertia. Similar ideas were presented in Tamrakar et al. [72], but without modeling renewable energy disturbances. Magdy et al. [16] presented a PI controller optimized using particle swarm optimization and combined with a digital frequency protection system in scenarios of (dis)connecting loads and renewable energy sources.

In the following sections, we discuss the main features and constructive advantages and disadvantages of the most common algorithms for virtual inertia control, focusing on the load-frequency stability, implementation complexity, and performance against disturbances. We categorize the revised implementations into three groups: advanced, classical, and hybrid control as detailed in Figure 4.

Advanced	Hybrid	Classical
Reinforcement Learning	Model Predictive Control	Coefficient Diagram Method
Fuzzy-Logic Control	Particle Swarm Optimization + PI Controler	H-infinity

Figure 4. Classification of algorithms for virtual inertia control. PI—proportional integral.

3. Classical Control Algorithms

The major features of classical control algorithms are as follows:

- Classical optimization. The optimization is based on the reaction to disturbances, which are approximated by a transfer function or state-space representation. Usually, classical optimization are applied to slow processes [73].
- Simplicity. Classical algorithms have a simple control structure, which enables effective manual tuning and requires low computational power.
- High robustness. Classical algorithms can be highly robust, but require a specific design procedure.

3.1. H-Infinity

H-infinity, H_{∞} , achieves the synthesis of an optimal controller by considering microgrid disturbances and uncertainties via state-space representation, which can provide high robustness and simple hardware realization. However, the main difficulty is the necessity of designing an accurate state-space description for tuning the controller [33,35]. Frequency control based on H_{∞} was used in [33,35,74–76]. The solution presented in [35] applies a linear fractional transformation in the optimal H_{∞} regulator design as the basis for modeling microgrid uncertainties z, such as system inertia H, damping properties D, and phased locked-loop (PLL) delays (ω_n and ζ).

 H_{∞} optimization performs in offline mode and is more vulnerable to low-inertia nonlinearities than data-driven algorithms. At the same time, synthesis of the robust model by H_{∞} provides reliable frequency support. For example, Kerdphol et al. [33] implemented this method, which was successfully tested with 95%, 45%, and 15% of the nominal system inertia and using two types of disturbances: (1) 10% of step changes in load power demand and (2) mismatch in microgrid generation by increased time constant of the governor and time constant for the turbine. Kerdphol et al. [35] reported an H_{∞} controller tested with 100% and 10% system inertia in a scenario with 80% renewable energy penetration. However, the common limitation of the H_{∞} method is the notable peaks during (dis)connection of power plants. H_{∞} requires a detailed understanding of classical control theory and optimization, which does not require powerful hardware for operation. Nevertheless, the synthesized control model is a high-order transfer function and often requires order reduction [33,35]. The biggest difficulties with H_{∞} optimization are the procedure for developing an accurate state-space representation and the manual estimation of disturbances. The optimization based on application of the H_{∞} controller is summarized in Algorithm 1.

Algorithm 1 Design of the H_{∞} controller

- 1: Define the state vector $x^{\mathsf{T}} = [\Delta f, \Delta P_m, \Delta P_g, \Delta P_{ACE}, \Delta P_{inertia}, \Delta P_W, \Delta P_{PV}, \Delta f_{PLL1}, \Delta f_{PLL2}]^{\mathsf{T}}$
- 2: Define the distribute vector $w^{\mathsf{T}} = [\Delta P_{wind}, \Delta P_{solar}, \Delta P_L]^{\mathsf{T}}$
- 3: Define the control input $u = \Delta f_{PLL}$ and output $y = \Delta f_{PLL}K(s)$
- 4: For a given microgrid, derive the state-space model with defined vectors
- 5: Design the optimal H_{∞} controller using the linear fractional transformation technique
- 6: Validate the designed *K*(*s*) controller using a close-loop inequality equation, and if needed, repeat the optimization procedure

3.2. Coefficient Diagram Method

Controllers based on the coefficient diagram method (CDM) rely on an algebraic optimization approach through polynomial state-space representation and the Routh–Hurwitz stability criterion [77,78], where the theoretical basis is constituted to satisfy the Lipatov–Sokolov stability criterion [79–82].

Similar to H_{∞} , the optimization procedure is designed for offline mode. The implementation of a controller based on the CDM in Ali et al. [36] produced frequency stability in a range less than ± 0.1 Hz in a scenario with 100% inertia and two types of disturbances: (1) 10% step load perturbation and (2) random load demand. In contrast to H_{∞} , it can mitigate peaks after the (dis)connection of renewable energy sources. However, the solution uses a two degrees of freedom system structure expressed as N(s)/D(s), which is designed to track a limited number of disturbances. The main drawback of CDM controller synthesis is similar to H_{∞} : it relies on a good understanding of classical control theory optimization. However, it can be implemented using relatively simple hardware. In contrast to H_{∞} , CDM optimization performs without requiring order reduction and uses the coefficient method instead of the Bode diagram [36,83]. However, the validation of synthesized control by Routh–Hurwitz or Lipatov–Sokolov stability criteria depends on the order of the synthesized control system [36,81–83]. The design procedure is summarized in Algorithm 2, which was adopted from the flowchart provided by [36].

Algorithm 2 CDM algorithm

- 1: Define polynomial equation for microgrid modeling
- 2: Define external disturbances $d = [P_{wind}, P_{solar}, P_L]$ and reference input $r = \Delta f_{ref}$ and CDM controller as K(s)
- 3: Calculate the K(s) output system as $y = \Delta P_{inertia}$ and the input system as $u = \Delta f$ with external disturbances and reference input
- 4: Calculate the polynomial of the designed *K*(*s*) control system with microgrid external disturbances
- 5: Validate the designed K(s) control system
- 6: if the stability conditions of optimal CDM controller are verified then, go to step 10
- 7: else Check the value of the stability indices and the stability limits
- 8: Calculate the desirable CDM controller $K_{target}(s)$
- 9: Compare $K_{target}(s)$ and K(s),
- 10: **if** the model is validated **then**
- 11: A robust K(s) controller is obtained
- 12: Check the robustness of the system response
- 13: **else** Repeat the procedure
- 14: end if

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15: end if
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4. Advanced Control Algorithms

The major features of advanced control algorithms can be expressed as follows:

 Adaptation to uncertain conditions. Advanced control algorithms may provide adaptive reactions to disturbances that were not predicted.

- Prediction-based optimization. Fast processes, such as electrical frequency variation, are easier to predict than postreaction. This principle gives additional advantages, because data-based optimization follows the events prediction model. The drawback of the approach is the necessity to design a memory buffer for data recording and further prediction-based tuning.
- Online learning. Data-driven optimization implies recorded data analysis of controlled processes. When conditions are changing radically, this approach provides a strategy for optimization of controller parameters in parallel with real-time control.
- Complexity. Advanced algorithms require a powerful computing system. The main benefit from complexity is effective multiloop control and adaptation to process dynamics.

4.1. Reinforcement Learning-Based Controller

Reinforcement learning (RL) is an agent-based and model-free machine learning algorithm [84]. The main approach of RL optimization is based on trial and error, which allows direct validation of the artificial neural network (ANN)-based controller with the control object and prediction of negative consequences [37,84–86]. The benefit of this method is mandatory data-driven optimization, which is naturally designed for online learning. In [37], RL was compared with H_{∞} , producing slightly better performance in terms of frequency stability in scenarios with 100%, 80%, and 40% inertia and connection of wind, solar, and thermal plants during the launch of industrial and residential loads, and 20% RES penetration. Since the algorithm uses a deep neural network, it requires strong computational hardware and is relatively complex for implementation. The method requires selection of an optimal action $a(t)^*$ at each step s(t) and takes a long time. For RL, it is necessary to design a proper reward system and to choose the right training strategy, which may differ [37,87–89]. For example, in previous works [87,88], the RL optimization for frequency support was performed by approximated dynamic programming. In contrast, Skiparev et al. [37] used the deep deterministic policy gradient to train an RL-based controller for virtual inertia emulation. The optimization mechanism using the RL algorithm is summarized in Algorithm 3.

Algorithm 3 Reinforcement-learning-based algorithm

- 1: Define the actor and critic neural networks
- 2: Define $a_t = \Delta P_{inertia}$, $s_t = \Delta f_t$, and $s_{t+1} = \Delta f_{t+1}$ of RL controller
- 3: Define the desirable total reward for the RL controller r_{target}
- 4: Start training the RL-based controller
- 5: Receive initial process observation of microgrid dynamics as state s_1
- 6: Select action a_t of the actor network according to current policy and disturbances exploration
- 7: Execute action a_t of the actor network
- 8: Observe reward r_t and state s_{t+1} using the critic network
- 9: if $r \ge r_{target}$ then Controller training successfully completed
- 10: else Continue training
- 11: end if

4.2. Fuzzy Logic Controller

Fuzzy logic controller design provides effective manual optimization compared with other advanced algorithms. Several examples of frequency regulation can be found in the literature [34,62,90–94]. Since fuzzy-logic-based controllers can be manually tuned, the data-driven approach is optional. Correct configuration of the controller can create a robust system. Kerdphol et al. [34] applied a standard fuzzy logic controller for virtual inertia control, which was capable most of the time of holding Δf inside the ±0.1 Hz band with 80%, 60%, and 30% system inertia in scenarios with 20% and 80% RES penetration and mismatch in primary/secondary control loops. Controller design requires a good understanding of fuzzy rules design principles. In addition, the method requires powerful

hardware for implementation. However, it uses fuzzy logic without an optimizer, which can be considered a drawback, since it requires the manual design of the optimal fuzzy rules [92,95].

5. Hybrid Control Algorithms

Hybrid algorithms inherit features from both categories. Model predictive control (MPC) is an example of a controller that cannot be classified into either of the abovementioned categories. Optimization can be based on state-space representation [45] or input/output (I/O) relation approximated by the data-driven approach [96]. The PI controller optimized by particle swarm optimization (PSO) is another hybrid example, combining a simple controller with the data-driven approach [16].

5.1. Evolutionary Optimization

Particle swarm optimization is a popular evolutionary algorithm inspired by collective species behavior such as flocks of birds [97]; stochastic optimization should provide the best performance through searching for a global minima. The particle swarm strategy is a stochastic data-driven optimizer that enables online learning [16,56,98,99]. Magdy et al. [16] used PSO for optimal tuning of a PI controller via searching the global minima of a microgrid, which provided robust control with 100%, 80%, and 30% system inertia. The performance of the optimal PI in Magdy et al. [16] showed relatively stable frequency support with 100%, 50%, and 30% system inertia and with 57% RES penetration. In contrast with other solutions, Magdy et al. [16] applied a dynamic model of a microgrid with digital protection, which provided additional frequency stability. PI/PID is a widely used controller in the power industry due to its simple construction [100–102]. However, the PSO algorithm is a self-learning optimizer, which is more complex for implementation. To produce an optimally tuned PI controller, the optimizer has to consider the state-space dynamic modeling of microgrid uncertainties, which requires a relatively long time to find optimal settings. The PSO procedure is summarized in Algorithm 4, adopted from [16].

Algorithm 4 PSO algorithm

- 1: Define microgrid state-space matrix
- 2: Define state vector $X^{\mathsf{T}} = [\Delta f, \Delta P_g, \Delta P_m, \Delta P_{WT}, \Delta P_{PV}, \Delta P_{inertia}]^{\mathsf{T}}$
- 3: Define external disturbances vector $W^{\mathsf{T}} = [\Delta P_{Wind}, \Delta P_{Solar}, \Delta P_L]^{\mathsf{T}}$
- 4: Define the control output signal as $Y = [\Delta f]$
- 5: Compute the state-space model for a given microgrid with defined inputs and outputs
- 6: Initialize the D-dimension of particles as PI/PID controller coefficients
- 7: Perform optimization by minimization of the fitness function for each particle
- 8: Calculate the velocity and current position of each particle. Validate the optimized PI/PID controller
- 9: if stopping criteria of PI/PID controller are met then
- 10: Optimal parameters of PI/PID are obtained
- 11: **else** Repeat optimization

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12: end if
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5.2. Model Predictive Control

The model predictive controller (MPC) requires the development of a robust prediction model based on a detailed representation of the process dynamics via collected data [45,103,104]. As a hybrid algorithm, the MPC can be implemented with data-driven [105] or finite-time-horizon [46,106] optimization approaches. Kerdphol et al. [45] applied finite impulse response optimization for model prediction based on the virtual inertia emulation with microgrid state-space representation.

Regarding optimization, MPC can provide real-time learning through data-driven and finite-horizon approaches. According to Kerdphol et al. [45], MPC performance is higher than that of the fuzzy-logic-based controller, and may provide better Δf stability during (1) (dis)connection of RES power, (2) sudden load change, and (3) mismatch in the main thermal generation scenarios with 100%, 50%, and 25% system inertia and 34% RES penetration. Implementation of the model-prediction-based controller depends on the type of prediction model. The controller requires the calculation of each time sample and heavily depends on the designed model used in the predictions of microgrid disturbances [45,72]. Specifically, Kerdphol et al. [45] used the finite impulse response, which considers each sampling instant in the prediction of microgrid disturbances. The general concept of MPC optimization is summarized in Algorithm 5.

Algorithm 5 MPC algorithm

- 1: Define the MPC controller as K(s)
- 2: Define the MPC controller input as $u = \Delta f$, output as $y = K(s)\Delta f$, and the desired profile as $r = \Delta f_{ref}$
- 3: Predict the microgrid dynamics for the current time
- 4: Optimize the first control step of K(s)
- 5: Adjust the first control step according to MPC control rules
- 6: Implement the local MPC controller
- 7: if Evaluate the disagreement of tracking consensus with constrains then
- 8: End MPC optimization
- 9: else Repeat optimization
- 10: end if

6. Recent Directions and Trends

One goal of this study was to highlight the popularity of various control methods for virtual inertia emulation reflected in the recent literature. Such trends are explored in this section based on the contextual analysis of additional virtual inertia control. Based on this analysis, we explain the motivation for the choice of several optimal control methods and try to better understand why and when the reviewed methods are most efficient. Special attention is paid to the analysis of relevant keywords describing each method and application area. The fuzzy logic controller, model predictive control, coefficient diagram method, and *H*-infinity methods are well-defined by their names. However, reinforcementlearning and evolution algorithms are often defined by a specific strategy. Therefore, we used several of the most common types of these optimizations during our literature search. The keywords we used for the control methods are summarized in Table 3. The search was also restricted to the title, abstract, and keywords fields.

Table 3. Search expressions that were used in the literature search.

Primary Expression	Secondary Expression	Third Expression
"virtual inertia control"	"microgrid"	"FLC OR Fuzzy Logic Controller" "MPC OR Model predictive control" "PI/PID" "EA OR GA OR Evolution algorithms OR Genetic algorithms " "CDM OR Coefficient diagram method" " H_{∞} OR H-infinity"
		"PSO OR Particle swarm optimization "
		"RL OR Reinforcement learning"

Figure 5 depicts the rising trend in publications on virtual inertia control over an 11-year period. The Scopus database produced 404 papers and IEEE Xplore produced 239 papers.



Figure 5. Yearly number of publications in the period from 2010 to 2020 on virtual inertia control.

The frequency-support-related algorithms mostly continued the rising trend, as detailed in Figure 6. To provide a more in-depth analysis, we selected several algorithms commonly used in frequency-control applications. Fuzzy logic and PI/PID appeared to be the most popular control algorithms. Publications indicate the stable interest in usage of PID controller, which can be further equipped with an additional optimization loop based on data-driven algorithms and/or combined with advanced controllers [16,62,99,107,108]. Due to the natural ability in finding global minima, evolution algorithms (e.g., PSO, firefly, and bat) are mostly combined with the fuzzy logic controller (FLC) and/or PID [16,62,99] as one of the most frequently used hybrid algorithms of the existing control loops. Model predictive controllers gained similar attention; in recent years, they have become the most popular. One notable rise was found in the usage of the reinforcement-learning-based strategies, which may become even more popular in the next years due to their ability to perform effective study based on interactions with the environment [37,85,88]. Therefore, we think that the data-driven algorithms will attract more attention in the coming years due to the growing prevalence of data mining and cloud technologies.



Figure 6. Trends in the frequency-support algorithms in microgrids. FLC—fuzzy logic controller, MPC—model predictive control, EA—evolution algorithm, RL—reinforcement learning, H_{∞} —H-infinity, CDM—coefficient diagram method.

Figure 7 depicts the search results for the specific technologies used for frequency regulation in microgrids. Energy storage appears to be the most widely used technology. Virtual synchronous generators, virtual inertia, and phase locked-loop have small numbers of publications, since each technology related to synthetic inertia generation is individual



and requires specific design and case studies. Notably, many possibilities exist for research into VSG/VI-related applications [12,22].

Figure 7. Trends in frequency-control technologies in microgrids. ESS—energy storage system, VSG—virtual synchronous generator, VI—virtual inertia, PLL—phased locked-loop.

Based on analysis of the above trends, it is reasonable to conjecture that in the coming years, the virtual inertia problem will remain in the focus of the community. The isolated microgrid, as a part of the general power grid, faces several important challenges such as active and reactive power balance, power losses in transmission lines, grid frequency outmatching, power production/consumption balance, among others [109]. Most microgrids use simplified models of domestic loads, power plants, and energy storage systems. The European Commission reported the potential research challenges in the renewable energy area in the period of 2021–2027:

- Integrated local energy systems, microgrids, and modular solutions [110–113];
- Cross-border cooperation in transmission grids [110,114–117];
- Electrical transport (cars, trucks, ships, etc.) [110,118–120];
- Effective energy management in domestic appliances (HVAC, boilers) by demand-side management technologies [110,113,115,121,122];
- Solutions for the integration of energy systems and coupling of different energy vectors, networks, and infrastructures in the context of a digitalized, green, and cybersecure energy system [110,113,123].

According to the REN21 report, 63% of world experts agree that by 2050, power generation will focus on centralized or decentralized renewable energy [119] and 71% agree that the transition to 100% renewable energy on a global level is feasible and realistic [119]. In addition, most experts agree that renewable energy should provide at least 32% of the EU energy consumption by 2030 [2,119]. Hence, there is a clear need for continuing the research on and adoption of various solutions, supporting the integration of renewable energy sources; microgrids will most likely play a key role in achieving these goals.

7. Conclusions

Here, we reviewed recent works related to virtual inertia control methods designed to solve the frequency regulation problem in islanded microgrids, with an attempt to better understand the unique characteristics, common uses, and mathematical foundations of the most popular control methods. The control techniques on which we chose to focus were selected following an in-depth content analysis of various sources from the main databases, as detailed in Section 6. This analysis revealed interesting trends in the current research, and may help to understand why certain control methods are more efficient in different circumstances (Table 4), and which control strategies will gain popularity in the coming years.

	Hand. App.	Online/ Offline	Advantages	Drawbacks	Computational Complexity	Robustness	Optimization Complexity	Refs.
ssical algorithms	Robust H- infinity	Offline	 Robust frequency control Strong overshoot minimization 	 Significant peaks during connec- tion disturbances Need for order reduction Limited robust- ness 	Medium	High	Medium	[36,74,75,124– 126]
Clas	Coefficient diagram method	Offline	Higher robustnessNo need for order reduction	• Limited robust- ness	Medium	High	Medium	[36,81,83,127]
ced algorithms	Fuzzy-logic- based con- troller	Online	• Flexible reaction	 Limited by fuzzy rules adaptation Manual optimiza- tion Long compu- tational time 	High	High	High	[16,34,45,128]
Advanc	Reinforcement- learning- based controller	Online	 Reward learning system Advanced feed- back from system High robustness 	 Available sample data are needed Specific to the re- ward/punishment optimization 	Very High	High	Very High	[37,85,87,88, 129]
ł algorithms	PI/PID and particle swarm op- timization	Online	 Low numeric complexity Simple controller	 Convergence to global optimal solution is not guaranteed Limited robust- ness 	Low	Low	Low	[16,56,98]
Hybric	Model predic- tive control	Online	 High robustness Fast reaction based on predic- tion Fast optimization 	 Need data reserved for prediction model Complex optimization 	High	High	High	[45,46,70,72, 106,130]

Table 4. Comparison of virtual inertia control algorithms: advantages, drawbacks, and quality criteria.

For instance, the data show that evolutionary algorithms methods are widely used for tuned PI/PID controllers probably since this enables the analysis of stochastic scenarios with nonlinear constraints. However, evolutionary algorithms may converge to local minima and are therefore not suitable for every application. In such cases, classical control methods seem to be the natural choice since they provide simple and effective solutions to the virtual inertia problems whenever grid dynamics are well-defined. If there is uncertainty in the grid dynamic and nonlinear constraints, fuzzy-logic-based controllers are used extensively, although they are limited to specific and manually defined rules; in cases with a large number of rules, the needed resources increase significantly. The controllers based on the coefficient diagram method principle seem to be the least popular method, maybe due to their limitation of tracking only a limited number of disturbances. Artificial neural networks are also increasing in use due to the increasing amounts of available data; specifically, reinforcement-learning methods are commonly used for solving complex problems when a fully satisfactory algorithm is lacking. In our opinion, these trends may change in the near future due to global initiatives related to the integration of electric vehicles into microgrids and due to the continuing integration of renewable energy sources and beyond-the-meter technologies, which may lead to more available data and thus favor the use of new and more efficient controllers with a focus on datadriven approaches.

Concerning future research, since microgrids are increasingly decentralized and less regulated by governments, it is often impractical to study them from the perspective of one single entity with unlimited information and control span. Therefore, the recent increasing trend in studies of virtual inertia control for isolated microgrids will likely continue. Whereas classic control techniques are still mainly the focus of the community, the wide adoption and integration of technological innovations such as the Internet of things (IoT), cloud technologies, and data processing powers will likely start shifting the main attention toward data-driven control techniques in the coming years. Another topic of interest may be combining virtual inertia control with suitable energy storage as a supportive technological solution in isolated microgrids. To answer this challenge, the development of new optimal control methods can be considered a possible avenue for future research.

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial neural network
EA	Evolution algorithms
ESS	Energy storage system
CDM	Coefficient diagram method
FLC	Fuzzy logic controller
GRC	Generator rate constraint
HVAC	Heating, ventilation, and air conditioning
LFC	Load-frequency control
MPC	Model predictive control
PCC	Point of common coupling

- PID Proportional-integral-derivative
- PLL Phased locked-loop
- PSO Particle swarm optimization
- RL Reinforcement learning
- RES Renewable energy sources
- RoCoF Rate of change of frequency
- VI Virtual inertia
- VSG Virtual synchronous generator

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