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Uncertainty representation in investment planning of low-carbon power systems

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A R T I C L E I N F O

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A B S T R A C T

Power system operators and planners are dealing both with the integration of unparalleled levels of variable renewable energy sources and deep uncertainties that originate from new technological developments, changing regulatory frameworks, unknown investment, operational costs of technologies, etc. An inadequate representation of the uncertainties may result in a substantial risk of deploying inflexible investment solutions incapable of adapting efficiently to evolving scenarios. In this context, this work studies the effects of increasing the granularity used to represent the long-term uncertainty by analysing its impact on the resulting optimal portfolios of new transmission lines, battery energy storage systems and pumped-hydro storage systems. The studies are conducted on an instance of the Australian power system described by the system operator for planning purposes, including four types of uncertainty granularity, namely deterministic representation, and 2-stage, 3-stage and 4-stage stochastic representations. To address the computational challenges associated with the large mixed-integer linear stochastic problems, the different instances are reformulated using Dantzig-Wolfe decomposition, enabling the use of a column generation approach to solve the investment problem. The case study applications show substantial adjustments in the investment portfolios as uncertainty granularity changes, with a clear tendency to increase battery storage investment as uncertainty is better represented.

I. Introduction

Going forward, electricity systems will need to integrate increasing amounts of variable renewable energy sources (VRES), requiring substantial investments in transmission networks and energy storage infrastructure. Planning these investments optimally, though, require advanced mathematical models [1]. This is so since, first, the planning problem needs to recognize the significant levels of uncertainty faced in the long-term from various uncertainty sources (demand growth, distributed energy resources (DER) deployment, penetration of VRES, etc.), which is hard to incorporate without increasing computational burden [2]. Also, energy storage plants can feature many different technologies, including batteries, pumped hydro, flywheels, etc. that needs to be differentiated in planning models [3]. Furthermore, energy storage originates the need to incorporate many operational details within the planning models, increasing their complexity. Hence, planning models combining both long-term uncertainties and storage technologies can be significantly challenging.

Most industry-based studies still uses deterministic models to determine, in practice, power system plans [4,5,6]. Despite this, there has been an increasing focus in the academia on models that can explicitly cope with uncertainty [1, 7, 8]. From these models (divided into stochastic and robust optimization models [1]), stochastic ones promise a more efficient cost/risk balance since risks can be better quantified through probabilities. Importantly, the vast majority of stochastic models for planning are two-stage [7, 9, 10], but multi-stage models are being proposed lately in order to better capture the decision dynamics [1, 7, 8, 11,12,13].

In recent years, there has also been an increasing interest in the

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Nomenclature

Parameters

A_m	Matrix to couple operation and investment in node m
$\widetilde{A}_m$	Matrix to summarize investment constraints in node m
$C_m^{I/O}$	Vector of investment/operational cost in node m [A$]
$C_{g,m}^{fuel}$	Fuel cost of generator g in node m [A$/MW]
C_g^{rp}	Ramp-up cost of generator g [A$/ΔMW]
C_g^R	Upward reserve cost of generator g [A$/MWh]
$C_g^{sd/up}$	Shut-down/Start-up cost of generator g [A$]
$D_{\omega,n,t}$	Demand in week ω, bus n and time t [MW]
Dt_g/Ut_g	Minimum down/up time of generator g [h]
$\overline{E}_s^{C/E}$	Energy capacity of candidate/existing storage plant s [MWh]
$\overline{F}_l$	Maximum capacity of line l [MW]
$\mathscr{F}_g/\wp_g$	Full/Partial outage rate of generator g
$\overline{Fr}$	Factor to limit the capacity of lines to share reserves
H	Number of hours within a week
$\overline{I}_m$	Vector of maximum installed infrastructure in node m
$\overline{L}_l$	Maximum capacity of candidate line l [MW]
$\overline{M}$	Big-M number
$nG_{g,m}$	Total available units of generator g in node m
$\overline{P_g}/\underline{P_g}$	Maximum/Minimum capacity of generator g [MW]
$\overline{P}_s^{C/E}$	Maximum capacity of existing/candidate storage s [MW]
$Pl_{\upsilon,t,\omega}$	Available capacity of VRES υ in time t and week ω
$\overline{Pr}_{\upsilon,m}$	Maximum capacity of renewable generator υ in node m[MW]
r	Discount rate
$R_{n,t}^0$	Reserve requirement of bus n in time t [MWh]
$\overline{rp}_g$	Ramp rate limit of a generator g
u_g	Unavailability of generator g
$Voll$	Value of lost (or curtailed) load [A$/MWh]
W_ω	Number of times representative week ω is repeated within a year
yr_m	Number of years from node m to root node
α_g	Derating factor of generator g due to partial outage
$\eta_s^{ch/d}$	Charge/Discharge efficiency of storage plant s
$\overline{\mu}_b^B/\overline{\mu}_l^L$	Maximum number of investments in candidate BESS b/ line l
$\xi_{g,\omega}$	Capacity factor of hydro generator g in week ω
$\Pi_{b,m}^B$	Investment cost of BESS b in node m [A$]
$\Pi_{l,m}^L$	Investment cost of line l in node m [A$]
$\Pi_{p,m}^{PS}$	Investment cost of PS p in node m [A$]
τ	Factor to limit the maximum reserve capacity of generators
φ_m	Probability of node m
ψ_s	Duration of reserve provision by storage plant s [h]

Variables

$E_{s,t}$	Energy (State of Charge) of storage plant s in time t [MWh]
$F_{l,t}$	Power flow of line l in time t [MW]
$Fr_{l,t}^{fw/rv}$	Forward/Reverse reserve flow of line l in time t [MW]
I_m	Vector of installed infrastructure in node m
$\mathfrak{I}_m$	Vector of total installed units in node m
O_m	Vector of operational variables in node m
$P_{g,t}/\mathrm{Pr}_{\upsilon,t}$	Power output of generator g / VRES υ in time t [MW]
$P_{s/b/p,t}^{ch/d}$	Power charged/discharged of storage plant $s/b/p$ in time t [MW]
$Pf_{n,t}$	Curtailed load of bus n in time t [MW]
$R_{g,t}$	Reserve of generator g in time t [MWh]
$R_{s,t}^{C/E}$	Reserve of candidate/existing storage plant s in time t [MW]
$rp_{g,t}$	Change/ramp of power output of generator g in time t [MW]
$sd_{g,t}$	Number of units of generator g shutting down in time t
$up_{g,t}$	Number of units of generator g starting up in time t
$X_{s,t}$	Binary variables defining the charge/discharge status of storage plant s in time t
$\lambda_{m,j}$	Binary variable to select column j for node m
$\mu_{l,m}^L$	Candidate line l in node m
$\mu_{b,m}^B$	Candidate BESS b in node m
$\mu_{p,m}^{PS}$	Candidate PS p in node m
$\mathscr{X}_{g,t}$	Online units of generator g in time t

Sets

$a(m)$	Set of ancestor nodes of node m
$B_n/\widehat{B}_n$	Set of existing/candidate BESS in bus n
G_n	Set of generators in bus n
G_n^H	Set of run of river generators in bus n
G_n^R	Set of reservoir generators in bus n
J_m	Set of total columns added in node m
$L_n/\widehat{L}_n$	Set of existing/candidate lines in bus n
L_n^{IN}/L_n^{OUT}	Set of lines incoming / outcoming to / from bus n
M	Set of nodes in the scenario tree
M^S	Set of sibling nodes in the scenario tree
N	Set of buses in the 5-bus system
$PS_n/\widehat{PS}_n$	Set of existing/candidate PS plants in bus n
$S_n/\widehat{S}_n$	Set of existing ($PS_n \cup B_n$) / candidate ($\widehat{PS}_n \cup \widehat{B}_n$) storage in bus n
T	Set of hours within a representative week
ϑ_m	Set of operational feasible decisions in node m
Υ_n	Set of renewable generators in bus n
Ω_m	Set of weeks within one year in node m

incorporation of operational details/constraints in planning problems. Like uncertainty, this affects the computational burden too. To address the latter, different solution methods have been proposed, from more straightforward heuristic/metaheuristic approaches [14], to more sophisticated decomposition methods such as Benders [11] and Dantzig-Wolfe (DW) decomposition [15] that can make use of the problem structure to increase the size of the problems that can be effectively solved. Most of these studies, however, do not discuss how different granularity levels in the uncertainty representation impact the final solution, particularly that of the first stage, which is the one being implemented in practice.

In this context, this paper proposes a multi-stage stochastic optimization model that co-optimizes investments in transmission assets and storage technologies against an array of long-term uncertainties. Its multi-stage nature allows to better capture the decision dynamics, thus enabling anticipative strategic decisions in network and storage technologies that should be made well in advance for them to provide flexibility and adaptability in the presence of uncertainty.

The candidate storage technologies considered in the model correspond to battery energy storage systems (BESS) and pumped-hydro storage systems (PS), which have distinctive techno-economic parameters. Among these parameters, the time required for these technologies to be built and commissioned (also referred to as lead time) is of particular interest in the analysis, with PS lead time being significantly longer than that of BESS. This expansion problem is reformulated using a DW decomposition method and solved using a column generation algorithm to address the large size of the problem [15]. The model includes an hourly representation of the operation through a set of typical weeks (describing each year under analysis) and ensures feasibility against unit commitment constraints. This results in a set of independent subproblems representing each typical week, which can be tackled through distributed computing.

This paper presents various case study applications based on the Australian power system using actual scenarios by the Australian Energy Market Operator (AEMO) [5]. Particularly, the optimal expansion plan of a 4-stage stochastic approach is presented, whose results are compared with the outcomes determined by a deterministic model (those considered by industry) and other, simpler stochastic approaches. In effect, in these simpler approaches, we use different granularity levels in the uncertainty representation through 2-stage and 3-stage uncertainty. Hence, the contributions of this work are as follows:

- Determine the performance of optimal stochastic solutions with various granularity levels in the uncertainty representation, comparing the results among the deterministic model, 2-stage model, 3-stage model, and 4-stage model.
- Identify the optimal portfolio of storage and network investments under the above approaches.
- Determine the value of different storage technologies (in terms of cost savings) on an equivalent network of the Australian power system under different representations of uncertainty.
- Identify the stream of investments across time under different uncertainty representations, with a particular focus on the investments implemented within the first stage.

The rest of this paper is structured as follows. Section II presents the co-optimization model of storage and transmission infrastructure. Section III details the case studies along with the corresponding input data. Section IV presents the results and discussion; and finally, Section V concludes.

II. The stochastic co-optimization planning model

A. Mathematical formulation

The model presented in this section expands from [1] and is a multi-stage stochastic transmission-storage expansion problem that seeks to minimize the expected investment and operational cost in the planning horizon, including investments in transmission and storage systems and considering a detailed operation of generators with an hourly resolution. Thus, operationally, the model includes traditional unit commitment constraints such as minimum power output, ramp rate limits and operating times (minimum startup and shutdown times). The operation considers existing storage as PS and virtual power plants (VPP). Uncertainty is represented by means of a scenario tree, which is built considering as sources of uncertainty demand growth, VRES penetration and DER deployment. Every node of the scenario tree is composed of multiple operating conditions. Hence, investment decisions remain the same across the operating conditions of a node, while dispatch decisions can be adapted to every operating condition.

The investment options under consideration are transmission lines, BESS and PS. Due to the delay given by construction times, a lead time is considered between the decisions is being made and the final commissioning. Finally, several years (e.g., 5 years) are grouped in an epoch. Hence, every stage of the multi-stage model corresponds to an epoch.

1) Objective function

The objective function is shown in (1). It minimises the sum of the expected operational and investment cost of the electrical system for all the nodes m of the multi-stage scenario tree. The investment cost considers the annuitized costs of lines, PS and BESS. Moreover, the operational cost is given by the operation of a set of typical weeks representing one year, and it includes fuel, ramping and reserves costs, start-up and shut-down costs of thermal units, as well as the value of lost load (VOLL). The ramping cost is modelled as in [16].

$$Minimize \sum_{m\in M}\frac{\phi_m}{(1+r)^{yr_m}}\left\{\sum_{n\in N}\left(\sum_{p\,\in\,\widehat{PS_n}}\Pi^{PS}_{p,m}\mu^{PS}_{p,m}+\sum_{b\,\in\,\widehat{B_n}}\Pi^{B}_{b,m}\mu^{B}_{b,m}+\sum_{l\,\in\,\widehat{L_n}}\Pi^{L}_{l,m}\mu^{L}_{l,m}\right)\right.$$
$$\left.+\sum_{\omega\,\in\,\Omega_m}W_\omega\sum_{n\in N}\sum_{t\,\in\,T}\sum_{g\in G_n}\left(C^{fuel}_{g,m}P_{g,t}+C^{rp}_{g}rp_{g,t}+C^{up}_{g}up_{g,t}+C^{sd}_{g}sd_{g,t}+C^{R}_{g}R_{g,t}+Voll.Pf_{n,t}\right)\right\} \quad (1)$$

1) Investment constraints

To capture the construction time of new infrastructure, we consider lead times modelled through non-anticipativity constraints. For simplicity, next we present the constraints for particular lead time values, but they can be straightforwardly adjusted. Hence, for the construction of lines and PS, the model considers a lead time of one epoch. For this reason, these technologies cannot be installed in the first epoch as shown in (2)-(3). The non-anticipativity constraints impose that the investment in sibling nodes (i.e., nodes from the same parent) is the same for the candidate lines and PS (4)-(5). The irreversibility of investment decisions is imposed through (6). We assume that BESS can be installed without a delay/lead time (within the same epoch), which reflects the reality and a key benefit of this technology (fast deployment). BESS and lines investments decisions are represented through integer variables, and they consider an investment limit (7)-(8). PS investment is a binary decision, which indicates whether the projects are deployed or not.

$$\mu^{L}_{l,1}=0 \qquad \forall\, l\in\widehat{L}_n,\ n\in N \quad (2)$$

$$\mu^{PS}_{p,1}=0 \qquad \forall\, p\in PS_n,\ n\in N \quad (3)$$

$$\mu^{L}_{l,m}=\mu^{L}_{l,m'} \qquad \forall\, l\in\widehat{L}_n,\ n\in N,\ m,\ m'\in\{M^s\backslash m=m'\} \quad (4)$$

$$\mu^{PS}_{p,m}=\mu^{PS}_{p,m'} \qquad \forall p\in\widehat{PS}_n,\ n\in N,\ m,\ m'\in\{M^s\backslash m=m'\} \quad (5)$$

$$\mu^{L}_{l,m},\mu^{B}_{b,m},\mu^{PS}_{p,m}\geq\mu^{L}_{l,a(m)},\mu^{B}_{b,a(m)},\mu^{PS}_{p,a(m)}\ \forall\, b\in\widehat{B}_n,\ p\in\widehat{PS}_n,\ l\in\widehat{L}_n,\ n\in N,m\in\{M\backslash m=1\} \quad (6)$$

$$0 \le \mu^{B}_{b,m} \le \overline{\mu}^{B}_{b} \qquad \forall\, b \in \widehat{B}_n, n \in N, m \in M \tag{7}$$

$$0 \le \mu^{L}_{l,m} \le \overline{\mu}^{L}_{l} \qquad \forall\, l \in \widehat{L}_n,\; n \in N, m \in M \tag{8}$$

1) Operational constraints

a) Power and reserve balance

Eq. (9) ensures the power balance for all buses and time periods. Similarly, equation (10) ensures the reserve requirement is balanced at each bus and time. Notice that reserve can be shared across various buses, which requires to maintain capacity reserved in the transmission lines too.

$$\begin{aligned} D_{\omega,n,t} &= Pf_{n,t} + \sum_{g\in G_n} P_{g,t} + \sum_{l\in L^{IN}_n} F_{l,t} - \sum_{l\in L^{out}_n} F_{l,t} \\ &\quad + \sum_{\upsilon\in \Upsilon_n} Pr_{\upsilon,t} + \sum_{s\in S_n}\left(P^{d}_{s,t} - P^{ch}_{s,t}\right) \\ &\quad + \sum_{s\in \widehat{S}_n}\left(P^{d}_{s,t} - P^{ch}_{s,t}\right) \;\; \forall\, \omega \in \Omega_{\mathbf{m}}, \mathbf{t} \in \mathbf{T}, \mathbf{n} \in \mathbf{N}, \mathbf{m} \in \mathbf{M} \end{aligned} \tag{9}$$

$$R^{0}_{n,t} = \sum_{g\in G_n} R_{g,t} + \sum_{p\in PS_n} R^{E}_{p,t} + \sum_{s\in \widehat{S}_n} R^{C}_{s,t} + \sum_{l\in L_n}\left(Fr^{fw}_{l,t} - Fr^{rv}_{l,t}\right) \;\forall\, \boldsymbol{t} \in \boldsymbol{T}, \boldsymbol{n} \in N \tag{10}$$

a) Generators constraints

The constraints of the conventional generators are given by (11)-(26). These constrains consider a clustered unit commitment. This approach consists in clustering units with similar technical parameters to use integer variables instead of binary variables and thus reduce the problem size [17, 18]. The constraints are imposed in (11)-(16), and they include: the maximum number of units of each cluster; the unit commitment state equations, which relates the online units, the generator starting up and generators shutting down; minimum up/down times. Moreover, the maximum/minimum output of a generator are given by (17)-(18). The maximum percentage of reserve that the committed generation can supply is shown in (19). The maximum run-of-river generation (which changes monthly depending on historical data) is presented in (20). The capacity factor of hydro units constraints the amount of energy that can be generated by reservoir units in (21). The maximum generation limit considers the outage rates as presented in (22). Besides, the conventional generators have a maximum ramp rate limit, which is captured in (23)-(24). The ramps are calculated in (25)-(26) to assign ramping costs. The VRES are constrained by the availability of the resource in (27).

$$\mathscr{X}_{g,t} \le nG_{g,m} \qquad \forall t \in T, g \in G_n, n \in N \tag{11}$$

$$\mathscr{X}_{g,t} = \mathscr{X}_{g,t-1} + up_{g,t} - sd_{g,t} \qquad \forall\, t > 1 \in T, g \in G_n, n \in N \tag{12}$$

$$\mathscr{X}_{g,t} \ge \sum_{t' \in \{1:t\}} up_{g,t'} \qquad \forall\, t \le Ut_g \in T, g \in G_n, n \in N \tag{13}$$

$$\mathscr{X}_{g,t} \ge \sum_{t' \in \{t-Ut_g:t\}} up_{g,t'} \qquad \forall\, t > Ut_g \in T, g \in G_n,\; n \in N \tag{14}$$

$$nG_{g,m} - \mathscr{X}_{g,t} \ge \sum_{t' \in \{1:t\}} sd_{g,t'} \qquad \forall\, t \le Dt_g \in T, g \in G_n,\; n \in N \tag{15}$$

$$nG_{g,m} - \mathscr{X}_{g,t} \ge \sum_{t' \in \{t-Dt_g:t\}} sd_{g,t'} \qquad \forall t > Dt_g \in T, g \in G_n,\; n \in N \tag{16}$$

$$P_{g,t} + R_{g,t} \le \overline{P_g}.\mathscr{X}_{t,g} \qquad \forall t \in T, g \in G_n, n \in N \tag{17}$$

$$\underline{P_g}.\mathscr{X}_{g,t} \le P_{g,t} \qquad \forall t \in T, g \in G_n, n \in N \tag{18}$$

$$R_{g,t} \le \tau.\,\overline{P_g}.\mathscr{X}_{g,t} \qquad \forall t \in T, g \in G_n, n \in N \tag{19}$$

$$P_{g,t} \le \overline{P}_g.nG_{g,m}.\xi_{g,\omega} \qquad \forall t \in T, g \in G^{H}_n,\; n \in N \tag{20}$$

$$\sum_{t\in T} P_{g,t} \le H.\overline{P}_g.nG_{g,m}.\xi_{g,\omega} \qquad \forall g \in G^{R}_n,\; n \in N \tag{21}$$

$$P_{g,t} \le nG_{g,m}\overline{P_g}\left(1 - \left(\mathscr{F}_g + \wp_g(1-\alpha_g)\right)\right) \qquad \forall t \in T, g \in G_n, n \in N \tag{22}$$

$$P_{g,t} - P_{g,t-1} \le \mathscr{X}_{g,t-1}.\overline{rp}_g.\overline{P_g} + up_{g,t}.\underline{P_g} \qquad \forall\, t \in T, g \in G_n,\; n \in N \tag{23}$$

$$P_{g,t-1} - P_{g,t} \le \mathscr{X}_{g,t}.\overline{rp}_g.\overline{P_g} + sd_{g,t}.\underline{P_g} \qquad \forall\, t \in T, g \in G_n,\; n \in N \tag{24}$$

$$P_{g,t} - P_{g,t-1} - up_{g,t}.\underline{P_g} \le rp_{g,t} \qquad \forall\, t \in T, g \in G_n, n \in N \tag{25}$$

$$P_{g,t-1} - P_{g,t} - sd_{g,t}.\underline{P_g} \le rp_{g,t} \qquad \forall\, t \in T, \forall\, g \in G_n, n \in N \tag{26}$$

$$Pr_{\upsilon,t} \le \overline{Pr}_{\upsilon,m}.Pl_{\upsilon,t,\omega} \qquad \forall\, t \in T, \upsilon \in \Upsilon_n, n \in N \tag{27}$$

a) Storage constraints

The existing storage plants consider two technologies: PS and VPP. These technologies can provide energy arbitrage, and PS can also supply reserves. Eqs. (28)-(31) constrain the energy balance, the maximum energy storage capacity and the charging/discharging rates of both technologies. Eqs. (30) and (31) prevent simultaneous charge and discharge actions. Moreover, PS provides reserves considering the current state variable in (32), which does not allow PS to change its state of charge to provide reserves. The reserves are also constrained in (33) by the maximum energy available.

$$E_{s,t} = P^{ch}_{s,t}\eta^{ch}_s - P^{d}_{s,t}\big/\eta^{d}_s + E_{s,t-1} \qquad \forall t > 1 \in T, s \in S_n,\; n \in N \tag{28}$$

$$E_{s,t} \le \overline{E}^{E}_{s} \qquad \forall t \in T, s \in S_n, n \in N \tag{29}$$

$$P^{ch}_{s,t} \le \left(1 - X_{s,t}\right)\overline{P}^{E}_{s} \qquad \forall t \in T, s \in S_n, n \in N \tag{30}$$

$$P^{d}_{s,t} \le X_{s,t}.\overline{P}^{E}_{s} \qquad \forall t \in T, s \in S_n, n \in N \tag{31}$$

$$P^{d}_{p,t} - P^{ch}_{p,t} + R^{E}_{p,t} \le \overline{P}^{E}_{p}.X_{p,t} \qquad \forall t \in T, p \in PS_n,\; n \in N \tag{32}$$

$$R^{E}_{p,t}.\psi_p \le E_{p,t-1} \qquad \forall t > 1 \in T, \forall\, p \in PS_n,\; n \in N \tag{33}$$

The candidate storage plants are constrained by the energy balance (28), the energy capacity and charge/discharge power (34)-(36). Moreover, candidate PS considers a similar model as the existing PS, being also constrained by (30)-(33). On the other hand, the charging/discharging rates of candidate BESS are constrained by its state of charge and $\overline{M}$ (which is a large number) in (37)-(38). The latter constraints also impede simultaneous charge and discharge actions. Moreover, candidate BESS can provide reserves while charging or discharging as shown in (39).

$$E_{s,t} \le \overline{E}^{C}_{s}.\mu^{B/PS}_{s,m} \qquad \forall\, t \in T, s \in \widehat{S}_n, n \in N \tag{34}$$

$$P^{ch}_{s,t} \le \overline{P}^{C}_{s}.\mu^{B/PS}_{s,m} \qquad \forall\, t \in T,\; s \in \widehat{S}_n,\; n \in N \tag{35}$$

$$P^{d}_{s,t} \le \overline{P}^{C}_{s}.\mu^{B/PS}_{s,m} \qquad \forall\, t \in T,\; s \in \widehat{S}_n,\; n \in N \tag{36}$$

$$P_{b,t}^{ch} \le \left(1 - X_{b,t}\right)\overline{M} \qquad \forall\, t \in T, b \in \widehat{B}_n, n \in N \tag{37}$$

$$P_{b,t}^{d} \le X_{b,t}.\overline{M} \qquad \forall\, t \in T, b \in \widehat{B}_n, n \in N \tag{38}$$

$$P_{b,t}^{d} - P_{b,t}^{ch} + R_{b,t}^{C} \le \overline{P}_b^C.\mu_{b,m}^B \qquad \forall\, t \in T, b \in \widehat{B}_n,\; n \in N \tag{39}$$

a) Transmission lines

The lines are modelled with a transportation model, which considers only Kirchhoff's first law. The maximum and minimum line flows are constrained by (40)-(41). These equations consider that the reserves can be imported/exported between connected buses. The imported/exported reserves are limited in (42)-(43) by a factor $\overline{Fr}$ to prevent transmission line of being used only to provide reserves.

$$F_{l,t} + Fr_{l,t}^{fw} \le \overline{F}_l + \mu_{l,m}^L.\overline{L}_l \qquad \forall\, t \in T, l \in L_n, n \in N \tag{40}$$

$$-\left(\overline{F}_l + \mu_{l,m}^L.\overline{L}_l\right) \le F_{l,t} - Fr_{l,t}^{rev} \qquad \forall\, t \in T, l \in L_n,\; n \in N \tag{41}$$

$$0 \le Fr_{l,t}^{fw} \le \overline{Fr}\left(\overline{F}_l + \mu_{l,m}^L.\overline{L}_l\right) \qquad \forall\, t \in T, l \in L_n, n \in N \tag{42}$$

$$0 \le Fr_{l,t}^{rev} \le \overline{Fr}\left(\overline{F}_l + \mu_{l,m}^L.\overline{L}_l\right) \qquad \forall\, t \in T, l \in L_n, n \in N \tag{43}$$

B. DW decomposition and column generation algorithm

The resulting problem is a large mixed-integer linear problem, which results in prohibitive execution times and memory limits even for the most advanced commercial solvers. In order to make this problem tractable and avoid oversimplifications, the DW decomposition is implemented as in [8, 15, 19]. The planning problems have a block diagonal structure, which means that each year of the time horizon can be seen as an independent problem; thus, this decomposition splits the problem into a master problem and several slave subproblems. To implement the decomposition, the problem is reformulated obtaining a block diagonal structure as shown in (44)-(48), which is as follows: The compact form of the objective function is shown in (44). Eq. (45) relates the investment in node m with the investment in its ancestor nodes. The non-anticipativity constraints are summarized in (46). The available infrastructure limits the operation, and it is constrained by the maximum investment limit (47). Eq. (48) shows the feasible region of operation and investment.

$$\min\left\{\sum_{m\;\in M}\varphi_m\left(C_m^{I\;T}I_m + C_m^{O^T}O_m\right)\right\} \tag{44}$$

$$\mathfrak{I}_m \le \sum_{\mathfrak{a}\;\in\;a(m)} I_{\mathfrak{a}} \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{45}$$

$$\widetilde{A}_m.\mathfrak{I}_m \le 0 \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{46}$$

$$A_m.O_m \le \mathfrak{I}_m \le \overline{I}_m \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{47}$$

$$O_m \in \vartheta_m \;\wedge\; I_m, \mathfrak{I}_m \in \;\mathbb{Z}^+ \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{48}$$

The feasible region of available infrastructure in the scenario tree node m is defined in (49). This region is an integer polyhedron, where any point can be expressed as a finite combination of integer points $\{\widehat{I}_{mj}\}_{j\in J_m}$, such that each $\widehat{I}_{m,j}$ has an optimal operation $\widehat{O}_{m,j}$. The available infrastructure and the associated operation are given in (50) and (51).

$$\mathbb{I}_m = \{\mathfrak{I}_m \in \;\mathbb{Z}^+ \mid \exists O_m \in \;\vartheta_m,\; A_m O_m \le \mathfrak{I}_m \le \overline{I}_m\}\; \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{49}$$

$$\mathfrak{I}_m = \sum_{j\in J_m}\lambda_{m,j}\widehat{I}_{m,j}, \sum_{j\in J_m}\lambda_{m,j} = 1,\; \lambda_{m,j} \in \{0,1\}\; \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{50}$$

$$O_m = \sum_{j\in J_m}\lambda_{m,j}\widehat{O}_{m,j} \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{51}$$

Thus, by replacing equations (50) and (51) in the reformulated problem we get the master problem, which is defined by (52)-(57). Eqs. (53) and (54) have π_m and ψ_m as dual variables. Moreover, these equations ensure that only one vector of operation and one of infrastructure are selected.

$$MP:\; \min\left\{\sum_{m\;\in M}\varphi_m\left(C_m^{I\;T}I_m + \sum_{j\in J_m}C_m^{O^T}\lambda_{m,j}\widehat{O}_{m,j}\right)\right\} \tag{52}$$

$$\sum_{j\in J_m}\lambda_{m,j}.\widehat{I}_{m,j} \le \sum_{\mathfrak{a}\;\in\;a(m)} I_{\mathfrak{a}}\;\; [\boldsymbol{\pi_m}] \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{53}$$

$$\sum_{j\in J_m}\lambda_{m,j} = 1\;\; [\boldsymbol{\psi_m}] \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{54}$$

$$\widetilde{A}_m.I_m \le 0 \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{55}$$

$$I_m \le \overline{I}_m \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{56}$$

$$\lambda_{m,j} \in \{0,1\},\; I_m \in \;\mathbb{Z}^+ \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{57}$$

Then, the slave problem is defined by (58)-(60). This problem is constrained by the investment constraints (2)-(8) and operational constraints (9)-(43).

$$sp(m):\; \min\varphi_m.C_m^{O^T}.O_m - \mathfrak{I}_m.\pi_m - \psi_m \tag{58}$$

$$A_m.O_m \le \mathfrak{I}_m \le \overline{I}_m \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{59}$$

$$\mathfrak{I}_m \in \;\mathbb{Z}^+ \qquad \forall\, \boldsymbol{m} \in \boldsymbol{M} \tag{60}$$

The column generation algorithm corresponds to the interplay between the master problem and the slave problems to find a solution for the original problem, and it is described as follows: First, a set of feasible columns are obtained as solutions of the slave problems to feed the master problem. Columns with negative reduced cost could improve the objective value of the master problem. Second, a relaxed version of the master problem (MP_{LP}) is optimized to extract the dual variables to calculate new columns with the slave problems. This process is repeated until reaching an optimal gap in the MP_{LP}. Then, a master problem with integer variables (MP_{MIP}) is solved. If this problem also has a gap below the optimal gap, the process stops; otherwise, new columns are calculated until the gap in MP_{MIP} is reached.

III. Case study

A. Input data

The National Electricity Market (NEM) is comprised of five regions: Victoria (VIC), Tasmania (TAS), South Australia (SA),

New South Wales (NSW) and Queensland (QLD). These regions compose the 5-bus model shown in Fig. 1, which illustrates the generators and existing lines along with the candidate lines and storage plants. The features of the candidate storage plants are shown in TABLE I. The PS projects include Snowy 2.0 in NSW and Battery of the Nation (BON) in TAS. The costs of these projects are 5,733 MMA$ [20] and 2, 805 MMAU$ [21] (MMAU$ refers to million Australian dollars). Similarly, TABLE II shows the existing line capacities, the number and size of candidates lines and their annuitized investment costs [22]. The batteries' lifetime is 15 years, and the lifetime considered for PS and lines is 50 years.

To alleviate the computational burden, two techniques have been implemented. Firstly, the unit commitment of the NEM has been included through a clustered unit commitment, which reduces

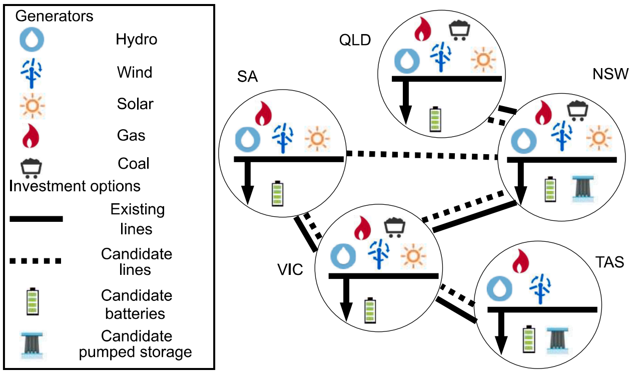

Fig. 1. 5-bus model of the NEM, including generators and candidate investments.

dispatchable generators from around 250 to 40 representative generators. These generators were chosen with a k-means clustering method, selecting between 2 and 5 generators per technology and per bus. We implemented the clustering method developed in [18]. The research carried out in [17] and [18] has studied how sensitive the operational results to the clustering method are. Secondly, each node of the scenario tree considers 12 representative weeks of a year, operating the system with an hourly resolution. These weeks are also selected with a k-means clustering method, based on the following features of the load curve: minimum, average and maximum demand, the maximum and minimum slope of the demand, and the total energy consumed in each bus.

We consider 4 types of conventional generators: open cycle gas turbine (OCGT), combined cycle gas turbine (CCGT), coal and hydro. TABLE III shows the techno-economic parameters of the generators [23, 24,25]. Besides, the model includes different fuel cost depending on the technology, bus and year [22].

The VOLL is 15,000 [A$/MWh] [26]. The discount rate applied is 6.3% [22]. The spinning reserve requirements are 673 MW, 666 MW, 273 MW, 194 MW, 498 MW for NSW, QLD, SA, TAS, VIC, respectively [22]. These amounts of reserves are the level of idle capacity necessary in each bus to meet reliability requirements (covering the loss of the largest single generation unit and the necessary forecast errors). Due to ramp-rate limits, it is assumed that conventional generators can provide up to 10% of their capacity as reserve. Transmission lines can use up to 50% of their capacity to share reserves. The model also considers that VPPs do not supply reserves. All of the above are in line with the assumptions made by AEMO in its Integrated System Plan [27].

B. Multi-stage scenario tree

The multi-stage scenario tree is based on 5 *base* scenarios designed by AEMO for the Integrated System Plan [27]. These base scenarios represent different levels of VRES, installed coal and gas generators, and different assumptions affecting DER growth (amounts of VPP, behind-the-meter batteries, electric vehicles and rooftop solar PV). Thus, these base scenarios represent different levels of decentralization and decarbonization levels and are the following ones: Slow, Central, Fast, High DER and Step[1]. Fig. 2 shows the penetration of different technologies in the NEM and the annual energy demand for each AEMO's base scenario.

Then, we combine these five base scenarios in time to create the scenario tree. To reduce the number of branches in the tree (and the number of total scenarios originated by the combination of base scenarios), two key assumptions are made. Firstly, a scenario can only evolve from a certain level of decarbonization/decentralization to a higher one. Following this criterion, it is possible to ignore several combinations (for example, a transition from a Step state to a Slow one). Secondly, since AEMO does not provide probabilities of transition from a given scenario to another we have assumed that the different sibling nodes (from the same parent) feature the same probability. Thus, the scenarios in the different stages (second, third and fourth stage) are equiprobable, allowing straightforward comparison among the scenarios. The resulting scenario tree obtained is shown in Fig. 3. In this tree, each node represents a 5-years period (epoch) and displays the accumulative probability (i.e., the probability of a "leaf" node represents the probability of the associated scenario).

[1] We have also included a sensitivity of Step scenario called "Step HD_year", which has a higher penetration of VPP and behind-the-meter batteries (following the penetration on the High DER base scenario in the mentioned year).

TABLE I
CHARACTERISTIC OF CANDIDATE STORAGE PLANTS.

Location	Storage	Round-trip efficiency [%]	Capacity - Duration
All nodes	BESS	81	200 MW - 2 hours
TAS	PS	75.7	1,700 MW - 21.6 hours
NSW	PS	75.7	2,000 MW - 168 hours

TABLE II
EXISTING LINE CAPACITIES, NUMBER AND SIZE OF CANDIDATES LINES AND THEIR ANNUITIZED COST.

Candidate	Installed lines [MW]	Candidate lines [MW]	Number of candidate lines	Cost [A $/MW]
SA-NSW	0	800	1	2,487,500
SA-VIC	850	200	20	1,986,000
VIC-TAS	480	750	2	2,487,125
VIC-NSW	700	200	18	2,066,343
NSW-QLD	950	200	30	1,808,614

TABLE III
PARAMETERS OF CONVENTIONAL GENERATORS.

	CCGT	OCGT	Coal	Hydro
Ramping cost [A$/ΔMW]	0.3	1.2	3.6	-
Start-up cost [A$/MW]	15	100	170	-
Reserve cost [% fuel cost]	1.5	1.7	93.5	
Ramp rate [% of maximum capacity]	90	50	25	100
Minimum power output [% of maximum capacity]	30	10	40	0
Unavailability [%]	1.9	2.7	19.8	2.3
Heat rate [GJ/MWh]	11.3	24.6	11.5	-
Start-up time [h]	5	6	10	0
Shut-down time [h]	1	1	4	0

IV. Results and discussion

In this section, we determine optimal investment decisions under several approaches (deterministic and stochastic ones), studying the impacts of two key assumptions undertaken in stochastic planning problems: (i) the number of stages and (ii) the lead time of storage deployment.

A. Impact of grannularity levels in the uncertainty representation

This section explores how the investment portfolios and the expected costs are affected by different granularity levels in the uncertainty representation. The granularity levels are represented by different number of decision stages in the scenario tree, including 2-stage, 3-stage and 4-stage models (see Fig. 4). We keep constant, though, the number of epochs equal to four. We also compare the results from these stochastic problems against the deterministic solution.

Fig. 5 summarizes the results of transmission and storage investment

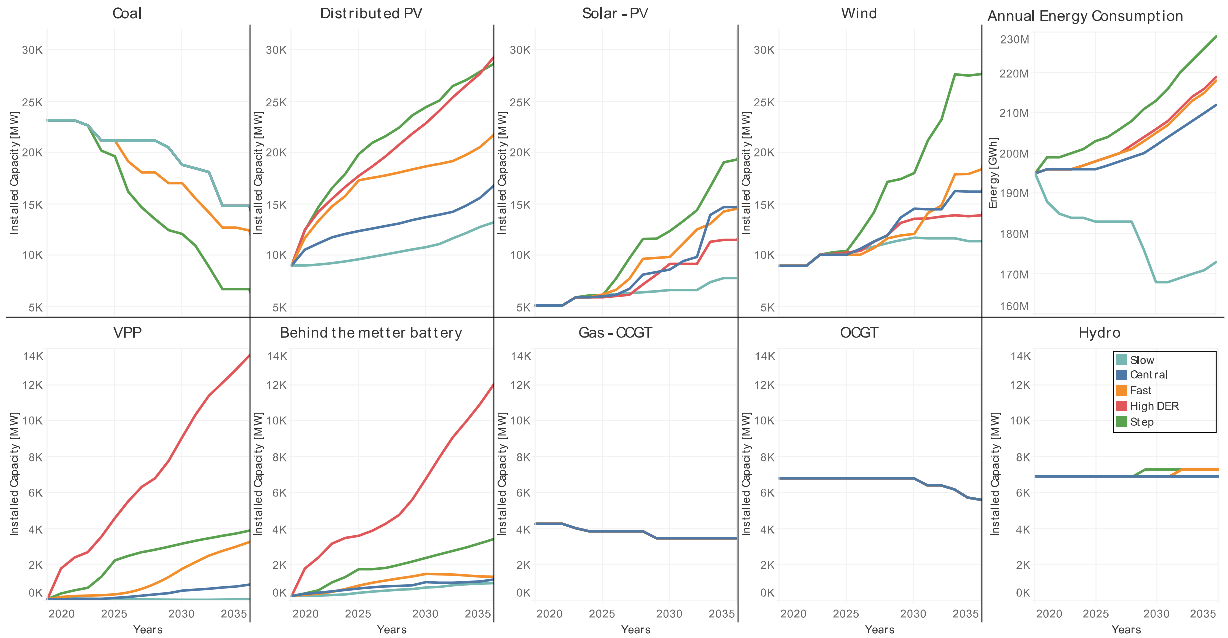

Fig. 2. Evolution for different AEMO's base scenarios of the installed capacity of NEM technologies and the annual energy consumption.

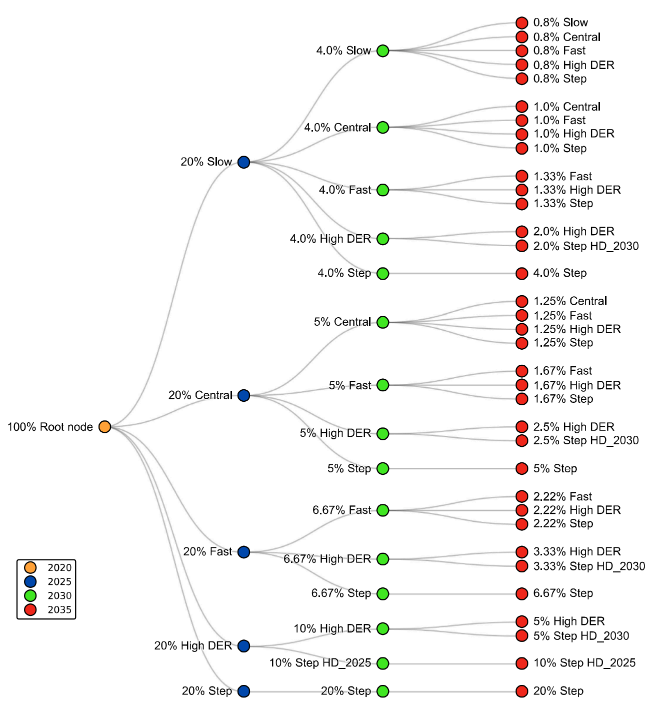

Fig. 3. Multi-stage scenario tree with 35 scenarios and node probability.

levels for the deterministic and the stochastic approaches. Each of this 3D plots shows the probability of installing a given level of capacity in each epoch. Particularly, Fig. 5(a) summarizes the results of the investment in QLD-NSW line; Fig. 5(b) depicts the total amount of BESS in the NEM; and Fig. 5(c) displays the probability of installing the PS projects. What stands out in Fig. 5 (a) are the important differences among the results of the different approaches. First, the maximum level of line investment (across the scenarios) decreases with the number of stages considered in the stochastic approach, so the 4-stage approach results in the lowest maximum investment. Second, by studying the detailed results per scenario, we observe that the line investments across the different scenarios is distributed in a narrower range by increasing the number of stages considered. Thus, the deterministic approach has scenarios with investment of 200 MW and 1400 MW in the second and third epochs, which contrast with the stochastic approaches where the minimum investment in the same epochs is 600 MW. Although these results are shown for QLD-NSW, the other candidate lines follow the same trend. Fig. 5(b) shows that the 3-stage and 4-stage approaches have a higher number of installed BESS than the deterministic and the 2-stage ones, increasing the expected levels of installed BESS. Thereby, by increasing the granularity of the uncertainty representation, the amount of installed BESS increases. By contrasting Fig. 5(c) and Fig. 5(b), it can be seen that the additional investment in BESS directly reduces the investment decisions associated to Snowy and BON in the medium and long term, respectively. However, when the penetration of VRES increases in the long term, the investment in Snowy increases along with the number of stages considered, and it is deployed in all the scenarios in the 4-stage approach. The observed trends in the storage investments indicate that by considering more granular uncertainty (4-stage approach), the value of storage can be captured in the long term even in scenarios with the lowest amount of VRES. Thus, the stochastic approaches with a higher uncertainty granularity invest in storage plants with shorter lead times.

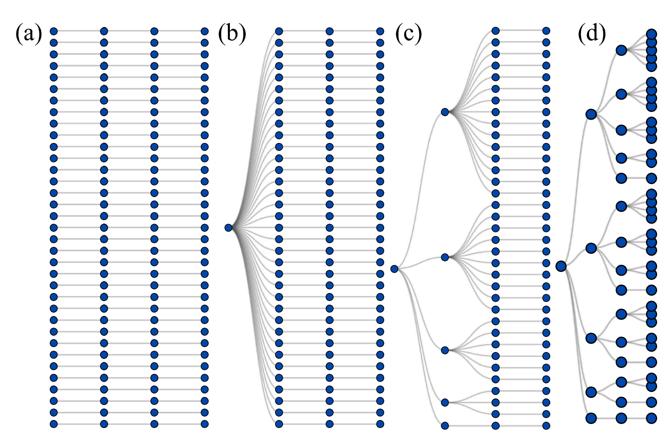

Fig. 4. Representation of uncertainty in the scenario tree with different granularity levels: (a) deterministic, (b) 2-stage, (c) 3-stage and (d) 4-stage approaches.

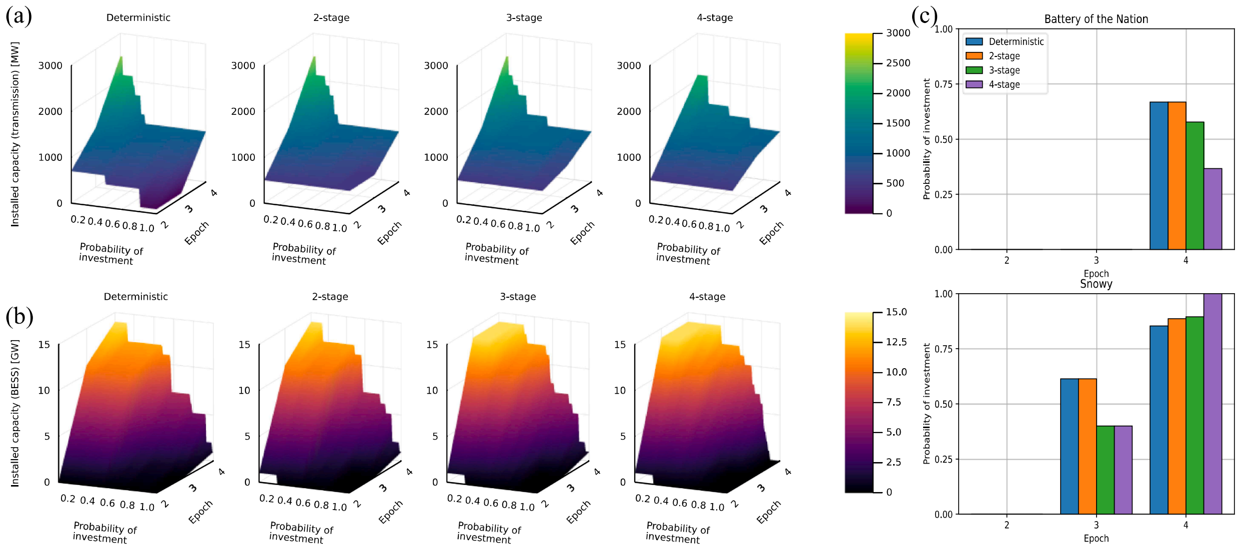

Fig. 5. Probability of different installed capacity along the epochs for investments in (a) QLD-NSW line and (b) BESS in the NEM for models with different granularity levels. (c) Probability of PS investment along the epochs for models with different granularity levels.

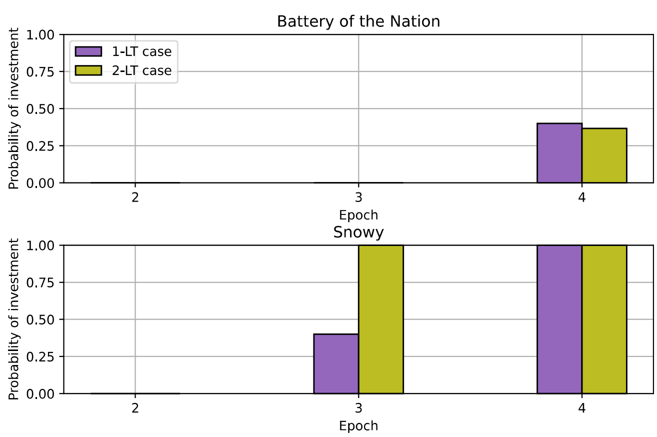

Fig. 6. Probability of PS investment along the epochs, models with different lead times.

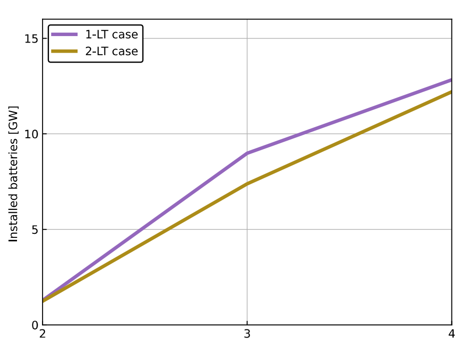

Fig. 7. Expected investment of BESS along the epochs, models with different lead times.

B. Impact of a higher lead time for PS projects

This section determines the impact of increasing the lead time of PS from one epoch (1-LT case) to two epochs (2-LT case), comparing them. To obtain the solutions, we use the 4-stage approach. Fig. 6 shows the probability of installing Snowy and BON for the 1-LT and the 2-LT cases in the different epochs. In the figure, Snowy is deployed for all the scenarios in the third stage of the 2-LT case. This means that the decision of investing in Snowy is made in the first stage, and it is decided earlier than in the 1-LT case. Fig. 7 shows the expected investment of BESS for the 1-LT and the 2-LT cases. Due to the earlier deployment of PS, the installed BESS are lower in the 2-LT.

Although there are technologies with faster construction times, the decision of building critical PS infrastructure is brought forward when its lead time increases. Also, the results shows that the capacity of BESS to defer PS projects is reduced due to the longer deployment times. Thereby, these results indicate that a more cautious (and potentially more realistic) consideration of the deployment time in a PS project is important not to delay key investment decisions and potentially save investment costs in further storage technologies.

V. Conclusions

The energy transition to a low-carbon future is introducing deep long-term uncertainties that are challenging the traditional power system planning approaches. In this context, this paper has discussed the influence of uncertainty granularity on the resulting optimal investment portfolio. We have introduced an expansion planning model that features the capacity to model complex scenario trees without compromising precision in the representation of the system operation. This is achieved by reformulating the expansion problem using Dantzig-Wolfe decomposition, which enables the use of distributed computing to tackle the tractability challenges. The model was tested on an instance of the Australian power system used by the system operator to conduct the so-called Integrated System Plan.

The results showed the benefits of considering a higher granularity in the representation of uncertainty. Portfolios obtained using 3-stage or 4-

stage stochastic models outperform the portfolios obtained using deterministic and 2-stage stochastic models when high uncertainty dominates the system's future. In this vein, we showed that the value of BESS investment options increases when uncertainty is better represented. In other words, deterministic and even 2-stage stochastic models underestimate the investment flexibility provided by BESS. The results also showed that the consideration of higher lead times for the deployment of PS reduces the capability of BESS of deferring those large investments.

The model presented in this paper and the analyses conducted based on its outcomes can be particularly interesting for power system planners seeking to identify flexible investment strategies when analyzing a wide portfolio of competing options. The model can conduct a relatively quick and precise analysis of the search space the planner encounters at the beginning of the planning process, thus allowing to narrow down the interesting investment options that must be studied further in subsequent stages of the process.

Future work can enhance the current model by including more detailed features of different storage technologies such as self-discharge ratio and degradation. Further, different risk metrics can be added to study how the planner make decisions according to its risk aversion.

Authorship statement

Manuscript title: Uncertainty representation in investment planning of low-carbon power systems

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the *journal Electric Power Systems Research (EPSR)*.

Authorship contributions

Category 1

Conception and design of study: *Moya, Moreno, Puschel, Mancarella;* acquisition of data: *Moya, Puschel*; analysis and/or interpretation of data: *Moya, Moreno, Puschel, Mancarella;*

Category 2

Drafting the manuscript: *Moya, Moreno, Puschel;* revising the manuscript critically for important intellectual content: *Moreno, Costa, Mancarella.*

Category 3

Approval of the version of the manuscript to be published:
Moya, Moreno, Puschel, Costa, Mancarella.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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