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MODEL PREDICTIVE CONTROL FOR POWER FLUCTUATION SUPPRESSION IN HYBRID WIND/PV/BATTERY SYSTEMS

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ABSTRACT

A hybrid energy system, the combination of wind turbines, PV panels and battery storage with effective control mechanism, represents a promising solution to the power fluctuation problem when integrating renewable energy resources (RES) into conventional power systems. This paper proposes a model predictive control (MPC)-based algorithm for battery management in a hybrid wind/PV/battery system to suppress the short-term power fluctuation on the 'minute' scale. A case study with data collected from a practical hybrid system setup is used to demonstrate the effectiveness of the proposed algorithm together with a Monte Carlo simulation-based sensitivity analysis. In addition to illustrating the complementarity between the fluctuations of wind power and PV power, the results prove the proposed MPC algorithm is effective in fluctuation suppression but sensitive to factors such as forecast accuracy and the desired range of power fluctuation.

Keywords: battery, hybrid energy system, model predictive control, fluctuation suppression, renewable energy resources.

INTRODUCTION

From a renouned wind/diesel setup [1] to an innovative renewable/fuel cell application [2], hybrid energy systems have been under consistent development for supplying electrical energy in urban, rural and remote areas with renewable-based energy solutions. By incorporting two or more energy conversion/storage technolgies, a carefully designed hybrid energy system can achieve a number of advantages in comparison to single source based system, such as flexible configuration, higher reliability, improved energy efficiency, lower levelized life-cycle electricity generation cost and a more stable power profile, etc., [3]-[6]. In the context of smart grid wherein advanced information and communication techlogies (ICT) and grid-side technogies are applied, such a hybrid system can be achieved through either an aggregation of geographically distributed energy components in a virtual power plant (VPP) [7] or a microgrid setup with grid-connected or islanded modes [8]**Error! Reference source not found.**, extending its orignal off-grid applications.

Among different hybrid solutions, the combination of wind turbines, PV panels and battery storage with effective control mechanism represents a promising solution to suppress the power fluctuation when integrating renewable energy resources (RES) into conventional power systems [9]-[13]. Such a hybrid Wind/PV/battery system can take advantage of a) the natural complementarity between wind and solar that could possibly lead to less power fluctuation and b) the buffering capability of battery that can be offered to further smoothen/limit the aggregated power output at different scales in both time and magnitude.

This paper presents a model predictive control (MPC)-based algorithm for battery management in a hybrid wind/PV/battery system to suppress the short-term power fluctuation, i.e., measured over time intervals spanning from 1 minute or less to 15 minutes, which is of big significance not only for the system investors, but also for power system operators [16]. In a hybrid system wherein the capacity and the technical characteristics of each unit are given, the algorithm aims to restrain the power fluctuation within a pre-defined range (e.g. 5% of total installed capacity of RES) through controlling the battery charge by taking the power forecast of renewables and a battery model as inputs. A case study with data collected from a practical hybrid system setup is used to demonstrate the effectiveness of the proposed algorithm together with a Monte Carlo simulation-based sensitivity analysis. In addition to illustrating the complementarity between the fluctuations of wind power and PV power, the results prove the control algorithm is effective in managing fluctuation but sensitive to factors such as forecast accuracy. Recommendations of improving MPC-based power fluctuation mitigating mechanism are given at the end of the paper.

MODEL PREDICTIVE CONTROL ALGORITHM FOR POWER FLUCTUATION SUPRESSION IN A HYBRID SYSTEM

As illustrated in Figure 1, based on the dynamic models of the controlled system and the predicted future events over a finite time horizon, the framework of MPC repeatedly enables online calculation of the optimum control point(s) for the control horizon while keeping the future in account.

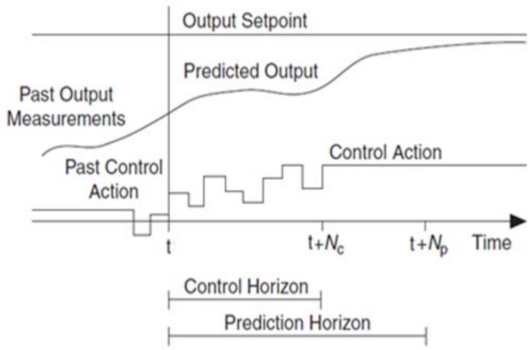

Figure 1: Schematic principle of MPC

When to apply MPC to a hybrid wind/PV/battery system for power fluctuation suppression, in order to avoid curtailing the renewable power, the optimum control point(s) typically refers to the power setpoint of battery for the current time slot, i.e., to set N_c to 1, while keeping the forecasted fluctuation over a planning period is minimized to a certain degree. Mathematical formulations of battery model, forecasted fluctuation of renewables and the control objective of fluctuation suppression are explained in this section.

1) Battery model

The dynamics of a battery system is modeled with a set of equations as in (1)-(4),

$$E(t+1) = E(t) + P_b(t) \cdot \Delta t \cdot \eta \tag{1}$$

$$SOC(t) = E(t)/E_{cap} \tag{2}$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{3}$$

$$\eta = \begin{cases} \eta_c & if\ P_b(t) \geq 0 \\ 1/\eta_d & if P_b(t) \leq 0 \end{cases} \tag{4}$$

$$P_{b,min} \leq P_b(t) \leq P_{b,max} \tag{5}$$

where the difference equation (1) models the energy variation of the battery system over a fixed time length Δt, and the equations (2)-(5) express the station of charge (SOC) equation, describe the constraint of SOC, define an intermediate variable η which is a function of charging efficiency η_c and discharging efficiency η_d, and denotes the power capacity constraint between the maximum discharging power $P_{b,min}$ (negative) and the maximum charging power $P_{b,max}$(positive), respectively.

2) Forecasted fluctuation of renewables

Assuming the real time production of renewables$P_r(t)$, i.e., the sum of wind power $P_{wind}(t)$ and solar power $P_{pv}(t)$, can be measured online, the power ramp $\delta(t)$ as defined in (6) denotes the absolute fluctuation of the aggregated power of renewables and battery between two continuous time instants.

$$\delta(t) = |P_r(t) - P_b(t) - P_r(t-1) + P_b(t-1)| \tag{6}$$

By replacing the measured renewable power with the a forecast $\widehat{P_r}(t+k|t)$ with the lead time $t+k$, the power ramp $\hat{\delta}(t+k)$ forecasted at time origin t can be therefore derived as in (7)

$$\hat{\delta}(t+k|t) = |\widehat{P_r}(t+k|t) - P_b(t+k) - \widehat{P_r}(t+k-1|t) + P_b(t+k-1)| \tag{7}$$

3) Power fluctuation suppression

The control objective as in (8) denotes how the MPC controller suppresses the forecasted fluctuation over one planning period $N_p$when the decision is made at time origin t. By controlling the battery charge $P_b(t+k)$ in the planning period and $P_b(t)$ for the current time slot, the fluctuation will be suppressed within $[-\delta_{max,}\delta_{max}]$ as much as possible, wherein the positive parameter δ_{max} reflects the desired boundary of power fluctuation such as 5% of total installed capacity of RES. The weighting coefficients $\omega_{p_b,k}$ and ω_t reflect the relative importance of forecasted fluctuation and the measured fluctuation at time origin t. The former coefficients can be adjusted according the confidence level of the forecasting (i.e. open-loop focused), the latter coefficient can be used to correct the inaccurate control decisions based on the measured fluctuation (i.e. close-loop focused).

$$\sum_{k=1}^{N_p} \omega_{p_b,k}\left(\hat{\delta}(t+k) - \delta_{max}\right)^2 + \omega_t(\delta(t) - \delta_{max})^2 \tag{8}$$

It is worthwhile to note that when battery is controlled in a typical passive manner, i.e. to control the battery charge to suppress the instant power ramp without considering the forecast which equals to setting ω_t to a much larger value than $\omega_{p_b,k}$, it could result in an even larger power ramp for the following time slot if the following power ramp follows the same direction as the present one. By applying MPC-based control algorithm, this problem can be addressed given an accurate forecast. Further, for a battery with limited energy capacity, MPC-based control algorithm could optimally allocate the battery capacity in order to handle forecastable large power fluctuations by reserving the capacity for future use.

CASE STUDY

To prove the effectiveness of the proposed algorithm, this section applies the previously described control algorithm to a test system through the following three studies,

S.1 Complementarity analysis between power fluctuations of wind turbines and PVs

S.2 Baseline scenario for testing the MPC-based control algorithm with perfect forecast

S.3 Sensitivity analysis for the MPC-based control performance to forecast errors

Test system and measured data

We create a hybrid system test case based on the experimental facility of SYSLAB in the technical university of Denmark. As illustrated in Figure 2, backboned by a 400V grid with flexible configuration, SYSLAB enables research and testing of control concepts and strategies for energy systems with distributed control and integrating a number of decentralized production and consumption components. For this particular study, as highlighted in Figure 2, a hybrid wind/PV/battery system is created, which consists of 2 wind turbines (10kW and 11kW), 3 PV plants (10kW, 10kW and 7 kW), resulting in a total installed capacity of 48kW renewables. In addition, a 15 kW/120 kWh vanadium redox flow battery is included for fluctuation suppression. Due to the cost concerns, one of the criteria for selecting a battery for fluctuation is the preference of high power over high energy. In the following analysis, the energy capacity of the battery is reduced to 20kWh to emulate a practical hybrid system setup.

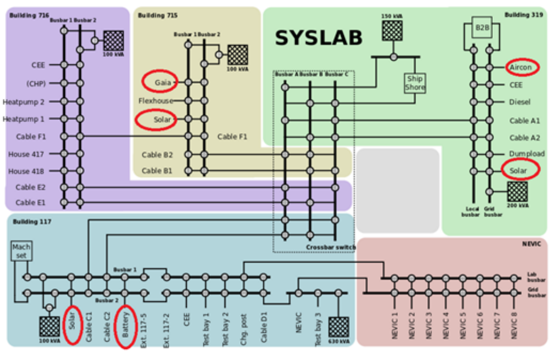

Figure 2: Electrical layout of SYSLAB

The aggregated power profiles of SYSLAB's wind turbines and PVs as in Figure 3 are measured on one minute-scale over two days respectively. The data is applied to the following studies S.1-S.3. During this sampled period, the maximum values of aggregated wind power and aggregated solar power reach 20kW and 17.4kW respectively.

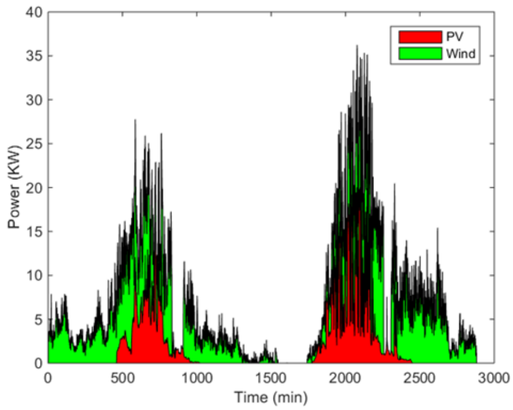

Figure 3: A two-day power profile of wind turbines and PVs measured on 1-minute scale

S.1 Complementarity analysis between power fluctuations of wind turbines and PVs

Figure 4 illustrates the power fluctuations of PVs, wind turbines and the aggregated portfolio respectively. The minute-by-minute fluctuation of each portfolio denoted by $||\delta||$ is normalized to the total installed capacity P_{norm} of that portfolio, e.g., P_{norm} is 27kW for the portfolio with only PVs. Table 1 shows a comparison in power fluctuations among the three portfolios. For both up and down power ramps, the smoothing effects through aggregating wind turbines and PVs reduce the maximum value of fluctuation by 5-28%.

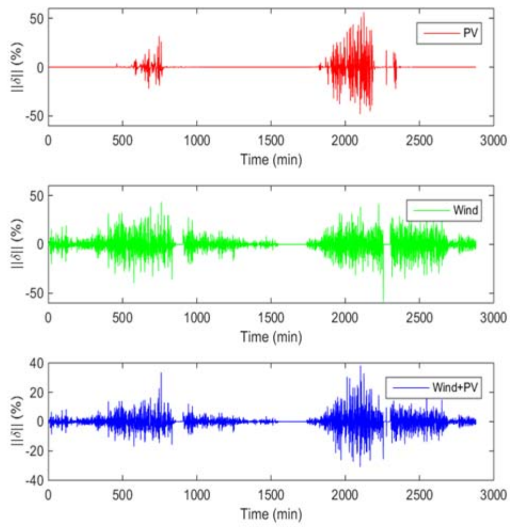

Figure 4: Normalized power fluctuation for PVs, wind turbines and aggregated portfolio

Table 1: Comparison of power fluctuation for different portfolios

	MAX_UP (%)	MAX_DOWN (%)
PVs	56	-48
Wind turbines	43	-59
PV+Wind	38	-31

S.2 Baseline scenario

The baseline scenario assumes a perfect forecast of renewables' production. Table 2 shows the parameter settings for the simulated study. During the simulated period, the battery charge is controlled minute-by-minute according to the MPC-based control algorithm described earlier. The simulation is performed in Matlab R2015 with "fmincon" function applied to solve this constrained optimization problem.

Table 2: List of parameter and variable settings

PARAMETER	VALUE
η_c	90%
η_d	90%
N_p	10
P_{norm}	48kW
δ_{max}	$5\% \cdot P_{norm}$
SOC_{min}	20%
SOC_{max}	80%
SOC_{ini}	50%
$P_{b,max}$	15 kW
$P_{b,min}$	-15 kW
E_{cap}	20 kWh
$\omega_{p_{b},k}$	1
ω_t	10

Figure 5 illustrates the effectiveness of the proposed MPC algorithm. Compared to the case without battery or any control, after implementing the MPC-based control algorithm to the battery the power fluctuation is completely suppressed within 5%. Figure 6 illustrates the correponding variation of the battery's SOC, which follows the change of power ramping in the same direction.

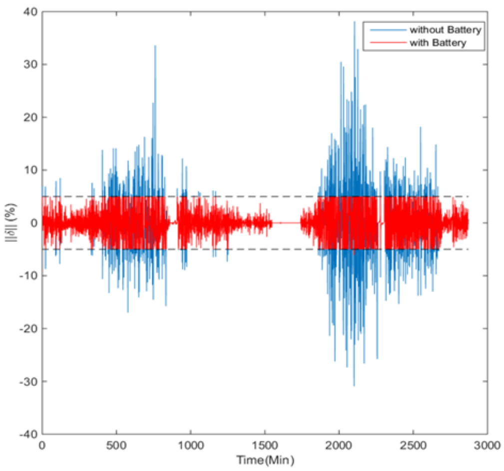

Figure 5: Comparison of power fluctuation of the hybrid system with and without battery (100% forecast accuracy)

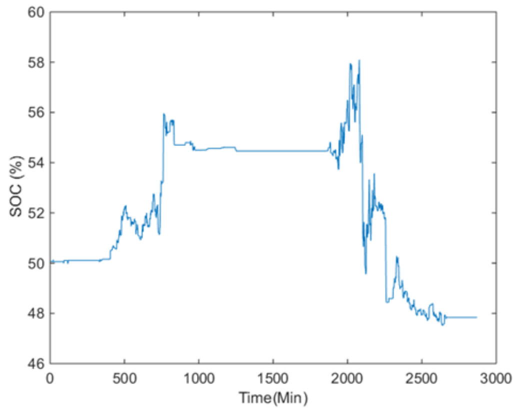

Figure 6: Variation of battery SOC under MPC

S.3 Sensitivity analysis

Given a fixed operational portfolio of a hybrid wind/PV/battery system, the performance of the proposed MPC algorithm is dependent on several factors δ_{max} , N_p and the accuracy of forecast. The two former factors δ_{max} and N_p can be optimally decided to a certain degree by following the grid code recommendations and by recurrently testing the performance with different value settings, etc. On the contrary, the algorithm's sensitivity to the forecast error becomes the key analyzing its robustness. This is because the short-term forecast errors (i.e. at minute scale) for stochastic renewables can be much more random compared to the errors of forecast with longer time scales [17]. For small/micro sized stochastic renewables, forecasting the short-term power production can be even more challenging. In this study, we hereby focus on analyzing the sensitivity of the proposed algorithm to the forecast errors.

To simulate the minute-by-minute forecast error during each planning horizon, a Monte Carlo-based alrogithms as in equations (9)-(11) are applied to randomly generate normally distributed forecast errors.

$$\hat{P}_r(t+k|t) \sim\sim N(p(t+k), \sigma(t+k|t)^2) \tag{9}$$

$$\sigma(t+k|t) = k \cdot \beta \tag{10}$$

$$0 \leq \hat{P}_r(t+k|t) \leq P_{norm} \tag{11}$$

where equation (9) introduces an random generator of the forecasted power $\hat{P}_r(t+k|t)$, which assumes the forecast error is subject to a normal distribution with the mean of zero and a standard deviation of $\sigma(t+k|t)$. To emulate the general effect of forecast, i.e., the variance of forecast error typically grows as the forecast horizon increases, a linear relationship between the standard deviation and the forecast horizon k assumed as in equation (10), wherein β is a constant between 0 and 1. Equation (11) ensures the forecasted power will not exceed the range of installed capacity. Figure 7 presents an example of how the forecast errors over a forecast horizon of 10 minutes are randomly generated at the 10th minute in the simulated period. The thick blue line shows the measured power, while the other dotted lines represent hundred forecasts which are generated according to the described algorithm.

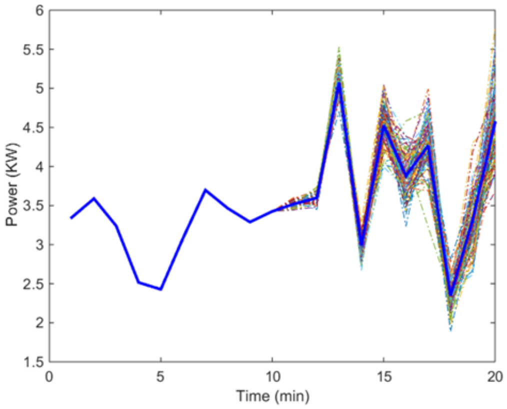

Figure 7: Randomly generated forecast errors $(\beta = 0.01)$

Figure 8 illustrates the distribution of control failures in 100 generated simulation cases. For each case, the forecast errors are randomly generated according the above algorithm with a 1-minute moving window along the simulation period of 2 days. On average, there are 2.3 times the controlled power fluctuation exceeds 5% of the total installed capacity in each simulated case. The average failure rate in the simulated period is therefore below 0.1%.

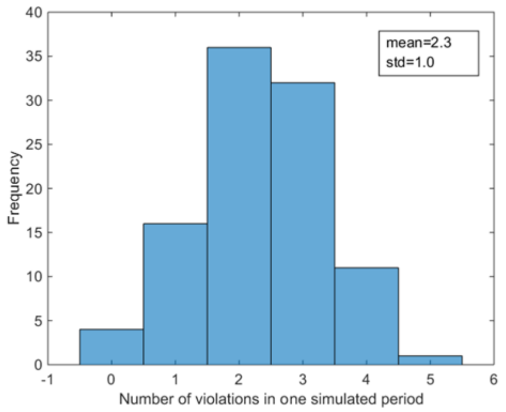

Figure 8: Histogram of control failures $(\beta = 0.01)$

Figure 9 illustrates the distribution of control failures in 100 simulation cases, within which the randomly generated forecast error for the upcoming minute has an average error of 10%. On average, there are 17.5 times control failure in each simulation, which corresponds to 0.6% failure rate. In these two Monte Carlo based simulations, the maximum value for the fluctuation after control is always below 30% of the total installed capacity.

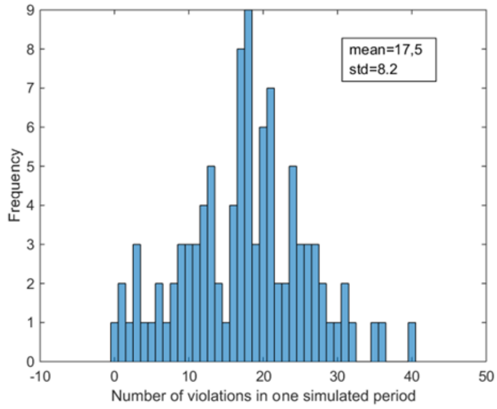

Figure 9: Histogram of control failures $(\beta = 0.1)$

CONCLUSION AND RECOMMENDATIONS

The paper proposes a MPC-based algorithm for battery management in hybrid wind/PV/battery systems to suppress the 1 minute-scale power fluctuation of stochastic renewables. In the presented practical hybrid wind/PV/battery setup, the complementarity between fluctuations of wind turbines and PVs can be cleared recognized, proving the value of developing hybrid renewable systems. After applying the proposed fluctuation suppression algorithm, the 1 minute-scale power fluctuation is further suppressed to a desired degree. Instead of using a specific forecast algorithm, Monte Carlo method is applied to randomly generate the 1 minute-scale forecast errors and to test how sensitive is the MPC algorithm to the forecast errors. The results show performance of the control algorithm is weakly sensitive to the forecast error. This could be due to several factors observed in this study, including

- more importance is given to the measured fluctuation,
- the energy capacity of the storage is relatively large,
- the forecast horizon is short,
- the forecast resolution is small.

These factors, especially the first two, to a great degree guarantee the robustness of the proposed algorithm. For instance, when the complete importance is given to the measured fluctuation, the battery would be able to perfectly suppress the fluctuation if its capacity of energy and power are infinite. Given the first two factors, the latter two factors also to certain degree ensure the SOC variation over the forecasted period is not big. All these factors result in there is always sufficient SOC of the battery to handle either forecast errors or forecastable large power fluctuations.

To further improve the applicability of the proposed MPC algorithm, several studies as following will be conducted in the future.

- perform a field test of the proposed algorithm in SYSLAB,
- develop optimal sizing solutions for the hybrid wind/PV/battery systems,
- develop optimal tuning of the control variables, such as weighting coefficients and forecast horizon,
- develop optimal dispatch algorithms for battery control in a hybrid system in order to manage power fluctuation and energy balance simultaneously.

These studies will further support a framework development under which MPC-based control algorithms for hybrid systems can be easily understood, developed and applied.

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