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Review

Control Strategies of Electric Vehicles Participating in Ancillary Services: A Comprehensive Review

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Abstract: With the emergence of the electric vehicle (EV) era in which the vehicle's embedded batteries can be exploited for grid support purposes, the role of EVs participating in ancillary services via vehicle-to-grid (V2G) technology cannot be disregarded. Although there are many forms of ancillary services, the most common services delivered by EVs are frequency regulation, frequency contingency, inertia, and voltage regulation. Numerous research studies have been conducted to propose the most effective control strategies for electric vehicle ancillary services (EVASs). In this paper, a comprehensive review is carried out on various control strategies for EVs with respect to their participation in ancillary services. The methodology applied for this review comprises a combination of thematic and historical reviews. The review explores the benefits and limitations of these control strategies and provides a clear understanding of the research gaps in the EVAS area. This review will provide a useful framework and a strong point of reference for researchers working in V2G controls for providing EVASs to a grid. V2G will be a way forward for future grids to accommodate more renewable resources and achieve sustainability pathways.

Keywords: electric vehicle (EV); vehicle-to-grid (V2G); ancillary services; review; control strategy

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1. Introduction

The global demand for EVs is increasing day by day, as shown in Figure 1. It is predicted that EVs will soon outnumber their counterpart: internal combustion engine vehicles (ICEVs) [1]. Furthermore, with the battery replacing the fuel tank, research states that EV batteries run in idle condition most of the time [2]. Based on these data, counter-flowing energy from the EV to the grid via vehicle-to-grid (V2G) technology could be possible [3]. Globally, several pilot projects have been successfully conducted [4]. From the electricity market standpoint, two markets exist: the energy market and ancillary services. Considering that V2G is not a priority for an EV owner, electric vehicle as an ancillary service (EVAS) is a more suitable contribution. The structure of modern power systems with the EVAS scheme is depicted in Figure 2. The grid consists of loads and generators. Normally, electricity flows from the power source to the load. When installed by using bidirectional charging, EVs could act as a load and power source.

An ancillary service is a service provided by supporting both the transmission and distribution levels in order to maintain reliable electric power system operations [5]. There are several types of ancillary services, such as frequency regulation, frequency contingency, inertia, voltage regulation, black start processes, and load following [6]. Frequency regulation ancillary services regulate the small perturbations of the operating frequency. On the other hand, frequency contingency ancillary services aim to restore more considerable frequency deviations, such as a deviation caused by a sudden loss of load generation or connecting load [7]. Inertia ancillary services provide additional inertia to the power system, preventing transient spikes that can damage the equipment [8]. Physically, frequency regulation and contingency ancillary services are implemented by the fast frequency response (FFR) unit. FFRs could comprise spinning (conventional rotational generator) or nonspinning units (converter-based power source). As is evident in its name, voltage ancillary services assist in controlling the voltage of the grid within specified tolerances. In reality, voltage regulation ancillary services could be supplied by synchronous condensers or static reactive power units such (capacitor/reactor bank). Black start ancillary services enable a restart with respect to the power system after a blackout event [9], while load-following ancillary services comprise a service balancing the supply and demand side of the power system continuously [10].

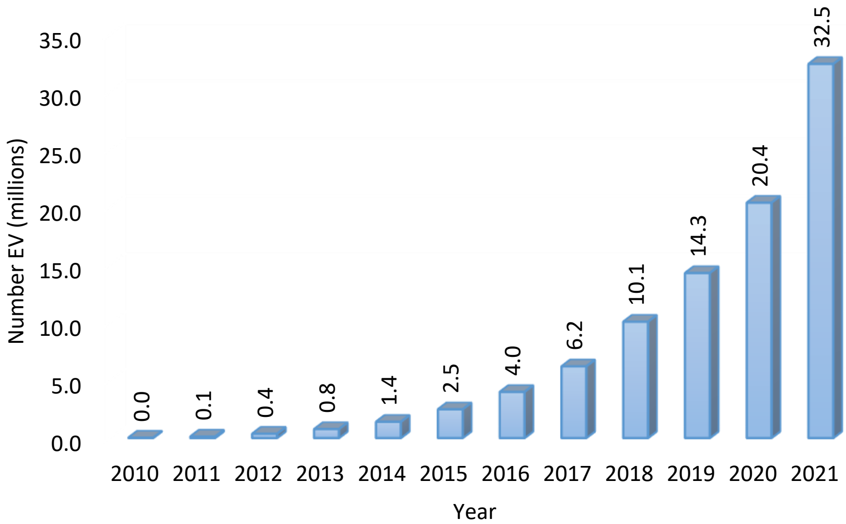

Figure 1. Growth of the global EV population in 2010–2021. Adapted from Ref. [1].

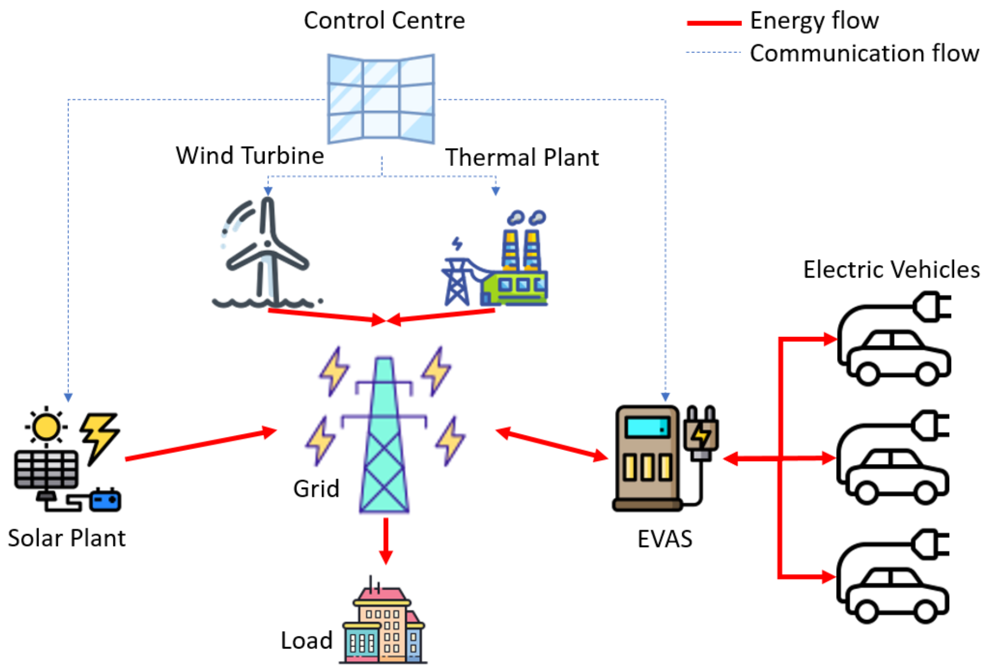

Figure 2. The modern power system scheme incorporating EVAS.

Short-term ancillary services include frequency regulation, frequency regulation, frequency contingency, inertia, and voltage regulation, while long-term ancillary services include black start and load following [11]. However, because this paper is primarily concerned with the short-term transient response analysis of control strategies, only the first class of ancillary services will be discussed. Furthermore, while EVs could theoretically provide black start services, research into this concept is still in its early stages [12].

Several reviews have been conducted on various ancillary services and their control techniques. Report [13] surveys the ancillary service provided by several types of energy storage components, such as flywheels, batteries, pumped storage hydropower, supercapacitors and compressed air. The authors in [14] examined the role of EVs in the smart grid, and they identified that one of the most important roles of EVs is to provide ancillary services. A significant portion of the discussion covered the aggregator and its centralized and decentralized approach. Report [15] discusses the applications, challenges, and solutions of V2G. V2G is referred to as mobile energy storage systems (MESSs), and the role of V2G as an ancillary service provider is discussed. The impact of V2G on the distribution network Is discussed in [16]. Article [17] presents an overview of EVAS with respect to V2G technology. The ancillary services discussed are primary frequency control (PFC), secondary frequency control (SFC), tertiary frequency control (TFC), and voltage control. In [18], EVs were used to support frequency control in microgrid scenarios. Several control strategies, such as droop control and adaptive neuro-fuzzy systems, were discussed briefly. Various optimization algorithms utilized for schedule charging (G2V) and discharging (V2G) activities were discussed in [19]. A comparative study was carried out in [20] on several power management approaches of V2G-participating frequency regulation. The comparative study considered several aspects, such as system architecture, optimization algorithm, time scheduling, and objective functions. Finally, in [21], charging (G2V) and discharging (V2G) strategies based on coordinated/uncoordinated, continuous/discrete, and direct/delayed control were discussed.

The main aim of this paper Is to carry out a comprehensive review on control approaches that have been proposed for EVAS, identify benefits and limitations of the control approaches, and provide recommendations. Each proposed EVAS control technique in the literature will be described briefly in this review, specifically on benchmark strategies for comparison purposes. The rest of the paper is organized as follows. Section 2 elaborates on methods used for this review. Section 3 discusses the control and optimization strategies applied for EVAS. Section 4 conducts a comprehensive literature review on the control and optimization strategies of EVAS and discusses various features of the individual control and optimization technique. The section primarily discusses the ancillary services provided by EV; hence, it is divided into four subsections that discuss frequency regulation, frequency contingency, and inertia and voltage regulation services. Considering the number of research articles in the frequency contingency service category, Section 4.2 is further classified into four major areas based on control variants: PID, fuzzy, MPC, and others. A detailed discussion of the direction of EVAS control–optimization research is presented in Section 5. A summary of the review is also presented, along with future direction of the research. Conclusions are highlighted in Section 6.

2. Methods

The methods applied in this review include a combination of thematic and historical review techniques, and the focus is only on a specific area; the results are presented historically from the past to the present [22]. First, various research papers related to the topic reviews were collected. The search terms "electric vehicles", "grid", and "control" were used. The term "ancillary services" was not used as a search term due to its unpopularity. The reason for this was based on experience; the explicit term "ancillary services" was not always found, despite the fact that the papers themselves discussed EV–grid integration, where ancillary services were the most likely method.

Despite the use of the term "control", many of the collected papers cover unrelated topics such as scheduling and dispatching order. Following the selection of only control-related papers, they were classified according to functionality: frequency regulation, frequency contingency, inertia, and voltage regulation. The thin line distinguishes frequency regulation from frequency contingency. To solve this, each frequency regulation and frequency contingency was defined by regulating small perturbations and restoring frequency deviation. Following classification, it was discovered that papers dealing with frequency contingency accounted for the lion's share of the total. To facilitate discussion, collected papers were further classified based on control variants such as PID, fuzzy MPC, and others. As a result, the number of papers in each variant was distributed fairly evenly. Finally, the results are served historically based on publication dates. In order to keep up to date, only publications that fall within a 10-year period are discussed.

3. Control and Optimization Strategies

3.1. Control Strategies

This section discusses the control strategies that can be used for EVs to participate in delivering ancillary services. A proportional integral derivative (PID) can be considered as one of the oldest control strategies [23]. The idea lies in taking anticipation based on current, past, and future error deviations from a set point. The transfer function of the PID controller is given by (1). Several variations based on the PID technique can be achieved, such as fractional order PID (FO-PID), tilt proportional integral derivative (TID), and integral double derivative (IDD). As its name suggests, rather than using an integer as the traditional PID, FO-PID generalizes the operator of the integral and derivative to be a fractional or even complex number [24]. Thus, the equation is given by (2). It is clearly observed that PID is a general form of FO-PID, with values of λ and δ equal to 1. While FO-PID modifies integral and derivative parts, the proportional part is replaced with the $s^{\frac{-1}{n}}$ compensator in IDD. Thus, the form is given by (3). This was first used in [25] for controlling robot manipulators:

$$C(s) = k_p + \frac{k_i}{s} + k_d s \tag{1}$$

$$C(s) = k_p + \frac{k_i}{s^\lambda} + k_d s^\delta \tag{2}$$

$$C(s) = k_t s^{-1/n} + \frac{k_i}{s} + k_d s \tag{3}$$

where the following is a breakdown of the variables.

$C(s)$ = controller transfer function in Laplace domain
k_p = proportional gain
k_i = integral gain
k_t = tilt gain
k_d = derivative gain
λ = integral operator order
δ = derivative operator order

A two-degree-of-freedom PID (2DOF-PID) comprises a modification of traditional PIDs added with a feedforward compensator, as shown in Figure 3 (left) [26]. One of its earliest enactments was to solve the vehicle suspension problem [27]. A derivative filter was used with PID to progress its performance. Hence, the arrangement is called PID with a derivative filter (PID-N), as shown in Figure 3 (right) [28]. While a conventional PID uses a single loop, a cascaded control PID (CC-PID) fulfils two control loops, primary and secondary, as demonstrated in Figure 4 [29]. The other variants of PID include PIPD, I-PD, and PI-D structure [30].

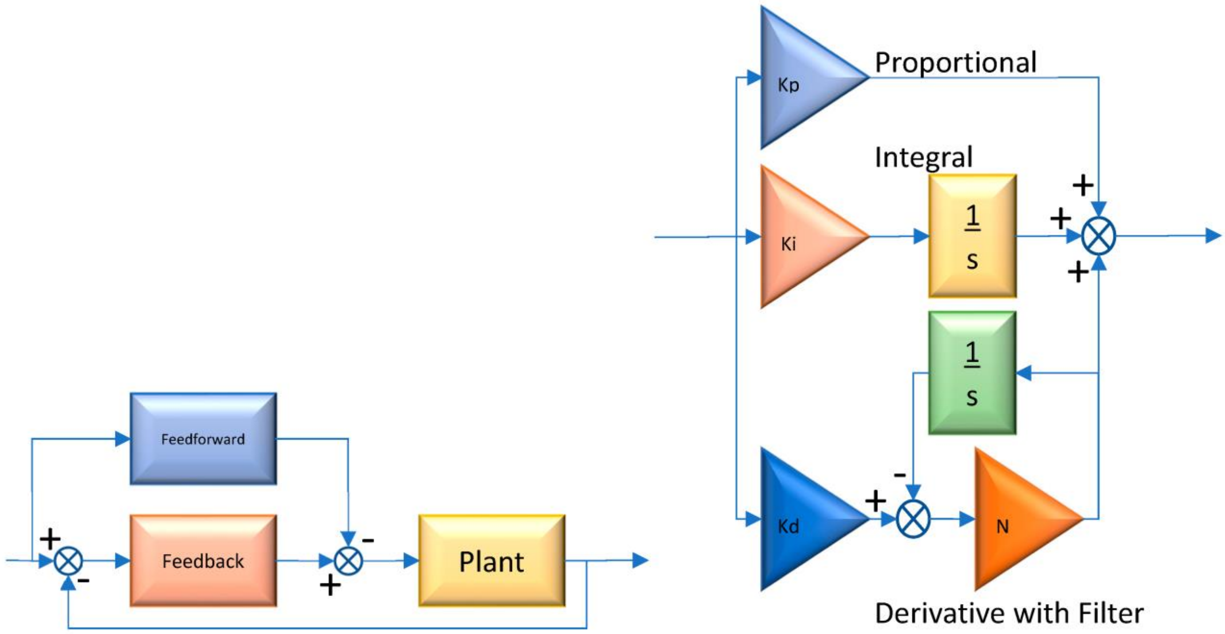

Figure 3. Schematic of 2DOF-PID (left) and PIDN structure (right).

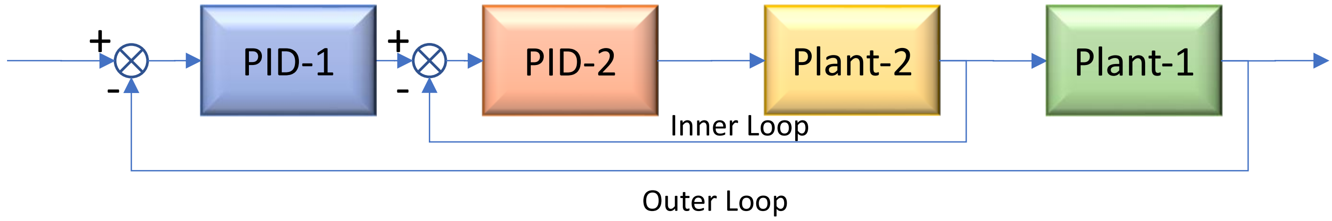

Figure 4. CC-PID schematic.

A fuzzy logic controller (FLC) can be considered as a second-generation control strategy after PID [31]. Similarly to PID, the error value is manipulated for corrective actions; however, rather than using calculus, FLC uses the membership function. In general, FLC overpowers PID in terms of the overshoot, settling time, and transient. Considering the benefit of the fuzzy controller, PID, and its expansion, several scholars combine those together: fuzzy-PID [32], fuzzy-FO-PID [33], and fractional-fuzzy [34]. As an improvement of the original FLC, the interval type-2 FLC (IT2-FLC) introduces an interval named the footprint of uncertainty [35]. This feature is beneficial for handling uncertainty.

A model-predictive controller (MPC) is a control method using the principle of optimizing one or several objective functions under one or several constraints and over a receding horizon window [36]. The objective function, constraint, and optimization algorithm selection are open options depending on several factors (designer, equipment, condition, etc.).

The reality of having highly unpredictable situations encourages scholars to generate a control methodology with uncertainty-enduring characteristics [37]. Methods that have such characteristics are grouped under the robust control method. Several popular types of these controllers include H-infinity (H_∞) and sliding mode control (SMC). The former is a robust control method based on the highest value of possible frequency gain (H_∞ norm) [38]. At the same time, the latter is another robust control based on sliding variables and sliding surfaces [39]. In SMC, the sliding variable swarms around the sliding surface in order to obtain robustness. One of its oldest fruitful enactments was to control induction machines [40]. While robust control methods approach real situations by anticipating worst-case scenarios, another variant, called adaptive control, adjusts its parameters [41].

Optimal control methods were invented and motivated by the observation that human beings maximize gains while preserving resources [42,43]. The physical objective and constraints are transformed into mathematical form so that an optimum solution can be computed via a particular algorithm. The most frequent objective functions applied include the minimization of the integral of the product of time and the absolute value of the error (ITAE), the integral of the absolute value of the error (IAE), the integral of the product of time and the squared value of the error (ITSE), and the integral of the squared value of the error (lSE) [44].

3.2. Optimization Algorithm

First reported in 2007, artificial bee colony optimization (ABCO) is a method influenced by the intelligent behaviour of honey bee swarms [45]. One of the first operations of this idea in the control area was for tweaking a PID controller [46]. The electrostatic phenomenon sparked the idea of a published algorithm titled artificial electric field algorithm (AEFA) [47]. The method of tuning a PID-based LFC-AVR was employed early in the control world [48]. Persuaded by the superior combination of an adaptive network and inference system, a hybrid rule titled adaptive neuro-fuzzy inference system (ANFIS) was published [49]. One of its earliest functionalities in the control optimization area was the gain scheduling of a PI speed controller with respect to DC drives [50]. Artificial neural networks (ANNs) were used for training [51]. In 1990, a dynamic system was identified and controlled [52,53].

The black hole phenomenon inspired a researcher to systematize an optimization algorithm named the black hole algorithm (BHA) [54]. The improvement of a secondary LFC in 2018 became one of its successes within control systems [55]. Differential evolution (DE) was first announced by Storn and Price, while its adaptive variant (adaptive differential evolution/ADE) was proposed by Liu and Lampinen [56,57]. Its first contribution to the control field was to optimize a PID controller [58]. Motivated by the flight skills of hummingbirds, the artificial hummingbird algorithm (AHA) was introduced [59]. Atom search optimization (ASO) is an optimization method motivated by the natural movement of an atom [60]. Its first involvement in control matter was for the scheduling gain of an FO-PID-controlled DC motor [61]. Motivated by the advantage of DE and PSO, a hybrid differential evolution particle swarm optimization (DEPSO) was organized [62]. An early connection with the control operation comprised calculating the parameters of PID-controlled two-area AGCs [63]. The behaviour of elephant herds inspired Wang et al. to publish an elephant herding optimization (EHO) algorithm [64]. It was tested firstly for PID-controlled LFCs [65]. The firefly algorithm (FA) was inspired by the natural behaviour of fireflies [66]. Its first success story in the control topic was in computing the parameters of a PID-controlled LFC [67]. The flower pollination algorithm (FPA) was first reported by Yang in 2012 [68]. One of the initial involvements in control optimization was to achieve an optimal static VAR compensator damping controller [69].

A genetic algorithm (GA) is a metaheuristic algorithm inspired by Darwin's evolutionary theory. The idea is based on a population that learns the existing condition and moves to a better future direction [70,71]. The early application of GA in the control area comprised a learning algorithm for FLC-controlled spacecraft autonomous rendezvous operations in [72]. Firstly initiated in 2014, grey wolf optimization (GWO) was inspired by the phenomenon of wolves hunting their prey [73]. One of the first employments of GWO comprised designing a static VAR compensator controller [74]. An algorithm called harmony search algorithm (HSA) was triggered by how musicians perform improvisation [75]. One of its first combinations with a control strategy was in tuning an interfaced-DG parallel inverter [76]. By mimicking the behaviour of particular hawk species while chasing its prey, the Harris's hawks optimization (HHO) was formulated [77]. The enhancement of an FO-PID-controlled DC–DC converter in 2016 was categorized as its initial linkage with the control system [78]. Taking the idea of how two countries in the classical era behaved, the imperialist competitive algorithm (ICA) was initialized [79]. One of the first verifications of this idea in the control strategy was for tuning the fuzzy-controlled pendulum-cart system [80].

In 2016, Mirjalili and Lewis published a technique named whale optimization algorithm (WOA) [81]. An early interconnection with optimal control methods was for tuning active disturbance rejection control (ADRC)-based automatic carrier landing systems (ACLSs) [82]. Inspired by the Sanskrit principle of achieving success and avoiding failure, an idea titled the Jaya algorithm (JA) was produced [83]. Tuning the fuzzy-based inertia emulator was one of its first advancements in control optimization [84]. Yazdani and Jolai made a mathematical model based on how a lion pride behaves [85]. One of its first engagements in the control world was for optimizing a PID-based LFC [86]. The linear matrix inequality (LMI) method is an optimization technique centred on forming linear inequality constraint equations in a matrix. Its combination with the Lyapunov theory was developed into a functional algorithm to analyse the stability of a system [87]. Following the approach of a mine bomb explosion, Ali et al. conceptualized the mine blast algorithm (MBA) [88]. One of its earliest executions in control optimization methods comprised tuning a robust PID [89]. By using the magnetic-orientation behaviour of particular bacteria, a magnetotactic bacteria optimization algorithm (MBOA) was proposed [90]. Early practicality in the control system comprised tweaking a fractional active disturbance rejection LFC [91]. The marine predator algorithm (MPA) is an algorithm taking the interaction between a predator and prey in a marine ecosystem as insight [92]. One of its very first collaborations in the control field was for the improvement of power system stabilizers (PSSs) and power oscillation dampers (PODs) [93].

The multiverse optimizer (MVO) idea was motivated by three astrophysics phenomena: black holes, white holes, and wormholes [94]. One of its earliest implementations in control operations was for the enhancement of a fuzzy-PID-based LFC [95]. Motivated by the goal of quicker and nonelitist characteristics, an improvement of the GA named nondominated sorting genetic algorithm II (NSGA-II) was recommended [96]. The design of lateral acceleration control operations for a nonlinear homing missile became one of its first introductions with respect to control techniques [97]. Invented by Eberhart and Kennedy, particle swarm optimization (PSO) was motivated by the behaviour of birds when flocking [98]. The initial implementation of this algorithm in the control system was to tune the SVC damping controller [99]. A Nobel laureate first introduced quadratic programming (QP), and it is aimed at solving portfolio problems [100]. Its earliest development in the control system can be traced back to 1986 when the idea was implemented to solve a robot manipulator problem [101]. When launched in 2017, the salp swarm algorithm (SSA) was motivated by the movement of salps when swimming in the ocean [102]. In the control area, the early execution of this scheme was for optimizing a PID-fuzzy active tuned mass damper (ATMD) [103].

Initially published by Mirjalili, the sine cosine algorithm (SCA) aims for the best solution by utilizing sine and cosine mathematical functions [104]. One of the primary uses of this algorithm in optimal control methods was for tuning PID-based two-area LFCs [105]. An observation of how a volleyball team interacts during competition motivated a group of researchers to publish the volleyball premier league algorithm (VPLA) [106]. One of its first applications in control practice was the optimization of a fuzzy FO-PI-PID with a derivative filter (FFOPI-PIDN)-based AGC [107]. An optimization named the equilibrium optimizer (EO) was published in 2020 [108]. One of its earliest exertions concerning control optimization was for a cascaded fractional fuzzy controller AGC optimization [109]. Motivated by business and management practices, a method named rolling optimization (RO) was published [110]. In the control field, one of its earliest recorded application was for tuning a synchronous motor controller [111]. The behaviour of particular microorganisms in their search for nutrients triggered some scholars to invent a procedure named the slime mould algorithm (SMA) [112]. One of its successful implementations in control practice was to tweak an FO-PID-based DC motor [113].

The seagull optimization algorithm (SOA) was inspired by how a seagull attacks and migrates [114]. Tuning a fuzzy controller AGC became one of its early establishments within control optimization [115]. Teacher and learner interactions motivated Rao et al. to create an algorithm termed teaching–learning-based optimization (TLBO) [116]. Historically, one of its earliest connections to control problems was tuning an interval type-2-fuzzy PID (IT2-FPID) controller of wheeled mobile robots [117]. A procedure named the water cycle algorithm (WCA) was formulated based on the cycle of water in nature [118]. Tuning an FLC-based standalone hybrid green power (SHGP) system became one of its earliest implementation in optimal control [119]. The motion of the wind in the atmosphere motivated several research experts in codifying a strategy named wind-driven optimization (WDO) [120]. One of its connections to control optimization methods comprised enhancing a D-STATCOM's PI controller in 2015 [121].

4. Literature Review

4.1. Frequency Regulation Service

Thirteen papers discussed the EVAS control method, providing frequency regulation services since 2012. A compilation of the control strategies of EVAS as frequency regulation services above is displayed in Table 1. A fuzzy load controller and fuzzy voltage controller (FLC-FVC) was proposed in [122]. Voltage regulation was also improved by using the proposed strategy in addition to frequency regulation. Moreover, the spinning reserve requirement was reduced. The authors in [123] suggested an autonomous distributed V2G control scheme for regulating frequencies. Compared to the condition without V2G, other than the regulating frequency, the scheme also reduces the spinning reserve required by the system. Ref. [124] offers the implementation of a fuzzy logic controller (FLC). In this study, the FLC was tested on the IEEE 39-bus system and actual data from Victoria, Australia. The results revealed that the FLC strategy performs better than [123] even in the situation without V2G. Researchers in [125] recommended using the real-time smart charging algorithm. In this study, a genetic algorithm (GA) was utilized to optimize the size of renewable energy farms. The research also used real data from Florida City by PJM. With the exception of regulating frequencies, the impact of EV charging on the grid was also minimized. The process of charging battery SoC holders (BSHs) with frequency regulation (CFR) was examined by [126]. Other than the control strategy, a framework named distributed V2G control (DVC) was also presented. Then, the combination rivalled with [18] and the case scenario without V2G. The frequency regulation objective was accomplished, and the main objective of fulfilling charging demands was not sacrificed. Frequency modulation control (FMC) methods were also investigated [127]. During a competition with a no-V2G scenario, frequency fluctuations decreased by 56%. In [128], decentralized primary frequency regulation control (DPFRC) methods were discussed. It was discovered that the discussed method was superior to the autonomous distributed control (ADC) method as a benchmark.

Table 1. EVAS as a frequency regulation service.

Ref.	Year	Control	Benchmark	Remark
[122]	2012	FLC-FVC	N/A.	Reducing spinning reserve, improving voltage regulation.
[123]	2012	ADV2G	Without V2G.	Reducing spinning reserve.
[125]	2014	RTSC	Without controller.	Optimized by genetic algorithm (GA) and involving the step of optimizing the size of renewable energy farms, applying real data from Florida City by PJM and minimizing the impact of the charging of PEVs relative to the grid.
[126]	2013	BSH-CFR	1. Without V2G, ADV2G [123].	Proposing the framework of the distributed V2G control (DVC).

Table 1. *Cont.*

Ref.	Year	Control		Benchmark	Remark
[124]	2017	FLC	2.	Without V2G, ADV2G [123].	Tested using the IEEE 39-bus system: actual data from Victoria, Australia, were used.
[127]	2017	Frequency modulation		Without V2G.	Successfully reduced frequency deviations while maintaining the EV owner's satisfaction level.
[128]	2018	DPFRC		Autonomous distributed control (ADC).	Featuring a balanced objective to maintain frequency stability and battery SoC.
[129,130]	2018 2019	ACE-ARR-based control	1.	Area control error-based optimal approach (ACE-OA), area control error-based proportional approach (ACE-PA), area regulation requirement-based optimal approach (ARR-OA), area regulation requirement-based proportional approach (ARR-PA).	Proposing a hierarchical control framework; control centre, EV aggregators, and EV charging stations.
[131]	2018	Decentralised control		Droop control.	90% SoC guarantee, featuring the suspension of charging when frequencies are too low.
[132]	2018	GPA		Coordinated control strategy [133].	Offering demand declaration strategy frameworks.
[134]	2019	Decentralised V2G/G2V		N/A.	Proposing a two-way communication and energy flow architecture using real data from PJM.
[135]	2019	SDV2G	1.	Without V2G, droop control, BSH-CFR [126].	Simulated in MATLAB environments; two conditions were applied: normal and worst condition.

A technique was introduced based on extracting area control error (ACE) signals [129,130]. An optimal dispatch (OD) algorithm was also featured to ensure the optimal allocation among EVs. In order to support such a technique, a hierarchical control framework consisting of the control centre, EV aggregators, and EV charging stations was also described. Combined with operations for regulating frequency, it was recognized that this technique also reduced the output of traditional generators. The experimentation performed in [131] pointed out the decentralized control scheme and correlated it with the droop control method. It was observed that the scheme was able to regulate frequencies without sacrificing the EV's SoC. Article [132] introduced the grouping power allocation approach. Additionally, a framework demand declaration strategy was also prepared. It was shown that this procedure was superior to the method introduced in [133]. The analysts in [134] advocated implementing decentralized V2G/G2V support by utilizing charge and discharge rates (C-rate/D-rate). In parallel, the study also demonstrated a two-way communication and two-way energy flow architecture. The analysis was carried out using factual data from PJM. The authors in [135] proposed a smart decentralized V2G (SDV2G) control method, and they discovered that the practice was more desirable than having no V2G condition and droop control [21]. Although papers were recently collected (2023), the most recent research on EVAS as a frequency regulated service was conducted in 2019. The research on this topic appears to have peaked, and the focus has shifted to EVAs as a frequency contingency.

4.2. Frequency Contingency Service

4.2.1. PID Variants

Since 2017, forty-four reports elaborated upon the control scheme of EVASs that support frequency contingency services using the PID model. The chronological development of PID control variants as EVAS frequency contingency services is provided in Figure 5, while a compilation of PID variants acting as EVAS frequency contingency services is provided in Table 2. FO-PID in accordance with FPA was investigated and analysed in [136–138]. It was determined that the combined FO-PID and FPA technique was more fitting than the PID controller, both with and without a filter. The usage of a Hebbian learning PID was explored in [139]. The fluctuation of wind power generators (WPGs) was also examined. It was observed that the method was preferable to PID and supervised Hebbian learning. FO-PID-ICA was presented in [140]. As a comparison, selected hybrid gravitational search and pattern search (HyGS-PS) and DE algorithms were used. It was revealed that the ICA optimization algorithm outruns both its rivals. The use of the combined FO-PID and SCA technique was investigated in [141,142]. It was recognized that the combined FO-PID and SCA technique was more prominently successful than PID-SCA, PID-PSO, and FO-PID-PSO. LOA was applied to tune the PID controller in [86]. The trial also included a FACTS device, which comprised a UPFC. It was shown that the proposal could minimize frequency deviations during disordered conditions.

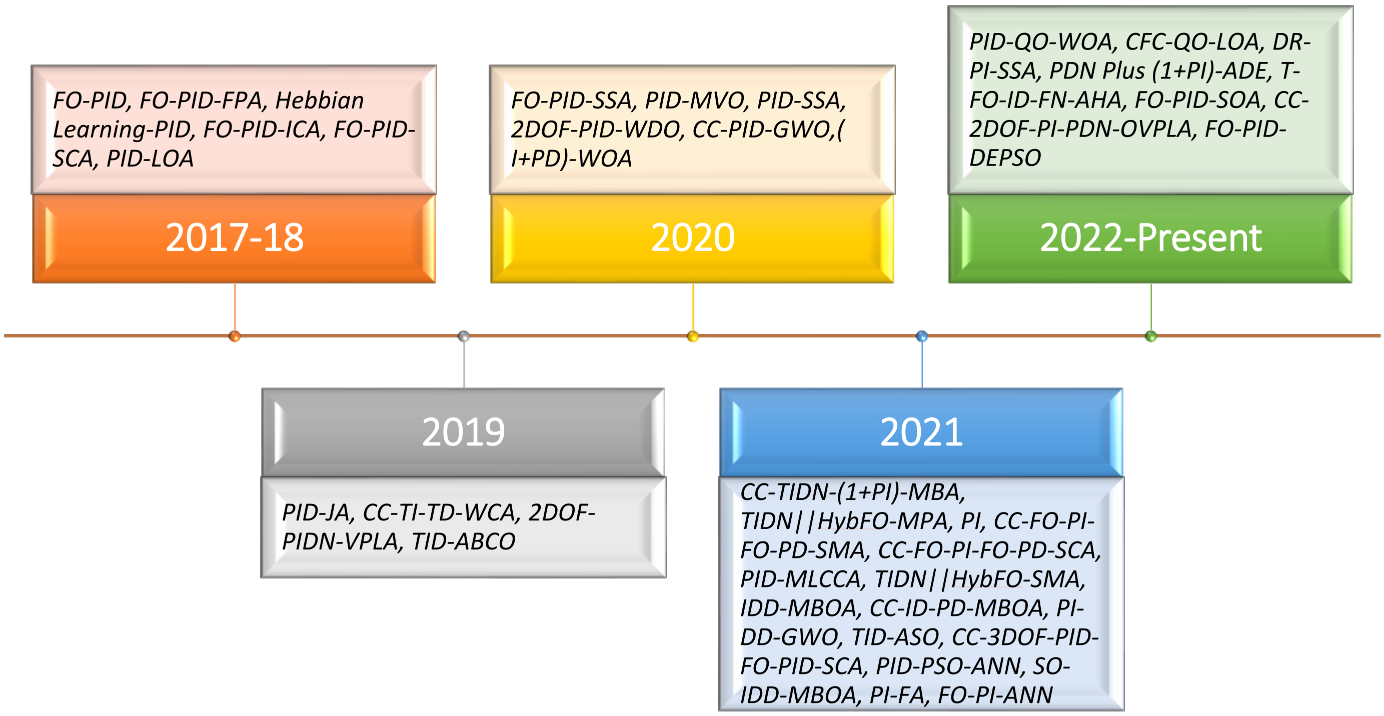

Figure 5. Chronological development of PID control variants as EVAS frequency contingency services.

Table 2. EVAS as frequency contingency services with the PID variant.

Ref.	Year	Control	Optimization	Benchmark	Remark
[136–138]	2017	FO-PID	FPA	PID, PIDN.	Simulated in a three-area power system incorporated by both HVAC and HVDC transmission interconnections.
[139]	2017	Hebbian Learning-PID	N/A	PID, supervised Hebbian learning.	Incorporating the fluctuation of WPG.
[140]	2018	FO-PID	ICA	Hybrid gravitational search and pattern search (HyGS-PS) algorithm, differential evolution (DE).	Comparing optimization algorithms rather than comparing control strategies.
[141,142]	2018	FO-PID	SCA	PID-SCA, PID-PSO, FO-PID-PSO.	Simulated using MATLAB/Simulink, applying the delay scenario on EV's aggregator side.
[86]	2018	PID	LOA	Without V2G.	Incorporating the FACTS device of UPFC.

Table 2. *Cont.*

Ref.	Year	Control	Optimization	Benchmark	Remark
[143]	2019	PID	JA	PID-GA, PID-PSO, PID-GWO.	Incorporating the fluctuation of WPG and PV.
[144]	2019	CC-TI-TD	WCA	PI, integral–tilt derivative (I-TD), CC-TI-TD without V2G.	Incorporating several scenarios: single-area, two-area, parameter variations, load variations, EV number variations, and communication delay.
[145]	2019	2DOF-PIDN	VPLA	Without V2G.	Simulated in a three-area power system by applying constant and variable distributed energy systems (DESs).
[146]	2019	TID	ABCO	TID-PSO, TID-GA, TID.	Simulated in a two-area power system by applying step and random load changes and assessing the controller's effectiveness by several control performance indicators (minimum damping ratio, peak overshoot, peak time, settling time, and ITSE).
[147]	2020	FO-PID	SSA	PID-PSO, PID-SSA, FO-PID-PSO.	Simulated in single-area and two-area power systems with two scenarios: single and multistep load changes. The control performance was monitored by using several indices: IAE, ITAE, and MAE.
[148]	2020	PID	MVO, SSA	Without V2G.	Incorporating two scenarios: step load change in area-1 and random load change in area-2. In addition, ISE performance indicators, such as settling time, rise time, overshoot, and undershoot, were captured.
[149]	2020	2DOF-PID	WDO	PID, PI, integral (I).	Incorporating various scenarios: variations in the steady-state load, system inertia, and step load changes. Settling time, overshoot, and undershoot were used as performance measurements.
[150]	2020	CC-PI-PD	SSA	Integral (I), PI, PID, PI-PD-PSO, PI-PD GWO.	Implementing numerous scenarios: step load perturbation, random load perturbation, variation of inertia constant, damping constant, and droop constant. Measuring ISE and settling time as performance indicators. Equipped study with stability analysis.
[151]	2020	CC-PID	GWO	PI-GWO, PID-GWO, CPID-PSO, CPID-GA.	Evaluating overshoot, undershoot, and ITAE as the performance indicators.
[152]	2020	I+PD	WOA	PIDN-WOA.	Simulated using MATLAB/Simulink in two-area systems.
[153]	2020	CC-TID Filter 1+PI	MBA	Integral (I), PI.	Using OPAL-RT's digital simulator.
[154]	2021	TIDN||HybFO	MPA	TIDN||HybFO-GA, TIDN||HybFO-MRFA, TIDN||HybFO-AEO, TIDN||HybFO.	Incorporating the scenarios of load changes, RES disorder, high-RES penetration, and system uncertainties. Applied ISE, IAE, ITSE, and ITAE as comparison parameters.
[155]	2021	PI	N/A	Without V2G.	Substantially fewer area control errors (ACEs) generated with V2G connected to the system.

Table 2. *Cont.*

Ref.	Year	Control	Optimization	Benchmark	Remark
[156]	2021	CC-FO-PI-FO-PD	SMA	PID-GA, PID-PSO, PID-SMA, FO-PID-GA, FO-PID-PSO, FO-PID-SMA, CC-FO-PI-FO-PD-GA, CC-FO-PI-FO-PD-PSO.	Incorporating the fluctuation of WPG and PV.
[157]	2021	CC-FOPI-FOPD	SCA	PI-GA, PI-SCA, PID-GA, PID-SCA, PI-PD-GA, PI-PD-SCA, FO-PI-FO-PD-GA, PI-PD-SCA.	Simulated in a three-area power system and used ITAE, overshoot, and undershoot for performance assessment.
[158]	2021	PID	MLCCA	N/A.	Monitoring the performance indicators, such as the minimum, maximum, average, and standard deviation, of the frequency.
[159]	2021	TIDN||HybFO	SMA	TIDN||HybFO-ALO, TIDN||HybFO-PSO, TIDN||HybFO.	Incorporating the fluctuation of WPG and PV.
[160]	2021	IDD	MBOA	Integral (I), ID, PI, PID, IDD-BBO, IDD-FA, IDD-PSO, IDD-GA, IDD-fuzzy.	Incorporating variations in solar irradiance.
[161]	2021	CC-ID-PD	MBOA	PID-MBOA, PIID-MBOA, PIDD-MBOA, CC-PD-ID-MBOA.	Implementing the demerit index (DI), which is the sum square value of the minimum overshoot (MO), minimum undershoot (MU), and time of settling (ToS), as the performance indicator.
[162]	2021	PI-DD	GWO	PIDN, PID, PI.	Incorporating AC–DC lines.
[163]	2021	TID	ASO	TID-ASO, TID-GOA, TID-SSA, TID-GWO, TID-SCA, TID-PSO.	Applying various scenarios such as random load disturbance (RLD), sinusoidal load disturbance (SLD), and pulse load disturbance (PLD). Assessing the performance indicator of overshoot, undershoot, and ITSE.
[164]	2021	CC-3DOF-PID-FO-PID	SCA	FO-PID-SCA.	Simulated by MATLAB/Simulink in a four-area power system. Measuring overshoot, undershoot, and settling time as the performance indicators.
[165]	2021	PID	PSO-ANN	CPID, FPID.	Involving several scenarios: variations in load, wind, and battery's state of health (SoH).
[166]	2021	SO-IDD	MBOA	ID, PID, IDD.	Using the demerit index (DI), which is the sum square value of the minimum overshoot (MO), minimum undershoot (MU), and time of settling (ToS), as the performance indicator.
[167]	2021	PI	FA	I-FA.	Implementing the scenarios of step load disturbances (SLDs) and random load disturbances (RLDs). Monitoring settling time, overshoot, and undershoot as performance indicators.
[168]	2021	FO-PI	ANN	PI, FO-PI.	Simulated in a three-area power system by evaluating settling time and overshoot as the performance indicators.
[169]	2022	PID	QO-WOA		Incorporate superconducting magnetic energy storage (SMES).
[170]	2022	CFC	QO-LOA	PID-BBO.	Incorporating superconducting magnetic energy storage (SMES).
[171]	2022	DR-PI	SSA	PI, PID.	
[172]	2022	PD-N Plus (1+PI)	ADE	PID-DE, PID-ADE.	Incorporating OPAL-RT and incorporating the fluctuation of WPG and PV.

Table 2. *Cont.*

Ref.	Year	Control	Optimization	Benchmark	Remark
[173]	2022	T-FO-ID-FN	AHA	PIDN, TIDN, FO-PIDN, FO-TIDN, T-FO-ID-FN-ABC, T-FO-ID-FN-BOA, T-FO-ID-FN-AEO, T-FO-ID-FN-PSO.	Incorporating fluctuation of WPG and PV.
[174]	2022	FO-PID	SOA	PIDD-SOA, PID-SOA, PI-SOA.	Incorporating superconducting magnetic energy storage (SMES).
[175]	2022	CC-2DOF-PI-PDN	OVPLA	2DOF(PI)-PDN-PSO, 2DOF(PI)-PDN-WOA, 2DOF(PI)-PDN-VPLA, 2DOF(PI)-PDN-OVPLA, integral-OHS, PID-BBO, 2DOF-TIDN-HSSDEA, PDF(1+FOD)-SSA.	Incorporating HVDC.
[176]	2022	FO-PID	DEPSO	PID-DEPSO.	Incorporating HVDC.
[177]	2022	FO-PID	N/A	PID, PD without PHEV, PI without PHEV, PID without PHEV, FO-PID without PHEV.	Simulated on a two-area system and applied ITAE as the control performance index.

The conventional PID was adjusted using JA [143]. The water cycle algorithm (WCA) was engaged to optimize CC-TI-TD in [144]. When this method was compared to PID, the integral–tilt derivative (I-TD), and no-V2G CC-TI-TD controller, it was observed that the obtained effect was more desirable. The two-degree-of-freedom PID with a derivative filter (2DOF-PIDN) was improved by using the new volleyball premier league algorithm (VPLA) [145]. It was demonstrated that the assortment reduces frequency disorders effectively. Simulations in [146] matched the tilt integral derivative (TID) and ABCO. It revealed that, with the same topology, the chosen optimization was better than PSO and GA. SSA was applied to optimize the parameter of the FO-PID [147]. Its practicality was described as outsmarting PID-PSO, PID-SSA, and FO-PID-PSO. MVO and SSA optimizations were used in trials on PID [148]. It was deduced that MVO was more advanced than SSA in terms of settling time, while SSA exhibited smoother results than MVO. Another study examined the combination of 2DOF-PID with WDO [149]. It was observed that the mixture was more promising than the I, PI, and PID. PI and PD were arranged in a cascade [150]. Then, SSO was applied to obtain the most optimum parameters. It was concluded that the entire system overcame the traditional integral, PI, and PID, and the cascaded structure with PSO and GWO optimization. P, I, and D controllers were cascaded, forming CC-PID. Then, the parameter was adjusted using GWO [151]. It was affirmed that this practice was more advantageous than PI-GWO, PID-GWO, CC-PID-PSO, and CC-PID-GA. A relatively new algorithm of WOA was implemented to find the most optimum gain of the sum of the integral and PD (I+PD) [152]. It was observed that the collaboration surpassed the results of PIDN-WOA. MBA was applied to tweak the parameters of the CC-TID with the 1+PI filter (TIDN-1+PI) [153].

An OPAL-RT digital simulator was also applied to verify the results. In summary, it was noted that the results of the procedure were ahead of the integral and PI. Article [154] suggested the option of using parallel TID with a hybrid-fractional order (TIDN||Hyb-FO) filter and MPA. It was depicted that the duo was finer than TIDN||HybFO optimized with GA, MRFA, AEO, or an individual TIDN and HybFO. Roshan and Ismayil proposed a PI controller [155]. They summarized that there were fewer generated area control errors (ACEs) when V2G was connected to the system. The experts in [156] proposed a cascaded control operation of FO-PI and FO-PD (CC-FO-PI-FO-PD) and SMA. Considering the fluctuation of WPG and SPV, it was discovered that the product of the proposition had better performances than PID-GA, PID-PSO, PID-SMA, FO-PID-GA, FO-PID-PSO, FO-PID-SMA, CC-FO-PI-FO-PD-GA, and CC-FO-PI-FO-PD-PSO. SCA was employed in CC-FO-PI-FO-PD [157]. The simulation showed that this conception outstrips PI-GA, PI-SCA, PID-GA, PID-SCA, PI-PD-GA, PI-PD-SCA, FO-PI-FOPD-GA, and PI-PD-SCA. In [158], a pair of conventional PIDs with a multilevel coordinated controlled charging algorithm (MLCCA) was fully explored. SMA was used to optimize TIDN||HybFO in [159]. In conclusion, this approach was more successful than TIDN||HybFO-ALO, TIDN||HybFO-PSO, TIDN, and HybFO. The simulation also absorbed the reality of WPG and PV fluctuations. Reference [160] verified the possibility of using MBOA when adjusting the I-DD. Variations in solar irradiance were also observed. It was revealed that the recommendation proved to be a better solution than the integral, ID, PI, PID, I-DD-BBO, I-DD-FA, I-DD-PSO, I-DD-GA, and I-DD-fuzzy. In [161], MBOA was used to calculate the control parameter of the CC-ID-PD. Then, it was realized that the result was more desirable than PID-MBOA, PI-ID-MBOA, PI-DD-MBOA, and cascaded PD-ID-MBOA. PI-DD was finetuned by GWO [162] in a system incorporating AC–DC lines. It was shown that the set of two algorithms was more powerful than PIDN, PID, or PI. Several experts employed ASO to enhance TID [163]. It was shown that this method was more assuring than TID-ASO, TID-GOA, TID-SSA, TID-GWO, TID-SCA, and TID-PSO. Article [164] introduced a cascaded control operation of a three-degrees-of-freedom PID-FO-PID (CC-3DOF-PID-FO-PID) featuring SCA. It was exposed that this application was more useful than FO-PID-SCA. A PID containing PSO-ANN was discoursed in [165]. It was recapitulated that the offering outshines CPID and FPID controllers. A static observer-I-DD enclosed by MBOA was investigated [166]. It was portrayed that the mixture scheme was more convincing than ID, PID, and IDD. A PI boosted by FA was evaluated [167]. It was recorded that the contribution was stronger than the I-FA. Article [168] thoroughly discussed an ANN-enhanced FO-PI. In conclusion, it was shown that the presentation was more excellent than the PI and FOPI. A system integrated by using superconducting magnetic energy storage (SMES) was used as a plant for the PID-QO-WOA [169]. A similar idea of implementing SMES was carried out in [170]. QO-LOA was used to improve a cascade fractional controller. It was disclosed that the implementation was more effective than PID-BBO. The disturbance rejection PI (DR-PI) control was amalgamated with SSA [171]. It was shown that the idea outshined PI and PID. An innovative ADE was employed on PDN Plus (1+PI) [172]. Then, the arrangement was modelled using OPAL-RT with the counting fluctuation of WPG and PV. This conception was more remarkable than PID-DE and PID-ADE. AHA was engaged in revealing the optimal condition of tilt FO-ID with a fractional filter (T-FO-ID-FN) [173]. In actual applications, the fluctuation of WPG and PV was also taken into account. It was divulged that the concept was more valuable than PIDN, TIDN, FO-PIDN, FO-TIDN, T-FO-ID-FN-ABC, T-FO-ID-FN-BOA, T-FO-ID-FN-AEO, and T-FO-ID-FN-PSO. The fresh SOA was exerted to augment FO-PID [174]. The system operates an SMES. It was communicated that the contribution overcomes PI-DD-SOA, PID-SOA, and PI-SOA. The 2DOF-PI-PD with a filter (2DOF-PI-PDN) assisted by OVPLA can operate a system that implements HVDC [175]. This constructing outstripped 2DOF(PI)-PDN-PSO, 2DOF(PI)-PDN-WOA, 2DOF(PI)-PDN-VPLA, 2DOF(PI)-PDN-OVPLA, Integral-OHS, PID-BBO, 2DOF-TIDN-HSSDEA, and PIDN(1+FOD)-SSA. FO-PID combined with DEPSO was promoted in [176]. This technique performs better than PID-DEPSO. FO-PID was implemented in [177]. The implementation defeated the results of using PID, PD, and PID with PHEV and FO-PID without PHEV.

Despite the fact that the criteria for papers collected are from 2012, it is clear that the research trend of EVAS for frequency contingency using PID variant began in the mid-2010s. The first wave of research focused solely on PID modification (e.g., FO-PID [140]) or PID plus optimization (e.g., PID-LOA [86], PID-JA [143]). By the end of the 2010s, the second generation of research had begun with the application of both PID modifications (e.g., CC-PID, TID, 2DOF-PID, PIDN) and novel optimization algorithms (WCA, VPLA, ABCO), such as 2DOF-PIDN-VPLA [145] and TID-ABCO [146]. Finally the recent trend is cascading of two modified PIDs, such as 3DOF-PID and FO-PID, yielding CC-3DOF-PID-FO-PID-SCA [164], or 2DOF-PI and PDN, yielding CC-2DOF-PI-PDN-OVPLA [175].

4.2.2. Fuzzy Variants

From 2018, nineteen papers explain the control system of EVAS-supporting frequency contingency services exercising the fuzzy scheme. The time order progression of fuzzy control variants as EVAS frequency contingency services is specified in Figure 6, while the collection of fuzzy variants acting as EVAS frequency contingency services is provided in Table 3. A decentralized-FLC was investigated in [178]. The method successfully outperformed the examined scenario, whereas V2G was not in the picture. An FLC optimized by ICA was proposed in [179,180]. A trial using the IEEE-39 bus determined that the proposal surpasses the results in [181] and PI-ICA controllers. General type-2 fuzzy logic sets (GT2FLS) combined with the MHSA were elaborated in [182,183]. The analysis also incorporated the uncertainty factor of WPG. It was observed that the control was finer than the optimal fuzzy-PI (OFPI), optimal interval type II fuzzy-PI (IT2FPI), PID, and fuzzy-PID (FPID). The investigators in [184] examined the polar fuzzy control method. In the simulation, several examined scenarios involved a sudden increase/decrease in wind speeds, load demand, and solar radiation. An additional method, the minimal-order observer, was applied to estimate the supply error. It was evident that the method was more prominent than conventional FLCs. The enhancement of [55] was completed in [185], in which MO-BHA updates the multiobjective-fractional order-fuzzy-PID (MO-FO-FPID). With the exception of being integrated with HIL, the experimentation also reflects the fluctuation of WPG and PV. It was confirmed that the performance was above the multiobjective-fuzzy PI (MO-FPI), multiobjective-interval type-2-FLC (MO-IT2-FLC), and multiobjective-PID (MO-PID). A novel TLBO was applied to regulate adaptive fractional order-fuzzy-PIDs (adaptive FOFPID) [186]. The simulation integrated the fluctuations of WPG and PV. It was confirmed that the mixture outperformed PID-TLBO, FO-PID-TLBO, fuzzy PID, and FO-FLC-PID. FLC-FO-PID was described in [187]. From simulations, it was concluded that the idea was superior to PID and FO-PID. A novel strategy named the FLC-data integrity check correction (FLC-DICC) method was proposed [188]. The strategy utilized ANN for forecasting and verifying integrities. In order to support this argument, a two-layer framework comprising a data integrity and correction check block in the first layer and an FLC in the second layer was also proposed. Later, the idea was confirmed by using data from Guwahati City collected from a regional power distributor provided by Assam Power Distribution Company Limited (APDCL). The adaptive enhancement version of FLC, named fuzzy-logic-based adaptive two-degree-of-freedom internal model control (FL-2DOF-IMC), was suggested [189]. The simulation incorporated a fluctuation in WPG. At the end of the study, it was shown that it was better than its nonadaptive version.

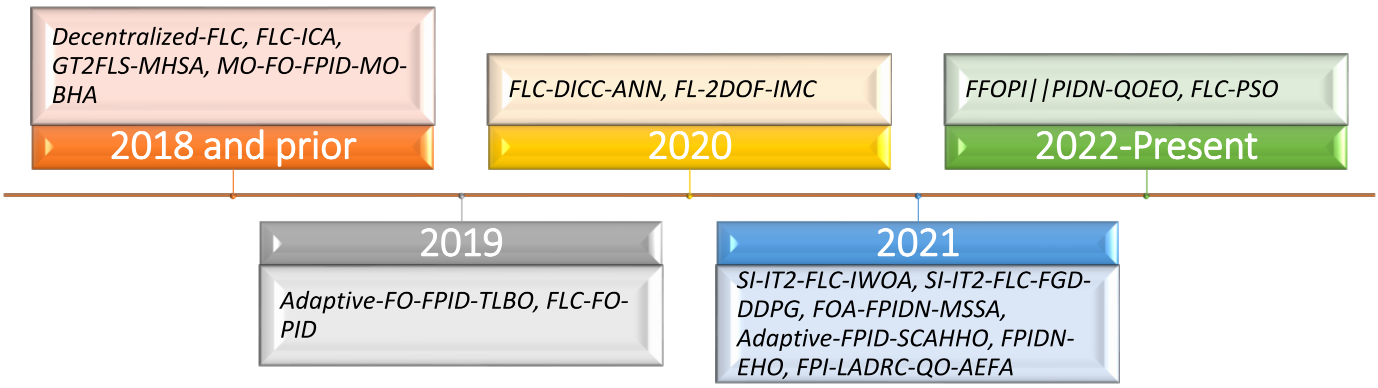

Figure 6. Time order progression of fuzzy control variants as EVAS frequency contingency services.

Table 3. EVAS as a frequency contingency service with fuzzy variants.

Ref.	Year	Control	Optimization	Benchmark	Remark
[178]	2015	Decentralized-FLC	N/A	Without V2G.	
[179,180]	2016	FLC	ICA	H2/H∞-PSO [181], PI-ICA.	Tested using IEEE-39 Bus.
[182,183]	2016	GT2FLS	MHSA	Optimal fuzzy PI (OFPI), optimal interval type II fuzzy-PI (IT2FPI), PID, FPID.	Incorporating the fluctuation of WPG.
[184]	2017	PFLC	N/A	FLC.	Tested with several scenarios with a sudden increase/decrease in wind speed V_W, load demand, and solar radiation φ, and a linear increase in φ. Minimal-order observer method was applied to estimate the supply error.
[185]	2018	MO-FO-FPID	MO-BHA	Multiobjective-PID (MO-PID), multiobjective-FPI (MO-FPI), multiobjective-IT2-FLC (MO-IT2-FLC).	Incorporating the fluctuation of WPG and PV and incorporating hardware-in-the-loop (HIL) simulations.
[186]	2019	Adaptive-FO-FPID	TLBO	PID- TLBO, FO-PID- TLBO, FPID, FO-FLC-PID.	Incorporating the fluctuation of WPG and PV.
[187]	2019	FLC-FO-PID		PID, FO-PID.	
[188]	2020	FLC-DICC	ANN	FLC.	Using data from Guwahati City collected from a regional power distributor provided by Assam Power Distribution Company Limited (APDCL), using ANN for forecasting and integrity check, proposing a 2-layer framework: data integrity and correction check block in the first layer and an FLC in the second layer.
[189]	2020	FL-2DOF–IMC		Nonadaptive TDF-IMC.	Incorporating the fluctuation of WPG.
[190]	2021	SI-IT2-FLC	IWOA	T1-FPD/FPI, PD/PI.	Adopting a hardware-in-the-loop (HIL) simulator.
[191]	2020	SI-IT2-FLC	FGD-DDPG	FGD-SIT2-FPID, GD-SIT2-FPID, A-SIT2-FPID, S-SIT2-FPID, T1-FPID, and PID.	Incorporating real-time setup (RTS) space for results verification.
[192]	2021	FOA-FPIDN	MSSA	PI, PI-GA, PI-BFOA, PI-PSO, hBFOA-PSO, PI-NSGA-II, PIDN-NSGA-II, fuzzy PI-PS, fuzzy PI-PSO.	Incorporating variations of PV and WPG.
[193]	2021	Adaptive FPID	SCAHHO	PI, PI-GA, PI-BFOA, PI-PSO, hBFOA-PSO, PI-NSGA-II, PIDN-NSGA-II, fuzzy PI-PS, fuzzy PI-PSO, AFPID-MMFO.	Using OPAL-RT's digital simulator, involving the modern elements of a hybrid power system (HPS); ultracapacitor (UC), super magnetic energy storage (SMES), and fuel energy storage (FES).
[194]	2021	FPIDN	EHO	PI, PID, PIDN.	Incorporating modern devices: unified power flow controller (UPFC), interline power flow controller (IPFC), fuel cells (FC), redox flow batteries (RFB), and superconducting magnetic energy storage (SMES).

Table 3. *Cont.*

Ref.	Year	Control	Optimization	Benchmark	Remark
[195]	2021	FPI- LADRC	QO-AEFA	Integral (I), PI, PID, PIDN, FPI, LADRC, PID-BBO.	Involving fluctuation of PV and WPG.
[196]	2022	FFOPI||PIDN	QOEO	FFOPI||PIDN-WOA, FFOPI||PIDN-EO, FFOPI||PIDN-OEO, an optimal output feedback controller, integral-OHS.	Incorporating HVDC, considering variables SPV and WPG, and incorporating Bode plot analyses in the design phase.
[197]	2022	FLC	PSO	N/A.	Applying two scenarios (normal and abnormal) while using the performance evaluation of the maximum frequency deviation, average frequency deviation, frequency regulation generator cost, frequency regulation EV cost, and restoration time.

There was an attempt to use an improved WOA to set the parameters of a single-input interval type-2 FLC (SI-IT2-FLC) [190]. A hardware-in-the-loop (HIL) simulator was included in the simulation. The proposition was shown to be more effective than T1-FPD/FPI and PD/PI. The same authors proposed SI-IT2-FLC, with the substitution of IWOA for reinforcement learning (RL) [191]. A self-tuning fractional gradient descent (FGD) algorithm and adaptive deep deterministic policy gradient (DDPG) technique were introduced. The simulation's result showed that the plan outplayed FGD-SIT2-FPID, GD-SIT2-FPID, A-SIT2-FPID, S-SIT2-FPID, T1-FPID, and PID. A fractional order adaptive-fuzzy PIDN (FOA-FPIDN) was optimized by an MSSA that was controlling a system containing variations of PV and WPG [192]. It was determined that the technique overpowered PI, PI-GA, PI-BFOA, PI-PSO, hBFOA-PSO, PI-NSGA-II, PIDN-NSGA-II, fuzzy-PI-PS, and fuzzy-PI-PSO. A sine-cosine-adopted Harris's hawks optimization (SCAHHO) was picked out as a combination for the adaptive fuzzy PID (AFPID) [193]. The investigated system comprised the modern elements of a hybrid power system (HPS), ultracapacitor (UC), fuel energy storage (FES), and SMES. Later, using OPAL-RT's digital simulator, it was revealed that the pairing was more beneficial than its benchmark (PI, PI-GA, PI-BFOA, PI-PSO, hBFOA-PSO, PI-NSGA-II, PIDN-NSGA-II, fuzzy-PI-PS, fuzzy-PI-PSO, and AFPID-MMFO). A model with a unified power flow controller (UPFC), interline power flow controller (IPFC), fuel cells (FCs), redox flow batteries (RFB), and SMES was used as the object of a fuzzy PIDN (FPIDN)-EHO arrangement [194]. It was unveiled that this method was more attractive than PI, PID, and PIDN. A complex strategy named the fuzzy-PI-linear active disturbance rejection control (FPI-LADRC) was improved by QO-AEFA [195]. The simulation was accomplished in a fluctuating PV and WPG environment. It was exposed that the proposition was more fitting than the integral, PI, PID, PIDN, fuzzy-PI, LADRC, and PID-BBO controllers. Parallel fuzzy fractional order PI-PID controllers with a filter (FFOPI||PIDN) were matched with QOEO [196]. The design phase was executed with a Bode plot analysis in a system involving HVDC and fluctuated SPV and WPG. The finding was that the FFOPI||PIDN-QOEO combination delivered more results than FFOPI||PIDN-WOA, FFOPI||PIDN-EO, FFOPI||PIDN-OEO, optimal output feedback, and the integral-OHS controller. Dissemination [197] elaborated upon the pairing of FLC-PSO.

It is observable that there are three subcategories in fuzzy variants. The first is fuzzy plus optimization (e.g., FLC-ICA [179,180], FLC-PSO [197]). The second subcategory is a hybrid of fuzzy and PID variants (e.g., MO-FO-FPID, MO-BHA [185], adaptive-FO-FPID-TLBO [186]). The higher computation requirement of the second subcategory is compensated by its superior result.

4.2.3. MPC Variants

A variety of experiments described the control routine of EVAS-maintaining frequency contingency services exercising the MPC types. An assortment of MPC variants acting as EVAS frequency contingency services is shown in Table 4. Multiple MPC (MMPC) pairs with quadratic programming (QP) were discussed in [198]. It was declared that the suggestion outplays the PID controller and conventional MPC. Analysis [199] examined multivariable generalized predictive control (MGPC) methods equipped with quadratic programming (QP). The controlled autoregressive and integrated moving average (CARIMA) model completed the prediction process. It was demonstrated that the results were finer than the PI controller and FLC. A decentralized MPC (DMPC) was discussed in [200,201]. It was uncovered that this particular configuration of MPC outplayed the centralized MPC as well as conventional PD controllers. As a continuation of [199], the generalized predictive controller (GPC) and CARIMA were mixed with rolling optimizations [202]. Additionally, a controllable load was implemented. It was summarized that the performance surpasses the PI controller. In [203,204], the MPC was explored. It was demonstrated that the suggestion was more powerful than the PI and PID controller. Dissemination [205], which operates the linear–quadratic regulator-robust model-predictive control (LQR-RMPC) method, summarized its advantages over type-II fuzzy-PID, MPC, PID, and fuzzy controllers. The adaptive intelligent model-predictive control (AIMPC) method in combination with SCA was presented and discussed in [206]. It was reported that the method excels over PID and adaptive fuzzy MPC methods.

Table 4. EVAS as a frequency contingency service with MPC variants.

Ref.	Year	Control	Optimization	Benchmark	Remark
[198]	2015	MMPC	QP	PID, MPC.	Applying several cases of SoC (30%, 50%, 65%, and 79%).
[199]	2015	MGPC	QP	PI, FLC.	The prediction was performed by the controlled autoregressive and integrated moving average (CARIMA) model.
[200,201]	2018	DMPC		PID, CMPC.	
[202]	2019	GPC	Rolling optimization	PI.	CARIMA was used as a predictive model, incorporating a controllable load.
[203,204]	2019	MPC		PI, PID.	Using ITAE, IAE, and ISE as performance evaluation.
[205]	2021	LQR-RMPC	N/A	Type-II fuzzy-PID, MPC, PID, fuzzy.	Applying scenarios of wind disturbance, load disturbance, parameter uncertainties, and islanded microgrid operation.
[206]	2022	AI-MPC	SCA	PID, adaptive fuzzy MPC.	Simulated various scenarios: single load perturbation (SLP), random load perturbation (RLP), wind/solar PV variation, and parameter uncertainties. Assessing the sum of the squared errors (SSEs) and mean of the squared errors (MSEs).

4.2.4. Other Variants

There are diverse trials defining the control practice of EVAS-preserving frequency contingency services with outlines other than PID, fuzzy, and MPC-type methods. The time order evolution of other variants as EVAS frequency contingency services control is detailed in Figure 7, while a collection of fuzzy variants acting as EVAS frequency contingency services is shown in Table 5. The scholars in [207] demonstrated and promoted an online reinforcement learning (RL)-based goal representation adaptive dynamic programming (GrADP) method as a supplementary control signal to a PI controller. It was shown that the procedure surpassed the PI controller and FLC. The authors in [181] proposed a robust controller (H2/H∞) associated with PSO. It was shown that that the method was preferred over [123] and the PI controller. The trial in [133] explored the coordinated control strategy. It was shown that the procedure improves frequency stability and renders the incorporation of renewable energy smoother. Simple linear control (SLC) methods were proposed in [208]. Taken together with SLC, it also defined the hardware's design based on IC556 and ICM7216. Then, an analysis using the region of asymptotical stability (RAS) was performed. IEEE Case 3 and IEEE New England were implemented as case studies. Several experts demonstrated the frequency regulation capacity-expected V2G (FRC-EV2G) control method [209]. This work was an enhancement of [126], which was also published by the same group. Conjointly, they also proposed a framework to support this strategy.

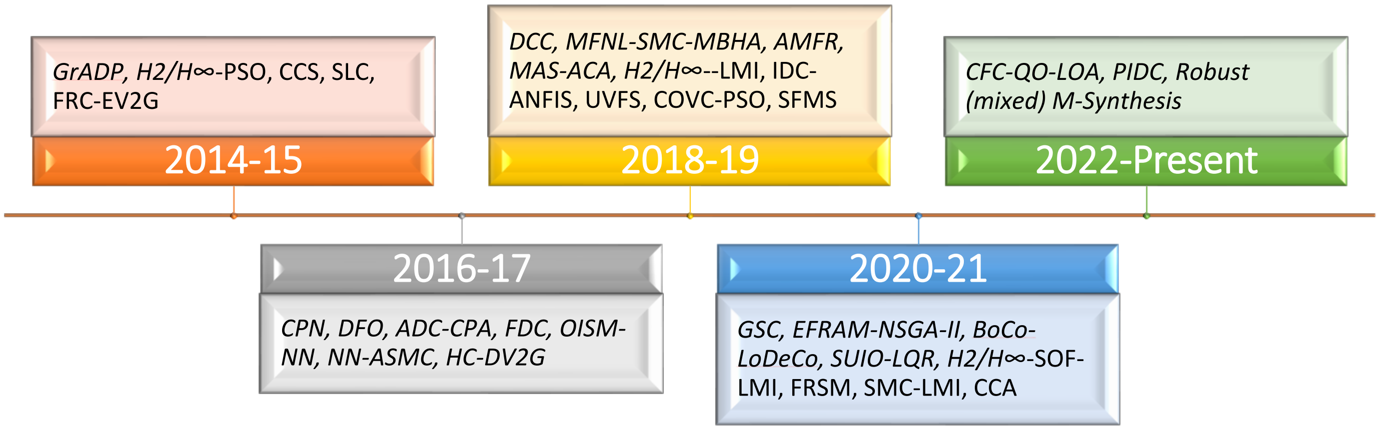

Figure 7. Time order evolution of other variants as EVAS frequency contingency services control method.

Table 5. EVAS as a frequency contingency service with other variants.

Ref.	Year	Strategy	Optimization	Benchmark Strategy	Remark
[207,210]	2014	GrADP	N/A	PI, FLC, FLC-PSO.	Incorporating the scenario with EV constraints and communication delay.
[181]	2014	H2/H∞	PSO	Autonomous distributed V2G control [123], PI.	Using IAE as a performance indicator.
[133]	2014	CCS	N/A	Without V2G.	Simulated in a two-area power system and using the scenarios of step and random load variations.
[208]	2015	SLC	N/A	Without V2G.	Incorporating hardware design, incorporating an analysis using the region of asymptotical stability (RAS), using IEEE Case 3 and IEEE New England.
[209]	2015	FRC-EV2G based control	N/A	Without V2G.	Improvement of [126], proposing the framework of supplementary frequency regulation (SFR) with V2G.
[211]	2016	CPN -based control	N/A	FRC-EV2G-based control [209].	Reducing frequency fluctuations, using actual data from PJM-ERCOT, proposing a framework comprising power generation, transmission, and substations.
[212]	2016	DFO	N/A	Open loop, optimal state feedback, LRO.	Incorporating HVDC link.
[213]	2017	ADC	CPA	N/A.	Investigated by scenario with respect to positive and negative changes in frequency.

Table 5. *Cont.*

Ref.	Year	Strategy	Optimization	Benchmark Strategy	Remark
[214]	2017	FDC	N/A	N/A.	The design process incorporates a Bode plot and eigenvalue analysis.
[215]	2017	OISM	NN	PID.	A neural network observer was designed to predict the PV power disturbance.
[216]	2017	NN-ASMC	N/A	PI, SMC.	Investigated by the scenario of load and parameter variation.
[217]	2017	HC-DV2G	N/A	Without V2G, FLC.	Two levels of control; lower-level controller is a local (decentralized) fuzzy controller for each parked PEV, and the upper-level controller is a centralized coordinate of the power flow in the entire grid.
[218]	2018	DCC	N/A	Centralised cooperative control.	
[55]	2018	MFNL-SMC	MBHA	PID, fuzzy-PID, MPC.	Involving HiL real-time simulation.
[219]	2018	AMFR	N/A	Without V2G.	No control centre, simulated using IEEE 14 bus system.
[220]	2018	MAS	ACA	N/A.	Investigated by the scenario of load variations and time delay.
[221]	2019	H2/H∞	LMI	N/A.	Incorporating the fluctuation of WPG and PV.
[222]	2019	IDC	ANFIS	Droop control, ODC.	Involving control of voltage, simulated using a 14-bus test MG.
[223]	2019	UVF	N/A	Without V2G.	Involving control of voltage.
[224]	2019	COVC	PSO	DVC [209], without V2G.	Incorporating a hierarchical distributed control framework.
[225]	2019	SFMS	N/A	N/A.	Involving power hardware-in-the-loop (P-HiL) experiments.
[226]	2020	GSC	N/A	Droop control.	Using Great Britain data as a case study.
[227]	2020	EFRAM	NSGA-II	N/A.	Using a reduced model of the Nordic power system.
[228]	2020	BoCo-LoDeCo	N/A	El-Co, Ba-Co, Sm-Ch-Co, Bo-Co.	
[229]	2021	SUIO	LQR	UIO-LQR, Luenberger observer-LQR.	Incorporating the fluctuation of WPG and PV.
[230]	2021	H2/H∞ -SOF	LMI	H∞-SOF.	Simulated using various scenarios: single-area/three-area power system and step/random load variations. Monitoring the parameters of ISE, mean absolute error (MAE), mean squared error (MSE), and standard deviation as performance indicators.
[231]	2021	FRSM	N/A	Without FRSM.	Using the Jeju Island power network as a case study.
[232]	2021	SMC	LMI	PID.	
[233]	2021	CCA	N/A	N/A.	Incorporating power hardware-in-the-loop (PHIL) simulation.
[234]	2022	PI-DC	N/A	Droop control.	Incorporating real data from PJM.
[235]	2022	Robust (mixed) M-synthesis	N/A	FLC, H∞, μ-synthesis, mixed-μ controller.	Incorporating the fluctuation of WPG and PV.

An improvement of [207] was completed by changing the PI into PID [210]. A new comparison was established by optimizing the FLC with particle swarm optimizations

(PSOs). The improvement exceeded the PI controller and new FLC-PSO's performance. A coloured Petri net-based (CPN) control method was disseminated in [211]. A framework comprising power generation, transmission, and substation was shown. Verification was performed with actual data from PJM-ERCOT. The results showed that its performance was preferred compared to [209]. A distributed functional observer (DFO) control method was proposed in [212]. The scenario also involves an HVDC link. It was shown that the strategy chosen was more desirable than the open loop, optimal state feedback, and Luenberger reduced-order observer (LRO) controller methods. The scholars in [213] used an adaptive droop control and consensus priority algorithm (ADC-CPA). With the intention to increase confidence levels, the result was also verified by using an FPGA board. The authors in [214] used a frequency-droop controller. The method incorporated a Bode plot and eigenvalue analysis. The experts in [215] revealed that an observer-based integral sliding mode (OISM) control featuring a neural network was superior to a PID. A neural network observer was applied to predict PV power disturbances. The authors in [216] used neural-network-based adaptive sliding mode control (NN-ASMC) as the object of discussion. It was achieved that the mixture exceeded the PI and SMC both with and without V2G.

Hierarchical centralized–decentralized V2G (HC-DV2G) control methods were depicted in [217]. In the framework proposed, the fuzzy controller managed the lower-level (decentralized) controller for each parked PEV, while the upper-level controller coordinates the power flow in the entire grid. It was examined that this scenario was better than no-V2G and conventional FLC conditions. The distributed cooperative control (DCC) was expanded upon in [218]. It was perceived that compared to centralized cooperative control methods, it was superior with respect to anticipating wind uncertainty and provided quicker communication. A model-free nonlinear sliding model controller (MFNL-SMC) optimized with MBHA was proposed by [55]. A hardware-in-the-loop (HIL) real-time simulation was also completed for authentication processes. It was detected that the outcome was more desirable than the fuzzy-PID, MPC, and PID. Asynchronous method frequency regulation (AMFR) was depicted in [219]. The asynchronous features of this method require no control centres. The system proved to work well in simulations using the IEEE 14 bus system. Multiagent system (MAS) control methods were investigated in [220]. The average consensus algorithm (ACA) was applied as a rule among EVs. It was proven that the technique was able to anticipate disturbances in the system. A group of experts offered a linear matrix inequality (LMI) robust optimized controller [221]. The simulations in [146] matched the tilt integral derivative (TID) and ABCO. The results revealed that, with the same topology, the chosen optimization was better than PSO and GA methods. Conventional droop control methods trained by an adaptive neuro-fuzzy inference system (ANFIS) were proposed in [222]. Simulated using a 14-bus test MG droop control method, the results surpass overall droop controllers (ODC) and untrained droop controllers. Not only did the frequency deviation become better, but the voltage was also controlled within tolerance levels. Several scholars suggested the unification of the voltage–frequency (UVF) control strategy [223]. The suggestion successfully outperformed the condition, whereas no V2G was involved. The co-optimal V2G control (COVC) controller parameter was optimized by using PSO [224]. A hierarchically distributed control framework was proposed to support the strategy. As a result, it was confirmed that the idea was more successful than that in [209] and the no-V2G condition. A group of experts applied the smart fleet management strategy (SFMS) [225]. The experimental hardware test not only used software but was also performed by using power hardware-in-the-loop (P-HiL) simulations.

In [226], a Great Britain dataset was applied for grouping strategy control (GSC) methods. It was summarized that this strategy beat the performance of droop control. The simulations in [227] made use of the Nordic power system. A combination of the enhanced frequency responsive aggregate model (EFRAM) and nondominated sorting genetic algorithm II (NSGA-II) was suggested. A bounded control–low degradation control (BoCo-LoDeCo) method was submitted in [228]. The investigator concluded that it performed better than other schemes: elementary control (ElCo), balance control (BaCo), smart charging control (SmChCo), and bounded control (BoCo). The stochastic unknown input observer-linear quadratic regulator (SUIO-LQR) strategy was investigated in a system with the fluctuation of WPG and PV [229]. It was presumed that the option was more acceptable than UIO-LQR and the Luenberger observer-LQR controller. H2/H∞ static output feedback (SOF) was equipped with the LMI algorithm [230]. It was resolved and shown that the selection was more attractive than using the H∞-SOF controller. Using the Jeju Island power network as a case study, the frequency regulation with SoC management (FRSM) strategy was carried out [231]. It was substantiated that the proposal was more credible than the condition with no FRSM. Simulations were performed to examine the LMI-optimized sliding mode control (SMC) method [232]. It was shown that the couple delivered better results over the PID controller. The coordinated control algorithm (CCA) was proposed in [233]. The results were validated against power hardware-in-the-loop (PHIL) tests. Real data from PJM were applied to investigate power-imbalance-based droop control (PI-DC) [234]. It was observed that the console overtakes the performance of the droop controller. In a system with fluctuating WPG and PV, the robust (mixed) M-synthesis strategy was replicated [235]. It was discovered that the result outdistanced FLC, H∞, µ-synthesis, and mixed-µ controllers.

4.3. Inertia Service

There are eight articles that discuss how EVAS controls provided inertia services ten years ago. A collection of control techniques for EVAS as inertia services is shown in Table 6. A combination of inertia emulation and droop control was proposed and investigated in [236]. The results show that the combined inertia emulation and droop control strategy performed better than only using inertia emulation/droop control individually. Several experts advocated a virtual synchronous machine (VSM) structure [237]. Liu et al. proposed a synchronverter as a model of inertia services by EVAS [238]. The T-S fuzzy control method also stipulated the reference charging power. Moreover, an adaptive algorithm was applied to the frequency drooping coefficient to adjust the changing conditions. A similar technique as the method proposed in [237] was proposed in [239]. The improvement of its predecessor comprised the implementation of the multiobjective-PSO (MO-PSO) algorithm to adjust its parameter. A two-stage control was presented and was proven to be better than an integral controller [240]. A droop-virtual inertia controller technique similar to [236] was reported in [241]. The simulation was performed using an OPAL-RT simulator while involving faults such as a disturbance scenario and PV fluctuations. The self-adjusted feature was introduced in [242], and it was verified that it was healthier than [241]. A noninteger MPC combined with an improved whale optimization algorithm (IWOA) was installed in the inertia service EV [243]. It was reported that services were delivered more compared to MPC and model-free SMC. In order to guarantee verifications, real-time simulations based on dSPACE hardware and the fluctuation of WPG and PV were involved.

Table 6. EVAS as an inertia service.

Ref.	Year	Strategy	Optimization	Benchmark	Remark
[236]	2015	Inertial emulation-droop control	N/A	Droop control, inertial emulation.	
[237]	2016	VSM	N/A	N/A.	Applying the scenario of step load changes and sudden islanding.
[238]	2018	Synchronverter	N/A	N/A.	Proposing T-S fuzzy control for stipulating the reference charging power, the frequency drooping coefficient is calculated using an adaptive algorithm.
[239]	2019	VSM	MO-PSO	N/A.	

Table 6. *Cont.*

Ref.	Year	Strategy	Optimization	Benchmark	Remark
[240]	2019	Two-stage control	N/A	Integral control.	Applying the scenario of both grid-connected and islanded operations.
[241]	2019	Droop-virtual inertia controller	N/A	N/A.	Using an OPAL-RT simulator involving faults such as a disturbance scenario and incorporating PV fluctuations.
[242]	2020	Self-adjusting inertia emulation control	N/A	Droop-virtual inertia controller [241].	
[243]	2021	Noninteger MPC	IWOA	MPC, model-free SMC.	Involving real-time simulations based on dSPACE hardware and incorporating the fluctuation of WPG and PV.

4.4. Voltage Regulation

Although there are not as many EVASs for frequency regulation and contingency, there are some scientific papers that demonstrate EVAS control modes in delivering voltage regulation services. A collection of studies on using EVAS in voltage regulation is shown in Table 7. An FLC was used in [244]. This paper used real data with a 56-node distribution network from Guwahati City. In this paper, voltage was not only regulated, but the load profile was also flattened. An EV-based dynamic voltage restorer (DVR) was implemented in [245]. A distributed MPC as a control strategy was simulated [246]. In order to support this, a framework titled DMPC is also outlined in the table.

Table 7. EVAS as a voltage regulation service.

Ref.	Year	Strategy	Remark
[244]	2012	FLC	Using real data with a 56-node distribution network from Guwahati City, not only regulating the voltage but also flattening the load profile.
[245]	2013	DVR	
[246]	2022	DMPC	Proposes the DMPC framework.

5. Discussion and Future Research Directions

Similar to the other fields of technology, control techniques also evolve from time to time. In the case of PID variants, it is forecasted that issues such as automatic tuning and event-based control methods will attract the attention of many researchers [247]. For the MPC, possessing a finite horizon, which later causes instability issues, pushed research studies to solve these issues [248], while for fuzzy variants, the research path will be the implementation of the type-2 fuzzy model and the combination with other control techniques (e.g., adaptive-fuzzy, robust-fuzzy, etc.) [249]. As many control topologies combine with an algorithm, forming an optimal control duo, advances in the optimization will produce many variations that can be experimented [250]. Outside of control variants, the rise of artificial intelligence (AI) and its possible applications in control applications result in more research studies in this field [251]. As a controllable plant, EVAS will surely become a focus in developing previously illustrated control techniques. Thus, it can be predicted that the trend of EVAS control research will comprise the implementation novel conventional control variants and the application of an advanced algorithm for optimization.

From a grid point of view, in future, it is not only renewable energy (SPV and WPG) that will be connected but also advanced energy sources such as SMES, UC, and FCES. For SMES, several trials have been reported, such as in Bonneville Power Administration, Washington, where results as significant as 30 MJ have been reported [252]. As for FCES, Siemens has plants in Germany and Dubai, while Mitsubishi Power Americas aims to store 150 GWh by the mid-2020s [253,254]. The dynamics of these plants and their variations (fluctuation, sudden change, etc.) will enrich possible scenarios in the grid. Henceforward, this will provide possibilities for EVAS controls, achieving the most appropriate solution. With the high demand for external computer simulation verifications and increased economic feasibility, it is projected that the usage of hardware-in-the-loop (HiL) simulations will increase in the future. Furthermore, originating from the aerospace area, there is an open possibility of the employment of digital twin (DT) methods for EVAS control verification [255].

While several services are open for EVAS, most research studies accomplished advances in frequency regulation and contingency services. On the contrary, only a handful of reports have been published with respect to inertia and voltage regulation services. With the emergence of virtual inertia technology and its market opening in several countries, there is a massive possibility for EVAS to fill this research gap [256]. Hence, it is predicted that more research will be conducted on EV inertia service control operations in the coming years. The same condition is applied to voltage regulation services. Although EVs merely act as energy lenders to their parallel capacitor for voltage regulation, with the massive growth of EVs and their investment-free battery features, it is predicted that voltage-regulation EVASs will be popular in the future and the control strategy for this type of service will be an attractive topic of future research studies.

Another low-hanging fruit could be obtained from the recent trend of EVAS as a frequency contingency service, which cascades two PID controllers to achieve better results. A similar approach could be used to simulate fuzzy and MPC variants with two fuzzy or two MPC controllers cascaded. Although there will be an increase in computation burden, with recent advancements in computation technology, such as faster CPU, GPU utilisation for computation, and parallel computing, this gap has the potential to be explored further.

6. Conclusions

In this paper, comprehensive studies on the control strategy implemented on EVASs were outlined. A brief explanation of control theory was presented. A short description of the optimization algorithm and its initial involvement in control techniques was provided. Then, with the aim of reviewing the control strategies of EVAS, literature surveys were conducted on each ancillary services category. Due to the presence of numerous papers in the frequency contingency service category, subcategorization was performed by control variants: PID, fuzzy, MPC, and others. Although considered the most ancient compared to other variants, PID is ahead of its competitors for its computational simplicity and pace. However, for fuzzy variants, while their characteristic of non-numerical has advantages of initial development, it also has a negative drawback in terms of tuning difficulties. Moreover, its back-to-back process of fuzzification–defuzzification also impacts the matter of expensive computation. As the most recent development, MPC is superior regarding its objective result; however, regarding the process of continuous optimization over a moving receding horizon, the computation burden is even more significant than the previous one. With the influx of novel development of optimization algorithms, especially metaheuristic ones, ample opportunity is open for mixing and matching it with existing control strategies.

For all four EVAS categories, each paper was summarized to provide insight for any prospective scholars who plan to conduct research in a similar field. By reading this paper, future research duplication can also be prevented, and any remaining research gaps in this field can be determined with more clarity. In addition, the future direction of research in this area was also presented. This work shows that there are prospective areas for research, especially with respect to the inertia and voltage regulation service ancillary market. With the progression of trends such as novel control techniques, artificial intelligence/machine learning/deep learning implementation, various sophisticated energy storage, and their dynamics, the field of EVAS control is promising for further investigation.

Finally, considering the similarity of frequency contingency–inertia ancillary services, it is recommended to replicate the already-matured EVAS frequency contingency pattern into an inertia ancillary service case. In addition, the novelty of training techniques and nonconventional energy storage could also be placed into the picture.

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Abbreviations

2DOF	Two-degree-of-freedom
ABCO	Artificial bee colony optimization
ACA	Average consensus algorithm
ADC	Autonomous distributed control
ADE	Adaptive differential evolution
ADRC	Active disturbance rejection control
AEFA	Artificial electric field algorithm
AHA	Artificial hummingbird algorithm
AIMPC	Adaptive intelligent model-predictive control
AMFR	Asynchronous method frequency regulation
ASMC	Adaptive sliding mode control
ASO	Atom search optimization
BHA	Black hole algorithm
BSH	Battery SoC holders
CARIMA	Controlled autoregressive and integrated moving average
CC	Cascaded control
CCA	Coordinated control algorithm
COVC	Co-optimal V2G control
CPA	Consensus priority algorithm
CPN	Coloured Petri net-based
DCC	Distributed cooperative control
DE	Differential evolution
DEPSO	Differential evolution particle swarm optimization
DFO	Distributed functional observer
DPFRC	Decentralized primary frequency regulation control
DVC	Distributed V2G control
DVR	Dynamic voltage restorer
EFRAM	Enhanced frequency responsive aggregate model
EHO	Elephant herding optimization
EO	Equilibrium optimizer
EVAS	Electric vehicle as an ancillary service
FGD	Fractional gradient descent
FLC	Fuzzy logic controller
FMC	Frequency modulation control
FO-PID	Fractional order PID
FPA	Flower pollination algorithm
FPID	Fuzzy PID

FRC	Frequency regulation capacity
FRSM	Frequency regulation with SoC management
GA	Genetic algorithm
GPC	Generalized predictive controller
GrADP	Goal representation adaptive dynamic programming
GSC	Grouping strategy control
GWO	Grey wolf optimization
HC-DV2G	Hierarchical centralized–decentralized V2G
HHO	Harris's hawks optimization
HIL	Hardware-in-the-loop
HSA	Harmony search algorithm
ICA	Imperialist competitive algorithm
IT2	Interval type-2
JA	Jaya algorithm
LMI	Linear matrix inequality
LQR	Linear–quadratic regulator
LRO	Luenberger reduced-order observer
MAS	Multiagent system
MBA	Mine blast algorithm
MBOA	Magnetotactic bacteria optimization algorithm
MFNL	Model-free nonlinear
MGPC	Multivariable generalized predictive control
MMPC	Multiple model-predictive controller
MO	Multiobjective
MPA	Marine predator algorithm
MVO	Multiverse optimizer
NSGA-II	Nondominated sorting genetic algorithm ii
OD	Optimal dispatch
ODC	Overall droop controllers
OISM	An observer-based integral sliding mode
PI-DC	Power-imbalance-based droop control
PSO	Particle swarm optimization
QO	Quasi-opposition
QP	Quadratic programming
RAS	Region of asymptotical stability
RL	Reinforcement learning
RMPC	Robust model-predictive control
RO	Rolling optimization
SCA	Sine cosine algorithm
SDV2G	Smart decentralized V2G
SFMS	Smart fleet management strategy
SLC	Simple linear control
SMC	Sliding mode control
SOA	Seagull optimization algorithm
SOF	Static output feedback
SSA	Nondominated sorting genetic algorithm ii
SUIO	Stochastic unknown input observer
TI/D	Tilt integral/derivative
TLBO	Teaching–learning-based optimization
UVF	Unification of the voltage–frequency
VPLA	Volleyball premier league algorithm
WCA	Water cycle algorithm
WDO	Wind-driven optimization
WOA	Whale optimization algorithm

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