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Wind power smoothing using demand response of electric vehicles

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ABSTRACT

Large penetrations of wind power is prevented in most power systems, mainly because it is highly stochastic. One important aspect of this uncertainty is the large power gradients that wind farms may impose to the grid. To mitigate such undesirable fluctuations, this paper proposes a power smoothing service using the demand response of electric vehicles connected to the adjacent networks. A hierarchical controller is proposed, in which the top layer calculates the ramp rate and sends a request signal to all participant vehicles. In the second layer, a fuzzy controller is developed introducing two fuzzy indices that measure how ready each vehicle is to participate in mitigating large positive and negative fluctuations. These indices are inferred from the state-of-charge and time-to-departure of the vehicle, and are used as the participation factors of the vehicle to provide this service. As much as possible, the proposed controller tries to supply the required service by controlling the vehicles charging load instead of using V2G, which wears out their expensive batteries. Numerical studies on microgrids with high penetrations of wind power corroborate the success of the proposed algorithm in limiting the power fluctuations as well as charging the vehicles in proper time.

1. Introduction

According to the International Energy Agency, without decisive actions, global energy-related GreenHouse Gas (GHG) emissions will more than double by 2050, and different strategies and roadmaps are needed to prevent this trend [1]. Then, due to the significant role of electric power generation in GHG emission, renewable energies and especially the wind energy has been drastically increasing since decades. However, wind energy is highly stochastic and may impose some problems on the network, especially at high penetration levels. Although wind farms are usually connected to the subtransmission or distribution networks, in the case of high penetration level, their fluctuations will be visible from the transmission network and may affect the overall system optimality, power quality, and system stability [2,3]. Therefore, some utilities, such as ERCOT, have some specific regulations such as the Ramp Rate Limit (RRL) for the interconnection of renewable resources [4–6].

The RRL expressed in MW ramp up/down per minute (MW/min), is usually in the range of ramp rate capability of regulation reserves of the network. For instance, in Maui Island in Hawaii with around 300 MW of total generation capacity, wind farms are restricted to an RRL of ± 1 MW/min [7]. Such regulations try to reduce system-wide power fluctuations and frequency deviations. If a high ramp-up occurs, the wind farm can easily reduce its output power to meet the RRL. However, in order to overcome unacceptable ramp-downs, we need some positive reserves. Sørensen et al. [8] investigated power fluctuations of two offshore wind farms in Denmark, focusing solely on large ramp-downs. They have shown that the probability of a ramp-down occurring is considerable. Delta Control is a well-accepted industrial approach for providing required positive reserve. It maintains wind turbines at levels below their MPP [4,6,9]. Jaramillo [10] reports that using delta control to limit the ramp rate up/down of a wind farm to 0.1 PU/min may reduce its total energy yield by 18%. Hansen and Papalexopoulos [2] use practical data of an isolated network where the total installed capacity of wind generators is less than 25% of the peak load, and showed that 14% of total yieldable wind energy was curtailed in 2009 due to the network security issues. Therefore, some wind farms have installed banks of energy storage devices to provide positive and negative reserves instead of curtailing some portions of yieldable wind energy [4,5,7]. But, any kind of energy storage device is highly expensive, especially when we realize that there is no or low opportunity for arbitrage revenue from power smoothing storage systems [11]. This is why this paper proposes using Demand Response (DR) of electric vehicles for power smoothing instead of installing banks of batteries.

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Nomenclature

List of Acronyms

ARR	Amplified Ramp Rate
ERCOT	Electric Reliability Council of Texas
EV	Electric Vehicle
G2V	Grid-to-Vehicle
MPP	Maximum Power Point
OBC	On-Board Charger
PCC	Point of Common Coupling
RRI	Ramp Rate violation Index
RGV	Readiness for Grid to Vehicle
RRL	Ramp Rate Limit
RRLS	Ramp Rate Limiting Service
RRS	Ramp Rate Signal
RVG	Readiness for Vehicle-to-Grid
SOC	The State of Charge
STD	Standard Deviation
TTC	Time remained To fully-charged
TTD	Time remained To Departure
V2G	Vehicle-to-Grid
WRS	Wind Reduction Signal
WWI	Wasted Wind energy Index

In fact, huge EV fleets are expected to be on the road in the future. As transport contributes so heavily to GHG emissions, the International Energy Agency's blue map scenario establishes a target by 2050 of 100 million out of the estimated 180 million light-duty vehicles produced annually being EV of all types [1]. With such a huge penetration level, EVs may impose a very heavy charging load on the power grid, which should be taken into account in the design and operation of power systems [12]. Two approaches are proposed in the literature to mitigate the loading effect of EVs, including smart charging or Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) [13,14]. In the first approach, EVs are intended to be charged during off-peak hours, while in the second, EVs can also inject power to the network using their bidirectional power converters. Although both approaches were originally innovated for load leveling, they have a great potential for providing different services and improving the network and market performance [13,15]. It is worth noting that despite of highly stochastic behavior of EVs, they can provide considerable storage resources for different DRs, especially in high penetration levels [13–21]. DR, which is essential for reliable and secure operation of future power systems [22] and should be considered in all operation and expansion plans of the grid [23], facilitates higher integration of renewable energies through rendering different auxiliary services [16,22]. However, there are some limitations in providing DR through V2G and G2V, mainly due to uncertainties in availability of EVs and the aging impact of V2G on highly expensive batteries of EVs [16].

V2G is suggested in [17] for the use in the wide integration of uncertain wind energy, and especially for increasing the participation of this stochastic resource in energy markets. The work considers the wearing costs associated with frequent battery charge/discharge. In another work, a fuzzy controller is proposed for daily load leveling using the V2G capability of a large number of EVs parked in the neighboring area [18]. The State of Charge (SOC) of the batteries and the hour of the day are the inputs to the fuzzy system of that work.

In most reported works, including [14,15,17,18], EVs' capabilities are used for steady state applications, such as load shifting, valley filling and energy market enhancement. Very few works have proposed V2G or G2V for improving system transients. Venayagamoorthy et al. [19] propose a controller that alleviates the shocks of wind farms using V2G of Evs parked in a parking lot connected to the same bus. This reference does not consider the available energy and power of the parking lot, whereas the existence of enough number of EVs in the parking and their SOCs or batteries capacities are stochastic, and it is possible the parking lot cannot provide or absorb enough power to mitigate the power shock. A deterministic analytical model is proposed in [20] to calculate the available power capacity of a V2G parking lot. However, the main problem in this regard is the uncertain amount of power and energy each EV can provide or chooses to provide. Jannati et al. [21] propose an algorithm to smooth the power fluctuations of wind farms by the use of smart parking lots. Supposing enough EV resources, they developed an algorithm to select the best parking lots in the first level and the best EVs in the second level of their controller. For the first level the decision is made based on the number of EVs parked in the parking lots, and for the second level the main decision is based on the SOC of vehicles. It means the available power and energy are the main decision parameters in their approach, but, the Time remained To Departure (TTD) is practically very important for participation of EVs in such a service. EVs with high SOCs but low TTDs are less interested in such a service than those with lower SOC but much higher TTDs.

In this paper, we propose the use of EVs parked in an area to provide a power smoothing or a Ramp Rate Limiting Service (RRLS) for embedded or neighboring stochastic renewable energies having the same Point of Common Coupling (PCC). Using this approach, a considerable part of the fluctuations of renewables will be invisible from the viewpoint of the transmission system and one significant obstacle to high penetrations of wind farms will be removed. Similarly, the proposed approach can alleviate fluctuations from rapid changes in distribution load.

While [19–21] rely on the available energy or power of the vehicles for providing required services, due to uncertainties regarding availability of Evs or their readiness to provide the smoothing service, we propose two fuzzy variables for each vehicle indicating its readiness for negative and positive ramp rates. The fuzzy variables, Readiness for Vehicle-to-Grid (RVG) and Readiness for Grid-to-Vehicle (RGV), are inferred from the instantaneous SOC and the estimated TTD of the vehicle. Finally, based on the sign of the required power, either the RVG or RGV is selected to determine the participation factor. Subsequently, the total power needed at the PCC for the service is shared among all vehicles connected to the microgrid, based on their instantaneous participation factor and their charger's capacity. The final command, which is sent from the fuzzy controller located on the charging station to the vehicle's On-Board Charge controller (OBC), determines how much power the EV should produce or consume at a given time.

The proposed fuzzy controller attempts to meet the RRL by, as much as possible, controlling the charging load, G2V, instead of discharging the batteries, V2G. If the EVs cannot or the controller estimates they won't be able to meet the RRL, a Wind Reduction Signal (WRS) is sent to the wind turbines to reduce their power in order to meet the RRL. Our numerical studies performed on two systems show that the proposed fuzzy algorithm is highly effective in meeting the RRL, and wind farms are rarely requested to contribute in RRLS. Therefore, delta control, which wastes some amount of wind energy to provide a positive reserve, is not beneficial while we have enough RVG resources.

The remainder of the paper is organized as follows. The problem and the goal of this paper are described in Section 2. Section 3 presents the stochastic model for wind power and its fluctuations. In the next section, EV charger is modeled; while the proposed hierarchical fuzzy controller is the subject of Section 5. Before presenting the results of numerical studies in Section 6, two performance evaluation indices are proposed in Section 5 for better comparison of the results. Conclusion and references are the next sections of the paper.