Intelligent Control and Robotic for Precision Livestock Farming

Dr. Congcong Sun
Agricultural Biosystems Engineering Group, WUR

1st EAAP Conference on Artificial Intelligence 4 Animal Science

Zurich, 4-6 June 2025

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My background

2015 PhD Automatic, Robotics &Vision, *Institut de Robòtica i Informàtica Industrial (CSIC-UPC),* Spain
2021 Postdoc, *Institut de Robòtica i Informàtica Industrial (CSIC-UPC)*, Spain

2021 - Now Assistant Professor, *WUR*, the Netherlands
2022 - Now Lab Manager*, AI for Agro-Food Lab*, *WUR*, the Netherlands

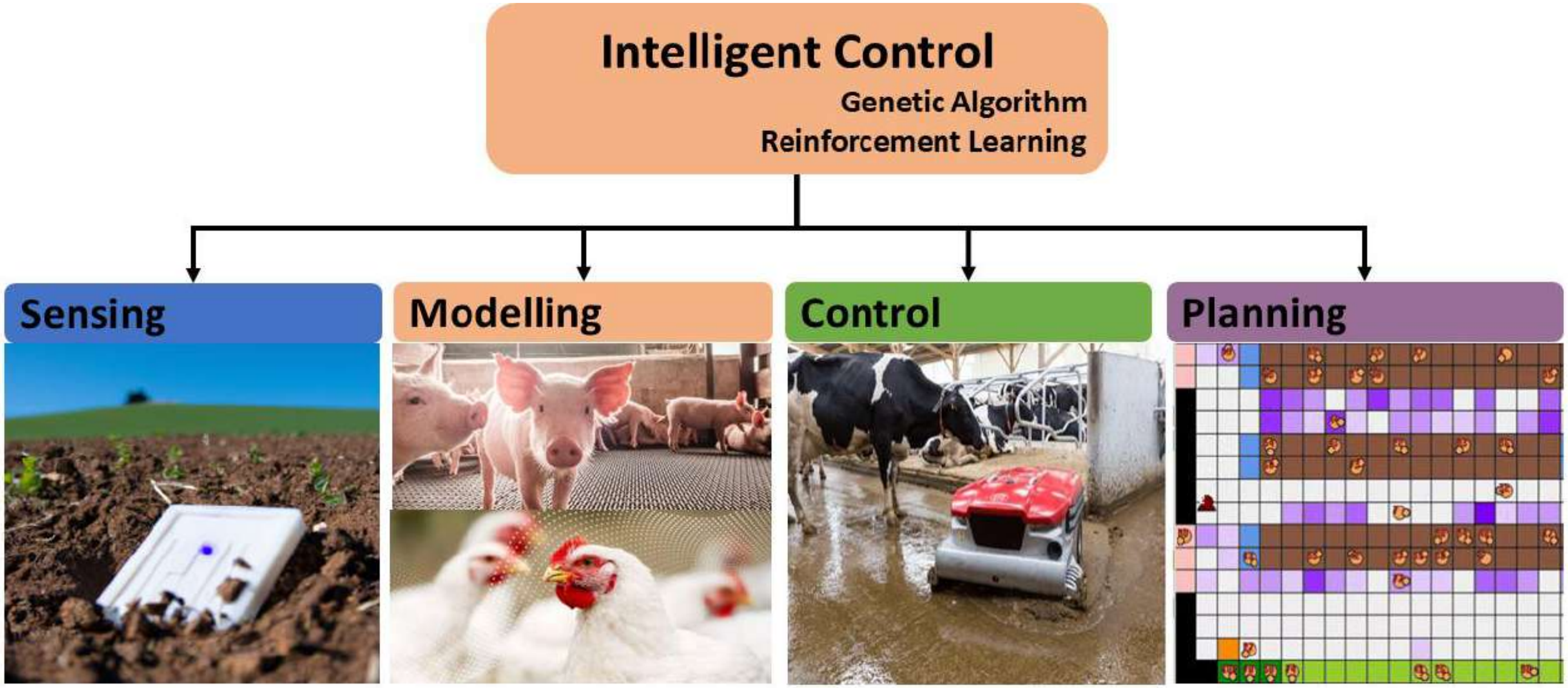

Fig. 1 My research topics

Agricultural Biosystems Engineering Group

"To enhance, exploit and disseminate the potential of technology in primary Agricultural production processes to fulfil the needs of mankind and nature in a sustainable way"

Sensing	**Design**	**Research & Education Staff**	**30**
Modeling	**Robotic**	**PhD**	**55**
Control	**Vision**	**MSc./BSc. Thesis student**	**65**

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Agricultural Biosystems Engineering Group

Peter Groot Koerkamp

Professor & chair

Eldert van Henten

Professor

Gert Kootstra

Associate professor

Nico Ogink

Researcher

André Aarnink

Researcher

Marc Bracke

Researcher

Rik van der Tol

Researcher

Marjolein Derks

Assistant professor

Simon van Mourik

Assistant professor

Munnaf Abdul

Assistant professor

Mahboubeh keyvanara

Assistant professor

Congcong Sun

Assistant professor

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Agricultural Biosystems Engineering Group

Current research lines

1. Machine vision and robotics – Gert Kootstra
2. Self-learning in control and robotics – Congcong Sun

3. Modelling and control – Simon van Mourik
4. Planning, control of Robotic – Mahboubeh keyvanara

5. Precision livestock farming – Rik van der Tol
6. Design of agricultural production systems – Marjolein Derks

7. Measurement technology for environmental aspects – Nico Ogink, André Aarnink & Marc Bracke

8. Eco-smart Sensing Technology

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Challenges in Livestock Industry

Livestock Industry face three dilemmas

- Animal health and welfare
- High biosecurity
- Fragile for disease
- e.g. African Swine Fever

- Environmental Sustainability
- High GHG emission
- Manure management
- Water pollution

- Lack of skilled human labor
- Physically demanding
- Less attractive to younger generations

Towards Optimal, Green & Automated PLF

Common Trends Livestock Industry

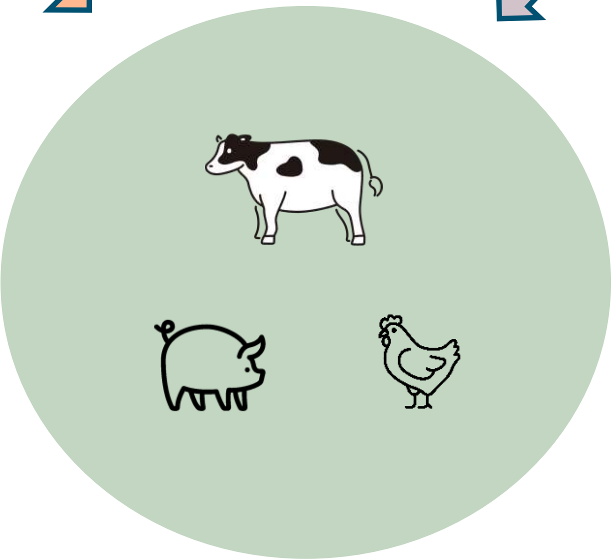
Climate Control

- Animal Welfare
- Heat/cold Stress
- Energy Efficiency

Emission Reduction

- Low emission control
- Ammonia mitigation
- CH4 mitigation

NH_3 CH_4



Robotic

- Sensing
- Robotic
- Artificial Intelligent

AI

Manure Management

- Scraping system
- Aerated liquid manure
- Manure belt system

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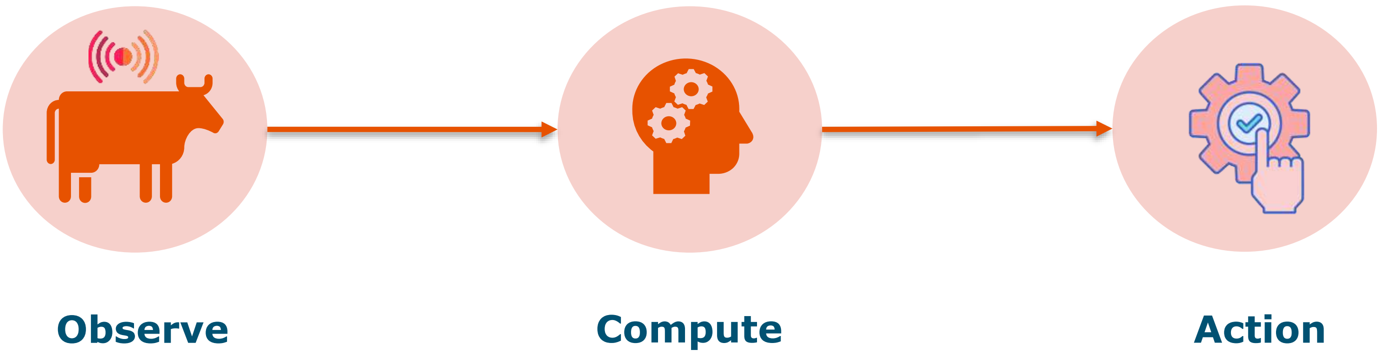
What does control mean?



Achieve expected operation/output through manipulating controlable elements

Different types of control methods

- **PID (Proportional-Integral-Derivative)** : widely used for regulating, stabilizing processes
- **Classical Model-based Control**: based on mathematical model of system, *e.g. MPC*
- **Intelligent Control**: learn from data, adapt to changing environment, *e.g. RL, data-driven MPC*

The selection of control algorithm depends on ***characteristic of the system***, **level of understanding and models available**, ***the desired performance***.

Fig. 2 PID

Fig. 3 MPC

Fig. 4 RL

Why intelligent control is important for livestock?

Agro-food production:

- involves physical, chemical, biological complexities
- does not always have an accurate model
- has lots of uncertainties and variability
- Besides, we are arriving an autonomous era

Fig. 5 Precision livestock farming

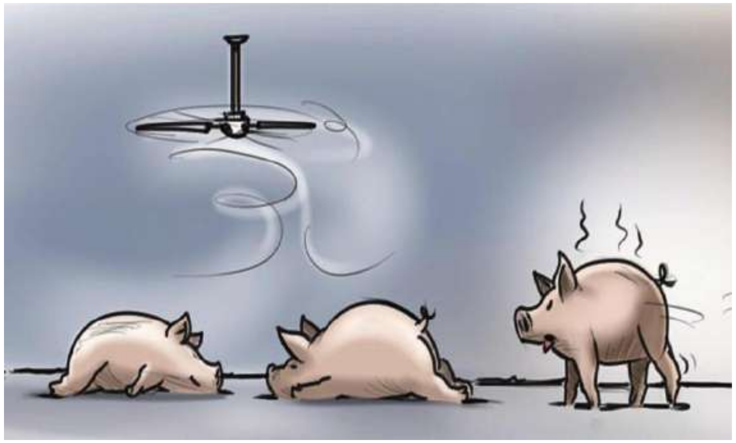


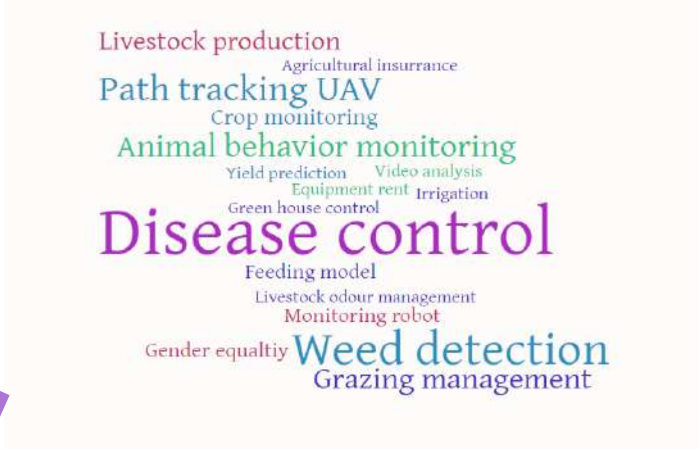
Fig. 6 Pig farm ventilation control

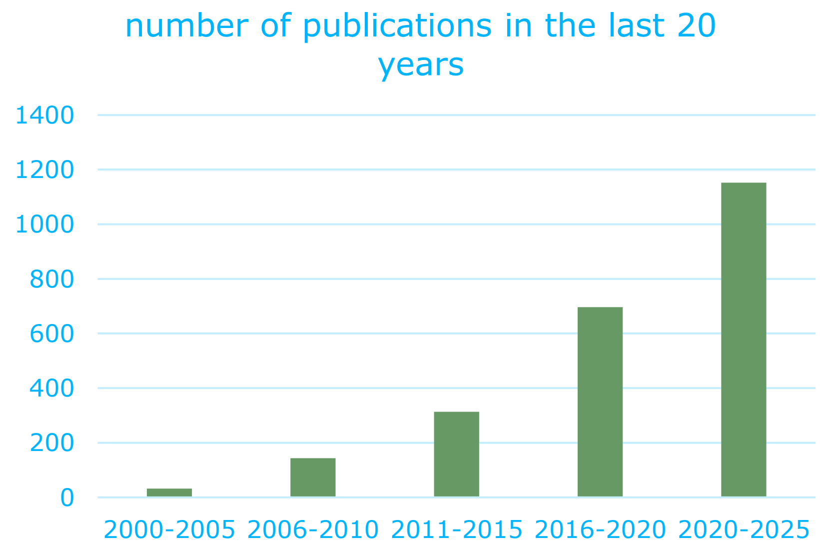
Current situation

Keywords:
Intelligent Control && Agriculture
Intelligent Control && Livestock

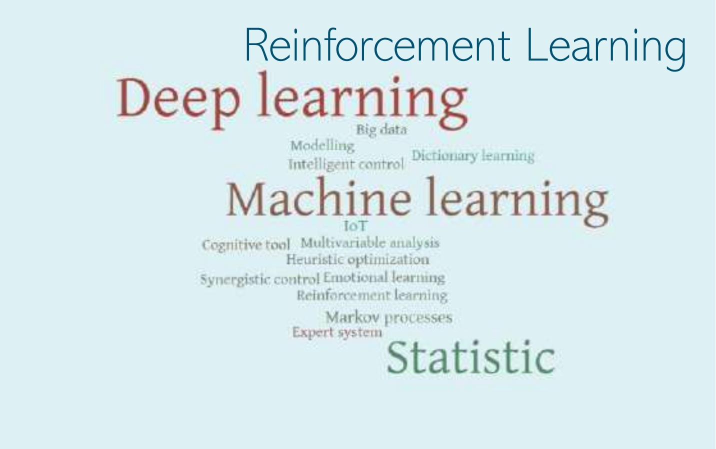
2338 papers between 2000-2025 in Scopus

Applications





Methods



MPC v.s. Reinforcement Learning

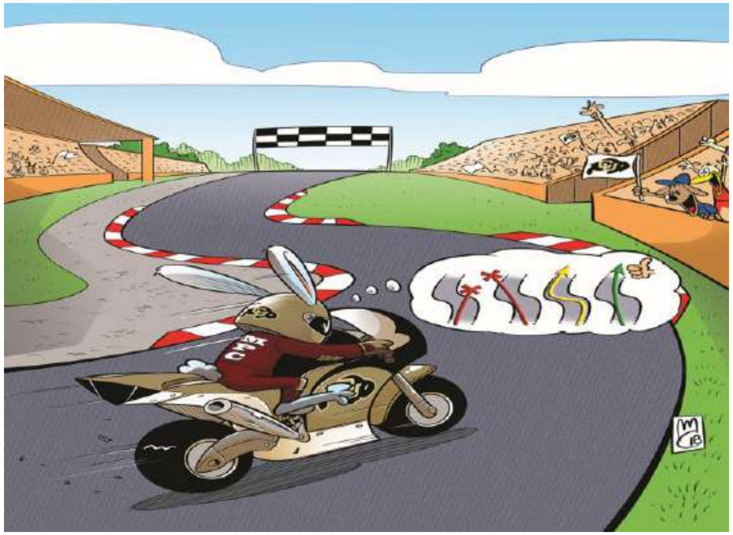


Fig. 7 Model Predictive Control

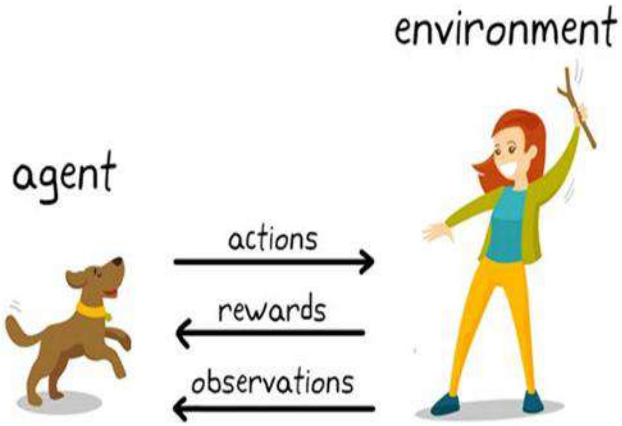


Fig. 8 Reinforcement Learning

MPC v.s. Reinforcement Learning

MPC	RL
Rely on good model	Can be model free
Optimize based on a model	Learn for decision making
Easily handles constraints	Difficult in handling constraints
Struggle with long-term prediction	Infinite prediction horizons
High computation efforts for uncertainties	Inherently robust
Low adaptability	High adaptability

Intelligent Control for Optimization

*Intelligent control for optimization to achieve **sustainable** & **efficient** Livestock production.*

Motivations:

- World's **growing population** will require **50%** more **food** by 2030 compared to 1998.
- Livestock farming is one of the **most important** protein **producers** worldwide.
- Livestock farming is among the **most exposed sectors** to **climate changes**.
- **One-thrid** of greenhouse gas **emissions** come from **livestock**.

Intelligent Control for Optimization

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Use Case: Climate Control of poultry house using RL

George Truijens

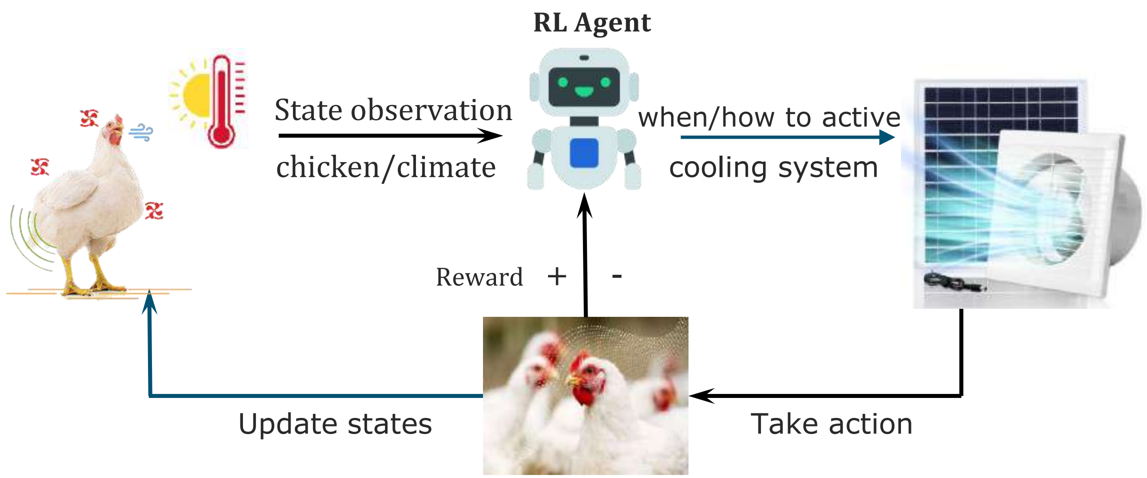

Fig. 9 Poultry house ventilation system control using Deep Reinforcement Learning

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C. Sun et. al, HeatSense WP2 Report. Wageningen University & Research, 2024.

Climate Control

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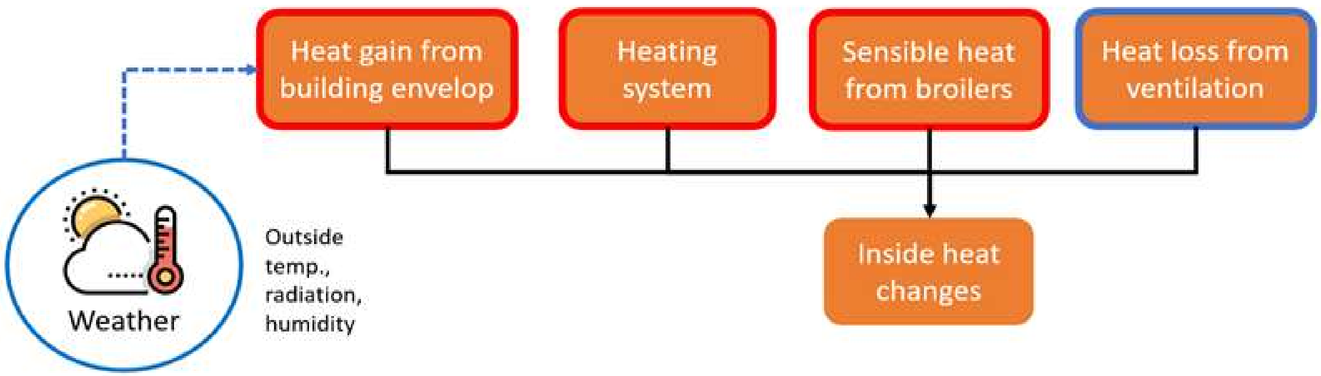

- The indoor climate is computed by:

$$\rho_{air} C_p V_T \, {}^{dT_i}/_{dt} = Q_{envelop} + Q_{heater} + Q_{sen} + Q_{vent}$$

C. Sun et. al, HeatSense WP2 Report. Wageningen University & Research, 2024.

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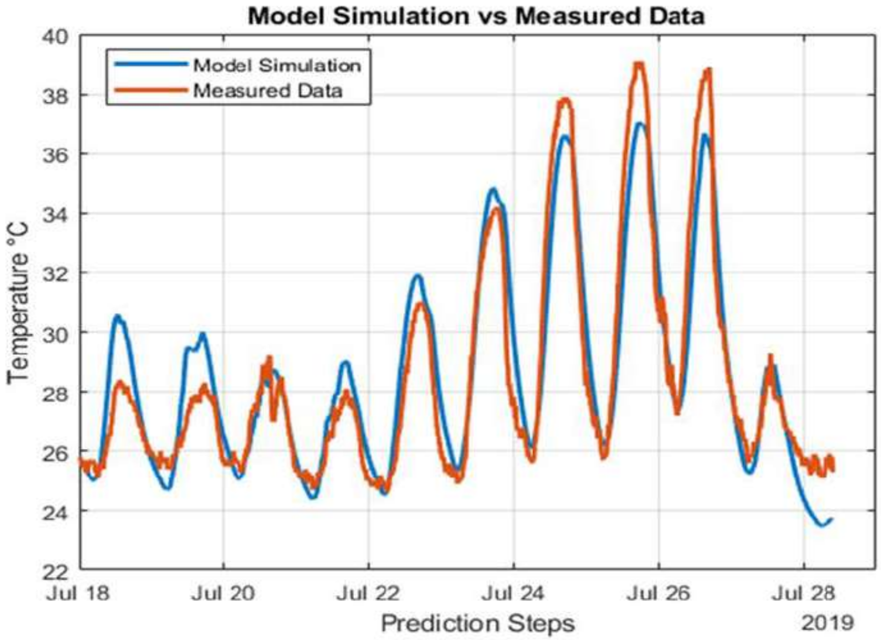
- Modelling Performance in a poultry barn at Arcen:



C. Sun et. al, HeatSense WP2 Report. Wageningen University & Research, 2024.

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Use Case: Climate Control of poultry house using RL

- Reward Function: $R = -\left|T_{in} - T_{target}\right| - \lambda_P P - \lambda_\varepsilon \varepsilon$
- Comfort temperature [16, 25]
- Poultry barn at Arcen, July 18-31, 2019, 5% noise, RL trained 1500*100 steps
- Baseline: full speed ventilation & evaporative cooling
- Default: existing control system

C. Sun et. al, HeatSense WP2 Report. Wageningen University & Research, 2024.

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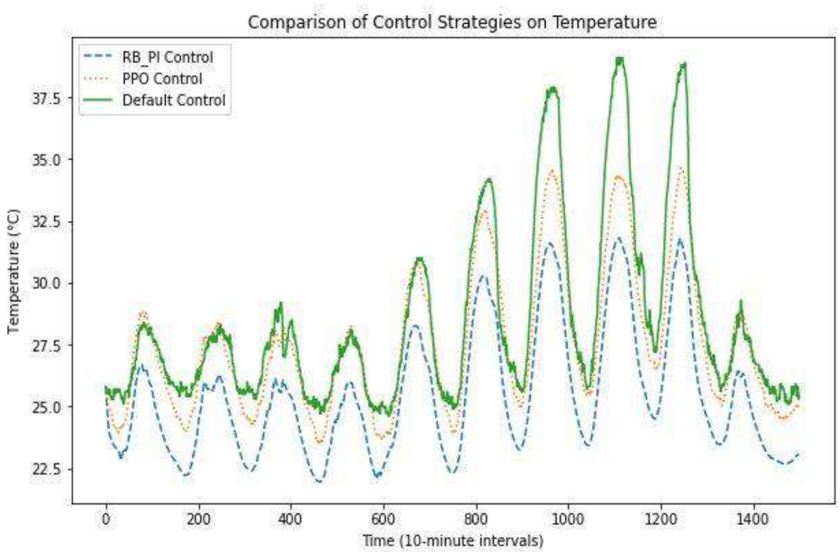

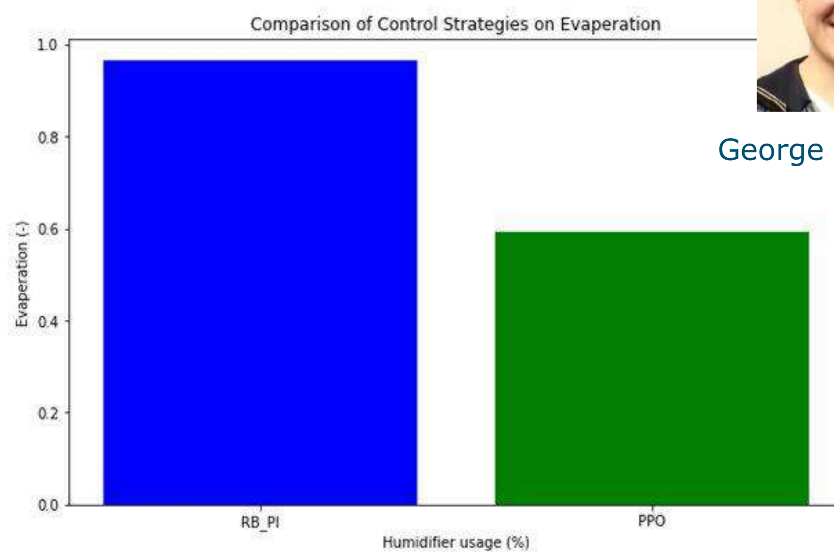

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- RL has best balance reduce heat stress v.s. minimize energy consumption.
- To fully prevent heat stress need upgrade capacity of ventilation system

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C. Sun et. al, HeatSense WP2 Report. Wageningen University & Research, 2024.

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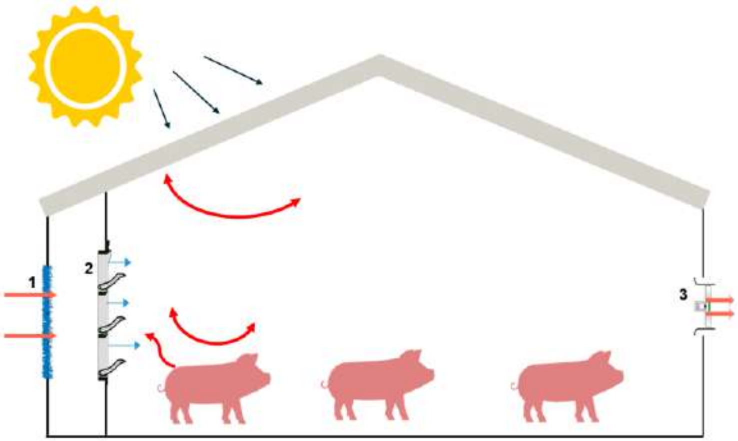
Use Case: Pig-farm Thermal Environment Control at High Humidity Area

Mason, Wei

- Thermal ventilation model based on enthalpy
- Control both temperature and humidity
- Adjust ventilation rate in real time



1: cooling pad

2: inlet valves

3:outlet fan

M. Wei et. al, Modeling and Optimal Control of Thermal Environment in Pig Houses. Wageningen University & Research, 2025.

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Mason, Wei

- Thermal ventilation model based on enthalpy

$$H_{in} = H_{out} + \frac{Q_{pig} + Q_i + Q_d}{3.6\rho\dot{V}}$$

H_{in} indoor enthalpy; H_{out} outdoor enthalpy;

Q_{pig} heat exchange between pig and indoor air;

Q_i heat contribution from insulatio layer;

Q_d heat dissipation from devices, e.g. low power lamps;

ρ: *air density*; $\dot{V}$: *required ventilation rate*

M. Wei et. al, Modeling and Optimal Control of Thermal Environment in Pig Houses. Wageningen University & Research, 2025.

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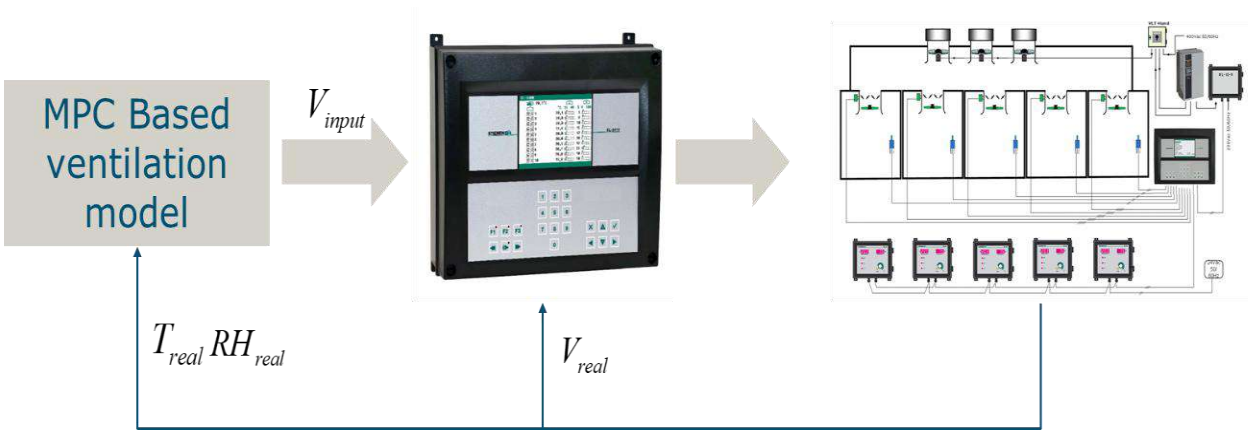
Mason, Wei

- Model Predictive Control

$$\min_{u} \sum_{k=0}^{N-1} \left(\lambda_T \left(T_{in} - T_{ref} \right)^2 + \lambda_H \left(RH_{in} - RH_{ref} \right)^2 + \lambda_E u_k^2 \right)$$



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Use Case: Pig-farm Thermal Environment Control at High Humidity Area

Mason, Wei

- Bandwidth Control

M. Wei et. al, Modeling and Optimal Control of Thermal Environment in Pig Houses. Wageningen University & Research, 2025.

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Use Case: Pig-farm Thermal Environment Control at High Humidity Area

- Applied in a pig farm at Shantou, Guangdong, with 88 sows:

Mason, Wei

M. Wei et. al, Modeling and Optimal Control of Thermal Environment in Pig Houses. Wageningen University & Research, 2025.

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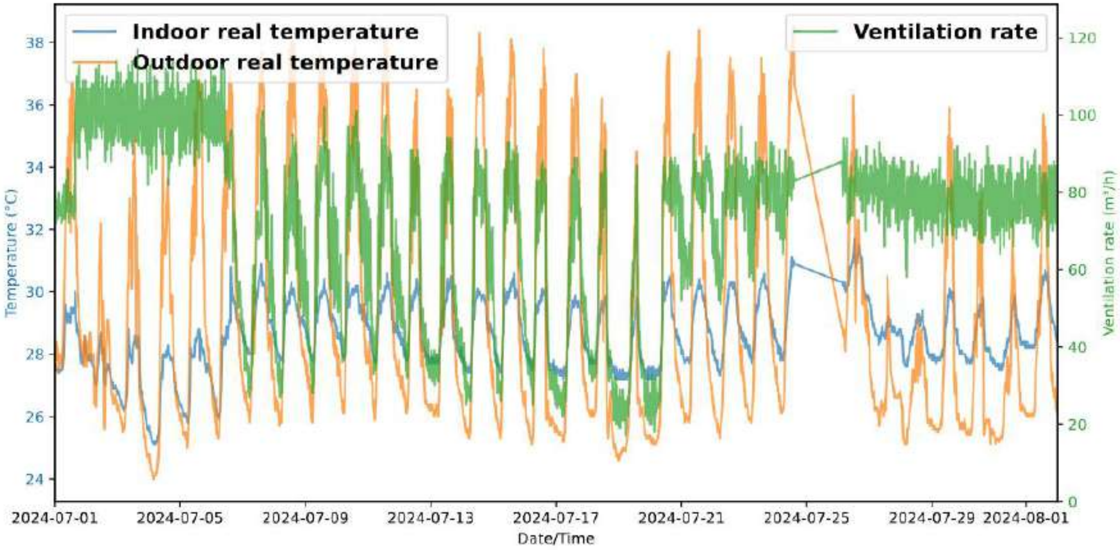
Mason, Wei

- 3 periods 010124-290224;010324-310524;010624-010824



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Mason, Wei

- Modelling performance:

Time Period	RMSE (°C)	MAPE (%)	SD (°C)	R^2
22/01/2024-23/01/2024 (Winter)	1.23	8.6	1.72	0.78
28/03/2024-29/03/2024 (Spring)	0.81	4.3	1.05	0.86
20/07/2024-21/07/2024 (Summer)	0.60	1.5	0.66	0.90

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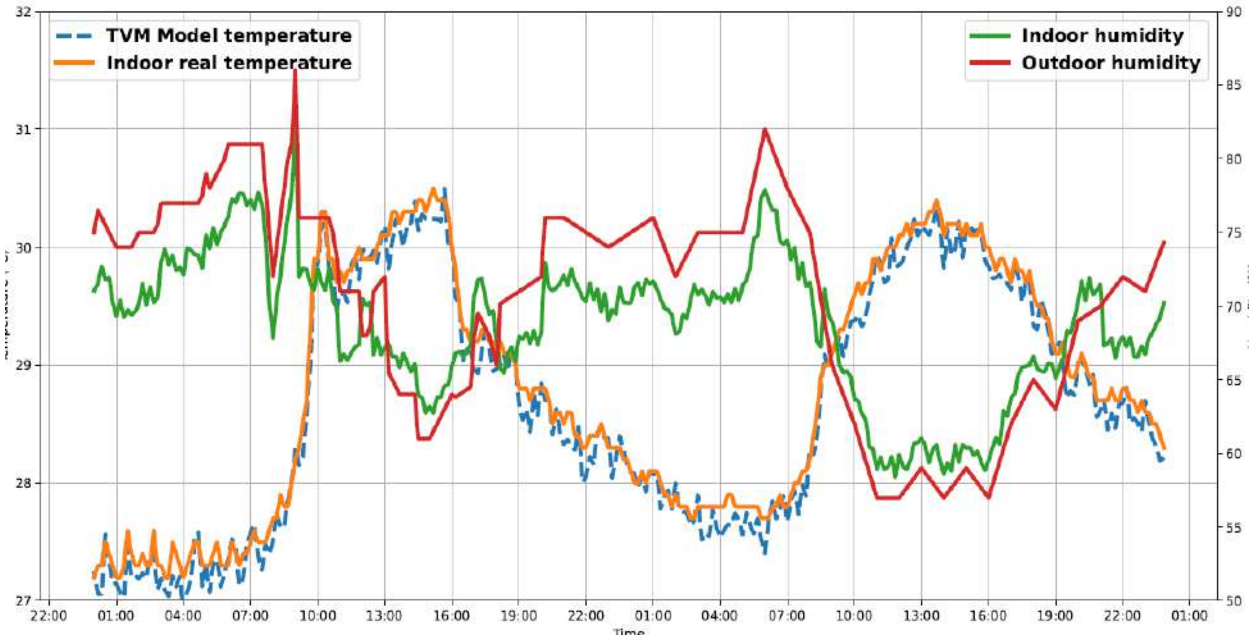
Mason, Wei

- Modelling performance (Period 3):



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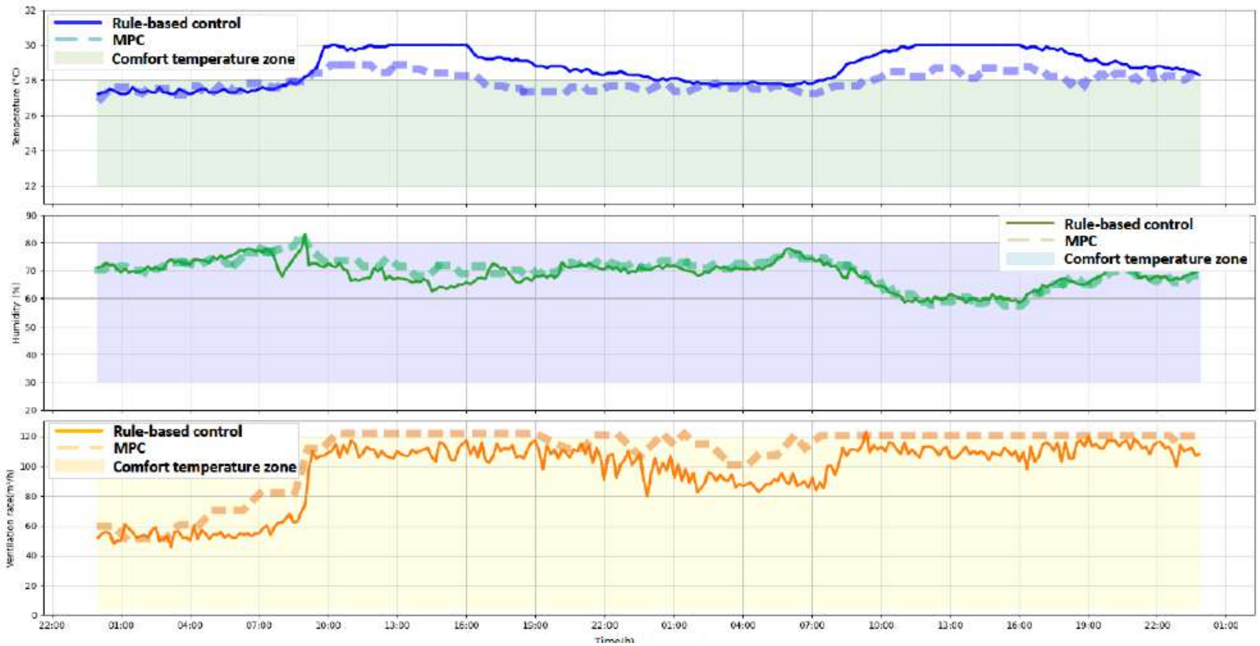
Mason, Wei

- Control performance (Period 3):



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Mason, Wei

- Control performance:

Performance Metric	Spring		Summer		Winter	
	MPC	Rule-based Control	MPC	Rule-based Control	MPC	Rule-based Control
Comfort Temperature Zone (Time Percentage)	100%	91%	83%	43%	98%	97%
Comfort Humidity Zone (Time Percentage)	100%	83%	85%	80%	100%	100%
Energy Consumption (kWh)	62.1 kWh	64.6 kWh	91.2 kWh	80.8 kWh	15.4 kWh	15.2 kWh

M. Wei et. al, Modeling and Optimal Control of Thermal Environment in Pig Houses. Wageningen University & Research, 2025.

Emissions Reduction

*Intelligent control for optimization to achieve **sustainable** & **efficient** Livestock production.*

Use Case: Ammonia emission control in poultry house

- ECO Air Care
    - Treat outlet air by acidic spraying water
    - Average ammonia emission reduction of 90%
    - We want to control desired amount of $NH3$ emission per animal place per year

Daan, Geurt

D. Geurt et. al, Modelling and control of an air scrubber for ammonia emission reduction in poultry houses. Wageningen University, 2024.

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Emissions Reduction

*Intelligent control for optimization to achieve **sustainable** & **efficient** Livestock production.*

Use Case: Ammonia emission control in poultry house

- Model Predictive Control:

Daan, Geurt

$$J = |C_{out,t} - C_{ref}|$$

$$pH_{min} < pH_t < pH_{max}$$

$$\min_{C_{out,1},\, C_{out,2}, \ldots, C_{out,H};\, pH_1, pH_2, \ldots, pH_H} |C_{out,t} - C_{ref}|$$

D. Geurt et. al, Modelling and control of an air scrubber for ammonia emission reduction in poultry houses. Wageningen University, 2024.

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Daan, Geurt

Desired NH_3 emission per animal place per year (g NH_3 animal^{-1} year^{-1})	Corresponding $C1$ level (mg m^{-3})	Actual NH_3 emission per animal place per year (after control) (g NH_3 animal^{-1} year^{-1})	RMSE (-)	Average *pH* over the control period (-)
30	1.03	33.99	0.31	2.93
39	1.34	40.60	0.18	3.18
45	1.56	45.91	0.10	3.34
50	1.73	50.29	0.07	3.55
60	2.08	58.05	0.05	3.86

D. Geurt et. al, Modelling and control of an air scrubber for ammonia emission reduction in poultry houses. Wageningen University, 2024.

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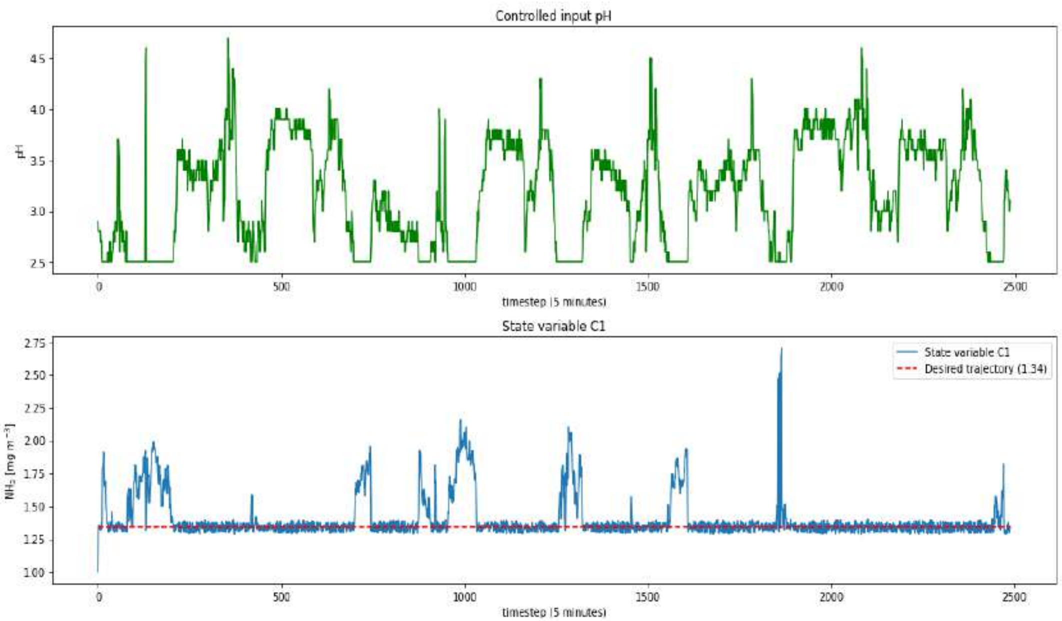

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Intelligent Control for Autonomous Production

*Intelligent control of robotic system of livestock system for **autonomous production**.*

Motivations:

- **lackness** of **labor** in livestock sector **requires** autonomous **robots**
- Livestock robot is more **acceptable** due to **less challenges** in **ethical** and **regulations**.
- By 2025, the agriculture **robotic** industry is set to **rise** round **US$87.9 billion**
- **Operation, planning** and **efficiency** challenges exist in agrobot applications

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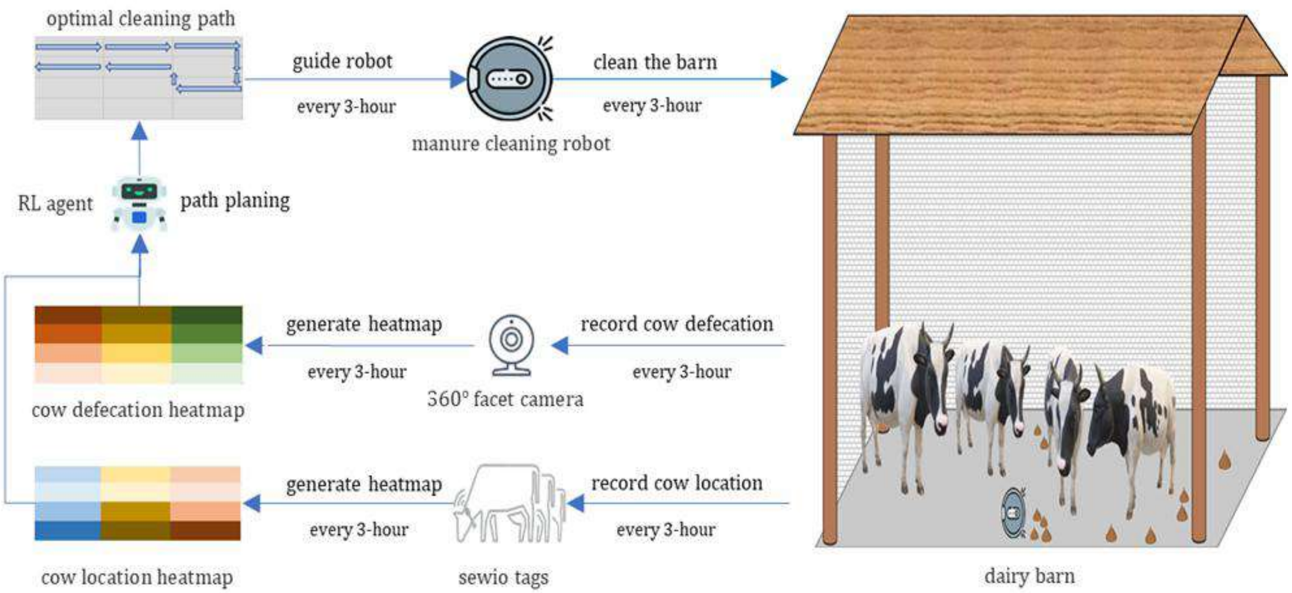
Intelligent Control for Autonomous Production

Intelligent control of robotic system of livestock system for ***autonomous production****.*

Use Case: Path planning and safe control of manure cleaning robots

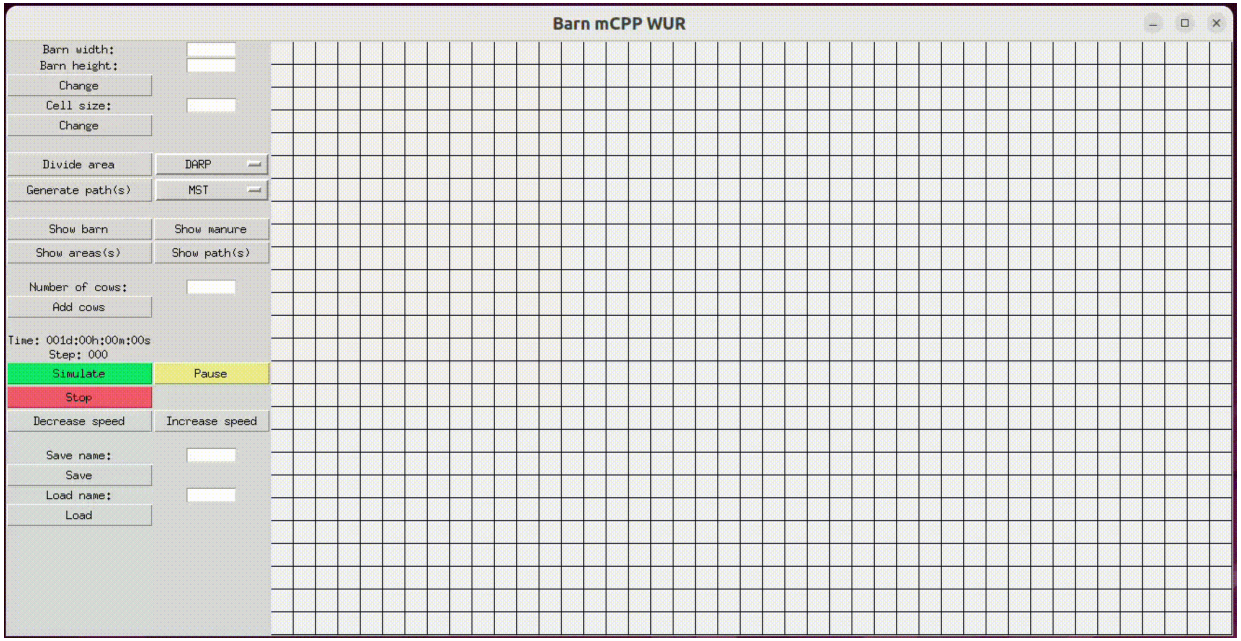


C. Sun et. al, Path planning of manure-robot cleaners using grid-based reinforcement learning. COMPAG, 226, 109456, 2024.

Robotic for Precision Livestock

Intelligent control of robotic system of livestock system for ***autonomous production****.*

Use Case: Path planning and safe control of manure cleaning robots



Luis Ponce Pacheco

L. Ponce Pacheco et. al, Design of multi coverage path-planning for collaborative manure-removing robots in dairy barns, Wageningen University, 2025.

Robotic for Precision Livestock

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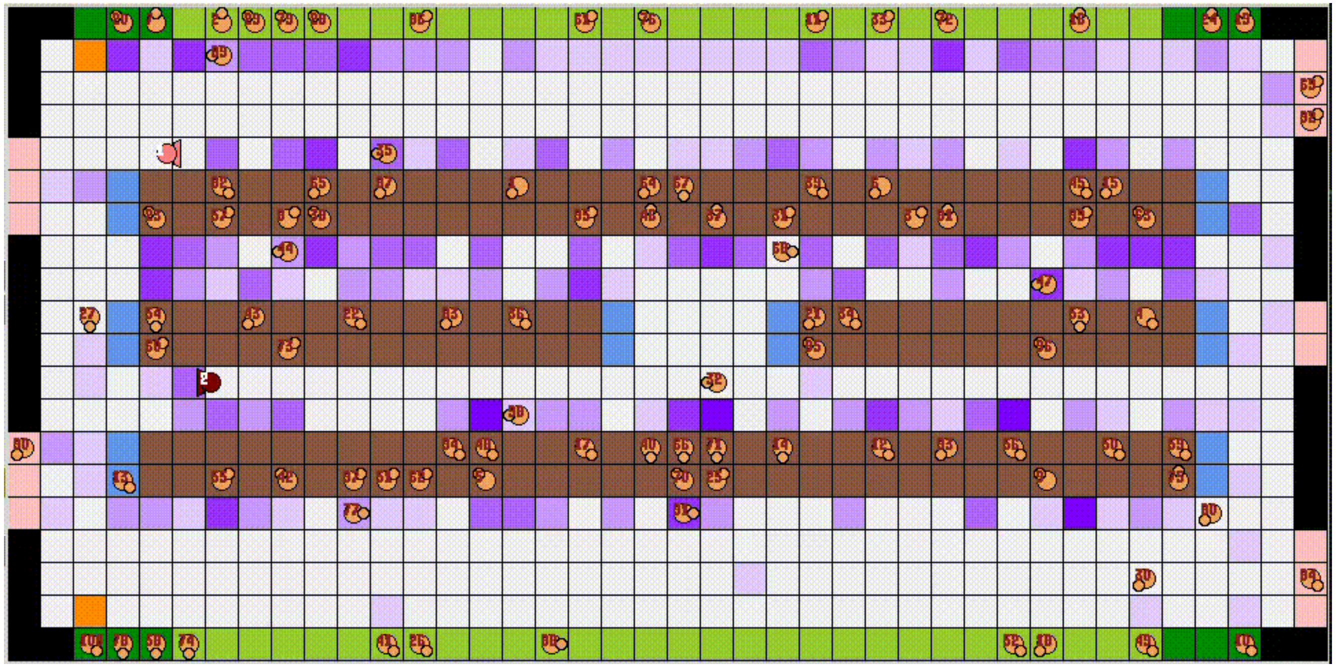
Use Case: Path planning and safe control of manure cleaning robots



Luis Ponce Pacheco

— innovators in agriculture —

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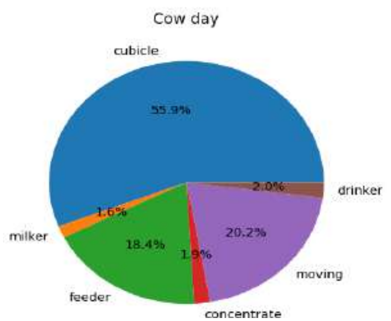

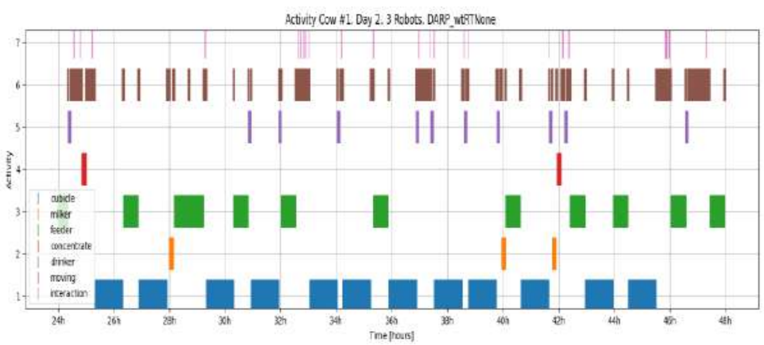

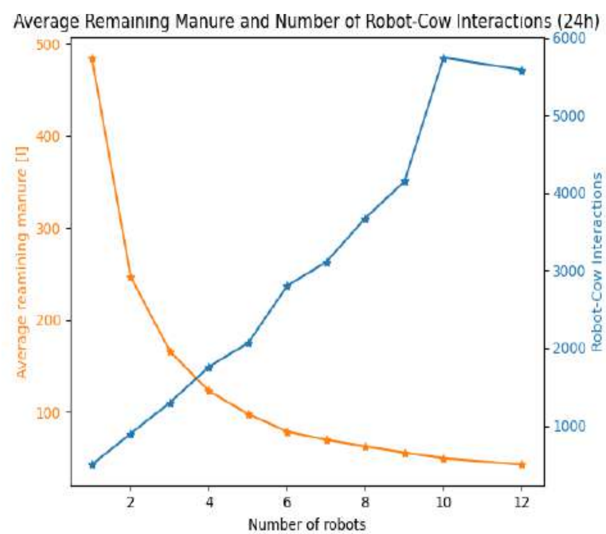

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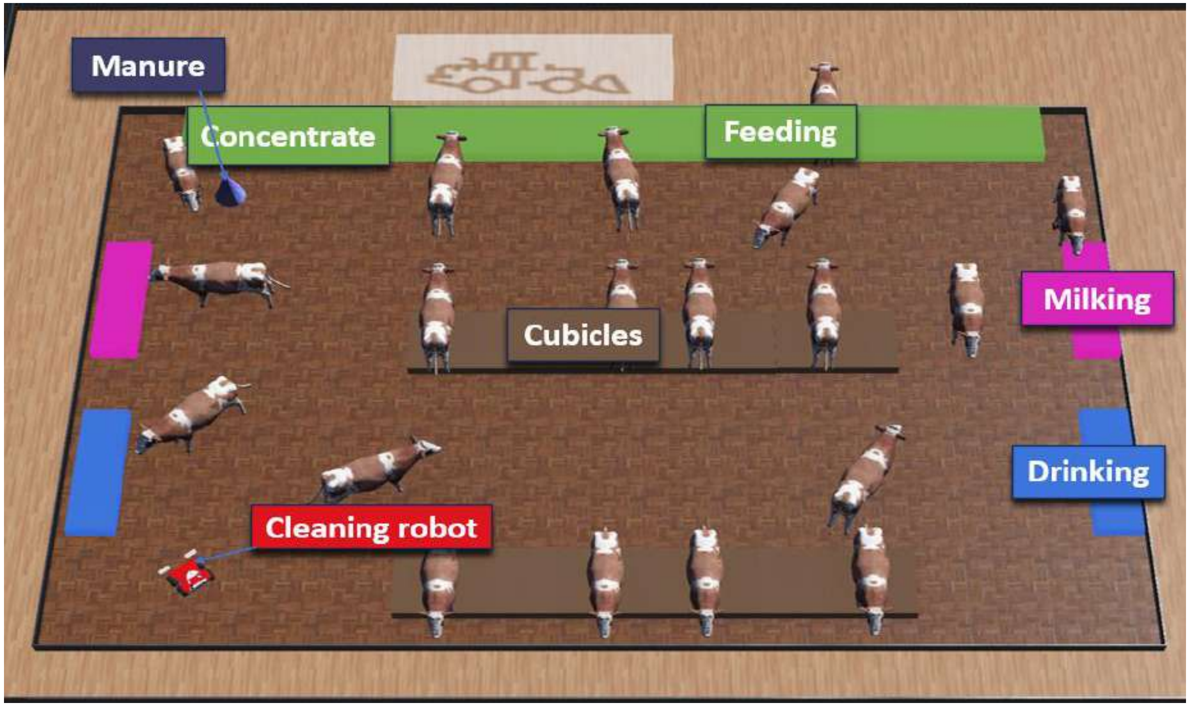

Wei Wei

innovators in agriculture

W. Wei et. al, Multi-objective Hierarchical Reinforcement Learning for Efficient and Safe Manure Robot Cleaning in Dairy Barns, Submitted IROS, 2025.

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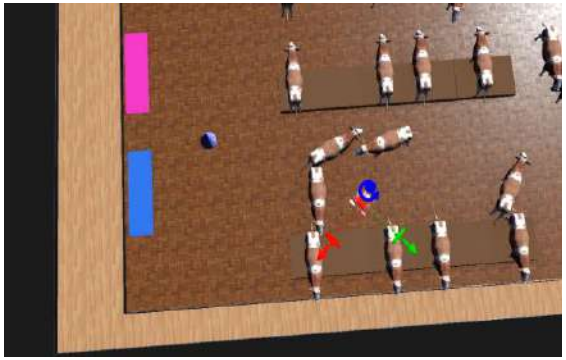
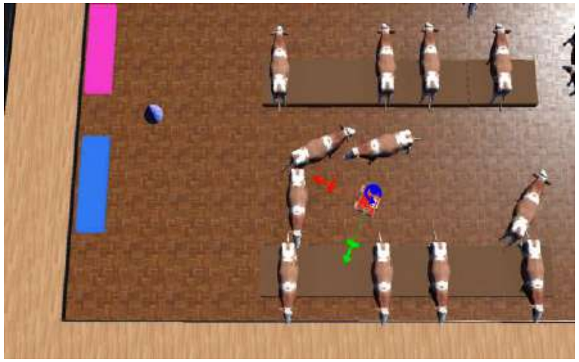
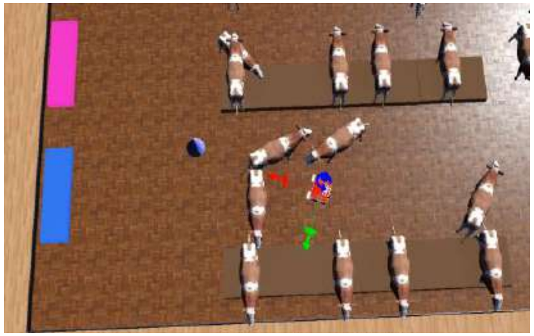


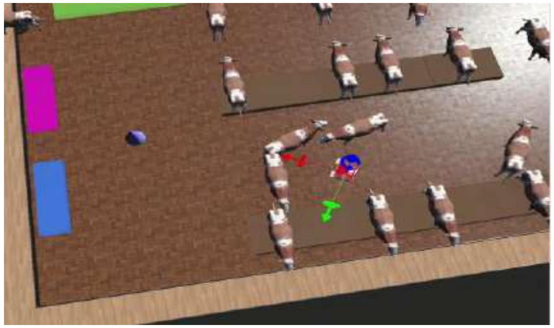
Vanilla PPO



Maskable PPO



CVaR PPO



OURS

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Robot surrounded by cows:
Vanilla PPO: Crashes into nearby obstacles and fails to find a way out.
Maskable PPO: Searches for a safe path but gets stuck in loops without reaching the target.
CVaR PPO: Experiences minor collisions but eventually finds a path around the resting area to reach the target.
Ours: multi-objective hierarchical RL, takes longer to search but ultimately reaches the target safely.

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W. Wei et. al, Multi-objective Hierarchical Reinforcement Learning for Efficient and Safe Manure Robot Cleaning in Dairy Barns, Submitted IROS, 2025.

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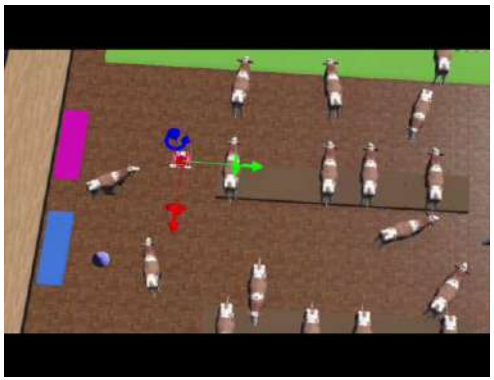
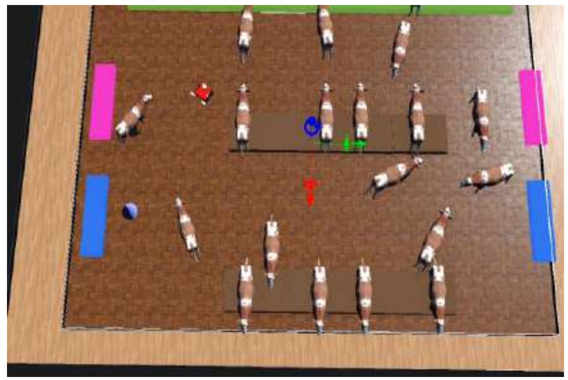
Robotic for Precision Livestock

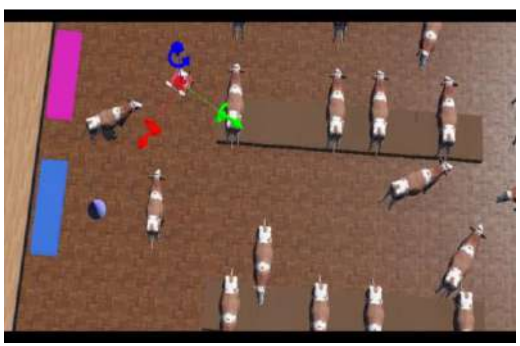
*Intelligent control of robotic system of livestock system for **autonomous production**.*



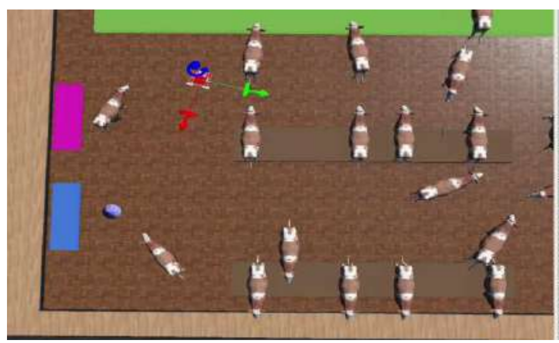
Vanilla PPO



Maskable PPO



CVaR PPO



OURS

Wei Wei

Robot interacting with cows:
Vanilla PPO: Moves aggressively, often colliding with cows.
Maskable PPO: Avoids cows but follows their movement direction, leading to inefficiencies.
CVaR PPO: Reaches the target with minor collisions.
Ours: Successfully reaches the target without collisions, demonstrating superior adaptability and safety.

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Use Case: Path planning and safe control of manure cleaning robots

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PERFORMANCE OF THE PROPOSED METHODS AGAINST BASELINE METHODS.

Methods	Success ↑ (%)	Collision ↓ (%)	Time ↓ (min)	Energy ↓ (KWh)	NH_3 Reduction ↑ (kg/m^3)	Cleaning ↑ (kg/min)
Vanilla PPO [12]	66.67%	33.34%	146.69	1.986	0.035	0.5717
Maskable PPO [19]	81.08%	20.27%	75.24	1.003	0.093	0.9015
CVaR PPO [26]	89.83%	10.43%	**32.68**	0.436	0.1243	1.9535
Ours	**95.33%**	**5.3%**	35.78	**0.477**	**0.144**	**1.8695**

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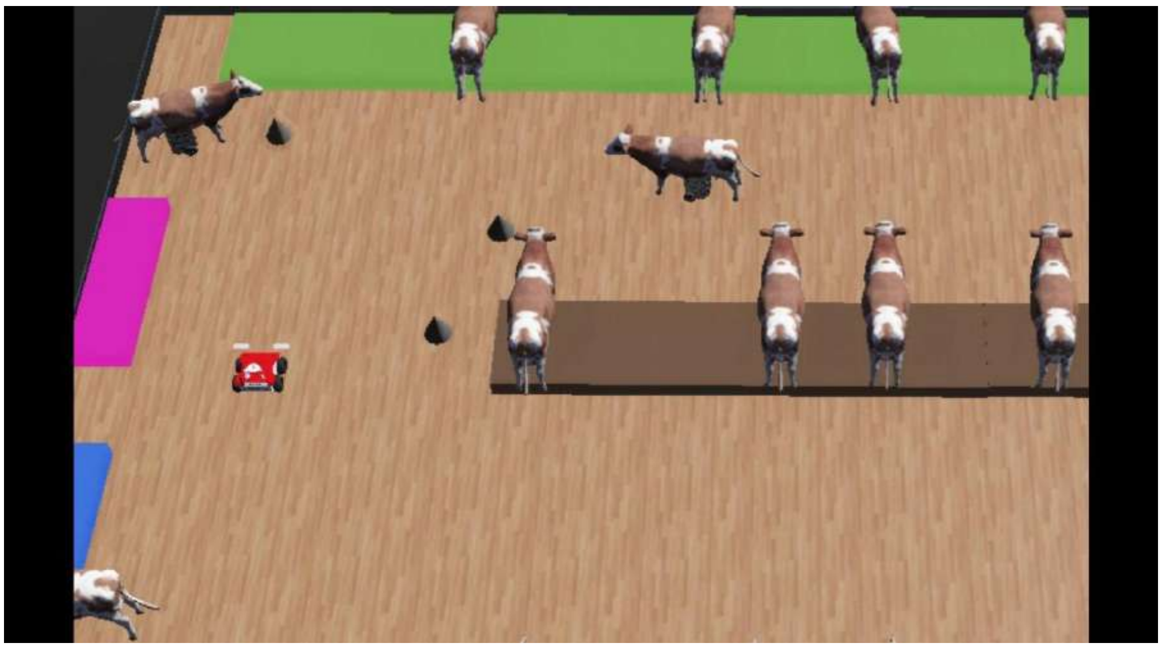
Multiple tasks



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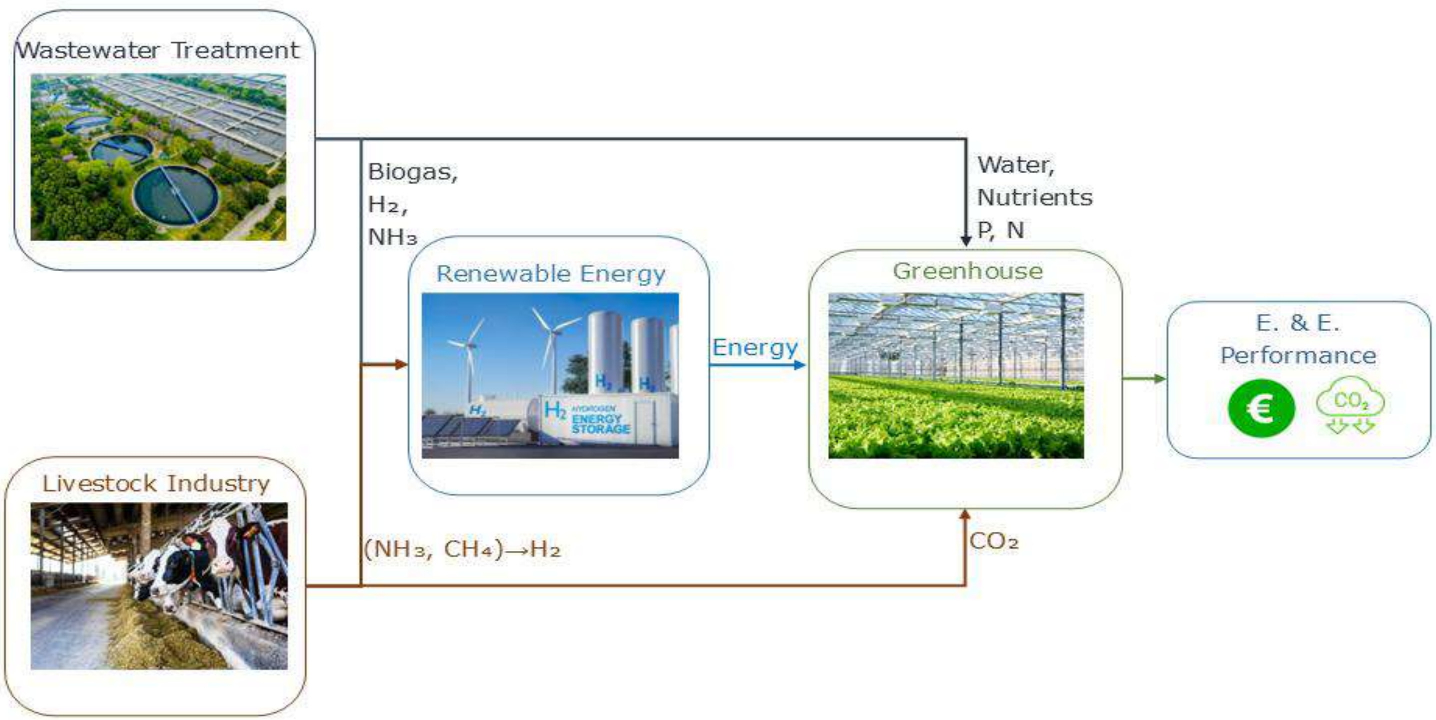
Challenges of applying Intelligent Control?

- Being able to learn on live systems from limited samples
- Deal with unknown and potentially large delays in system actuators, sensors or rewards
- Learn and act in high-dimensional state and action spaces
- Reason about system constraints
- Learn from multi-objective or poorly specified reward function
- Provide system operators with explainable policies

Other ongoing project

NWO-FFAR: Greenhouse in Transition (2026-2031)



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Questions?

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