SimSEE

https://simsee.org

Simulación y Despacho Óptimo de Sistemas Eléctricos

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The keys to the kingdom

Part I

- **Optimal operation**
- **Hydraulic, wind and solar variability**
- **Bellman's recursion and curse**

Part II

- **ROCF, short-circuit, powerflow**
- **DBESS**
- **The OddFace Investment Optimizer**

The ultimate goal

Let the tree not hide the forest nor vice versa

Time horizons for operation and analysis

- **milliseconds:** Generator statism - distributed control / Protections.
- **seconds:** Frequency regulation - generator instructions.
- **minutes:** Rotating Operating Reserve (2.1% of Demand)
- **10 to 20 minutes:** Flexible Reserve (2.1% of Demand)
- **>= 20 minutes:** Cold Reserve. (3% of Demand; 20 minutes)

- **hours:** Monitoring of Hourly Demand
- **days:** Scheduling of resource use
- **months:** Reservoir optimization and fuel management
- **years:** Investment optimization

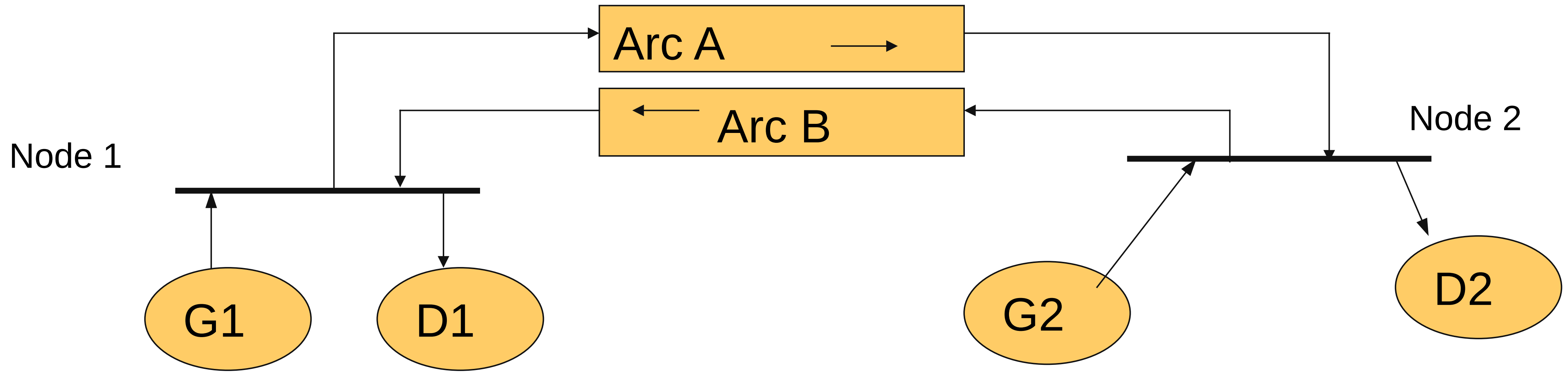
Security

$ Optimization

SimSEE, a simulation platform as a toolbox
Why and for what?

A model is a simplified representation of reality

Nodes, Arcs, Generators and Demands



Energy dispatch programming horizons

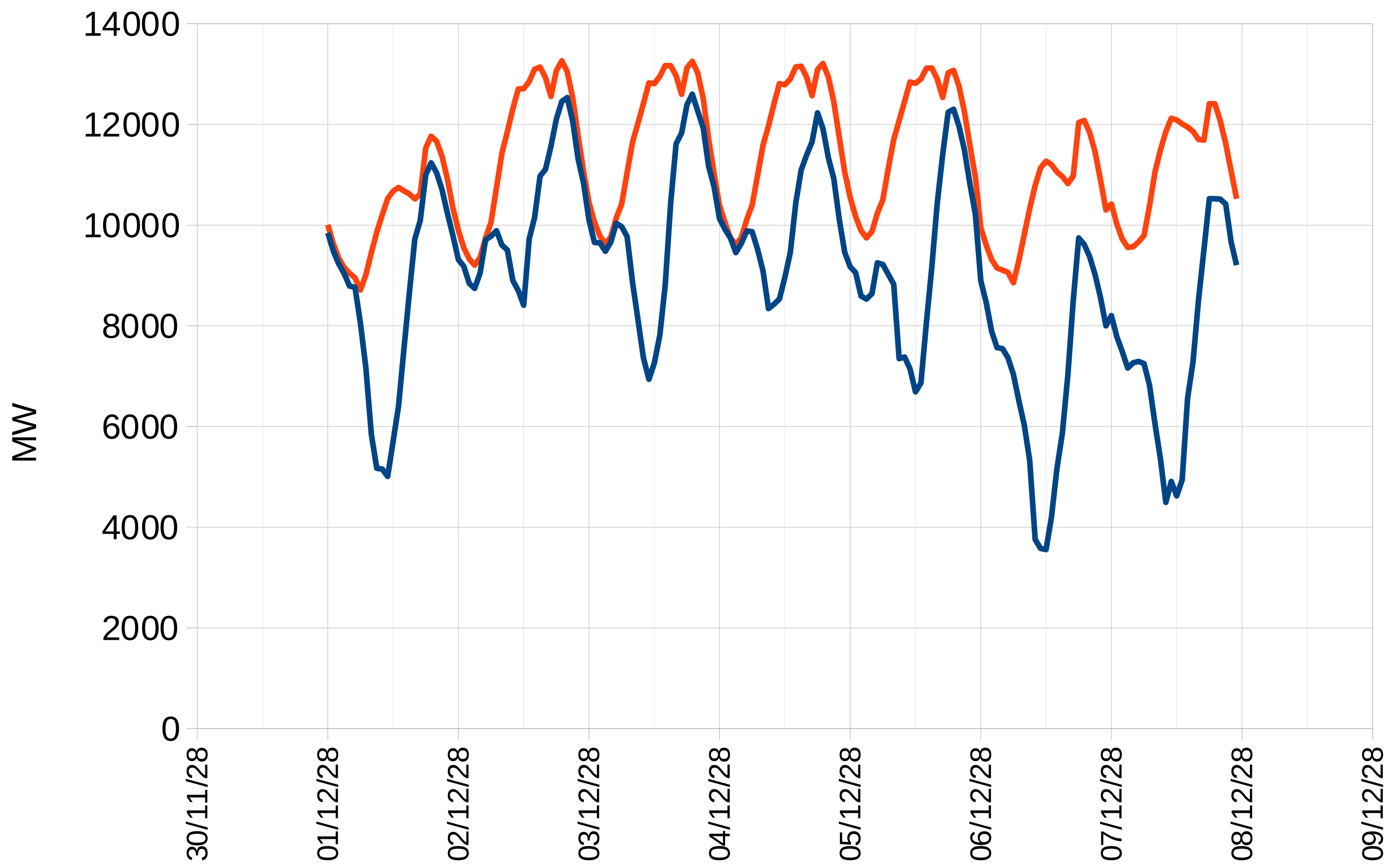
- **Seasonal Programming**
  (every 6 months; 1.5 years; weekly time step).
- **Weekly Programming**
  (every week; 10 days; daily and hourly time step).
- **Daily Programming**
  (every day; 10 days; daily and hourly time step).
- **Hourly Programming**
  (every hour; 10 days; hourly time step).

Resolution of the dispatch in a time step in **TIME BLOCKS**

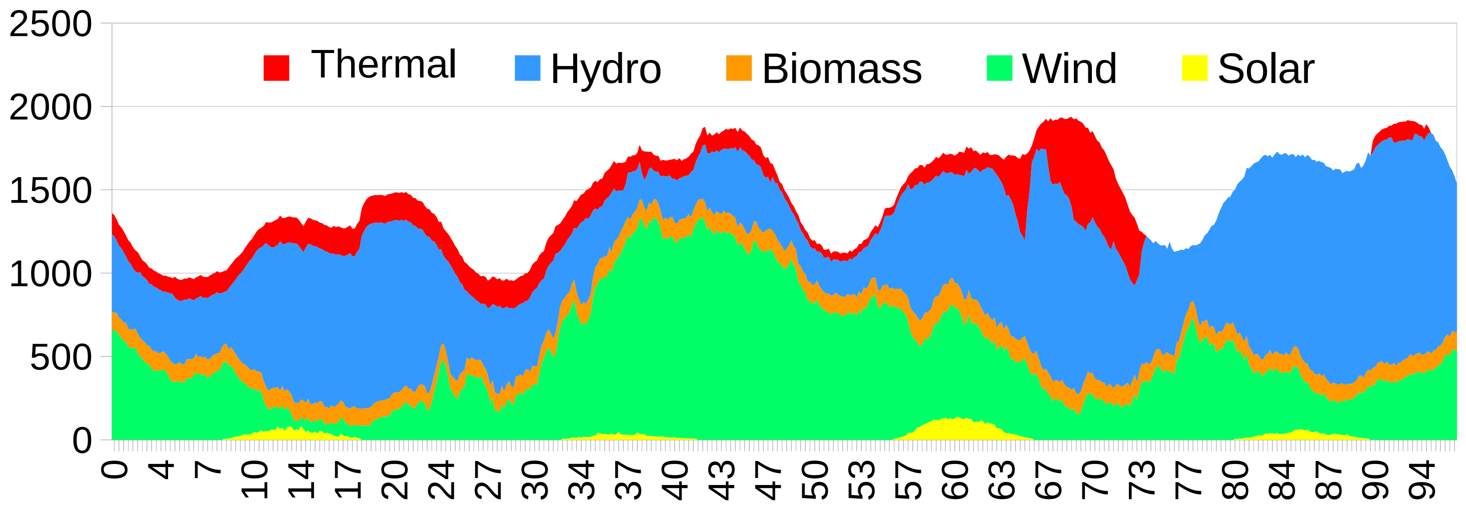
(Postes in Uruguay, Patamares in Brasil)

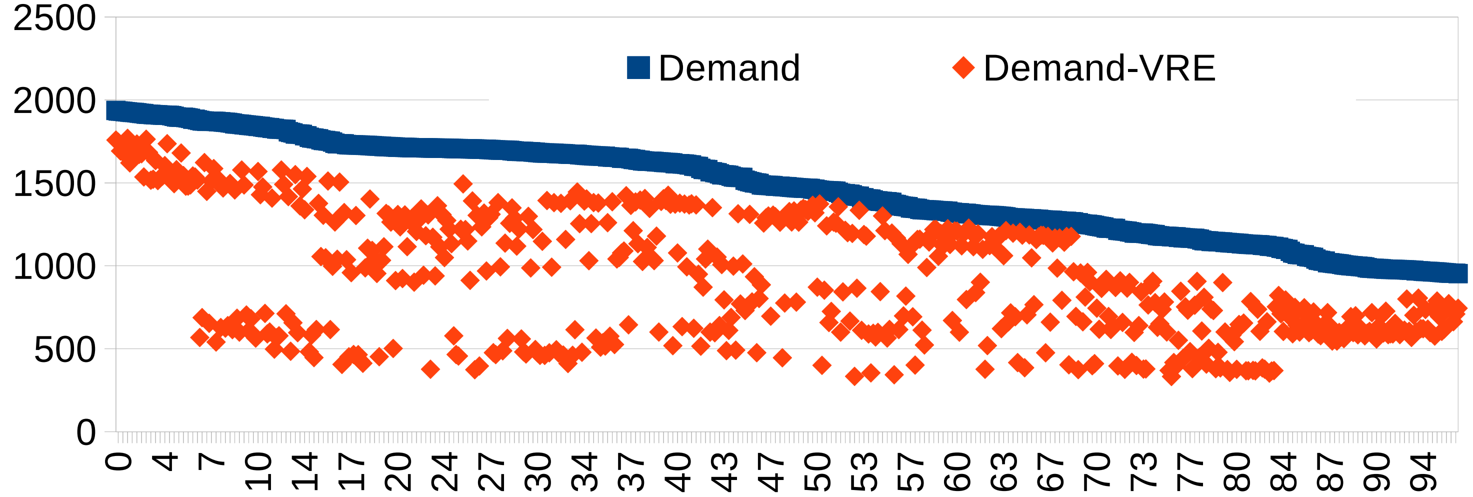
- In order to simulate with time steps greater than one hour and try to adequately reflect the power balance requirements, it is common to resort to subdividing the time step into TIME BLOCKS by reordering the hours of the time step by their power requirement.
- TIME BLOCKS have been used in almost all power system optimization/simulation tools for decades.
- Traditionally, the Monotonic Load Curve is constructed (by ordering the hours of a typical time step from highest to lowest Demand power) and the average of each group is selected as representative of each TIME BLOCK.

The massive incorporation of Wind and Solar leads to the need to consider Net Demand



Just one example, 4 days of july-2018-Uruguay





Time blocks defined from the Load Monotony.

Does it make sense with systems with high integration of wind and solar?

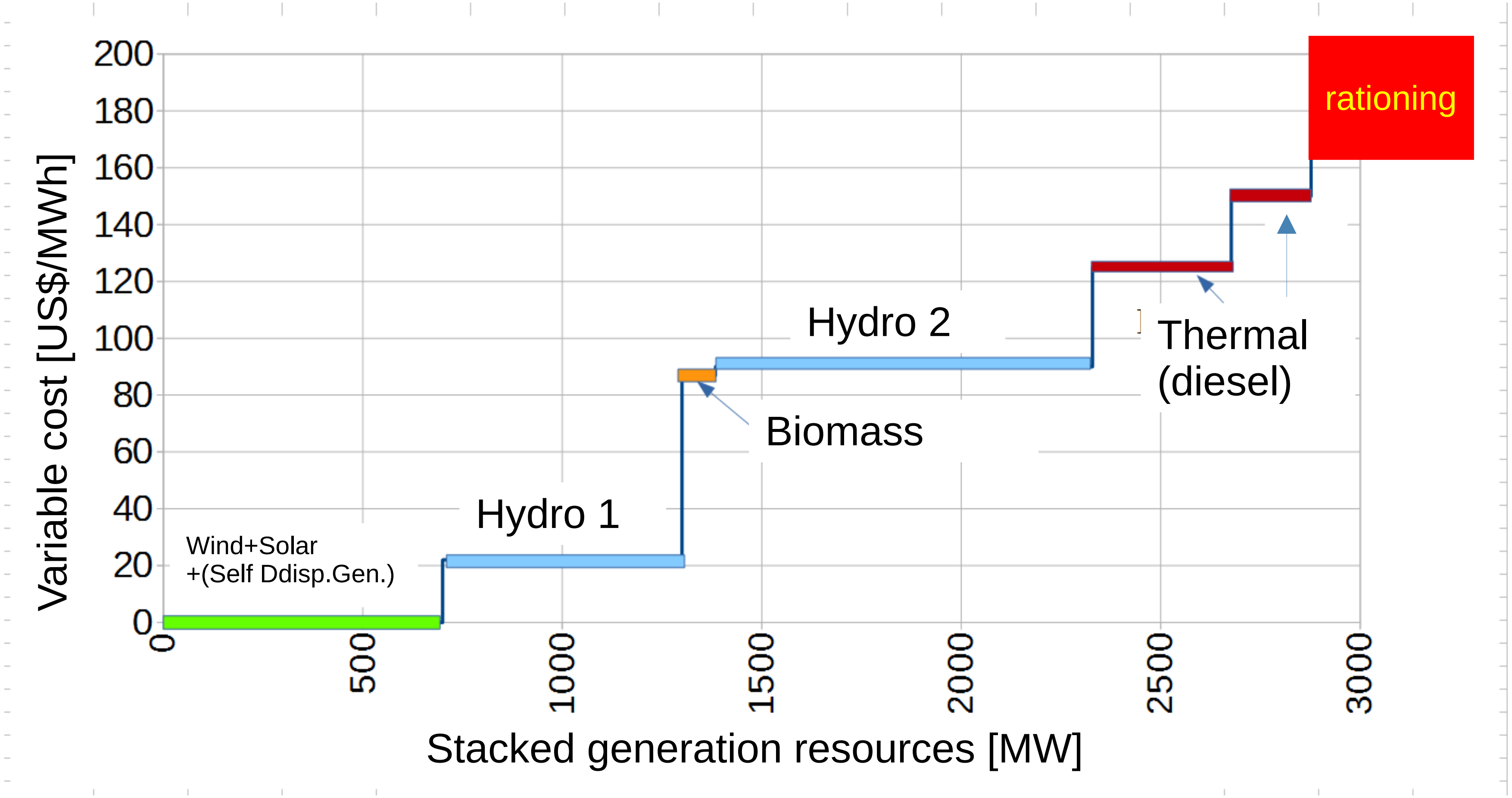
Source: ADME - SCADA ten-minute time series

SimSEE uses a dynamic time blocks definition technique

Operation Policy

Classic example: **Merit order**

Resources stacked in order of increasing variable cost



The variable cost of hydroelectric plants is the result of optimization and reflects the future value of leaving water stored in lakes.

Optimal operation of a dynamic system

Optimal dispatch is a "Stochastic Dynamic Programming problem"

Using stored resources (water) today reduces operating costs today but increases those tomorrow, and vice versa.

An optimal policy is one that reduces the expected value of the future operating cost of the system

Min <FC>

$$X(t) = \begin{bmatrix} x_1 \\ x_2 \\ \cdots \\ x_n \end{bmatrix}$$

System State
Information vector that captures what is relevant from the system's past.

Equation of state evolution:

$$X_{k+1} = f(X_k, u_k, r_k, k)$$

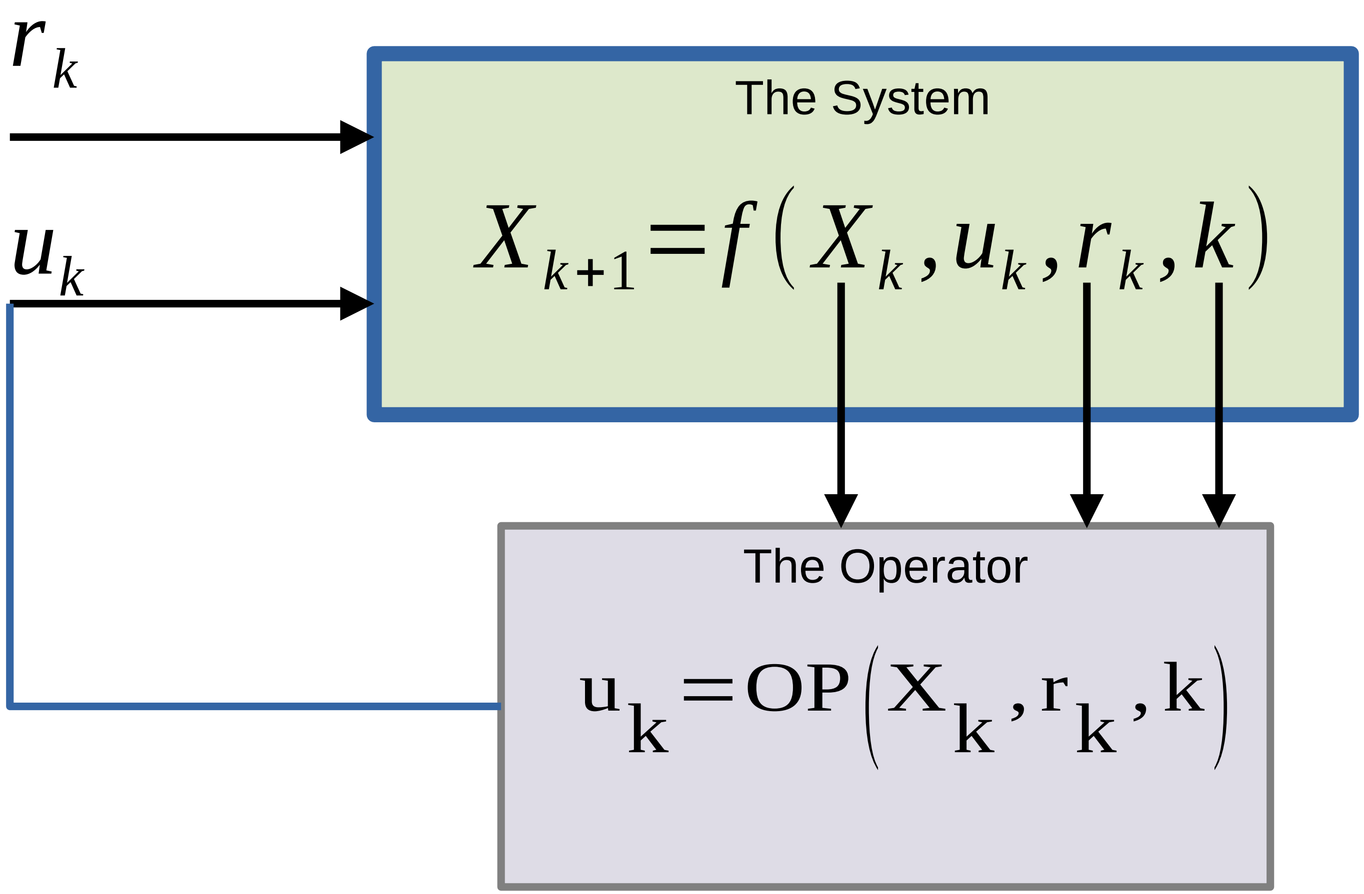
Stage cost:

$$sc_k = c(X_k, r_k, u_k, k)$$

Future Cost:

$$FC(X, k) = \left\langle \sum_{h=k}^{\infty} q^{h-k} sc_h \right\rangle_{R,U}$$

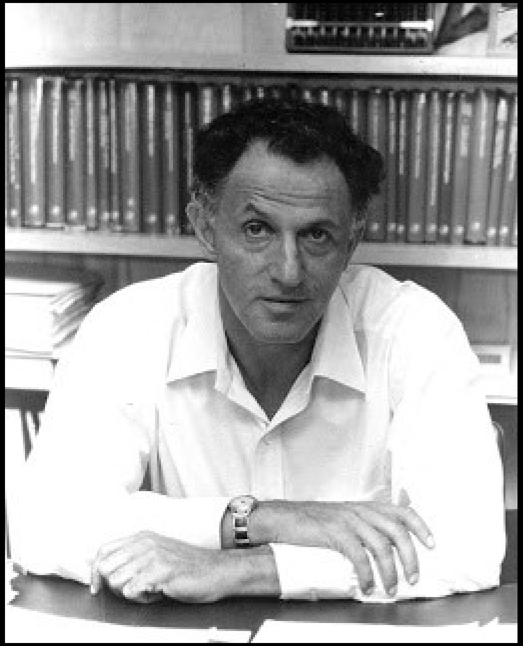
The Operator and the Operating Policy



Optimal Policy for the time step k

Dynamic Programming 1957

Bellman's recursion



Richard Ernest Bellman (1920–1984)

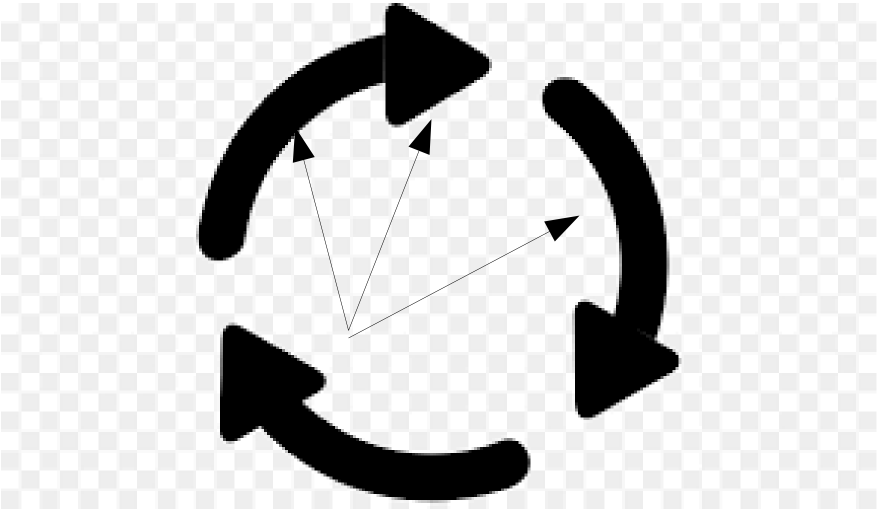
$$FC(X,k) = \left\langle \min_{u_k} \left\{ sc(X,u_k,r_k,k) + q\,FC(X_{k+1},k+1) \right\} \right\rangle_{\{r_k, r_k+1, \ldots\}}$$

- If we know the future cost function FC(X,k+1) at the start of step k+1, then we can compute the future cost function FC(X,k) at the start of step k. This recursive process, backwards in time, allows us to obtain the optimal policy if the FC function were known at some future time for every state X of the system. It can be shown that going far into the future, it does not matter what value is considered for the function FC(X,k_far_future) for determining the present values.
- The factor q is the discount factor of the money at time step.

Classic weapons against the Bellman curse

- Chaining of optimizations with different horizons and time steps (months, weeks, days, hours). Long_Term, Medium_Term and Short_Term.
- In the Long term, HEAVY state variables are considered and more volatile variables are added in the Medium and Short Term.
- Reducing the state of stochastic processes.
- Subdivision of the time step into Hourly Blocks
- SDDP, Rolling Horizon,
- **Reinforcement learning**

The **Little Tractor**... fighting the Bellman Curse
Reinforcement Learning of the Operation Policy



https://simsee.org/investigacion/tractorcito.html

Machine learning applied to the operation of fully renewable energy systems

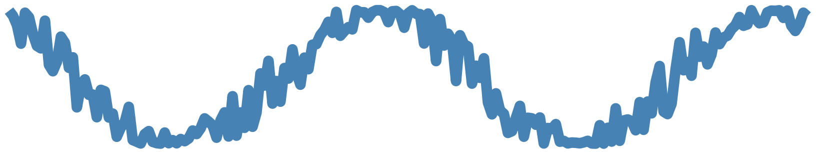
Learning the optimal joint operation of the energy systems of Uruguay, Brazil, Paraguay and Argentina

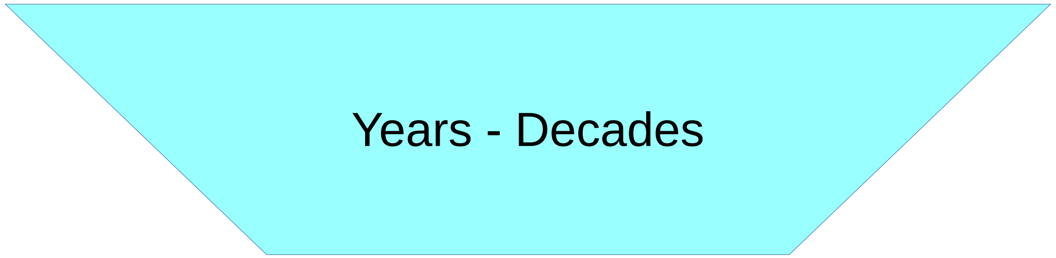
Modeling uncertainty
(Stochastic processes)
Sources of randomness

- Demand
- Water inputs to hydroelectric plants
- Wind speed
- Solar radiation
- Prices in neighboring markets
- Fuel prices
- Fuel availability
- Accidental breakdowns

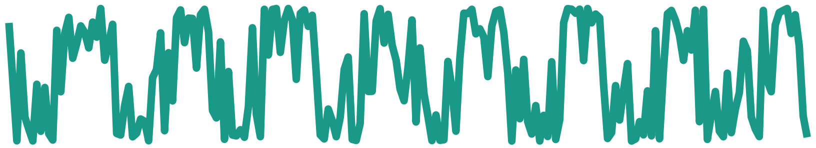
Characterization of variability

Water contributions for hydroelectric plants





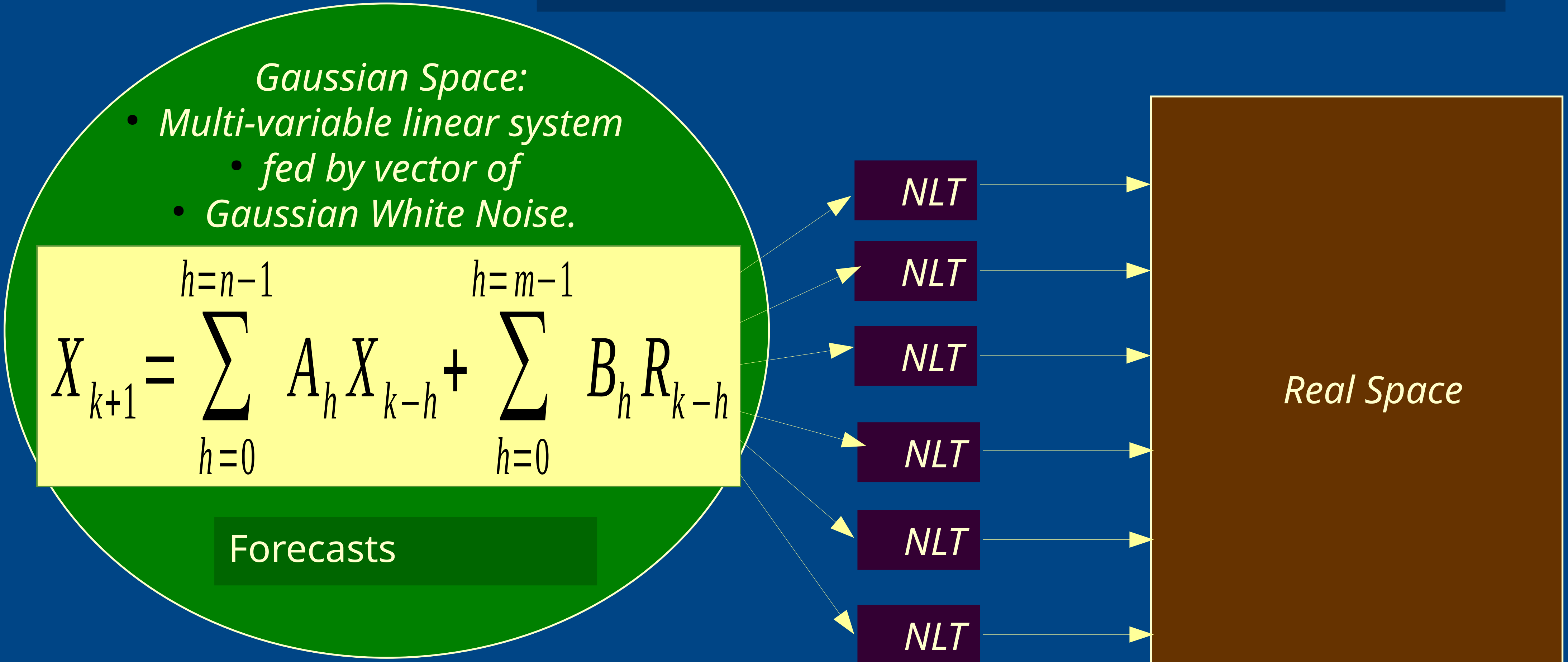
Solar and wind



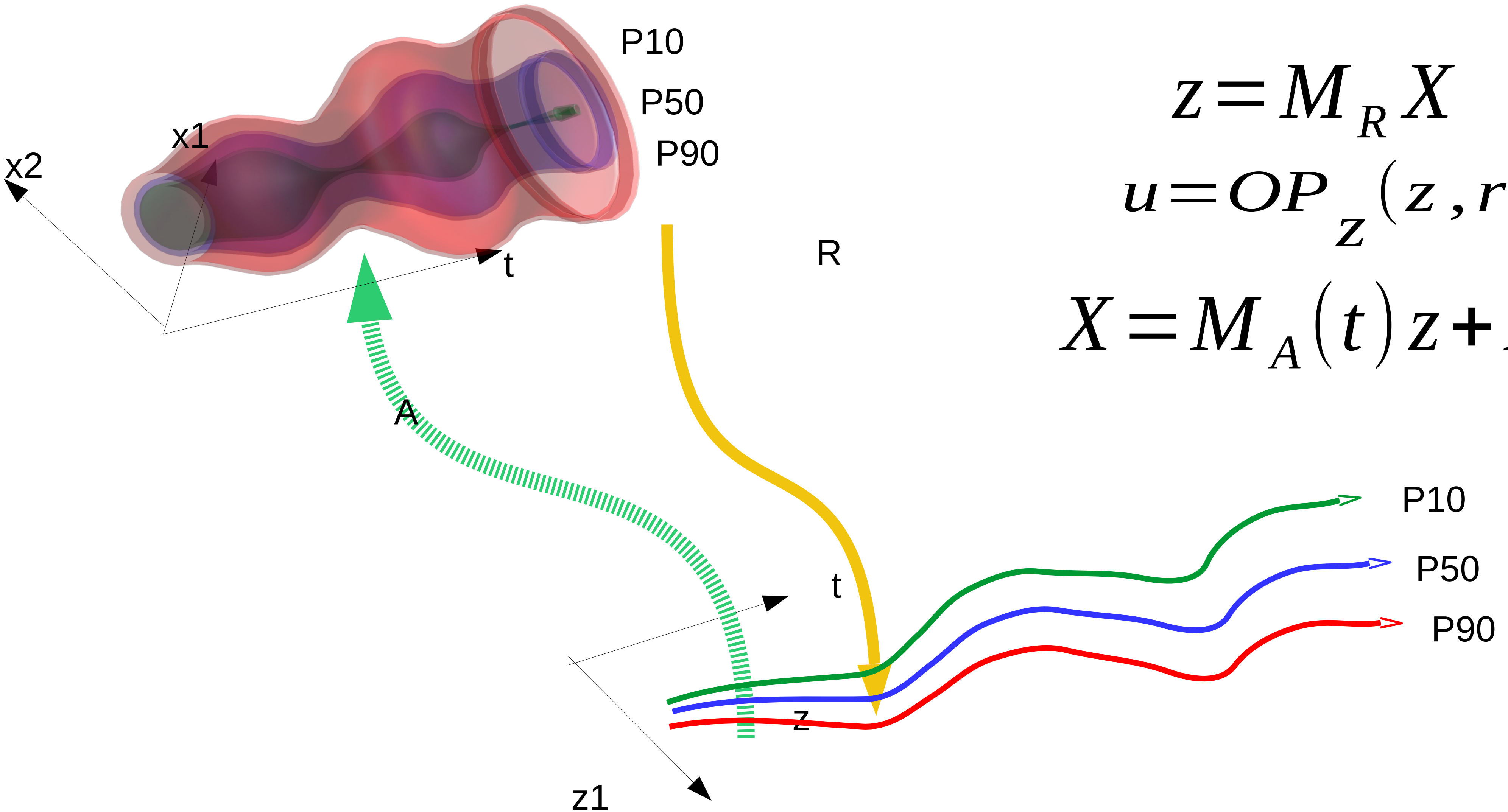
Weeks - Months

CEGH Modelling

- Reproduces amplitude histograms of the series.
- Reproduces correlations between the series and with their past data..



Gaussian space forecasting treatment with reduction



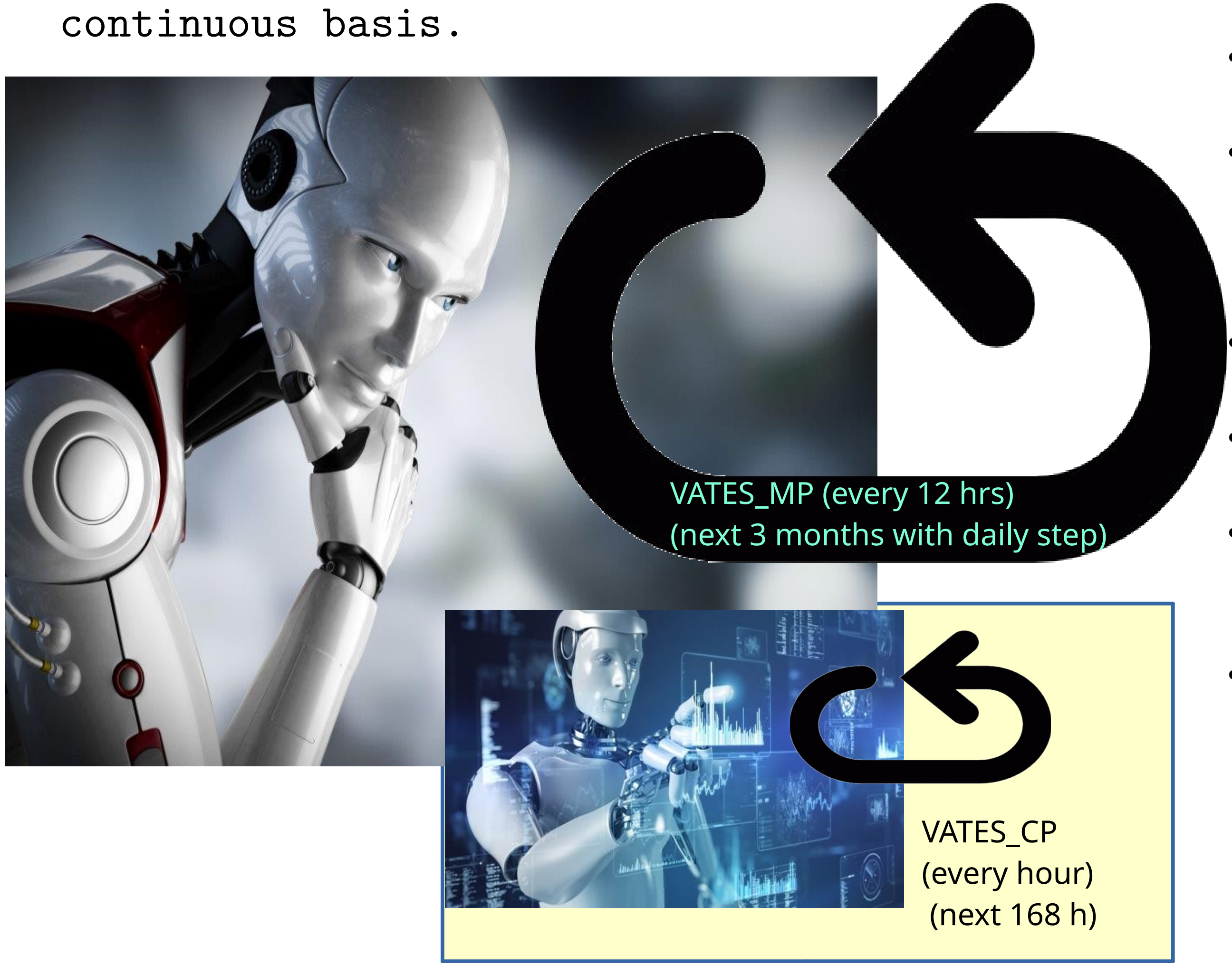
$$z = M_R X$$

$$u = OP_z(z, r, t)$$

$$X = M_A(t) z + B_A(t) w$$

Administración del Mercado Eléctrico

Robots VATES: Energy dispatch with integration of the NIS status and forecasts on a continuous basis.



- At ADME we have two Robots that are permanently solving the optimal dispatch.
- Both assimilate the information on the state of the system and on the forecasts of rainfall, wind, solar radiation and Demand and resolve the optimal operation policy.
- One Robot analyzes the next three months with daily detail and publishes the results twice a day.
- The other analyzes the next seven days with hourly detail and publishes the results every hour.
- Both robots use the Bellman Recursion, which condemns us to not be able to continue adding state variables and details to the system model.
- This led us to develop a new generation of Robots based on Artificial Intelligence techniques to try to escape the Bellman Curse.

VATES_CP: https://latorrex.adme.com.uy/vates/
VATES_MP: https://latorrex.adme.com.uy/vatesmp/

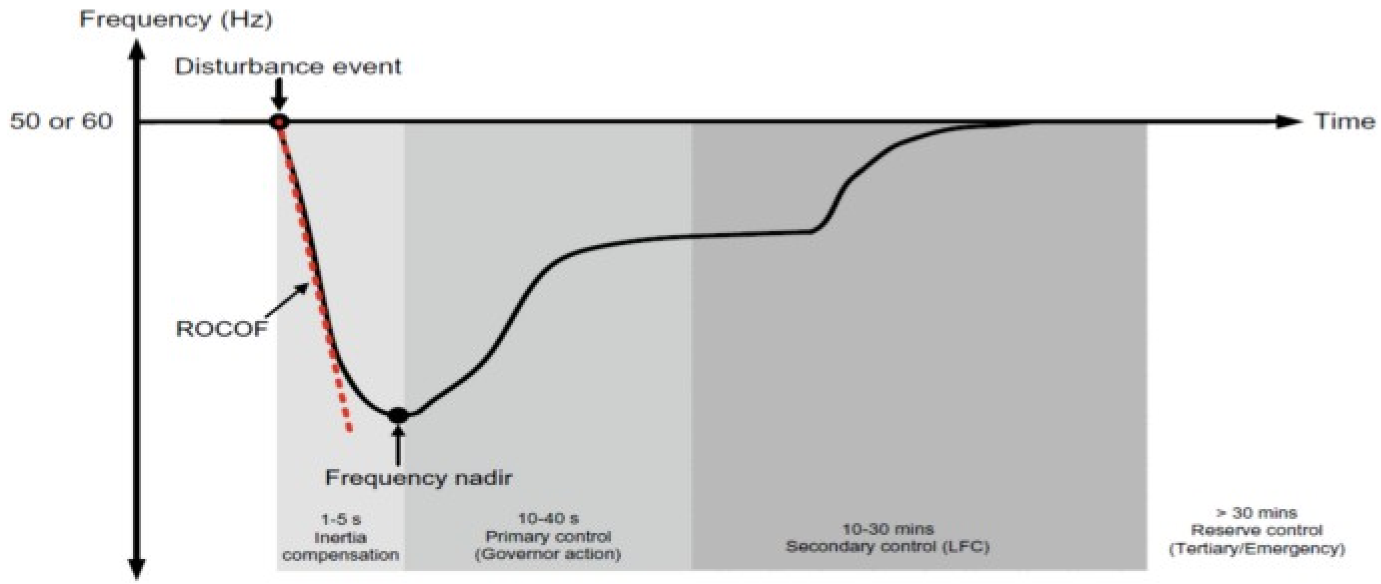
PART II

- RoCoF, Powerflow and Voltage stability
- Operationg DBESS
- Optimizing the long-term investment plan


Risk of loss of inertia due to increase in
Variable Renewable Energy (VRE)

Rotational inertia determines the ROCOF at the beginning of the frequency response to a contingency.

- Lower limit frequency
- Initial response time (Tr): 2s
- Total response time (Te): 15s
- RoCoF limit proposed: 0.5 Hz/s



It is desirable to have sufficient rotating inertia to limit the RoCoF to values that give sufficient time for the primary frequency control to operate in the face of the Most Severe Single Contingency expected at any given time.

Typical values of H[s]

Production Type	Mean H [s]	Loading factor [-]
Nuclear	5,9	0,96
Fossil Brown coal/Lignite	3,8	0,81
Fossil Peat	3,8	0,59
Fossil Hard coal	4,2	0,70
Fossil Gas	4,2	0,60
Fossil Coal-derived gas	4,2	0,54
Fossil Oil	4,3	0,40
Fossil Oil shale	4,3	0,40
Hydro Run-of-river and poundage	2,7	0,61
Hydro Water Reservoir	3,7	0,56
Hydro Pumped Storage	3,5	0,46
Wind Onshore	0,0	-
Wind Offshore	0,0	-
Solar	0,0	-
Other renewable	3,5	0,50
Geothermal	3,5	0,83
Other	3,8	0,56
Waste	3,8	0,28
Marine	3,8	0,50
Biomass	3,3	0,70

$H = (\frac{1}{2} J w^2) / (MVA)$

- **In the resolution of the energy dispatch in SimSEE, it is allowed to impose conditions that guarantee a certain rotating inertia, impossing a minimum value of the Net Demand. Its has two mode of control (static or dynamic).**
- Technologies are changing rapidly and power electronics devices that allow the generation of Synthetic Inertia are already being tested. In the future, the rotating inertia in windmills, the energy stored in the DC bus capacitors of inverters and battery banks will provide the synthetic inertia that will allow the continued incorporation of VRE without problems.

Static RoCoF (fixed minimum Net-Demand)

During the process of assembling the time blocks into which the time step will be subdivided, the Net Demand is calculated.
In each block, the cuts to the VRE generation that are necessary to satisfy a given minimum Net Demand value are applied, thus forcing the dispatch of synchronous generation units, providing inertia to the system.

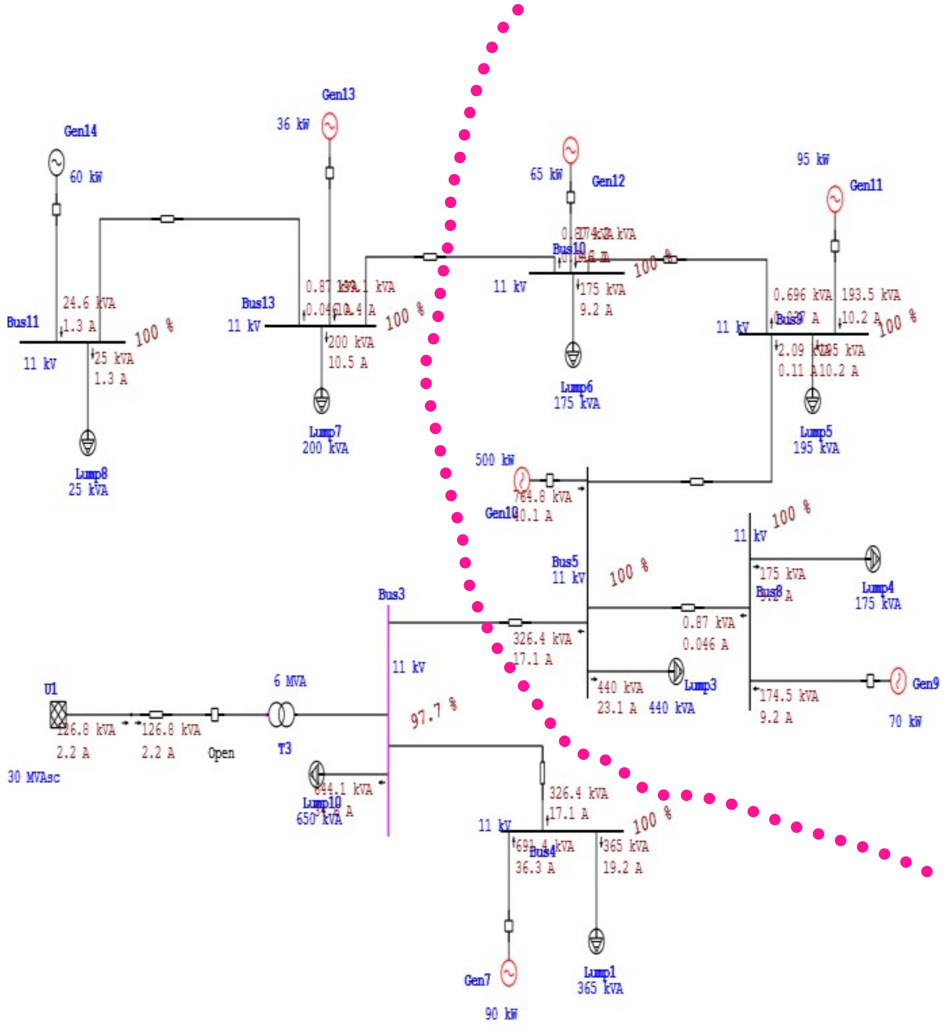
Dynamic RoCoF control (variable minimum Net-Demand)

- Setting minimum net demand
- Incorporation into the RoCoF compliance optimization/simulation loop

[0] Calculate VRE availability
[1] Calculate VRE constraints
[2] Solve step dispatch
[3] Calculate rotating inertia
[4] Determine the Most Severe Single Contingency
[5] Calculate the time for the primary control action
[6] Calculate Response Time Margin
[7] If Margin is significant (5%)
    [7.1] If Margin > 0
        + Reduce minimum Net Demand requirement
    [7.2] If Margin < 0
        + Increase minimum Net Demand requirement
    [7.3] I need to ITERATE

[8] If I need to iterate and the maximum number of iterations was not reached, return to [1]

Representation of power flow restrictions in energy dispatch resolution



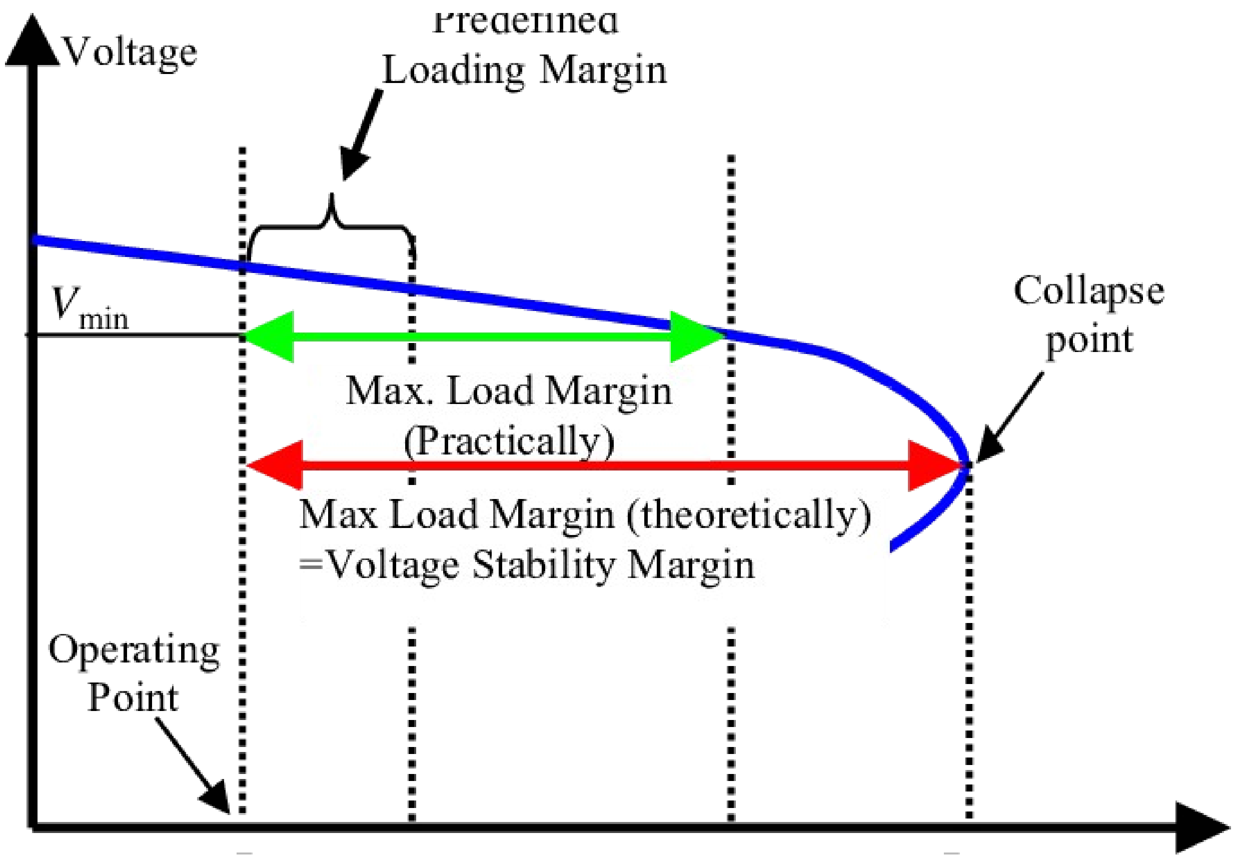
- Cutting restrictions

$$r_{LB} \leq \sum_k \alpha_k P_k + \alpha_0 \leq r_{UB}$$

α_k Actor k cut participation factor

P_k Power dispatched from actor k

Dispatch requirement for voltage stability
Short-Circuit Power Scoring Constraint



$$\sum_k s_k a_k \geq \sum_k D_k \beta_k + s_0$$

s_k	short circuit score assigned to each unit of the generator k
a_k	Indicates the number of units of the generator k that are coupled in the energy dispatch of the hour
D_k	power required to demand k
β_k	factor MW to score of Demand k
s_0	minimum score

DBESS

OddFace

Genetic optimizer applied to investment planning

OddFace

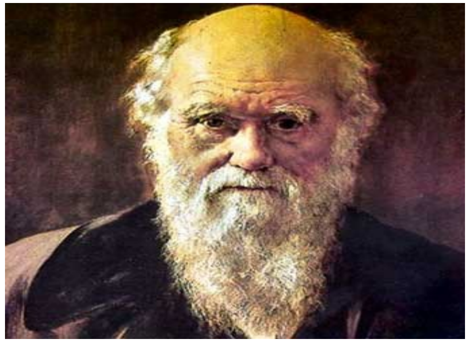
Optimizador **d**istribido **d**e **F**unciones de **a**lto **c**osto de **e**valuación

$$\min_{IP} \langle FC(IP) \rangle$$
$$IP \in D$$

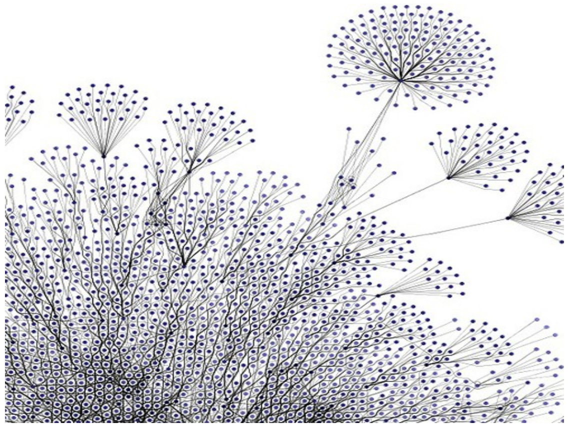
Distributed Optimizer for High Evaluation Cost Functions

many variables + uncertainties

Genetic algorithms



Principle of Natural Selection *(1859)*

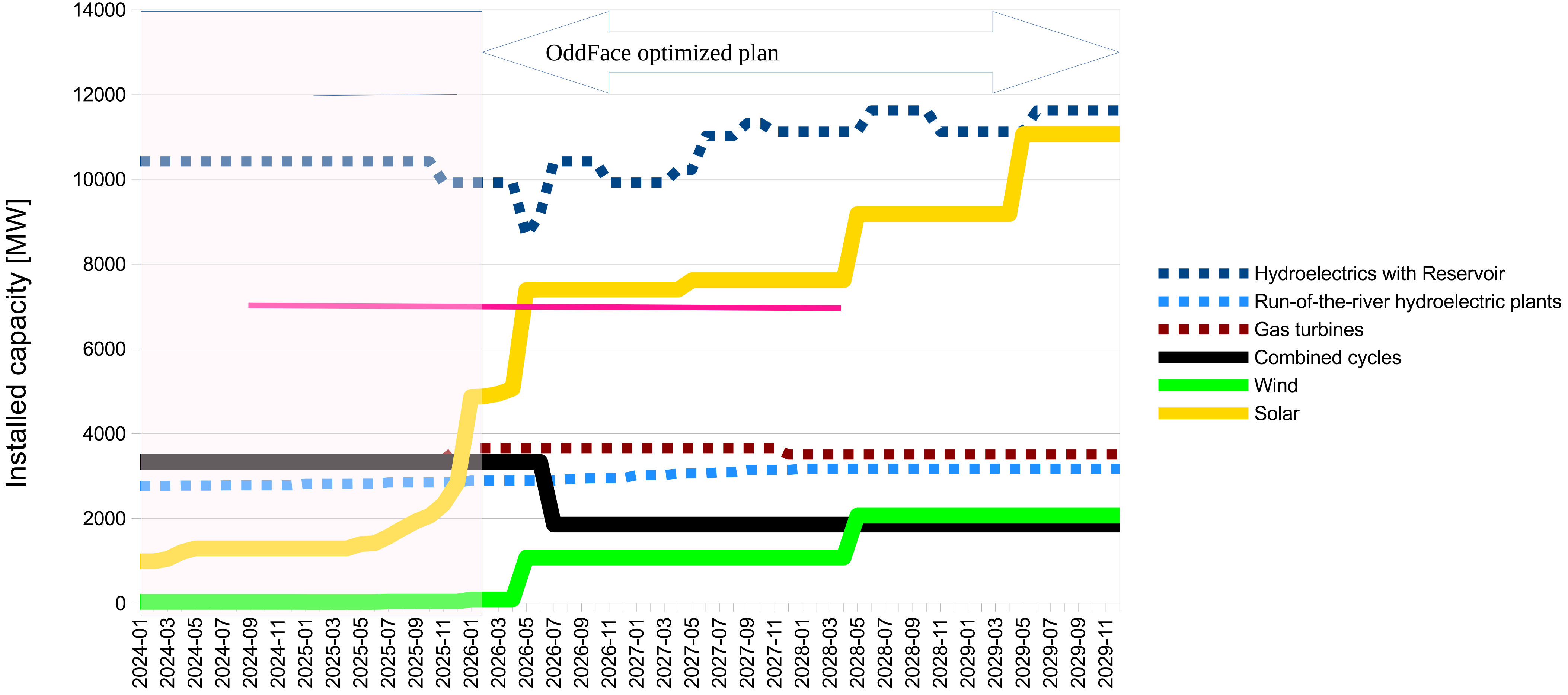


BRUTE FORCE

Generation expansion options

	Wind_Offshore	Wind_Onshore	Solar	Gas turbine	Combined cycle
CAPEX[US$/kW]	3600.00	1260.00	660.00	835.00	845.00
Network[US$/kW]	0.00	0.00	0.00	0.00	0.00
O&M[US$/kW]	744.06	276.20	96.95	112.74	136.41
Total [US$/kW]	4344.06	1536.20	756.95	947.74	981.41
Annuity [US$/kW-año]	385.33	136.27	67.14	84.07	87.05
MWh/year	4380.00	3504.00	1927.20	1314.00	3504.00
Fuel Cost [US$/MWh]	**0.00**	**0.00**	**0.00**	**100.00**	**50.00**
O&M Variable [US$/MWh]	**0.00**	**0.00**	**0.00**	**7.13**	**7.13**
LCOE [US$/MWh]	87.97	38.89	34.84	171.11	81.97
Modules considered in OddFace	Wind_Offshore	Wind_Onshore	Solar	Gas turbine	Combined cycle
UI/UG	28	11	40	1	1
UG [MW]	1.8	1.8	0.5	60	180
MW	50.4	19.8	20	60	180
MUS$/UI	**218.9**	**30.4**	**15.1**	**56.9**	**176.7**
MUS$/UI	218.9	29.8	20.3	56.9	176.7
Availability factor	0.95	0.95	0.95	0.91	0.91
Availability [hours/year]	8322	8322	8322	8000	8000
Payment for availability [US$/MW-h]	46.30	16.37	8.07	10.51	10.88

OddFace result (The winning IP)



DNA and OP Learning
(Cultural heritage)

When using **SimSEE** in conjunction with **El Tractorcito** it is possible to use this functionality.

Using the same concept of chronic evaluation, the “learning opportunity” was implemented.

The same DNA has had as many evaluation opportunities as simulations and associated with the DNA it then has a FC(X,k) corresponding to its OP.

When individuals are crossed and a new one is created (which has not yet been evaluated) it is “born” with the FC(X,k) of its parent with fewer evaluations. In this way, “what has been learned” is transmitted from generation to generation.

... agile so as not to miss the train and slow so as not to get on the wrong one ...

Thank you very much for your attention!