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Optimal integrated energy systems design incorporating variable renewable energy sources

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ABSTRACT

The effect of variability in renewable input sources on the optimal design and reliability of an integrated energy system designed for off-grid mining operation is investigated via a two-stage approach. Firstly, possible energy system designs are generated by solving a deterministic non-linear programming (NLP) optimization problem to minimize the capital cost for a number of input scenarios. Two measures of reliability, the loss of power supply probability (LPSP) and energy index of reliability (EIR), are then evaluated for each design based on the minimization of the external energy required to satisfy load demands under a variety of input conditions. Two case studies of mining operations located in regions with different degrees of variability are presented. The results show that the degree of variability has an impact on the design configuration, cost and performance, and highlights the limitations associated with deterministic decision making for high variability systems.

1. Introduction

Mining is an energy intensive operation, accounting for a significant portion of the energy demand of the industrial sector. More than 80% of the electricity generated in Northern Chile, for instance, is consumed by copper mining operations (Nielsen, 2011), while mining alone accounted for over 30% of total industrial energy demand in Canada in 2010 (Natural Resources Canada, 2013). With the increase in demand for metals, mining operations are being forced to move to more remote locations, where grid electricity may be unavailable. Currently, such mining operations are operated with fossil fuels. However, the high operating costs associated with diesel generation and transport, coupled with the introduction of greenhouse emission limits, have forced the mining industry to seek cheaper, cleaner energy generation alternatives.

Renewable energy is considered to be the most promising solution to the energy problem and several mining operations already integrate renewables to some degree (Paraszczak and Fytas, 2012). However, renewables integration has been limited due to the challenge of intermittency in generation, making renewables unsuitable for use as the primary energy source in continuous processes which require generation systems with high reliability. Energy storage integration is therefore critical if renewables are to be incorporated into such systems. As a result, the integration of energy storage options such as pumped hydro and batteries with renewable generation, especially wind-PV hybrid systems, has been the focus of a lot of recent work (Yang et al., 2009; Baker et al., 2012; Castronuovo et al., 2013; Ma et al., 2014; Amusat et al., 2015b).

Several methodologies have been applied to solving problems involving the sizing of renewable energy systems, all of which are reviewed in Chauhan and Saini (2014). The methods are based on two approaches for representing renewables variability. The first approach is chronological simulation, in which variability is represented using time-series data. This method takes into account variability within a given time period (usually a year). This approach is computationally burdensome (Yang et al., 2009) and requires the availability of historical data. This is the most commonly used approach and has been applied extensively to PV-wind-battery systems (Yang et al., 2008; Diaf et al., 2008; Al-Shamma'a and Addoweesh, 2014; Kaabeche and Ibtiouen, 2014). The second approach uses probabilistic techniques to incorporate the stochastic nature of the renewable resource, thus eliminating the need for time-series data. Tina et al. (2006) applied an analytical approach based on the convolution technique to the design of a hybrid wind-PV system, with probability density functions used in the representation of variability. Gooding et al. (2014) also

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Nomenclature

α receiver absorptivity, unitless
$\chi_s(t)$ salt fill level for tank s at instant t, unitless
ΔT^c temperature difference between compressor inlet and outlet [K]
$\Delta T^{\mathrm{turbine}}$ temperature difference between turbine inlet and outlet [K]
ΔT_s difference between tank and ambient temperatures [K]
Δt time interval of charging or discharging [h]
η^{comp} AA-CAES compressor efficiency, unitless
η^{gen} AA-CAES generator efficiency, unitless
η^{motor} AA-CAES motor efficiency, unitless
η^{pump} PHES pump efficiency, unitless
η^{st} thermal-to-electrical energy conversion efficiency, unitless
$\eta^{turbine}$ AA-CAES turbine efficiency, unitless
η^{tur} PHES turbine efficiency, unitless
η_{hel} heliostat efficiency, unitless
η_{inv} inverter efficiency, unitless
$\eta_{pv}(t)$ photovoltaic efficiency over generation period, unitless
γ specific heat ratio, unitless
$\dot{D}^{el}(t)$ instantaneous electrical demand [MW]
$\dot{D}^{th}(t)$ instantaneous thermal demand [MW]
$\dot{D}^{el}_{\tau}$ electrical demands of plant during interval τ [MW]
$\dot{E}^{d}(t)$ energy supplied directly from PV generation [MW]. Includes electrical energy to be dumped due to excess generation.
$\dot{E}^{h}_{s}(t)$ instantaneous rate of heat addition to tank s via heater [MW]
$\dot{E}^{d}_{\tau}$ direct electricity rate to plant from PV during interval τ [MW]
$\dot{E}^{out}_{j,\tau}$ electrical output from unit j to plant over during interval τ [MW]
$\dot{E}^{in}_{j}(t)$ energy input into storage option j [MW]
$\dot{E}^{out}_{j}(t)$ energy supply rate to plant from storage option j [MW]
$\dot{E}^{out}_{j}(t)$ instantaneous electrical output from storage unit j [MW]
$\dot{E}^{gen}_{PV}(t)$ electrical energy output from PV [MW]
$\dot{E}^{h}_{s,\tau}$ heating requirement of tank s during interval τ [MW]
$\dot{G}^{DNI}(t)$ instantaneous direct normal irradiance [W/m^2]
$\dot{G}^{tot}(t)$ instantaneous global horizontal irradiance [W/m^2]
$\dot{H}^{in}_{s}(t)$ rate of enthalpy addition to storage tank s during charge [MW]
$\dot{H}^{out}_{s}(t)$ rate of enthalpy removal from storage tank s during discharge [MW]
$\dot{m}^{in}_{PHES}(t)$ mass flowrate of water into upper reservoir over charging period [m/s]
$\dot{m}^{out}_{PHES}(t)$ average flowrate of water out of upper reservoir during discharge [m/s]
$\dot{m}_c(t)$ average mass flowrate of air into compression system during charging [kg/s]
$\dot{m}_t(t)$ average mass flowrate of air into AA-CAES turbines during discharge [kg/s]
$\dot{Q}^{conv}(t)$ rate of heat loss from absorber via convection [MW]
$\dot{Q}^{heating}_{j}(t)$ heat to plant from storage option j [MWh]
$\dot{Q}^{loss}_{s}(t)$ rate of heat loss from storage tank s [MW]
$\dot{Q}^{rad}(t)$ rate of heat loss from absorber via radiation [MW]
$\dot{Q}^{TES,in}(t)$ heat flowrate into TES [MW]
$\dot{Q}^{TES,loss}(t)$ rate of heat loss from TES [MW]
$\dot{Q}^{TES,out}(t)$ heat flowrate out of TES [MW]
$\dot{Q}^{gen}_{PT}(t)$ thermal energy output from PT [MW]
ρ density [kg/m^3]
A_c total heliostat aperture area [m^2]
A^{gen}_{i} area of generation unit i [m^2]
A_p installed area of photovoltaics [m^2]
A_{tank} area of storage tank [m^2]
c_p specific heat capacity [J/kg K]
C^{gen}_{i} nominal capacity of generation option i [MW]
C^{out}_{j} energy supply capacity of storage option j [MWh]
C^{s}_{j} storage capacity of option j [MWh]
EE external energy requirement [MWh]
$EENS_y$ probability-weighted expected energy not supplied for design y [MWh]
EIR_y energy index of reliability of design y
g acceleration due to gravity [9.81 m/s^2]
h reservoir height difference [m]
$H^{acc}_{s}(t)$ instantaneous energy accumulation in storage tank s [MWh]
i generation option
j storage option
$LPSP_y$ loss of power supply probability for design y, unitless
$m^{s}_{AA-CAES}(t)$ mass of air in cavern at instant t [m^3]
n polytropic exponent for compression or expansion, unitless
N_c number of compression stages, unitless
n_g number of generation options
n_s number of storage options
N_t number of AA-CAES expansion stages, unitless
N_{design} number of designs
N_{eval} number of design evaluations
p exponent for salt fill level in heat loss expression, unitless
R_A specific gas constant of air [286.7 J/kg K]
$S_j(t)$ accumulated energy in storage option j at time t [MWh except otherwise stated]
$T^{TES}(t)$ temperature of thermal energy store [K] at time t [K]
$T_{cell}(t)$ photovoltaic module cell temperature [°C]
U^{s}_{j} energy-specific cost of storage option j [€/kWh]
U^{gen}_{i} unit cost of generation option i [€/m^2]
U^{loss}_{s} tank heat loss coefficient [W/m^2 K]
U^{out}_{i} capacity-specific cost of storage option j [€/kW$_e$]
V_s volume of thermal energy store [m^3]
y design number, $y = 1, 2 \ldots N_{design}$
z design evaluation number, $z = 1, 2 \ldots N_{eval}$

adopted a probabilistic approach to modelling variability for energy systems design, with several operating states defined in order to determine the system reliability. A similar modelling approach was also used by ElDesouky (2014), where a PV-wind-thermal generation scheduling problem was solved by using an adaptive hybrid technique combining a genetic algorithm (GA) and an artificial neural network (ANN). However, this approach cannot account for the dynamic changing performance of the hybrid energy system (Chauhan and Saini, 2014). Thus, works involving energy storage dynamics are based on chronological simulation.

While these and several works account for daily and seasonal variability in the optimal design of hybrid PV/wind/storage systems, all consider fixed renewable input conditions, with system reliability defined in terms of demand satisfaction under