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Stochastic model of wind-fuel cell for a semi-dispatchable power generation

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HIGHLIGHTS

- Semi-dispatchable generation based on time series analysis.
- Hybrid system for distributed generation with zero frequency and voltage instability.
- Hybrid system management implementing model predictive control.
- Short-term forecast to create power generation trajectory.

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ABSTRACT

Hybrid systems are implemented to improve the efficiency of individual generation technologies by complementing each other. Intermittence is a challenge to overcome especially for renewable energy sources for electric generation, as in the case of wind power. This paper proposes a hybrid system as an approach for reducing and overcoming the volatility of wind power, by implementing storage technology, forecasts and predictive control. The proposed hybrid system, which is suitable for the distributed generation level, consists of a wind generator, an electrolyzer, hydrogen storage and a polymer electrolyte membrane fuel cell, which are embedded in one complete system with the wind power. This study uses historic wind speed data from Mexico; the forecasts are obtained using the recursive least square algorithm with a forgetting factor. The proposed approach provides probabilistic information for short-term wind power generation and electric generation as the outcome of the hybrid system. A method for a semi-dispatchable electric generation based on time series analysis is presented, and the implementation of wind power and polymer electrolyte membrane fuel cell models controlled by a model predictive control approach is developed.

1. Introduction

Renewable energies are increasingly being used to generate electricity. Integration to the network, however, requires adjusting the new technologies in order to meet the established norms. Wind and photovoltaic renewable energy generation technologies are up to now the most developed and, in both, intermittence is the major issue to attend for connection to the grid.

Studies concerning non-dispatchable generation combined with storage which focus on isolated networks are [1–3] where a DC configuration is proposed for the renewable energy integration and storage is implemented to increase the use of wind power and reduce the operation of backup systems. For stand-alone systems employing two or more technologies to generate electricity is common.

Another way to deal with intermittence is to combine the wind power generation with the forecast, in order to more accurately plan how to use the generated power and how to participate in market regulation [4,5]. The wind power uncertainty has been another research topic as in [6] where wind power forecasting uncertainty is investigated in the unit commitment. The study of levelized costs of grid-connected wind turbines with energy storage device (ESD) [7,8] or renewable sources implemented as distributed generation (DG) [9], as well as the analysis of the wind energy in Germany [10], are examples of the many studies in the implementation of renewable energies.

The issue with intermittence in wind power can be decreased when a forecast model is implemented. The approach suggested in this study uses an ESD to stabilize the inherent variations and

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Nomenclature

E	open circuit voltage
F	Faraday constant
H	hydrogen
H_{2used}	volume of hydrogen required by the FC
I	current
l	impulse response
M	number of points in average filter
N	future outputs for a horizon
n	number of cells
O	oxygen
p	ambient pressure
P	active power
P_{el}^{nom}	electrolyzer nominal power
P_{fc}^{nom}	fuel cell nominal power
P_{t+k}^{ref}	power reference trajectory
$\widehat{P}_{t+k}^{w}$	forecasted wind power
P_o	balance power
P_w	actual and forecasted wind power
P_ϕ	power flow to/from storage elements
P_{elmax}	activation vector of electrolyzer
P_{el}	electrolyzer power
P_{fcmax}	activation vector of FC
P_{fc}	fuel cell power
R	ideal gas constant
T	temperature
t	time
V	voltage
V_c	cell voltage
V_g	gas volume
V_{act}	activation voltage
V_{H_2}	volume of hydrogen
V_{ohm}	ohmic voltage
V_{trans}	transport voltage
X	matrix of past observations
Y_{t+1}	forecast one step ahead
Y_t	historic data
z	number of excess electrons
Greek	
Δt	age of the data
Γ_{el}	threshold of low level percent of storage
Γ_{fc}	threshold of min percent of storage for FC
λ	forgetting factor
μ	correction for the mean value
ω	weight
ϕ	storage level
ϕ_0	last value of storage level
Θ	weight of past observations
θ	vector of weight of past observations
ε	white noise

to balance the deviations of the actual wind power to better meet the planned network infeed. The purpose of the ESD is to reduce the intermittence with the implementation of a filter and to be able to meet the short-term planned production of the hybrid system (HS) at the distribution level. To keep a stable frequency in the network, what matters for the operation of the transmission system is not so much the variation in production but the unpredictability of the production which is study in this work.

The major contribution in this paper, as shown in the following sections, is the ability to change the output power of the HS from a non-dispatchable to a semi-dispatchable generation giving the capability to inform the independent system operator (ISO) to program the network dispatch. The flexibility of power dispatch depends greatly on the short-term prediction and the storage characteristics to reduce the variations of the power generated by the wind turbine.

Unlike other studies, this paper proposes an advance energy management system (AEMS) to overcome the effect on the frequency when the HS, relying solely on clean energy sources without depending on fossil power plants, is connected as DG.

2. Implemented models

The sample size of historic data implemented in the forecast model was given by measurements over a period of three months with a resolution of 10 min.

2.1. Forecast model

Energy forecasting is particularly meaningful when considering wind power because of the cost relation, dispatch planning and market operations [11], the focus in this paper is dispatch planning.

The sample data used for the forecast was given by a three months with a resolution of 10 min (12,960 measurements) but the complete study was made for a whole year. Even though the collected measurements data covers a year, in this study only the first week of results was shown so the reader can truthfully see the behavior of the hybrid system and the output power in a clear way.

2.1.1. Autoregressive model

In this model, the current value of the process was expressed as a finite, linear aggregate of previous values of the process. The AR model is a classic forecast model implemented in time series analysis. An AR(ρ) model relates ρ historic observations to the value Y_{t+1}

$$Y_{t+1} = \mu + \sum_{i=0}^{\rho-1} \Theta_i Y_{t-i} + \varepsilon_{t+1} \tag{1}$$

$$Y_{t+1} = \hat{Y}_{t+1|t} + \varepsilon_{t+1} \tag{2}$$

from Eq. (1), μ is a term correcting the mean value, Θ_i is the coefficient of each past observation Y_{t-i} describing its influence on the next value Y_{t+1}, and finally ε_t is assumed to be white noise [12,13]. This is an iterative process, meaning that a six-steps-ahead forecast is required to calculate (2), to upgrade Y_t plugging in the last forecast value generated, and to repeat the process:

$$\hat{Y}_{t+k|t} = \mu + \sum\nolimits_{i=0}^{\rho-1} \hat{\theta}_i \hat{Y}_{t+k-(i+1)|t} \tag{3}$$

$\hat{Y}_{t+k-(i+1)|t}$ is equal to the observation if the observation exists; otherwise, it is equal to the prediction. An AR process is a linear process characterized by a finite number of terms.

2.1.2. Recursive least square with forgetting factor [14]

Notice that the k-step AR(ρ) model can be written as