Integrated AI-based Climate Modeling and Stochastic Optimization

to design and operate economic, flexible and resilient large-scale energy systems

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DTU PES Summer School, May 2026

PSR

PSR

PSR integrates consulting studies, development of advanced analytical tools and research on energy systems

Our team has 160 people with degrees in optimization, energy systems, statistics and computer/data science

We work in 70 countries in all continents

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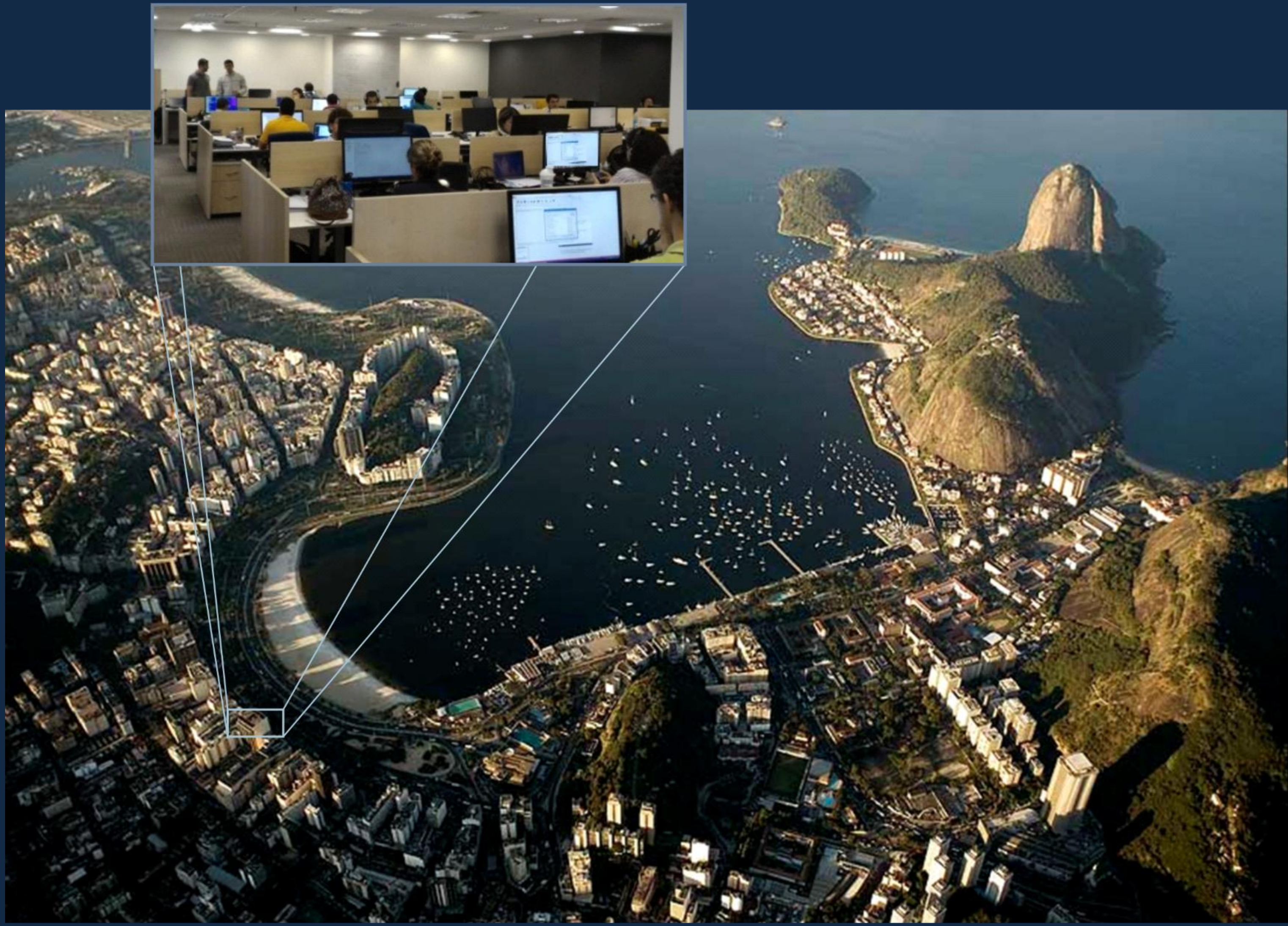
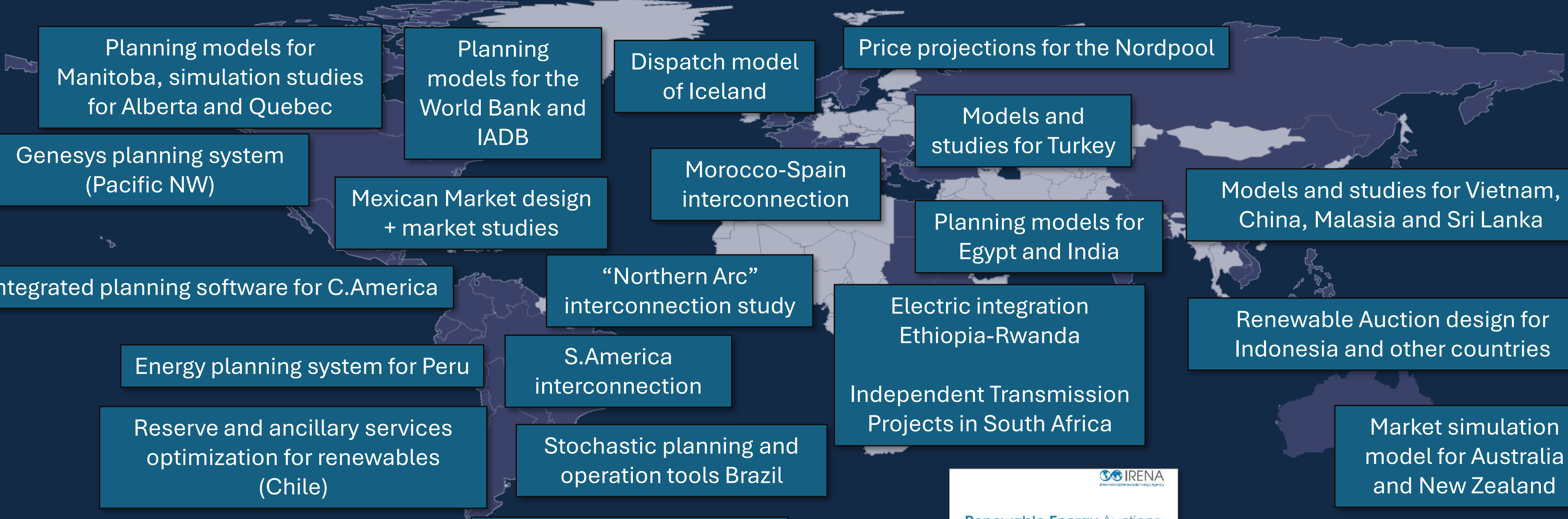


We work in 70 countries in all continents



Planning models for Manitoba, simulation studies for Alberta and Quebec

Genesys planning system (Pacific NW)

Planning models for the World Bank and IADB

Mexican Market design + market studies

Dispatch model of Iceland

Morocco-Spain interconnection

Price projections for the Nordpool

Models and studies for Turkey

Planning models for Egypt and India

Models and studies for Vietnam, China, Malasia and Sri Lanka

Integrated planning software for C.America

"Northern Arc" interconnection study

Electric integration Ethiopia-Rwanda

Independent Transmission Projects in South Africa

Renewable Auction design for Indonesia and other countries

Energy planning system for Peru

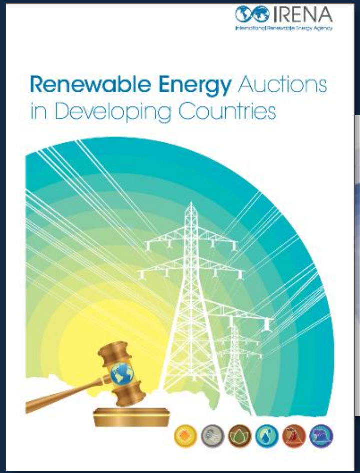
S.America interconnection

Reserve and ancillary services optimization for renewables (Chile)

Stochastic planning and operation tools Brazil

Market simulation model for Australia and New Zealand

Climate change studies in Latin America



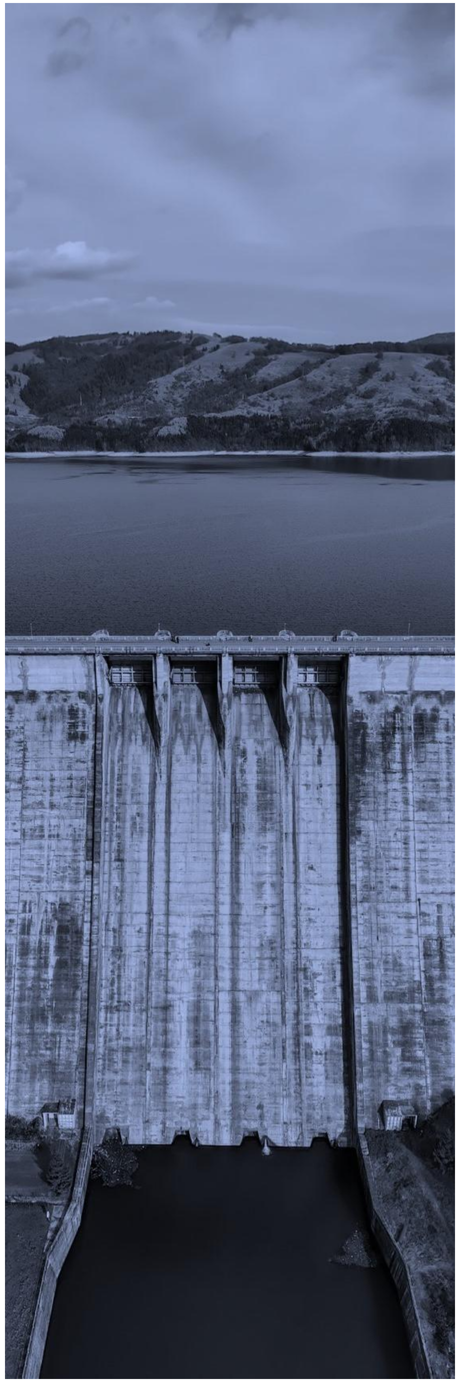
Americas: all countries in South and Central America, United States, Canada and Dominican Republic

Europe: Austria, Spain, France, Scandinavia, Belgium, Turkey and the Balkans region

Asia: China (Shanghai, Sichuan, Guangdong and Shandong), India, Pakistan, Nepal, Philippines, Singapore, Malaysia, Kirgizstan, Sri Lanka, Tajikistan and Vietnam

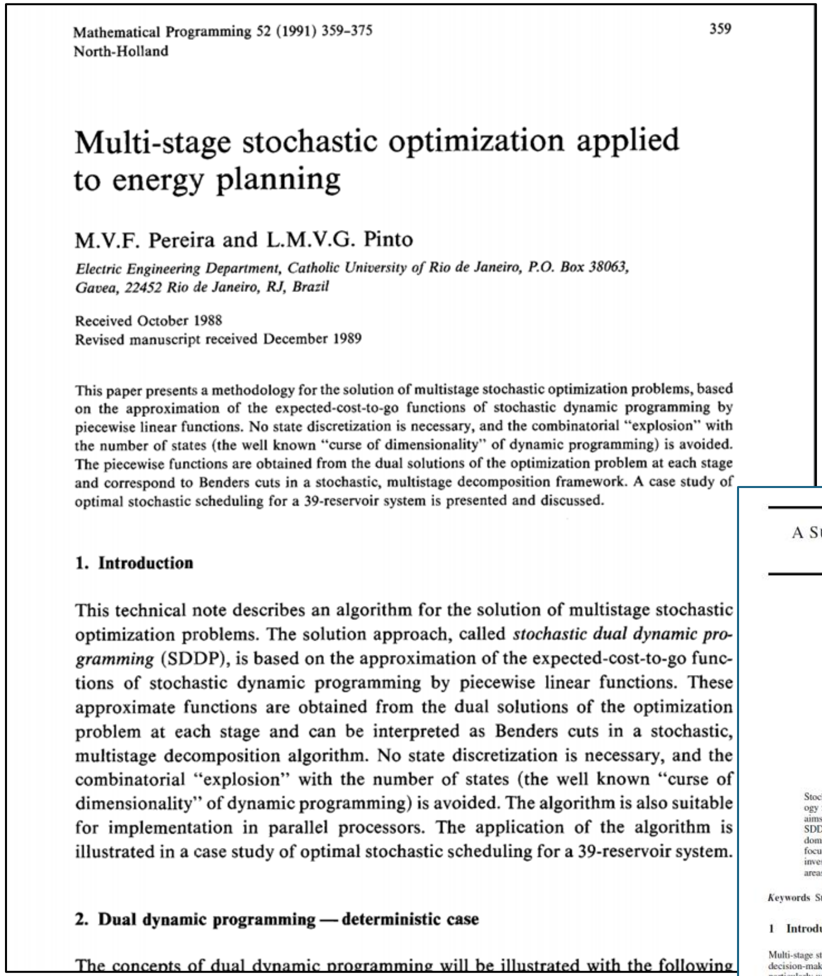
Oceania: New Zealand

Africa: Morocco, Tanzania, Mozambique, Rwanda, Namibia, Egypt, Angola, Sudan, Ethiopia and Ghana



1 | SDDP as core method

PSR core optimization method: SDDP



Mathematical Programming 52 (1991) 359-375 359
North-Holland

Multi-stage stochastic optimization applied to energy planning

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Received October 1988
Revised manuscript received December 1989

This paper presents a methodology for the solution of multistage stochastic optimization problems, based on the approximation of the expected-cost-to-go functions of stochastic dynamic programming by piecewise linear functions. No state discretization is necessary, and the combinatorial "explosion" with the number of states (the well known "curse of dimensionality" of dynamic programming) is avoided. The piecewise functions are obtained from the dual solutions of the optimization problem at each stage and correspond to Benders cuts in a stochastic, multistage decomposition framework. A case study of optimal stochastic scheduling for a 39-reservoir system is presented and discussed.

1. Introduction

This technical note describes an algorithm for the solution of multistage stochastic optimization problems. The solution approach, called *stochastic dual dynamic programming* (SDDP), is based on the approximation of the expected-cost-to-go functions of stochastic dynamic programming by piecewise linear functions. These approximate functions are obtained from the dual solutions of the optimization problem at each stage and can be interpreted as Benders cuts in a stochastic, multistage decomposition algorithm. No state discretization is necessary, and the combinatorial "explosion" with the number of states (the well known "curse of dimensionality" of dynamic programming) is avoided. The algorithm is also suitable for implementation in parallel processors. The application of the algorithm is illustrated in a case study of optimal stochastic scheduling for a 39-reservoir system.

2. Dual dynamic programming — deterministic case

The concepts of dual dynamic programming will be illustrated with the following

A Survey on the Applications of Stochastic Dual Dynamic Programming and its Variants

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Abstract

Stochastic Dual Dynamic Programming (SDDP) is widely recognized as the predominant methodology for solving large-scale multistage stochastic linear programming (MSLP) problems. This paper aims to contribute to the extant literature by conducting a comprehensive survey of the literature on SDDP within the realm of practical applications. We systematically identify and analyze the various domains where SDDP has been successfully employed to tackle MSP problems, with a particular focus on real-world problems afflicted by the so-called *curse-of-dimensionality*. Furthermore, we investigate the factors that have facilitated or hindered the adoption of SDDP in specific application areas, shedding light on the limitations and potential barriers to its widespread utilization.

Keywords Stochastic Dual Dynamic Programming; Approximate Dynamic Programming; Stochastic Programming

1 Introduction

Multi-stage stochastic programming (MSP) is a class of mathematical problems dealing with optimization of sequential decision-making under uncertainty. Solving real-world problems through MSPs presents considerable challenges, particularly when navigating extensive planning horizons and uncertainty scenarios. Such problems frequently run into the infamous *curse-of-dimensionality*, a phenomenon describing the exponential growth in computational requirements as the dimensionality of a certain problem increases.

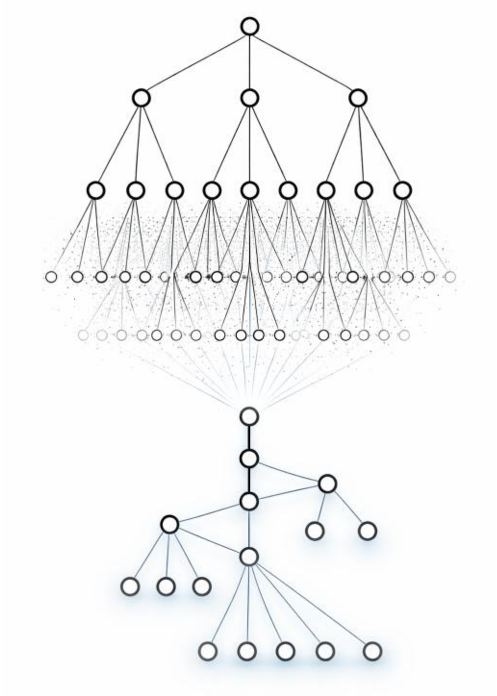
Enter Stochastic Dual Dynamic Programming (SDDP). Introduced in the seminal work by Pereira and Pinto (1991), SDDP proposes a powerful solution to bypass many of the obstacles associated with MSP problems, particularly the curse-of-dimensionality. Rooted in the principles of dynamic programming and duality, SDDP decomposes an MSP problem, iteratively approximating the expected cost-to-go functions without needing to tackle the entire problem space at once. Consequently, what previously seemed intractable becomes more computationally feasible, allowing practitioners to address large-scale MSP problems in various sectors, from energy planning to supply chain optimization.

The conception of SDDP marked a paradigm shift in the approach to sequential decision-making under uncertainty. Previously, dealing with uncertainty often required, on one hand, simplification and even relaxation of the problem. This potentially leads to suboptimal solutions or ones that failed to mirror the full complexity of a real-world problem. On the other hand, solving the entire scale of MSPs through a tedious exploration and exploitation of the full scenario tree results to expensive computational efforts. However, with SDDP, it became possible to retain much of the intricacies of MSPs while still navigating through the expanse of uncertainties and stages.

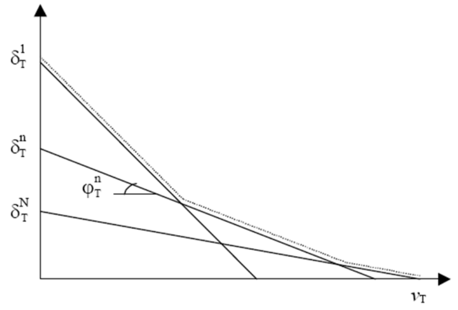
- PSR has been solving **multistage decision-making problems** under uncertainty since its foundation by Mario Pereira in 1987
- Our flagship methodology: the **SDDP** (Stochastic Dual Dynamic Programming) method (multistage stochastic Benders decomposition)
- Seminal paper with 3,000+ citations on Google Scholar, one of the most cited papers in the operations research and energy planning fields,
- SDDP has been the **state-of-the-art** solution method for large-scale multistage stochastic programs, having been applied to practical problems from several fields and enriched by numerous improvements and enhancements, more than 8,000 citations

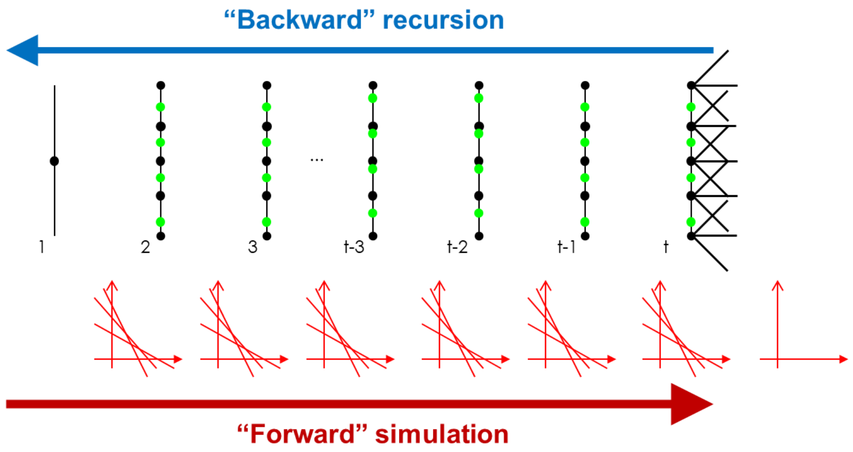
The SDDP logic

- Storage (hydro reservoirs, batteries) and flexible assets create intertemporal trade-offs with correlated uncertainties in decision-making processes
- Motivation for SDDP: explicit scenario trees would have a "combinatorial explosion" of branches along the stages and quickly become intractable; Discretized stochastic dynamic programming also becomes intractable for a larger number of storage states ("curse of dimensionality")
- This is the setting in which SDDP becomes essential: system uncertainty through disaggregated chronological scenarios instead of explicit full trees, avoiding the curse of dimensionality



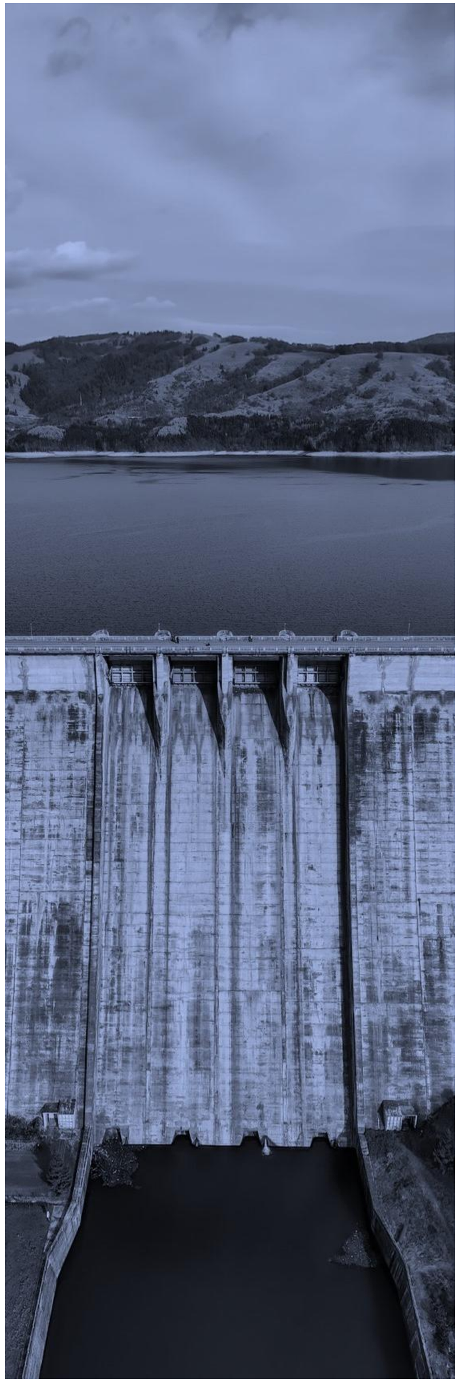
$$
\begin{aligned}
\alpha_{T-1}(v_{T-1}) = \quad & \text{Min } c_{T-1}(u_{T-1}) + \alpha_T \\
& \text{subject to} \\
& \qquad v_T = v_{T-1} - u_{T-1} - s_{T-1} + a_{T-1} \\
& \qquad v_T \le \overline{v} \\
& \qquad u_{T-1} \le \overline{u} \\
& \qquad \alpha_T \ge \varphi_T^n v_T + \delta_T^n \qquad \text{for } n = 1, \ldots, N
\end{aligned}
$$





SDDP extensions

- Distributed processing and application of cloud computing
- Represents uncertainties on inflows, renewable production, fuel prices, electricity market prices
- Modeling of risk aversion: Conditional value-at-risk has been the standard of the industry
- Handling nonconvexities:
  - Benders decomposition requires convexity in the problems during the backward phase; therefore, nonconvex constraints such as integer variables for unit commitment must be convexified (for example, linear relaxation)
  - Stochastic Dual Dynamic Integer Programming (SDDiP), Support Vector Machine (identification of valid and non valid cuts around each state) and Progressive hedging have been used by us to overcome convexity issues



2 | SDDP with High Performance Computing as PSR flagship model

SDDP as an industrial application by PSR

The SDDP model by PSR is a tool that represents all types of generation (hydro, thermal, renewables etc.); storage (pumped storage, batteries, reservoirs etc.); electricity networks (multi-area or full transmission); gas networks and fuel storage

Chronological hourly resolution (ramps etc.) and non linearities (e.g. variable head and unit commitment)

Objective functions: Minimize risk-adjusted operation cost subject to reliability constraints; maximize expected revenues; and others

Clients all over the world (ISO, traders, banks, generators, regulators, consumers, consultants, universities, etc)

Hydroelectric plants

- Detailed representation for each reservoir
- Storage and flow rate limits through turbines, spillways, head effect, infiltration and others;
- Stochastic inflow model representing seasonality, time and spatial correlations
- Modeling of specific climatic phenomena (such as El Niño), etc.
- Ramping constraints

Thermoelectric plants

- Unit commitment constraints
- Fuel availability
- Fuel contracts (including take-or-pay clauses)
- Thermal efficiency curves
- CO_2 and other pollutants emission
- Ramping constraints

Variable Renewable Energy *(VRE)*
Time Series Lab Model

- Definition of VRE historical generation through global reanalysis database
- Stochastic VRE power production model, generating future synthetic scenarios with hourly resolution
- VRE scenarios are temporally and specially correlated with hydro inflows

Transmission Network

- Kirchhoff laws
- Power flow limits
- Quadratic losses
- Security constraints
- Limits on export and import among electric areas, sum of flow constraints and others;

Natural Gas Network

- Gas production and transportation constraints
- Production capacity in the fields
- Pipeline flow limits and losses

Batteries and others fast response storage devices

- Storage capacity
- Charge/discharge capacities
- Efficiencies
- Ramping constraints.

SDDP 18

Integrated Energy System Planning Platform

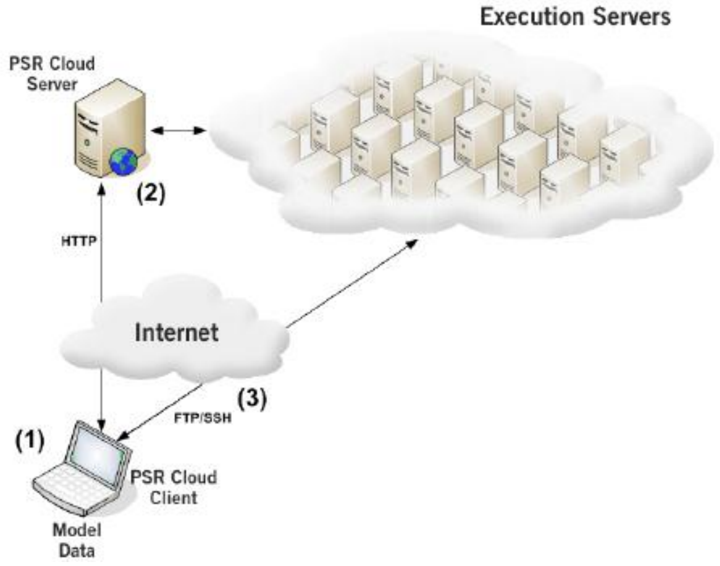
SDDP OptGen CORAL OptMain

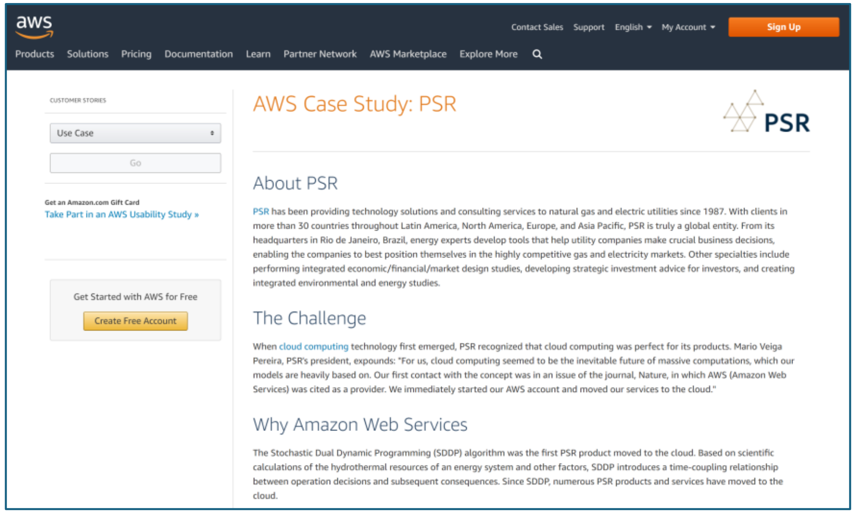
SDDP 18 brings together operation, expansion, reliability, and maintenance planning into a single, unified platform. With a redesigned interface, powerful modeling capabilities, and full support for energy supply chains, this version enables consistent, high-resolution studies across multiple technologies, decision layers, and time horizons.

From power systems to hydrogen, gas, biomass, and water, SDDP 18 supports the co-optimization of infrastructure and operations across sectors — backed by PSR's state-of-the-art stochastic optimization engine.

SDDP is very suitable for cloud computing

- We started to use Amazon's Cloud (AWS) in November 2006, one month after it was created.
- According to AWS, PSR was the first user in Latin America, of any area
- We then developed a cloud-based platform:
  - Manages the remote execution of models (e.g. SDDP)
  - A distributed process environment (cloud computing)
  - Avoids the need for acquiring expensive "local" infrastructure to run studies
  - "SDDP Cloud" commercially available by PSR in 2009





AWS Case Study: PSR

About PSR

PSR has been providing technology solutions and consulting services to natural gas and electric utilities since 1987. With clients in more than 30 countries throughout Latin America, North America, Europe, and Asia Pacific, PSR is truly a global entity. From its headquarters in Rio de Janeiro, Brazil, energy experts develop tools that help utility companies make crucial business decisions, enabling the companies to best position themselves in the highly competitive gas and electricity markets. Other specialties include performing integrated economic/financial/market design studies, developing strategic investment advice for investors, and creating integrated environmental and energy studies.

The Challenge

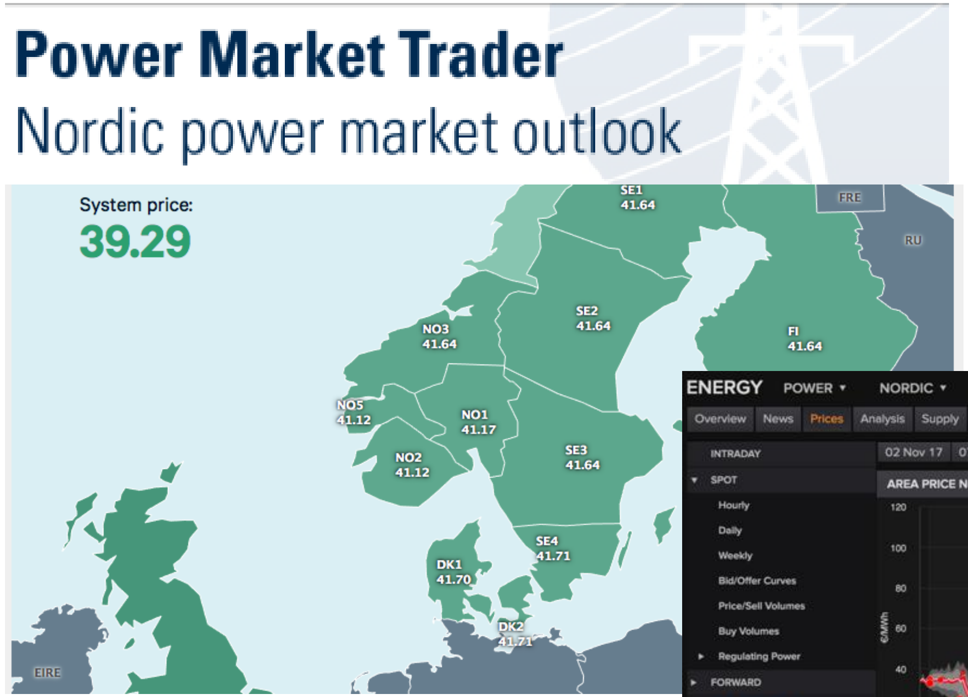
When cloud computing technology first emerged, PSR recognized that cloud computing was perfect for its products. Mario Veiga Pereira, PSR's president, expounds: "For us, cloud computing seemed to be the inevitable future of massive computations, which our models are heavily based on. Our first contact with the concept was in an issue of the journal, Nature, in which AWS (Amazon Web Services) was cited as a provider. We immediately started our AWS account and moved our services to the cloud."

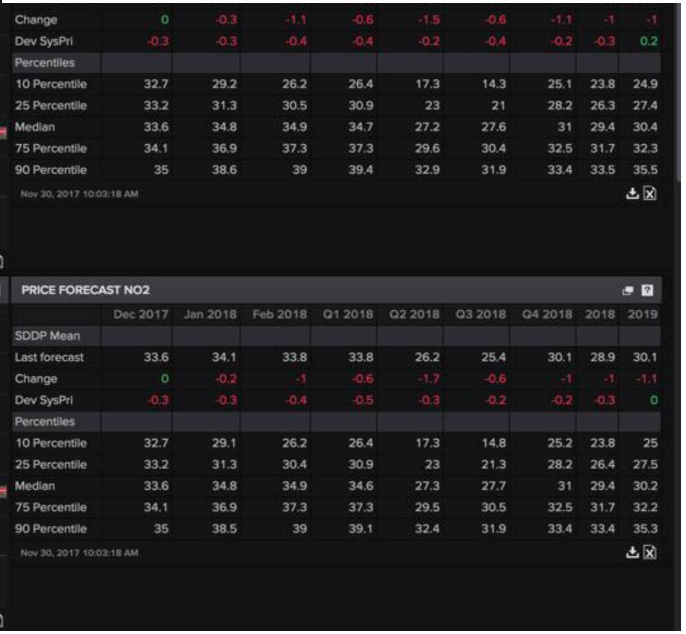
Why Amazon Web Services

The Stochastic Dual Dynamic Programming (SDDP) algorithm was the first PSR product moved to the cloud. Based on scientific calculations of the hydrothermal resources of an energy system and other factors, SDDP introduces a time-coupling relationship between operation decisions and subsequent consequences. Since SDDP, numerous PSR products and services have moved to the cloud.

Example of aplication SDDP Nordic

https://www.youtube.com/watch?v=K5s98kgQJ6Q





Change	0	-0.3	-1.1	-0.6	-1.5	-0.6	-1.1	-1	-1
Dev SysPri	-0.3	-0.3	-0.4	-0.4	-0.2	-0.4	-0.2	-0.3	0.2
Percentiles									
10 Percentile	32.7	29.2	26.2	26.4	17.3	14.3	25.1	23.8	24.9
25 Percentile	33.2	31.3	30.5	30.9	23	21	28.2	26.3	27.4
Median	33.6	34.8	34.9	34.7	27.2	27.6	31	29.4	30.4
75 Percentile	34.1	36.9	37.3	37.3	29.6	30.4	32.5	31.7	32.3
90 Percentile	35	38.6	39	39.4	32.9	31.9	33.4	33.5	35.5

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PRICE FORECAST NO2

	Dec 2017	Jan 2018	Feb 2018	Q1 2018	Q2 2018	Q3 2018	Q4 2018	2018	2019
SDDP Mean									
Last forecast	33.6	34.1	33.8	33.8	26.2	25.4	30.1	28.9	30.1
Change	0	-0.2	-1	-0.6	-1.7	-0.6	-1	-1	-1.1
Dev SysPri	-0.3	-0.3	-0.4	-0.5	-0.3	-0.2	-0.2	-0.3	0
Percentiles									
10 Percentile	32.7	29.1	26.2	26.4	17.3	14.8	25.2	23.8	25
25 Percentile	33.2	31.3	30.4	30.9	23	21.3	28.2	26.4	27.5
Median	33.6	34.8	34.9	34.6	27.3	27.7	31	29.4	30.2
75 Percentile	34.1	36.9	37.3	37.3	29.5	30.5	32.5	31.7	32.2
90 Percentile	35	38.5	39	39.1	32.4	31.9	33.4	33.4	35.3

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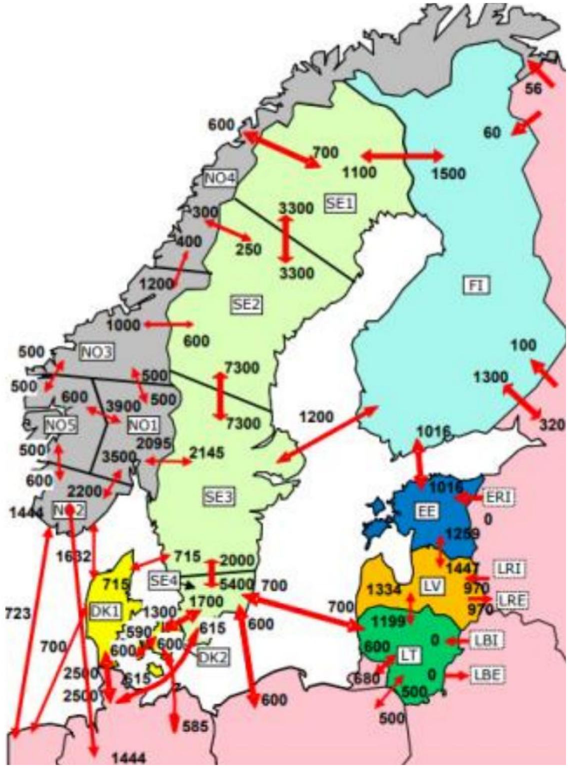
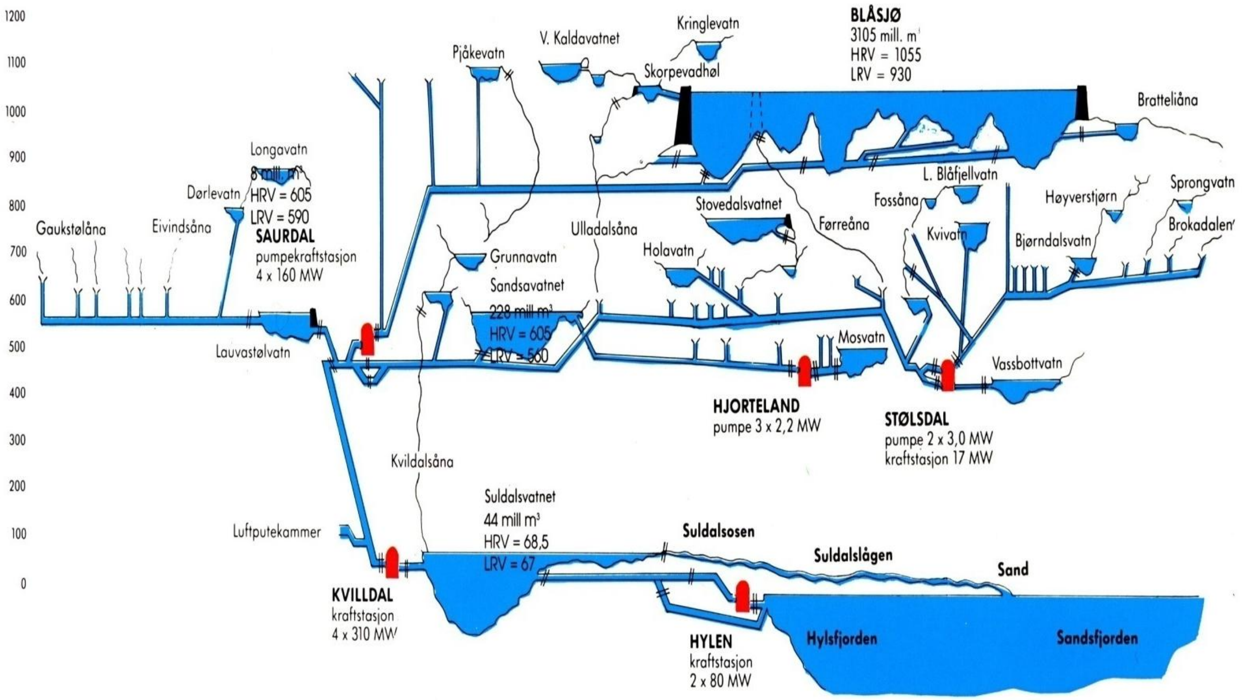
Nordic Power Market Insight: the SDDP mid-term fundamental price model

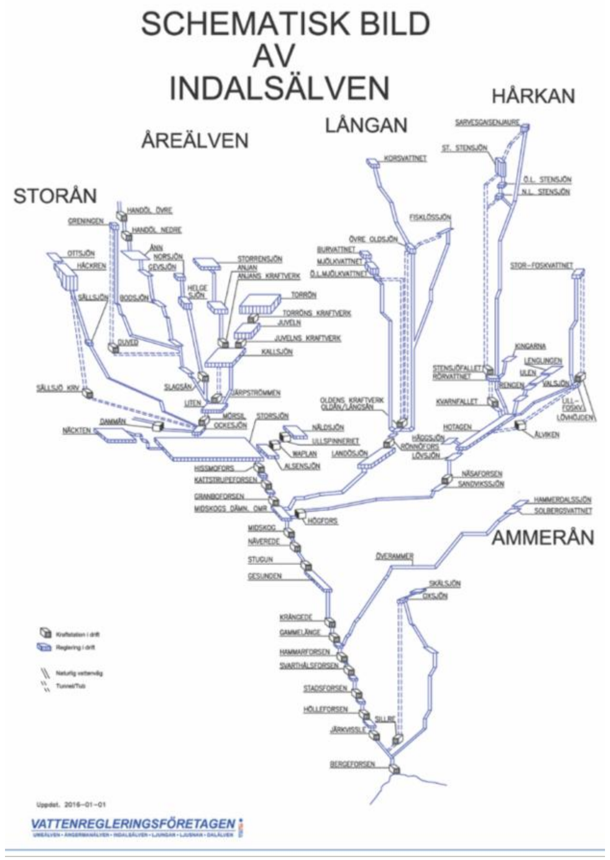
Service started 2009
LSEG - London Stock Exchange Group (previously Refinitiv and Point Carbon)

Modeling of complex hydro cascades

12 Nordic Bid Zones







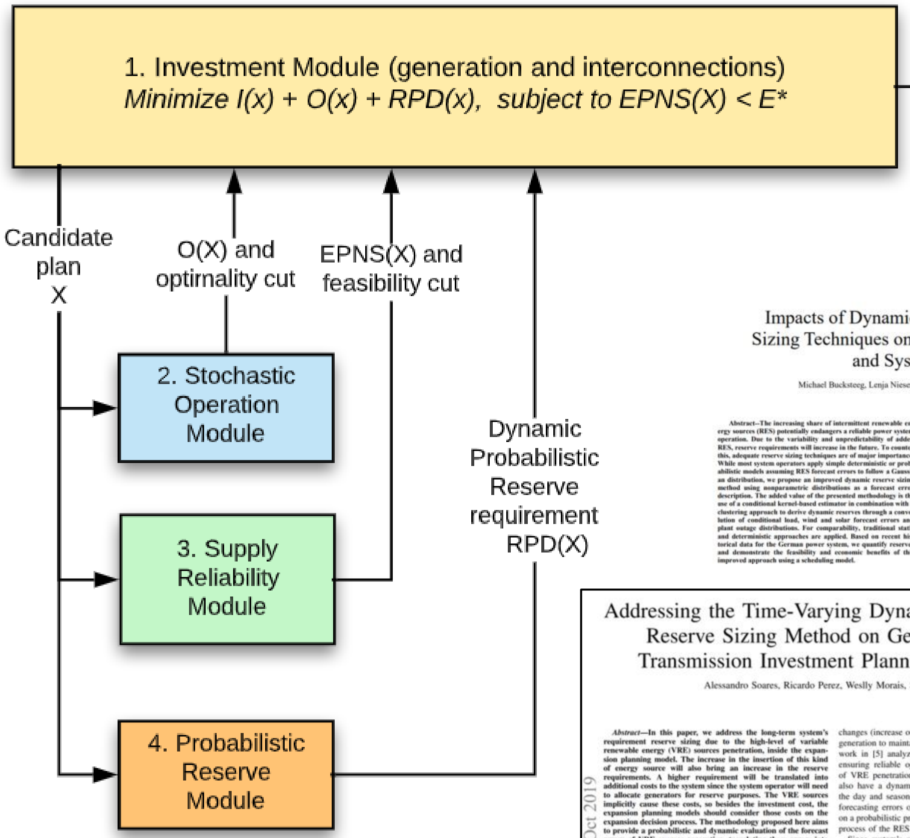
Capacity Planning with flexibility constraints

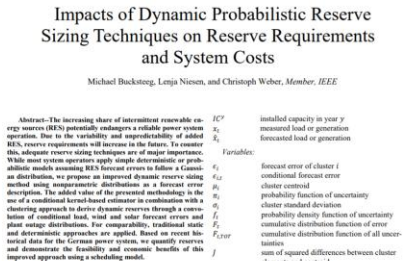
Benders decomposition optimizes the trade-off between investment decisions and the expected value of operative costs obtained from SDDP

The reserve requirement must be a decision variable for the expansion planning model

Dynamic probabilistic reserves (DPR) can be co-optimized together with the investment decisions in an embedded way (endogenously)

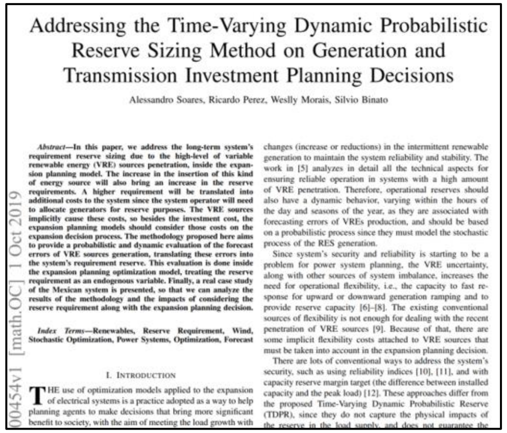
Renewable investment decisions will be made considering the indirect cost that those plants brings to the system by increasing the reserve requirements





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

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

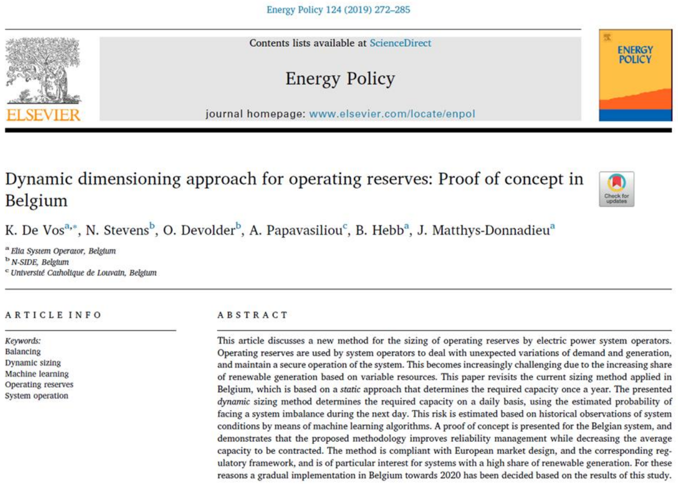


Addressing the Time-Varying Dynamic Probabilistic Reserve Sizing Method on Generation and Transmission Investment Planning Decisions

Alessandro Soares, Ricardo Perez, Wesly Morais, Silvio Binato

The co-optimization allows one to represent the *renewables spatial portfolio effect* (negative spatial correlations imply in less reserve requirement than positive correlations): strategy avoids the concentration of renewables in the same region

Example of DPR (case of Chile)



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ENERGY POLICY

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

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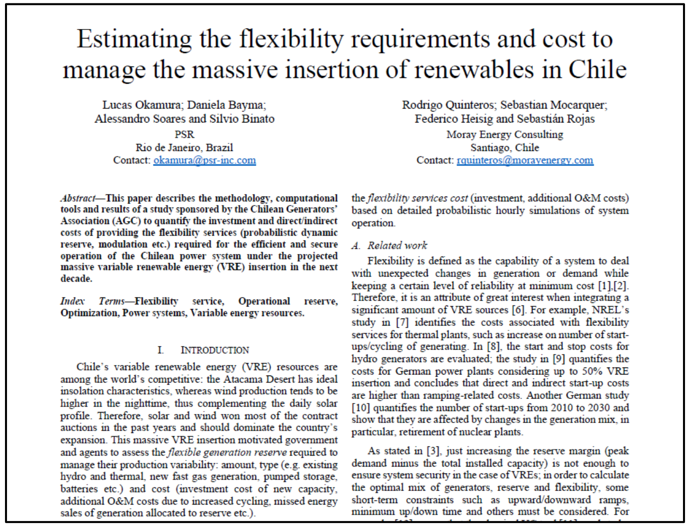
ABSTRACT

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.



Estimating the flexibility requirements and cost to manage the massive insertion of renewables in Chile

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Moray Energy Consulting
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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.**

I. INTRODUCTION

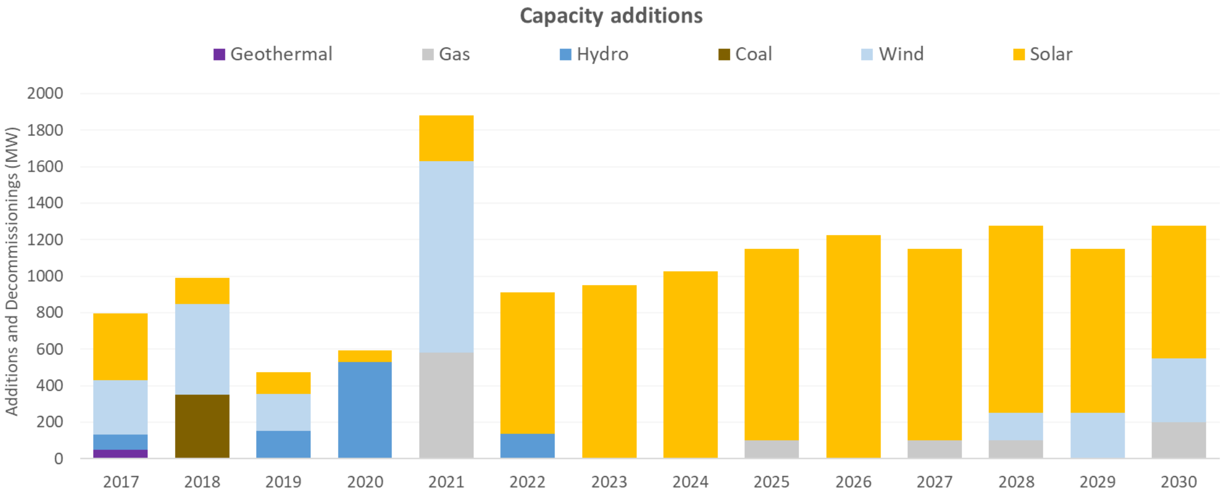
Chile's variable renewable energy (VRE) resources are among the world's competitive: the Atacama Desert has ideal insolation characteristics, whereas wind production tends to be higher in the nighttime, thus complementing the daily solar profile. Therefore, solar and wind won most of the contract auctions in the past years and should dominate the country's expansion. This massive VRE insertion motivated government and agents to assess the *flexible generation reserve* required to manage their production variability: amount, type (e.g. existing hydro and thermal, new fast gas generation, pumped storage, batteries etc.) and cost (investment cost of new capacity, additional O&M costs due to increased cycling, missed energy sales of generation allocated to reserve etc.).

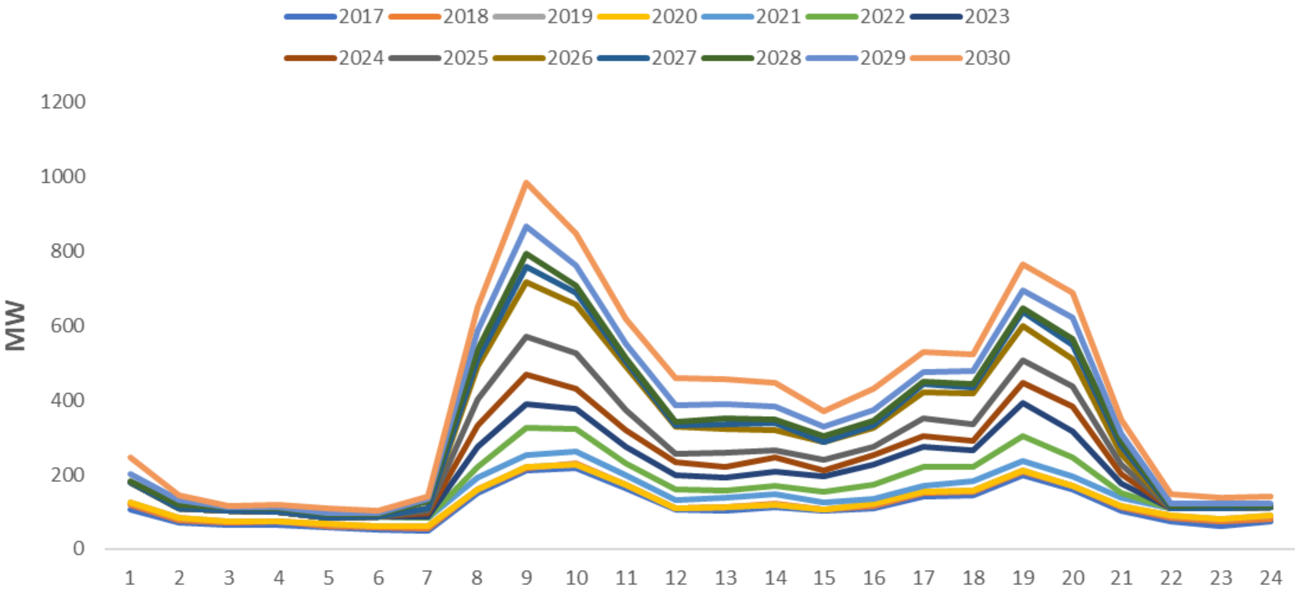
the *flexibility services cost* (investment, additional O&M costs) based on detailed probabilistic hourly simulations of system operation.

A. Related work

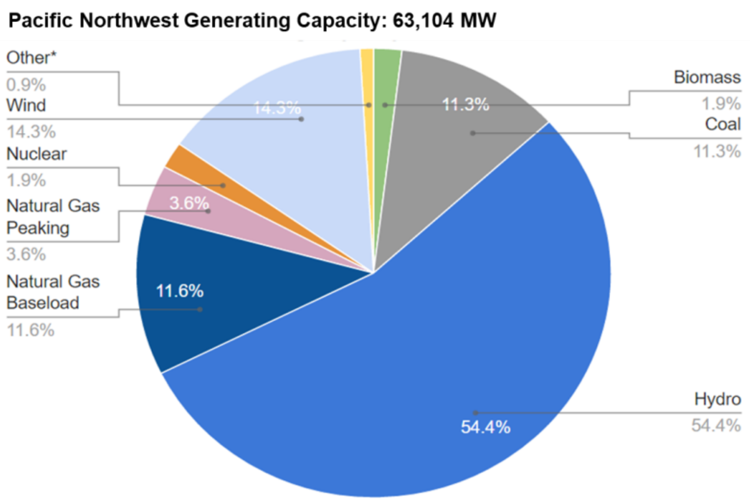
Flexibility is defined as the capability of a system to deal with unexpected changes in generation or demand while keeping a certain level of reliability at minimum cost [1],[2]. Therefore, it is an attribute of great interest when integrating a significant amount of VRE sources [6]. For example, NREL's study in [7] identifies the costs associated with flexibility services for thermal plants, such as increase on number of start-ups/cycling of generating. In [8], the start and stop costs for hydro generators are evaluated; the study in [9] quantifies the costs for German power plants considering up to 50% VRE insertion and concludes that direct and indirect start-up costs are higher than ramping-related costs. Another German study [10] quantifies the number of start-ups from 2010 to 2030 and show that they are affected by changes in the generation mix, in particular, retirement of nuclear plants.

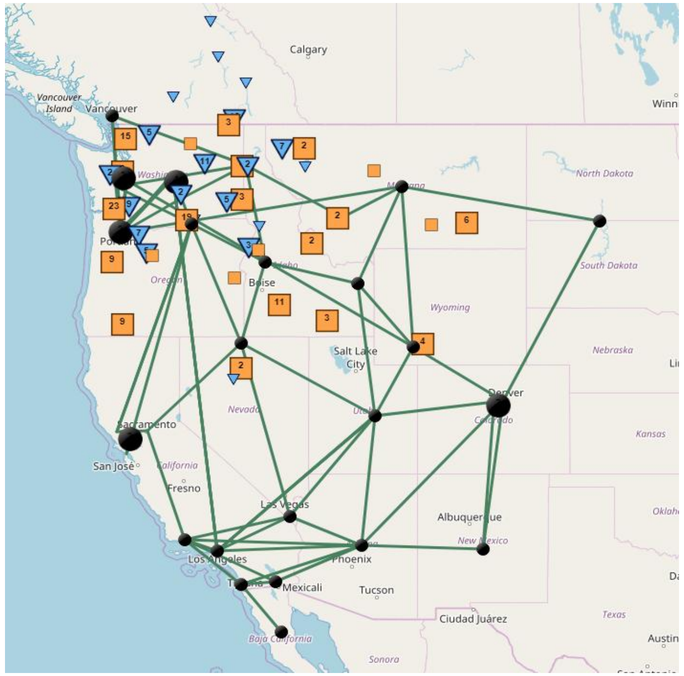
As stated in [3], just increasing the reserve margin (peak demand minus the total installed capacity) is not enough to ensure system security in the case of VREs; in order to calculate the optimal mix of generators, reserve and flexibility, some short-term constraints such as upward/downward ramps, minimum up/down time and others must be considered. For





The Genesys 2.0 model





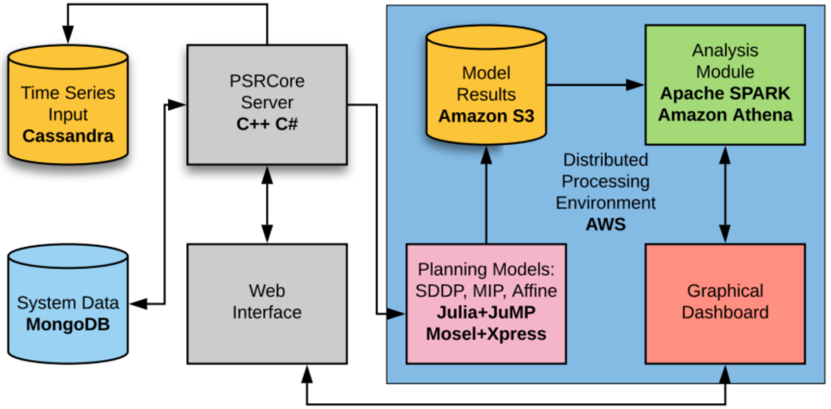
- Emulate the real-life operation with as many details as possible
- Assess performance indices (LOLP, generation marginal costs etc.)
- Taking into account load uncertainty
- Inflow + Renewable uncertainty
- Large share of hydro generation with detailed operation
- 15 balancing markets

The problem solved

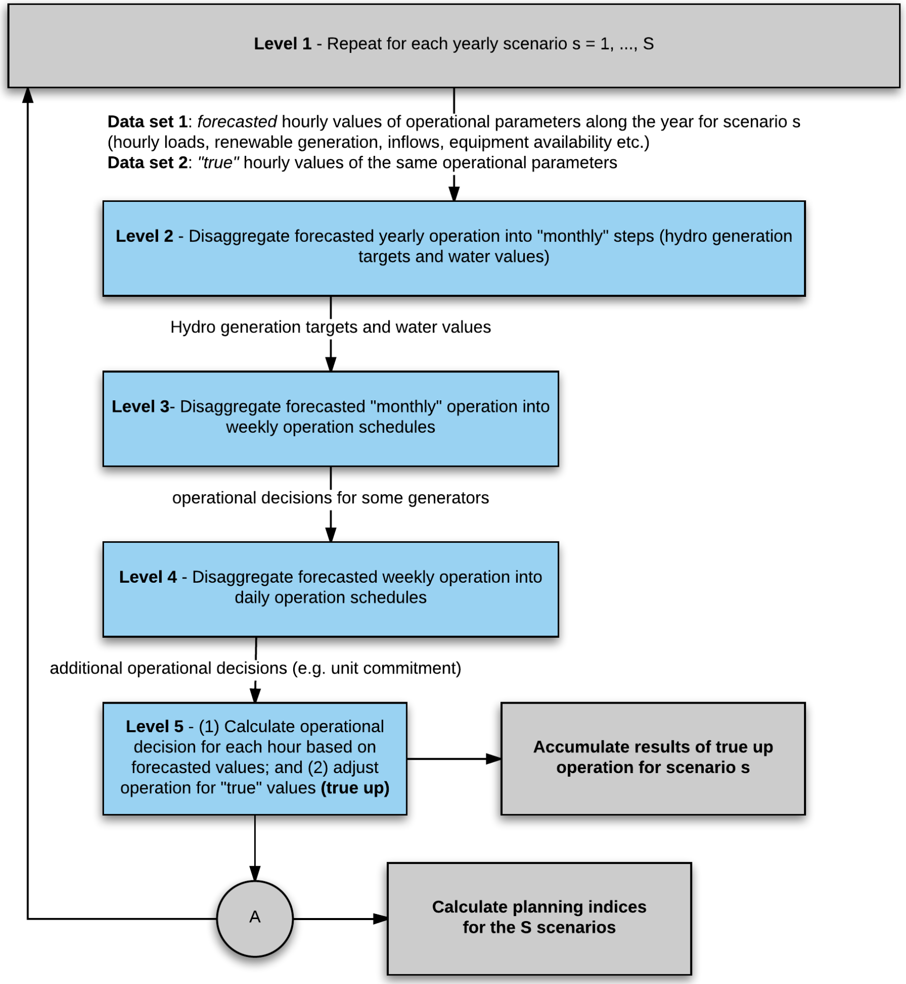
- Medium term planning (weeks ahead): water values, “slow” unit commitments
- Day ahead operation: Fuel contracts, Market trading
- Hour ahead operation
- Detailed hydro-thermal operation: real time operation (“true up”)
- Redispatch under uncertainty: with limited resources

Repeat for 6,000 scenarios and solve in 8 hours!

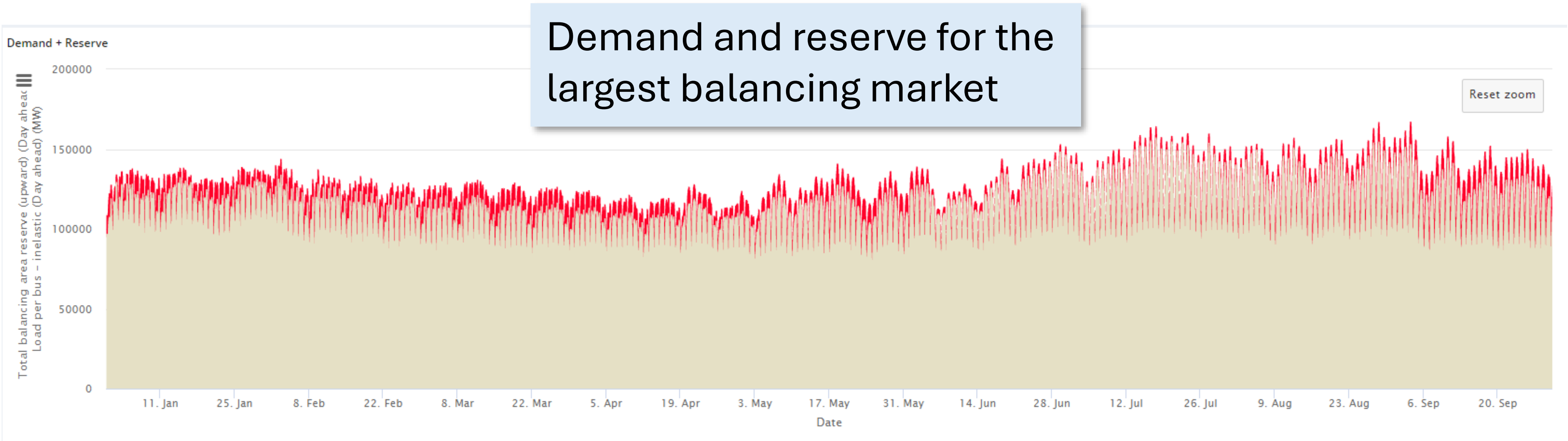
Total 108 million MIPs, 10 Tbytes output files

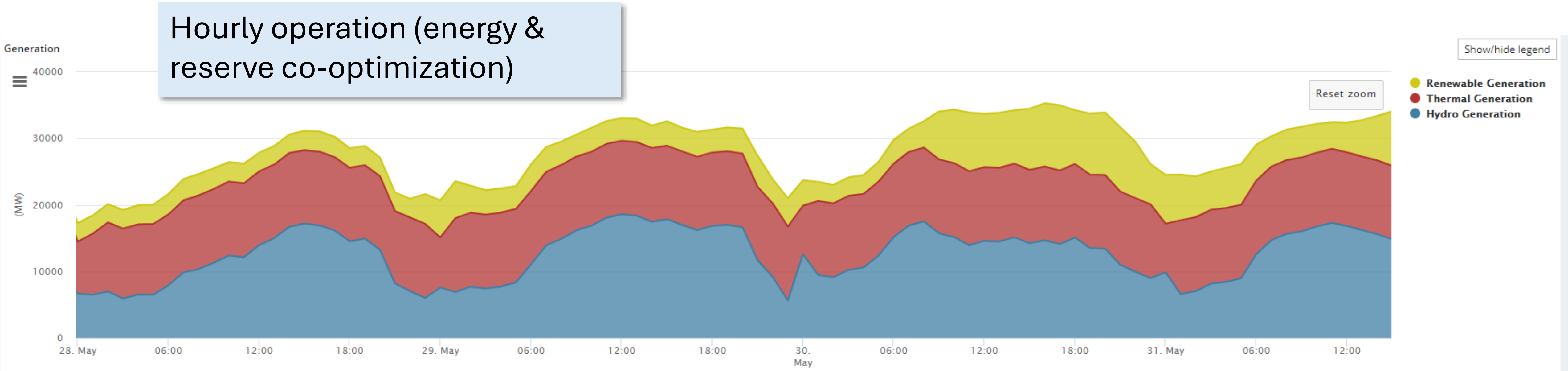


Solved in about 6 hours using PSR Cloud with 30,000 cores



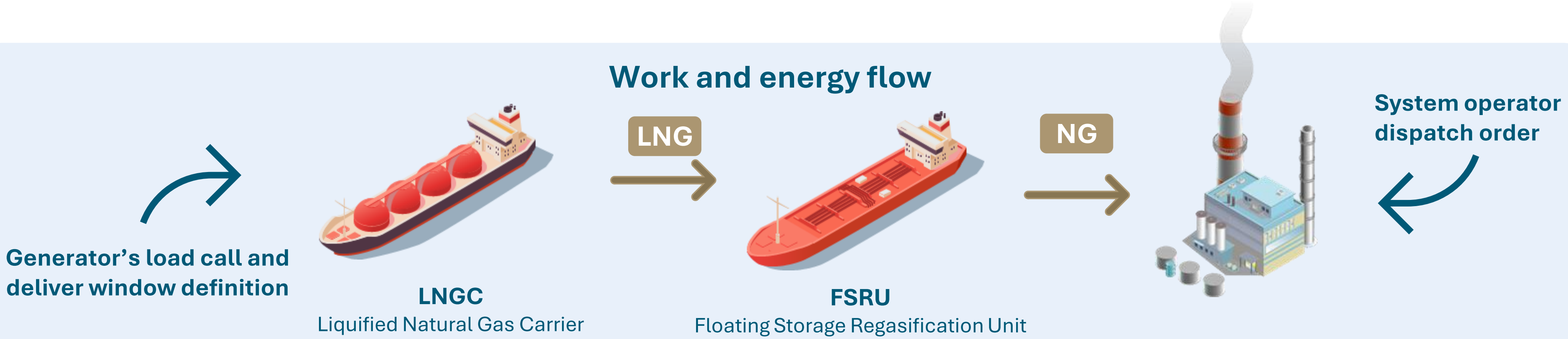
Optimal operation Genesys 2.0 (US Pacific Northwest)W





Optimal LNG contracting and scheduling for power generation

Work and energy flow



OPERATIVE CONSTRAINTS

- Power plants' activation sequency
- FSRU activation and hibernation
- Fuel transfer rate limits
- Fuel consumption curve

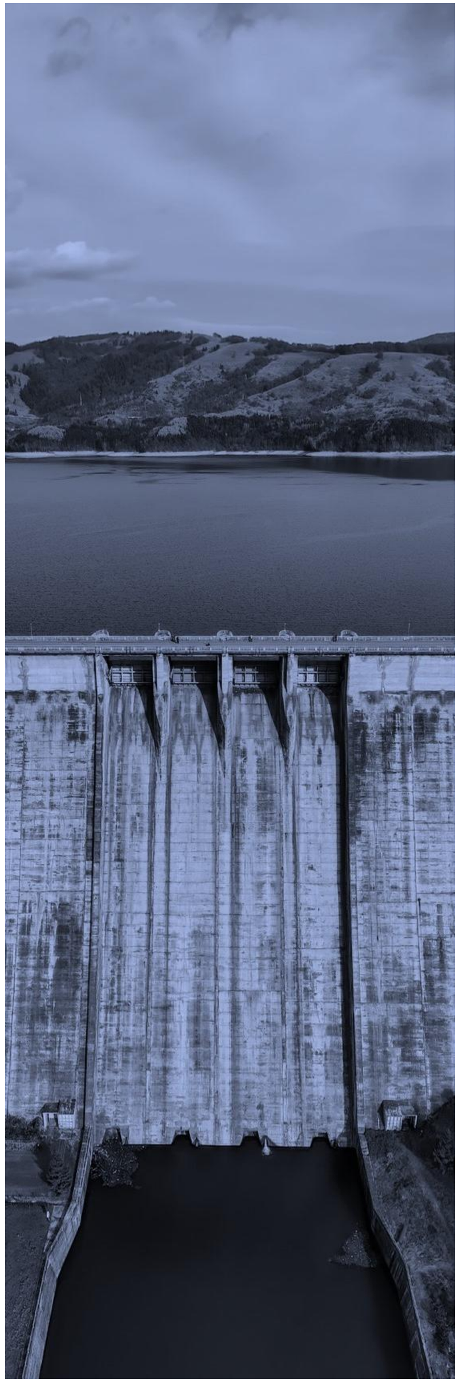
SOURCES OF UNCERTAINTIES

- Meteoceanographic conditions
- LNGC logistics
- Regulatory services
- Dispatch uncertainty
- Carrier fuel load volume

ADVANCED MODELING

- Deliver window allocation
- Multiple thermal plants with different fuel balances
- Fuel loan
- Split nomination calls

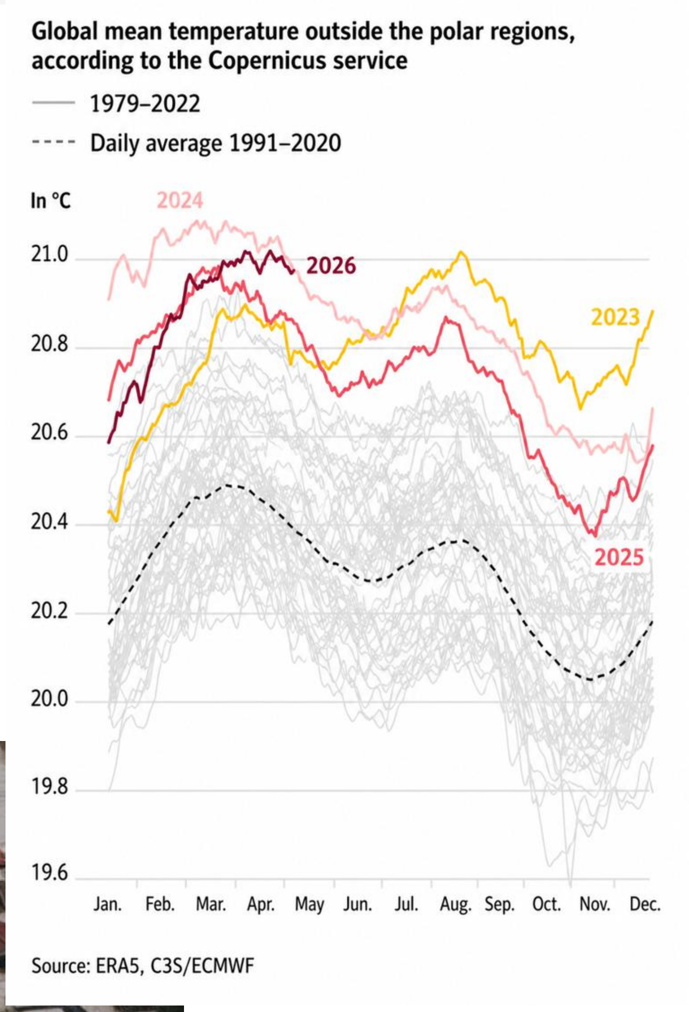
Due to the high number of binary variables, the problem is decomposed using Progressive Hedging



3 | Integrated AI-based Climate Modeling and Stochastic Optimization

Why this topic matters now: the “new normal” for weather / climate

- The energy transition is increasing reliance on weather-sensitive resources: hydro, wind, and solar
- The “**New Normal**” for weather / climate has arrived: strong evidences that the extreme events that took place worldwide in 2023 and 2024 are structural
- Possibly / probably the situation will get worse
- It is urgent to **adjust the stochastic scenarios** of inflow, wind, temperature etc. and operation + planning criteria to the new reality
- **Adaptation** measures (resilience) are as important as mitigation



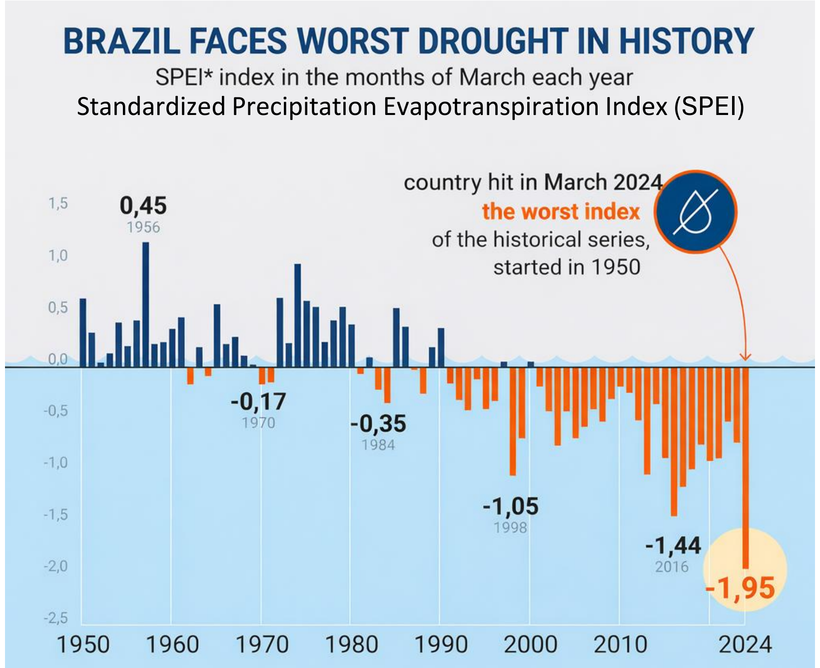
CLIMATE CRISIS

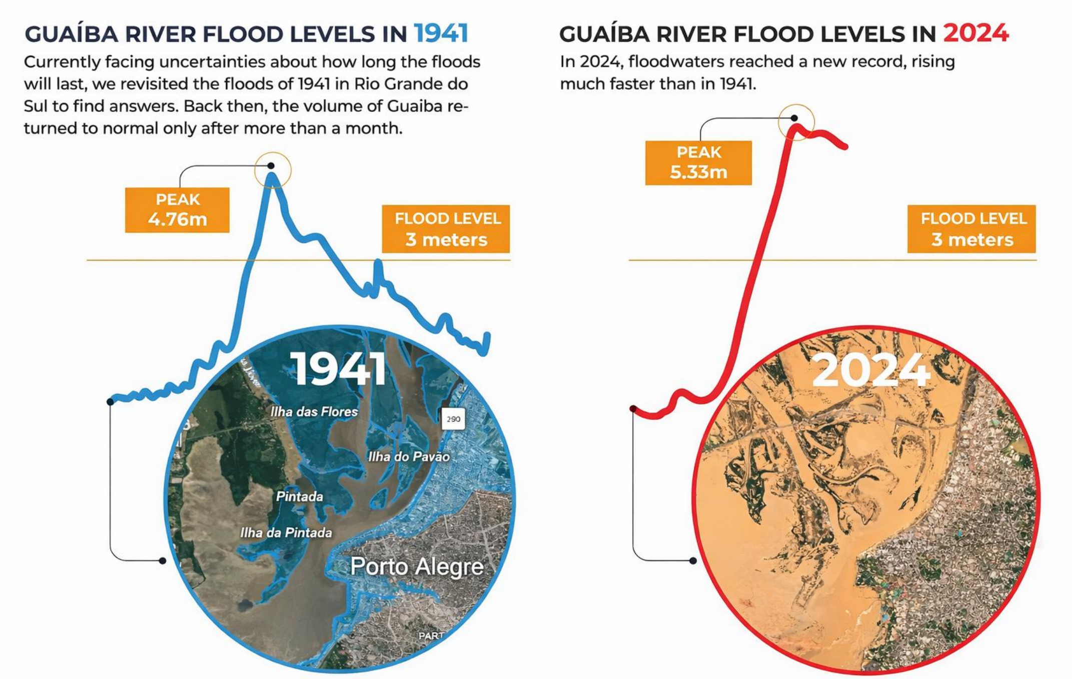
Heat waves: Brazil surpasses 50 days per year of high temperatures

The core problem: planning under non-stationary uncertainty

The issue is not just volatility, it is a structural change in probability distributions

- Climate change affects the distribution of inflows, temperature, wind, radiation, and extreme events;
- PSR studies highlight lower averages in some cases and heavier tails: higher probability of droughts and floods;
- **Traditional stationary models** assume future statistical properties equal the past: **increasingly fragile**;
- This affects energy planning as a whole: operation, adequacy, investment decisions.

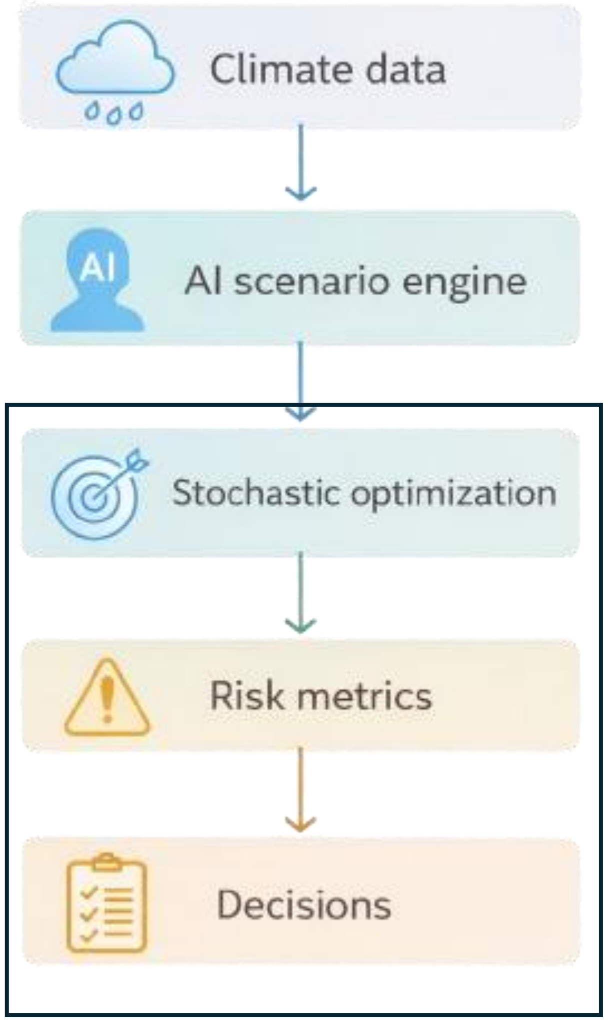




PSR Integrated Framework: from weather to decisions

- **PSR's framework integrates:** climate information, AI-based scenario generation, stochastic optimization, risk metrics, and economic / resilience assessment;
  - **Produce climate-change adapted scenarios → quantify system impacts → evaluate benefit-cost of adaptation measures**
- Requires multidisciplinary integration of meteorology, AI, physical system modeling, and optimization.

Better energy decisions require connecting climate science to economic and operational models.



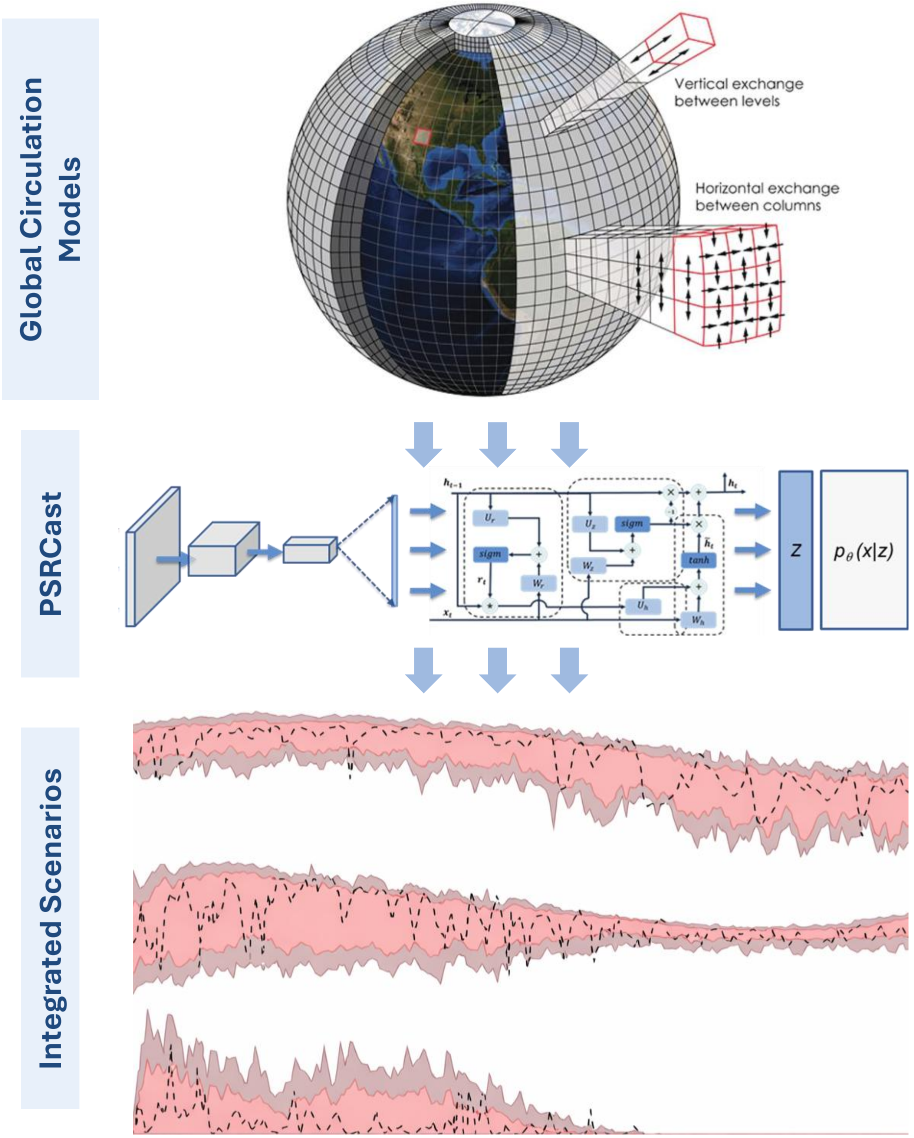
SDDP-based methods

AI-Based Climate Modeling: PSRCast

- PSRCast generates **integrated scenarios** for temperature, insolation, precipitation, wind, inflows, and other energy-relevant variables across short, medium, and long-term horizons
- Uses information from well-established meteorological / climate groups such as ECMWF* and GFS and from AI Large Weather Models such as Google's Graphcast

PSRCast uses AI and external forecasts produced by publicly available climate models

Translates global climate information into integrated stochastic scenarios for energy decisions, ensuring coherence between ensemble forecasts from different circulation models and horizons (day ahead to > 30 years ahead)

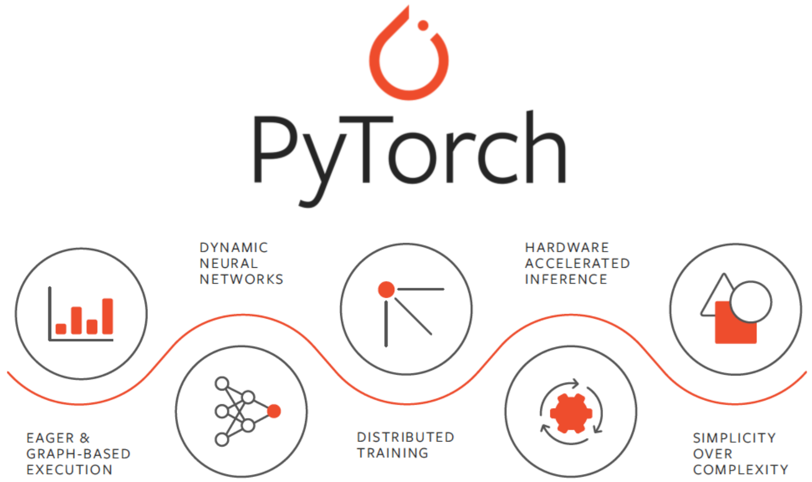


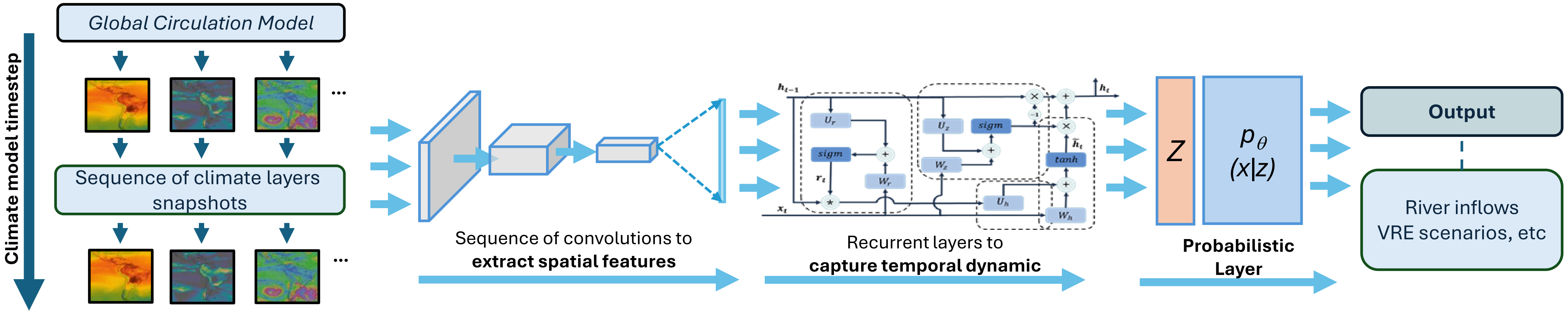
*ECMWF: European Centre for Medium-Range Weather Forecasts; GFS: Global Forecast System (NOOA), a National Centers for Environmental Prediction (NCEP) weather model

How PSRCast Works

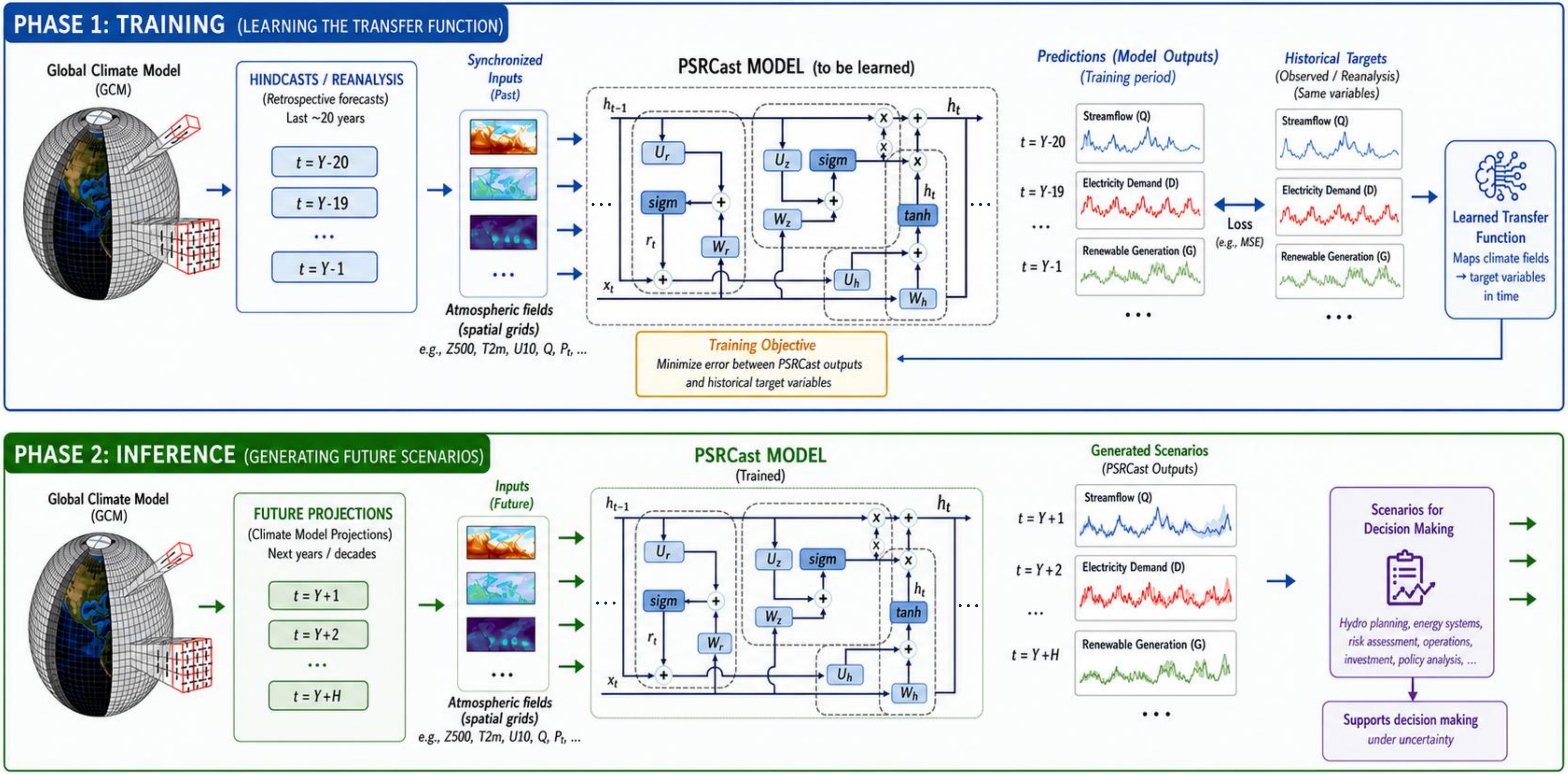
PSRCast uses modern deep learning to capture spatial patterns, temporal dynamics, and probabilistic uncertainty.

- Architecture (implemented using the ***PyTorch*** framework) combining:
  - Convolutional layers to identify spatial patterns
  - Recurrent layers to capture temporal dynamics;
  - Probabilistic/generative layers to represent distributions and generate scenarios;
- The framework preserves spatial and temporal correlations across multiple variables and locations.
- The output is not a single forecast: it is a stochastic representation suitable for decision-making

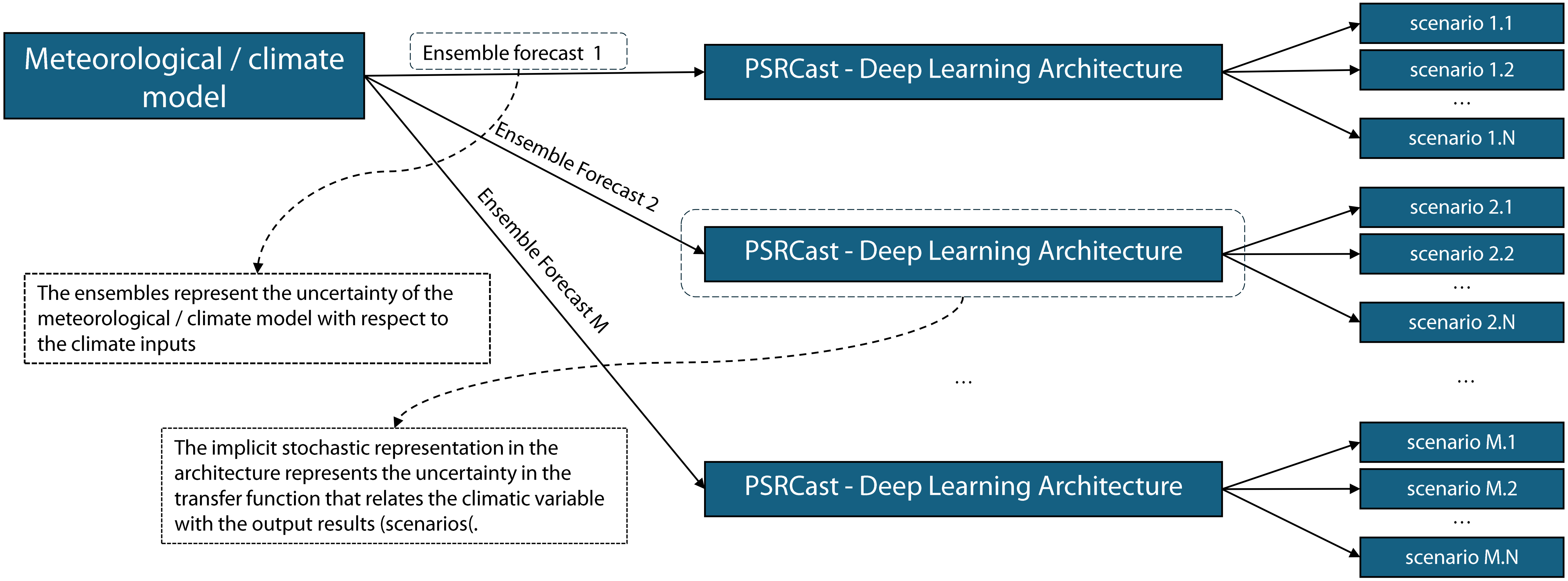




How PSRCast Works



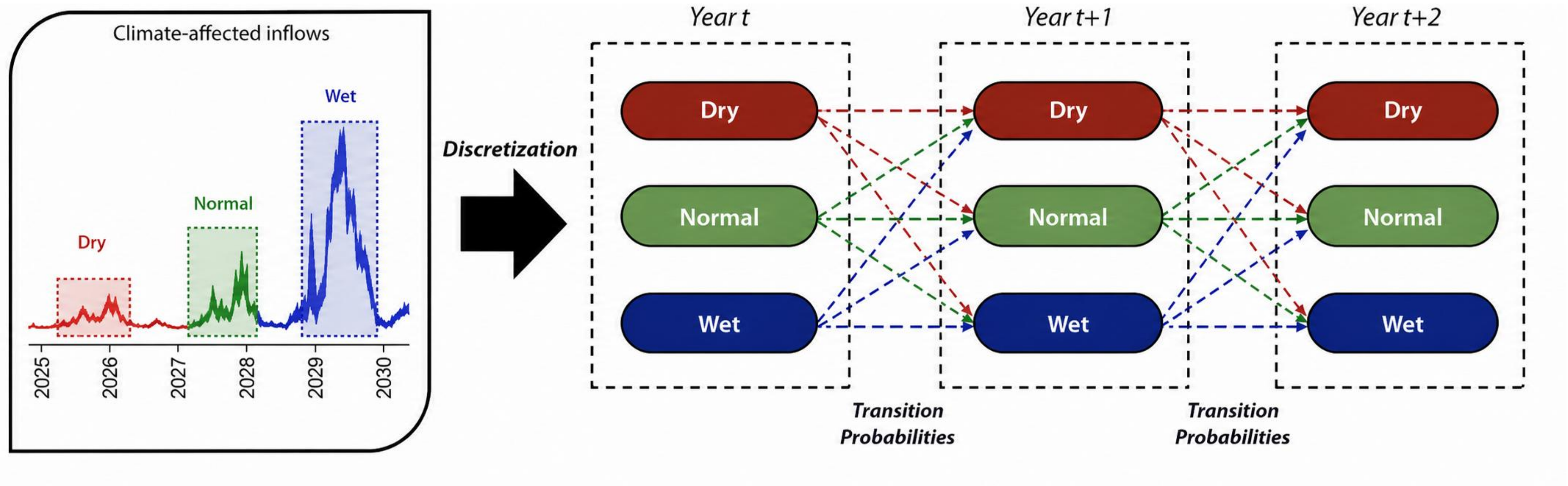
Generating multiple scenarios



- Climate models typically produce a set of possible future projections, known as an ensemble, rather than a single deterministic forecast, due to the high uncertainty associated with long-term climate predictions;
- The combination of the uncertainty of the meteorological model, represented by the ensemble, with the uncertainty captured by the architecture results in a set of plausible integrated scenarios (inference applied to each ensemble)

Hybrid SDDP-Markov Model

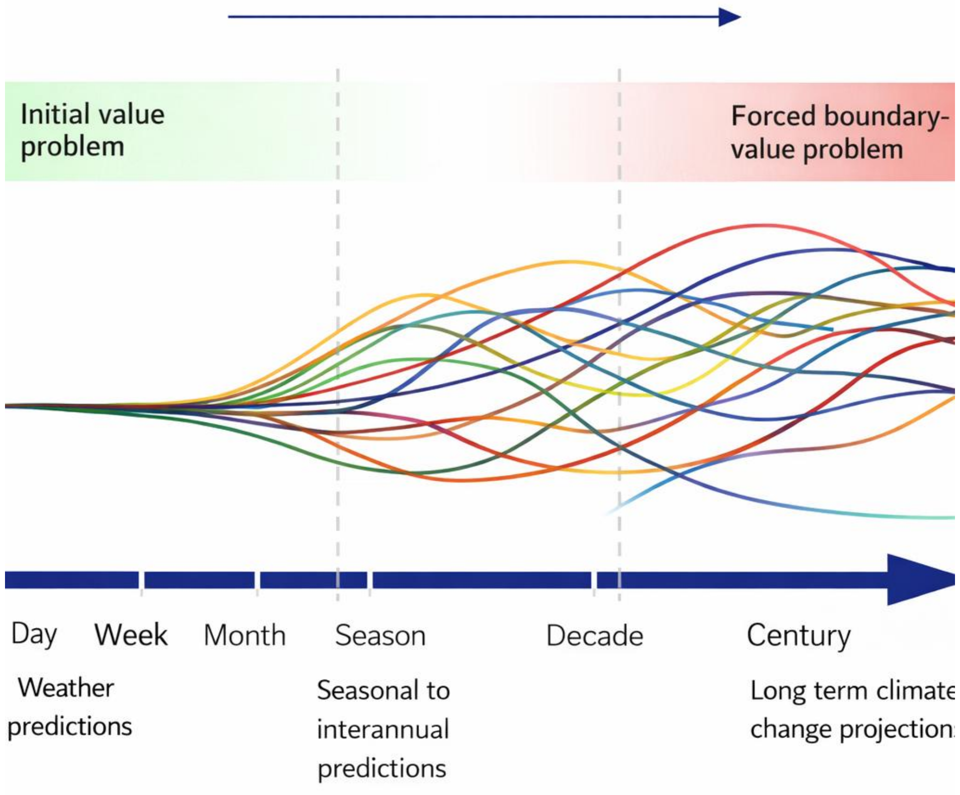
- SDDP usually requires the inflows to be represented by **PAR(p) models**, which are **convex**;
- Climate-affected scenarios exhibit more frequent extreme droughts and floods: not well represented by linear PAR(p) models
- PSR's solution: represent inflows using Markov-chain segments (Ex:, drought, normal, wet)
- The hybrid model adjusts a PAR(p) inflow model for each cluster of a Markov chain applied to the PSRCast scenarios. This allows the representation of non-stationarity and macroclimatic events
- All the **analytical properties of the SDDP** algorithm (upper and lower bounds, convergence to the global optimum etc.) **remain valid**



Climate Model Uncertainty: There Is No Single "True" Future

Decision-making must be robust not only to scenarios, but also to disagreement among climate models.

- Even state-of-the-art operational global circulation models already produce materially different trajectories beyond short lead times;
- This divergence grows rapidly with forecast horizon, becoming dominant at seasonal-to-decadal scales;
- This multiplicity is intrinsic to a nonlinear chaotic climate system — it will not disappear with more computing power;
- Planning should explicitly **consider uncertainty about the underlying climate model itself**;
- This motivates robust and **regret-based** decision criteria.



Decision-Making Under Model Uncertainty

When the true future distribution is uncertain, minimizing expected cost under one assumed model may be fragile.

- PSR has used **minimax regret** as an effective way to choose stochastic model parameters;
- The logic: evaluate the consequence of choosing model A when model B turns out to be closer to reality;
- This is related to **distributionally robust thinking**, increasingly relevant in energy planning under climate uncertainty;
- The goal is not only to reduce average cost, but robustness against being wrong.
- We are currently applying the same minimax regret framework to represent the uncertainty of IPCC climate models in long-term planning studies

Regret Matrix Example

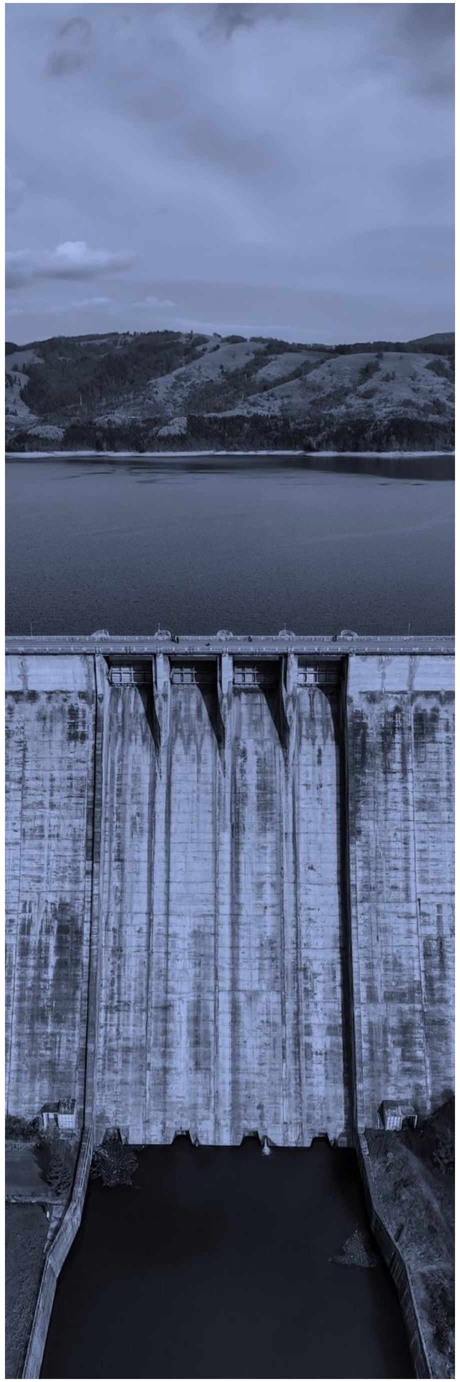
Cost Differences Compared to the Best Model

	ACCESS-CM2	ACCESS-ESM1-5	BCC-CSM2-MR	CMCC-CM2-SR5	EC-Earth3	GFDL-ESM4
ACCESS-CM2	$0	$2.4B	$3.1B	$4.0B	$3.5B	$2.8B
ACCESS-ESM1-5	$1.8B	$0	$2.0B	$3.6B	$2.9B	$3.3B
BCC-CSM2-MR	$2.2B	$1.5B	$0	$2.7B	$2.1B	$2.5B
CMCC-CM2-SR5	$3.5B	$3.7B	$2.6B	$0	$3.0B	$4.1B
EC-Earth3	$2.9B	$2.6B	$1.8B	$3.2B	$0	$2.7B
GFDL-ESM4	$2.1B	$2.8B	$1.9B	$3.8B	$3.0B	$0

Best Model

Moderate Regret

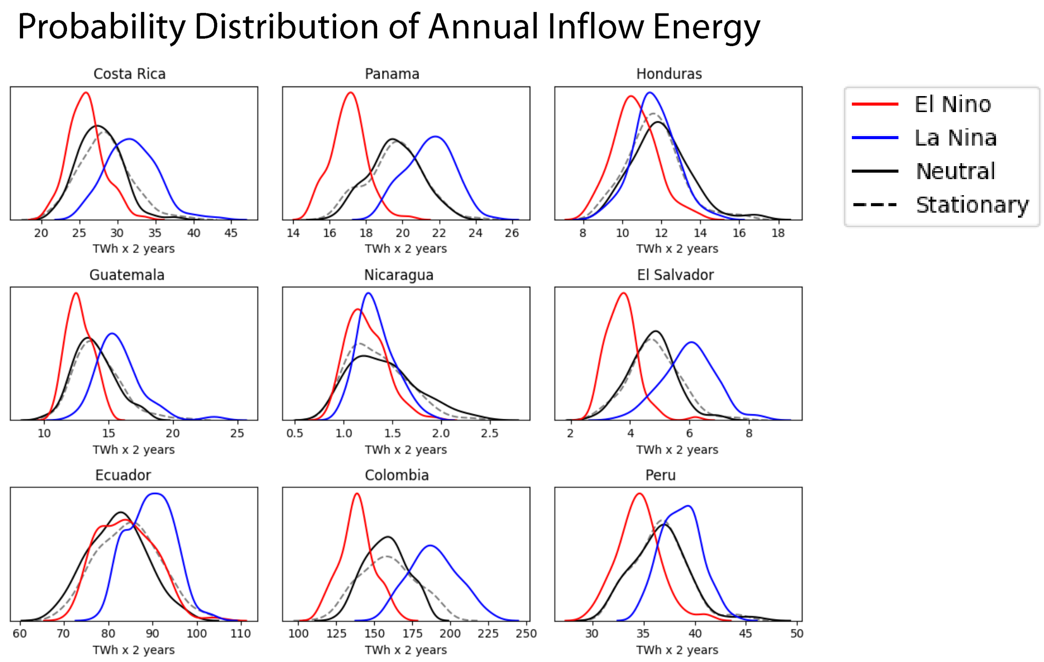
High Regret

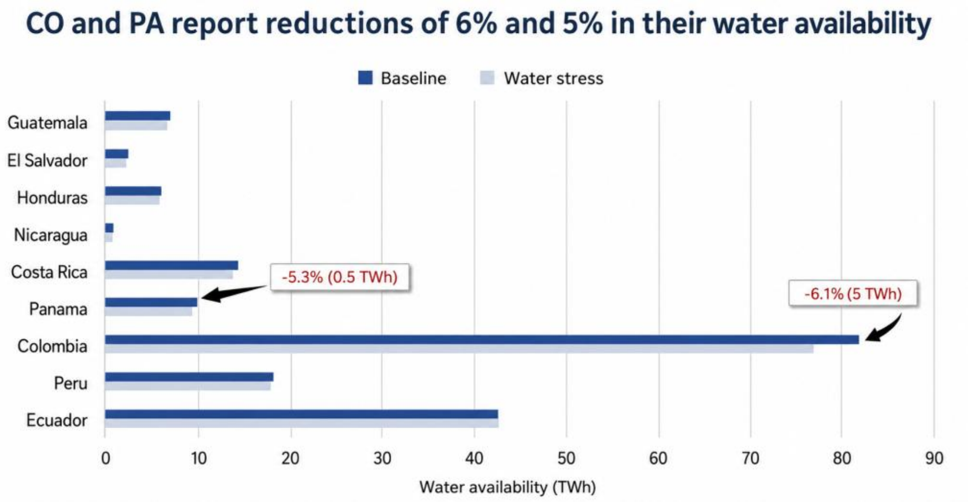


4 Example of applications

Example: Assessment of hydrological stress scenarios in a Colombia–Panama Interconnection Evaluation Study (2025-2035)

- The hydrology of the Andean and Central American countries is strongly influenced by interannual climate cycles such as El Niño–Southern Oscillation events, including El Niño and La Niña;
- We calibrate hydrological scenario generation models conditioned on the occurrence of these events (i.e., the model learns the relationship between streamflow variability and the prevailing climate regime — El Niño, La Niña, or neutral conditions);
- Based on this calibration, hydrological stress scenarios can be simulated from different climate models for the future;
- **Research question**: can we have more extreme El Niño/La Niña events in the future? How the power system reacts/adapts to that?

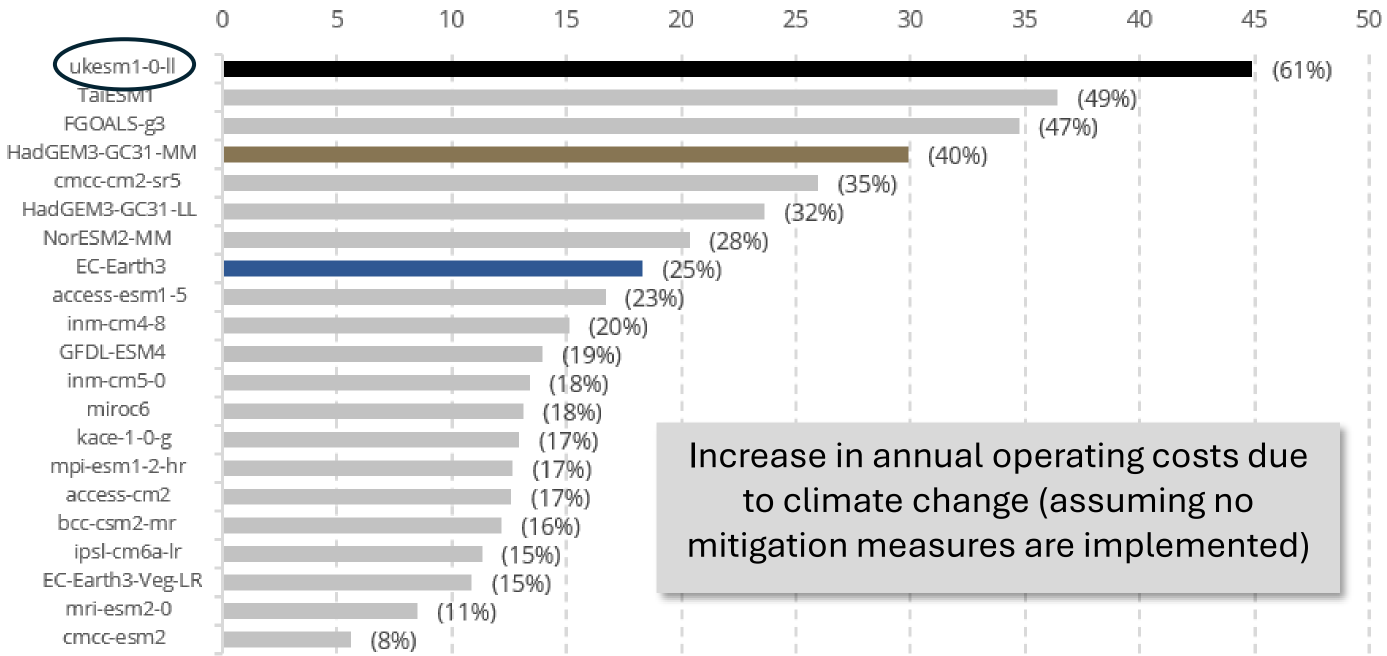




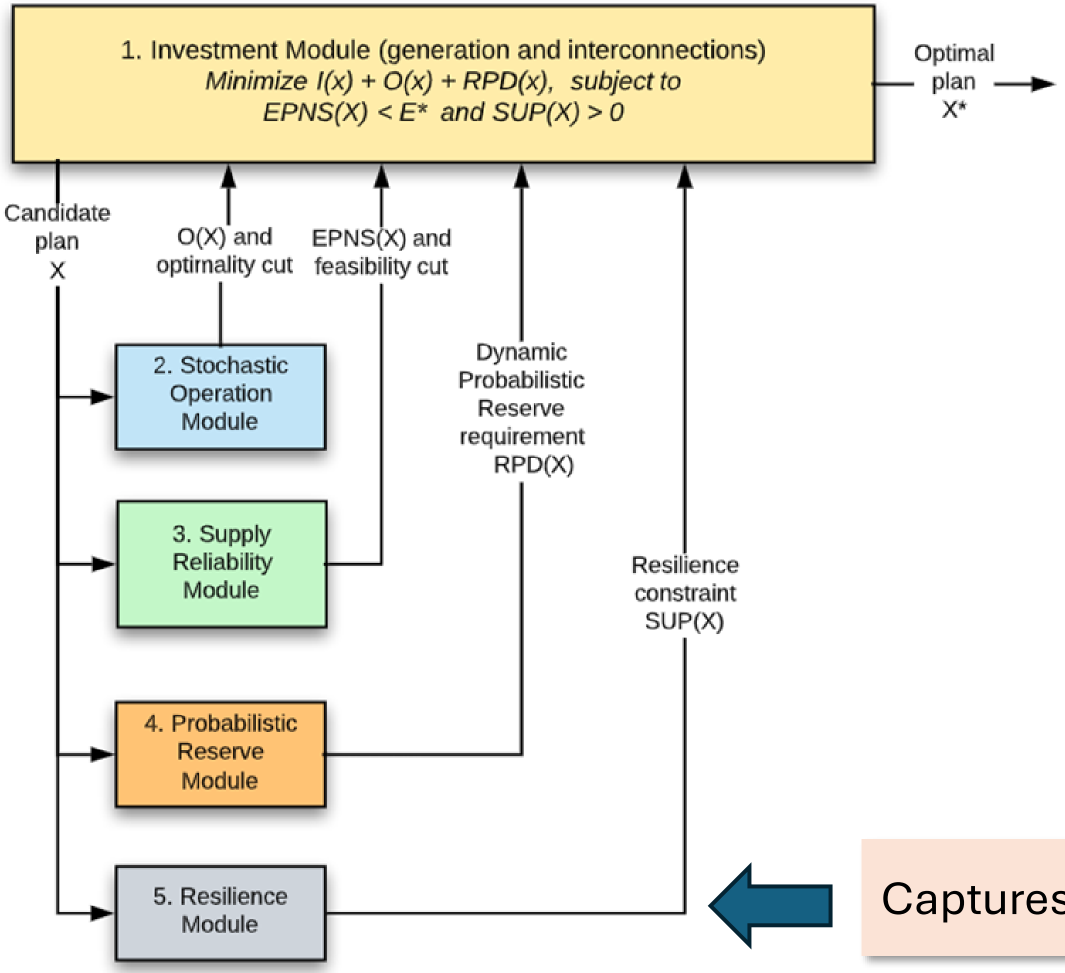
Example: Long-term climate change analysis for Brazil's power system (2040-2070).

- Similar study for Brazil: Utilizing large ensemble of global climate models, we construct estimates of future hydroelectric, solar, and wind generation patterns;
- **Research questions**: what are the impacts of climate change in the power system and how to react/adapt to that? What are the adaptation strategies and costs?

Climate Model	Hydro Generation Variation					Solar Generation Variation					Wind Generation Variation				
	SIN	SE	SU	NE	NO	SIN	SE	SU	NE	NO	SIN	SE	SU	NE	NO
HadGEM3-GC31-MM	-7%	-6%	36%	-17%	-30%	1.0%	1.4%	-0.6%	0.6%	0.0%	2%	0%	7%	1%	-1%
GFDL-ESM4	-18%	-13%	-2%	-42%	-28%	0.9%	1.5%	-0.6%	-0.4%	-0.3%	12%	0%	5%	13%	27%
EC-Earth3	-2%	-1%	35%	-31%	-10%	0.9%	1.6%	-1.5%	-0.1%	-1.6%	2%	0%	5%	1%	-13%
NorESM2-MM	-10%	-8%	13%	-27%	-21%	0.3%	0.6%	-0.3%	-0.3%	-0.6%	3%	0%	4%	3%	-3%
mri-esm2-0	8%	10%	25%	-3%	-3%	-1.1%	-1.2%	-2.0%	-0.7%	-1.3%	0%	0%	1%	0%	-7%
ukesm1-0-ll	-20%	-20%	22%	-32%	-42%	2.2%	2.5%	-0.4%	2.2%	2.2%	8%	0%	6%	8%	7%
EC-Earth3-Veg-LR	14%	12%	37%	12%	5%	0.0%	0.5%	-0.9%	-1.0%	-2.7%	-11%	0%	-14%	-10%	-13%
access-cm2	-2%	1%	51%	-23%	-34%	1.0%	1.1%	-1.9%	2.0%	1.5%	7%	0%	5%	7%	6%
HadGEM3-GC31-LL	-5%	-5%	39%	-9%	-32%	0.9%	1.2%	-0.6%	0.8%	0.8%	3%	0%	7%	2%	4%
cmcc-esm2	5%	10%	24%	-23%	-5%	1.6%	1.5%	0.6%	2.4%	1.3%	5%	0%	5%	5%	0%
cmcc-cm2-sr5	-11%	-6%	20%	-44%	-28%	2.6%	3.0%	1.0%	2.0%	1.9%	5%	0%	6%	5%	3%
ipsl-cm6a-lr	3%	5%	7%	-23%	10%	0.2%	0.8%	-0.7%	-0.9%	-2.6%	6%	0%	9%	5%	-2%
inm-cm4-8	4%	-3%	28%	-36%	31%	2.0%	2.6%	0.3%	1.0%	2.2%	0%	0%	-1%	0%	2%
inm-cm5-0	4%	2%	19%	-25%	14%	1.0%	1.3%	-0.3%	0.2%	1.9%	0%	0%	-1%	0%	5%
bcc-csm2-mr	-6%	0%	17%	-26%	-29%	0.1%	0.4%	-0.6%	-0.3%	-3.0%	5%	0%	11%	3%	0%
mpi-esm1-2-hr	-2%	-3%	28%	-16%	-8%	0.9%	1.4%	-0.3%	-0.2%	-1.1%	3%	0%	8%	2%	-4%
FGOALS-g3	-17%	-18%	20%	-49%	-22%	0.3%	1.5%	-1.7%	-2.4%	-2.6%	2%	0%	7%	1%	-7%
kace-1-0-g	0%	1%	47%	-12%	-28%	0.9%	1.0%	-1.0%	1.2%	1.3%	8%	0%	12%	7%	12%
access-esm1-5	-3%	-1%	54%	-21%	-35%	0.4%	1.0%	-1.5%	-0.9%	-0.6%	4%	0%	6%	3%	-2%
miroc6	-3%	-1%	11%	-19%	-10%	0.6%	0.8%	1.3%	-0.3%	0.5%	2%	0%	7%	1%	4%



Capacity Planning with flexibility + resilience constraints



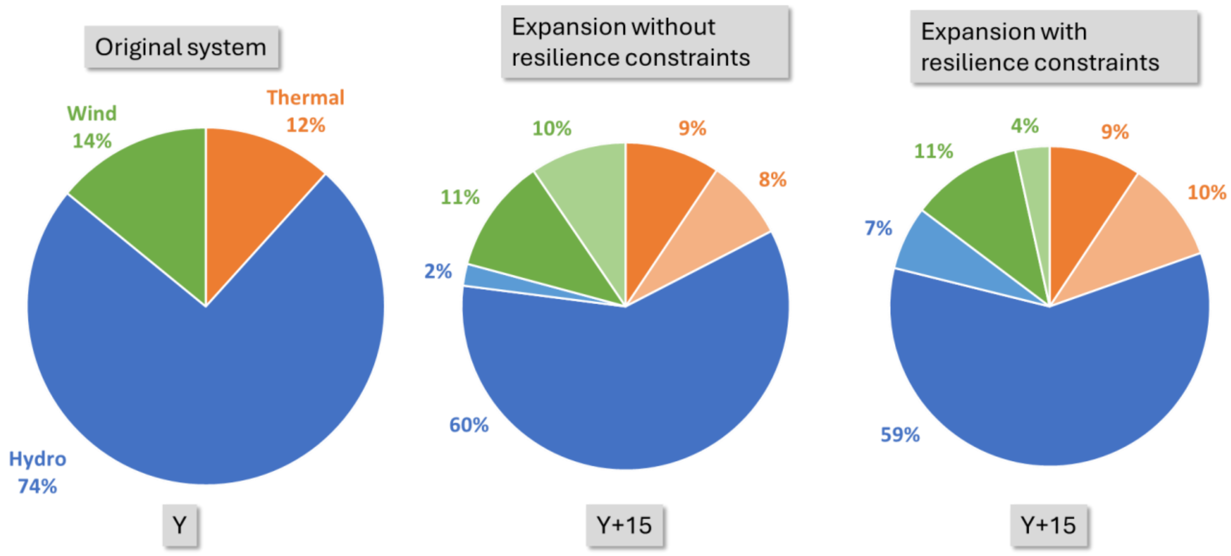
- **PSR structures adaptation around three steps:**
  - generate extreme scenarios
  - assess physical and operational impacts
  - evaluate benefit-cost of adaptation measures
- This framework applies to power systems, transmission and distribution assets, sanitation systems, and hydro dam safety

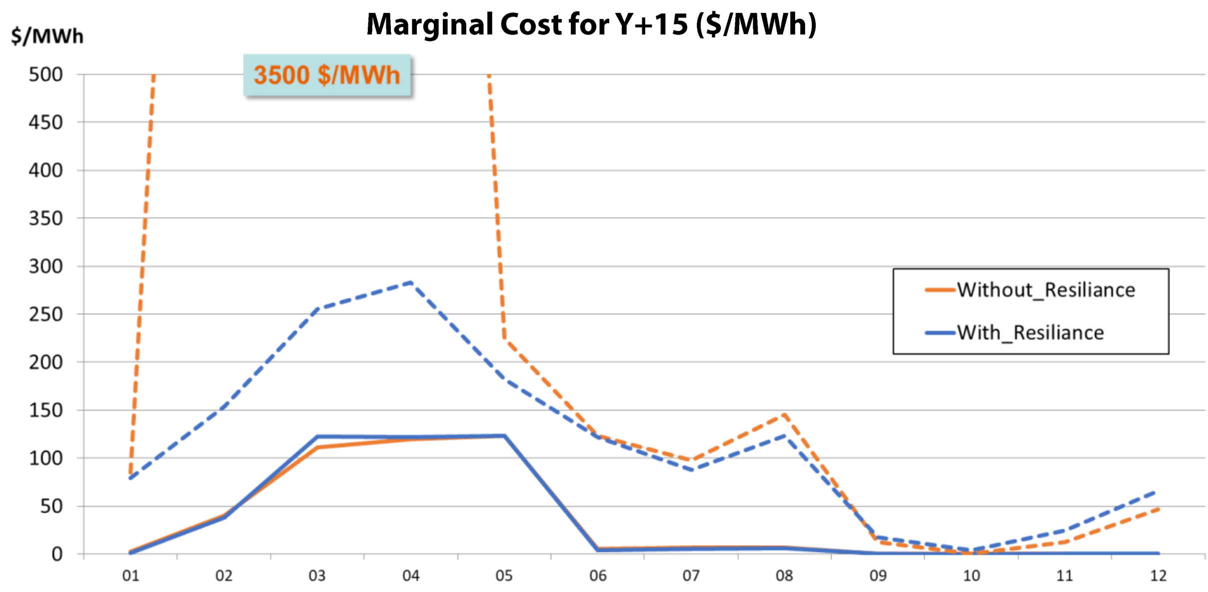
Captures high-impact low-probability (HILP) events produced by PSRCast

Example: resilience study in Costa Rica

Research question: how to plan with resilience?

Resilience event: severe wind reduction





Change in the supply mix: more diversification on the supply

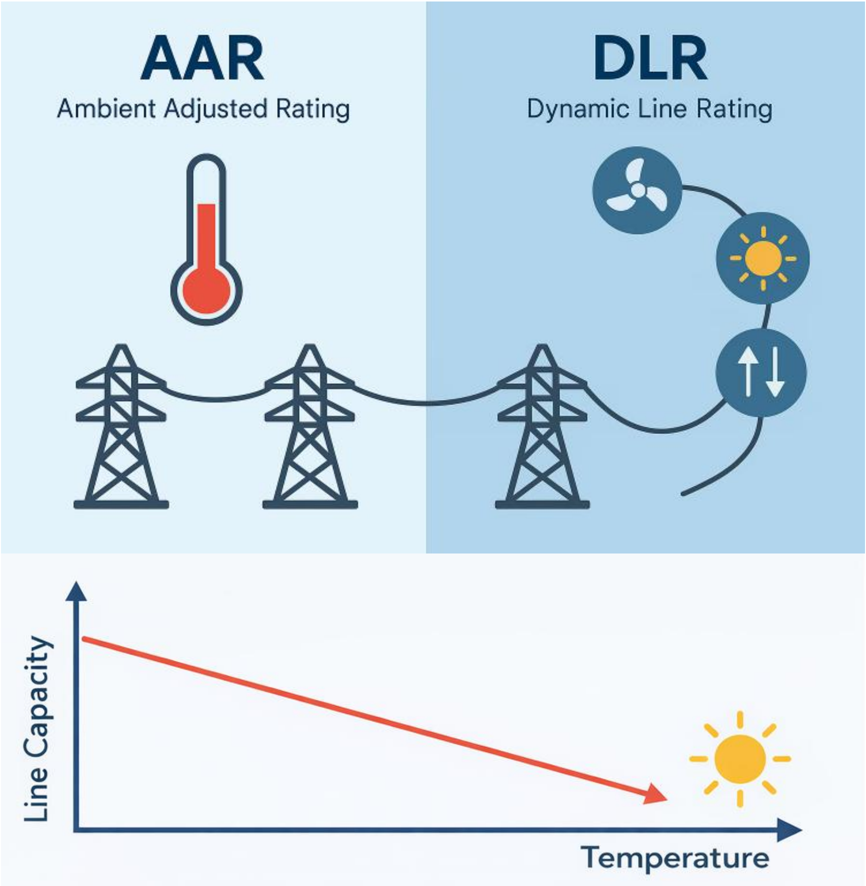
The extreme event is supported with lower marginal costs

Resilience means **more diversification** and avoids excessive costs to consumers in case of extreme events

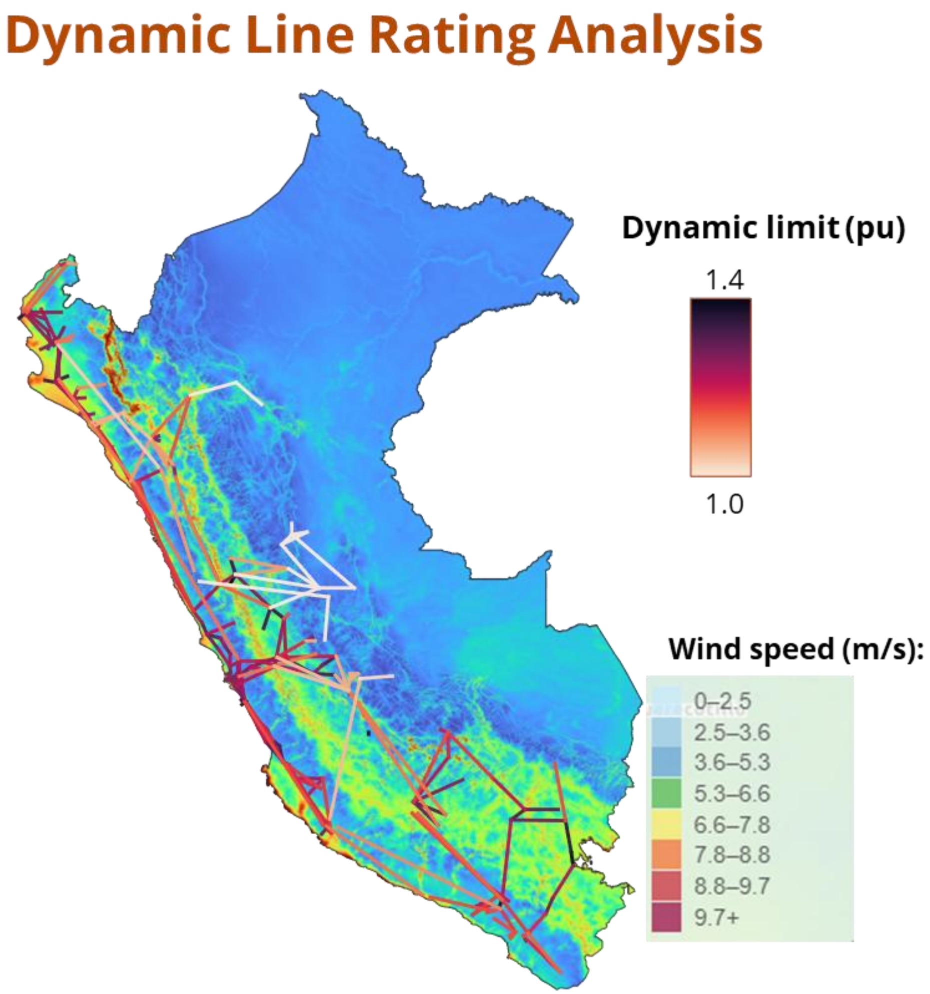
Network Constraints and Weather-Dependent Grid Performance

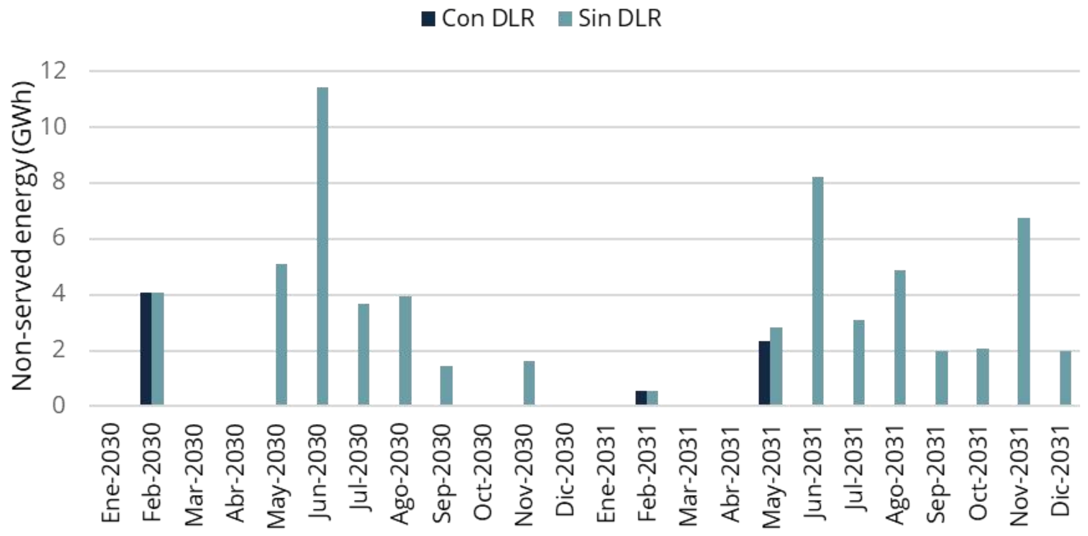
The energy transition is increasingly constrained by networks, and climate affects network capability as well.

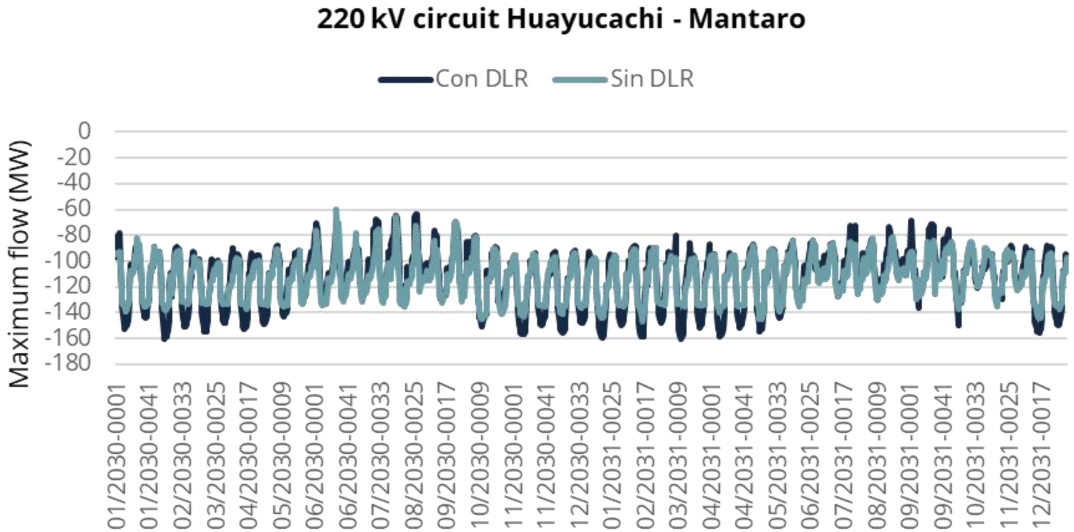
- Renewable-rich systems require congestion-aware operation and expansion planning;
- **Dynamic Line Rating**: wind and temperature scenarios along transmission corridors calculate line capacity per stage and scenario in PSR models;
- The same logic represents temperature impacts on thermal plant efficiency and equipment reliability;
- Weather-sensitive equipment parameters can be incorporated without changing the optimization algorithm itself.

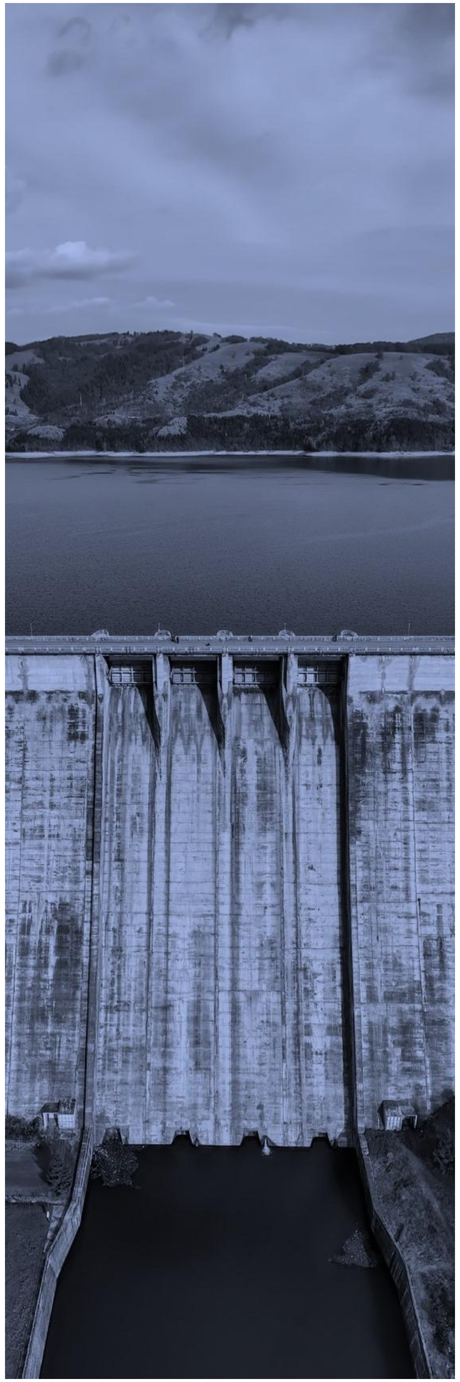


Transmission expansión in Peru with DLR (2036–2050)









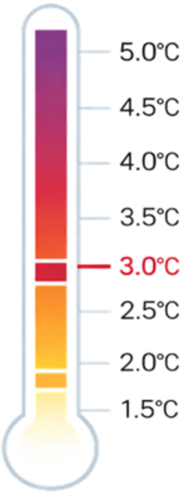
5 | Key takeaways

Climate risk management is a new priority

A new set of risks is now shaping strategic decisions

FINANCIAL
Assess impacts on cash flows of projects and companies

INSURANCE
Develop new methodologies for calculating exposures and revise premiums



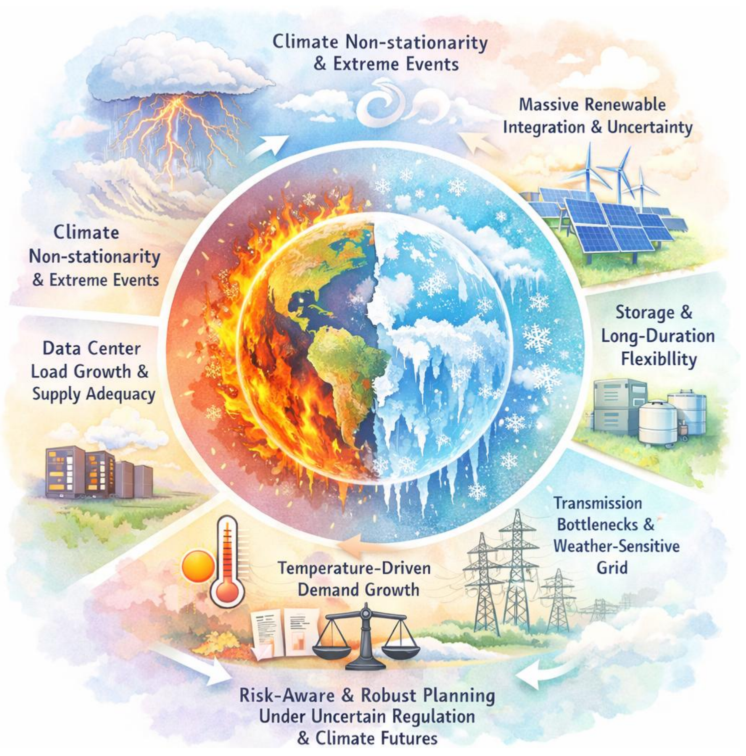
INFRASTRUCTURE
Anticipate changes in the frequency of extreme events to adapt infrastructure

REGULATORY AND LEGAL
Revise regulatory frameworks and contract clauses to mitigate litigation

ENERGY PRODUCTION
Adapt planning to structural shifts in the availability and volatility of renewable resources

Key Takeaways

- Historical data alone is no longer enough for large-scale energy planning under climate change
- AI-based climate modeling improves the generation of decision-relevant stochastic scenarios
- Multistage stochastic optimization translates those scenarios into economically efficient and risk-aware decisions
- Flexibility, resilience, and network constraints must be treated jointly
- The future of energy planning lies in integrating better climate intelligence with better stochastic decisions



The energy transition needs integrated climate intelligence and stochastic decision support

In addition to the classic literature, further reading

- J. Dias (2024), *Deep Learning for Hydroelectric Optimization: Generating Long-Term River Discharge Scenarios with Ensemble Forecasts from Global Circulation Models* (https://arxiv.org/abs/2412.12234)

- J. Dias (2023), *Long-Term Hourly Scenario Generation for Correlated Wind and Solar Power combining Variational Autoencoders with Radial Basis Function Kernels* (https://arxiv.org/abs/2306.16427)

PSR Analytics Report May 2026:

- Can AI agents learn to operate a hydrothermal system? An experiment in reasoning, domain capabilities, and Model Context Protocol
- SDDeeP: Blending Optimization and Reinforcement Learning for Hydrothermal Dispatch
- GPU-Based Algorithms for Large-Scale Optimization
- How AI reasoning unlocked the next generation of software engineering
- AI reasoning in math and coding: a stochastic generation-expansion solver

Request the upcoming PSR Analytics Report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