Can a Wind Turbine Learn to Operate Itself?
Evaluation of the potential of a heuristic, data-driven self-optimizing control system for a 5MW offshore wind turbine

Stefan G IORDANOV
Maurizio COLLU
Yi CAO

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Trondheim, Norway

www.cranfield.ac.uk

Context & problem statement

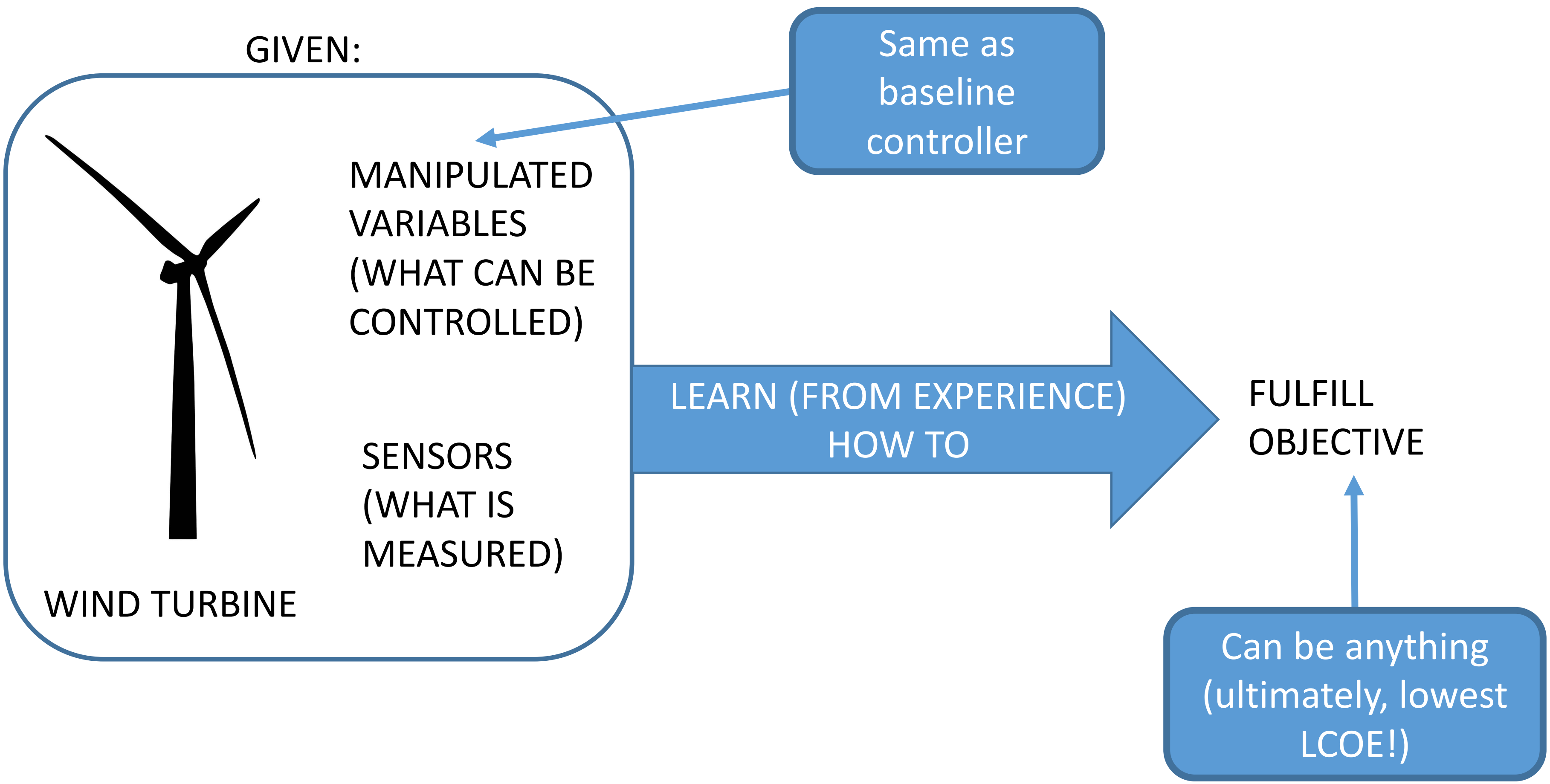
- Larger wind turbines, more complex loads
- Larger wind farms, more complex interactions
- Large amount of real-time data from monitoring system, only used for monitoring

MHI Vestas V164-8.0MW
[http://www.mhivestasoffshore.com/innovations/]

- Substantially benefit from more advanced control strategies
- BUT performance VS reliability

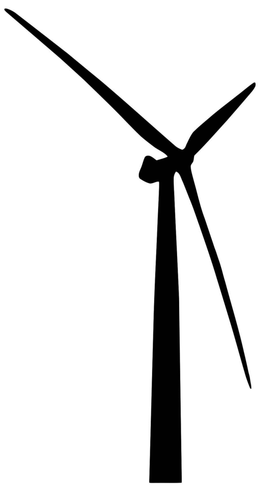
SIEMENS SWT-8.0-154
[http://www.siemens.com/global/en/home/markets/wind/turbines/swt-8-0-154.html]

Aim: can it learn from experience the optimum control strategy?



First step: check that it performs as well as baseline controller

GIVEN:



MANIPULATED VARIABLES (WHAT CAN BE CONTROLLED)

Same as baseline controller

SENSORS (WHAT IS MEASURED)

WIND TURBINE

LEARN (FROM EXPERIENCE) HOW TO

OBJECTIVE: MAXIMISE POWER (region 2)

Compare performance against baseline controller

Case study

SYSTEM

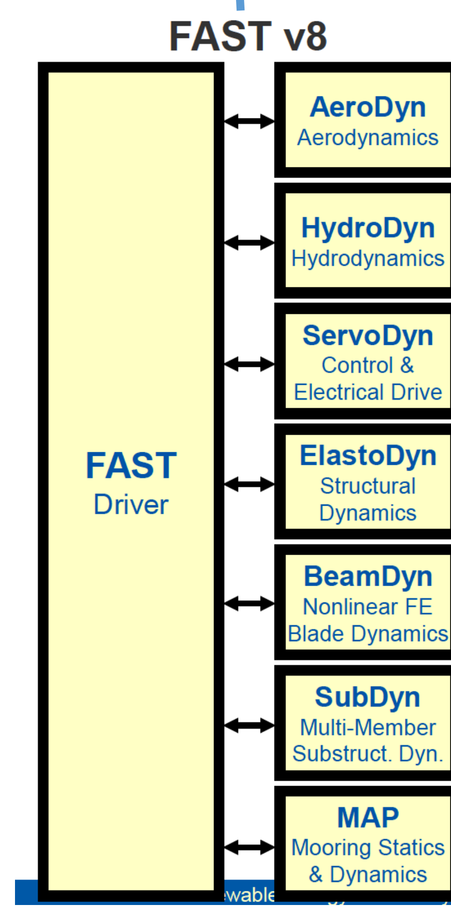
NREL 5MW offshore WT

LOAD CASES

Steady wind speed
(no turbulence)
(6 to 12 m/s)

Turbulent wind speed
(6 to 12 m/s)

"VIRTUAL" EXPERIENCE (LEARNING FROM SYNTHETIC DATA)



Methodology: global Self-Optimising Control (gSOC)

Brief review

- SOC: defining functions of process variables such that, when held constant, optimal operation is achieved (Skogestad 2000)
- Cao (2014): model-free approach (no linearisation) → global SOC
- Already proven at industrial level in the processing industry: oil reservoir waterflooding, 30% in Net Present Value

Methodology: gSOC

- Define objective function
  u = manipulated
  y = sensors
  d = disturbances

$$J = \varphi(u, y, d)$$

- The deviation is approximated as (deviation → 0 near opt)

$$J_{i+1} - J_i = \sum_{j=1}^{n_u} \frac{dJ}{du_j}(u_{i+1,j} - u_{i,j})$$

- Define controlled variables ($\theta = coefficients$)

$$CV(y, \theta) = \frac{dJ}{du} = 0$$

- Obtain θ through regression

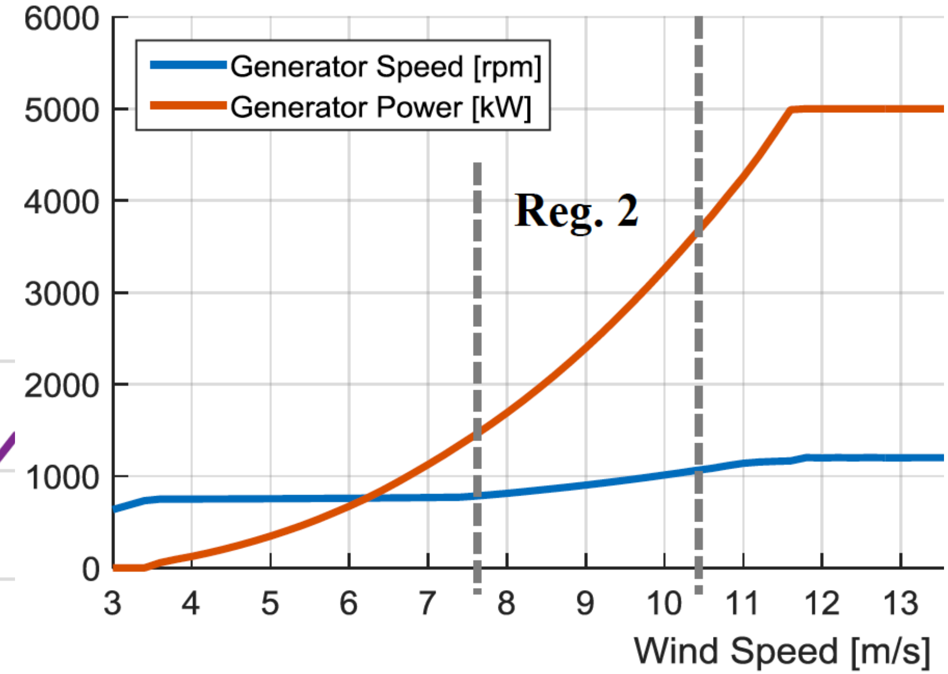
$$min_\theta \sum_{i=1}^{N} \sum_{p=i_1}^{i_k} \left(J_p - J_i - \sum_{j=1}^{n_u} CV_j(y, \theta)\left(u_{p,j} - u_{i,j}\right)\right)^2$$

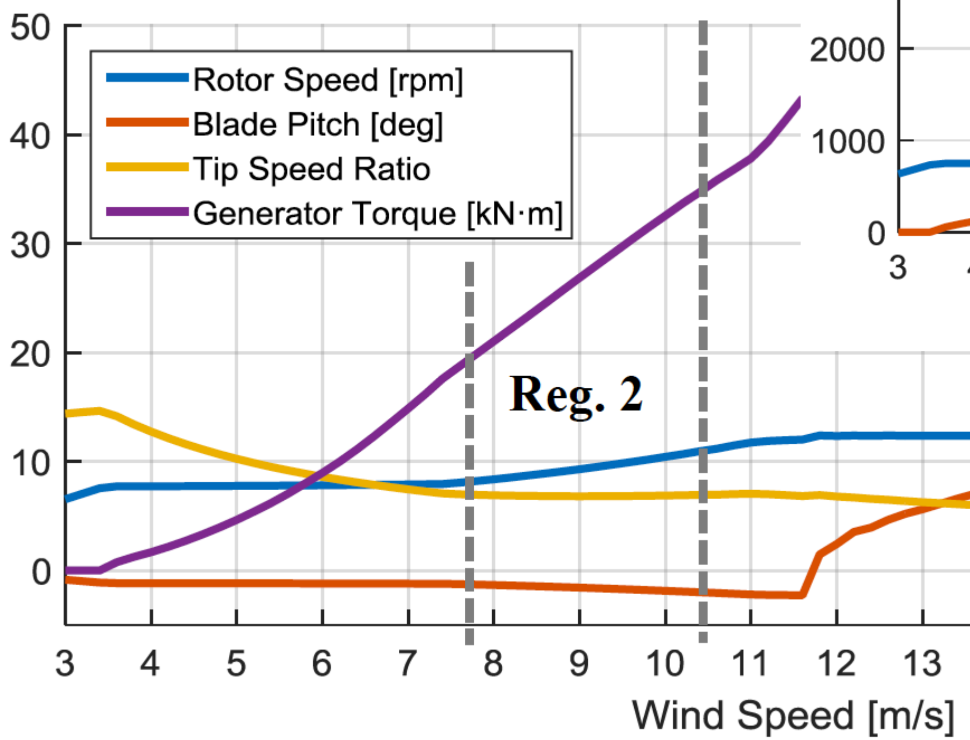
Methodology: gSOC applied to Wind Turbine

- Define *u, y, d* $$u = [\Gamma, \beta], \quad y = [\Gamma, \beta, \omega_G, P], \quad d = [v]$$
- Define objective function $$P = \Gamma \cdot \omega_G \cdot \eta$$
- Then, deviation is $$P_{i+1} - P_i = \frac{dP}{d\Gamma}(\Gamma_{i+1} - \Gamma_i) + \frac{dP}{d\beta}(\beta_{i+1} - \beta_i)$$
- CVs $$\frac{dP}{d\Gamma} = CV_1 = \theta_0 + \theta_1 \cdot \omega_G + \theta_2 \cdot \Gamma$$ $$\frac{dP}{d\beta} = CV_2 = \theta_3 + \theta_4 \cdot \omega_G + \theta_5 \cdot \beta$$
- For each disturbance value, build sample matrix [20 x 6] → “experience”
  - 6 pitch angles
  - 20 generator torques
- Then θ_i obtained through regression

Results (1): yes, it learns!

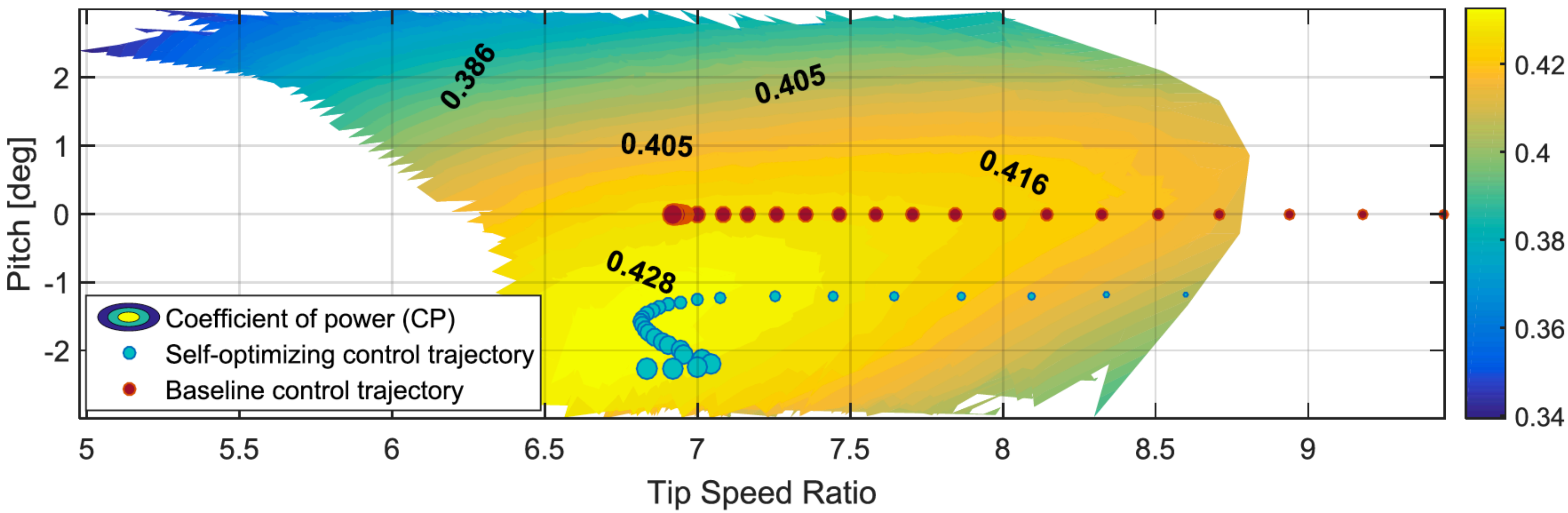
Maximise power →





← How?
It learned to keep constant TSR (varying Γ) and β !

Results (2): slightly better strategy



→ gSOC tracks maximum CP better than baseline control → learnt from experience

→ Not a substantial advantage, but proving that can perform well as approach: use it to discover control approaches with more complex objectives

Conclusions

- The global self-optimising control strategy gSOC is able to deliver the same performance (in terms of energy extracted) as conventional control system
- Easy development and implementation, flexible, scalable
- → does not compromise reliability / ease of use when scaled up to consider:
  - More sensor signals
  - More actuators

Next steps

- The "ideal" control strategy should (long-term vision):
  - minimise the Levelised Cost of Energy (LCoE) [cost/kWh]
  - taking into account all the data available

- Next steps: ***discover new optimum control strategies***

  - Numerical → Include in the objective function "J" additional criteria, e.g.:
    - 1 p and 3p loads on the blades – equivalent fatigue damage load
    - Loads at the tower base – equivalent fatigue damage load
    - Multiple wind turbines
    - …

  - Experimental → small scale wind turbine tested in wind tunnel

  - Feedback to simple, non data-driven control strategies