DYNAMIC MODELS AND CONTROL STRATEGIES FOR ABSORPTION-BASED CARBON CAPTURE PROCESSES

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1. Context and Objective
2. Recap from HiPerCAP 2015 (Melbourne, Australia): Dynamic models, Control strategies, Control analysis and Advanced control
3. Control-optimization framework
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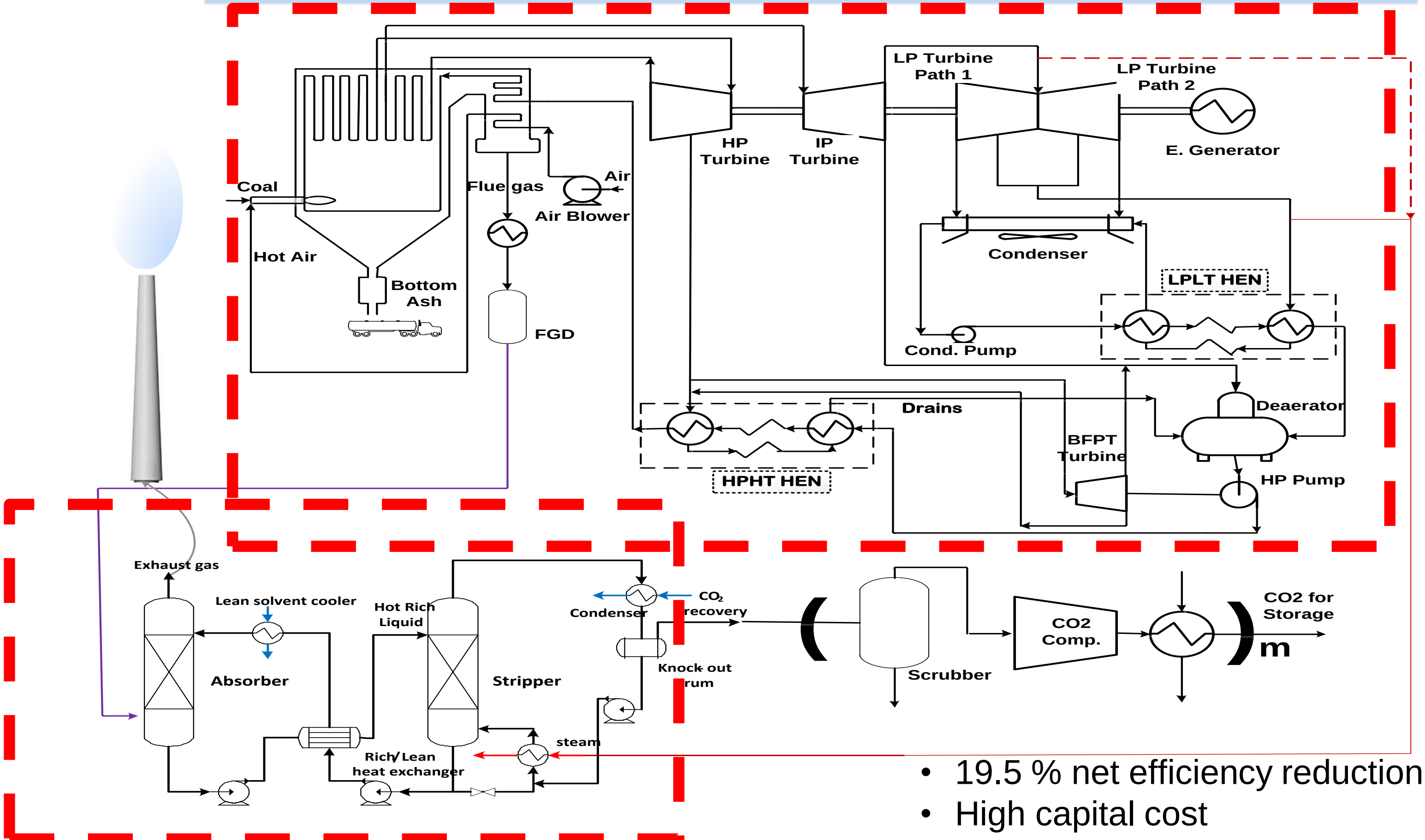
5. Implementation for emissions trading schemes
6. Conclusions

Context: A domain of operational uncertainties

Coal-fired power plant retrofitted with an absorption-based post combustion CO_2 capture process (PP-PCC)



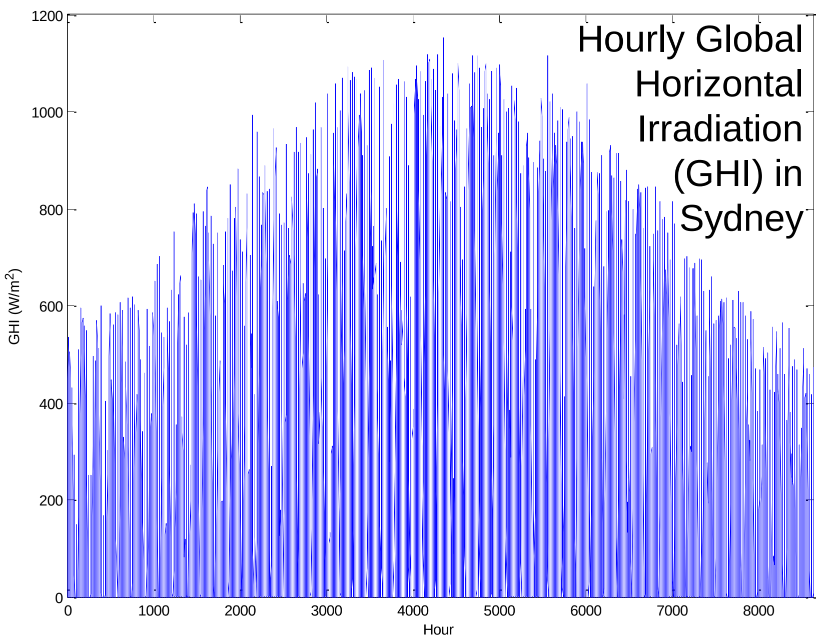
- 19.5 % net efficiency reduction due to PCC
- High capital cost
- Large scale integration issues
- Flexibility in operation

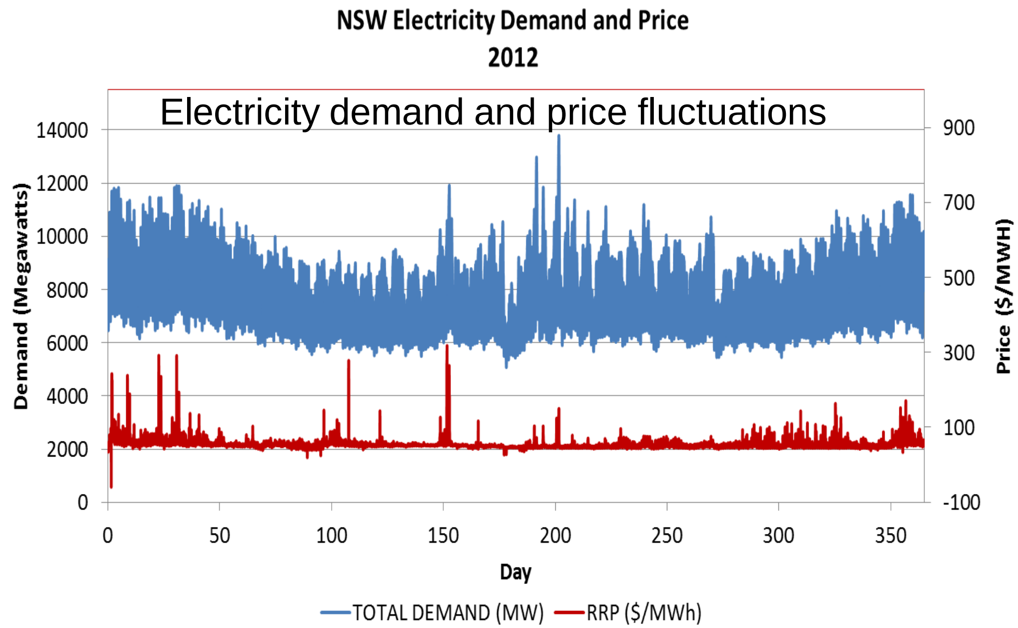
Rajab Khalilpour and Ali Abbas, HEN optimization for efficient retrofitting of coal-fired power plants with post-combustion carbon capture. International Journal of Greenhouse Gas Control, 2011. 5(2): p. 189-199.

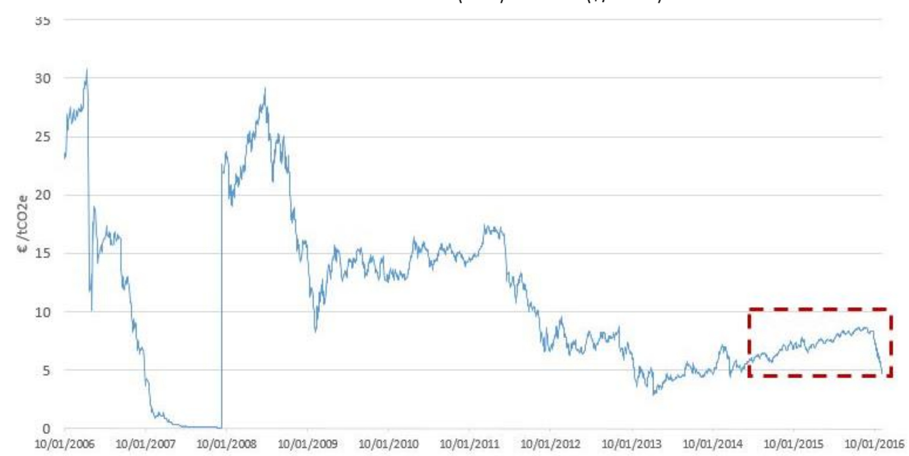
Context: A domain of operational uncertainties

Technical uncertainties

- solar GHI,
- electricity price,
- electricity demand, &
- carbon price.







Context: A domain of operational uncertainties

Policy uncertainties:

- Australia:
  - Carbon tax legislation started in July 2012,
  - scrapped July 2014, and
  - currently we have the **Emissions Reduction Fund (ERF)** proposed in 2015
- China: emissions trading scheme
- Internationally: Paris Meeting December 2015

Flexible Operation

Integration of PCC into coal-fired power plant requires **understanding dynamic and flexible operations**.

The PCC plant must respond flexibly to two significant scenarios:

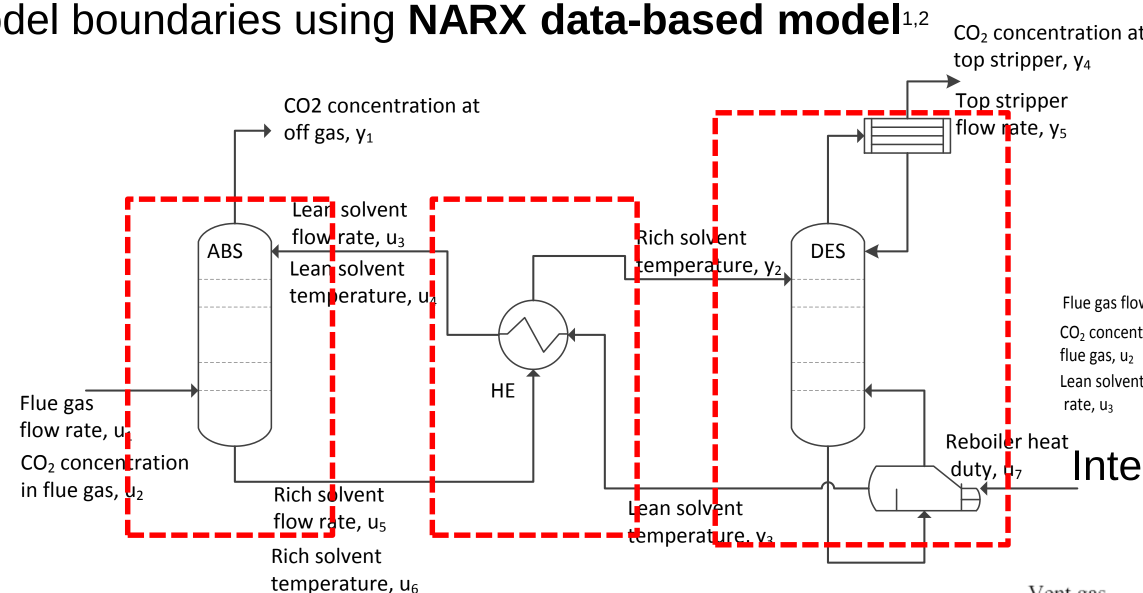
1. Power plant operations at full and partial loads, and
2. Considering fluctuations in electricity and carbon prices.

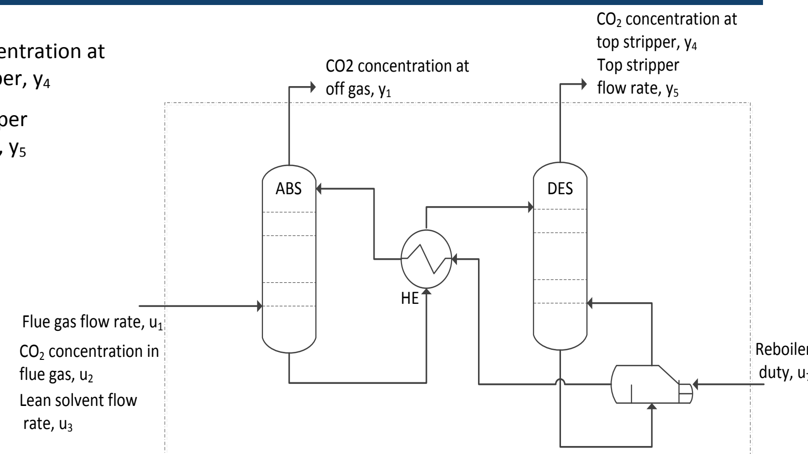
The objective is to develop a model-based strategy for operational management of flexible amine-based post combustion CO2 (PCC) process.

ReCAP from previous HiPerCAP

Dynamic modelling

Model boundaries using **NARX data-based model**[1,2]



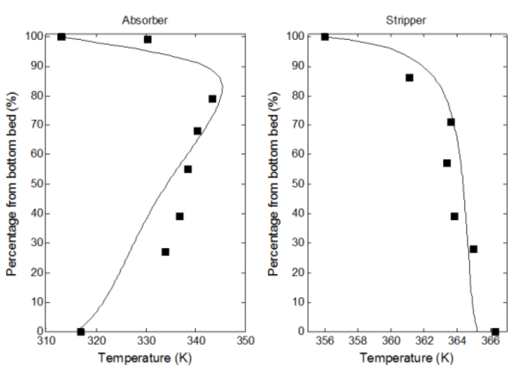


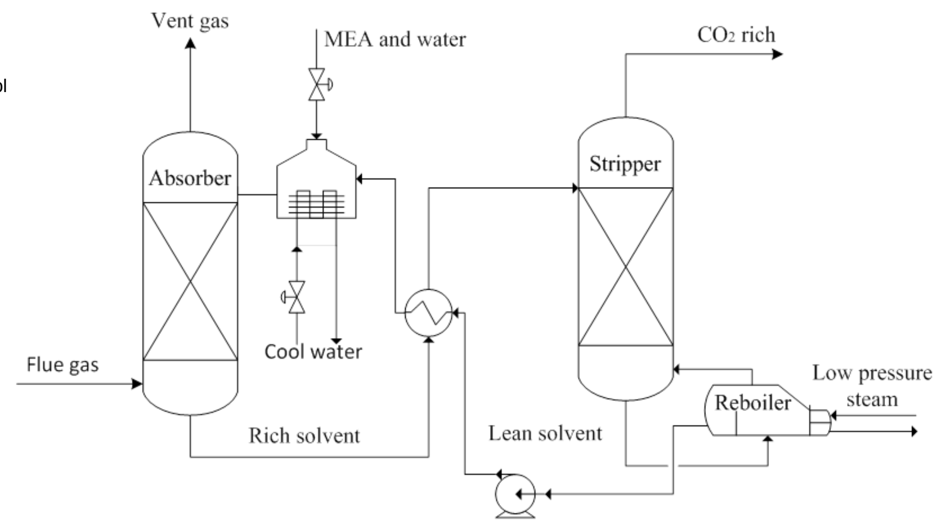
Integrated **NARX data-based model**

[1]Norhuda, A. M., Ashleigh , C., Paul, F. & Ali, A. 2014. Dynamic Modelling and Simulation of Post Combustion CO2 Capture Plant. *CHEMECA 2014: Western Australia*
[2]Norhuda, A. M., Ashleigh , C., Paul, F. & Ali, A. 2014. Dynamic modelling, identification and preliminary control analysis of an amine-based post-combustion CO2 capture pilot plant. Journal of Cleaner Production (in review)

Mechanistic model[3]

Column temperature profiles from the simulation (line) and the pilot plant study (dot) for the pilot plant test no. 47[4].





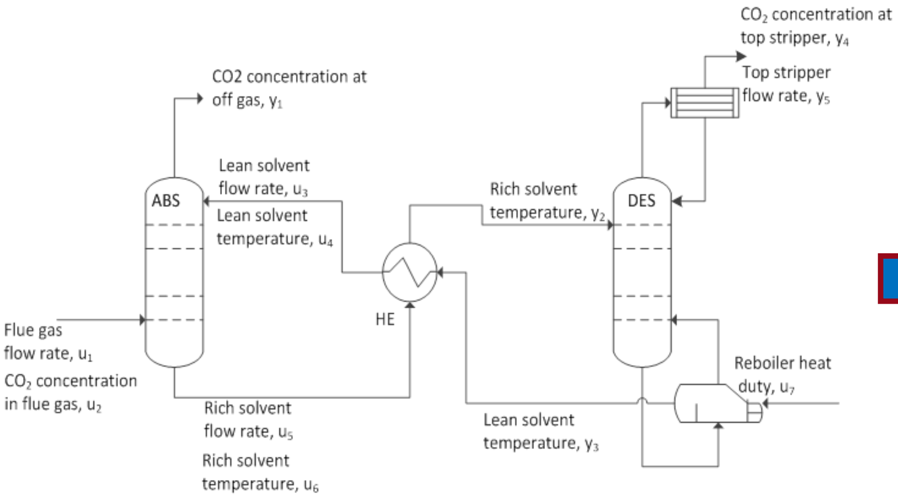
[6]Minh Tri Luu, Norhuda Abdul Manaf, Ali Abbas. Control strategies for flexible operation of amine-based post-combustion CO_2 capture systems. Journal of Greenhouse Gas Control (accepted with revisions)
[4]Dugas, R. E. 2006. Pilot Plant Study of Carbon Dioxide Capture by Aqueous Monoethanolamine. M.S.E. Thesis, The University of Texas

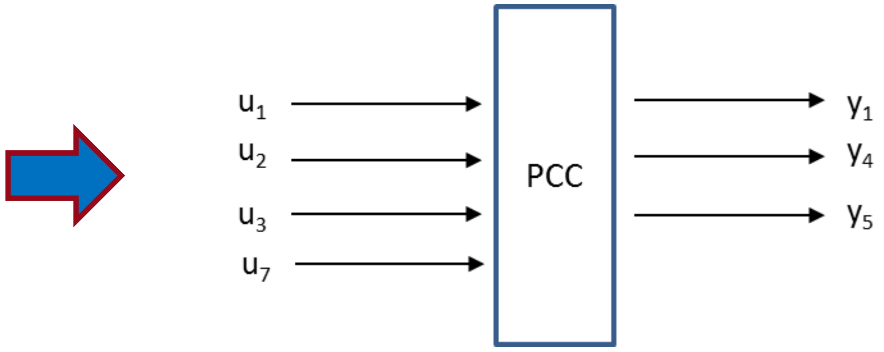
Control Approach

Identified 2 key performance metrics:

1. Carbon capture efficiency, $CC\ (\%) = \frac{(y_4/100)\ y_5}{u_1\ (u_2\ /100)}$

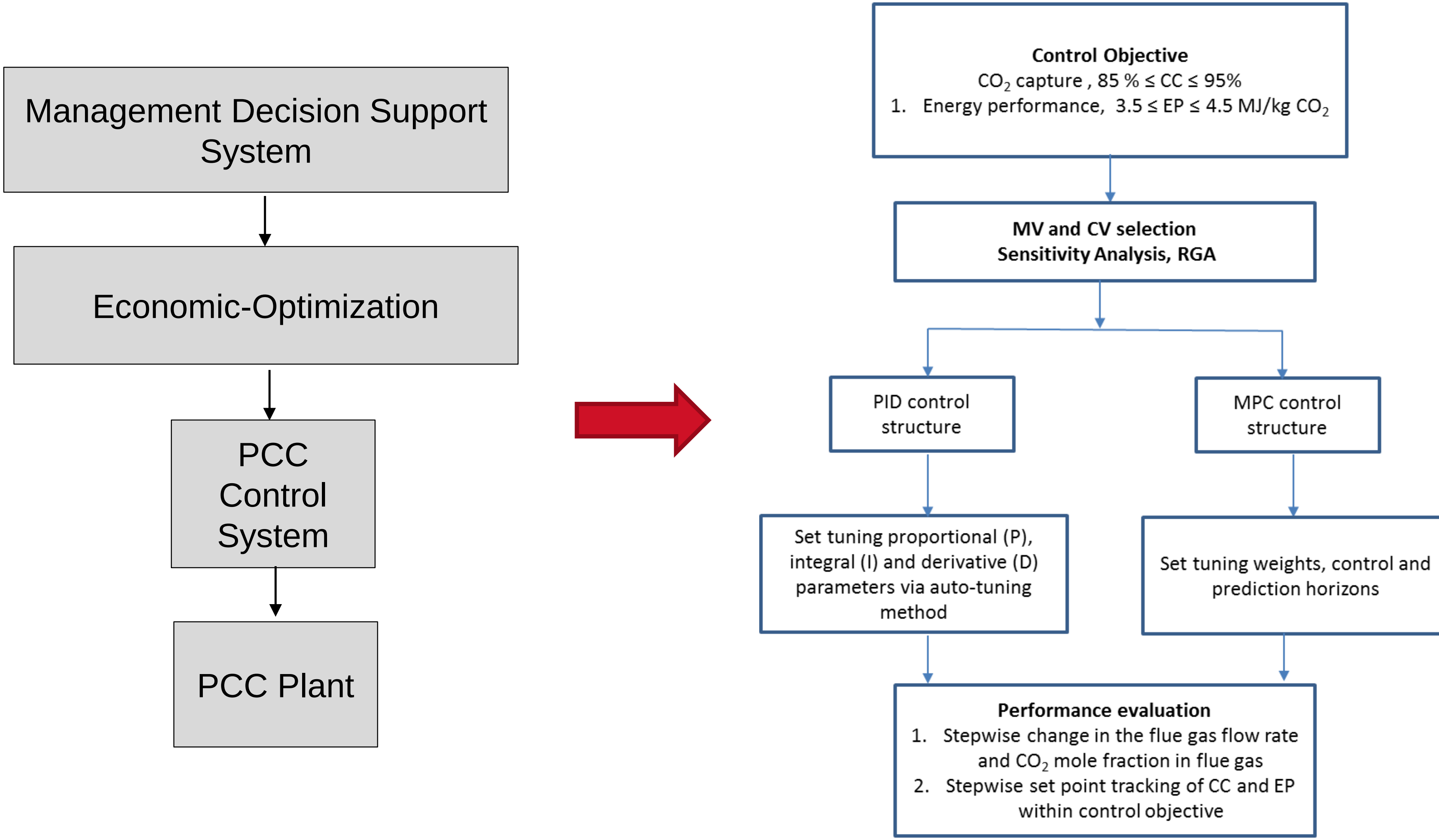
2. Energy performance, $EP\ (\text{MJ/kg}) = \frac{u_7}{(y_4/100)\ y_5}$





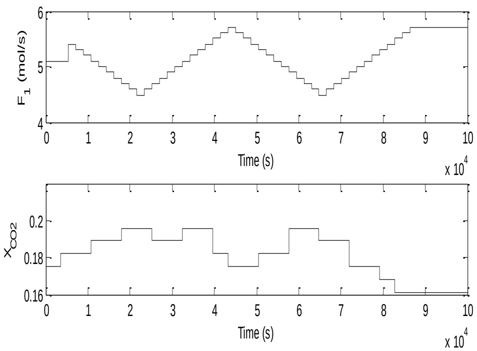
Reduced 4 x 3 PCC systems model

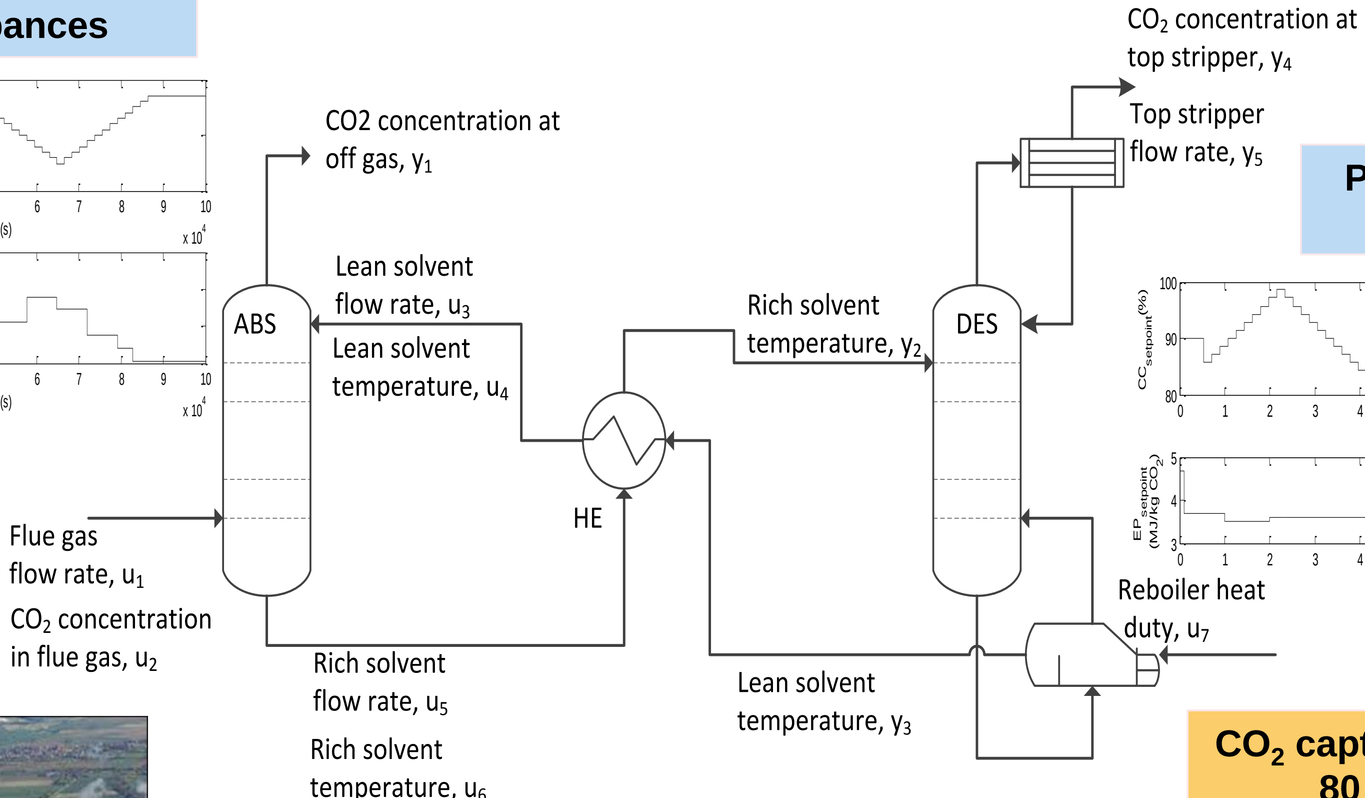
Control Approach



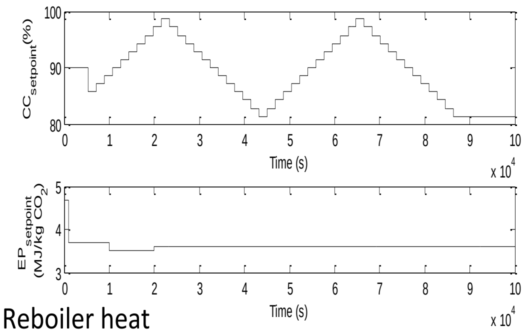
Control Approach – Controllability Analysis

Upstream disturbances





PCC control objective

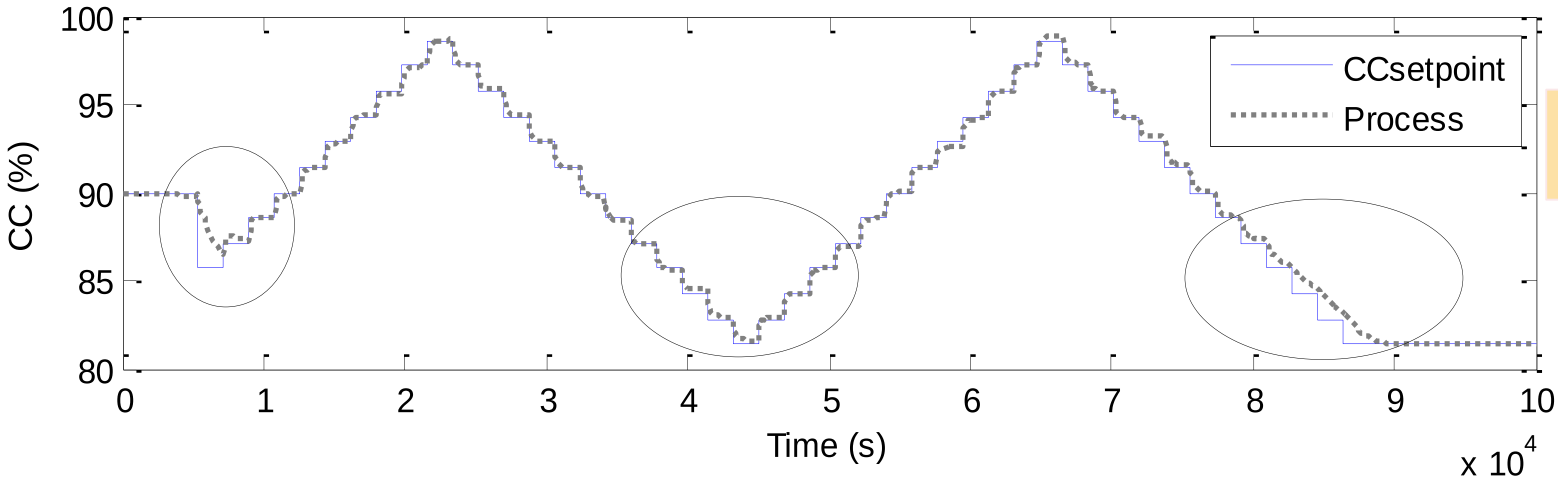


CO_2 capture, CC% = 80 ~ 95%

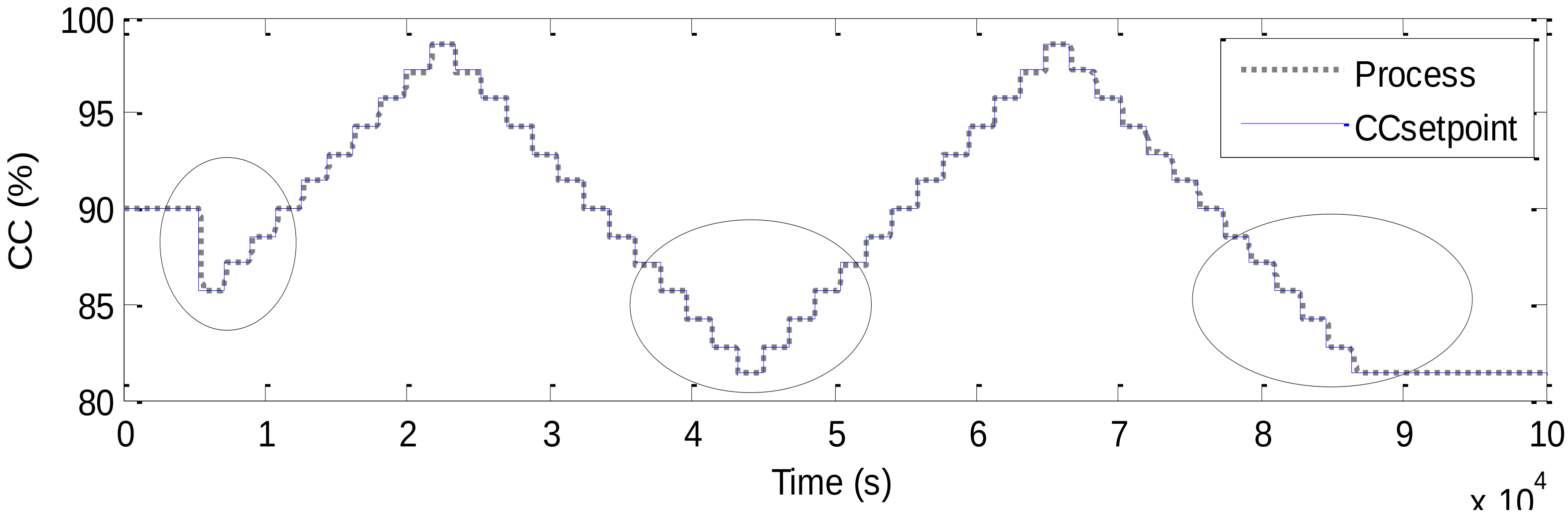
Energy Performance, EP = 3.5 ~ 4.5 MJ/kg CO_2

Control Approach – Controllability Analysis

Controllability analysis on set point changes and rejection disturbances.



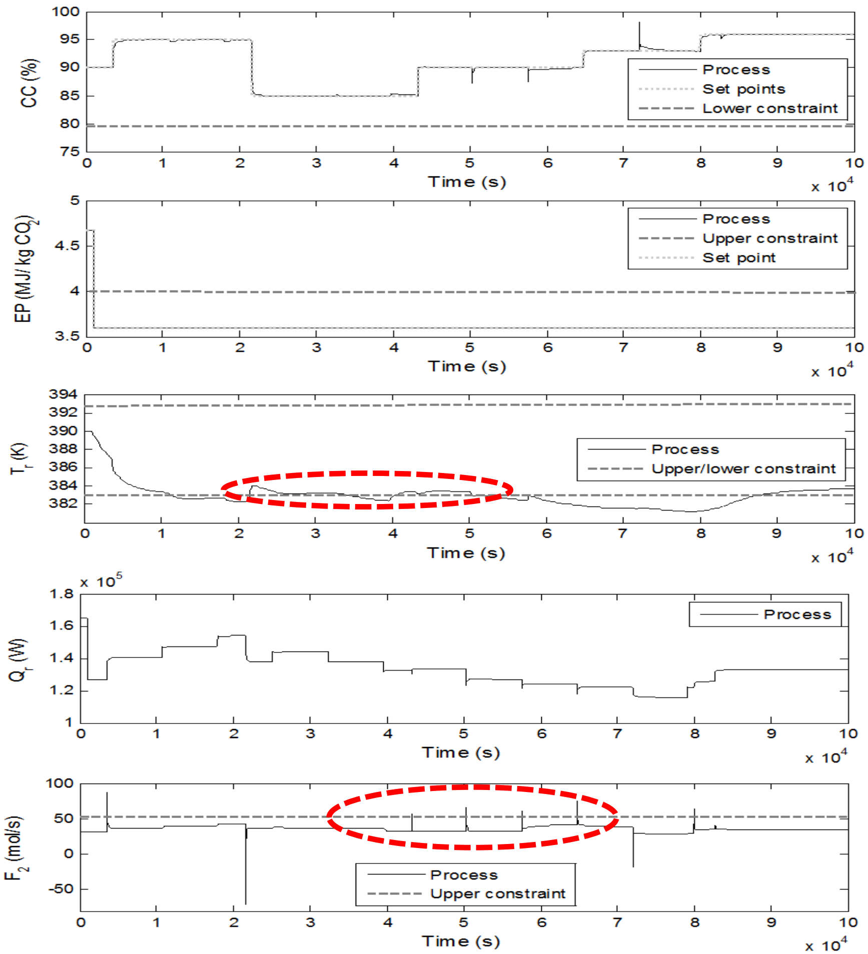
PID Controller



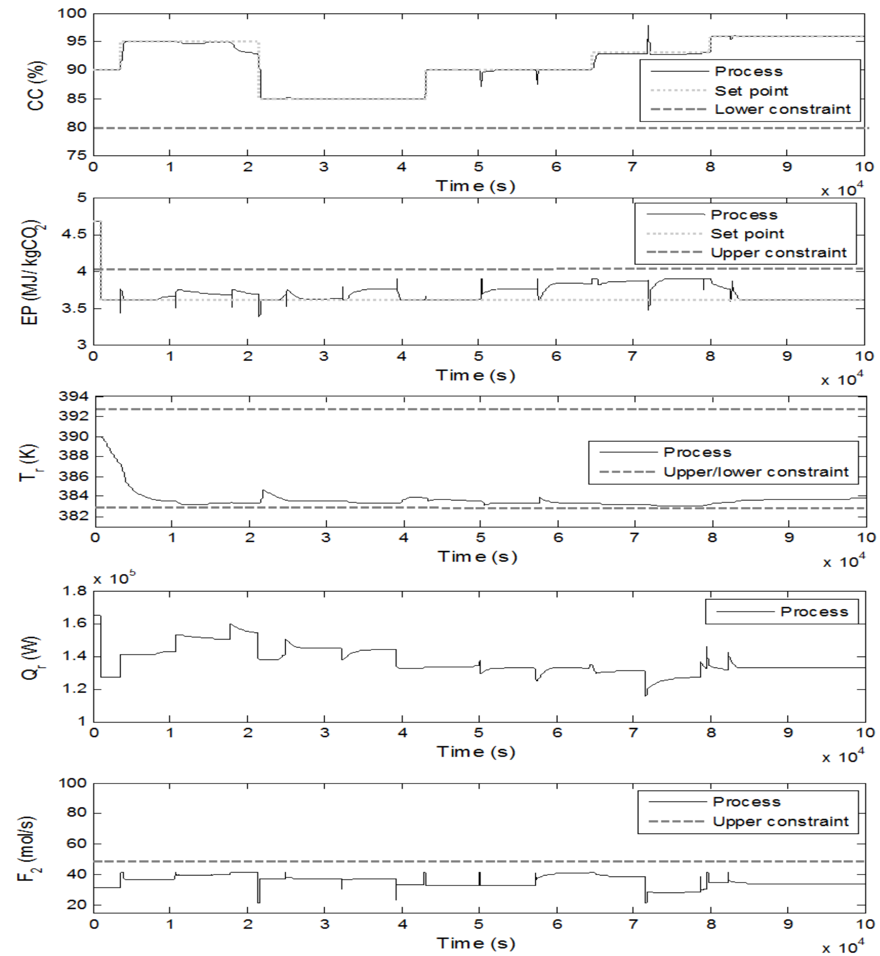
MPC Controller

Control Approach – Controllability Analysis

Control performance under process operational constraints



PID Controller



MPC Controller

Control-optimization framework

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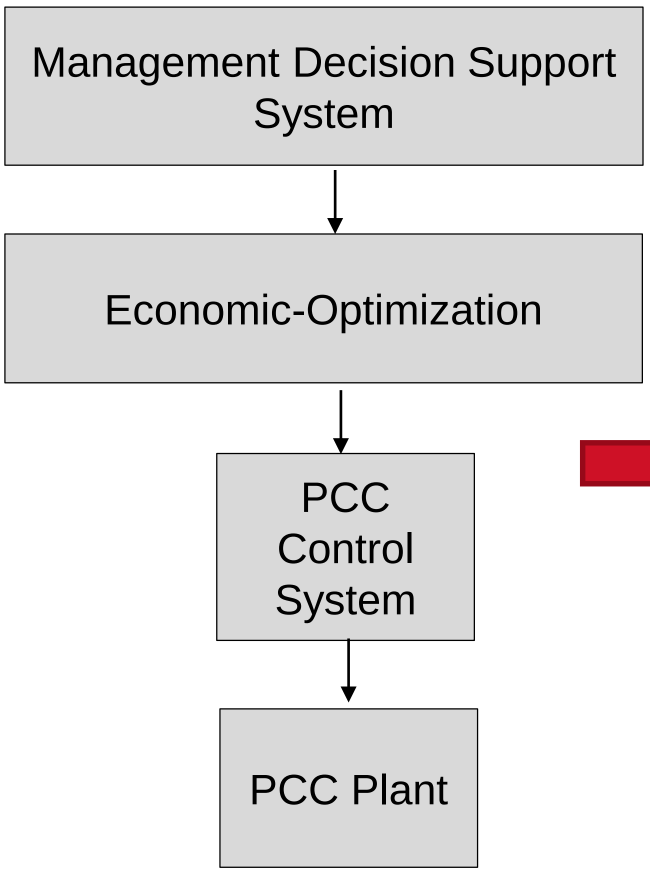
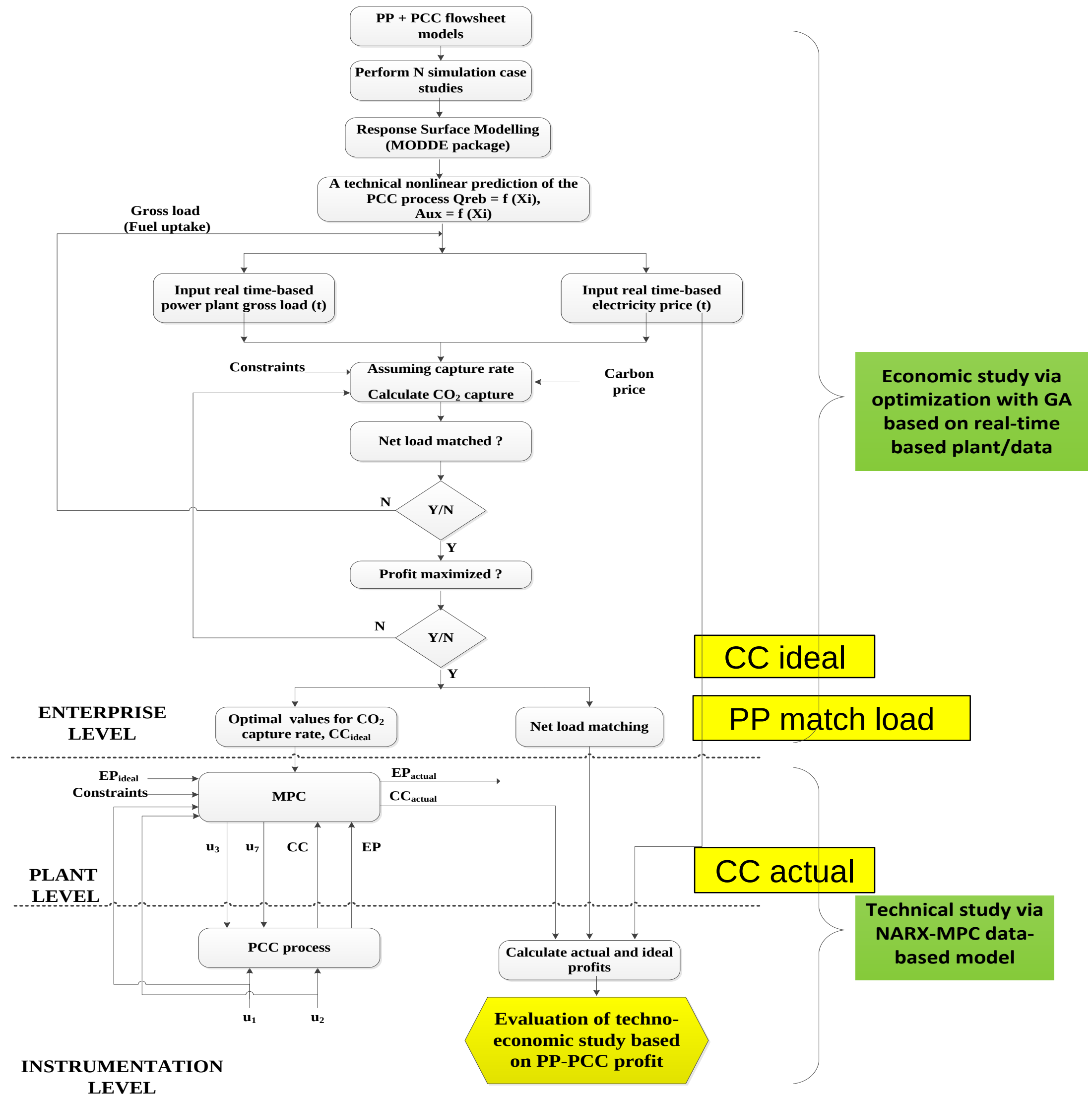
Control-Optimization Approach





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Control-Optimization Algorithm

The optimization formulation is summarised as:

Objective function:	Maximize Revenue(t, P_e, x_1,x_2,C_t)
	s.t.
Process model:	Q_reb (x_1,x_2), E_Aux (x_1,x_2)
Initial conditions:	x_1= CR^I, x_2= PPL^I
Process variables bounds:	CR_{Min} (20%) < x_1 < CR_{Max} (90%)
	PPL_{Min} (250 MW) < x_2 < PPL_{Max} (700 MW)
Constraints:	$h(x_1,x_2) < 0$

Where;

x_1= the capture rate (%)

x_2 = the power plant load (MW Gross)

P_e = electricity price

C_t = carbon price

Q_reb = Reboiler energy

E_Aux = Auxiliary energy

CR^I, CR_{Min} and CR_{Max} = the initial, lower bound and upper bound carbon capture rates

PPL^I, PPL_{Min} and PPL_{Max} = the initial, minimum and maximum power plant loads

h = the process inequality constraints (net electricity output of the power plant does not exceed the historical net load of the power plant at a particular time.)

Control-Optimization Approach

PP-PCC plant revenue

Rev-PP

$$Revenue = \int P_e * (Power\ plant\ net\ load - PCC\ penalty) * dt - $$
$$- \int C_t * CO_2\ emitted\ dt \ - P_{PP} - P_{PCC}$$

A **B** **C**

Rev-PP:	Revenue generated through selling of electricity
A:	Cost of CO2 emission
B:	Power plant operating cost (PP-OPEX)
C:	PCC operating cost (PCC-OPEX)

Control-Optimization Algorithm

Analysis for 24 hrs: Simulate techno-economic scenarios for:

- A 24-hour operation,
- Based on 2011 electricity prices[3] and at
- Constant carbon prices (\$5/tonne CO_2, \$25/tonne CO_2, \$50/tonne CO_2)

Run analysis for 2 modes:

1. Fixed operation mode (This is the benchmarking base case which runs at constant capture rate of 90%)
2. Flexible operation mode (variation in power plant load and carbon capture rate)

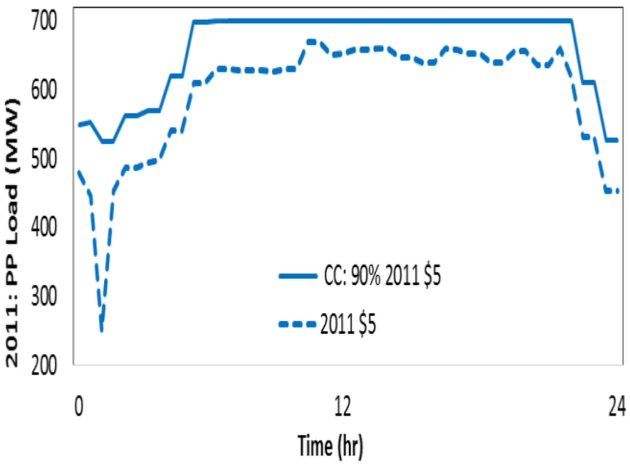
Analysis for full year: Repeat analysis above for:

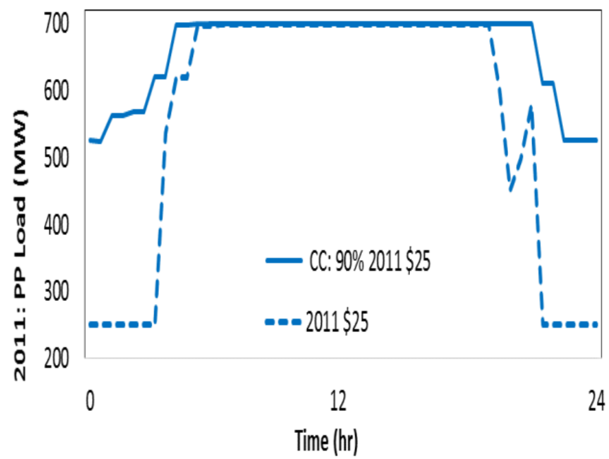
- A yearly operation,
- Based on 2011 and forecasted 2020 electricity prices and at
- Market driven carbon price.

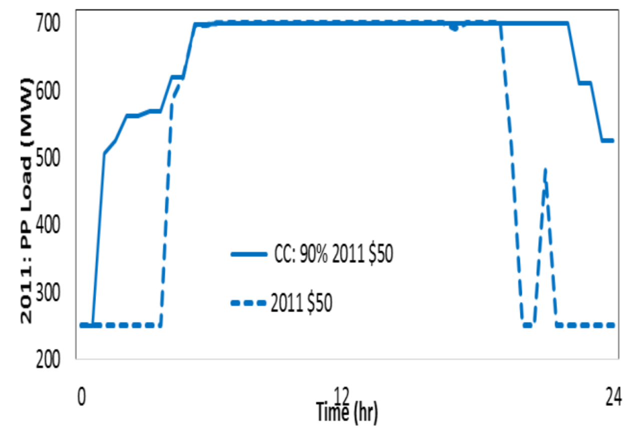
[3] Electricity price data: AEMO (Australian Energy Market's Operator)

Control-Optimization: Algorithm

Analysis for 24 hours:
30 min. time intervals; Fixed mode (90% capture rate) & Electricity price: 2011



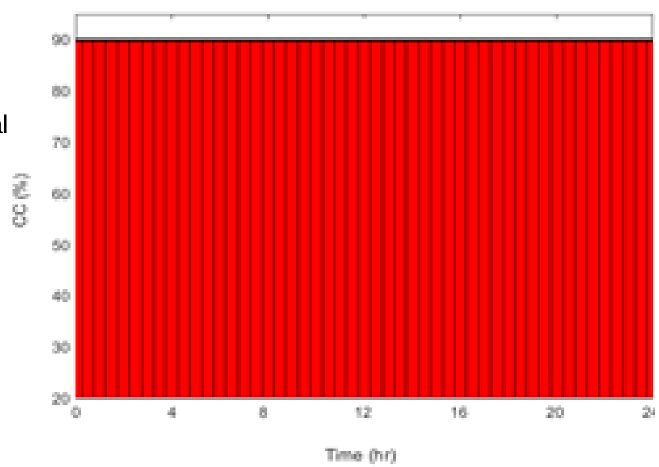


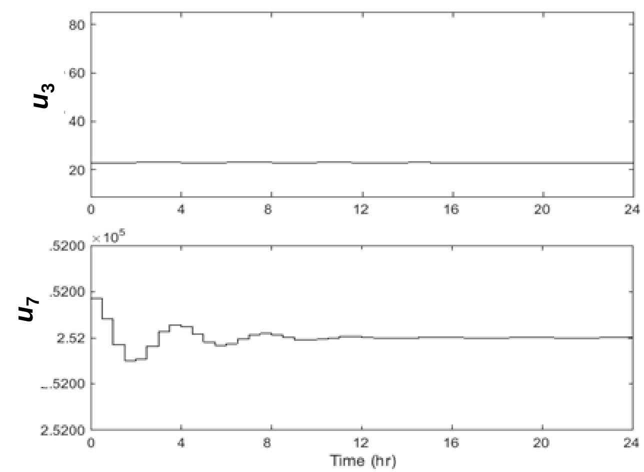


ENTERPRISE LEVEL

PLANT LEVEL

Black line: CC_{ideal}
Red bar: CC_{actual}





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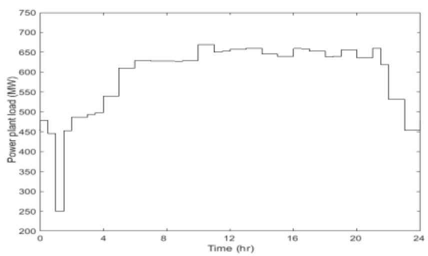
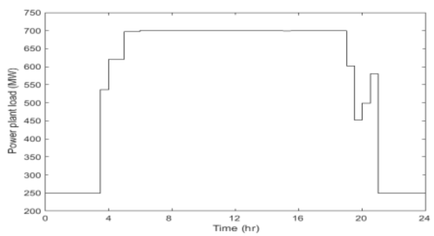
Analysis for 24 hours:
30 min. time intervals; Flexible mode (variable capture rate) & Electricity price: 2011

Control-Optimization: Algorithm

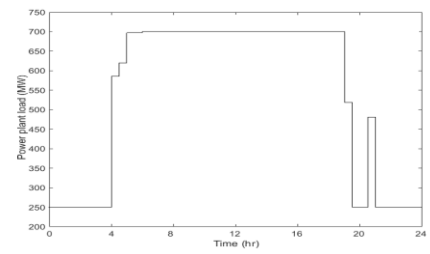
(a-i)



(b-i)



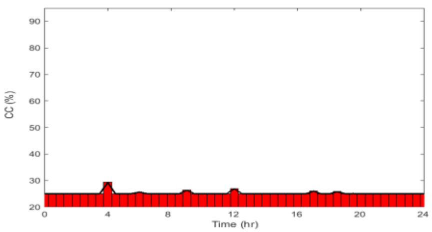
(c-i)



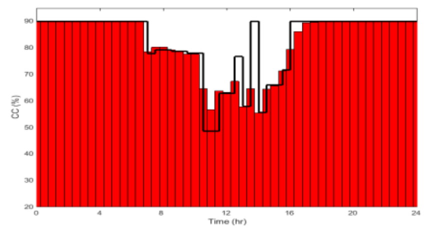
PP load

Economic-Optimization responses

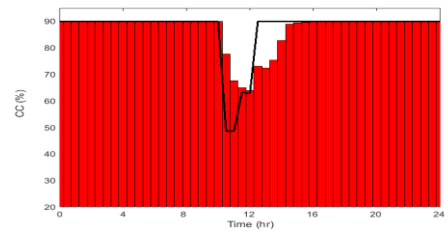
(a-ii)



(b-ii)



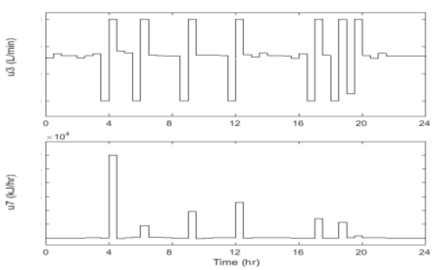
(c-ii)



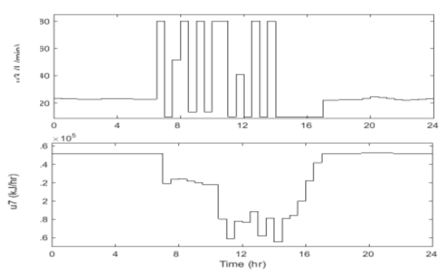
CC%
[CCideal & CCactual]

Advanced Control responses

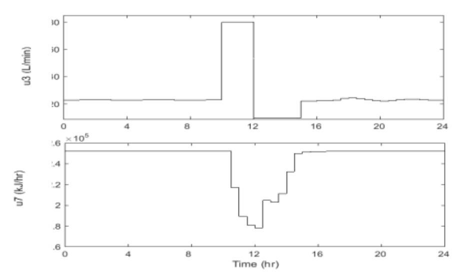
(a-iii)



(b-iii)



(c-iii)



u_3 = lean solvent flow rate

u_7 = reboiler heat duty

Carbon Tax: \$5/ tonne-CO_2

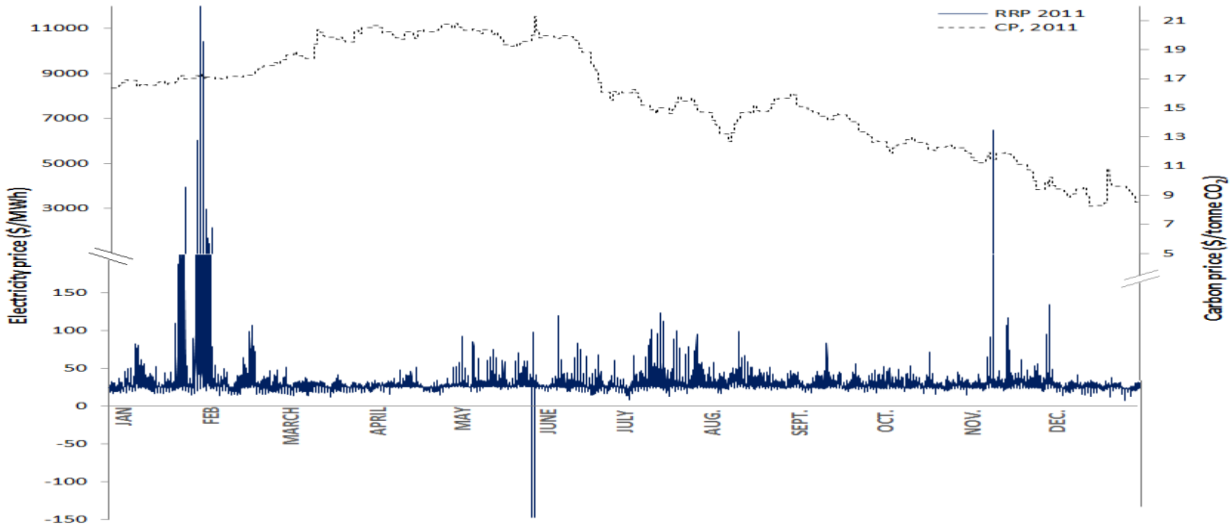
Carbon Tax: \$25/ tonne-CO_2

Carbon Tax: \$50/ tonne-CO_2

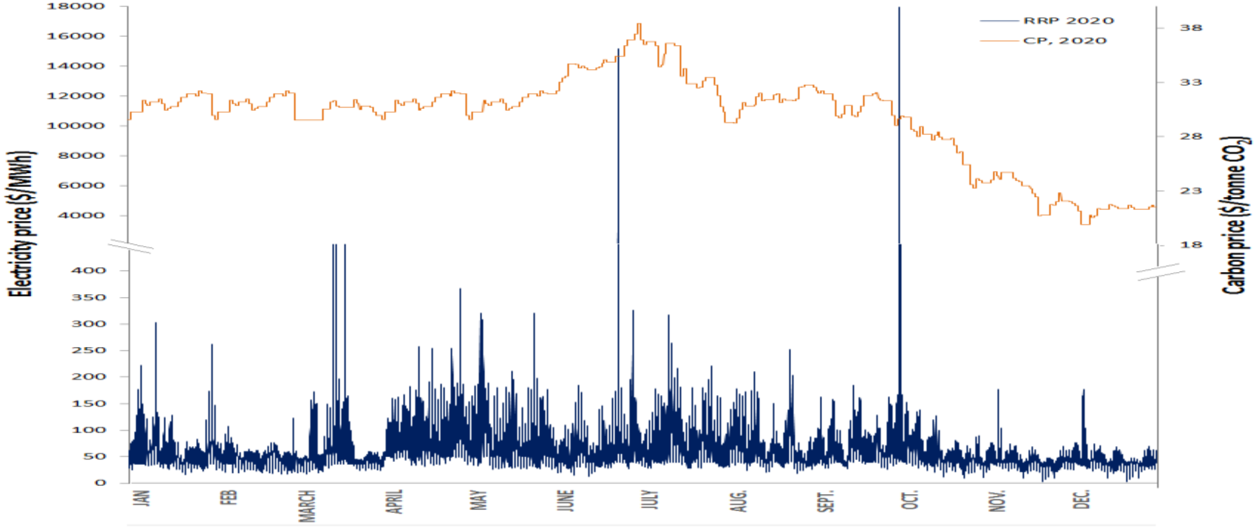
Control-Optimization: Algorithm

Analysis for full year:
Electricity and carbon prices for 2011 and 2020

2011 electricity and Carbon prices



2020 electricity and Carbon prices

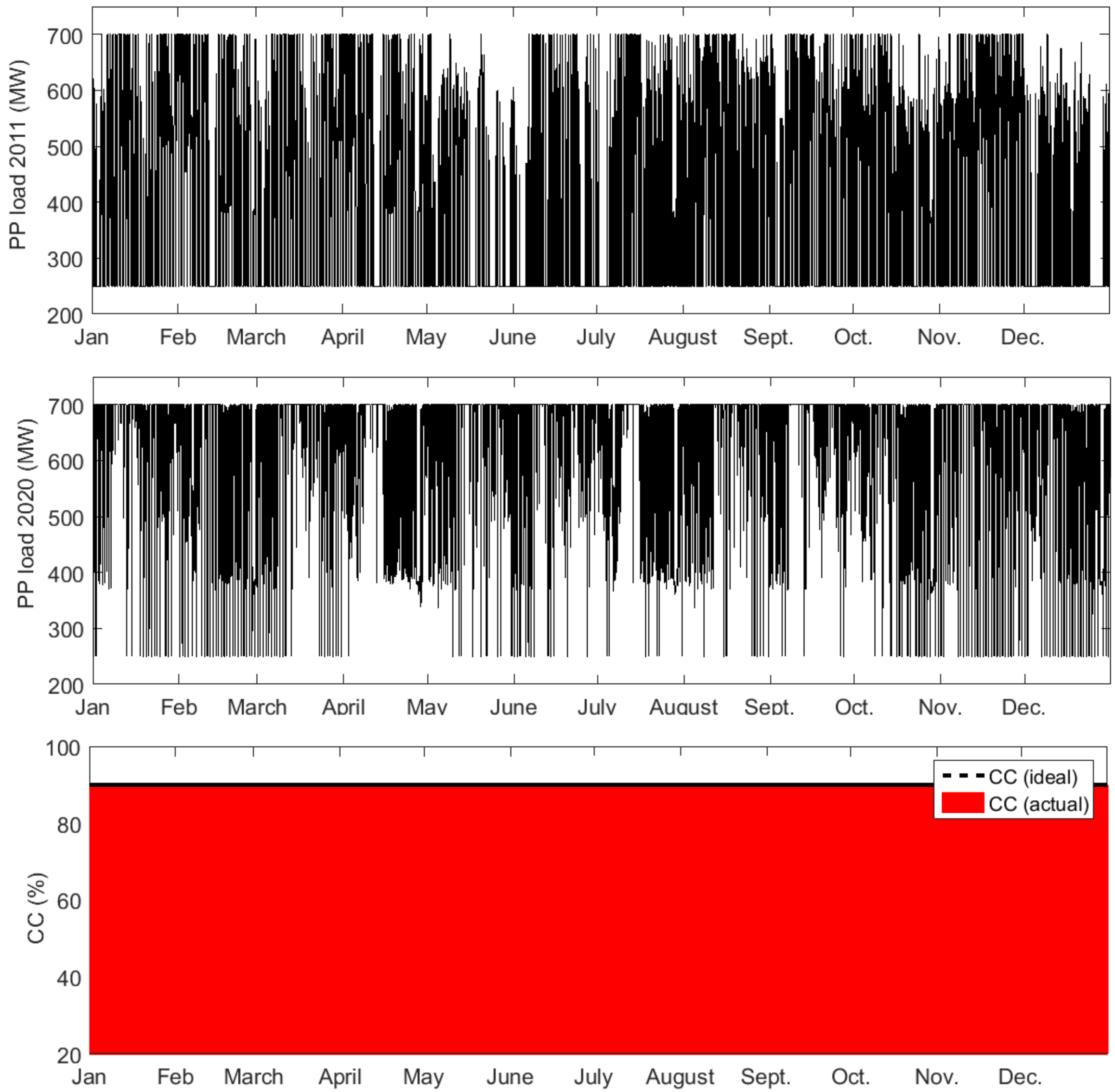


Control-Optimization: Algorithm

Analysis for full year:
30 min. time intervals; Fixed mode (90% capture rate) & Electricity price: 2011 & 2020

2011

2020



Analysis for full year:
30 min. time intervals; Flexible mode (variable capture rate) & Electricity price: 2011

Control-Optimization: Algorithm

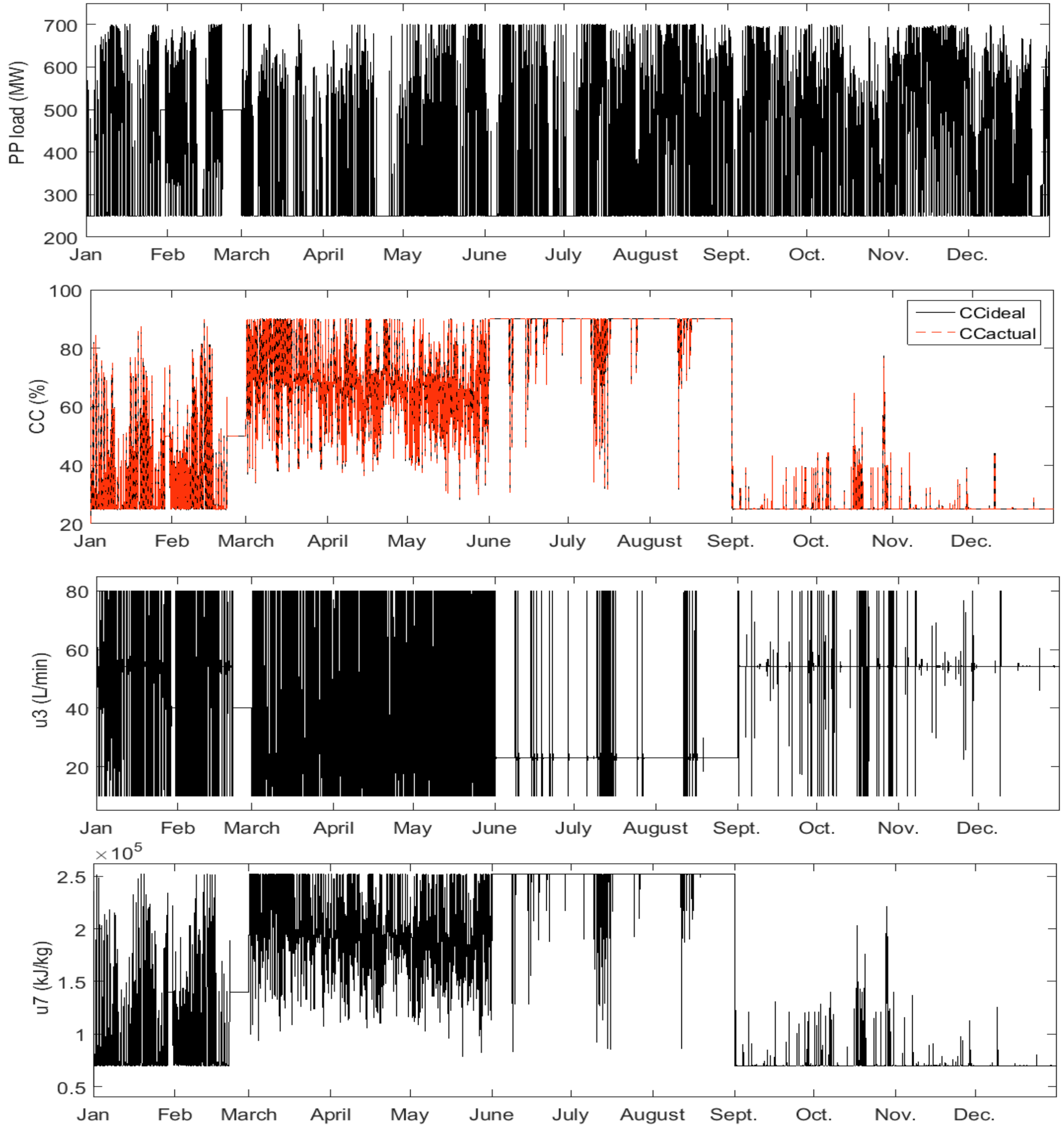
2011

Power plant load

Capture rate

Lean solvent flowrate

Steam flowrate



Control-Optimization: Algorithm

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Analysis for full year:
30 min. time intervals; Flexible mode (variable capture rate) & Electricity price: 2020

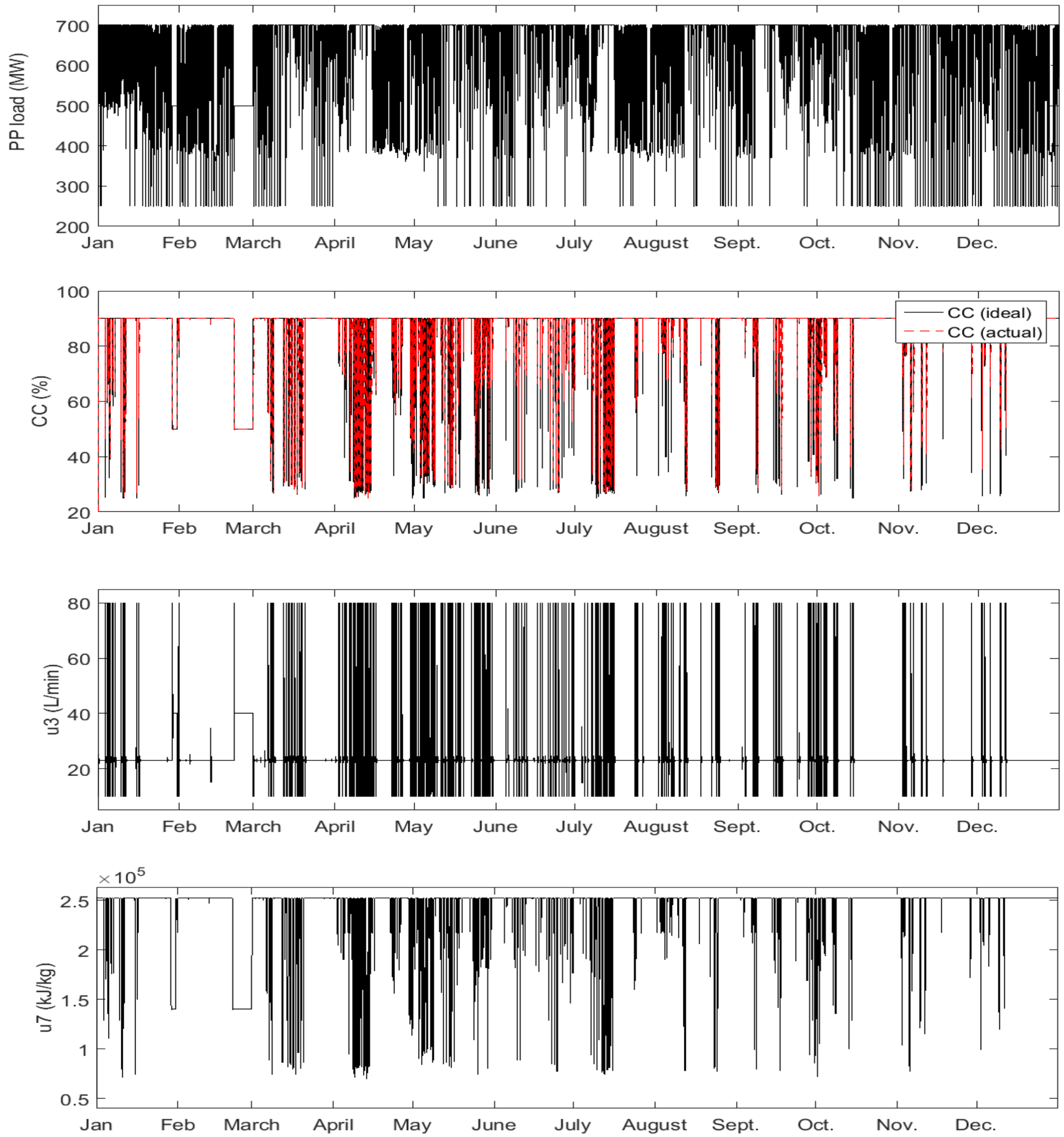
2020

Power plant load

Capture rate

Lean solvent flowrate

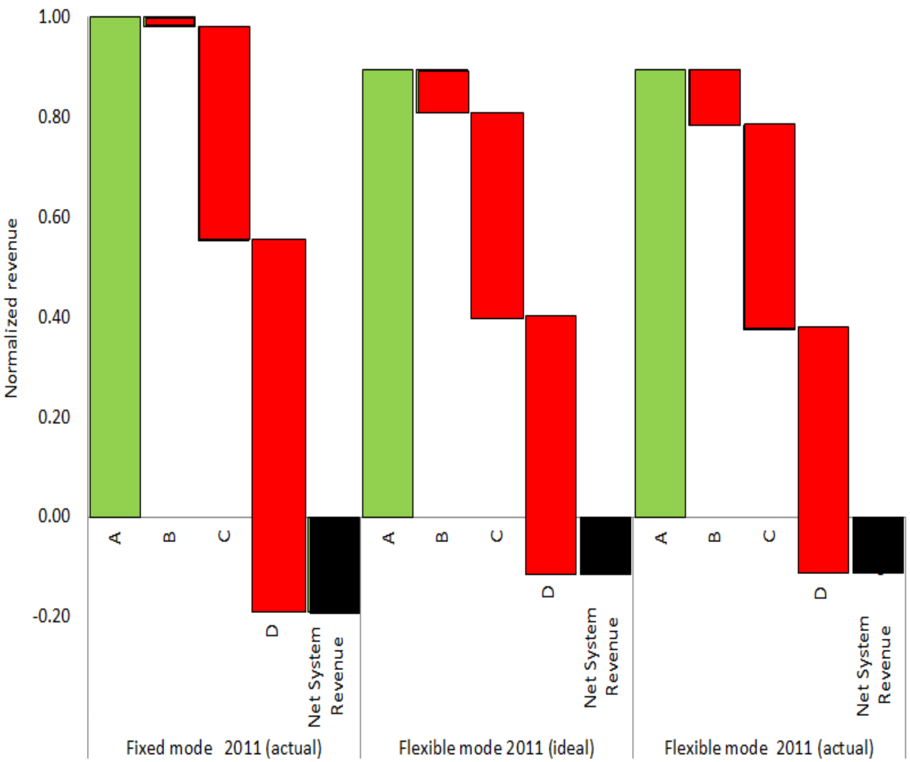
Steam flowrate



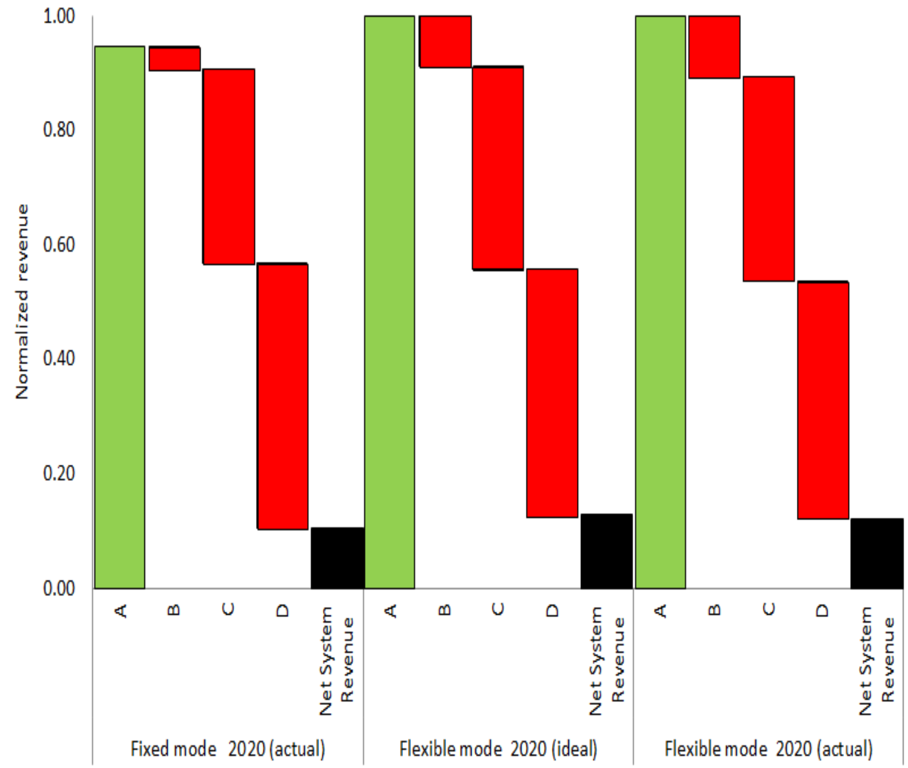
Control-Optimization: Algorithm

Revenue breakdown for power plant retrofitted with PCC

2011



2020



$$Net\ System\ Revenue = A - B - C - D$$

A = Revenue generated through selling of electricity

B = Cost of CO_2 emission (carbon price paid)

C = Power plant

D = PCC operational costs

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Implementation for solar-assisted carbon capture

Flexible Operation - Objective

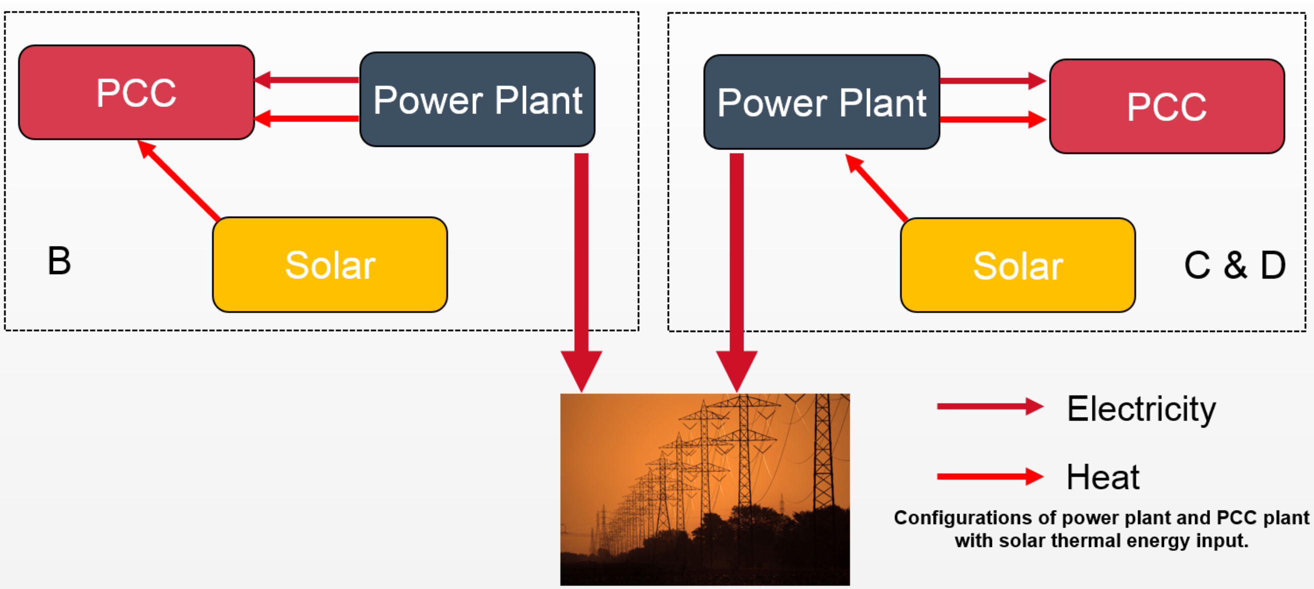
RESEARCH OBJECTIVE is to optimize system revenue through flexible operation of power plant load and PCC process (carbon capture rate) for the following scenarios:

A. Power plant and PCC process only.

B. Power plant and PCC process with solar thermal energy used in PCC process

C. Power plant and PCC process with solar thermal repowering of power plant

D. Power plant and PCC process with solar thermal repowering of power plant (net load matched with historical power plant load)



Configurations of power plant and PCC plant with solar thermal energy input.

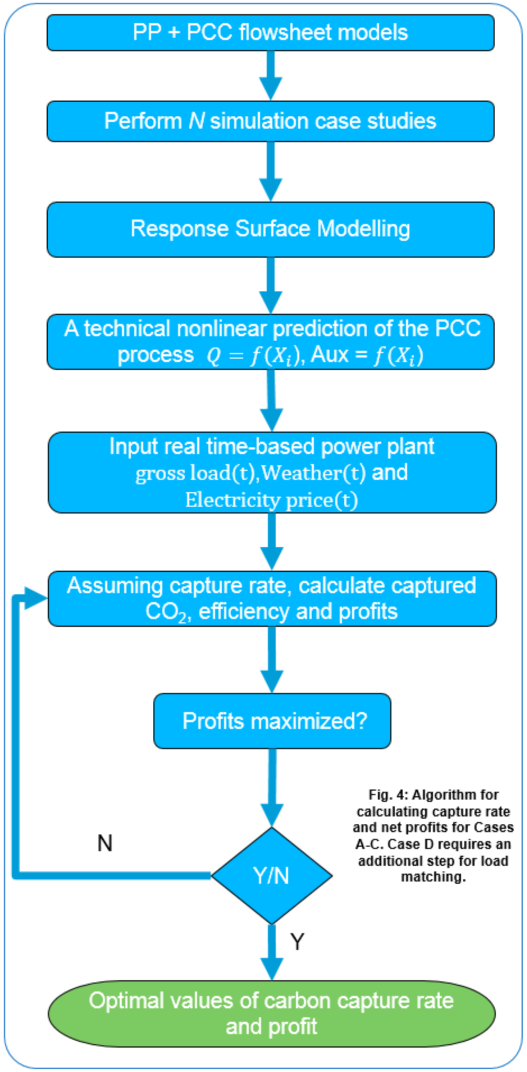


Fig. 4: Algorithm for calculating capture rate and net profits for Cases A-C. Case D requires an additional step for load matching.

Flexible Operation - Methodology

Objective function

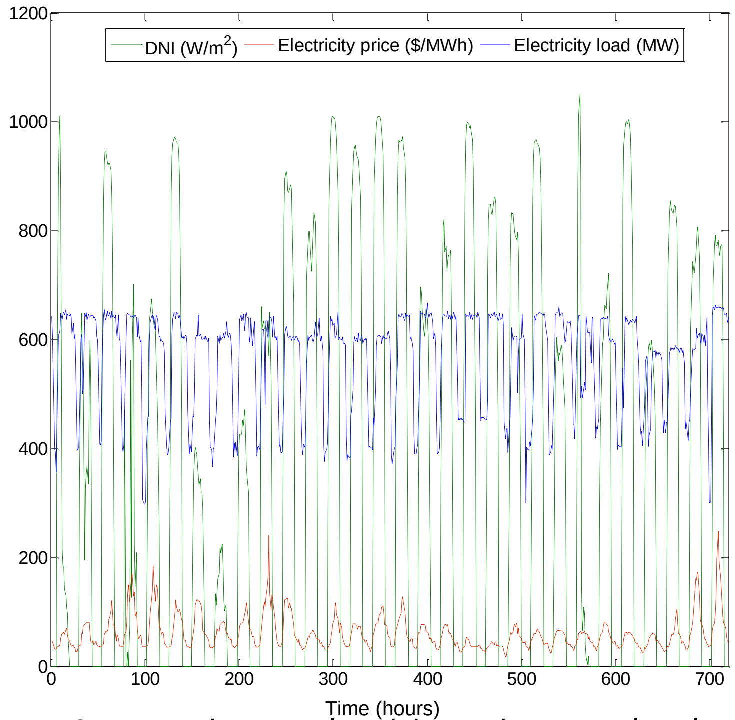
$$R_{systen} = \int (PP\ net\ load(t) - PCC\ penalty(t)) \cdot p_{elec}(t)\,dt$$

$$- \int (CO_2\ emitted\ (t)) \cdot p_{CO_2}(t)\,.dt$$

$$- P_{PP,OPEX}(A,TS) - P_{PCC,OPEX}(A,TS)$$

$$- P_{sol,OPEX}(A,TS) + \int p_{REC}.SF(t).OPP.dt$$

- Revenue from extra electricity generation (blue)
- Revenue from RECs (yellow)
- Carbon tax liable (green)
- OPEX of system (red)



One month DNI, Electricity and Power plant load profile for a black coal power plant near Sydney.

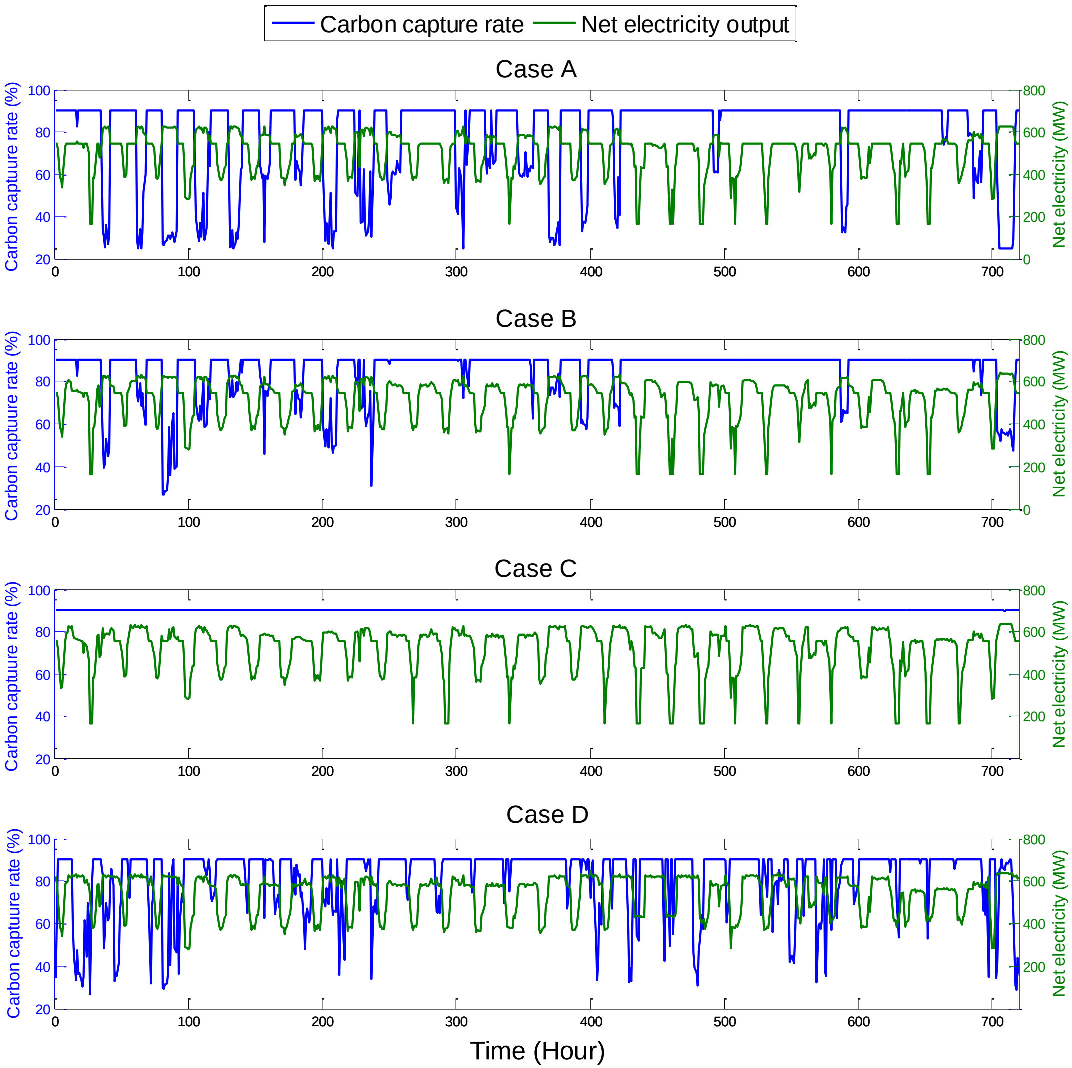
Constraints

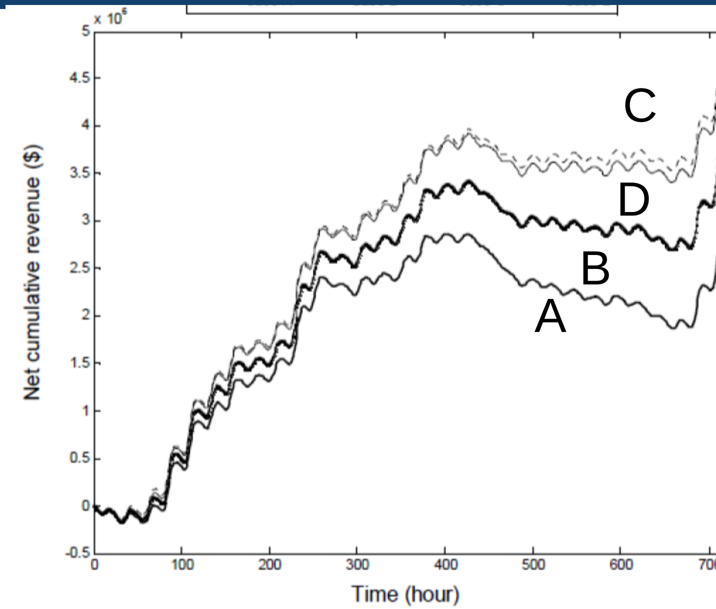
- 25% < Capture rate < 90%
- 250MW < Power plant load < 700MW

Case Study

- 660MW black coal power plant near Sydney, Australia.
- Carbon tax assumed to be \$25/tonne-CO_2 and \$50/tonne-CO_2.

Flexible Operation - Results





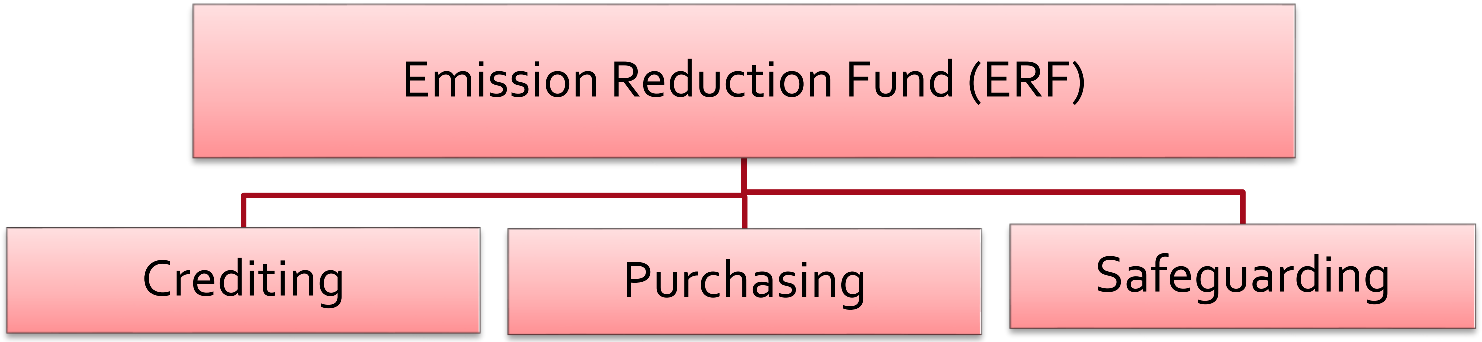
Carbon tax = $25/tonne-$CO_2$	Case A	Case B	Case C	Case D
Cumulative power production (GWhe)	368	374.5	374.1	391
Cumulative profit (k$)	2896	3831	**4776**	4640
Cumulative emissions (ktonne-CO_2)	88.5	61.0	39.2	76.0
Carbon emission intensity (tonne-CO_2/MWh)	0.24	0.16	**0.10**	0.19

Implementation for emissions trading schemes

Control-Optimization Framework: implementation with the ERF

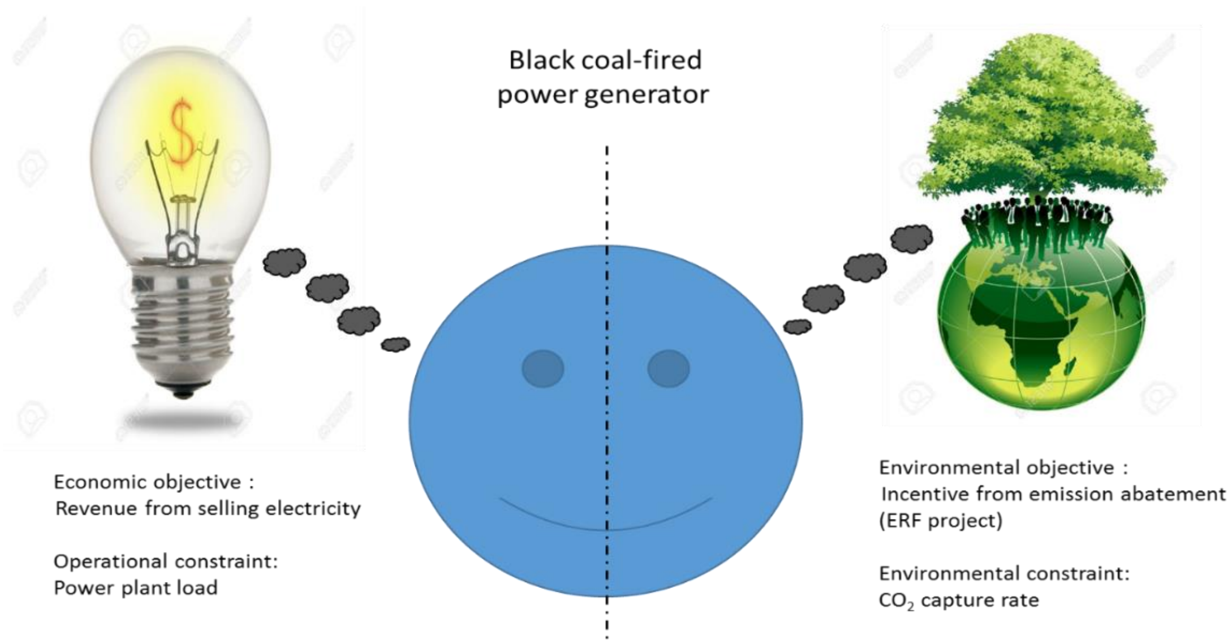
Australia's Emissions Reductions Fund (ERF) Scheme:

- A voluntary scheme that aims to provide incentives to adopt new practices and technologies to reduce their emissions.
- Participants in the Scheme can earn Australian carbon credit units (ACCUs) for emissions reductions. One ACCU is earned for each tonne of carbon dioxide equivalent (tCO2-e) stored or avoided by a project.
- ACCUs can be sold to generate income, either to the government through a carbon abatement contract, or in the secondary market.



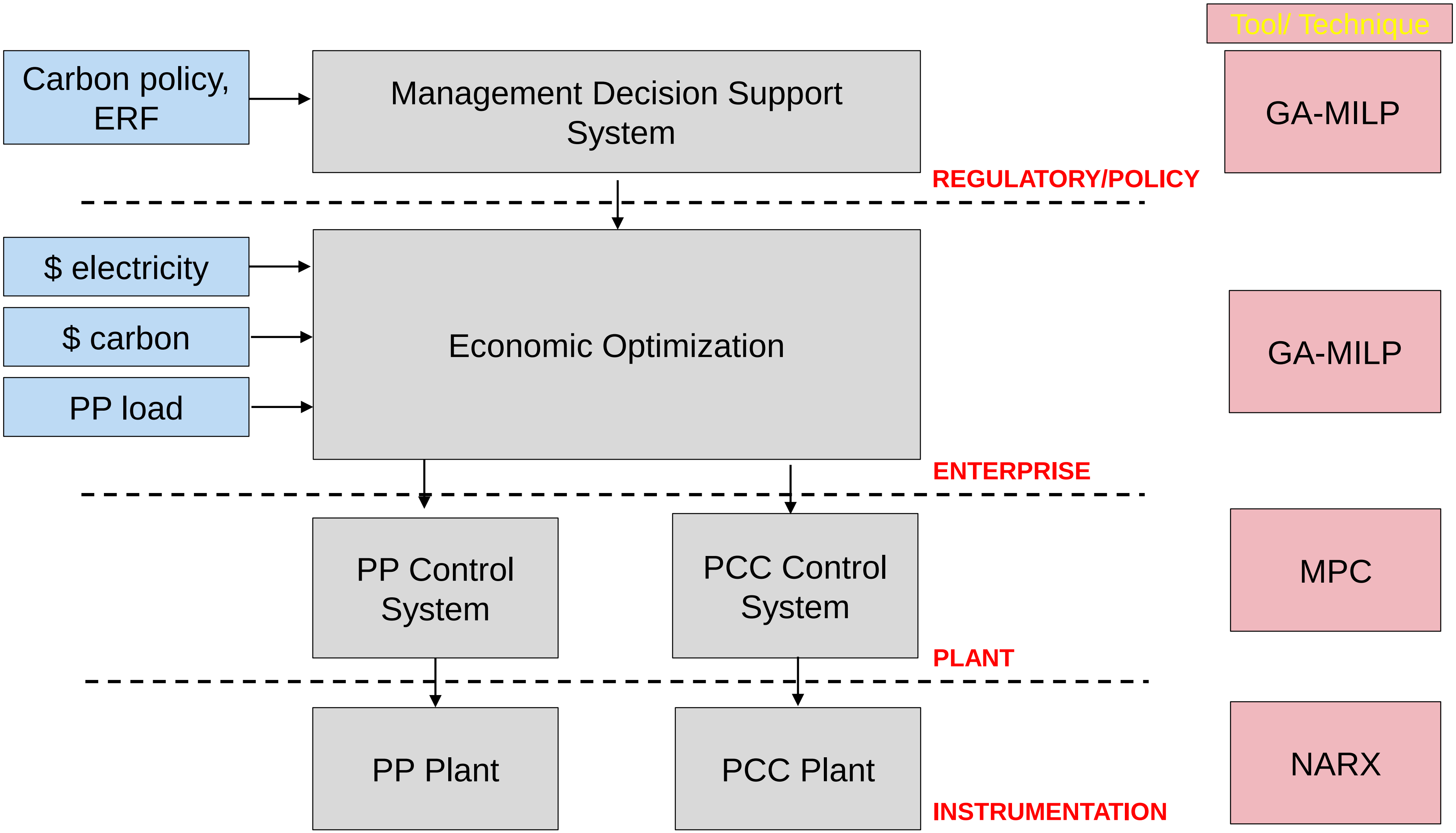
Control-Optimization Framework: implementation with the ERF

Application to Australia's Emissions Reductions Fund (ERF) Scheme

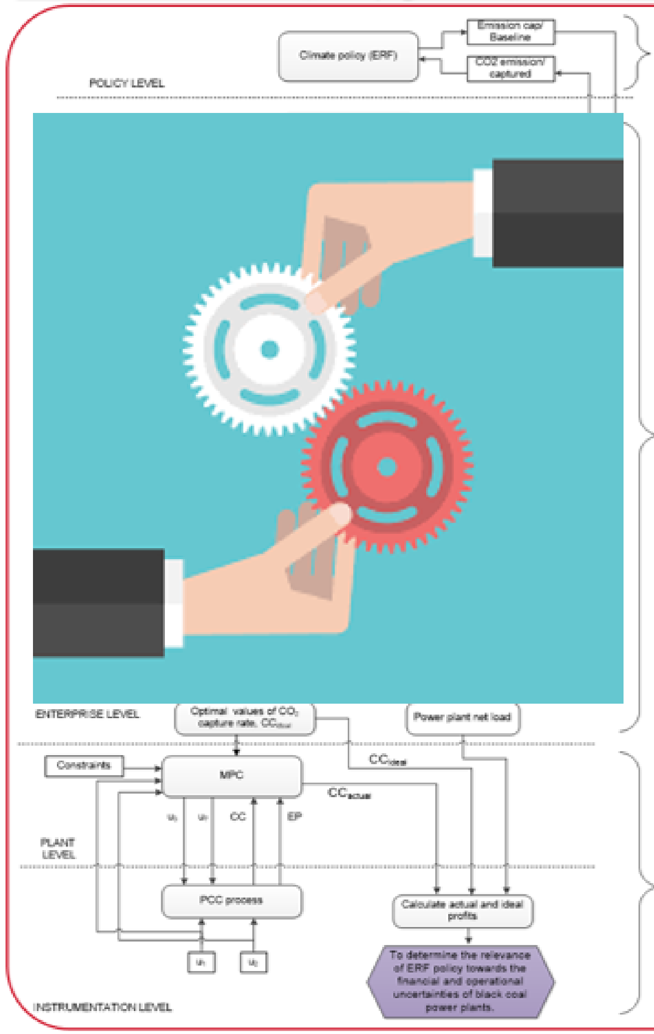


$$Economic\ objective = f\ (A, P_{ERF})$$

Opportunity



Control-Optimization Framework: implementation with the ERF



Reducing uncertainties:

1. Prediction of carbon capture profile and power plant net load over times (operational)
2. Prediction of net operating revenue over time (financial)

MINLP algorithm: Maximize plant net operating revenue by predicting & scheduling the operation of PP-PCC plant subject to 2 constraints:

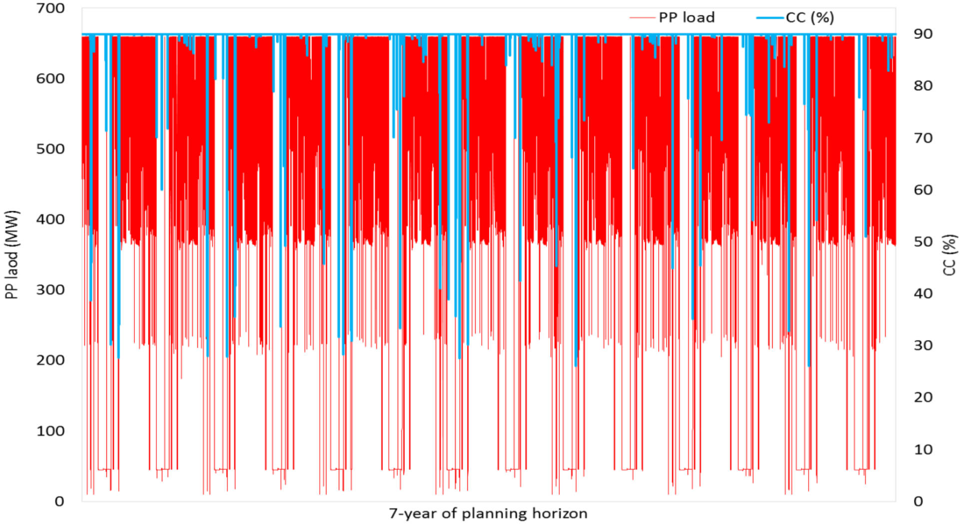
$$Max\ (Revenue) = \int P_e * (Power\ plant\ net\ load - PCC\ penalty) * dt + P_{ERF} - P_{PP} - P_{PCC}$$

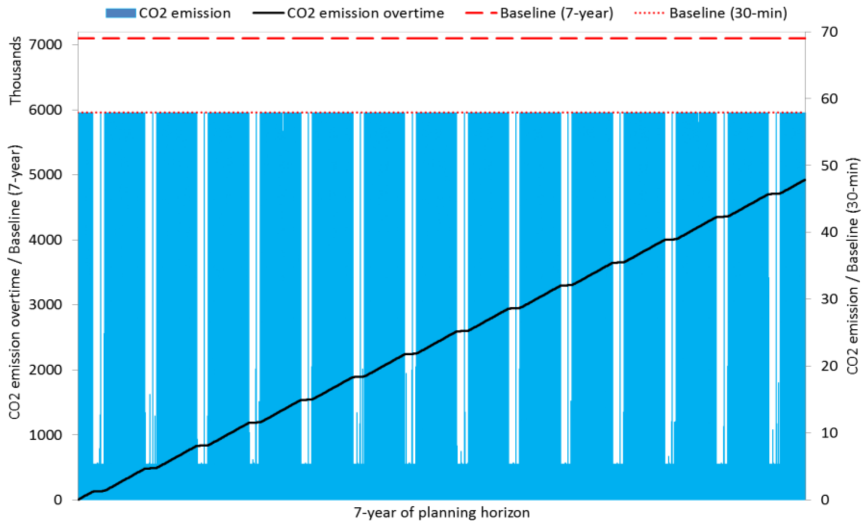
1. Operational constraint
2. Environmental constraint

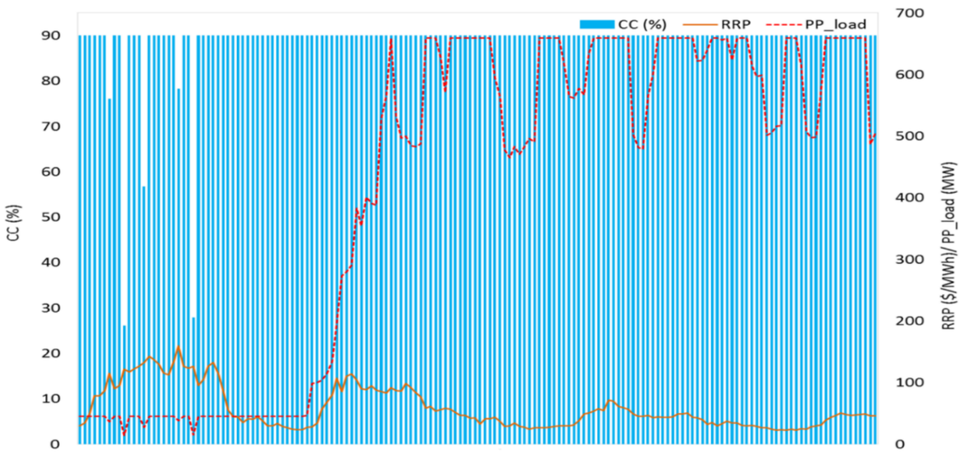
MPC algorithm: Predicting the carbon capture profile overtime

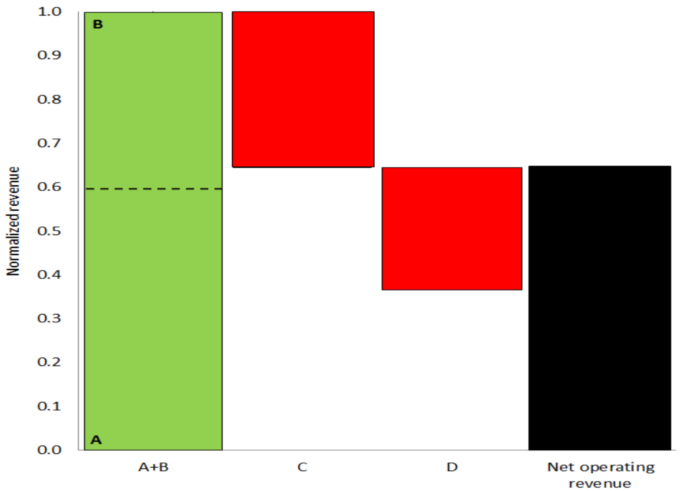
Control-Optimization Framework: implementation with the ERF

Application to Australia's Emissions Reductions Fund (ERF) Scheme









Conclusions/Implications

1. **Model-based control strategies are critical** to the success of carbon capture processes operating in a "rough sea" of dynamic variability and uncertainties.
2. **Proposed a temporal multiscalar decision support framework** for flexible **model-based** operation of carbon capture plants targeting low-carbon management of power plant emissions.
3. Going beyond the human capability, this framework will **enhance plant revenue** and **efficiency** and **reduce capture costs** through **flexible and well controlled operations**, especially in response to power loads, disturbance, market and weather conditions.
4. **Implications for policy**: Demonstrated the implementation of the framework on the Australian ERF scheme.
5. Potential for use in carbon trading for nationally or globally **networked carbon emissions trading schemes**. E.g. EU/China.
6. **Implication on capital cost**: use for precise sizing of the capture plant.

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THANK YOU!

http://sydney.edu.au/engineering/chemical/research/laboratory-for-multiscale-systems