Some thoughts on modeling in automatic control and its possible relationship with today's AI

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PID

$$u(t) = k_p e(t) + k_i \int_0^t e(\tau) d\tau + k_d \dot{e}(t)$$

- $u(t)$: control variable, $r(t)$: setpoint, $y(t)$: measured process variable, $e(t) = r(t) - y(t)$: tracking error
- k_p, k_i, k_d: gains

More than 95% of all industrial problems are solved by PID control, although many of these controllers are actually PI controllers because derivative action is not included (Åström & Murray: *Feedback Systems for Scientists and Engineers*, 2nd ed., 2008)

$\Downarrow$

POOR MODELING

Disadvantages of PID

- A certain level of expertise, especially in complex systems, is required
- Time-consuming gain tuning
- Lack of robustness with respect to parametric variations (aging, . . .)
- Integral windup
- . . .

MFC: Model-free control

M. Fliess, C. Join, Model-free control, *Int. J. Contr.*, 86, 2013, 2228-2252
Google Scholar: 1200 citations in less than 12 years

M. Fliess, C. Join, An alternative to proportional-integral and proportional-integral-derivative regulators: Intelligent proportional-derivative regulators, *Int. J. Robust Nonlin. Contr.*, 32, 2022, 9512-9524

Many successful applications all over the world in a wide variety of fields

MFC *ultra-local model*

Ultra-local model, only valid during a short time lapse,

$$y^{(\nu)} = F + \alpha u \tag{1}$$

for most input-output systems, under weak assumptions:

- α: constant parameter such that the 3 terms are of same magnitude
  $\Rightarrow \alpha$ does NOT need to be precisely estimated
- $F(y, \ldots, y^{(\mu \geq \nu)}, \ldots)$: the whole information on the unknown system (including the external **perturbations**)
- **Data-driven** estimate ($\nu = 1$, valid in most concrete situations)

$$F_{\text{est}}(t) = -\frac{6}{\tau^3} \int_{t-\tau}^{t} \left[(t - 2\sigma) y(\sigma) + \alpha \sigma (t - \sigma) \Delta u(\sigma) \right] d\sigma$$

where τ is small. In practice: real-time digital filter.

MFC: *Intelligent* P controller

Intelligent P controller (iP): $\boxed{u = -\dfrac{F_{\text{est}} - \dot{y}^* + K_P e}{\alpha}}$

- y^*: output reference trajectory
- $e = y - y^*$: tracking error
- K_P: tuning gain

$$\Downarrow$$

$$\dot{e} + K_P e = F - F_{\text{est}} \approx 0$$

STRAIGHTFORWARD GAIN TUNING ($K_P > 0$)
Guaranteed robustness - No antiwindup

MFC: Application to a bus

Speed control for ALSTOM buses

Training of 20 engineers in our techniques

« Dans le logiciel embarqué d'APTIS, nous avons implémenté une régulation de vitesse basée sur l'algorithme Commande Sans Modèle de la société AL.I.E.N.
Cette régulation de vitesse doit répondre à des critères :
•de dynamique : temps de réponse
•de charge : 14 tonne à vide jusqu'à 20 tonne en charge maximale
•et enfin de pente: du profil plat jusqu'à une pente de 12%!

Avec **un jeu de paramètre**, la Commande Sans Modèle a pu répondre à l'ensemble de ces exigences.
Comparée à un PI classique, la CSM est **plus robuste** et présente un gain indiscutable sur **le temps de validation** sur simulateur et sur bus électrique. »

MFC: Comparisons

Comparisons with other closed-loop control strategies conclude that MFC outperforms industry-standard strategies in a range of metrics:

- Artuñedo, A., Moreno-Gonzalez, M., Villagra, J.: Lateral control for autonomous vehicles: A comparative evaluation. Annual Rev. Contr. **57**, 100910 (2024).
- Michel, L., Braud, C., Barbot, J.-P., Plestan, F., Peaucelle, D., Boucher, X.: Comparison of different feedback controllers on an airfoil benchmark. Wind Energ. Sci. **10**, 177–191 (2025).
- ...

MFC: iP & PI

Elementary calculations on PI:

$u(t) = k_p e(t) + \int_0^t e(\tau)d\tau \Rightarrow \dot{u}(t) = k_p \dot{e}(t) + k_i e(t) \Rightarrow$

$\frac{u(t)-u(t-h)}{h} = k_p \frac{e(t)-e(t-h)}{h} + k_i e(t) \Rightarrow u(t) = u(t-h) + k_p(e(t) - e(t-h)) + hk_i e(t)$

Elementary calculations on iP: $u(t) = -\frac{F(t)-\dot{y}^*(t)+K_P e(t)}{\alpha}$

$F \approx \dot{y}(t) - \alpha u(t-h) \approx \frac{y(t)-y(t-h)}{h} - \alpha u(t-h) \Rightarrow u(t) = u(t-h) - \frac{e(t)-e(t-h)}{h\alpha} + \frac{K_P}{\alpha} e(t)$

$$\text{PI} \equiv \text{iP} \Leftrightarrow k_p = -\frac{1}{h\alpha},\ k_i = \frac{K_P}{h\alpha}$$

Only valid in discrete time ($h \neq 0$)

Easy extension to PID ($\nu = 2$)

MFC $\Rightarrow$ A conceptual result for PID

The **ubiquity** of PID:
A key property in process control in all human activities for many decades

$\Downarrow$

MFC permits:

- an explanation, perhaps for the first time;
- to showcase the difficulty of gain tuning.

$\Downarrow$

Better conceptual understanding of a classic industrial technology

Question: Why not replacing PID by MFC?

Easier to tune and implement & more robust

Model-Predictive Control (MPC)

Jacques RICHALET: Model predictive control (MPC) (*Automatica*, 1978)
Interesting reference: *La commande prédictive a gagné la partie* (Mesures, avril 2005)

MPC: Popular control schemes where **MODELS** are used for predicting the future behavior of the system over a *short* time window, the *horizon*.

Key rôles of various **OPTIMAL CONTROL** techniques: LQR, Dynamic Programming, Pontryagin's maximum principle, ...

Reset after a short time lapse $\neq$ traditional optimal control

Predictive Control without a Model

- Models via Artificial Neural Networks (ANNs) $\Rightarrow$ Machine-Learning
- Via the *ultra-local* model associated to *model-free control*. Large number of publications, especially in China, often with concrete applications.
- ...

MFPC: Model-free predictive control

Short time lapse $\Rightarrow \dot{y} = F + \alpha u$ becomes $\dot{y} = a + \alpha u$: elementary **flat** system, where $F \approx a$ approx. const., y **flat** output.
Lagrangian (cost function):

$$\mathcal{L} = (y - y_{\text{setpoint}})^2 + u^2 = (y - y_{\text{setpoint}})^2 + \left(\frac{\dot{y} - a}{\alpha}\right)^2$$

Criterion: $J = \int_{t_i}^{t_f} \mathcal{L} dt$
$\Rightarrow$Euler-Lagrange equation: $\frac{\partial \mathcal{L}}{\partial y} - \frac{d}{dt}\frac{\partial \mathcal{L}}{\partial \dot{y}} = 0$
$\Rightarrow$ non-homogeneous linear ODE (independent of a): $\ddot{y} - \alpha^2(y - y_{\text{setpoint}}) = 0$

Optimal solution: $y^\star(t) = y_{\text{setpoint}} + c_1 \exp(\alpha t) + c_2 \exp(-\alpha t)$
Boundary conditions: $y(t_i) = y_i$, $y(t_f) = y_{\text{setpoint}}$

$$\Downarrow$$

$$c_1 = \frac{y_i \exp(-\alpha t_f) - y_{\text{setpoint}} \exp(-\alpha t_f)}{\exp(\alpha t_i)\exp(-\alpha t_f) - \exp(-\alpha t_i)\exp(\alpha t_f)}$$

$$c_2 = -\frac{\exp(\alpha t_f)(y_i - y_{\text{setpoint}})}{\exp(\alpha t_i)\exp(-\alpha t_f) - \exp(-\alpha t_i)\exp(\alpha t_f)}$$

Subdivide the time interval $[t_0, t_N[$, $t_0 < \cdots < t_k < t_{k+1} < \cdots < t_N$. On each time interval $[t_k, t_{k+1}[$, repeat the above procedure.

Two examples

From the MPC literature

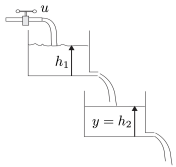
1. Two tanks (Europ. J. Contr. 2024): neural models (machine learning) & reinforcement learning.
2. Avoidance of unexpected obstacles (IFAC PapersOnLine 2021): neural models (machine learning) & reinforcement learning.

What is *reinforcement learning* (*RL*)?

Reinforcement Learning (RL) is an area of machine learning where algorithms learn to make decisions by trial and error, ultimately striving to maximize some cumulative reward. This technique draws inspiration from how humans and animals learn from feedback, adapting to complex, dynamic environments over time. Reinforcement Learning stands out in its capability to tackle problems where decision-making is sequential, and the consequences of actions unfold over time.

RL requires ridiculously large numbers of trials to learn any new task
(Yann LeCun)

Two tanks

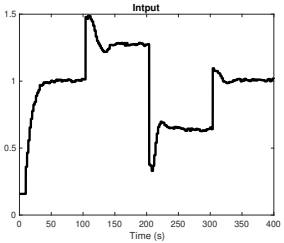


(1) Two tanks

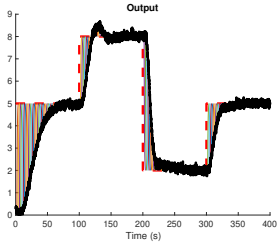
$$\begin{cases} s_1 \dot{h}_1 = u - k_1\sqrt{h_1} \\ s_2 \dot{h}_2 = k_1\sqrt{h_1} - k_2\sqrt{h_2} \end{cases} \tag{2}$$

$u \geq 0$: control variable, h_ι, $\iota = 1, 2$, $0 \leq h_\iota \leq 10$: water level, k_ι and s_ι: constant parameters.

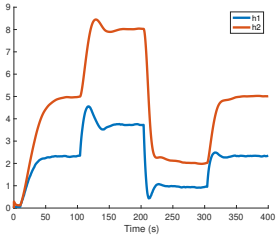
Two tanks: MFPC



(2) u (–)

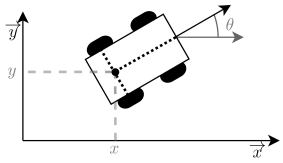


(3) Setpoint (- -) and y (–)



(4) Tank levels h_1 and h_2

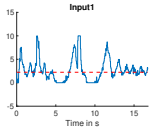
Autonomous robot: Dubins'car



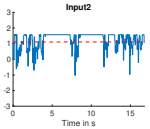
$$\begin{cases} \dot{x} = u_1 \cos(u_2) \\ \dot{y} = u_1(1+p)\sin(u_2) \end{cases} \tag{3}$$

- x, y: Cartesian coordinates of the middle of the rear axle;
- Control variables: u_1 (linear velocity), $\theta = u_2$ (angle with x axis);
- p ($-0.5 \leq p \leq +0.5$): uniformly distributed piecewise-constant perturbation.

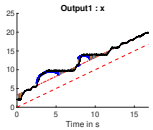
Autonomous robot: MFPC



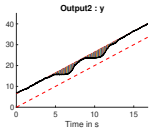
(5) u_1



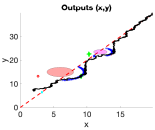
(6) u_2



(7) $x(t)$

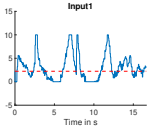


(8) $y(t)$

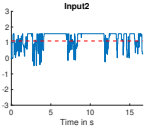


(9) (x, y)

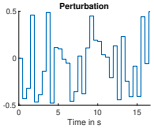
Perturbed autonomous robot: MFPC



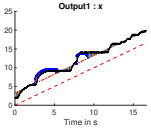
(10) u_1



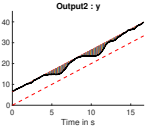
(11) u_2



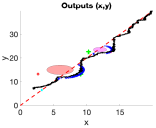
(12) p



(13) $x(t)$



(14) $y(t)$



(15) (x, y)

Today's AI & LeCun's program

Remarkable advances in modern AI (e.g. Generative AI) often rely on

- models striving for comprehensiveness (e.g. LLMs: Large Language Models),
- their associated machine learning mechanisms.

Yann LeCun' **program**:

- **Machine learning sucks**
- **I do favor MPC over RL. I've been making that point since at least 2016**

Analogy with program in math. research – Ex. Langlands program

Today's AI & LeCun's program

Our techniques comply with those program requirements:

- Supremacy of predictive control.
- Reduced rôle of machine learning (in today's meaning).
- Abandon of reinforcement learning in favor of model predictive control.

+

Giving up on modeling that is as accurate as possible

Connections with World Models & Energy-Based Models?

Energy& Infrastructure

Sam Altman, CEO of OpenAI, at the World Economic Forum Annual Meeting, January 2024:

We do need way more energy in the world than I think we thought we needed before ... I think we still don't appreciate the energy needs of this technology

Linking robotics and LLM, as increasingly popular, will fuel this trend

J. Wang et al., Large language models for robotics: Opportunities, challenges, and perspectives, *J. Automat. Intell.*, 4, 2025, 52-64

Our more subtle techniques should be less greedy.

References on model-free predictive control & AI

- C. Join, E. Delaleau, M. Fliess, Model-Free Predictive Control: Introductory Algebraic Calculations, and a Comparison with HEOL and ANNs. *Joint IFAC Conf.: SSSC, TDS, COSY*, Gif-sur-Vette, France, 30 June-2 July 2025. arXiv:2502.00443
- C. Join, M. Fliess, Avoidance of an unexpected obstacle without reinforcement learning: Why not using advanced control-theoretic tools? IEEE 2025 - 13th Int. Conf. Syst. Contr. (ICSC), Marrakesh, Morocco, October 22-24, 2025. arXiv:2509.03721