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Expansion planning under uncertainty for hydrothermal systems with variable resources

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ABSTRACT

The significant integration of variable energy resources in power systems requires the consideration of greater operational details in capacity expansion planning processes. In hydrothermal systems, this motivates a more thorough assessment of the flexibility that hydroelectric reservoirs may provide to cope with variability. This work proposes a stochastic programming model for capacity expansion planning that considers representative days with hourly resolution and uncertainty in yearly water inflows. This allows capturing high resolution operational details, such as load and renewable profile chronologies, ramping constraints, and optimal reservoir management. In addition, long-term scenarios in the multi-year scale are included to obtain investment plans that yield reliable operations under extreme conditions, such as water inflow reduction due to climate change. The Progressive Hedging Algorithm is applied to decompose the problem on a long-term scenario basis. Computational experiments on an actual power system show that the use of representative days significantly outperforms traditional load blocks to assess the flexibility that reservoir hydroelectric plants provide to the system, enabling an economic and reliable integration of variable resources. The results also illustrate the impacts of considering extreme long-term scenarios in the obtained investment plans.

1. Introduction

The large scale integration of Variable Renewable Energy (VRE) resources poses critical challenges on power system planning. In particular, the need to maintain supply and demand balanced at all times requires developing flexible and reliable power grids. Power system expansion has historically been supported by Expansion Planning (EP) tools, which have been addressed through mathematical programming for more than half a century [19]. Such optimization models need to be adapted to the new paradigm of massive integration of variable resources in power grids by re-thinking some often used assumptions and simplifications.

One of such assumptions in planning is that system load varies in a relatively predictable and slow manner, so that generation units' ramping constraints, minimum up and down times, and startup times and costs are negligible. Time is represented in these EP models through *load blocks*, which are obtained from a discretized load curve previously arranged on a decreasing order, called a *load duration curve*—typically one for each month. Electric demand and generation are then simply balanced for each load block, independently. This procedure ignores the chronology of time series and cannot accommodate unit commitment costs and constraints. Recent research and experience in systems with high VRE penetration have shown that ignoring operational constraints usually results in suboptimal investment plans [27].

Several recent works have focused on better representation of operations in EP. A novel approach is presented by Wogrin et al. [33], who discretize time into *system states* rather than load blocks. Each system state is defined by load and renewable generation level, and operational constraints are enforced between system states with a probabilistic method. A more widely used approach is the use of a *representative year* with hourly resolution for single-period investment planning. This time structure has been applied to incorporate a Unit Commitment formulation [24] and demand response [13] endogenously into EP models. This method captures the chronology of load and renewable resource profiles, and allows modeling inter-hour constraints.

A more suitable method for multi-period investment planning is the use of *representative days* with hourly resolution for each studied year, as applied by Fripp [7] and Nelson et al. [22]. This technique allows capturing hourly, seasonal, and yearly variations in load, resource

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Nomenclature

Sets and indices

$\Gamma_{h,s}$ Set of inflow scenarios that follow the same trajectory as inflow scenario s up to hour h
$\mathscr{B}$ Set of buses, indexed by b
$\mathscr{C}$ Set of connections in the water network, indexed by c
$\mathscr{C}_n^{in}$ Set of connections directed into water node n
$\mathscr{C}_n^{out}$ Set of connections directed out of water node n
$\mathscr{D}$ Set of representative days, indexed by d
$\mathscr{G}$ Set of all generators, indexed by g
$\mathscr{G}^H$ Set of hydro generators
$\mathscr{G}_b$ Set of generators located in bus b
$\mathscr{H}$ Set of hours, indexed by h
$\mathscr{H}_d$ Set of hours in day d
$\mathscr{H}_p$ Set of hours in period p
$\mathscr{L}$ Set of transmission lines, indexed by ℓ
$\mathscr{L}_b^{in}$ Set of transmission lines directed into bus b
$\mathscr{L}_b^{out}$ Set of transmission lines directed out of bus b
$\mathscr{N}$ Set of nodes in the water network, indexed by n
$\mathscr{N}^R$ Set of water nodes that are reservoirs
$\mathscr{P}$ Set of investment periods, indexed by p
$\mathscr{P}2$ Set of investment periods, indexed by p
$\mathscr{S}$ Set of inflow scenarios, indexed by s

Parameters

η_ℓ^L Transmission loss factor of line ℓ
η_g^H Hydraulic efficiency of hydro generator $g \in G^h$ [MW/(m^3/h)]
$\overline{B^G}_g$ Investment cap per period for generator g [MW]
$\overline{B^L}_\ell$ Investment cap per period for line ℓ [MW]
$\overline{C^G}_g$ Upper bound on capacity for generator g [MW]
$\overline{C^L}_\ell$ Upper bound on capacity for line ℓ [MW]
$\overline{V}_{n,h,s}$ Upper water volume storage limit for node n at hour h and inflow scenario s [m^3]
$\phi_{g,p}^{fuel}$ Fuel cost of generator g on period p [US$/MWh]
$\phi_{g,p}^{Gfix}$ Annual fixed Operations & Maintenance (O&M) costs of generator g on period p [US$/MW/year]
$\phi_{\ell,p}^{Lfix}$ Annual fixed O&M costs of transmission line ℓ on period p [US$/MW/year]
ϕ_g^{OM} Variable O&M costs of generator g [US$/MWh]
π_s Probability of inflow scenario s in any year
θ_h Scaling factor of hour h; i.e. the number of hours in a year that are represented by hour h
$\underline{V}_{n,h,s}$ Lower water volume storage limit for node n at hour h and inflow scenario s [m^3]
$b_{g,p}^G$ Existing built capacity of generator g that will be operational in period p [MW]
$b_{\ell,p}^L$ Existing built capacity of transmission line ℓ that will be operational in period p [MW]
$c_{g,h}$ Maximum generating capacity factor for generator g in hour h as fraction of installed capacity
f_p Factor to bring costs in period p to present value
$l_{b,h}$ Load in bus b and hour h [MW]
r_g^{up} Upward ramp rate of generator g as fraction of installed capacity
r_g^{dn} Downward ramp rate of generator g as fraction of installed capacity
V_n^i Initial stored water at each reservoir $n \in \mathscr{N}^R$ [m^3]
$w_{n,h,s}$ Natural water inflow into node n at hour h and inflow scenario s [m^3/h]
y_p Length of period p [years].

Variables

$B_{g,p}^G$ Capacity construction decision of generator g at period p [MW]
$B_{\ell,p}^L$ Capacity construction decision of line ℓ at period p [MW]
$C_{g,p}^G$ Cumulative capacity of generator g on period p [MW]
$C_{\ell,p}^L$ Cumulative capacity of line ℓ on period p [MW]
$E_{b,h,s}$ Energy curtailment in bus b at hour h under inflow scenario s [MW]
$F_{\ell,h,s}$ Power flow through line ℓ at hour h under inflow scenario s [MW]
$P_{g,h,s}$ Dispatch level of generator g at hour h under inflow scenario s [MW]
$V_{n,h,s}$ Stored water volume in water node n at hour h under inflow scenario s [m^3]
$W_{c,h,s}$ Water flow through connection c at hour h under inflow scenario s [m^3/h].

availability, and prices, leading to a better assessment of the required flexibility to accommodate high shares of VRE. Recent work by Poncelet et al. [28] analyzes methodologies to select the representative days from each year.

Another simplification still often applied in EP models that risks yielding uneconomical or unreliable plans is to take a deterministic approach and consider a single future scenario in each optimization. The volatility of energy resources' availability and cost, technological developments, and uncertain load growth motivate the endogenous inclusion of uncertainty in capacity expansion planning. Stochastic Programming (SP) has been used in EP to minimize expected costs of investment and operations in multiple scenarios. To account for operational uncertainty, work such as that by Jin et al. [12] and Park and Baldick [25] consider multiple load and wind profile scenarios with discrete probabilities.

The use of discrete scenarios has also been extended to the investment scale. A statistical procedure for load growth and fuel price scenarios is presented by Feng and Ryan [6], and expert opinion is used by Li et al. [17] to formulate climate change scenarios for multi-period EP. Munoz et al. [21] and Hobbs et al. [11] show that SP leads not only to economic plans under long-term uncertainty, but also to more reliable and adaptable systems. However, this method requires assigning discrete probabilities to each modeled scenario, which may prove a complex challenge for long-term uncertainties. Additionally, these works do not consider operational constraints that must be modeled in a chronological time framework, so flexibility requirements from VRE integration are not completely captured.

Water reservoirs in hydrothermal systems may be used to hedge against this uncertainty in multiple scales. Nevertheless, the representation of reservoir management details in EP has not received enough attention [10], due to the complexity of including constraints that link reservoir water levels throughout the time horizon, and because of the inherent uncertainty in water inflows. In systems with high VRE penetration, it becomes necessary to additionally include operational attributes of hydroelectric units, such as their high ramping capacity, to better asses the flexibility that these units may provide.

The standard to coordinate operations in hydrothermal systems, such as Chile, Sweden, Brazil, and others, is to use the Stochastic Dual Dynamic Programming (SDDP) methodology developed by Pereira and Pinto [26] or derived formulations to consider large inflow scenario trees and manage reservoirs over time. However, this method does not lend itself nicely to modeling operations in EP, since its optimal solution depends on the topology of the grid and, thus, cannot be endogenously incorporated. Some studies have used SDDP in expansion