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## Smoothing of renewable energy generation using Gaussian-based method with power constraints

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### Abstract

Integration of renewable energy resources to a power system can cause power fluctuations due to their intermittent nature. One way to reduce these effects is to smooth power production using energy storage systems (ESS). A typical approach to tackle the intermittency problem is to use ESS with traditional moving average method. Although it is easy to implement, the moving average method is affected by peaks and troughs during power generations which results in bigger battery sizes. In this paper, we propose a Gaussian-based smoothing algorithm that solves the pitfalls of the moving average methods. Besides smoothing, in big solar plants and wind farms such as in La Réunion island, the grid operator asks energy providers to provide power with a minimum difference from one time to another. We add this constraint on top of the smoothing problem. Then, we determine a minimum possible size of ESS so that the smoothed output power is maintained during the day-ahead forecast period. To test our approach, we use a day-ahead forecast and real data of an industrial site located in France. Bench-marking the moving average methods, we compare performances of the proposed algorithm using two metrics. Based on our simulation results, we obtained at least 34% improvement in smoothness measure and at least 19% reduced ESS size by using the proposed algorithm.

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**Keywords:** Renewable energy resources; energy storage systems, moving average smoothing; Gaussian smoothing;

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### 1. Introduction

Since the beginning of 21<sup>st</sup> century, developing clean energy and ensuring energy safety have gained much attention from the energy sector. At the heart of clean energy, there are distributed energy resources (DERs) such as solar panels, wind turbines, energy storage systems, and others. Microgrid facilitates the integration of these resources to a power system [1]. The microgrid concept assumes a cluster of small, independent power-generating equipment connected to computer systems that monitor, control and balance energy demand, supply and storage in response to changing energy needs. Microgrids can be classified into commercial and industrial, residential/building and military microgrids where there are onsite energy generations to support some or full energy demand. Detailed descriptions of microgrid systems are given in [1,2].

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Integration and control of DERs pose challenges to management and operation of power systems. For instance, the output of solar power changes frequently depending on the position of the sun and clouds. By the same way, wind power is subject to some of the same types of daily and seasonal variations. A key problem to be solved could be finding solutions on how to mitigate intermittent renewable energy resources and integrate them to a power system. A potential candidate solution to the challenge is to use ESS [3] such as electric double-layer capacitor [4], superconducting magnetic energy storage [5], fuel cells [6], and battery energy storage system (BESS) [7] to smooth out power fluctuations. The ESS can be used to store surplus energy and to shave peak demands. Furthermore, it can be used to fill voids created due to forecasting errors.

For smoothing power production of solar and wind, different approaches have been proposed in literatures. A moving average (MA) method was proposed by Ellis *et al.*[8] and Johnson *et al.*[9]. They used the MA method to mitigate short-term fluctuation of photovoltaic (PV) power using BESS. In [7], the MA approach was also used to control battery energy to reduce PV power fluctuation. An exponential moving average (EMA) method with hydrogen storage system was used in [10]. The EMA gives more weights on recent values. In both MA and EMA, length of averaging window determines how the storage systems charge or discharge. If the window is long, it requires the storage systems to cover the difference between the actual and smoothed powers, even if the fluctuation is not significant [11]. In [12], a fuzzy wavelet transform method was used to smooth out wind and solar power productions using batteries. Alam *et al.*[11] also proposed an approach for ramp-rate control of PV power fluctuations.

In this paper, we propose a Gaussian-based smoothing algorithm for mitigating solar and wind power fluctuations using BESS. Gaussian filters have been extensively used in computer vision and image processing domains [25]. In our work, we investigate it in energy domain for smoothing purpose. We compare performances of the proposed algorithm against MA and EMA methods using real and forecast datasets. On top of the smoothing problem, we include power level constraints between consecutive power productions. The motivation for this constraint is that in some places (such as La Réunion - region of France), it is mandatory that suppliers regulate power levels in order to sell their power generation to the utility grid. Taking into account this constraint, we then determine the minimum battery size in order to guarantee a power production curve. Our objective is to determine such a power production curve with minimum battery size for a day-ahead forecast period. The power production curve enables one to know precise power production of the renewable energy resources and it helps one to decide buying energy from the utility grid or spot market if energy demand is higher than energy supply.

The remainder of this paper is organized as follows. In section 2, we discuss few notations and models of DERs. Then, in section 3, we detail our problems and the proposed smoothing algorithms. We provide simulation results and discussions in section 4. Finally, in section 5, concluding remarks are given.

## 2. Notations and Models

In this section, we provide notations and models of wind, solar, storage systems and a description on spot market.

### 2.1. Wind power

Wind turbines generate electrical power by extracting kinetic energy from air flow using rotors and blades. A typical wind turbine is characterized by its *power curve* [13]. The power curve relates wind power to wind speed. The following equation gives the relationship between wind speed and power extracted from the wind [14]:

$$P_w = \frac{\rho}{2} * A_{wt} * c_p(\lambda, \theta) * v_w^3 \quad (1)$$

where  $P_w$  is power extracted from wind (W),  $\rho$  is air density ( $kg/m^3$ ),  $c_p$  is performance or power coefficient,  $\lambda$  is ratio  $v_t/v_w$  (ratio between blade tip speed  $v_t(m/s)$  and wind speed at hub height upstream the rotor  $v_w(m/s)$ ),  $\theta$  is pitch angle, and  $A_{wt}$  is area covered by rotor of wind turbine ( $m^2$ ). According to Betz's limit [15], the maximum power coefficient ( $c_p$ ) is limited to 16/27 (59.3%). No wind turbine can extract kinetic energy from wind speed higher than this coefficient. In our work, we set  $c_p$  to 25% which is a common setting for most wind turbines.

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