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Novel probabilistic optimization model for lead-acid and vanadium redox flow batteries under real-time pricing programs

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ABSTRACT

The integration of storage systems into smart grids is being widely analysed in order to increase the flexibility of the power system and its ability to accommodate a higher share of wind and solar power. The success of this process requires a comprehensive techno-economic study of the storage technology in contrast with electricity market behaviour. The focus of this work is on lead-acid and vanadium redox flow batteries. This paper presents a novel probabilistic optimization model for managing energy storage systems. The model is able to incorporate the forecasting error of electricity prices, offering with this a near-optimal control option. Using real data from the Spanish electricity market from the year 2016, the probability distribution of forecasting error is determined. The model determines electricity price uncertainty by means of Monte Carlo Simulation and includes it in the energy arbitrage problem, which is eventually solved by using an integer-coded genetic algorithm. In this way, the probability distribution of the revenue is determined with consideration of the complex behaviours of lead-acid and vanadium redox flow batteries as well as their associated operating devices such as power converters.

1. Introduction

Integration of renewable energies is seen as a way to harmonize technological progress with environment conservation. However, renewable natural resources are highly variable, which directly contrasts with the operating philosophy of energy conversion systems. To solve this dilemma, the adopted option has been to increase the flexibility of the power system by incentivizing consumers to modify their consumption behaviour or by installing energy storage devices in a centralized or de-centralized manner so that the power consumption from renewable sources is enhanced.

Many efforts have been made to develop devices capable to store energy at different magnitudes. According to their technical characteristics, storing technologies can be used for different tasks of power-system operation such as integration of renewable power generation, emergency and telecommunications power support, ramping and load following, peak-shaving, and load levelling [1]. However, their economic integration into energy business and electricity markets is difficult and depends on many important factors.

Regarding the techno-economic analysis for the integration of energy storage in European Union (EU) countries, according to the results reported by Zafirakis et al. in [2], those electricity markets with low degree of competitiveness and highly dependent on energy imports offered the highest opportunities for the successful incorporation of energy storage. In such markets, energy imports are used to cover peak loads, which results in high peak-prices and favourable conditions for energy storage operation. The transition toward a power system strongly based on renewable energies is currently under analysis in EU countries. According to the most recent studies, pumped hydroelectric storage (PHS) can play a key role in the mitigation of power fluctuation related to wind-power generation, while other technologies such as conventional batteries and hydrogen-based storage units are not economically viable [3]. In the United States, Bradury et al. [4], analysed the integration of a wide range of storage technologies in several electricity markets and concluded that economic benefit depends on charging and discharging efficiencies, the corresponding self-discharge ratios, and capacity. According to the study's results, economic benefit increases as the conversion efficiency of the corresponding storage

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Nomenclature

t	index of each element of the predicted prices (t = 1,...,T)
h	index of each element of the large-scale price database (h = 1,...,H)
p	index of each coefficient of AR part (p = 1,...,P)
q	index of each coefficient of MA part (q = 1,...,Q)
l	index for each lag of autocorrelation analysis (l = 1,...,L)
m	index for each MCS trial (m = 1,...,M).
g	Index of each generation of GA (g = 1,...,G)
k	index of each individual of GA (k = 1,...,K)
i	index of each individual of GA (i = 1,...,I)
b	index of each bit of individual $\vec{a}_k$ (b = 1,...,B)
AR_p	pth auto-regressive coefficient
MA_q	qth moving average coefficient
e_h	error of ARMA model at time h .
EP_h	electricity price at time h (€/MW h)
EP_{min}	minimum price of the large-scale price database (€/MW h)
EP_{max}	maximum price of the large-scale price database (€/MW h)
TEP_h	transformed electricity price at time h
$TSEP_h$	transformed and standardized electricity price at time h
FEP_t	forecasted electricity price at time t (€/MW h)
$FTEP_t$	forecasted transformed electricity price at time t
$FTSEP_t$	forecasted transformed and standardized electricity price at time t
Q_{stat}	Ljung-Box statistic
r_l	autocorrelation of the residuals at lag l
δ	significance level (0.05)
χ^2_δ	chi-square distribution with $L-P-Q$ degrees of freedom and significance level δ
F_N	CDF of a normal distribution
F_{EP}	CDF of the large-scale price database
$f_{FE,t}$	PDF of electricity price at time t (beta PDF)
$F_{FE,t}$	CDF of electricity price at time t (beta PDF)
α_t, β_t	parameters of beta PDF at time t
$f_{DA,t}$	PDF of electricity price at time t used for day-ahead prediction.
AFP	average forecasted prices (€/MW h)
$SDFP$	standard deviation of forecasted prices (€/MW h)
$ATEP_t$	averaged transformed electricity price at time t
$FEPS_{t,m}$	forecasted electricity price scenario at time t and trial m (€/MW h)
$NFEP_t$	normalized forecasted electricity price (€/MW h)
$NFEPS_{t,m}$	normalized forecasted electricity price scenario at time t and trial m
$u_{t,m}$	correlated random variable with normal distribution
φ	correlation coefficient
ξ	non-correlated variable with normal distribution
X	crossover rate of GA (ARMA model)
R	mutation rate of GA (ARMA model)
$f_{GA,s}$	fitness function of individual s
A	population of GA (ARMA model)
Z	population of GA (battery control)
$\vec{a}_k$	individual k of GA (ARMA model)
$\vec{z}_i$	individual i of GA (battery control)
a_b^k	value of bit b of individual $\vec{a}_k$
z_t^i	control decision at time t for individual i
NS	number of batteries in serial
NP	number of batteries in parallel
RV_i	revenue of individual i
$P_{SYS,t}$	power of battery bank at time t
$ZP_{SYS,t,i}$	power of battery bank at time t for individual i
$T_{A,t}$	ambient temperature at time t (K)
T_E	electrolyte temperature (K)
U_t	battery voltage under general conditions (V)
U_{min}	minimum battery voltage (V)
U_{max}	maximum battery voltage (V)
$U_{LAB,t}^C$	battery voltage of LAB under charging conditions (V)
$U_{LAB,t}^D$	battery voltage of LAB under discharging conditions (V)
$U_{VRB,t}^C$	battery voltage of VRFB under charging conditions (V)
$U_{VRB,t}^D$	battery voltage of VRFB under discharging conditions (V)
SOC_t	SOC at time t
SOC_{min}	minimum SOC
SOC_{max}	maximum SOC
DOD_t	DOD at time t
I_t	current of LAB (A)
P_t	battery power of VRFB (kW)
C_N	battery rated capacity (Ah for LAB and kWh for VRFB)
C_{10}	capacity in 10 h of LAB (Ah)
I_{10}	current in 10 h of LAB (A)
$I_{G,O}$	normalized gassing current for a 100 Ah battery (A)
$U_{G,O}$	nominal voltage under gassing conditions (V)
$T_{G,O}$	nominal temperature under gassing conditions (K)
$\eta_{INV,t}$	efficiency of the inverter at time t
$\eta_{V,t}^C$	voltage efficiency of VRFB during charging at time t
$\eta_{E,t}^C$	power efficiency of VRFB during charging at time t
$\eta_{VRB,t}^C$	efficiency of VRFB during charging at time t
$\eta_{V,t}^D$	voltage efficiency of VRFB during discharging at time t
$\eta_{E,t}^D$	power efficiency of VRFB during discharging at time t
$\eta_{VRB,t}^D$	efficiency of VRFB during discharging at time t
$\eta_{VRB,t}$	efficiency of VRFB at time t
IP_{INV}^1, IP_{INV}^2	inverter parameters
$VP_{LAB}^1 \cdots VP_{LAB}^{12}$	voltage parameters of LAB.
$VP_{VRB}^1 \cdots VP_{VRB}^7$	voltage parameters of VRFB
$CP_{LAB}^1 \cdots CP_{LAB}^3$	current parameters of LAB
$EP_{VRB}^1 \cdots EP_{VRB}^{20}$	efficiency parameters of VRFB

device improves provided that it has a relevant effect on the power transaction between the storage unit and the power system. On the other hand, the storage capacity of less than half a day offers higher benefits. In addition, the volatility of electricity prices and daily behaviour are important factors because the highest revenue is obtained under peak-price conditions.

Similarly, using data from the United States, de Sisternes et al. [5] concluded that storage technologies are particularly required when high reduction rates of carbon dioxide (CO_2) emissions are among the main goals. This was particularly observed for conventional battery technologies with low capacity (around 2 h), while storage units of higher magnitudes (specifically PHS- based with 10 h of duration) were found to be suitable when massive deployment was required. In Great Britain, interesting results were reported by Dunbar et al. in [6], where the influence of wind power generation on electricity prices and storage-unit profitability was evaluated. According to the observed results, the incremental capacity of wind-power generation could reduce electricity prices and reduce the frequency of price spikes, reducing the benefits obtained from the operation of storage units at peak prices. On the other hand, this situation could introduce uncertainty about the profitability of storage device installation due to yearly variations in revenue. In Germany, the transition to a power system powered by clean energies has been also analysed. Weitemeyer et al. [7] estimated that up to 50% of electricity demand could be supplied if the power generation mix was based on wind and solar energies combined with the appropriate capacity of flexible generation units. In this way, renewable power curtailment and energy storage integration could be avoided. However, if more than 80% of electricity demand has to be