Modal Analysis of Large Dataset, Intelligent and Optimal Control

applications to fluid mechanics and minigrids

séminaire au LAGA

F. Guéniat

florimond.gueniat@bcu.ac.uk

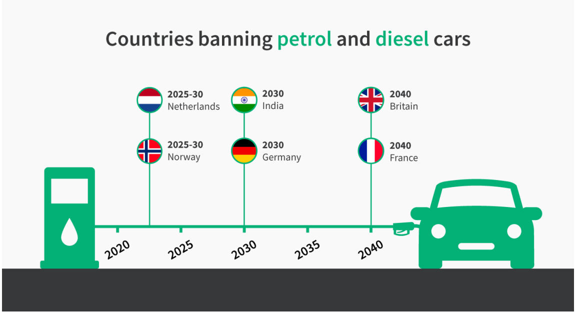
February 2022

Birmingham City University

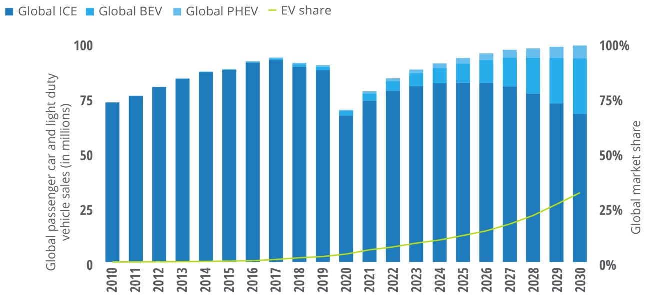
Outline

- Current context
- Understanding and Modelling : from Large to Sparse
- Deep Reinforcement Learning
  - Fluid Mechanics
  - Mini-grids
- Conclusions

Electric vehicles' Revolution



Market share of EV



Source : Deloitte

An unexpected issue ?

THE WALL STREET JOURNAL.

Subscribe | Sign In

English Edition ▾ | Print Edition | Video | Podcasts | Latest Headlines

Home World U.S. Politics Economy Business Tech Markets Opinion Life & Arts Real Estate WSJ. Magazine Search

SHARE

U.S.

California Wants Cars to Run on Electricity. It's Going to Need a Much Bigger Grid

The state has recently struggled with rolling blackouts due to tight power supplies. Going all electric in 15 years will dramatically increase electricity demand.

UPCOMING EVENTS

May 24 2021 — 12:30 PM - 1:00 PM EDT — Ask WSJ: A Closer Look at Biden's Tax Plans

May 26 2021 — 12:00 PM - 1:30 PM EDT — WSJ Women In: Women, Power and Equity

Jun 2 2021 — 11:00 AM - 3:00 PM EDT — WSJ Pro Cybersecurity Executive Forum

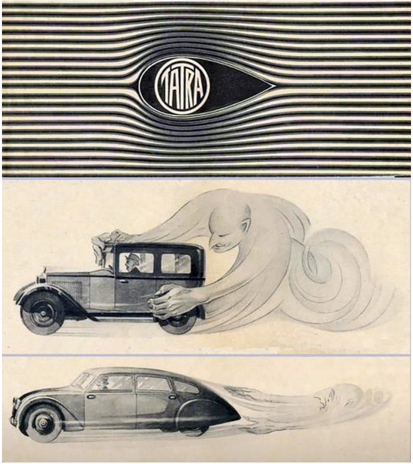
How to transition ?

By 2030, there will be no more ICE car sold.

40M vehicles - Energy equivalent to 20 to 50 nuclear plants.

Drag and Tatra's ad for the Tatra 77, circa 1930

It is the force resisting the movement due to the "friction" between the air and the car. It has been identified as important a while ago !



Drag

It is still an important selling point :

Tesla says the new Model S is the world's most aerodynamic production car

With a coefficient of drag that's just 0.208, the updated Model S narrowly beats out the Lucid Air, but there's a catch or two.

Daniel Golson Jan. 27, 2021 4:25 p.m. PT

LISTEN · 02:00

The Model S is one slippery sedan.
Tesla

Drag

It is still an important selling point :

The main reason is because the drag is responsible for 40% of the energy consumption.

Reducing the drag by 20% means :

- extending the range of EV
- diminishing emissions/green house gas
- reducing energy consumption/fuel consumption

by 8% - aka a few nuclear plants !

Access to Power

Electricity is a major challenge.

There is a need for more power.


The Economic Times | Industry
English Edition | E-Paper
Sign In
Special Offer on ET Prime
Home ETPrime Markets News Industry RISE Politics Wealth MF Tech Jobs Opinion NRI Panache ET NOW More
Auto Banking/Finance Cons. Products Energy Renewables Ind'l Goods/Svs Healthcare/Biotech Services Media/Entertainment More
Business News › Industry › Renewables › India may build new coal plants due to low cost despite climate change

India may build new coal plants due to low cost despite climate change

Reuters • Last Updated: Apr 19, 2021, 08:31 AM IST

Synopsis
Coal's contribution to electricity generation in India fell for the second straight year in 2020, marking a departure from decades of growth in coal-fired power. Still, the fuel accounts for nearly three-fourths of India's annual power output.

India may build new coal-fired power plants as they generate the cheapest power, according to a draft electricity policy document seen by Reuters, despite growing calls from environmentalists to deter use of coal.

IN THE SPOTLIGHT
Here's your chance to study medicine abroad

RELATED MOST READ MOST SHARED
Coal India retains production and offtake momentum in May
Coal India retains production and offtake momentum in May

India Times

- Economic growth
- Urbanisation
- Transition to digital society
- Electrification of the vehicle fleet

Access to Power

Electricity is a major challenge.

Many issues are not solved.


the Blackout report

Nigeria Power Grid Collapses For Second Time This Year

May 13, 2021 · Chris Owens · 0 Comment · Power News

The power grid across Nigeria completely collapsed on Wednesday morning (12 May) plunging much of the country into a blackout.

- Black Out (local or nation-wide)
- Connection to the Grid
- Prices

My takeaway

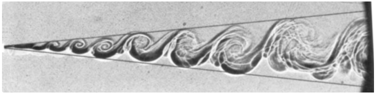
There is a global need for :

- Vehicles that are more energy efficient
  My main research : related to fluid mechanics and control engineering.
- Producing more (clean) energy
  1. Grids more efficient
  2. Grids more economically attractive

  My secondary research : related to grid engineering and control engineering.

Nonlinear systems

Both open and confined flows are complex, and has potentially an infinite number of DoF, but coherent structures seem to play a major role.



Brown & Roshko, (1974), *J. Fluid Mech.*

What is a coherent structure (see Chassaing, Hussain, Lumley ...) ?

- spatially localized
- significant contribution to the kinetic energy
- significant life-time
- recurrent phenomenon
- material frontiers
- etc.

Von 'Heartman' street
Isla Socorro ($Re > 10^{10}$!).
one can think of features extaction

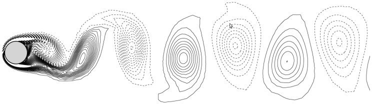
"In principle, concepts like coherent structures are best left implicit."

Hussain, "Coherent structures in a turbulent boundary layer", (1986) *Phys. Fluids.*

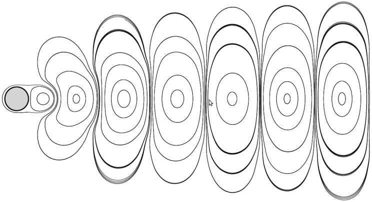
Several relevant frameworks exist to identify coherent structures.

Modal framework

The aim is to give a relevant representation of a dataset, *e.g.* the energy (POD) or the frequencies (Fourier).



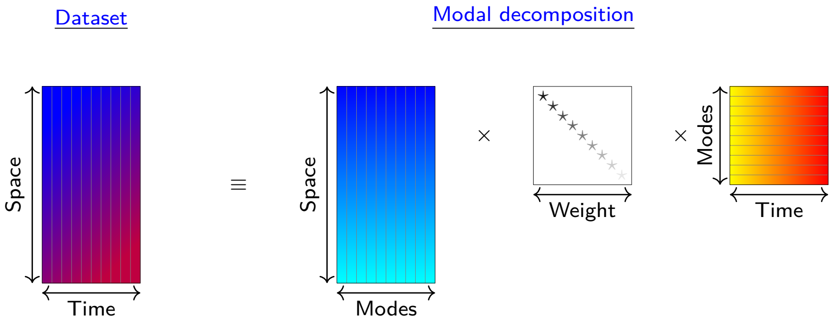
Cylinder wake



POD mode 1
Bergmann & Cordier, (2008) *J. Comput. Phys.*

Modal framework

The aim is to give a relevant representation of a dataset, *e.g.* the energy (POD) or the frequencies (Fourier).



It may lead to model reduction, through Galerkin-projection or truncature.
There is a natural connection with auto-encoder.

Big data

Understand fluid mechanics

- Numerous fields/points of view
  - Velocity
  - Pressure
  - Temperature
  - Concentration ...
- Large 3DnC simulations
- Hi-Res experimental snapshots

Leads to huge dataset

- number of points : $c \times n^d \times N$

with typically

	c	d	N	n
DNS	5	3	1000	124
Exp	2	2	10000	1000

How to **efficiently** identify coherent structures and/or the **most relevant** components from such a dataset ?
$\rightsquigarrow$ Observability and uncertainties have to be quantified.

Spatial properties inheritance [PoF2014]

Let consider a spatial bounded linear operator applied to the observable :

$$\boldsymbol{\nabla} \cdot y(x,t) = 0$$

By injecting the modal decomposition :

$$\begin{aligned} \boldsymbol{\nabla} \cdot y(x,t) &= \boldsymbol{\nabla} \cdot \left(\sum_i \alpha_i(t)\, \boldsymbol{\Phi_i}(x)\right) \\ &= \sum_i \alpha_i(t)\, \boldsymbol{\nabla} \cdot \boldsymbol{\Phi_i}(x) \\ &= 0. \end{aligned}$$

Then, when $\alpha_j(t)$ form an orthonormal basis, we have :

$$\begin{aligned} \int_{-\infty}^{\infty} \alpha_j(t) \sum_i \times \alpha_i(t)\, \boldsymbol{\nabla} \cdot \Phi_i(x)\, \mathrm{d}t &= \int_{-\infty}^{\infty} \sum_i \alpha_j(t) \times \alpha_i(t)\, \boldsymbol{\nabla} \cdot \Phi_i(x)\, \mathrm{d}t \\ &= \sum_i \boldsymbol{\nabla} \cdot \boldsymbol{\Phi_i}(x) \int_{-\infty}^{\infty} \alpha_j(t) \times \alpha_i(t)\, \mathrm{d}t \\ &= \boldsymbol{\nabla} \cdot \boldsymbol{\Phi_j}(x) \\ &= 0. \end{aligned}$$

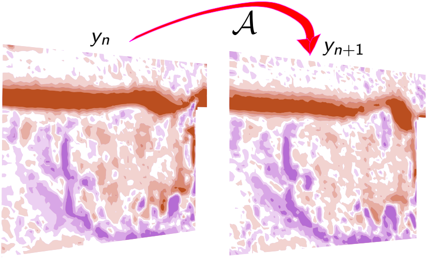
Henceforward, as for the observable y, the divergence of each mode is zero.

"We represent a fluctuating signal by the mean (time-averaged) contribution, the periodic wave and the turbulent motion. ."

Reynolds & Hussain, "The mechanics of an organized wave in turbulent shear flow", (1972) *J. Fluid Mech.*

What are dynamic modes ?

Schmid[1] ; Rowley[2] ;
→ Assume there exists an operator of evolution, $\mathcal{A}$, such as the y_k are realizations of a *nonlinear* process.



→ Find a similar matrix to $\mathcal{A}$. Dynamic modes are defined as eigenvectors of $\mathcal{A}$, computed thanks to the similar matrix.

1. Schmid *et al* (2008) *66th APS meeting* ; Schmid, (2010) *J. Fluid Mech.*
2. Rowley *et al*, (2009) *J. Fluid Mech.*

Defining the Evolution Operator $\mathcal{A}$ [PoF2014]

If Φ is the flow of the fluid dynamical system :

$$\boldsymbol{X}_{n+1} = \Phi_{\Delta t} \boldsymbol{X}_n,$$

and Π is the projector onto the experimental space (*i.e.* $y_n = \Pi \boldsymbol{X}_n$), $\mathcal{A}$ is defined by :

$$\mathcal{A} \circ \Pi = \Pi \circ \Phi_{\Delta t}.$$

Then,

$$\begin{aligned}
\mathcal{A} y_n &= \mathcal{A} \circ \Pi \boldsymbol{X}_n \\
&= \Pi \circ \Phi_{\Delta t} \boldsymbol{X}_n \\
&= \Pi \boldsymbol{X}_{n+1} \\
&= y_{n+1}
\end{aligned}$$

Spectral properties of DMD

When expressing a snapshot on the eigenspace of $\mathcal{A}$:

$$\begin{aligned} y_n &= \mathcal{A} y_{n-1} \\ &= \mathcal{A} \textstyle\sum_i a_i^{n-1} \phi_i, \quad \text{dec. on eigenspace} \\ &= \textstyle\sum_i A a_i^{n-1} \phi_i \\ &= \textstyle\sum_i a_i^{n-1} \nu_i \phi_i, \quad \text{using eigenvalues properties.} \end{aligned}$$

By recurrence :

$$y_n = \sum_i a_i^1 \nu_i^n \phi_i \equiv \sum_i \nu_i^n \phi_i,$$

Spectral properties of DMD

$$y_n = \sum_j a_i^1 \nu_j^n \phi_i \equiv \sum_j \nu_j^n \phi_i,$$

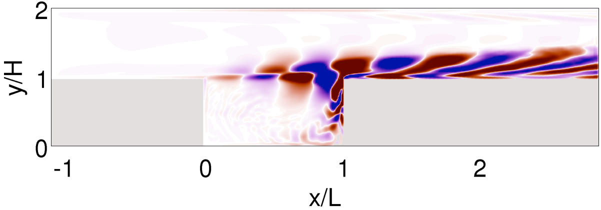
rewriting the eigenvalues :

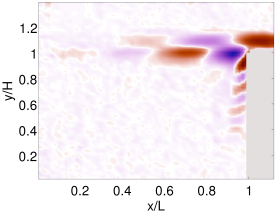
$$\nu = \rho \exp\left(\sqrt{-1}\omega \Delta t\right).$$

The method identifies

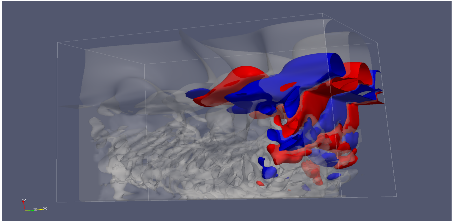
- growth rates ρ
- frequencies ω

Shear layer DMD mode [PoF2014]





Shear layer DMD mode [PoF2014]



DMD and uniform sampling

The DMD algorithm needs an uniform sampling.

Data problems

- Corrupted dataset
- Incomplete dataset
- Convergence of data pre/post-treatment

uniform sampling is not always possible

Experimental issues : example taken from Fluid Mechanics

Observable :
2D2C field (PIV) $\rightarrow 1000 \times 1000 px$
Frequencies of the flow :

1. one low ($\approx 0.1 Hz$) $\Rightarrow$ $10s$ of sampling at least
2. one high ($\approx 200 Hz$)$\Rightarrow$ sampling rate at $400 Hz$

Depth of images : 12-bit
Broad-band needed :
$bb = 400 \times 1000^2 \times 12 > 4 Gb.s^{-1}$
for at least $10s$

Unreachable for standard material

Non-Uniform DMD [PoF2015]

With the expression

$$y_n = \sum_j a_i^1 \nu_j^n \phi_i \equiv \sum_j \nu_j^n \phi_i,$$

we can write more generally :

$$\begin{array}{rclcl} y_{t_n} & = & \sum_j \nu_j^{t_n} \phi_j + \boldsymbol{e} & \approx & \nu_1^{t_n} \phi_1 + \nu_2^{t_n} \phi_2 + \dots \\ K & = & M\,V + R & \approx & M\,V. \end{array}$$

How to achieve this decomposition ?

$$K = M\,V + R \approx M\,V.$$

Pseudo-Vandermonde Matrix and Modes

V [3] is :

$$V = \begin{pmatrix} \lambda_1^{t_1} & \lambda_1^{t_2} & \dots & \lambda_1^{t_{N_t}} \\ \lambda_2^{t_1} & \lambda_2^{t_2} & \dots & \lambda_2^{t_{N_t}} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_m^{t_1} & \lambda_m^{t_2} & \dots & \lambda_m^{t_{N_t}} \end{pmatrix},$$

and M is the modes :

$$M = (\psi_1 \dots \psi_m)\,.$$

3. times t_i are taken arbitrary, not necessary ordered.

How to achieve this decomposition ?

Obtaining of the Spatial Modes

Matrix M is easily computed :

$$M \approx K\,V^{+},$$

where V^{+} is Moore-Penrose pseudo-inverse of V.

Obtaining the frequencies PoF2015

Compressed computing

A low number of modes is supposedly dominant $\rightsquigarrow$ Temporal spectrum of the system is sparse.

- Compressed sensing approach[4].
  $\rightsquigarrow$ m modes are chosen.
  $\rightsquigarrow$ only $\widetilde{N_t} \geq 2m$ are necessary.
- Clustering[5] components with similar spectral features, based on the sparse spectrum.
  $\rightsquigarrow$ Select $\widetilde{N_x} \ll N_x$ ones.

$\rightsquigarrow$ K is replaced by $\widetilde{K} \in \mathbb{R}^{\widetilde{N_x} \times \widetilde{N_t}}$

4. D.L. Donoho *et al.*, (2006) *IEEE T. Inform. Theory*
5. N_x is the size of the observable, and K is $N_x \times N_t$

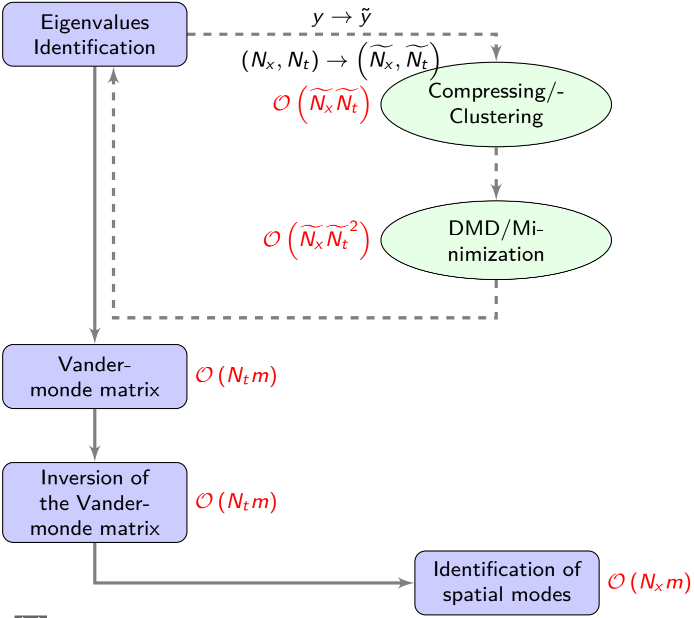

Eigenvalues Identification
$y \to \tilde{y}$
$(N_x, N_t) \to \left(\widetilde{N_x}, \widetilde{N_t}\right)$
Compressing/-Clustering
$\mathcal{O}\left(\widetilde{N_x}\widetilde{N_t}\right)$
DMD/Minimization
$\mathcal{O}\left(\widetilde{N_x}\widetilde{N_t}^2\right)$
Vandermonde matrix
$\mathcal{O}\left(N_t m\right)$
Inversion of the Vandermonde matrix
$\mathcal{O}\left(N_t m\right)$
Identification of spatial modes
$\mathcal{O}\left(N_x m\right)$

Illustration PoF2015

Efficiency of compressed approach

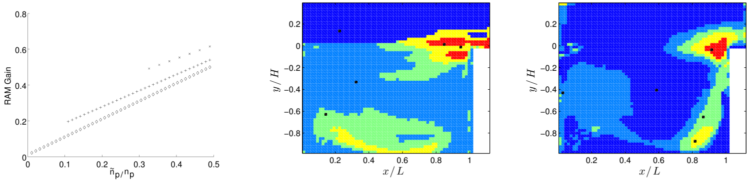
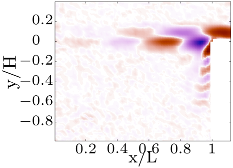


Illustration ICTAM2012,PoF2015

Results on the cavity flow

$St_L = 1.02$

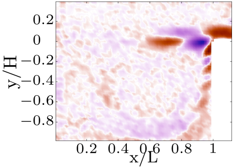


DMD mode

500 snapshots

7000 spatial points

$St_L = 1.02$

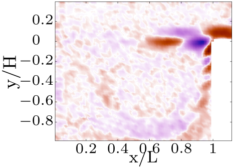


NU-DMD mode

10 randomly taken snapshots

7000 spatial points

$St_L = 1.02$



NU-DMD mode

10 randomly taken snapshots

10 spatial points

"Why go to so much effort to acquire all the data when most of what we get will be thrown away ?"

Donoho, "Compressed Sensing", (2006) *T. Inform. Theory*

Representation from a sparse observable[TCFD2016]

A hash function $\mathfrak{h} : \mathcal{R}^{n_e} \rightarrow \mathcal{N}$ associates an entry $\boldsymbol{y}$ with a key k.

$$\mathfrak{h}^{\boldsymbol{v},w}(\boldsymbol{y}) := h_0 + \left\lfloor \frac{\boldsymbol{v} \cdot \boldsymbol{y}}{w} \right\rfloor .$$

It can applied to any (sparse) observable y, embedded as

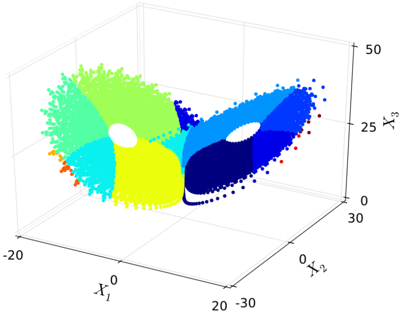
$$\boldsymbol{y} \equiv (y(t - \Delta t) \dots y(t - (n_e - 1)\Delta t)) ,$$

- ✓ every kind of observable (even 1-D)
- ✓ Very computational friendly

It is based on the Johnson–Lindenstrauss lemma

Representation from a sparse observable[TCFD2016]

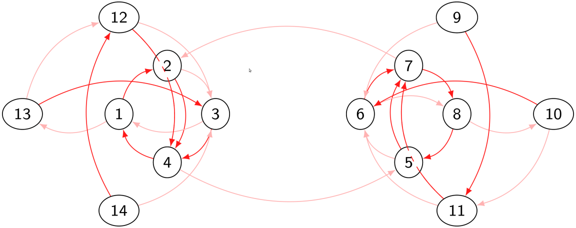
A hash function $\mathfrak{h} : \mathcal{R}^{n_e} \rightarrow \mathcal{N}$ associates an entry $\boldsymbol{y}$ with a key k.

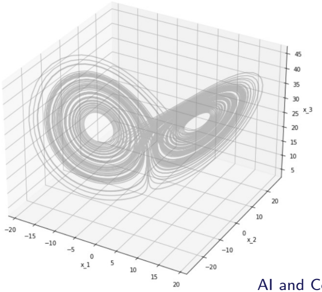


Keys (i.e., objects in the image space of $\mathfrak{h}$) generate a Voronoï paving of the observable space.

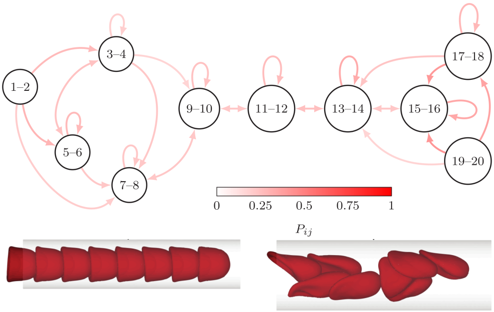
Modeling the dynamics

Based on transition probabilities from clusters to clusters, a stochastic model can be derived.

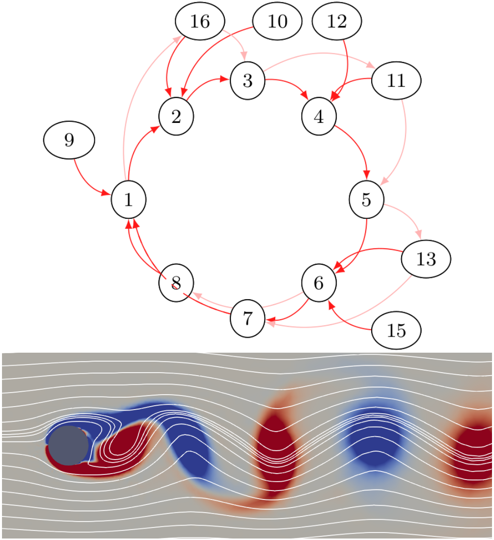




Blood Flow [PRE 2019]

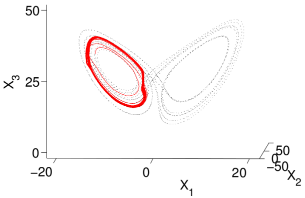


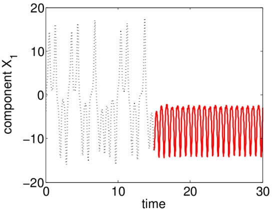
Flow past cylinder [TCFD 2016]



Control using Statistical Learning TCFD 2016

A control law is learned with statistical learning (really, it is reinforcement learning).





Control is turned on at $t = 15$.

" By trying all actions in all states repeatedly, [the agent] learns which are best overall, judged by long-term discounted reward . "

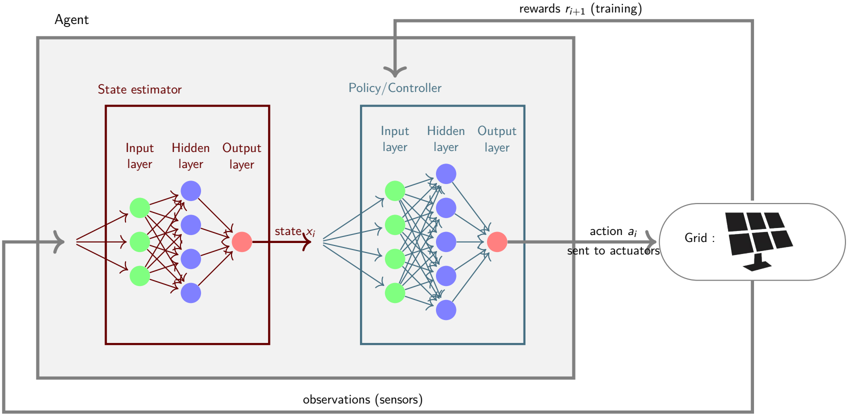
Chris Watkins, (1992), *Machine Learning*, 8, pp.279-292

Framework of Deep Reinforcement Learning

1. representation of the system : state x_s (can be discrete or continuous)
2. actuations : action a
3. policy : probability of chosing action a when in state x_s : $\pi(a|x_s)$
4. reward : quantifying how good is the transition from state x_s to state x_{s+1} under the action a : $r := r(x_s, a, x_{s+1})$
   User designed (and hard to design !)

The main objective is to identify the best policy, aka the one that will maximize the sum of rewards over time.

Framework of Deep Reinforcement Learning



Maximizing the rewards

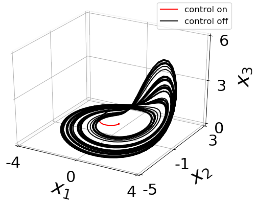
To each transition, from a state x_s to the state x_{s+1} is associated a reward r :

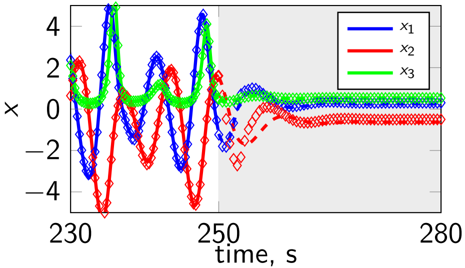
$$V_i = \lim_{k \to \infty} E\left[\sum_{s=1}^{k} \gamma^{s-1} r\left(x_s, \pi(x_s), x_{s+1}\right)\right]$$

The optimal policy means maximizing the quantity V.
It can be rewritten as the Bellman's equation :

$$V_i = r^{\pi}\left(\pi(i)\right) + \gamma \sum_j p\left(i, \pi(i), j\right) V_j.$$

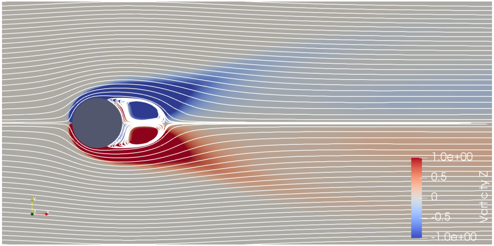
Roessler attractor



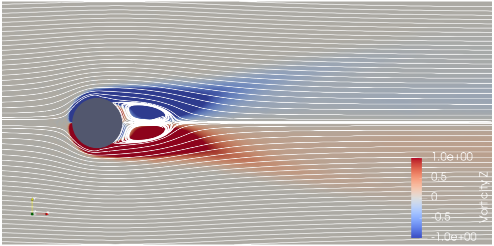


State components (solid line) and Predictions (marks) for the Roëssler system. Gray are : the control is turned on. It represents the oxidation of NADH by O1 when catalyzed by horseradish peroxidase.

Flow past bluff body



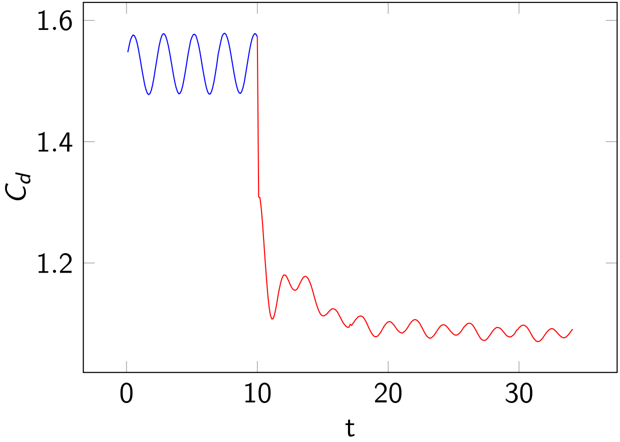
No control



Control

Flow past bluff body

The drag is reduced by almost 30% !



Power Balance

A mini grid is :

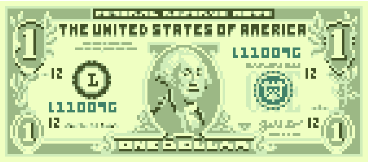
- Receiving power from the renewable sources : P_{re}
- Providing enough power to meet the consumer needs : P_{load}
- Buying/selling power to the grid : P_{grid}.
- Charging/discharging the battery : P_{batt}

and the power balance is :

$$P_{load} = P_{re} + P_{batt} + P_{grid}$$

The objective is to optimize the management of P_{batt} and P_{grid}.

So more users will desire one



Maximizing revenues

We want to optimize

- profits
  - sell (when high prices)
  - minimize buying (except when low prices)
- sustainability/investment via battery management
  - increase lifetime
  - identify correct sizing
  - less heating/risks with second hand battery
- delivery to the consumer (loads, grid and REs are all intermittent)

Challenges and constrains of Energy Management Systems

- Fast controller

  So it remains cheap/can work on different situations
- Cheap actuators/sensors

  Mostly metering, eventually connected
- Limited access to sensors/information

  So it is realistic

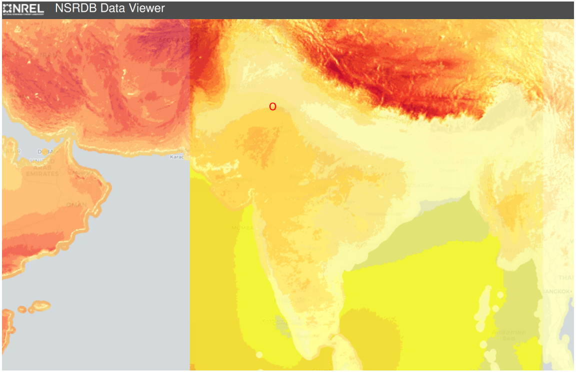
My belief : Data-driven methods are the best solutions !

- Physics informed But it is hard and expensive !
- Black Box But what do we know and understand ?

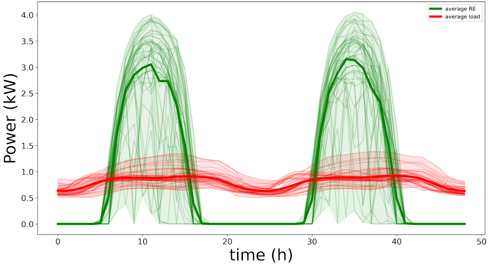
Situations can evolve during usage !

Source of data

- Load comes from the PJM Hourly Energy Consumption Data
- Production comes from the US National Solar Radiation Database, the data point is Panjab.



Numerical Results



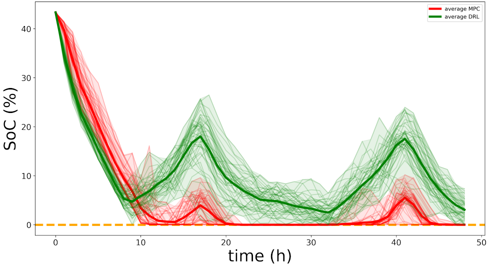
Considered control objectives are :

- user electric power demand satisfaction
- revenue maximization
- soon : minimizing battery operating costs

Constrains

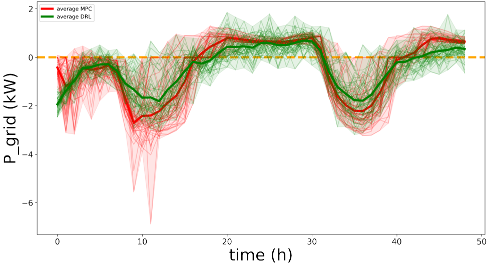
- exceeding/missing power variations
- soon : unreliable main grid

States of Charge



By its overall predictive nature, the DRL tends to take into account the worst possible scenarios, and hence still keep the SoC not at zero.
It also has a longer horizon that MPC.
It means a more resilient grid, able to respond to unpredicted/able demands.

Energy Market Participation



By its predictive nature, the DRL tends to

- sell 38% less
- buy 16% less

It leads into savings in battery life cycles - increasing the lifetime by 27%..

Identical performances and Considerable speedup

Once trained, the DRL allows to have quick system. It means the on-site requirements remain cheap.

	time (sec)	Value ($)
MPC	34.9 ± 3.8	27.9 ± 9.8
DRL	0.05 ± 0.003	28.5 ± 9.4
diff	6955%	3.8%

The speed up is around 7000%, and the overall performance are slightly increased.

Conclusions

- Model methodologies, from large data to sparse observations[1–4].
- Control methodologies[4–7].
- Smart Grid management[6–7].

All these fields still require a lot of multi-disciplinary work !

Some publications

1. *A Dynamic Mode Decomposition approach for large and arbitrarily sampled systems*, PoF 27, 2015
2. *Investigating mode competition and 3D features from 2D velocity fields in an open cavity flow by modal decompositions*, PoF 26, 2014
3. *POD-Spectral Decomposition for Fluid Flow Analysis and Model Reduction*, TCFD 27, 2013
4. *A statistical learning strategy for closed-loop control of fluid flows*, TCFD, 2016
5. *Deep Reinforcement Learning strategies for the reduction of the drag in the flow past buff bodies*, HEFAT 2021
6. *Modeling and Optimal Control of Energy Storage System For Battery Life Extension Via Model Predictive Control*, European Control Conference 2021
7. *Optimal operation of renewable energy microgrids considering lifetime characteristics of battery energy storage system*, Conference on Decision and Control 2021

More infos available on my website :

`www.gueniat.fr/publications.html`

Thank you for your attention.
If you have any questions, I will be pleased to answer those.