2023 IEEE PES GT&D

INTERNATIONAL CONFERENCE & EXPOSITION, ISTANBUL
CONFERENCE: MAY 22-25 | EXPOSITION: MAY 23-25

IEEE PES Power & Energy Society® | IEEE

Machine Learning applied to the operation of fully renewable energy systems

Ruben Chaer

Administración del Mercado Eléctrico (ADME)
Instituto de Ingeniería Eléctrica (IIE)
Facultad de Ingeniería
Universidad de la República Orienal del Uruguay

ADME iie FACULTAD DE INGENIERIA UNIVERSIDAD DE LA REPUBLICA URUGUAY

2023 IEEE PES GT&D

INTERNATIONAL CONFERENCE & EXPOSITION, ISTANBUL
CONFERENCE: MAY 22-25 | EXPOSITION: MAY 23-25

IEEE PES Power & Energy Society® | IEEE

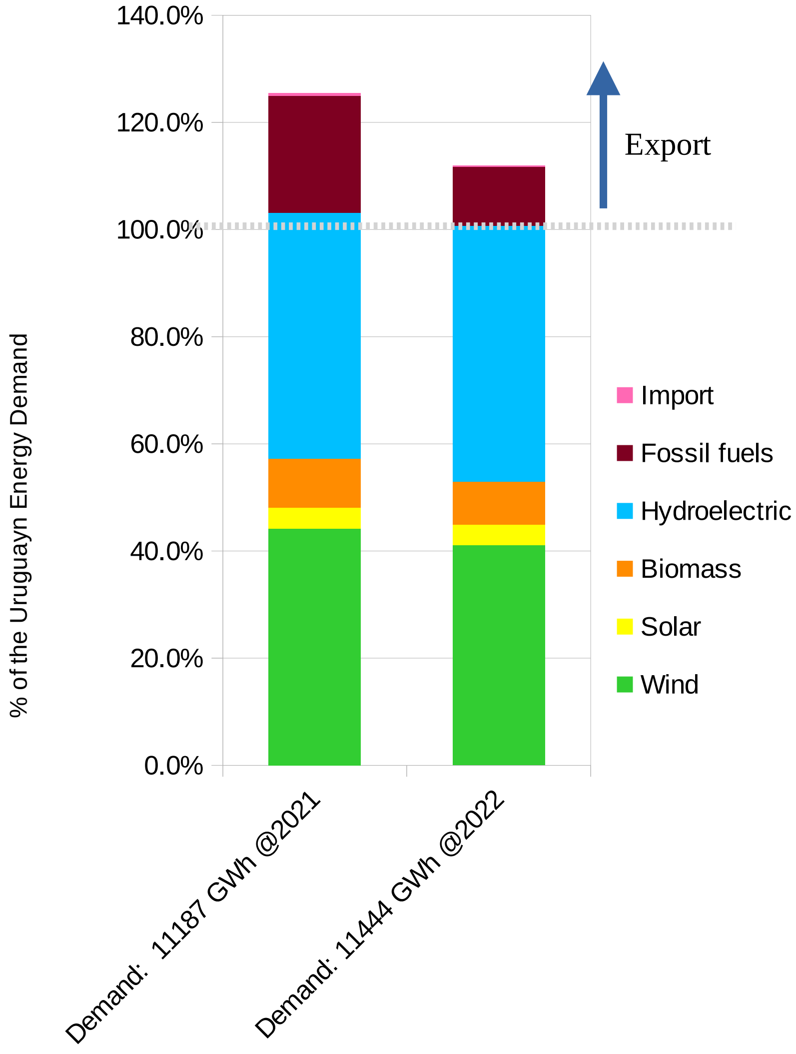
Machine Learning applied to the operation of fully renewable energy systems

Ruben Chaer

Administración del Mercado Eléctrico (ADME)
Instituto de Ingeniería Eléctrica (IIE)
Facultad de Ingeniería
Universidad de la República Orienal del Uruguay

ADME iie FACULTAD DE INGENIERIA UNIVERSIDAD DE LA REPUBLICA URUGUAY

Uruguayan Energy Market



- Uruguay's generation matrix is 90% renewable. Approximately 10% based on biomass, 30% on wind and solar and 50% hydropower.
- Wind an Solar are variable in terms of hours but firm in terms of weeks.
- Hydropower is stable in terms of hours but has strong annual variability.
- These random components result in a cost of the future operation with huge dispersion.

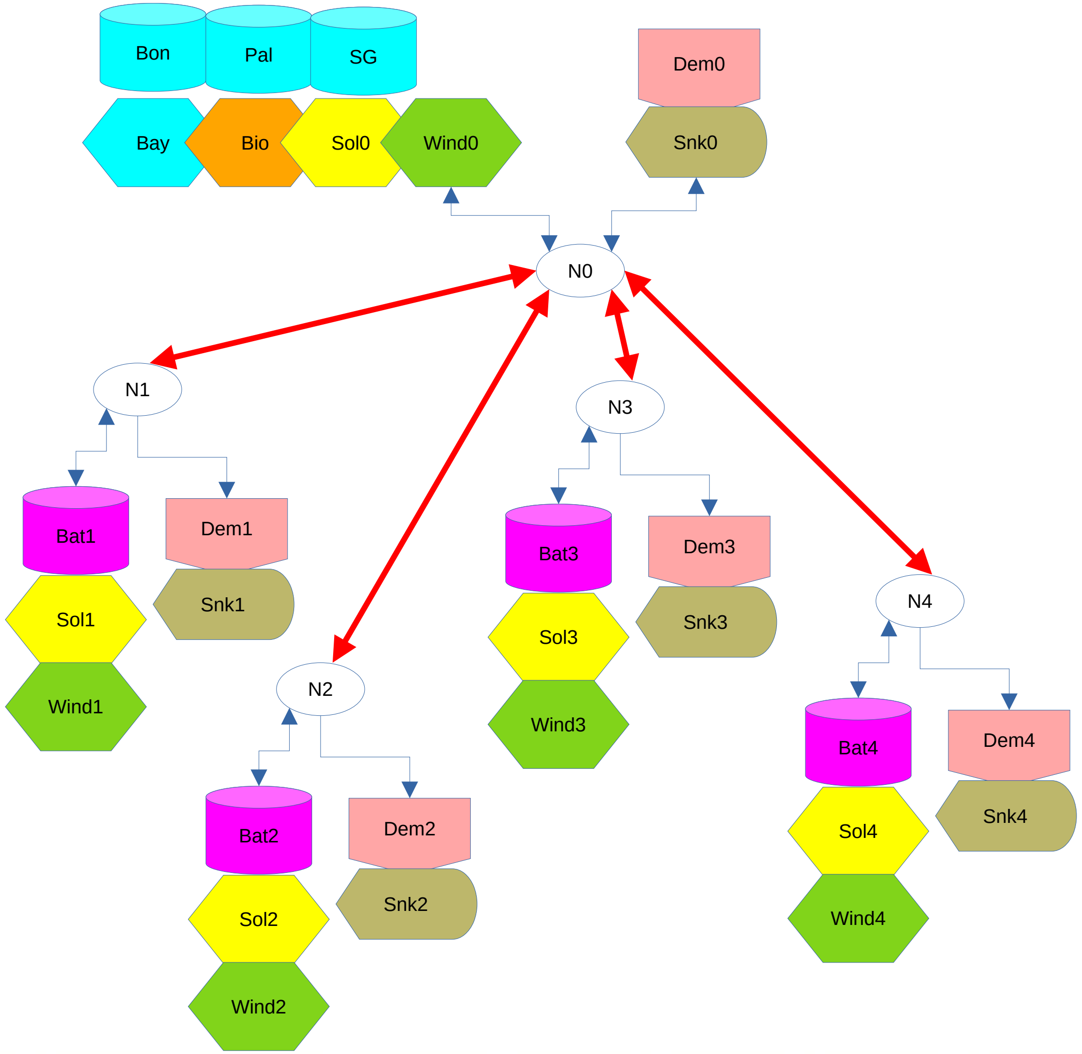
https://adme.com.uy

White paper:
Operación óptima de los recursos de generación de energía eléctrica (spanish)

Robots VATES: Energy dispatch with integration of the SIN 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.

Example case. Uruguay 2050 Hydro+Biomass+Solar+Wind+Battery banks



44 state variables:

- 3 lakes
- 40 battery-banks
- Pacific Ocean surface temperature anomaly in region 3.4

Bellman's Recursion*(*)***:**

- To store the future cost function in floating point, it is necessary 19.7 Tera-bytes
- Solving the recursion on a 48-core computer would take 286 years.

(*)assuming a year and a half with hourly steps and discretizing the state variables in 5 positions

Less than 12 hours to obtain a reasonable operation of the system!

The optimal dispatch of generation resources is a Stochastic Dynamic Programming problem.

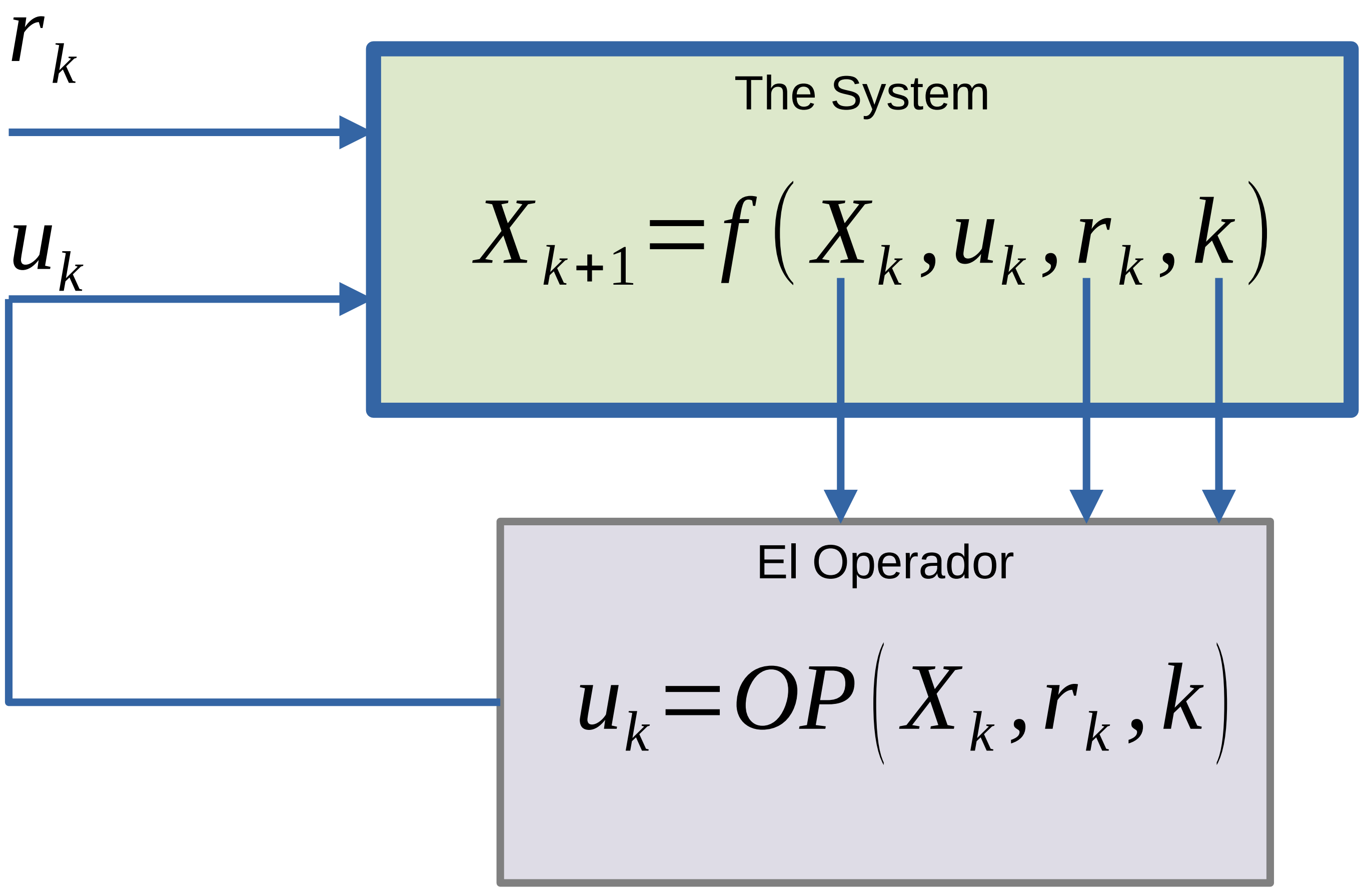
The use of stored resources (water) today reduces the operating costs of the present but increases those of the future, and vice versa.

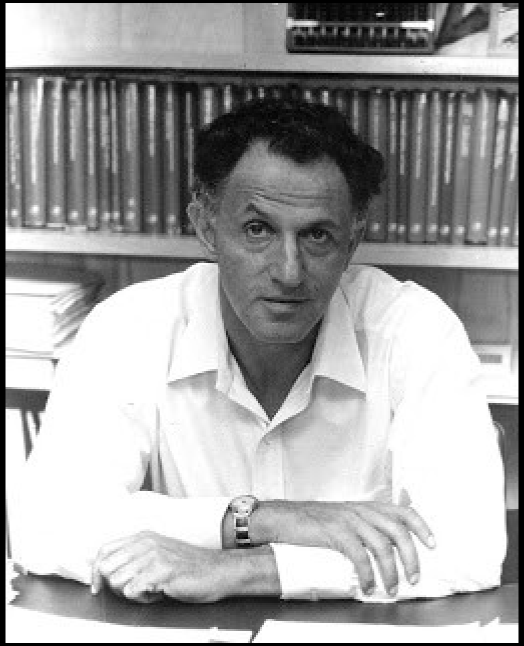
An optimal policy is one that reduces the expected value of the future operating cost of the system.

Min <Future Cost>

At the optimum, the variations of Present vs. Future are in equilibrium.

The Operator and the Operation Policy





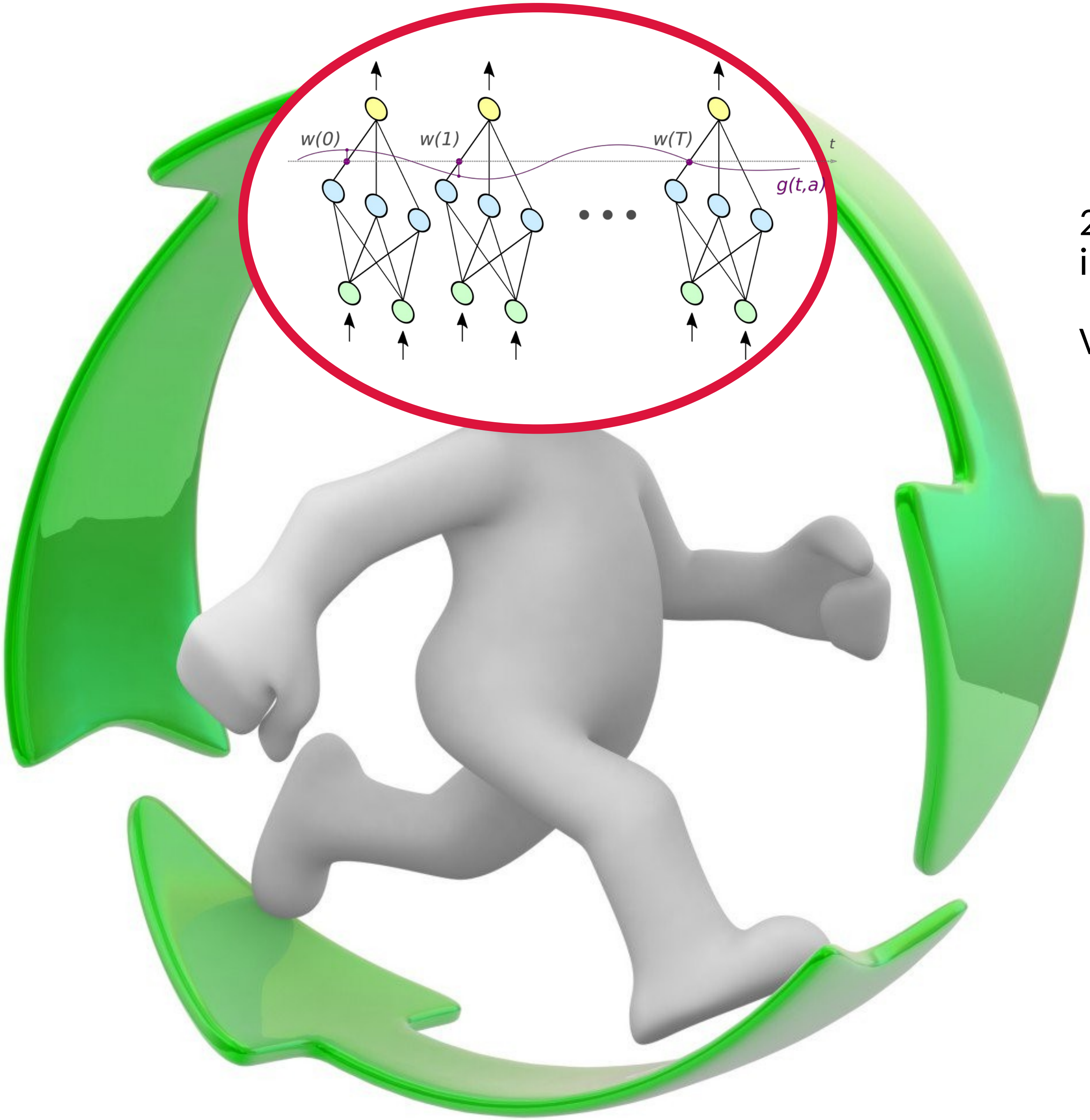
Richard Ernest Bellman (1920–1984)

- *Dynamic Programming* 1957
  Bellman recursion

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

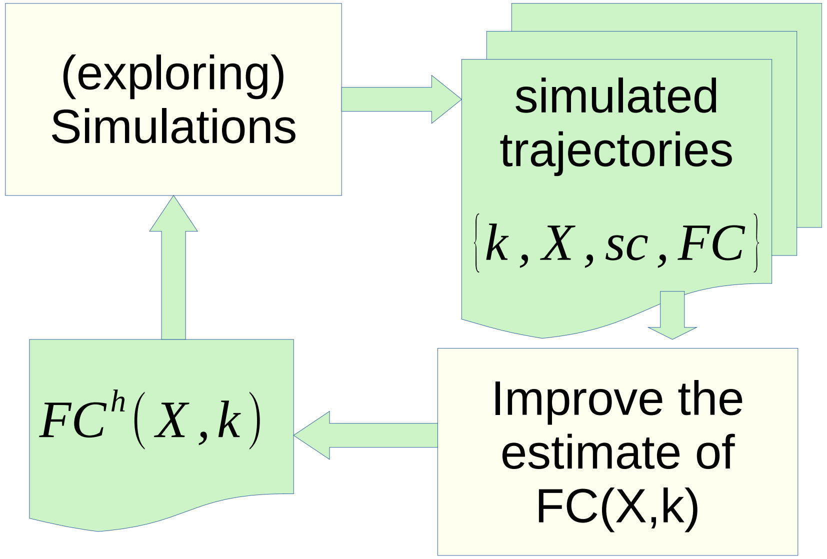
Bellman's Curse of Dimensionality

r_k
$\acute{X}$
$\acute{X}$
$\acute{X}$
u_k
X_k

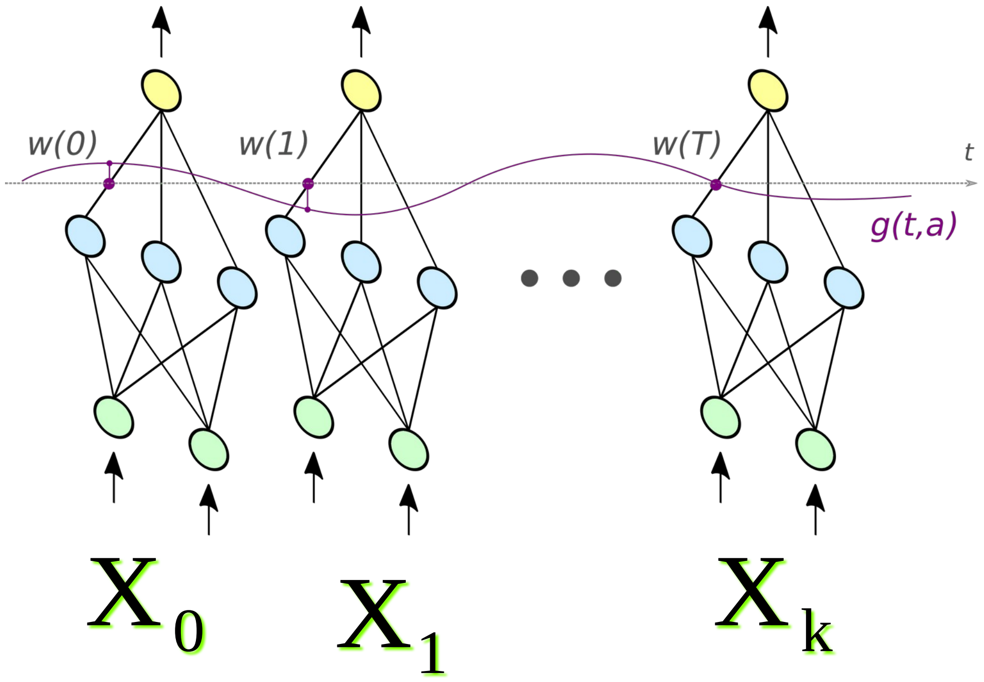


2nd generation of robots with artificial intelligence

VatesIA_MP y VatesIA_CP



FC(X) representation and regularizations



$$L = \sum_{k,g} L_{kg} + \lambda \sum_{k} \|\theta_k\|^p + \beta \sum_{k=2} \|\theta_k - \theta_{k-1}\|^2$$

Parsimony(t)

- TD
- Power series and harmonics

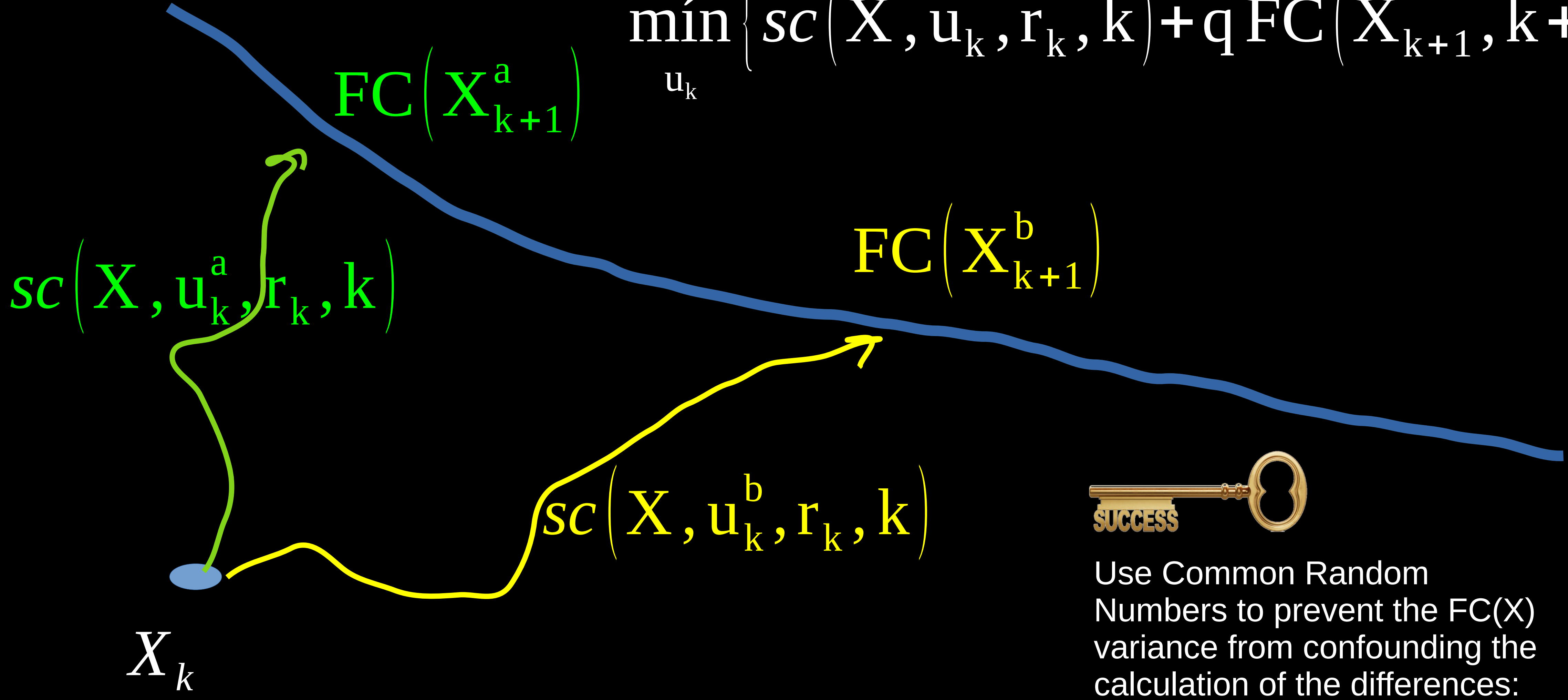
- p=2 : Ridge
- p=1 : Lasso

Approximate the differences instead of the function itself

$$L_{kg} = \frac{1}{4N^2} \sum_{i \neq j \in g} \left(\left(M(X_{kj}, \theta_k) - M(X_{ki}, \theta_k) \right) - \left(FC_{kj} - FC_{ki} \right) \right)^2$$

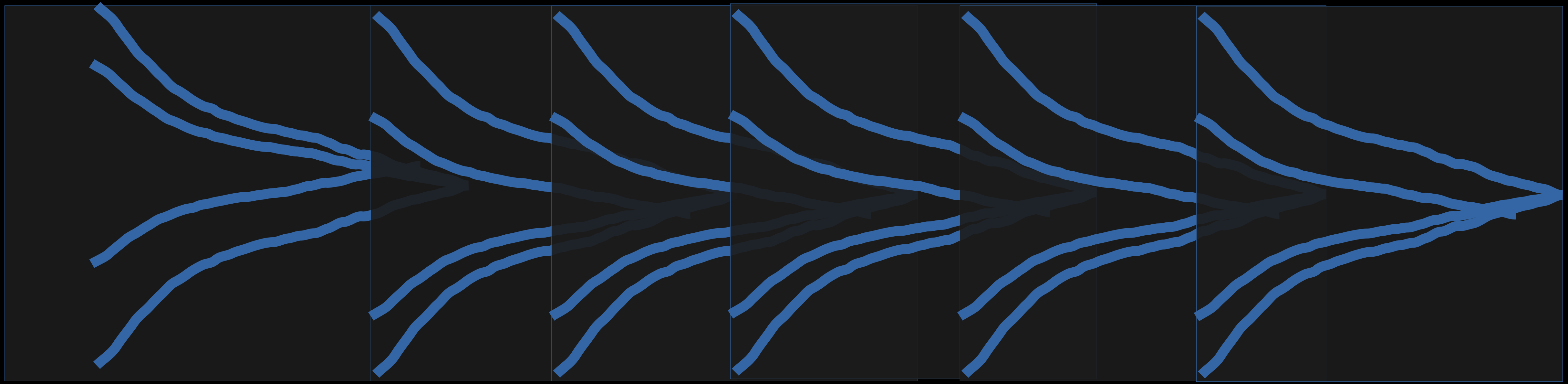
The information is in the FC(X) differences

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



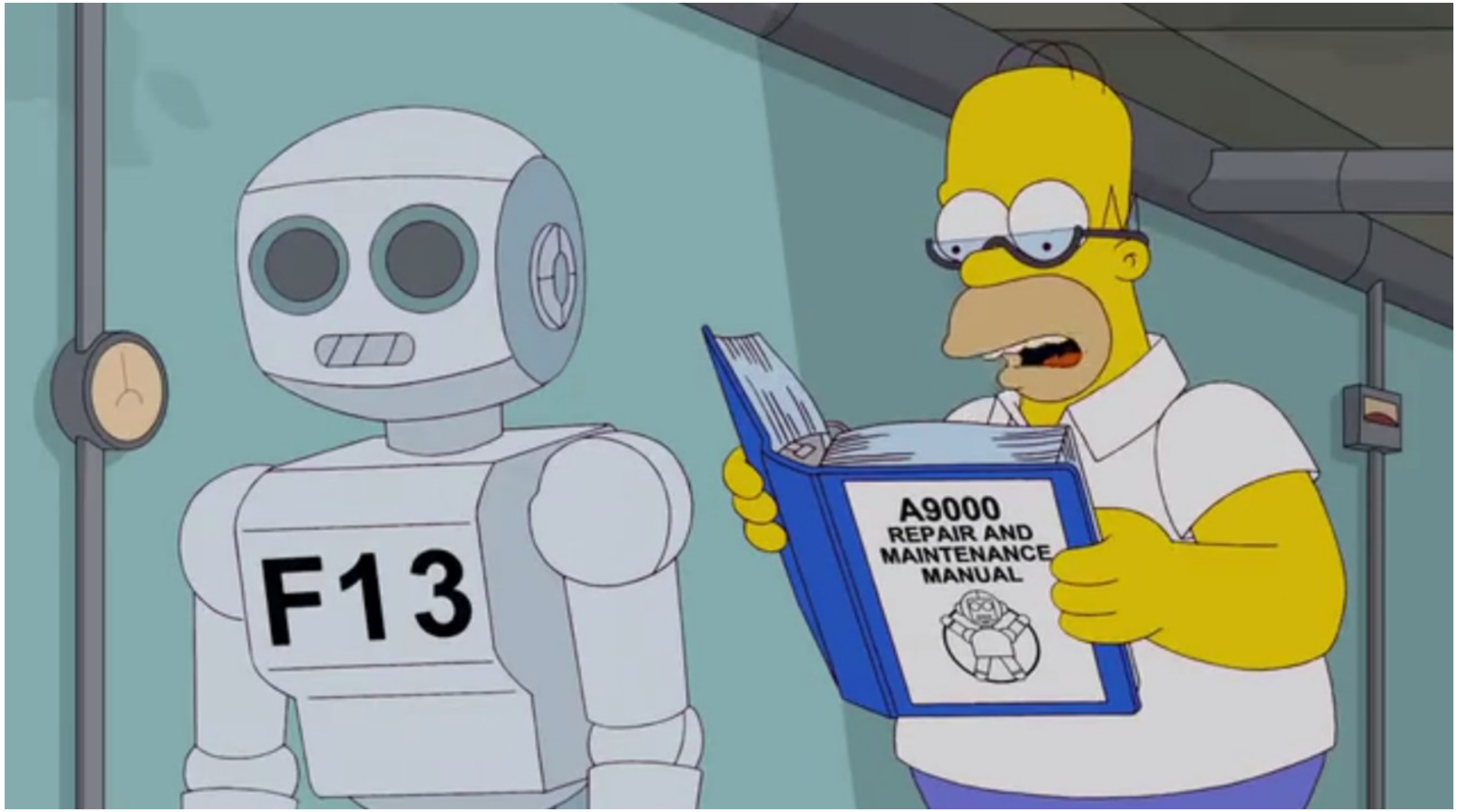
Use Common Random Numbers to prevent the FC(X) variance from confounding the calculation of the differences: FC(Xa) - FC(Xb) at the arrival states

Exploration Strategies



In a stable system, the use of CRN leads to convergence of trajectories and a consequent loss of exploration capability. Each NTD steps states are exploited to recover said capability.

In a continuously operated system, learning is also processed continuously. With the course of each real hour, the vector of neurons is moved, discarding the array of neurons corresponding to the elapsed hour and repeating the last one to continue in the learning loop



That's all folks!

Thank you for your attention.