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PV with multiple storage as function of geolocation

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ABSTRACT

A real PV array combined with two storage solutions (B, battery, and H, hydrogen reservoir with electrolyzer-fuel cells) is modeled in two geolocations: Oxford, UK, and San Diego, California. All systems meet the same 1-year, real domestic demand. Systems are first configured as standalone (SA) and then as Grid-connected (GC), receiving 50% of the yearly-integrated demand. H and PV are dynamically sized as function of geolocation, battery size B_M and H's round-trip efficiency η_H.

For a reference system with battery capacity $B_M = 10$ kW h and $\eta_H = 0.4$, the required H capacity in the SA case is ~1230 kW h in Oxford and ~750 kW h in San Diego (respectively, ~830 kW h and ~600 kW h in the GC case). Related array sizes are 93% and 51% of the reference 8 kW$_p$ system (51% and 28% for GC systems). A trade-off between PV size and battery capacity exists: the former grows significantly as the latter shrinks below 10 kW h, while is insensitive for B_M rising above it. Such a capacity achieves timescales' separation: B, costly and efficient, is mainly used for frequent transactions (daily periodicity or less); cheap, inefficient H for seasonal storage instead.

With current PV and B costs, the SA reference system in San Diego can stay within $2{\cdot}10^4$ \$ CapEx if H's cost does not exceed ~7 \$/kW h; this figure increases to 15 \$/kWh with Grid constantly/randomly supplying a half of yearly energy (6.5 \$/kWh in Oxford, where no SA system is found below $2{\cdot}10^4$ \$ CapEx).

Rescaling San Diego's array (further from its optimal configuration than Oxford's) to the ratio between local, global horizontal irradiance (GHI) and Oxford GHI, yields in all cases a 11% reduction of size and corresponding cost, with the other model outputs unaffected. The location dependent results vary to different extents when extending the modeled timeframe to 18 years. In any case, the variability stays within ± 10% of the reference year.

1. Introduction

Non-constant output is a major obstacle towards a widespread exploitation of wind and solar photovoltaic (PV) generation (Boyle, 2012; Steinke et al., 2013; Aghaei and Alizadeh, 2013; Denholm et al., 2016); energy storage is widely seen (Section 2) as the necessary addition for both the integration of large fractions of renewable electricity into the power Grid as well as the local utilization. Storage on the users' side can also free the Grid from the need of following demand. The price of batteries was still relatively high at the beginning of the 2010s (Mulder et al., 2013; Juul, 2012) but has then started to decline sharply; by some analysts (Hensley et al., 2012), this decreasing trend is projected to continue.

PV power is a typical example of highly inconstant renewable generation. Time-variability of solar irradiance on the Earth surface is due to the planet's rotation and revolution, which in turn correspond to separated timescales: day-night and seasonal cycles. The third source of irregularity is due to weather and climate, and is superimposed to the deterministic astronomical oscillations. It is termed intermittency in renewables literature and has a prominent effect on PV output, particularly in cloudy regions (see for example Colantuono et al., 2014a). Storage coupled to PV power must cope with these three sources of variance. The growing field of research of Energy meteorology (Emeis, 2012; Kleissl, 2013; Olsson, 1994) testifies the importance of environmental analysis for maximizing renewables' output and quantifying/reducing uncertainty (Correia et al., 2017; Prasad et al., 2015; Colantuono et al., 2014b). Several authors have suggested to combine various storage technologies to respond to such diverse timescales (e.g. Zhou et al., 2011; Glavin et al., 2008). Studies coupling batteries and hydrogen storage are reviewed in Section 2. Here, the same domestic load (this choice is explained in Section 4.4) in two geographical locations is considered: Oxford, UK, and San Diego, California. Firstly, demand is satisfied by PV (defined by the installed peak power) as the only power source, integrated with two coexisting storage reservoirs, schematized by their efficiency and cost: a long term hydrogen reservoir, H, coupled to electrolyzer and fuel cells, and a short term

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Table 1
Abbreviations and mathematical symbols. The latter can be either parameters or functions of time, in which case time dependency is indicated explicitly. Generation γ is the timeseries of either Oxford or San Diego, depending on the case being analyzed. It is normalized to the yearly-integrated yield of the 8 kW_p array considered for the Oxford case study. The scale factor X determines the fraction of the reference array too be used in each case. To visualize energy exchange, we assume H reservoir hierarchically "on top" of battery B which, in turn, is "above" the demand-provision balance. We therefore label as "uploaded" the power "going up" in this scheme (u^B and u^H) and as "downloaded" the power "going down" (d^B and d^H). Electricity provision comes from PV in the SA case and from PV plus Grid in the GC case.

Abbreviation	Definition
TS	Timeseries
SOC(s)	Storage reservoirs' state(s) of charge
B	Battery
H	Hydrogen Storage
Symbol	**Definition**
$\mathscr{S}()$	Heaviside's step function
$T = 1$year	Length of the problem in time
$0 \equiv t_0,t_1,...t_n,...,t_N \equiv T/t_1$	60 s time-steps; $N = T/60s \equiv 525600$
$d^B \equiv d^B(t_n)$	"Downloaded power" from B to demand in kW
$d^H \equiv d^H(t_n)$	"Downloaded power" from H to B in kW
$u^B \equiv u^B(t_n)$	"Uploaded power" from PV/Grid to B in kW
$u^H \equiv u^H(t_n)$	"Uploaded power" from PV/Grid to H in kW
$\lambda \equiv \lambda(t_n)$	Electric power load in kW
$\gamma \equiv \gamma(t_n)$	8 kW_p Ref. PV generation (kW) (see caption)
$\delta \equiv \delta(t_n)$	Generation - demand difference in kW
X	Scale factor of the 8 kW_p Ref. PV array
$\mathscr{B} \equiv \mathscr{B}(t_n)$	SOC of battery B in kW h
$\mathscr{H} \equiv \mathscr{H}(t_n)$	SOC of hydrogen storage H in kW h
η_H	Energy efficiency of hydrogen storage H
η_B	Efficiency of short term storage B
B_m	Battery minimum SOC threshold: 0.91 kW h
B_M	Battery capacity in kW h

battery B. Capacity of H (H_M) and PV array's size are dynamically determined as function of geolocation, B_M and η_H: demand at every time must be met, and the yearly-integrated value of demand must equal the yearly-integrated value of generation, after conversion inefficiencies have been taken into account. PV output and states of charge (SOCs) of the storage reservoirs are expressed as function of time in both geolocations. PV size is expressed by means of the scaling factor X, the fraction of the 8 kW_p array used as reference (see Appendix A and Table 1). The partition of storage into a long-term reservoir and a short-term, more efficient and smaller one is justified if a trade-off between storage cost and conversion inefficiency is possible.

Current storage technologies possess various efficiency levels; here, hydrogen H and battery B are characterized by their round-trip efficiency values η_H and η_B. H efficiency is given three values: η_H = 30%,40% and 50%, a range similar to what reported in Luo et al. (2015, Table 11 therein), while the battery efficiency is fixed at η_B = 85% (*ibid.*). The latter value can fall either within the lithium-ion (Rastler, 2010) or the lead-acid (Beaudin et al., 2010) efficiency interval. The smallest η_H value is the closest to currently available electrolysis/fuel-cell cycles; significant improvements may be expected with standardization and mass production, as hydrogen storage is still in the development phase (Luo et al., 2015). Engineering implementation is, however, beyond the scope of this analysis, the focus of which is energy balance. Environmental temperature is likely to impact round-trip efficiency of storage but would be difficult to define, as it depends not only on external temperature but also on buildings' features, placement of reservoirs within the property, resulting heat exchange with the environment, etc. The ample efficiency range we posit for H is comprehensive of any potential effect, included the high uncertainty on the performance that commercially-ready seasonal storage systems will achieve.

PV generation is then supplemented by a Power Grid able to provide only constant power. This scenario explores storage as a substitute of the current load-following pattern (e.g. Moshövel et al., 2015); the amount of long- and short-term storage needed on the user's side to accommodate such a constant supply is quantified. This idea is further extended that a partly random power provision is fed by utilities to domestic customers, to understand how users' storage may cope with a Grid that, besides not following demand, does not mitigate the variability on the supply side induced, for example, by wind and solar farms.

A simple CapEx analysis is then carried out, with the goal of comparing costs as system configurations vary in different geolocations. Such estimates provide a clue about the financial penalty potentially associated, across different Earth regions, with seasonal storage (and its combination with other system's components), the cost of which is highly uncertain. Finally, a long-term (18 yr) irradiance analysis is performed in both locations, to show how local irradiance variability differs from place to place, and what this implies for system sizing.

The main goal here is to highlight geographical/climate differences and the system behavior they induce as system's configurations vary through the parameter space. The sizing of a real system would have to account, for example, for year-to-year differences in solar generation and electricity consumption, failure rate, and other unpredictable factors; consequently, some form of uncertainty evaluation should be introduced, e.g. loss-of-load probability (LOLP, discussed by Celik, 2007; Klein and Beckman, 1987; Schenk et al., 1984, and many others). The impact of differences in PV generation over many years is addressed in Section 8, as well as the effect of varying demand. LOLP or similar metrics are not estimated here, as this would not make substantial contribution to frame the problem of multiple storage as function of climate and geolocation.

2. Literature review

Analyses carried out on sizing/performance of battery-hydrogen hybrid storage (BHHS) systems is reviewed in this Section. In very few cases a comparison between different geolocations has been attempted in the past: extant BHHS literature focuses on engineering implementation, control strategies and dispatching rules rather than the environment. Irradiance variability beyond the "typical year" assumption of commercial energy models is scarcely addressed. The recent paper of Zhang et al. (2017) points out the unsuitability of batteries and the advantages of hydrogen storage (high energy density and negligible leakage rate) to address irradiance seasonal imbalance affecting PV generation. They locate the imbalance in "Nordic countries"; imbalance is however significant everywhere on Earth, midlatitudes and tropics included. Scamman et al. (2015) compare the behavior of PV with BHHS in two geolocations: Heraklyon (with wind generation also present), Greece, and Phoenix, Arizona; this paper recognizes (as, from a different perspective, Cebulla et al., 2017) the importance of evaluating the behavior of a combination of load, generation and hybrid storage across different climates (performance in Reykjavik, Iceland, is also examined, with electricity entirely generated by a wind turbine). The case study therein considers a constant, 1 kW load; the authors conclude that their BHHS off-Grid system reduces the need for battery capacity, prolonging also battery life; a typical year of solar irradiance in each location is estimated using a commercial model. Marchenko and Solomin (2017) uses real irradiance data for an off-Grid system close to Lake Baikal, Russia; irradiance is measured during a time interval of 2 weeks per season and then extended using historical trends. Zhou et al. (2008) establish the size of a stand-alone BHHS and a geolocation comparison is carried out, dealing with modeled, 1-yr irradiance; the foci of the paper are system's engineering and dispatching rules. A similar comment may be made about Jacob et al. (2018). Advancing technology, rather than exploring the effects of environmental conditions, is also the prevalent interest of Cau et al. (2014), Maclay et al. (2007),Li et al. (2009), Jallouli and Krichen (2012), Kolhe et al. (2003), Gomez et al. (2009). Ulleberg (2004) mainly addresses control