Short-Term Stochastic Modeling of Virtual Power Plants with inclusion of Wind, Solar and Tidal Generation and Energy Storage

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***Abstract*—This paper provides a systematic comparison of three prominent Renewable Energy Sources (RESs) namely, wind, solar and tidal in regards to short-term volatility and their impact on the dynamic behavior of power systems. A Virtual Power Plant (VPP) model obtained through the aggregation of wind, solar and tidal generation is proposed. The effect of frequency control provided by wind/tidal turbine frequency controllers and an Energy Storage System (ESS) embedded in such a VPP are also considered. Simulation results indicate that the VPP with ESS is able to increase the reliability of RESs and effectively reduce short-term frequency fluctuations of the grid.**

***Index Terms*—Energy transition, solar generation, stochastic modeling, tidal generation, virtual power plant, wind generation.**

I. Introduction

A. Motivation

The Earth has adequate sources of renewable energy to cover the world's electrical power demand with the current technologies available [1]. However, due to the stochastic nature of the prominent Renewable Energy Sources (RESs), such as wind and solar, a single source solution will not suffice for the transition to a low-carbon society. Moreover, due to the dispersed nature and relatively small capacity of most RESs, it has to be expected that, in most cases, a mix of several technologies will be included at the distribution or even low voltage levels. There is thus the need for aggregated models of such resources, that are able to retain their stochastic behavior while allowing efficient simulations of the overall transmission system. This paper addresses this issue by proposing an aggregated model of a Virtual Power Plant (VPP) based on stochastic differential equations. The focus of the paper is on short-term dynamic analysis.

B. Literature Review

The volatility and uncertainty introduced through stochastic RESs such as wind, solar and tidal generation can negatively impact the reliability, security and resilience of those traditional power systems. Stochastic Differential Equations (SDEs) can be used to model such volatility and uncertainty in power systems. SDEs are continuous in time and can be readily incorporated into power system models that are typically modeled as differential-algebraic equations [2].

SDEs have been used to model the volatility of the individual sources of renewable energy. The stochastic modeling of wind power generation using SDE-based approaches has been considered in numerous studies. For example, in [3], a systematic method to build dynamic stochastic models from real-world wind speed measurement data is studied. Solar generation is the fastest growing energy source in power systems worldwide [4]. In [5] a novel solar irradiance model for short-term power systems analysis is presented where the model is formulated through SDEs with jumps based on measured solar irradiance data. The potential of tidal generation has been promising due to the high long-term predictability of tidal currents compared to other stochastic RESs. However, the short-term fluctuations (seconds to minutes) introduced by tidal currents are challenging to predict and can undesirably affect the power quality and system stability. A model for short-term fluctuations of tidal currents using SDEs is proposed in [6] based on real-world data.

The integration of stochastic RESs into power systems results in the system variables, such as the frequency and voltages becoming uncertain as well. In [7] a hybrid power system which includes RESs and Energy Storage System (ESS) where the uncertainties introduced by wind power, photo-voltaic (PV) power and loads are modeled is studied. In [8] the stochastic modeling of the Irish power system with the inclusion of tidal and wind generation is studied. In [9] a test case where ESS is used to mitigate the variations in tidal generation due to waves is studied. However, no power system study has been presented comparing these three RESs, namely wind, solar and tidal.

C. Contributions

The specific contributions of this paper are twofold:

- A collective study on stochastic modeling of wind (both onshore and offshore), solar and tidal generation where the offshore models take into consideration the effect of extensive transmission cables to offshore plant sites.
- Study the effect of the volatility introduced to electrical power systems by a VPP composed of wind, solar and tidal generation farms alongside RES and ESS frequency control to supply stochastic load variations.

D. Organization

The remainder of this paper is organized as follows. Section II outlines the stochastic models used in the case study for wind, solar and tidal generation as well as loads. The frequency control of wind and tidal generation is discussed in Section III. Section IV outlines the ESS model utilized alongside the VPP in the case study. In Section V, the test system is studied for each renewable generation technology and simulation results are presented. Finally, in Section VI, conclusion are drawn and future work is outlined.

II. Stochastic Modeling

In this paper, the stochastic processes of the presented simulations are constructed using the well-known Ornstein-Uhlenbeck (OU) SDE model due to its simplicity and adaptability. OU processes have been utilized to build stochastic models for loads as well as wind, solar and tidal generation. The general form of a OU SDE process is:

$$d\eta(t) = \alpha(\mu - \eta(t))dt + \sigma dW(t)\,, \tag{1}$$

where $\alpha,\ \sigma > 0$ and $W(t)$ is a Wiener process. α is the mean reversion speed of the process, $\eta(t)$, which defines the slope of its exponentially decaying autocorrelation. The process $\eta(t)$ is Gaussian distributed with mean μ and variance $\sigma^2/(2\alpha)$.

In this paper, the stochastic models are built using the technique presented in [3] for modeling wind speed. This technique enables modeling stochastic processes with non-exponentially decaying autocorrelations and, thus, allows reproducing processes that are a combination of fast and slower stochastic dynamics. Using this method a stochastic process $\rho(t)$ with an autocorrelation that can be described as a weighted sum of decaying exponentials:

$$R_\rho(t) = \sum_{i=1}^{n} w_i \exp(-\alpha_i \tau)\,, \tag{2}$$

can be defined, where $w_i > 0$. This is achieved by defining $\rho(t)$ as a weighted sum of n OU processes as defined in (1):

$$\rho(t) = \sum_{i=1}^{n} \sqrt{w_i}\, \eta_i(t)\,, \tag{3}$$

Further details on SDEs and this technique can be found in [3]. The stochastic models used in the case study of this paper for modeling loads, wind speed, solar irradiance and tidal current speed are all OU-based and presented here below.

A. Load Modeling

The stochastic load model is developed based on the widely known voltage dependent load model coupled with OU processes, as presented in [2]:

$$\begin{aligned} p_L(t) &= (p_{L0} + \eta_p(t))(v(t)/v_0)^k\,, \\ q_L(t) &= (q_{L0} + \eta_q(t))(v(t)/v_0)^k\,, \\ d\eta_p(t) &= \alpha_p(\mu_p - \eta_p(t))dt + \sigma_p dW(t)\,, \\ d\eta_q(t) &= \alpha_q(\mu_q - \eta_q(t))dt + \sigma_q dW(t)\,, \end{aligned} \tag{4}$$

where $p_L(t)$ and $q_L(t)$ are the active and reactive power of the load, respectively, and p_{L0} and q_{L0} are parameters representing active and reactive load powers at $t = 0$. $v(t)$ is the voltage magnitude at the bus where the load is connected and v_0 is the value of this voltage magnitude at $t = 0$.

Through the exponent k, the model in (4) can define whether the load is a constant power load ($k = 0$), a constant current load ($k = 1$) or a constant impedance load ($k = 2$). The volatility is modeled through the stochastic processes $\eta_p(t)$ and $\eta_q(t)$ which are formulated as OU processes, where the parameters α, μ and σ have the same meaning as in (1). In the case study, the uncertainty is set as $10\ \%$ of the nominal load power and the mean reversion speed is set to $\alpha_p = \alpha_q = 0.02$.

B. Wind Speed Modeling

The stochastic variation in wind speed within a 10-minute time period can be assumed to be Gaussian distributed around a certain mean wind speed [10]. Therefore, the wind speed model considered in the case study is in two parts. A constant mean wind speed v_c and a Gaussian stochastic process, $\rho_w(t)$. The wind speed model utilized for each wind farm connected to the test system is:

$$v_{\rm wind}(t) = v_c + \rho_w(t)\,, \tag{5}$$

where $v_{\rm wind}(t)$ is the modeled wind speed time-series and $\rho_w(t)$ is a stochastic process defined as (3). Hence, $\rho_w(t)$ has the probability distribution $\mathcal{N}(\mu_{\rho_w}, \sigma^2_{\rho_w})$ and an autocorrelation as in (2). The assumptions made for the wind speed model are listed in [8]. For the case study presented in this paper the standard deviation of the wind speed model is set to be 20% of the mean wind speed v_c for a onshore plant and 10% for a offshore plant. The parameters used to set the autocorrelation of the wind speed model are presented in [8] based on previous data analysis in [3].

C. Solar Irradiance Modeling

The solar irradiance model utilized in the case study is proposed in [5]. It models the clear-sky index of solar irradiance based on measured data. In that way, the flickers in the solar irradiance due to cloud movement are only considered as these are the variations that are of concern in short-term analysis of power systems. An OU process, $\eta_s(t)$, as presented in (1) is utilized to represent the solar clear-sky stochastic variations in the clear-sky index. The blockage of clouds passing the PV are modeled as jumps. The jumps in the model do not depend on the stochastic variable $\eta_s(t)$. Hence, they are additive noise and are directly added to $\eta_s(t)$ with the purpose of simplifying the numerical integration. The jumps are modeled as:

$$H(t) = m\, P(t)\,, \tag{6}$$

where m is the jump amplitude assumed to be a normally distributed random number, namely, $m \sim N(\mu_m, \sigma^2_m)$. $P(t)$ is a step function that is either 0 or 1, where the number of transitions per period are determined with a Poisson distribution. The duration of each jump is determined with a normal distribution $\delta \sim N(0, \sigma^2_\delta)$. $P(t)$ remains constant for a time δ whenever it is switched from 0 to 1 or vice versa.

This model represents the solar irradiance as measured at a single PV panel. The aggregation of a whole plant of PV panels is represented through the low-pass filter presented in [11], as shown in Fig. 1. The cut-off frequency of the filter is directly dependent on the square root of the plant area S, measured in Ha.

Further details on this stochastic solar irradiance model are provided in [5]. The parameters of the model used for this papers case study are based on the parameters found in [5] using the data set presented [12].

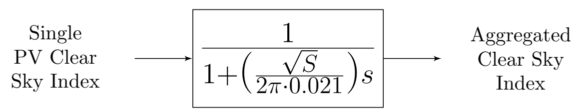

Fig. 1. The low-pass filter that represents the smoothing effect of a PV plant.

D. Tidal Current Speed Modeling

The tidal current speed model utilized throughout this paper vastly follows the proposed model in [8] which consists of three critical parts.

a. The predicted tidal current speed is modeled as a constant, v_{tc}. The fluctuations in the current speed due to the tidal astronomical phenomenon vary with a period of 6 to 12 hours hence, the mean tidal current speed over a 10 minute interval can be modeled as constant v_{tc}.
b. The stochastic turbulence, $\rho_{\mathrm{t}}(t)$, in the current speed is modeled using a stochastic process as defined in (3) and it is characterized in a similar way as for the wind speed (refer to Section II-B). The standard deviation of the tidal current speed is set to be 10% of the current speed and the autocorrelation parameters are set based on data analysis in [6].
c. Finally, $v_{\mathrm{waves}}(t)$ represents the effect of waves on the tidal current. These are modeled through the Stokes model coupled with the JONSWAP spectrum presented in further detail in [8].

The complete model for the modeled tidal current speed is:

$$v_{\mathrm{tidal}}(t) = v_{\mathrm{tc}} + \rho_{\mathrm{t}}(t) + v_{\mathrm{waves}}(t)\,. \tag{7}$$

III. Frequency control

To mitigate the uncertainty in the frequency introduced by variable renewable energy sources the utilization of frequency control of the energy source has been discussed, particularly for wind turbines. A common approach for wind turbine frequency control is to bypass the Maximum Power Point Tracking (MPPT) and set the power output based on the deviation of the measured frequency (droop control) and/or Rate of Change of Frequency (ROCOF) control. The combination of the two strategies proposed in [13] for wind turbines is used in the case study of this paper. The similarity between tidal and wind turbines allows for this frequency control to be adapted for tidal turbines as discussed in [8].

The frequency control used for both wind and tidal in the case study is shown in Fig. 2. The droop controller, with gain $1/R$, is comparable to the primary frequency controller of a synchronous machine. The ROCOF controller consists of a low-pass filter with time constant T_l , the time derivative of the frequency measurement and a gain K_l. The two controllers are complementary. The ROCOF control is faster and has its main effect in the very first instants after the frequency drop. However, the droop control is slower and mitigates the frequency deviation [13].

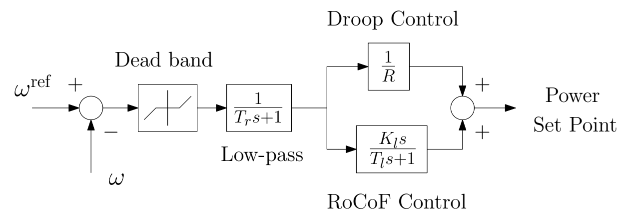

Fig. 2. The frequency control for wind and tidal turbines used in the case study.

IV. Energy Storage System

Energy Storage Systems (ESSs) have shown substantial potential in enhancing the transient stability of electrical power systems to maintain a smooth power production profile. The International Energy Agency (IEA) indicates that the addition of energy storage to stochastic RESs is particularly important for the Sustainable Development Scenario, where the share of variable renewable reaches 40% worldwide by 2040, and more than that in some regions [14]. Furthermore, the combination of ESSs with non-dispatchable RESs enhances the competitiveness of green technology within the energy market.

To represent the ESS in the case study in Section V the simplified ESS model presented in Fig. 3 is used [15]. The ESS is represented through decoupled active and reactive power controllers. The input signal ω is the systems Center of Inertia (COI) frequency that is regulated through the active power. The voltage at the point of connection v_{ac} is regulated through the ESS reactive power. The physical behavior of the storage system is synthesized by two lag blocks with the time constants $T_{P,\mathrm{ESS}}$ and $T_{Q,\mathrm{ESS}}$.

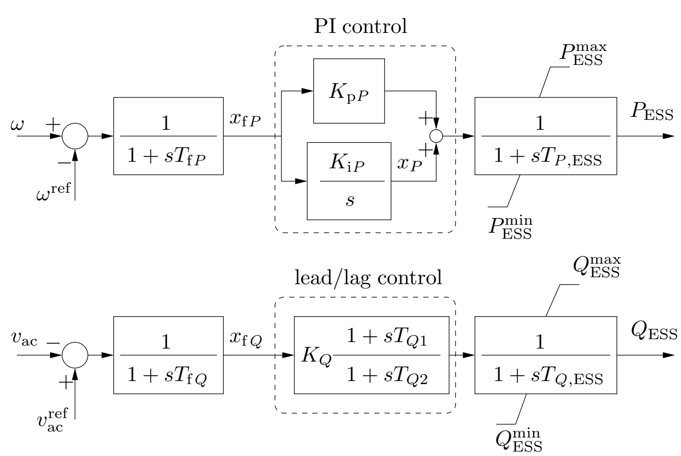

Fig. 3. The simplified ESS used in the case study.

V. Case Study

The test power system used for this case study is the Western System Coordinating Council (WSCC) 3-machine, 9-bus system. The system has three synchronous generators with Automatic Voltage Regulation, Power System Stabilisers and Turbine Governors. All dynamic data of the WSCC 9-bus system as well as a detailed discussion of its transient behavior are provided in [16].

The following modifications are made to the test system for this case study:

- The capacity of the synchronous generator, connected at Bus 2 is reduced by 20 MW.
- A renewable energy plant is connected to the system at Bus 7 with the power capacity 20 MW.
- An ESS is located at bus 8 in the modified system.
- The three loads of the system are modeled as stochastic using the model in (4).

In this case study five different sources of renewable energy are connected at Bus 7 individually. These are onshore wind, offshore wind, solar, tidal as well as a VPP that consists of a combination of onshore wind, solar and offshore tidal generation. In Fig. 4 the modified test system with the VPP connected at Bus 7 is shown. For both offshore wind and tidal generation the effect of extensive transmission cables to connect the offshore plant sites to the system are considered.

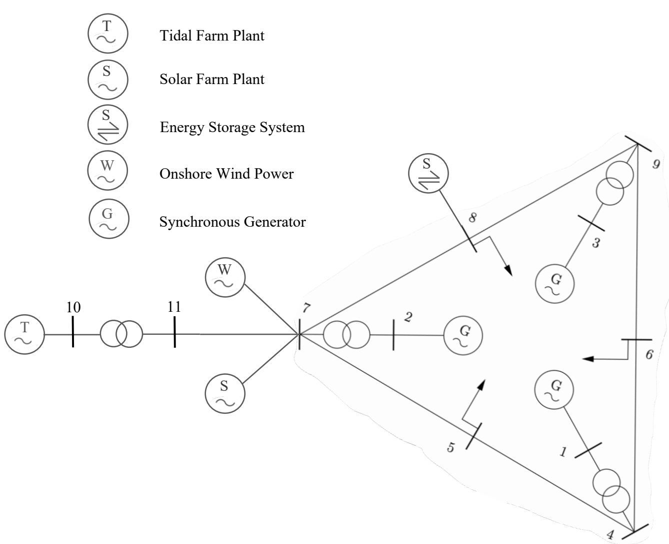

Fig. 4. The modified test power system used for the aggregated model study.

Dome, a Python-based software tool for power system analysis, was used to carry out all simulations [17].

For the results presented in Fig. 5-8, the test system is simulated once with a time step of 0.01 s for 100 s for each scenario. Figure 5 shows a comparison of the generated power of the RES supplied to Bus 7 for the different sources. This figure illustrates the different stochastic properties for each RES technology. Onshore and offshore wind generation have the smoothest active power profile, with offshore wind varying slightly more than onshore. During normal operation the tidal generation has a similar output as the wind generation. However, the tidal current can be disturbed by waves as is the case in this case study. This is the worst case scenario for tidal generation. Solar generation during a clear sky has the smoothest generation output. However, when clouds pass over the PV panels the generated output will ramp up and down. This can be seen in Fig. 5 at about 60 s where the solar generation output starts to ramp down.

The generation profile of the VPP shows that its variations are still greater than that of only wind and the rapid variations due to the tidal and solar generation do disturb the VPP output. However, by combining the different renewable sources the rapid fluctuations are smoother. This averaging effect of combining several stochastic processes is indeed a promising feature of VPPs obtained by the aggregation of RESs.

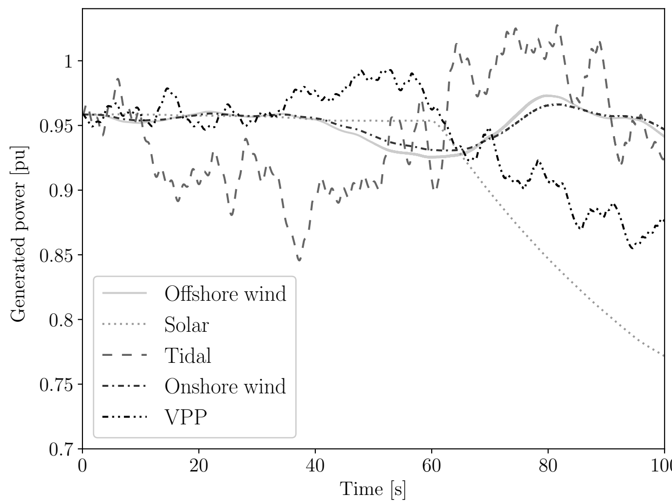

Fig. 5. The renewable generation supplied at Bus 7 in the test system.

The stochastic fluctuations of RESs impact on the system variables such as the bus voltages and frequency. In this paper we study the effect on the systems COI frequency, shown in Fig. 6 for the different RESs without any frequency control. The variations in the frequency are similar to the respective generation output variations. The frequency variations due to the different sources are up to 1% of the nominal frequency. These frequency variations can result in the system becoming unstable. Thus, they need to be mitigated. This can be done by installing frequency control.

In Fig. 7 the frequency control of wind and tidal has been installed as presented in Section III. It can be seen that the frequency control does not have much of an effect on the frequency variations due to wind speed variations. However, the frequency control works very well with the tidal turbines and thereby also the VPP. As the same frequency control is applied to both wind and tidal this difference can be mostly explained by the stochastic properties of the source that is the wind and tidal current speed. The frequency control seems to work better with a source that has a oscillatory output, like the tidal generation.

The system COI frequency for the test system with ESS is shown in Fig. 8. In this case the frequency variations have been reduced to be within 0.1% of the nominal system frequency for all the RESs.

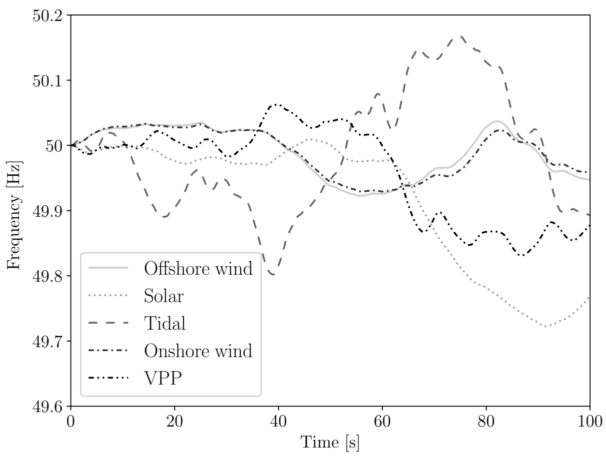

Fig. 6. The COI frequency of the system without control.

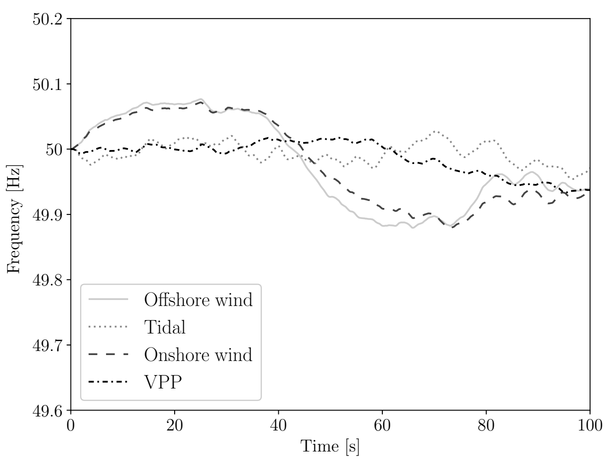

Fig. 7. The COI frequency of the system with wind/tidal turbine frequency control.

These results give an idea of the kind of volatility scenarios that can be expected in the system due to the different kinds of RESs. However, these results only show a single scenario for each source. To be able to study the effect of the different sources on the system frequency statistically the system is simulated using Monte Carlo method 1000 times for a duration of 200 s with a time step of 0.01 s. The resulting standard deviation of the COI system frequency for each case studied is shown in Table I. The results show that in all cases the frequency variations are reduced with installing the ESS. While the frequency control only improves the cases where tidal and VPP are the installed renewable generation. Statistically, the solar generation leads to the greatest variations in the frequency and the VPP will result in the lowest frequency variations with or without the ESS or frequency control of wind/tidal installed in the system.

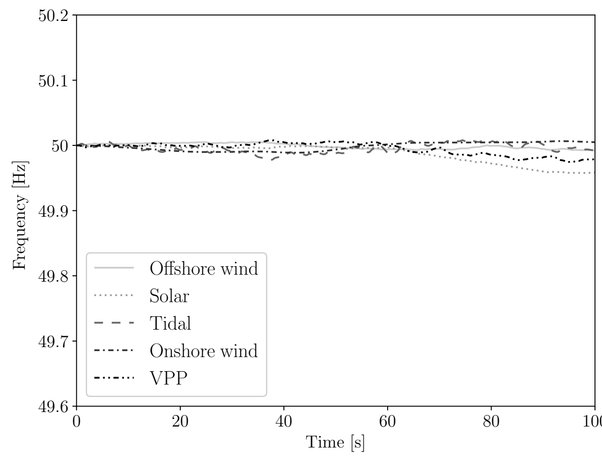

Fig. 8. The COI frequency of the system with ESS.

TABLE I
STANDARD DEVIATION OF THE COI FREQUENCY FOR THE DIFFERENT SCENARIOS CONSIDERED IN THE CASE STUDY

Renewable Generation	Standard deviation of COI frequency [Hz]		
	no control	with freq control	with ESS
Onshore Wind	0.079	0.077	0.013
Offshore Wind	0.082	0.080	0.012
Tidal	0.086	0.035	0.013
Solar	0.096	NA	0.020
VPP	0.066	0.034	0.009

VI. CONCLUSIONS

This paper provides a case study comparing the effect of the fluctuations of different sources of renewable energy on the system frequency. The RESs compared are on- and offshore wind, solar and tidal generation. An aggregated VPP is also proposed and studied, combining onshore wind, solar and offshore tidal generation. To mitigate the frequency variations introduced by the variable RESs both frequency control of wind/tidal and an ESS are installed in the system.

It is shown that the sources of renewable energy studied result in different kinds of frequency variations and can present different challenges. The tidal turbine frequency control can successfully mitigate frequency variations introduced by waves in the tidal current speed. The frequency variations for all RESs can be smoothed to acceptable levels with installing an ESS along side the source. Furthermore, using VPPs is a promising way to minimize the system frequency variations introduced through the RESs.

Future work will focus on introducing coordination between the RESs and the controllers and studying the integration of such an aggregated VPP model for electrical power systems such as the Irish grid.

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