Integrated multi-scale optimization of short- and mid-term uncertainties in pricing models

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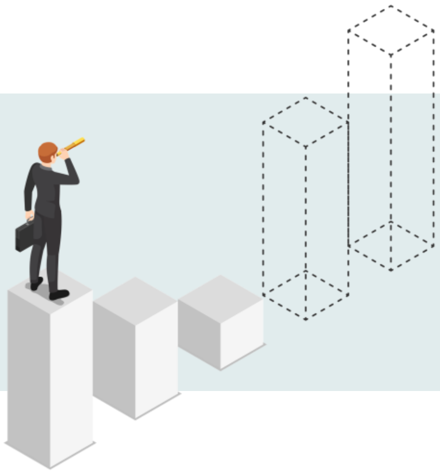
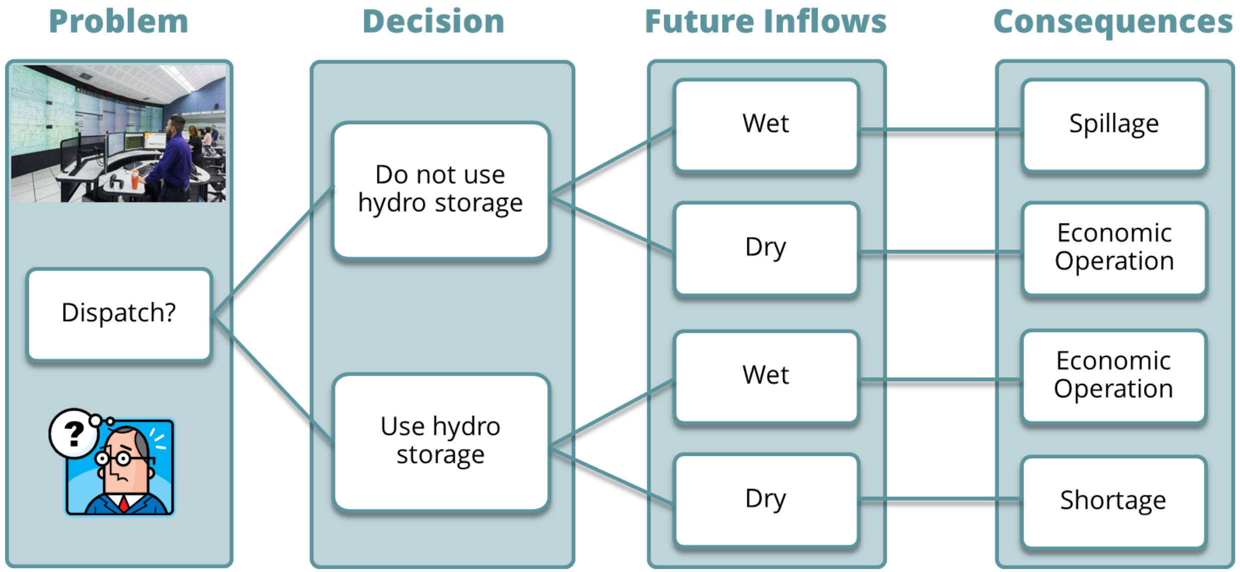
Introduction



Traditionally, it has always been common practice to incorporate uncertainty into long-term studies and historically, only hydros used to have state variables. With the entry of **renewables, the energy transition & Power-to-X** solutions, **other storage devices** have gained relevance. Moreover, we need to model **uncertainties in renewables**.



LT decision-making process under uncertainty

1st Level (Policy)

Strategic Operating Decisions

Focus on long-term impacts (FCFs)

Involves storage devices that create time-coupling between stages

Today's operating decisions impact future operating costs

Stochastic Dual Dynamic Programming (SDDP)

Global industry standard, with over 6000 citations in the scientific/engineering literature

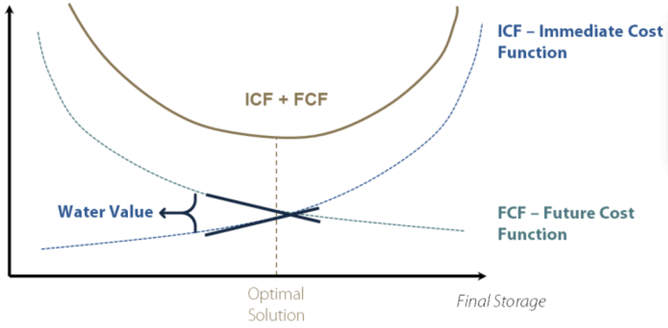
2nd Level (Simulation)

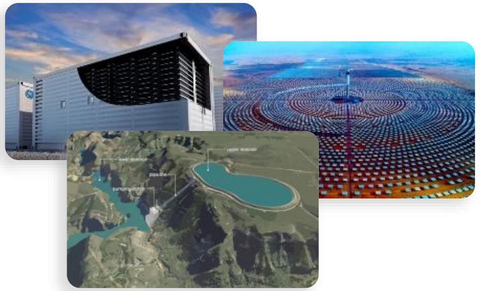
Tactical Operating Decisions

Focus on immediate conditions

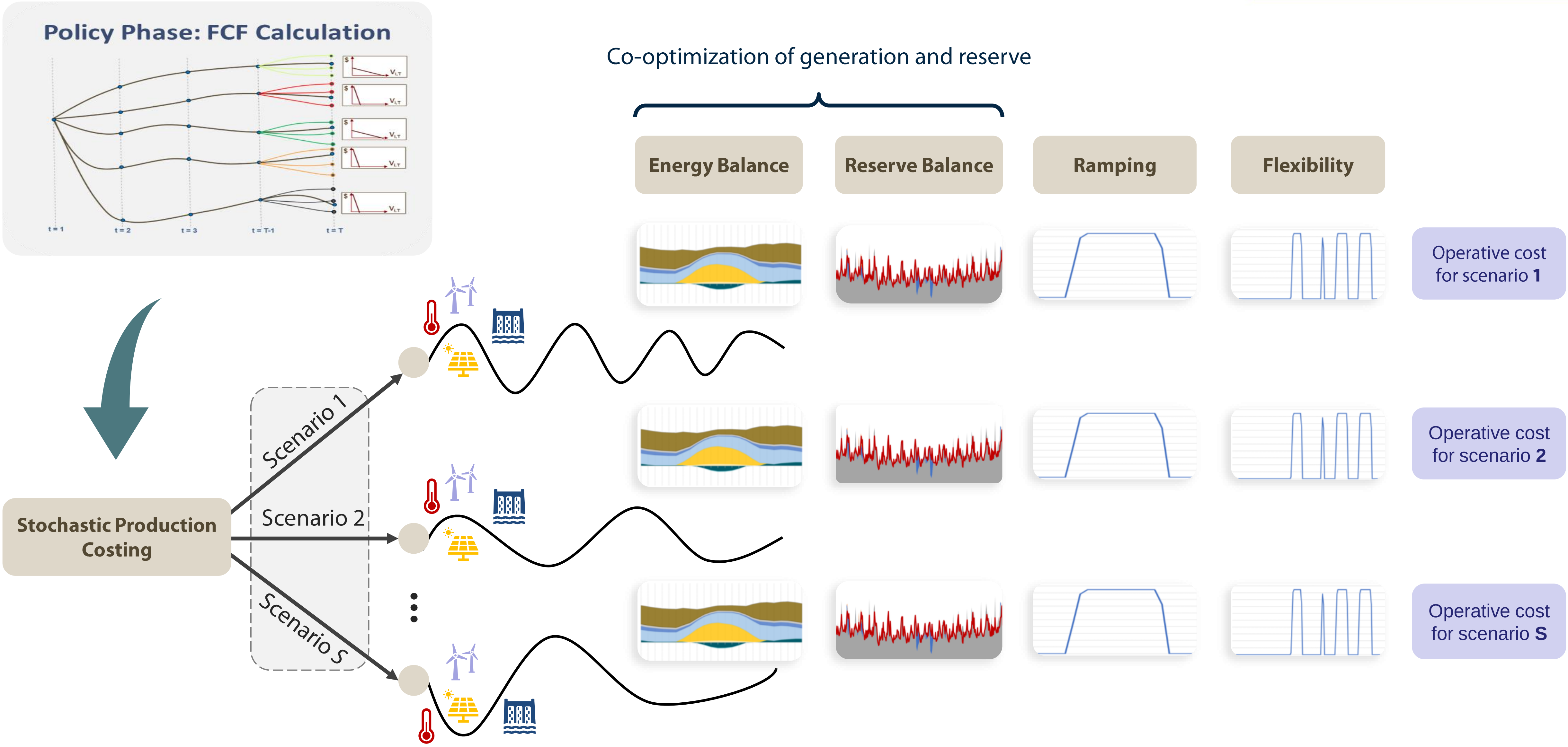
Solves a stochastic optimization problem that seeks to balance the trade-off between:

- Use intensely the available storage resources today, reducing the immediate costs.
- Keep storage fuller to reduce expected future costs, considering uncertainties.





Strategic + Tactical Phases



Summary of what we will see today

- Renewable generation modeling
- Reserves to amortize renewable intermittency
- Long-term dispatch scheduling under uncertainty
- Short-term dispatch scheduling under uncertainty

Renewable Modeling

Renewable modeling

Renewable Energy

General features

- Operation factor
- O&M and spilling costs
- Outage sampling and probability
- Concentrated Solar Panel (CSP) with storage representation

Physical characteristics

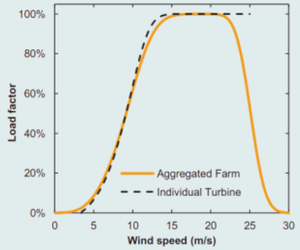
- Turbine characteristics
- Solar panel physical data

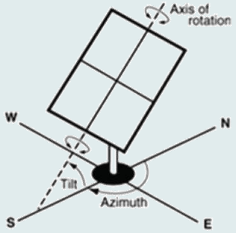
Georeferenced data

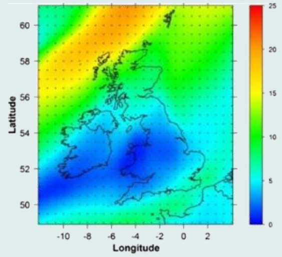
- Wind and solar irradiance data from geographic location

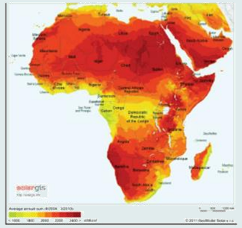
Generation data modelling

- Stochastic Variable Renewable Energy power production model, generating future synthetic scenarios with hourly resolution
- Scenarios are intertemporally and spatially correlated with hydro inflows









Reserves

Let’s start with a question…

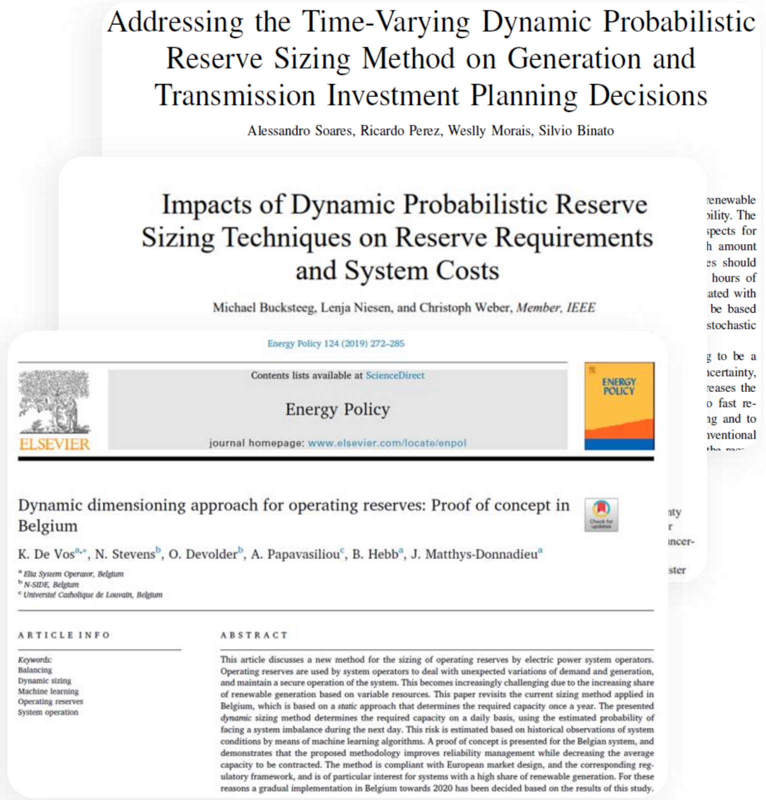
The dispatch planning is used to schedule the operation with the objective of the **expected** events.

The reserve services are used to adjust the operation and continue to supply the demand in the face of **unexpected** events.

Dynamic Probabilistic Reserve (DPR)

Reserve Requirement

- Generation Forecasting → $$G_{h_d} = E_{h_d}\left[e_h^s\right]$$
- Forecast error (variation "around" the forecast) → $$\delta_h^s = e_h^s - g_{h_d}$$
- Variation of the Unpredictable Generation → $$\Delta_h^s = \left|\delta_h^s - \delta_{h-1}^s\right|$$
- Probability Distribution Statistics → $$R(h) = (1-\lambda)E\left[\Delta_h^s\right] + \lambda CVaR_\alpha\left[\Delta_h^s\right]$$



Addressing the Time-Varying Dynamic Probabilistic Reserve Sizing Method on Generation and Transmission Investment Planning Decisions

Alessandro Soares, Ricardo Perez, Weslly Morais, Silvio Binato

Impacts of Dynamic Probabilistic Reserve Sizing Techniques on Reserve Requirements and System Costs

Michael Bucksteeg, Lenja Niesen, and Christoph Weber, *Member, IEEE*

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Dynamic dimensioning approach for operating reserves: Proof of concept in Belgium

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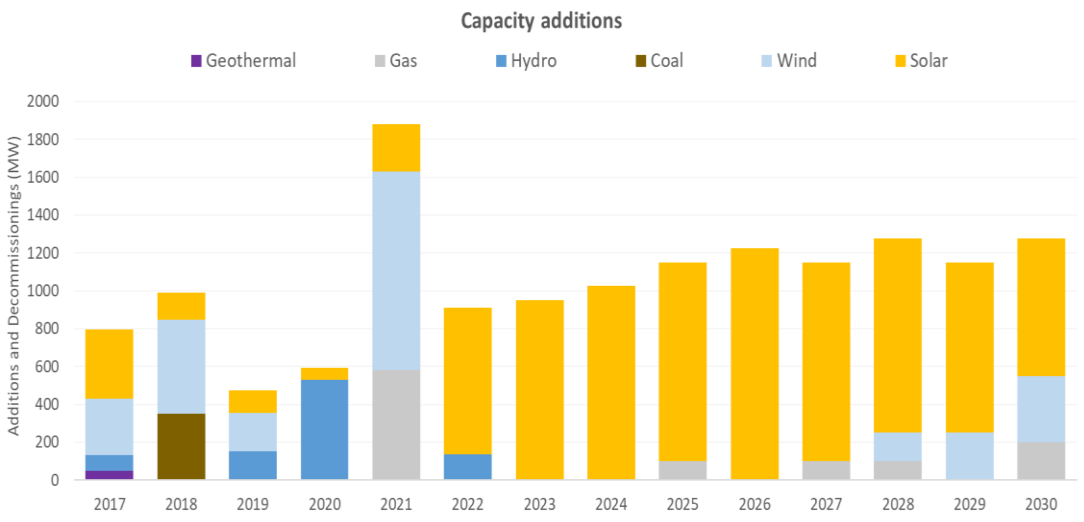
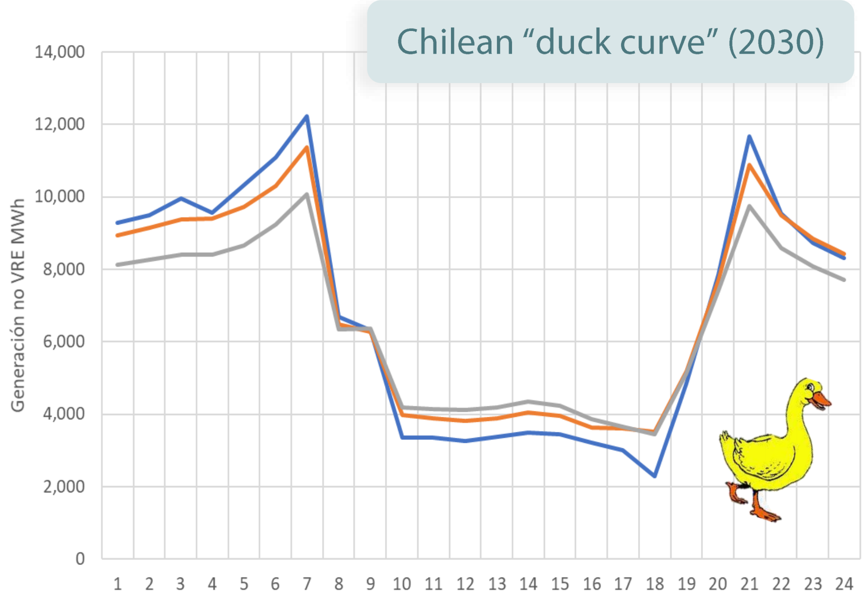
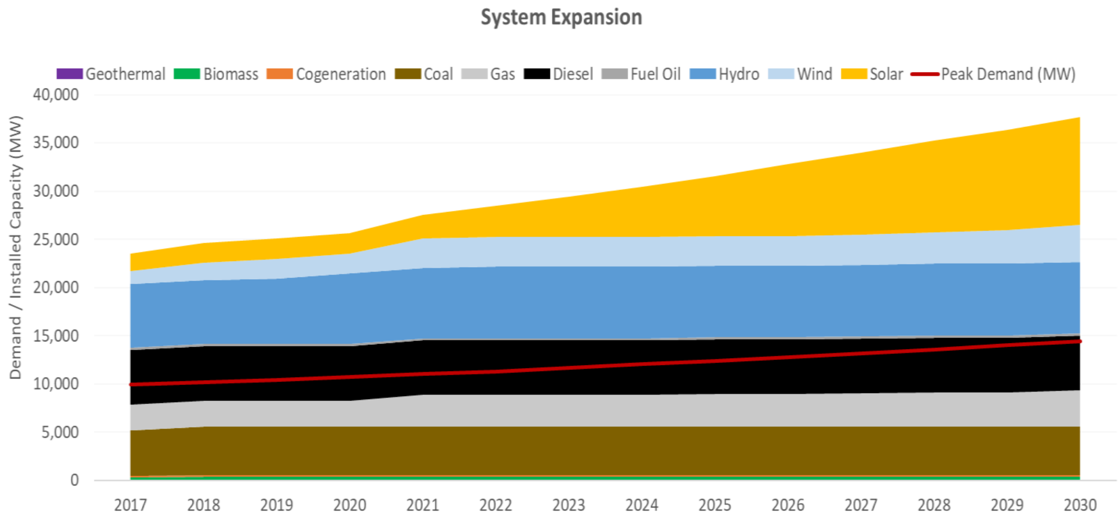
ABSTRACT

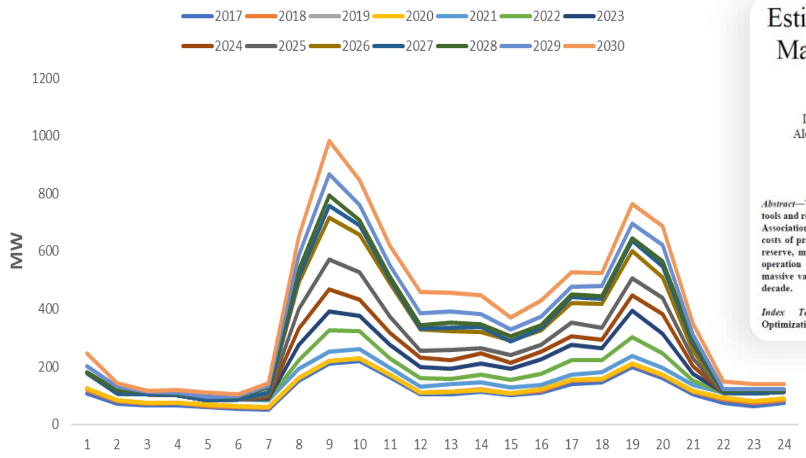
This article discusses a new method for the sizing of operating reserves by electric power system operators. Operating reserves are used by system operators to deal with unexpected variations of demand and generation, and maintain a secure operation of the system. This becomes increasingly challenging due to the increasing share of renewable generation based on variable resources. This paper revisits the current sizing method applied in Belgium, which is based on a *static* approach that determines the required capacity once a year. The presented *dynamic* sizing method determines the required capacity on a daily basis, using the estimated probability of facing a system imbalance during the next day. This risk is estimated based on historical observations of system conditions by means of machine learning algorithms. A proof of concept is presented for the Belgian system, and demonstrates that the proposed methodology improves reliability management while decreasing the average capacity to be contracted. The method is compliant with European market design, and the corresponding regulatory framework, and is of particular interest for systems with a high share of renewable generation. For these reasons a gradual implementation in Belgium towards 2020 has been decided based on the results of this study.

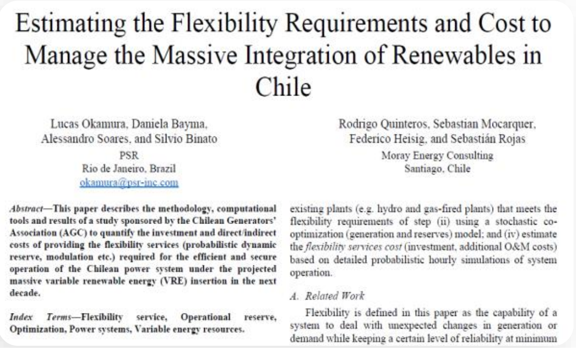
Chilean Case











Estimating the Flexibility Requirements and Cost to Manage the Massive Integration of Renewables in Chile

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***Abstract*—This paper describes the methodology, computational tools and results of a study sponsored by the Chilean Generators' Association (AGC) to quantify the investment and direct/indirect costs of providing the flexibility services (probabilistic dynamic reserve, modulation etc.) required for the efficient and secure operation of the Chilean power system under the projected massive variable renewable energy (VRE) insertion in the next decade.**

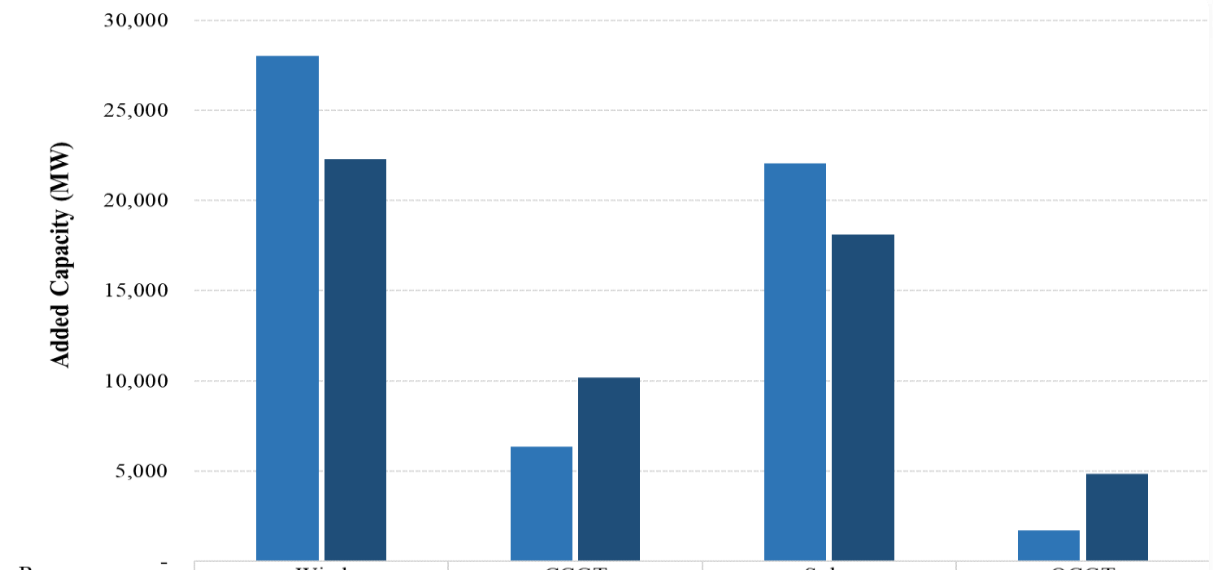
***Index Terms*—Flexibility service, Operational reserve, Optimization, Power systems, Variable energy resources.**

existing plants (e.g. hydro and gas-fired plants) that meets the flexibility requirements of step (ii) using a stochastic co-optimization (generation and reserves) model; and (iv) estimate the *flexibility services cost* (investment, additional O&M costs) based on detailed probabilistic hourly simulations of system operation.

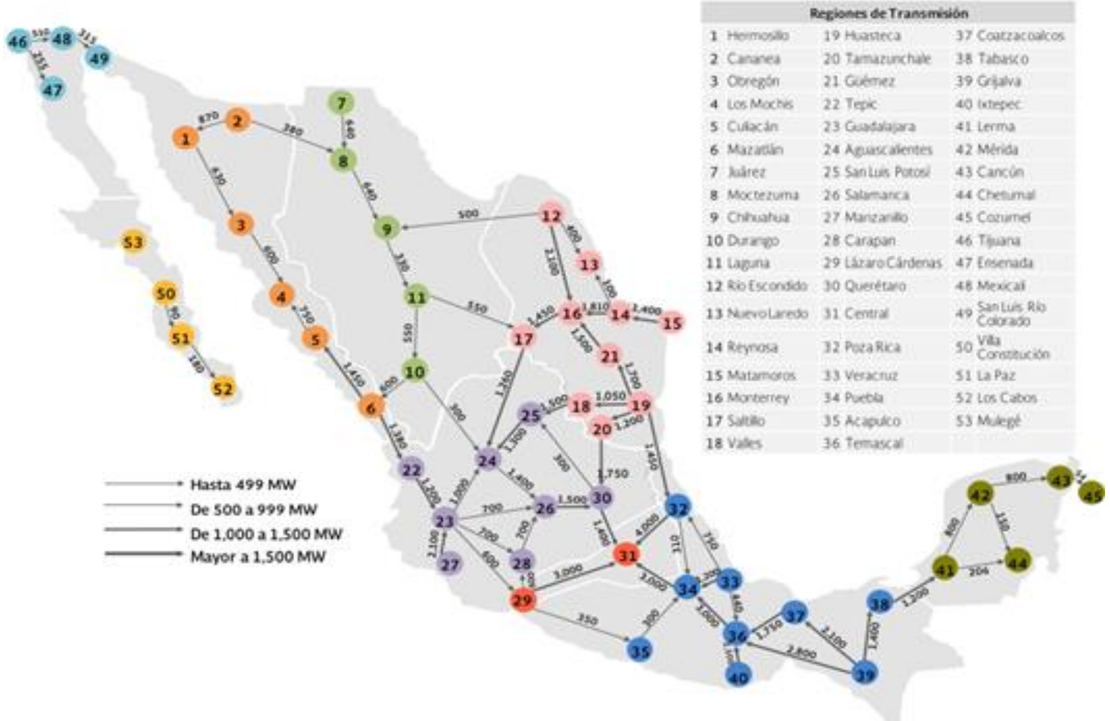
A. Related Work

Flexibility is defined in this paper as the capability of a system to deal with unexpected changes in generation or demand while keeping a certain level of reliability at minimum

Application in the Expansion of the Mexican System



Reserve	Wind	CCGT	Solar	OCGT
Demand	28,032	6,322	22,057	1,709
D + Intermittency	22,303	10,168	18,096	4,838



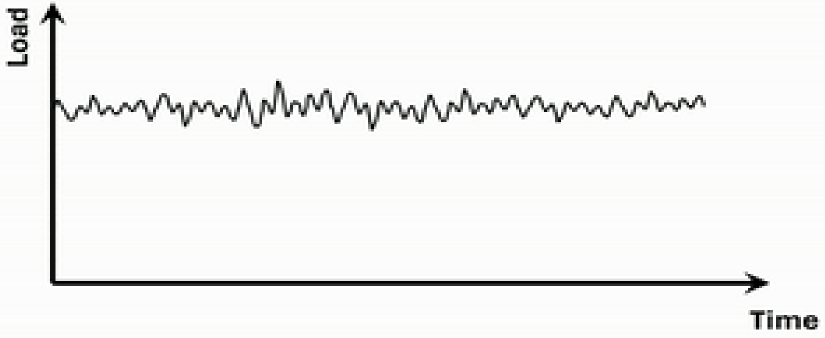
The idea of the Dynamic Probabilistic Reserve (DPR) is to contemplate not only the fluctuations in demand and failure of the largest generating unit when calculating the 2nd Reserve Requirement, but also the **intermittency caused by renewables in an integrated (embedded) manner**

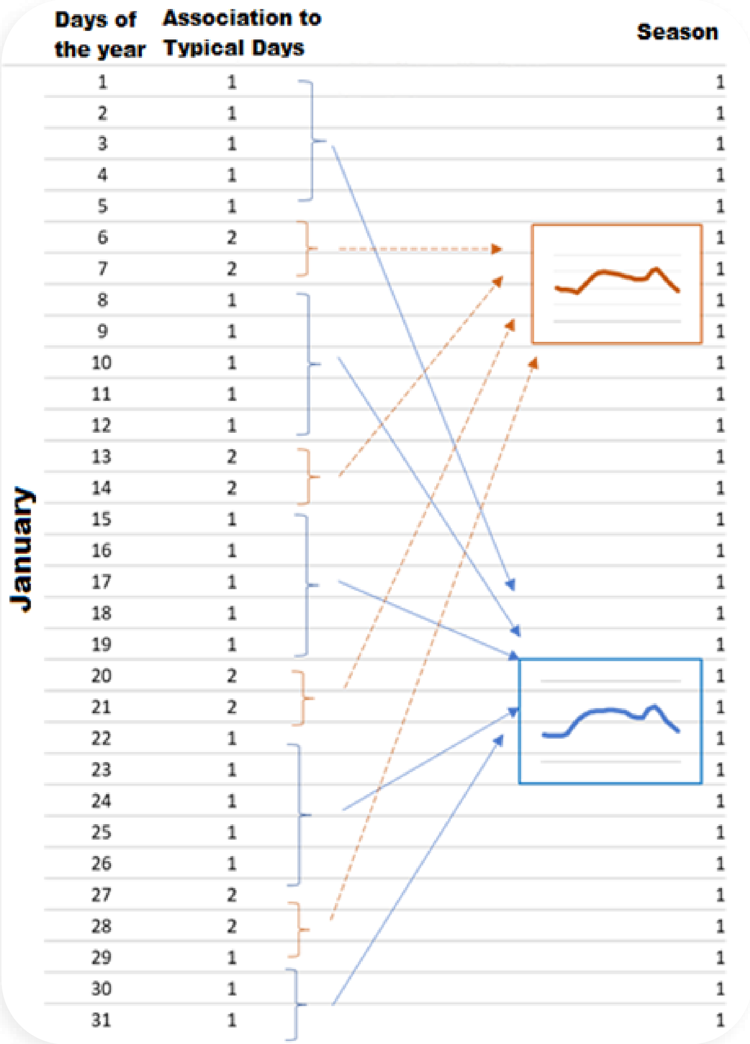
When DPR is considered in the expansion model, the share of VREs in the expansion plan decreases due to a higher Secondary Reserve Requirement (increases in operating costs when we consider intermittency in the reserve)

Long-term: typical days

Typical days for the long-term

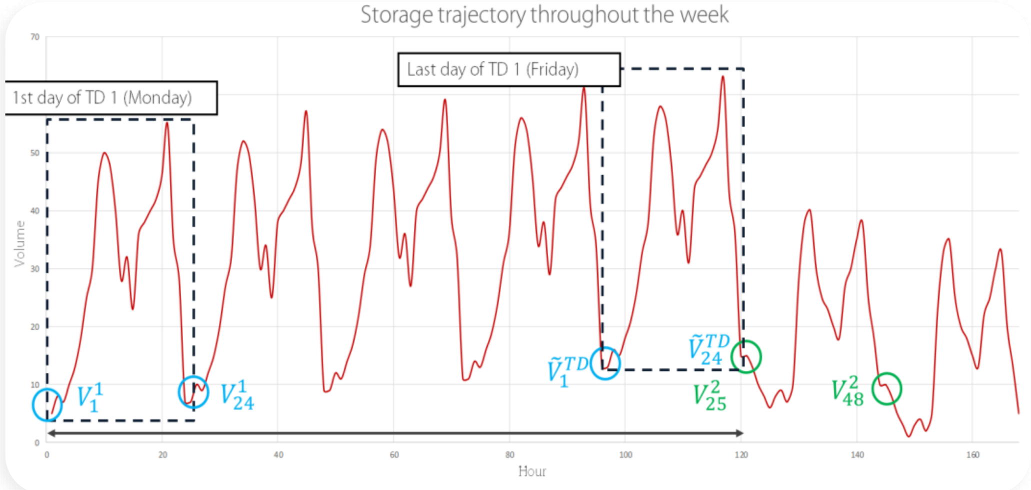
- Typical days are representative operative profiles
- Hourly resolution within each typical day
- The chronology is kept within each day. However, does it hold between the typical days?

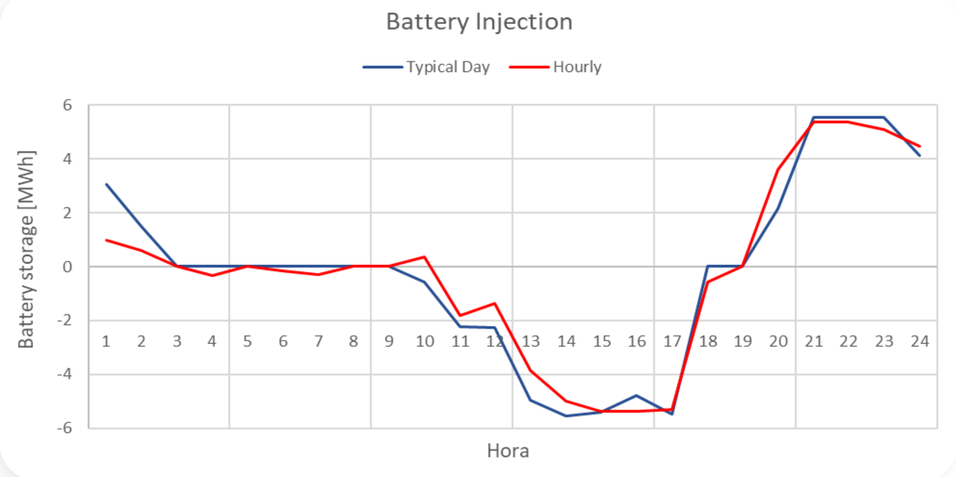


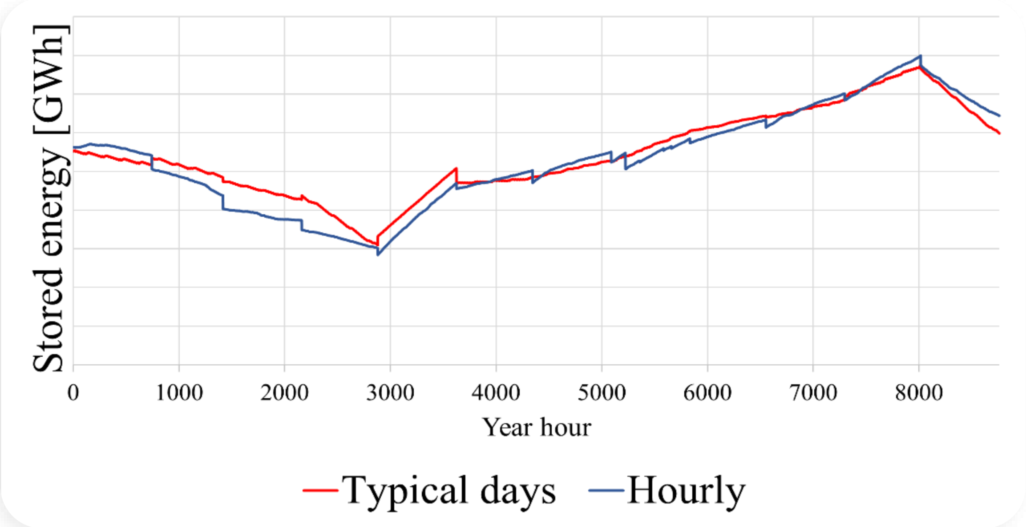


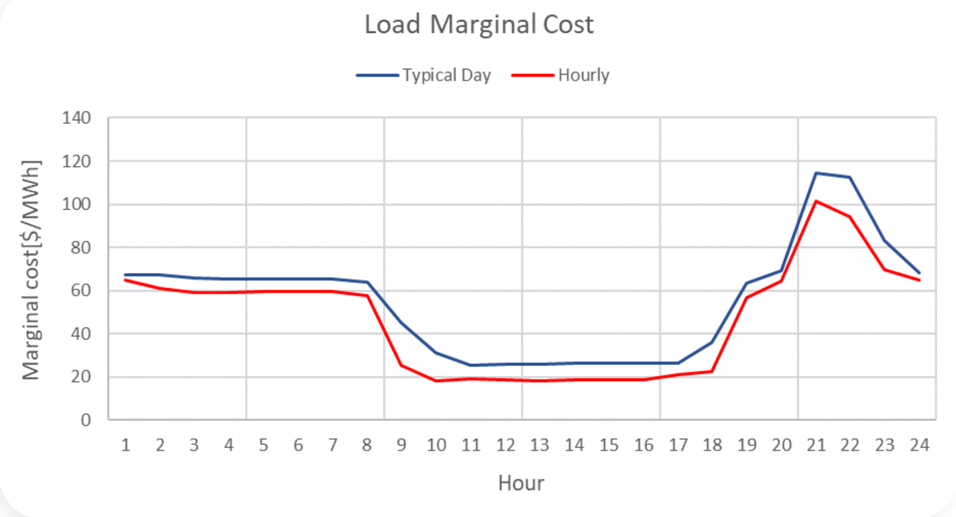
Days of the year	Association to Typical Days	Season
1	1	1
2	1	1
3	1	1
4	1	1
5	1	1
6	2	1
7	2	1
8	1	1
9	1	1
10	1	1
11	1	1
12	1	1
13	2	1
14	2	1
15	1	1
16	1	1
17	1	1
18	1	1
19	1	1
20	2	1
21	2	1
22	1	1
23	1	1
24	1	1
25	1	1
26	1	1
27	2	1
28	2	1
29	1	1
30	1	1
31	1	1

Typical days: LT Storage & Results









Short-term

Ensemble Forecast: Motivations

Historically, the ST dispatch scheduling (including unit commitment decisions) was solved in a deterministic way with the forecasts of demand, inflows, wind, solar

Inappropriate due to uncertainty in the forecast

Instead of representing a single prediction ➔ "Ensemble forecasts" of **precipitation**, **temperature**, **irradiation**, **wind**, etc.

Support from **official weather/climate models** such as ECMWF and NOAA/GFS

Coherence between "ensemble forecasts" for **different horizons** (6 months ahead – 2030)

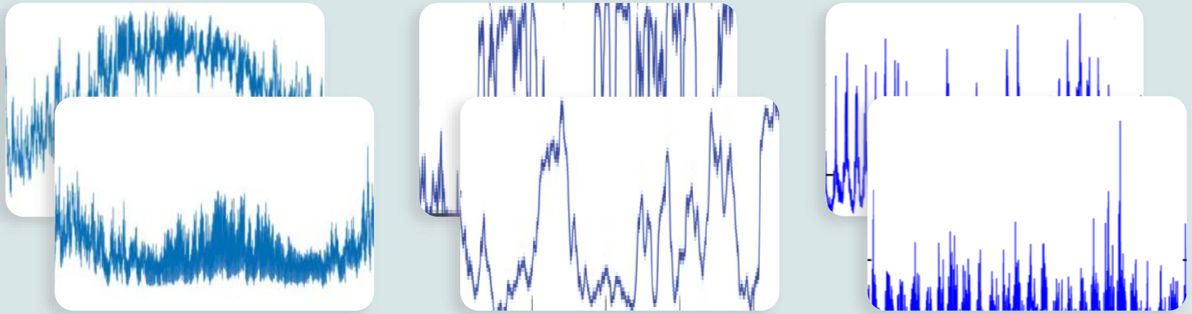
Production of **extreme climate scenarios**

Deep Learning Architecture: the neural network "learns" the complex nonlinear relationships between all variables, and also captures the dynamics of temporal/spatial probability distributions

Ensemble Forecast: Motivations

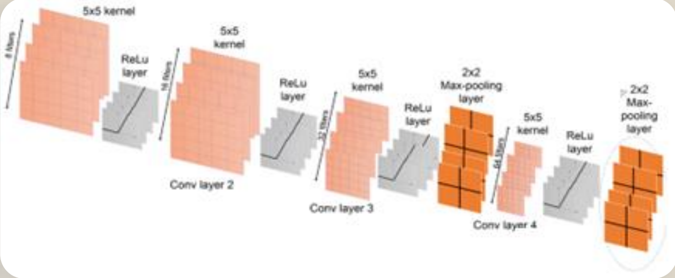
Sequence of historical hindcasts (ECMWF+GFS)

Sequence of historical observations

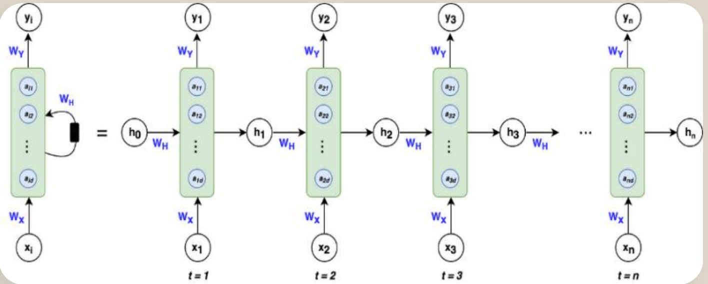


Deep Learning Architeture

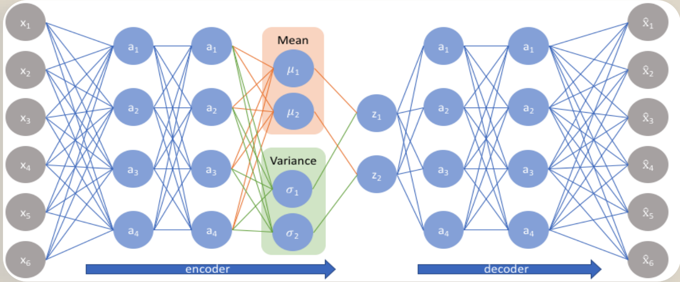
Convolutional Layers → Identify spatial patterns



Recurrent Layers → Identify temporal patterns

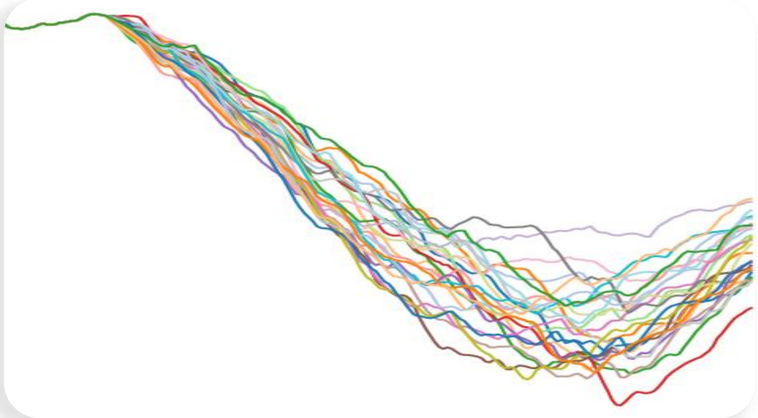


Variational Autoencoder Layers → Identify distributions

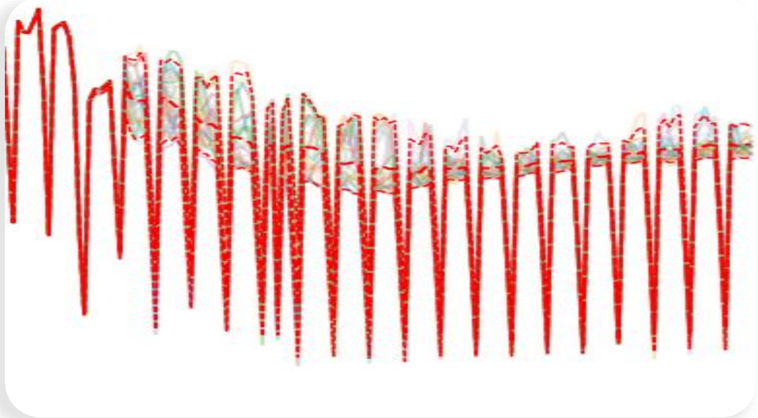


Ensemble Forecast: Motivations

Forecast of temperature scenarios - *ECMWF*

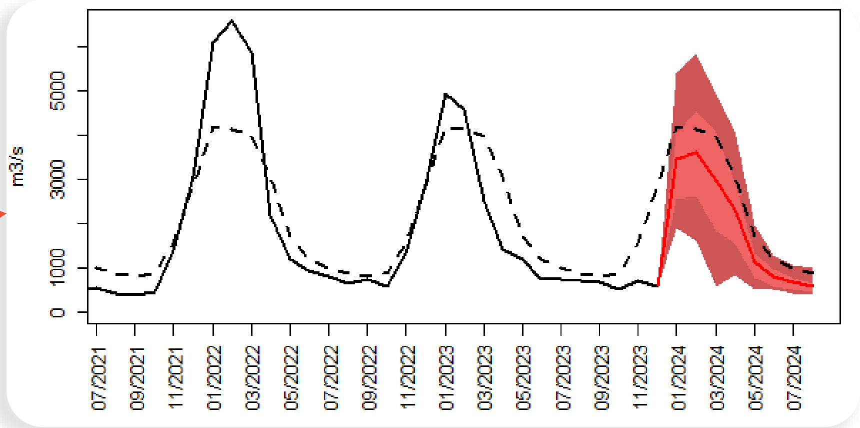


Forecast of demand scenarios based on temperature

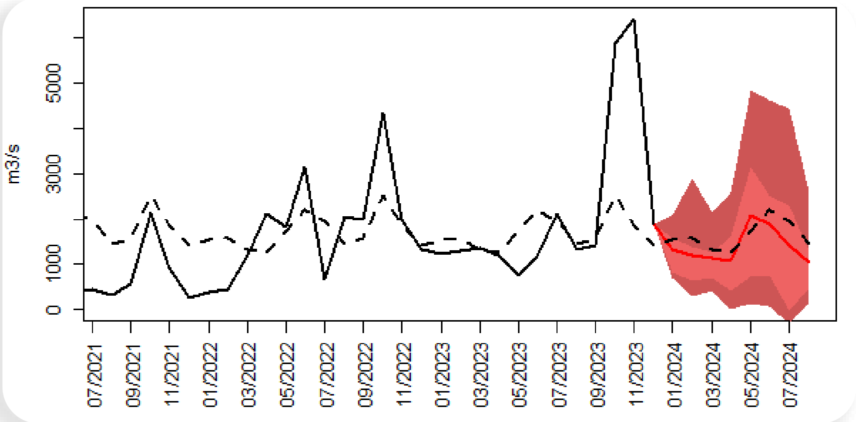


- Recent Historical Series
- Forecast (average value)
- Quantile 25% (sup/inf)
- Quantile 7.5% (sup/inf)
- Long-term average

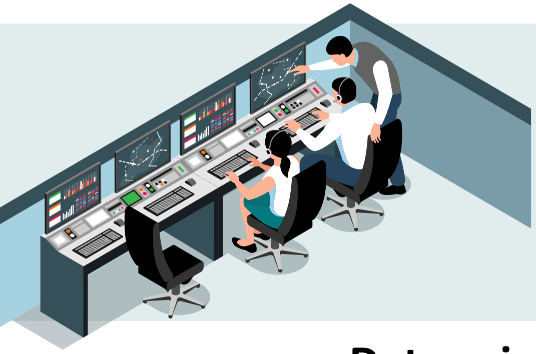
São Francisco Basin



Paraná Basin



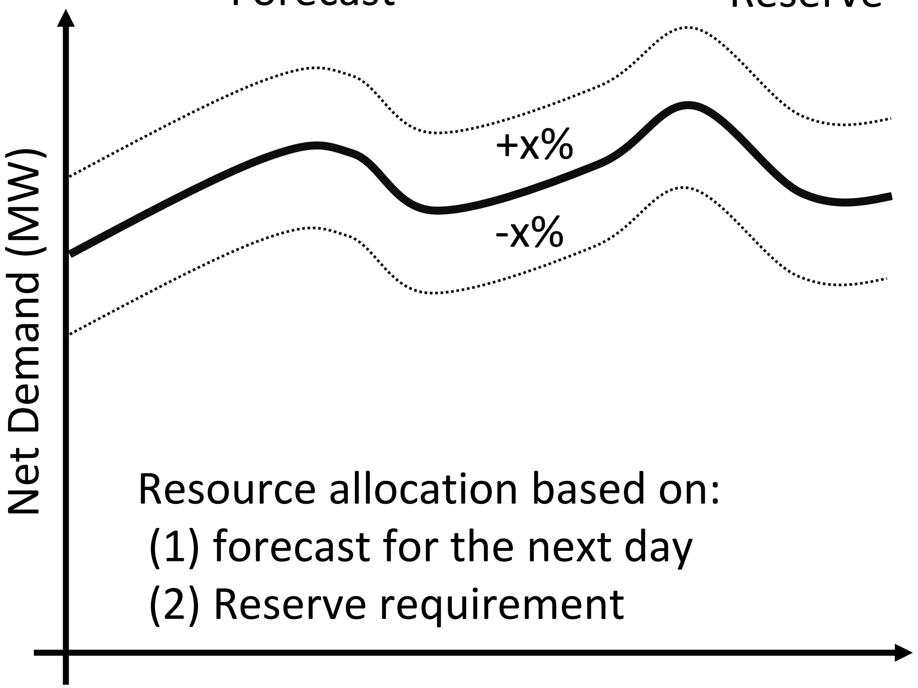
Short-term dispatch scheduling



Traditionally:

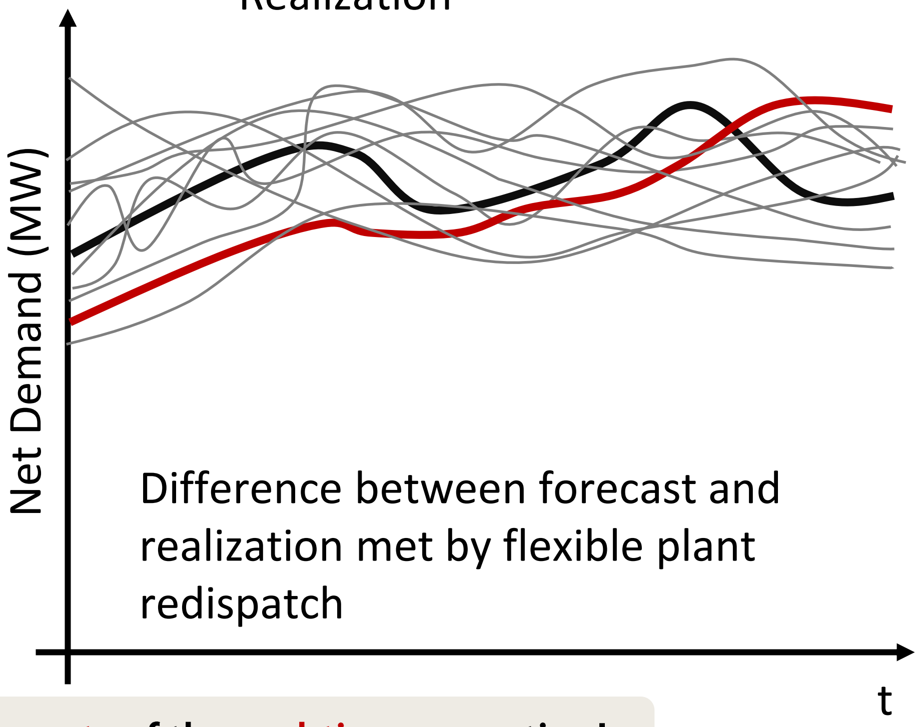
- Deterministic dispatch scheduling
- Indirect (implicit) representation of uncertainty through reserves

Deterministic Dispatch



Resource allocation based on:
(1) forecast for the next day
(2) Reserve requirement

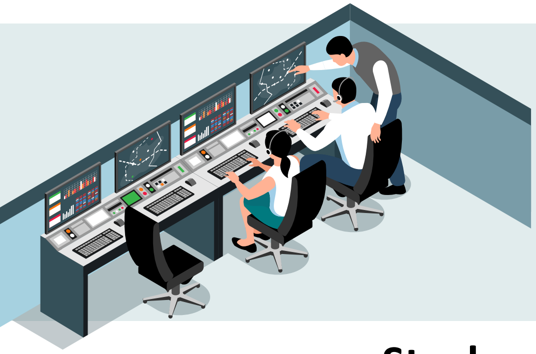
Real-time operation



Difference between forecast and realization met by flexible plant redispatch

Dispatch scheduling does not consider the redispatch costs of the real-time operation!

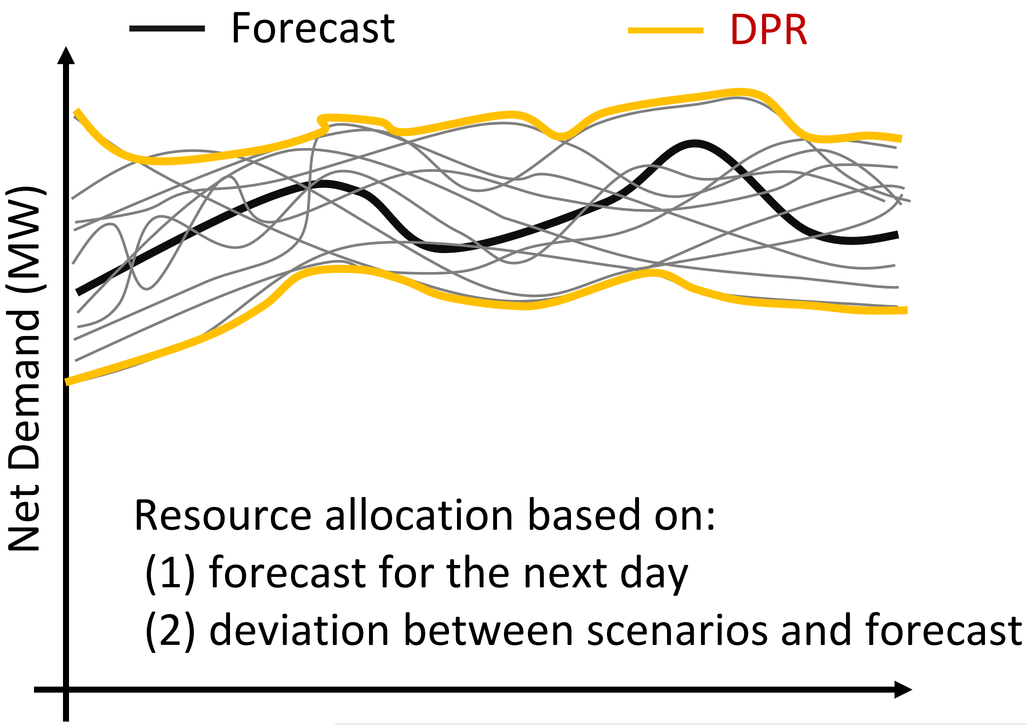
Short-term dispatch scheduling



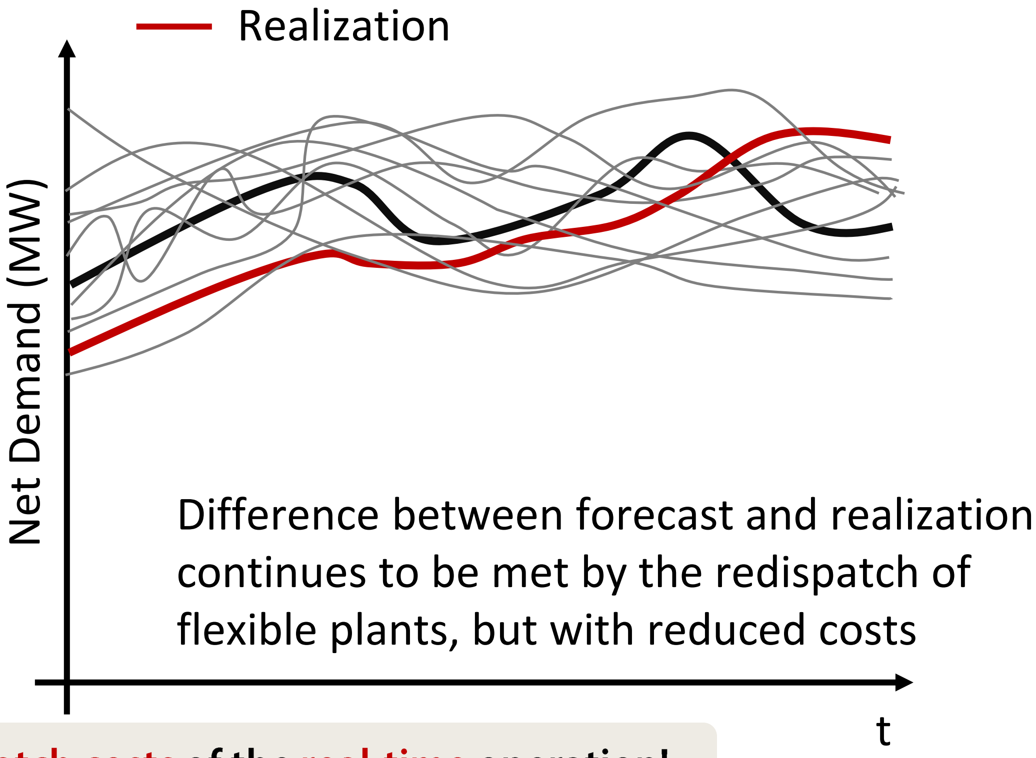
Proposal:

- Stochastic dispatch scheduling
- Explicit representation of uncertainty through scenarios (ensemble forecasts)

Stochastic Dispatch



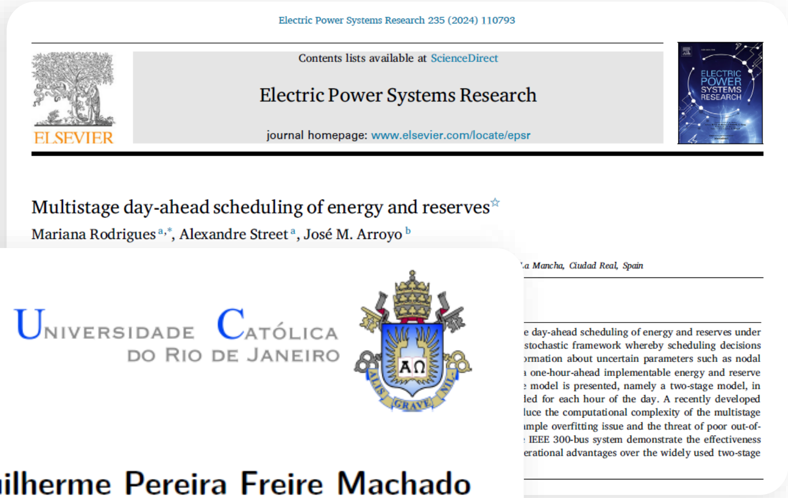
Real-time operation



Dispatch scheduling considers the expected redispatch costs of the real-time operation!

Solution: affine

- **Linear Decision Rule**
  - We limit the dispatch to be an affine function of the uncertainty (net demand)
  - ξ is the uncertainty of the problem (net demand of the scenario)
  - ξ^0 is the reference scenario
  - λ is the linear coefficient (it's the new decision variable)
  - g^0 is the dispatch result in the reference scenario


Electric Power Systems Research 235 (2024) 110793
Contents lists available at ScienceDirect
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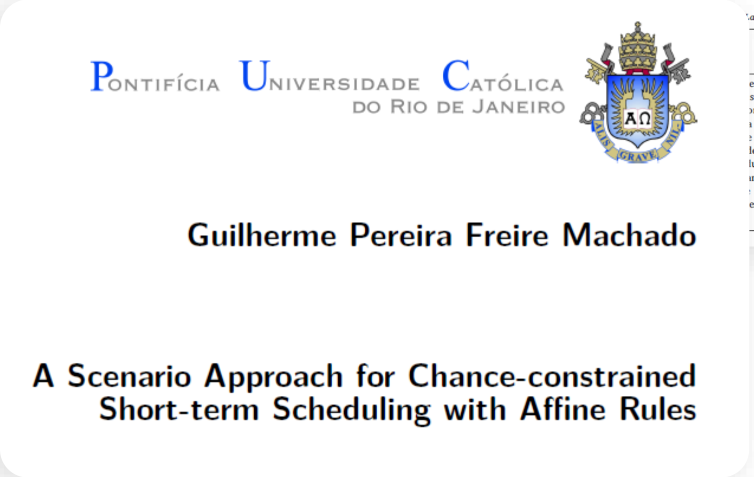
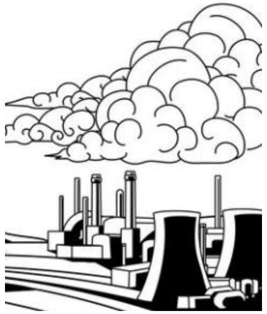
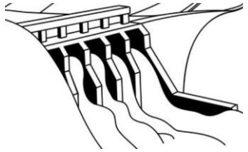
journal homepage: www.elsevier.com/locate/epsr
Multistage day-ahead scheduling of energy and reserves
Mariana Rodrigues [a,*], Alexandre Street [a], José M. Arroyo [b]

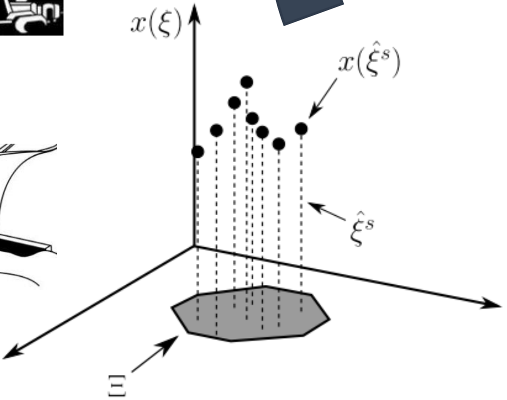

Pontifícia Universidade Católica do Rio de Janeiro

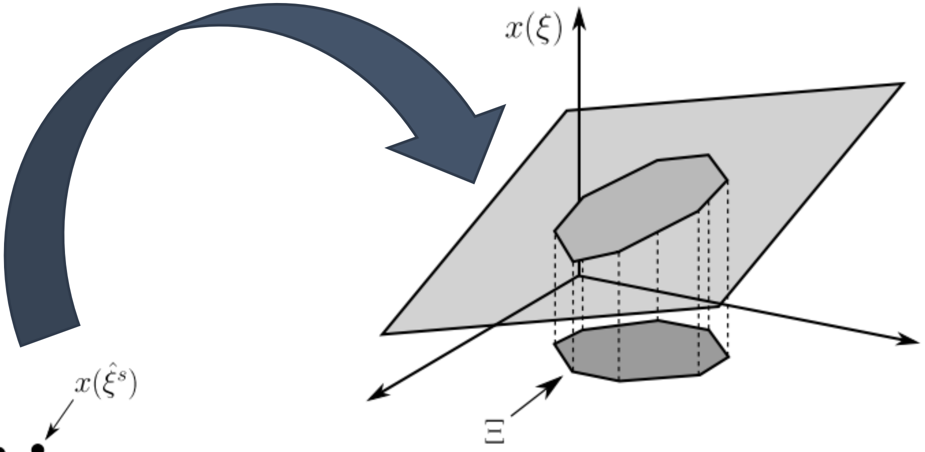
Guilherme Pereira Freire Machado

A Scenario Approach for Chance-constrained Short-term Scheduling with Affine Rules









$$g(\xi) = \lambda \cdot (\xi - \xi^0) + g^0$$

Solution: affine

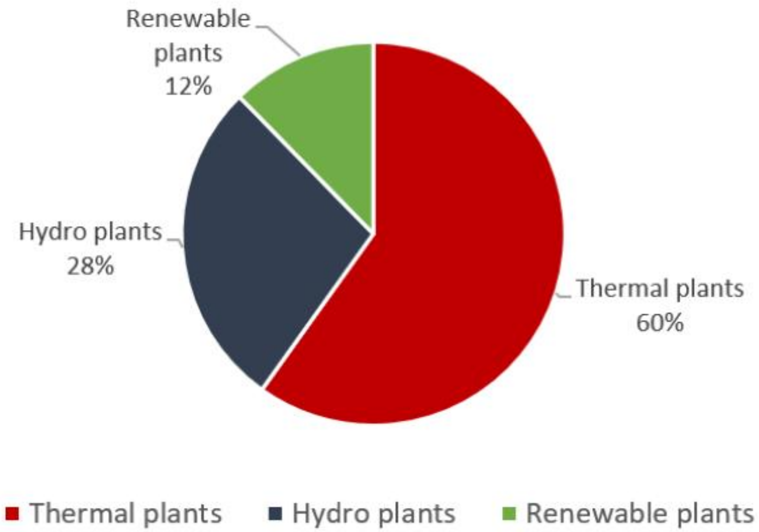
- **Linear Decision Rule**
  - We have a “normal” dispatch in the reference scenario and a dispatch with linear rules in the other scenarios

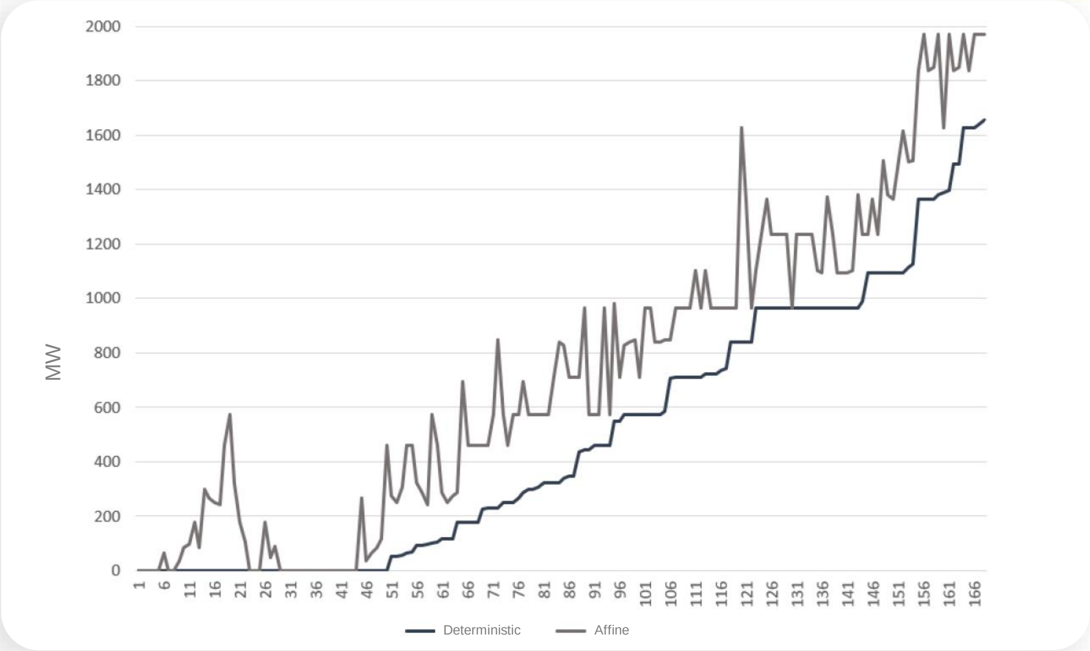
Reference scenario	Other scenarios

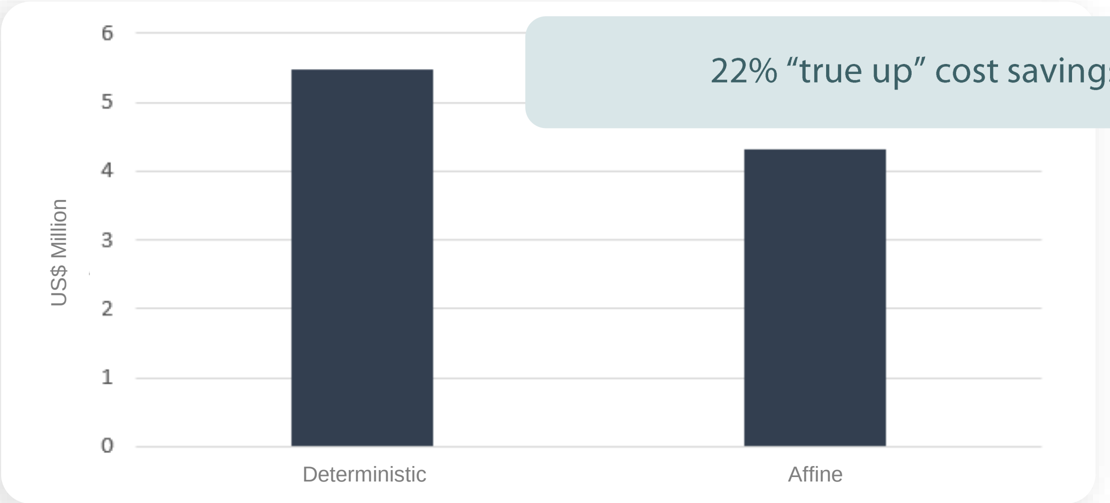
$$
\begin{aligned}
\min_{g_h^0, g_t^0} \quad & c_t \cdot g_t^0 + \alpha(V_h) \\
\text{s.t.} \quad & g_t^0 + g_h^0 + g_r(\xi^0) = d(\xi^0), \\
& \underline{\mathrm{G}}_t \leq g_t^0 \leq \bar{G}_t, \\
& \underline{\mathrm{G}}_h \leq g_h^0 \leq \bar{G}_h, \\
& g_t^0 \in \mathcal{G}_t, \\
& g_h^0 \in \mathcal{G}_h
\end{aligned}
$$

$$
\begin{aligned}
\min_{\lambda_h, \lambda_t} \quad & c_t \cdot g_t(\xi) + \alpha(V_h) \\
\text{s.t.} \quad & g_t(\xi) + g_h(\xi) + g_r(\xi) = d(\xi), \\
& \underline{\mathrm{G}}_t \leq g_t \leq \bar{G}_t, \\
& \underline{\mathrm{G}}_h \leq g_h \leq \bar{G}_h, \\
& g_t \in \mathcal{G}_t, \\
& g_h \in \mathcal{G}_h, \\
& g_h(\xi) = \lambda_h \cdot (\xi - \xi^0) + g_h^0, \\
& g_t(\xi) = \lambda_t \cdot (\xi - \xi^0) + g_t^0
\end{aligned}
$$

Case Study: Chile







22% “true up” cost savings

Conclusions

Key Takeaways

Operation planning models are increasingly important for safe operations in the face of uncertainties

Typical days present a good CPU time vs quality of results trade-off for long-term planning

Generating demand and renewable generation scenarios correlated with temperature can be a game changer

Reserves should be well calculated to amortize renewable intermittency

The variability of renewables need to be amortized by storage devices, transmission, reserve sharing, or demand response (e.g. flexibility aggreg.)

Affine decision rules appear to be a good solution for: week/day-ahead scheduling & tactical operating decisions in LT runs

During the dispatch scheduling with affine rules, day-ahead prices are calculated for the reference scenario

THANK YOU!

Any questions?

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