Green AI in Industry

Evidence from the Water Treatment Sector

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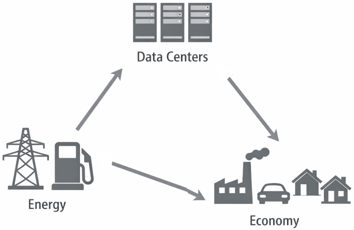
AI and the Energy Transition Challenges

- Growing attention to upstream data centers (e.g., Bonfiglioli et al. 2025; de Vries 2023)
- However, AI can also affect downstream energy use (Metcalfe et al. 2026; IEA 2025)
- This paper: Net effects of at-scale AI deployment on industry energy use



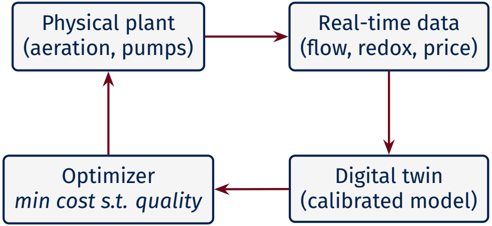
Digital Twins: A trending technology

What is a digital twin? A live virtual replica of a physical process that couples

- real-time sensor streams (flow, weather...)
- a calibrated process model
- an optimizer feeding decisions *back* to the plant.

Stylized facts

- Originated in aerospace (NASA, Apollo-era "pairing"); now diffusing through Industry 4.0
- Fast-growing but early-stage: ~30–40% reported annual growth, adoption concentrated in large, asset-intensive firms



The sense–model–optimize–actuate loop

Reported gains (non-causal) associated to digital twins.
⇒ **This paper**: first fleet-wide *causal* estimates.

Setting: Wastewater Treatment (WWT)

- **1.3%** of global GHG emissions (Ritchie 2020)
- **1%** of global electricity consumption (IEA 2016)

- Representative of class of industrial process that:
  - Use energy-intensive process to meet target unobservable in real time
  - (Optimal) energy requirements stochastic
  - Currently, threshold rules, manual control
  - Digital twins, AI can help optimize in real time
- Industrial drying, cooling, fermentation, metallurgy
- Pioneer: Only 1.1% (1.6%) of European firms in utilities (manufacturing) report using AI for decision-making in machine operations (Eurostat 2025)

AI Rollout

- **Staggered Rollout** from October 2022 to July 2025 across ≈200 plants.
- Exposure to AI is **non-absorbing**: outages, technical interruptions and manual deactivations move plants in/out of AI control.
- **Continuous Treatment**: Observe both initial installation and fraction of time during day for which AI controlled plant

- **AI Goal**: Minimize electricity costs subject to water quality constraints using real-time info (inflow, redox,...) via plant control system (e.g., aeration)

AI Rollout

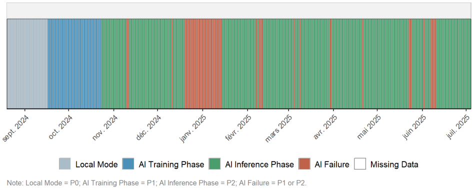


Figure: Roll-out at the plant-level

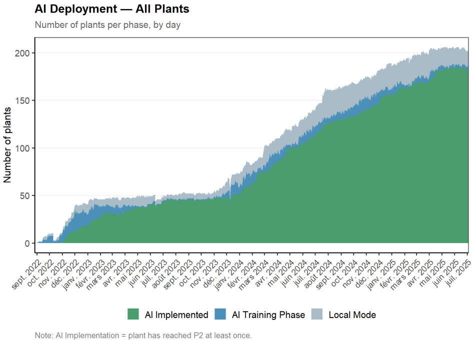


Figure: Roll-out at the aggregate-level

Effects on Energy Efficiency

After 10 weeks of AI treatment, the average total cumulative effect :

- Electricity demand: **-5.4%**
- Carbon footprint: **-6.0%**
- Electricity cost: **-8.2%**

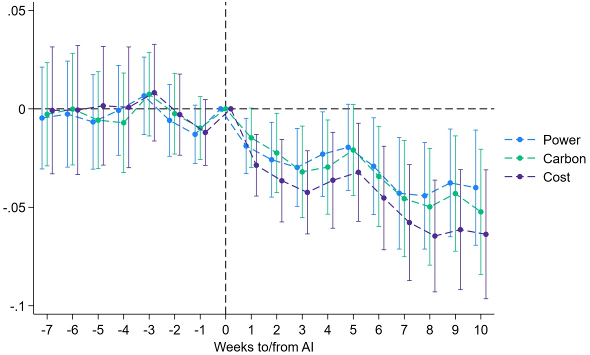


Figure: Event Study Estimation

Intraday Reallocation and increased price responsiveness

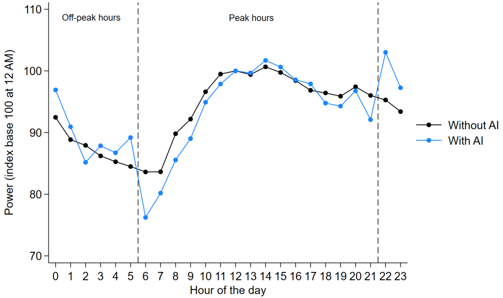


Figure: Daily relative Consumption Profiles With and Without AI

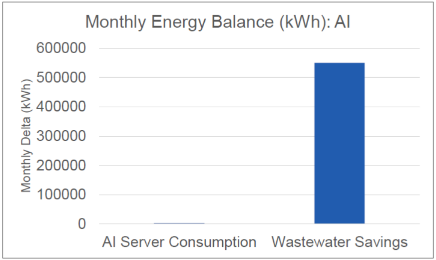
Electricity consumption:

- is **reduced by 15%** hour-to-hour when the tariff regime switches from off-peak to peak hour.
- **increases by 12%** hour-to-hour when the tariff regime switches from peak to off-peak hour

Net energy balance

- Upper bound of upstream AI electricity use: 35–49 MWh/year for all plants
- Downstream savings: $\sim$ **31 MWh/year per plant**

$\Rightarrow$ Upstream energy use **«1%** of downstream savings (in this context)



Greater Resilience to Operational Stress

The gains from AI are **not uniform**: they concentrate when the plant is under stress and static threshold rules break down.

Extreme meteorological events

- Storms and heavy rainfall cause sudden **hydraulic surges** (inflow spikes, dilution, wash-out risk).
- Rule-based control only **reacts** once the surge hits.
- AI ingests weather forecasts ⇒ **prepares buffer capacity hours ahead**, smooths the shock and sustains treatment capacity.

Chemical pollutant peaks

- High ammonium (NH_4^+) loads stress the process.
- AI manages the aerobic/anoxic balance **dynamically** instead of over-aerating by default, yielding a **"triple dividend"**:
  - fewer over-limit NH_4^+ episodes (quality)
  - lower nitrate NO_3^- (quality)
  - lower aeration energy even at high loads (cost)

⇒ **Resilience is a co-benefit of real-time optimization.**

Conclusion

- **Recap:** Using high-frequency data from a fleet of wastewater treatment plants, find that AI-driven digital twin yields substantial reductions in energy use, CO_2 emissions, energy costs. ; maybe also water pollution.
- **Interpretation**: Beyond the topic of GPTs energy footprint, specialized AI can become a lever for sustainable decarbonization with negative abatement costs.
- **Significance**: Extrapolating estimates into DICE-2023 suggests global welfare gains potential of $80 bil. (WWT) to $940 bil. (WWT+drying+galvanization)

Clément de Chaisemartin and Xavier D'Haultfoeuille. Difference-in-differences estimators of intertemporal treatment effects. *The Review of Economics and Statistics*, pages 1–45, 02 2024. ISSN 0034-6535. doi: 10.1162/rest_a_01414. URL https://doi.org/10.1162/rest_a_01414.

Wastewater treatment and the aeration margin

Treatment typically proceeds in three stages.

- Primary treatment removes large debris (screens, grit removal).
- Secondary treatment biodegrades organic matter using microorganisms. In activated sludge process, wastewater is aerated to “activate” the bacteria consuming organic pollutants. Nitrification/denitrification cycle.
- Some plants also operate tertiary processes (e.g., chemical treatment, and disinfection).
- Finally, sludge from primary and secondary stages is treated separately and reused.

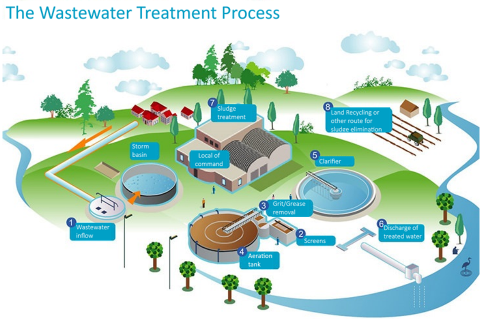


Figure: Diagram of a WWTP

Wastewater treatment and the aeration margin

- Activated sludge WWTP: aeration supplies oxygen in order to multiply bacterias (“activated sludge”) and eliminate nitrogen charges ; too little risks non-compliance, too much wastes energy.
- Prior to AI, rule-based automation. AI ingests high-frequency data from internal sensors (flow rate, redox...), external data (weather, time...) and effluent quality.
- Deployment phases: P0 (local), P1 (training), P2 (optimized AI control).

Figure: Aerial photo of a WWTP

Absolute Weekly Effects

	TWFE-OLS (Std. Error)	De Chaisemartin–D'Haultfoeuille (Std. Error)
Electricity consumption	-314.9^{***}	-606.8^{***}
	(97.8)	(233.2)
Carbon footprint	11.3	-22.8
	(10.5)	(18.9)
Electricity cost	-73.7^{*}	-199^{**}
	(38.5)	(87.9)

Notes: This table reports the estimated impact of AI usage on weekly outcomes at the plant level. We compare a standard two-way fixed effects (TWFE) estimator (Equation (**??**)) with the average cumulative total effect per plant over 10 weeks estimated using de Chaisemartin and D'Haultfoeuille (2024). Absolute effects are expressed in kilowatt-hours (kWh) for electricity consumption, $kgCO_2e$ for the carbon footprint, and euros for the electricity cost. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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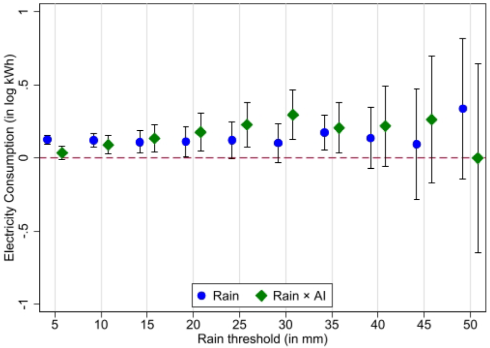
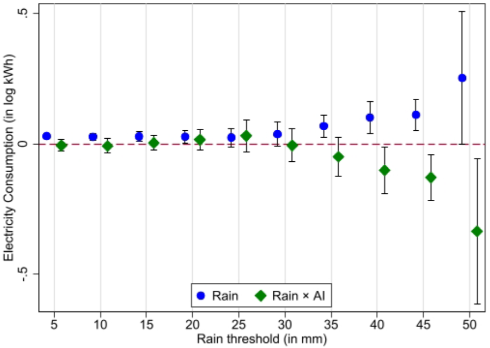
Extreme Rainfall



Thr.	5	10	15	20	25	30	35	40	45	50
IPW	10^2	10^3	10^3	10^4	10^4	10^4	10^4	10^5	10^5	10^5

(a) At the hour-level



Thr.	5	10	15	20	25	30	35	40	45	50
IPW	10^1	10^2	10^2	10^2	10^3	10^3	10^3	10^3	10^3	10^4

(b) At the day-level

▸ Daily consumption pattern with and without AI

Pollution Peaks and AI "Triple Dividend"

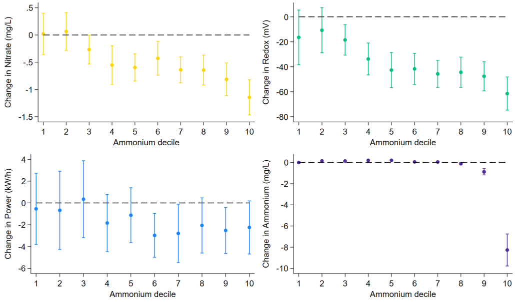


Figure: NH_4^+ Load and AI effect on (i) NH_4^+, (ii) NO_3^-, (iii) Oxydo-Reduction Potential and (iv) Electricity Consumption

AI makes a win-win-win in the management of polluted water (high ammonium concentration):

- Better management of the aerobic/anoxic balance ⇒ **Strong reduction of nitrate concentration.**
- Reduction in overall aeration to maintain good nitrification condition ⇒ **Reduction in electricity consumption for high ammonium loads.**
- Predictive behavior ⇒ **Collapse in the number of over-limit ammonium episodes** at a (negligible) cost for the 8 first deciles.