Tuning of a PID controller Using a Multi-objective Optimization Technique Applied to A Neutralization Plant

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Agenda

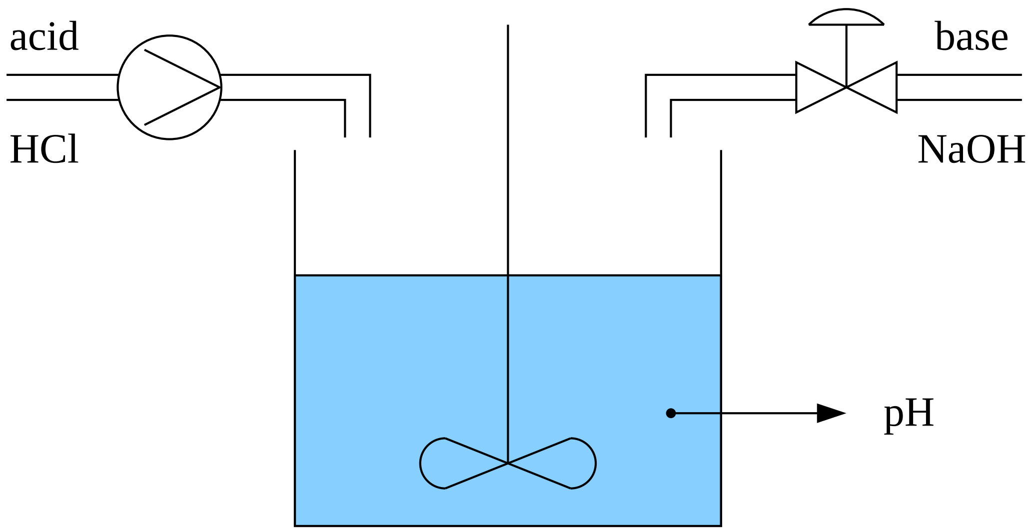
1. Motivation
2. Titration and Neutralization plant
3. Problem formulation & plant model
4. Fixed gain PID
   - Aggregation method
   - Multi-objective optimization
5. Gain-scheduled PID
6. Summary

1. Motivation

- Several objectives to be satisfied;
- Objective aggregation method requires preliminary knowledge;
- Chemical neutralization plant is highly nonlinear and time varying;
- PID is one most widely used controllers in industry [Åström95]
- Genetic Algorithms can solve non-convex and multi-objective optimization problems.

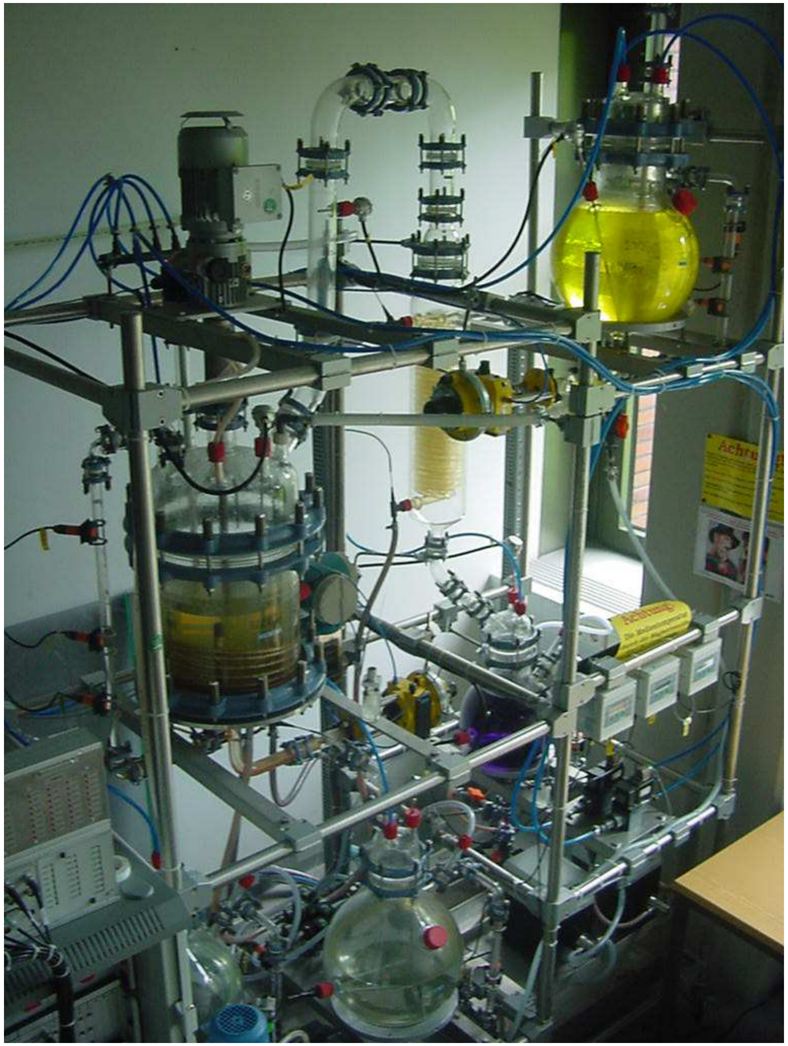
2. TINA - neutralization process

- Hydrochloric acid, pH = 1.7 ± 0.05;
- Sodium Hydroxide, pH = 12.5 ± 0.1;
- Separate loops control the
  - liquid level (210 ± 10 mm);
  - temperature in the reaction tank ($21 \pm 1\,^\circ\mathrm{C}$);
  - the mixer.



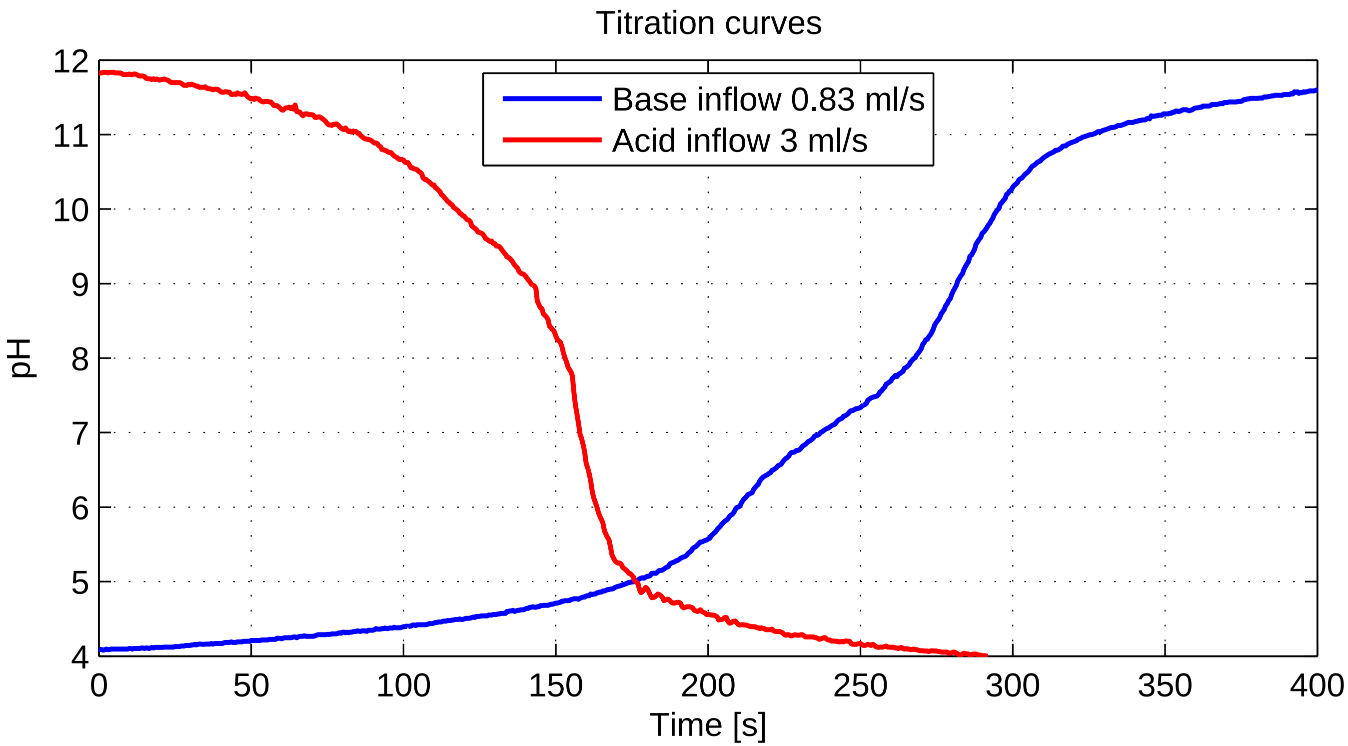
2. TINA

A laboratory scale chemical plant, allowing titration and neutralization of chemical substances.



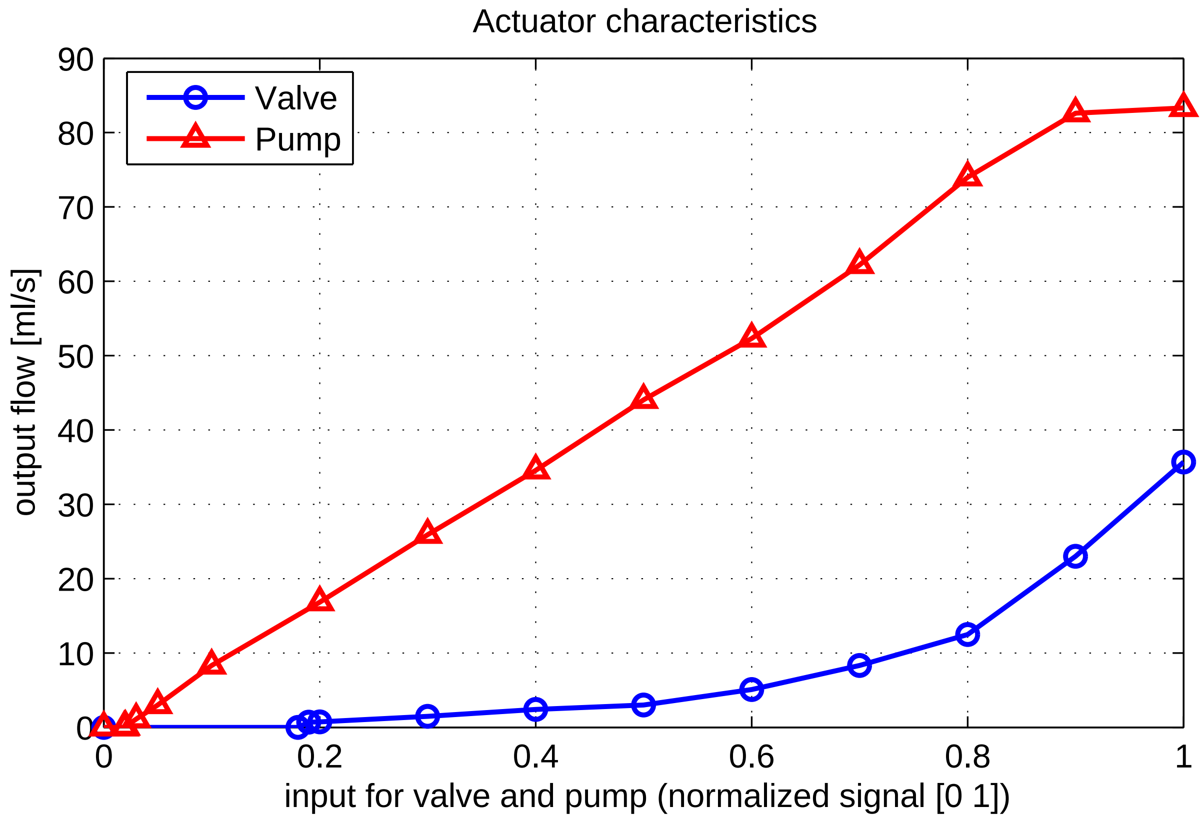
2. TINA - nonlinear behavior due to:

- operating points with very high and very low gain;
- saturation;
- time variations;
- longer time delay of the base actuator.



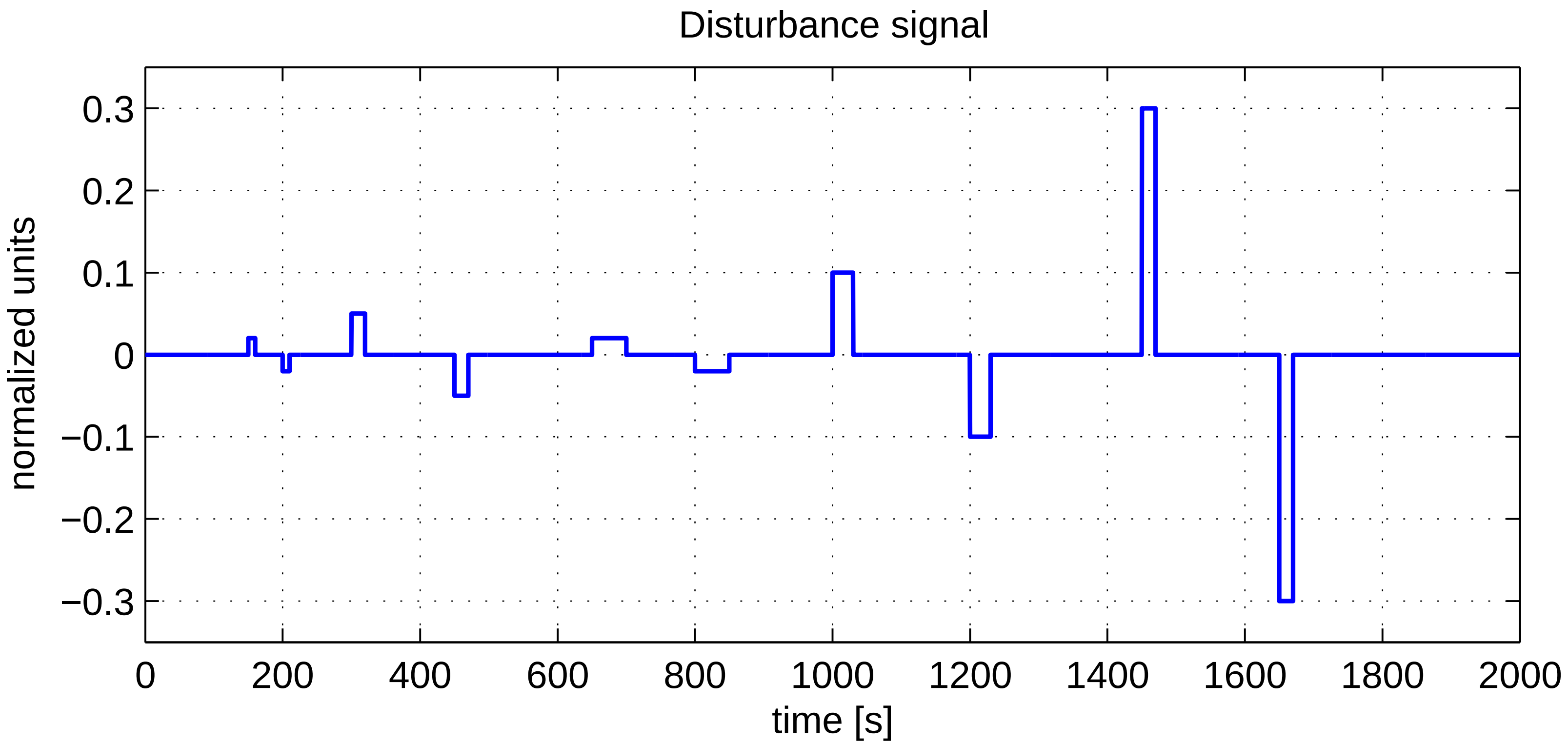
2. TINA - actuators

- Control signal is applied either to the valve (+) or the pump (-);
- The non-linear characteristics of the valve and the pump are linearized.



3. Control problem formulation

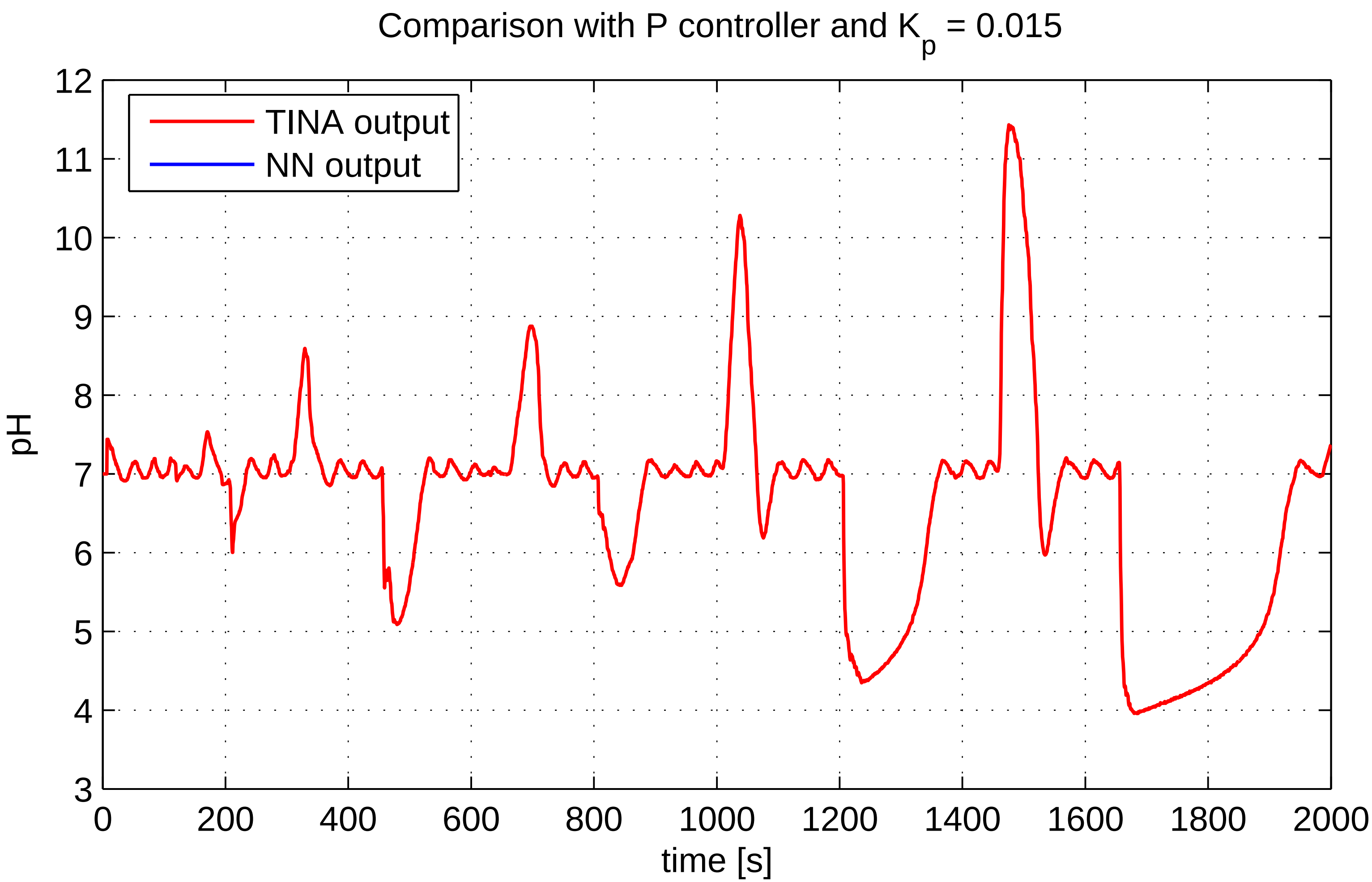
Stabilization (pH = 7) and disturbance rejection task is considered.



Closed loop identification was used to keep the system outside the saturation limits.

3. Model of the plant

The gathered data is used to train a Neural Network (NN).



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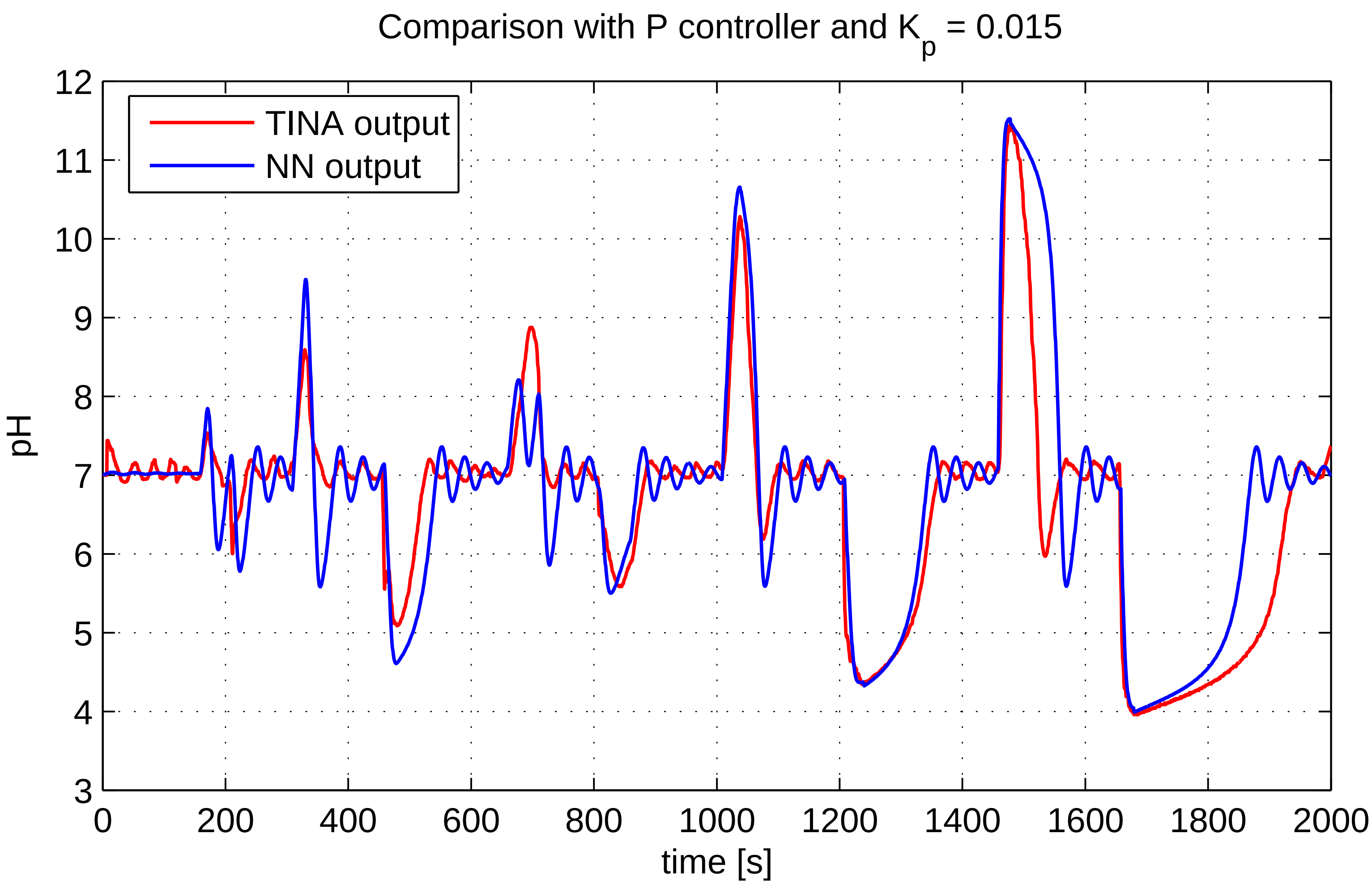

3. Design objectives

1. Minimal quadratic error $e(t) = r(t) - y(t)$

$$J_1 = \int_0^{T_s} e^2(t)dt \qquad (1)$$

2. Minimal absolute control $u(t)$

$$J_2 = \int_0^{T_s} |u(t)|dt \qquad (2)$$

where $T_s = 2000s$ - simulation time

The problem is non-convex due to the use of NN and the absolute control signal

4. Fixed Gain PID

$$K(z) = K_P + K_I \frac{T_s}{z-1} + K_D \frac{2z-2}{(T_s+2T_c)z + T_s - 2T_c} \tag{3}$$

where

$T_s = 0.5s$ - sampling time;

$T_c = 0.5ms$ - time constant for the derivative.

4. Objective Aggregation

$$J_a = J_1 + W J_2 \tag{4}$$

The value of W is set

- using information for the "raw" values of the objective functions and their importance;
- by try-and-error approach.

4. Genetic Algorithms

GA are direct, parallel, stochastic search method for

- global,
- non-convex,
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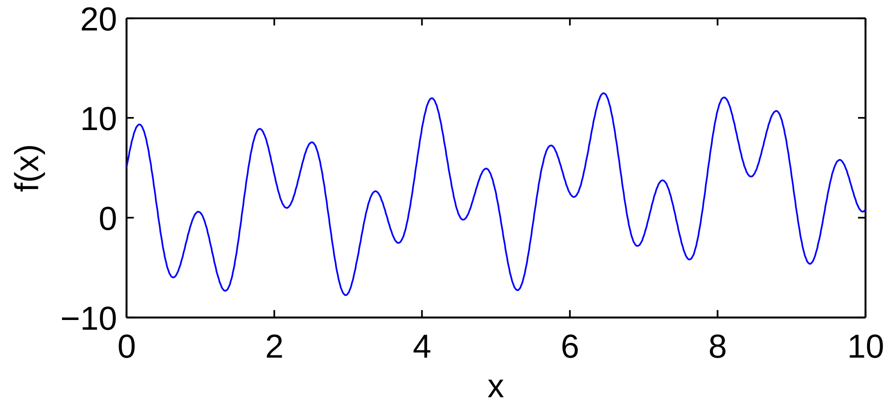

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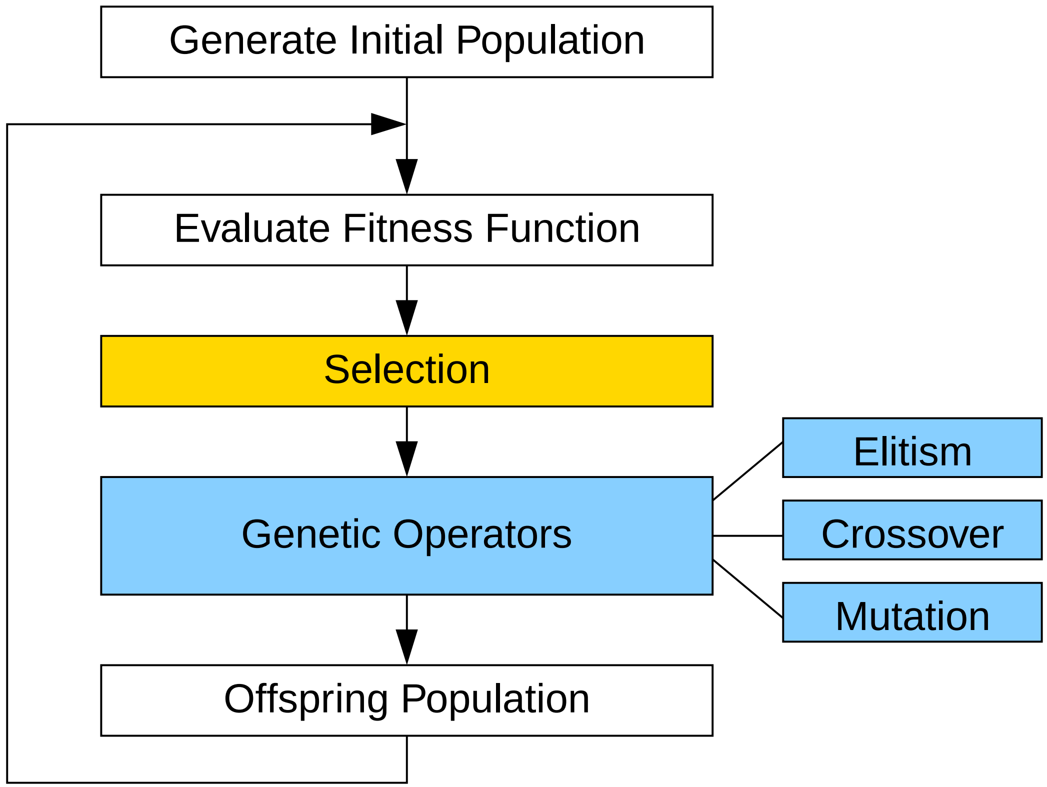

4. Aggregation method - results

Population size = 20; Generations = 200;

Mantissa-exponent variable coding: $K = p_1 10^{p_2}$

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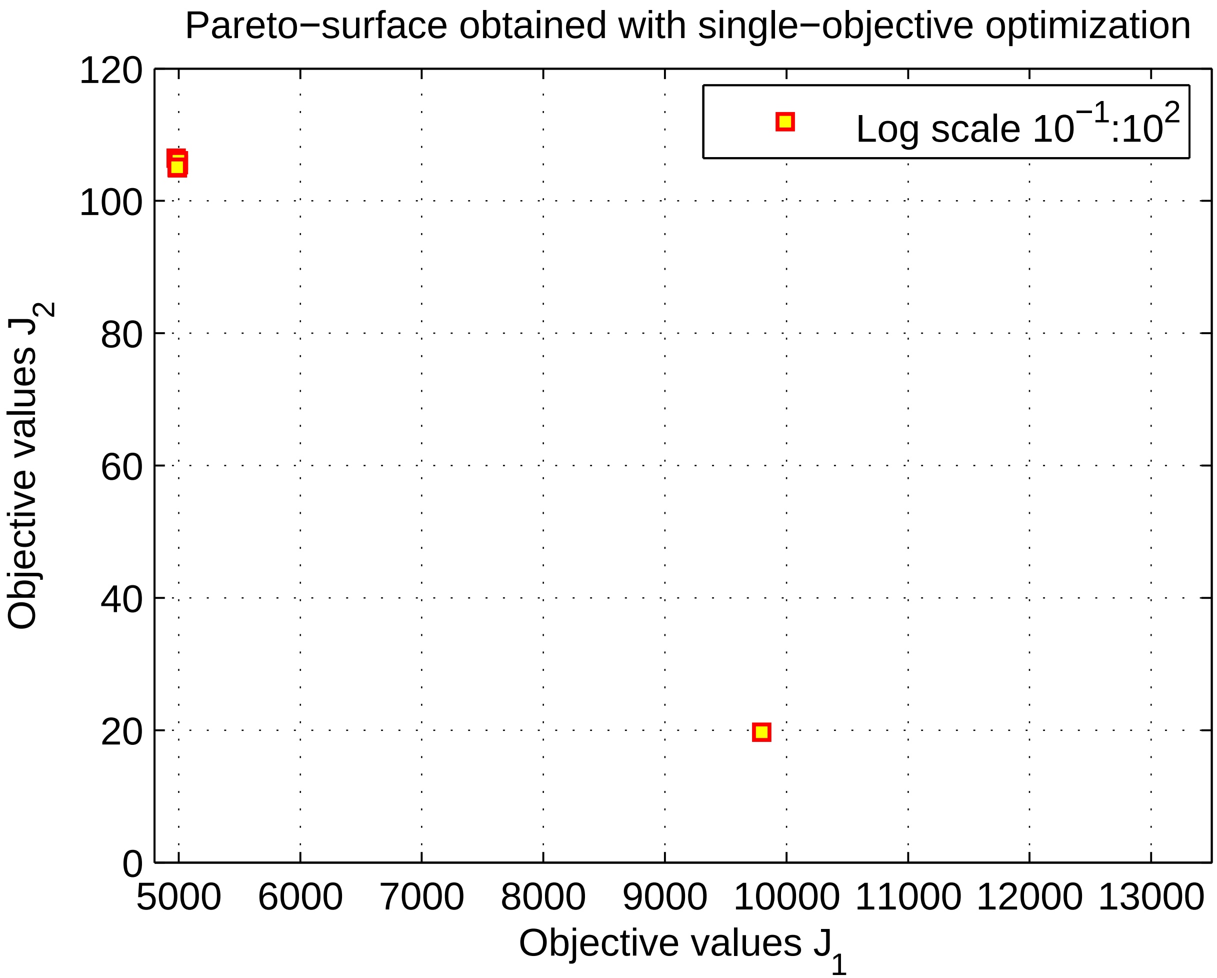

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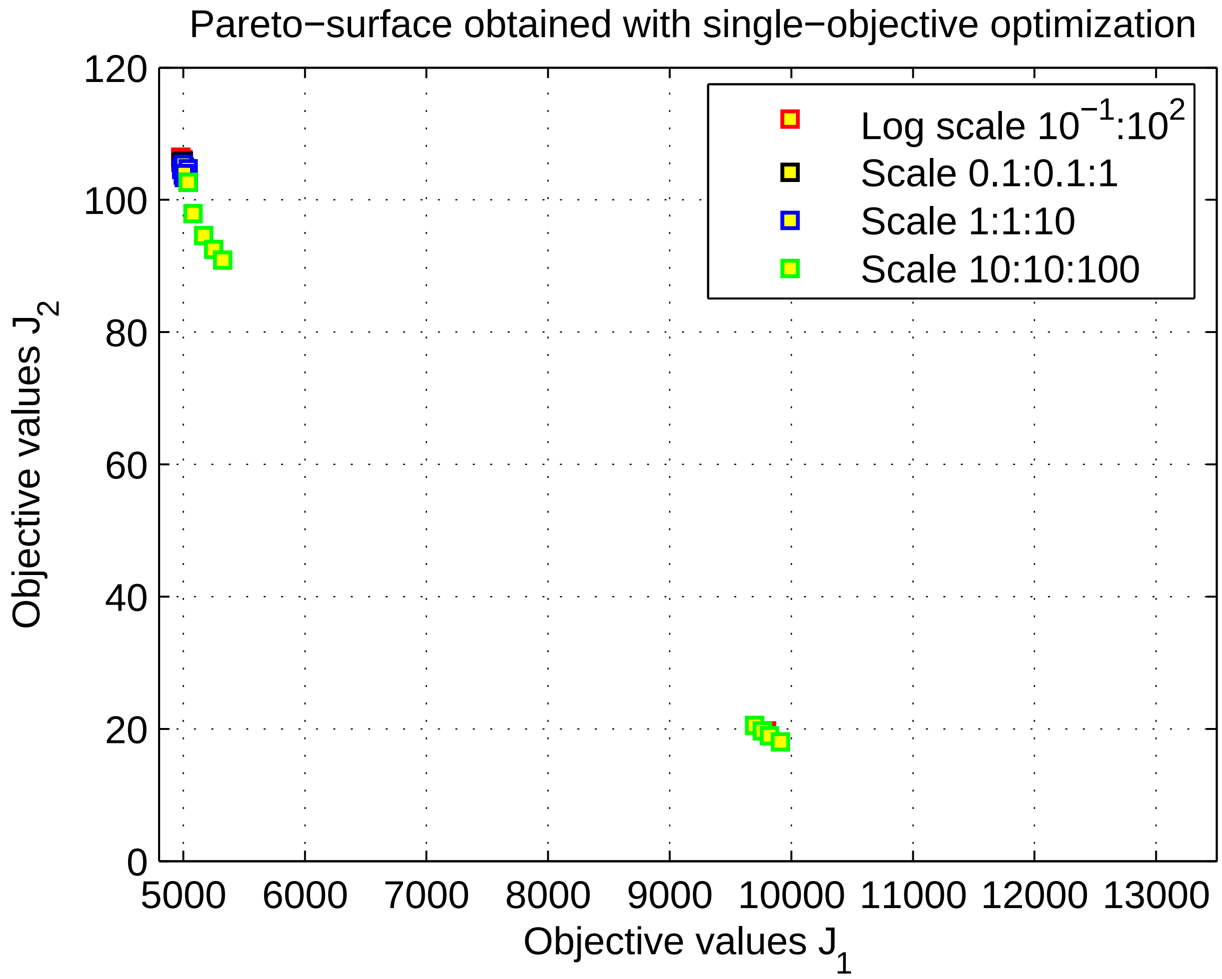

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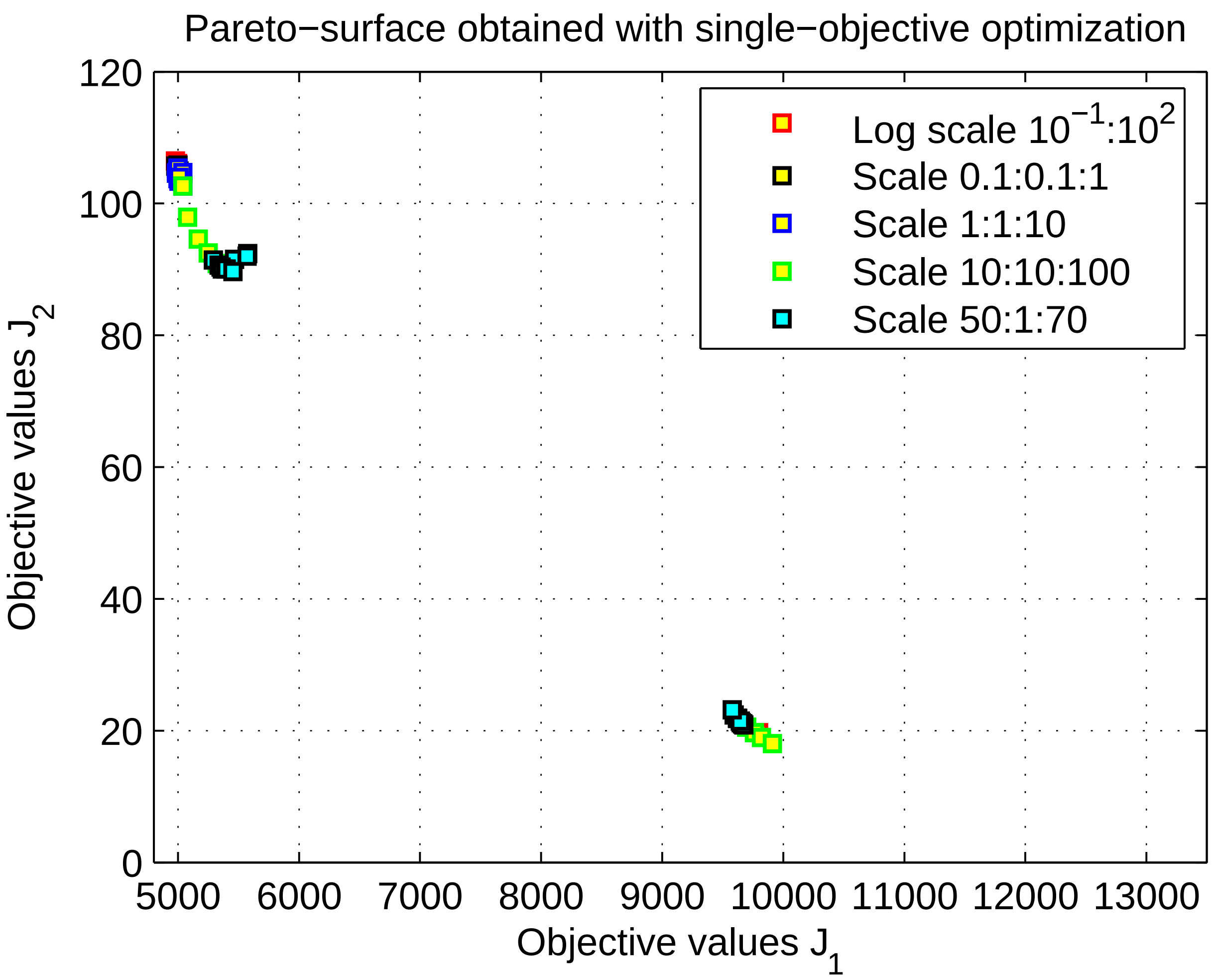
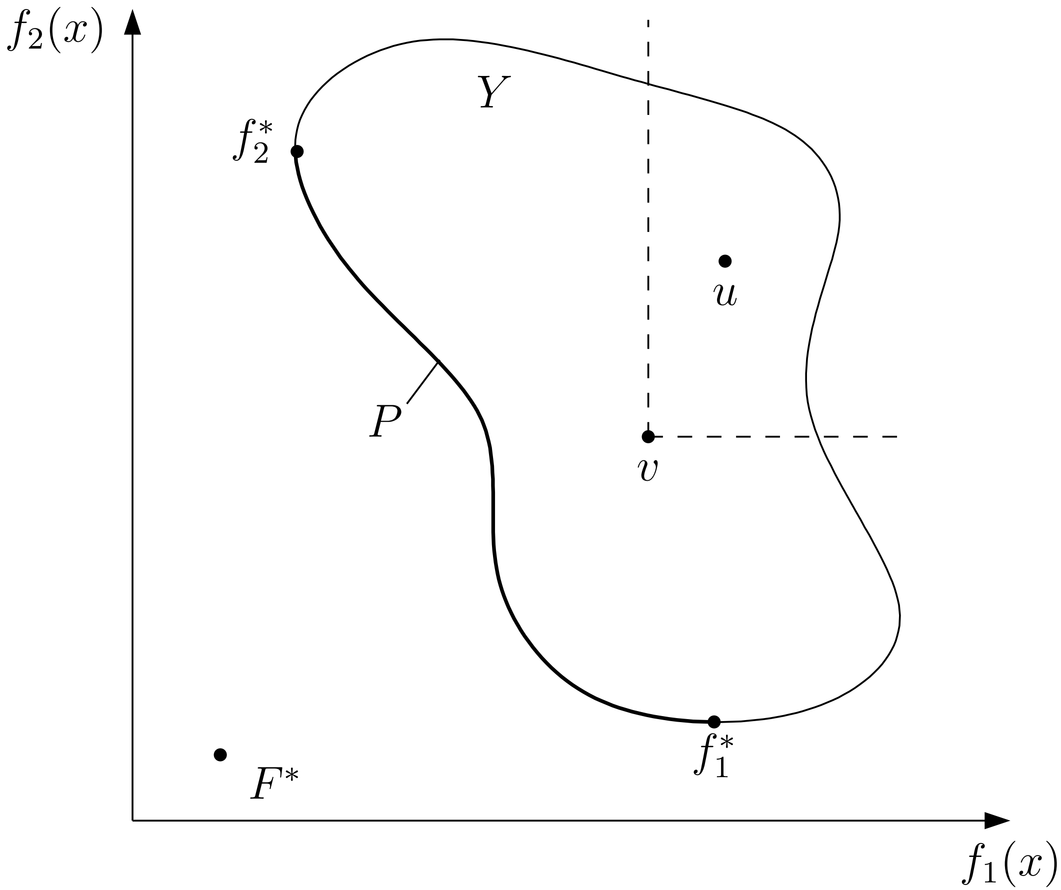


4. Multi-Objective GA (MOGA)

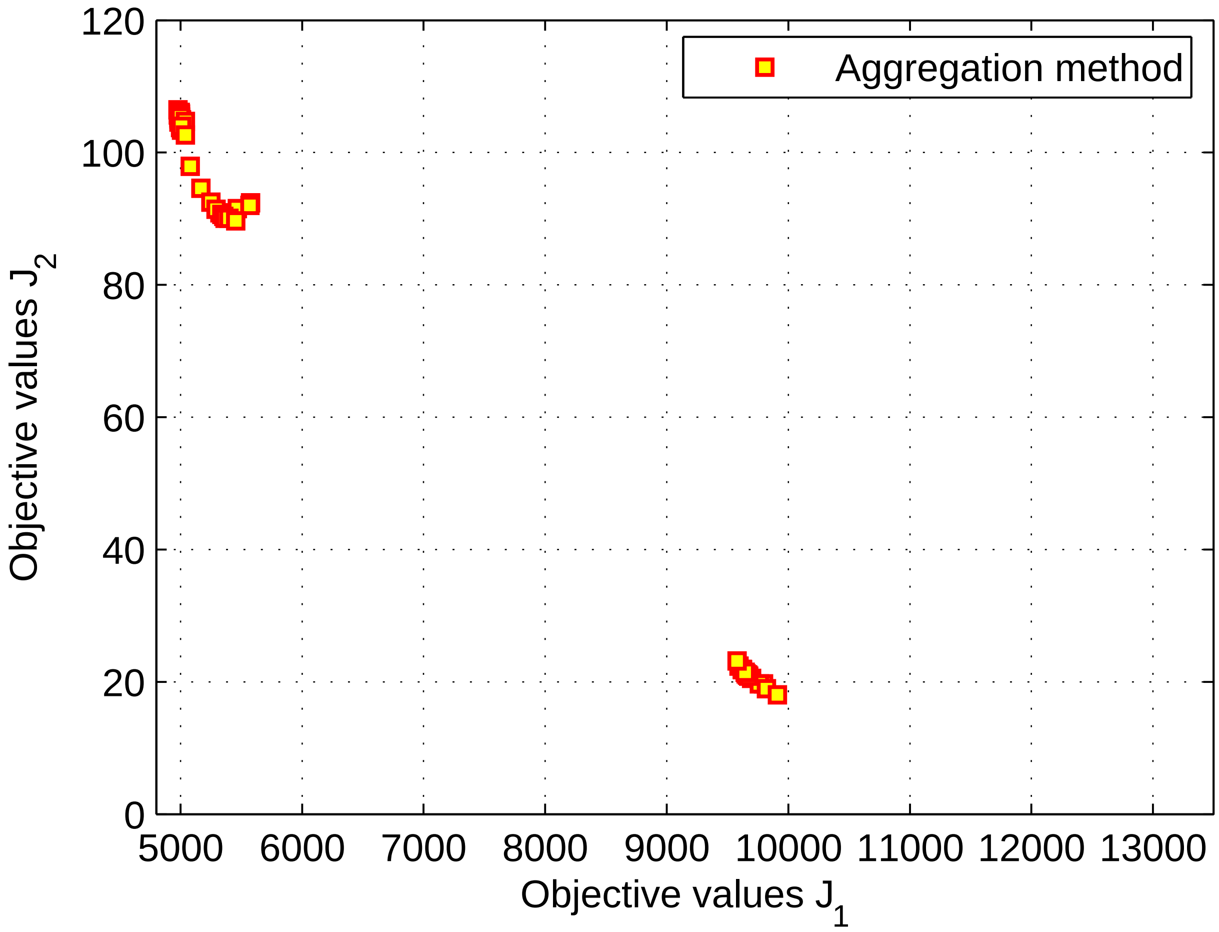
MOGA has differs from standard GA by the selection method. p.25.



The used MOGA here is Strengthen Pareto Evolutionary Algorithm 2 [Zitzler01].

4. MOGA optimization results

Population size and Pareto-set size of 50 controllers;
Generations = 200;



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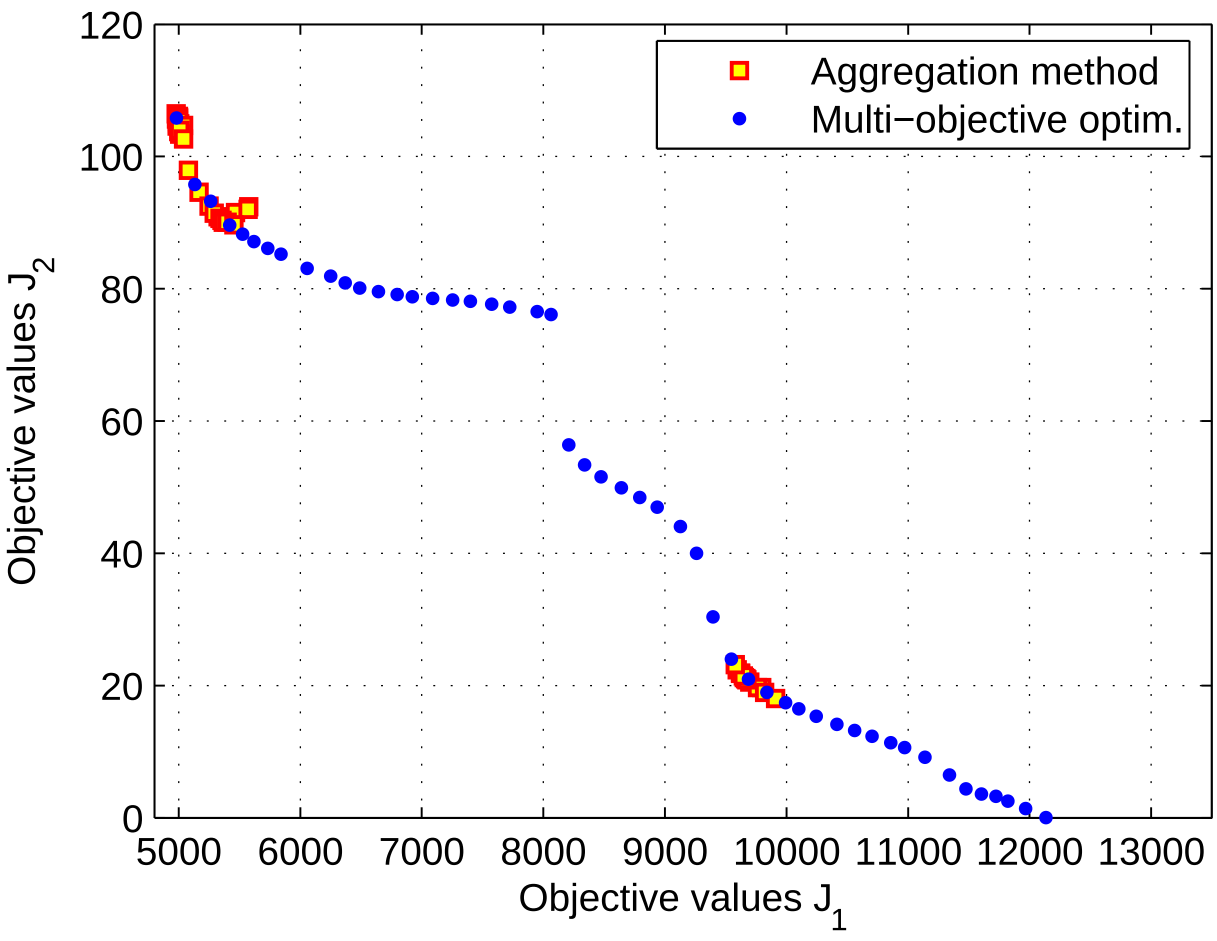

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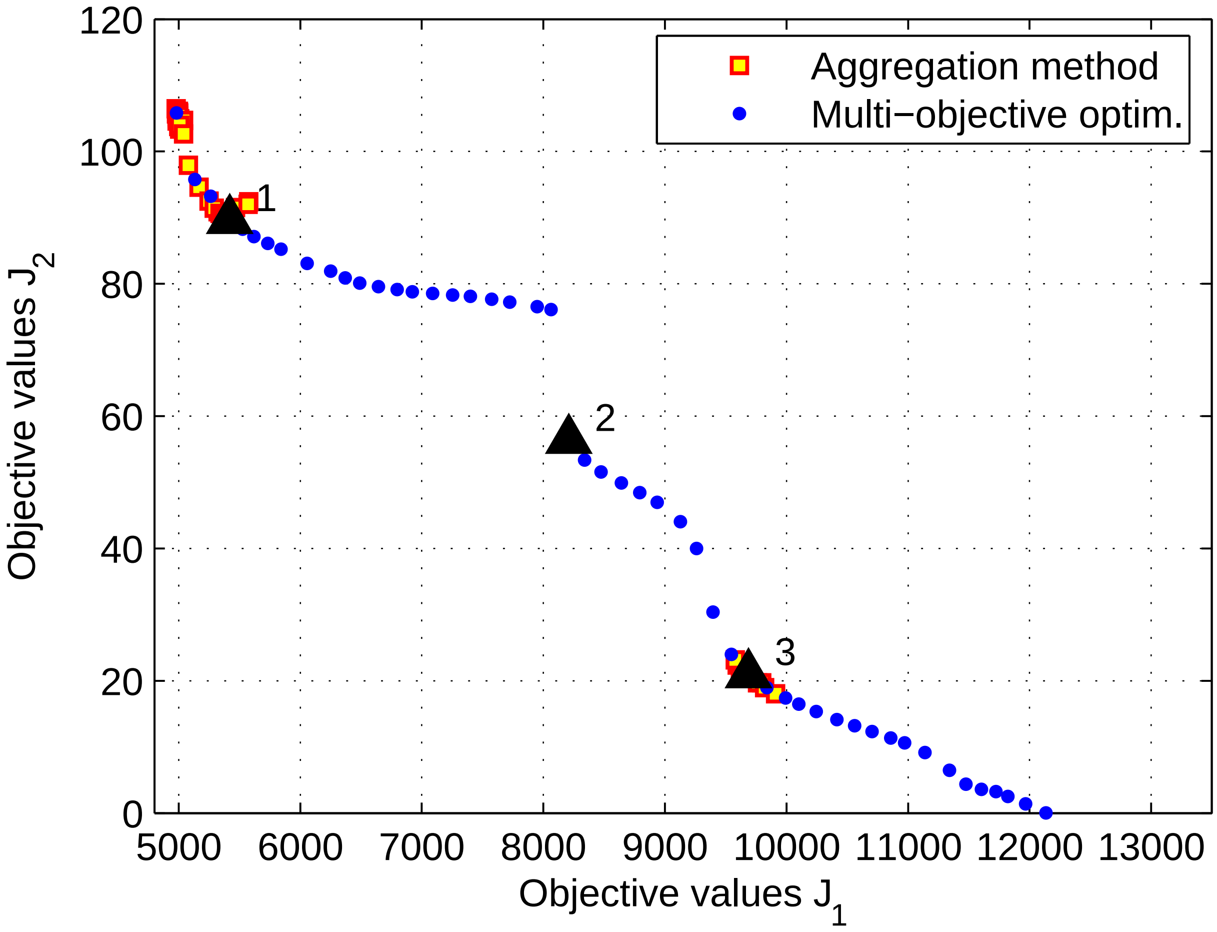
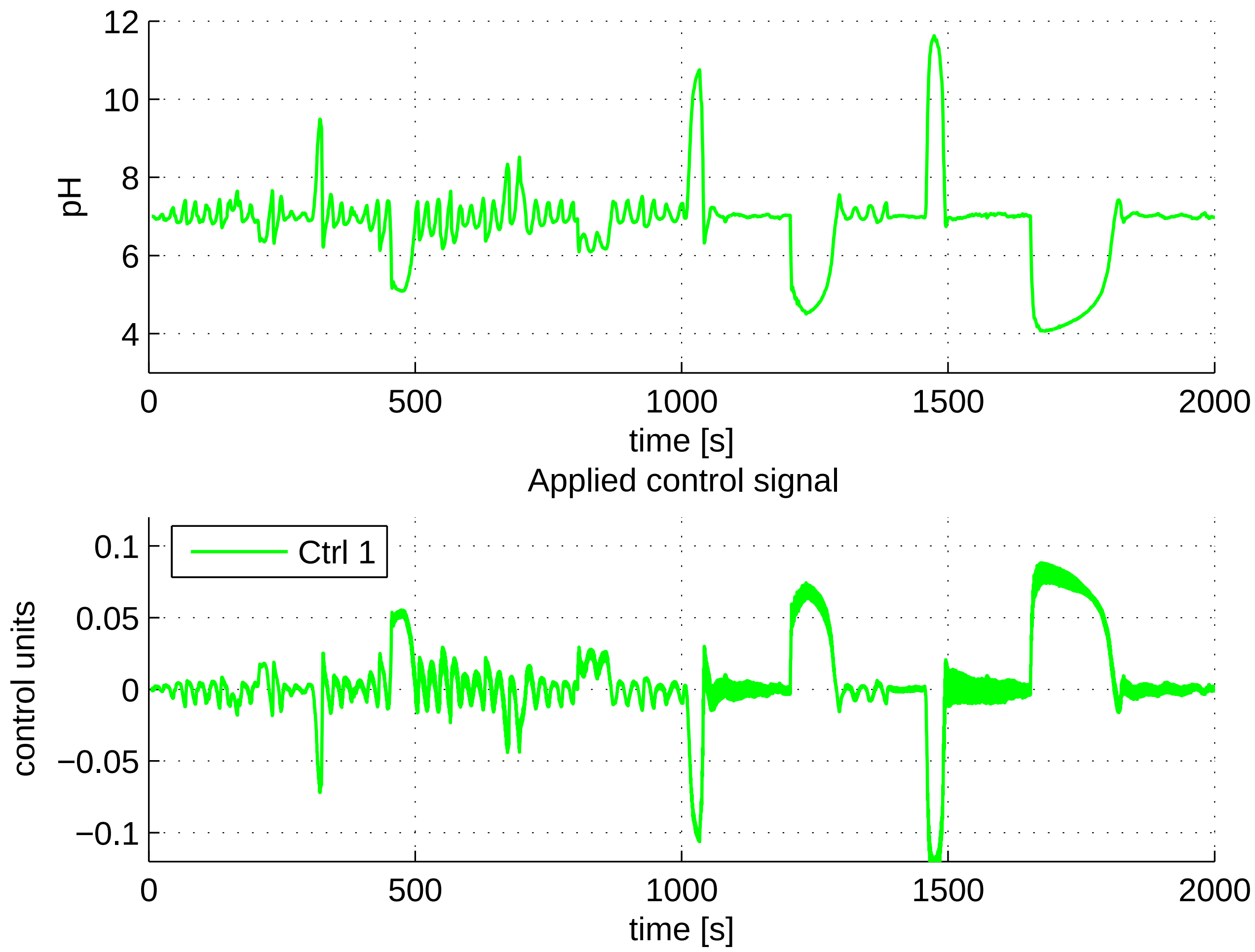


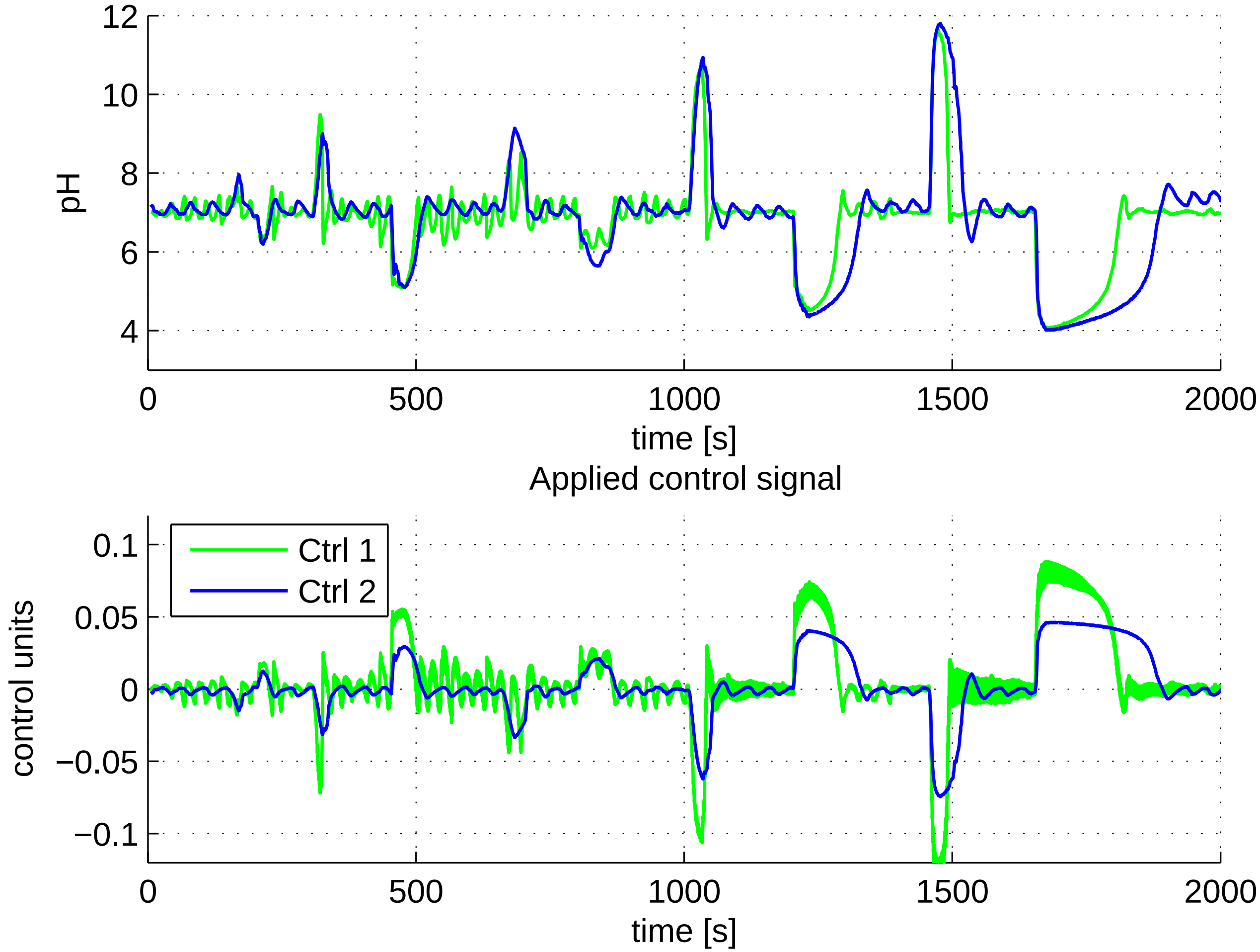
4. Experimental results

Controller 1 $\quad K_P = 0.0277; \quad K_I = 0; \quad K_D = 2.4 \cdot 10^{-3}$



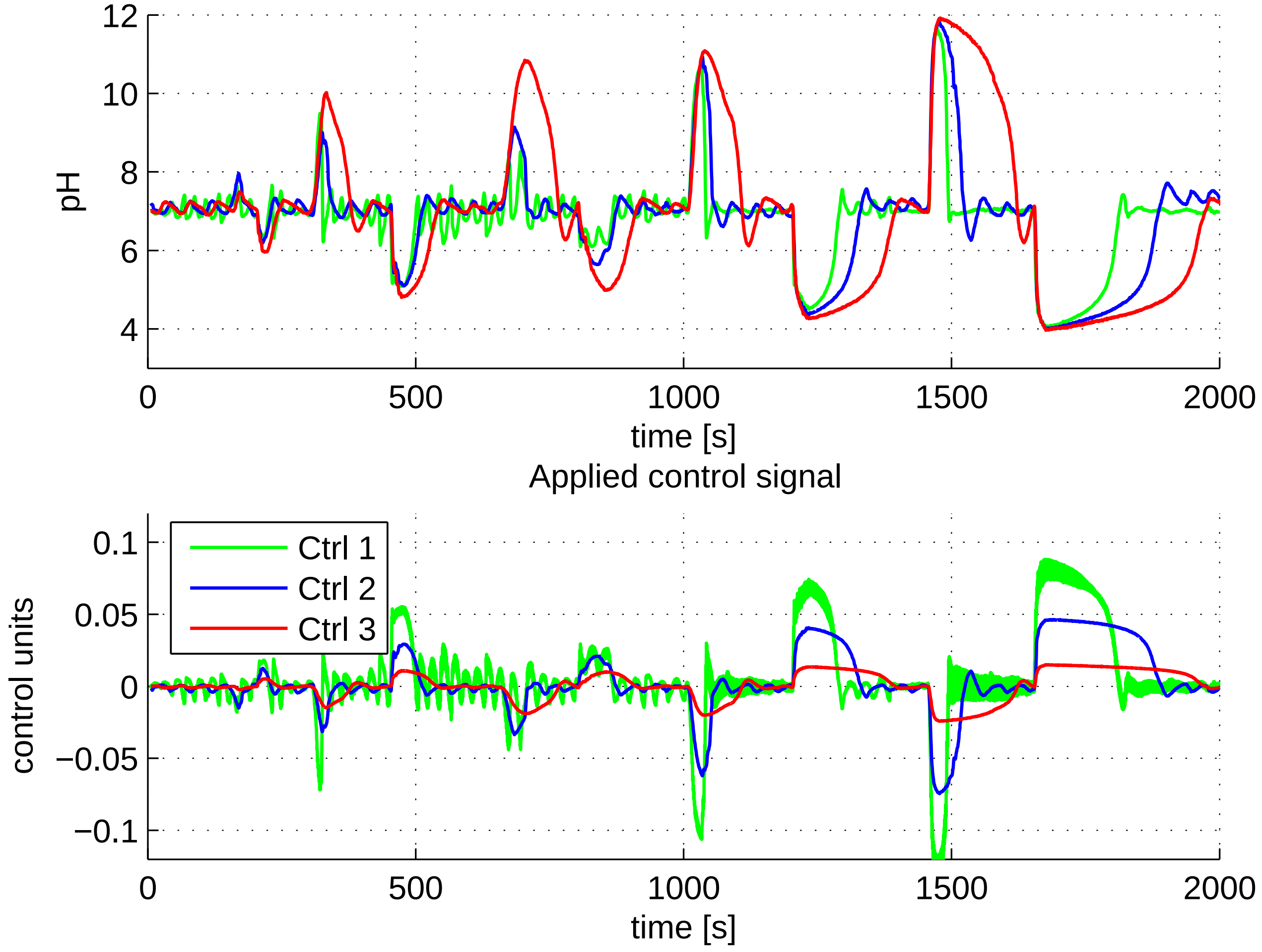
4. Experimental results

Controller 2 $\quad K_P = 0.0156; \quad K_I = 1.0 \cdot 10^{-5}; \quad K_D = 0$



4. Experimental results

Controller 3 $K_P = 0.0057; \quad K_I = 0; \quad K_D = 0$



4. Comparison

	Number of cost evaluations	Good Pareto surface
Aggregation	$52 \times 200 \times 20 = 208000$	NO
Multi-objective	$200 \times 50 = 10000$	YES

Some improvement might be possible for both methods if custom options are used.

$\Rightarrow$ Only MOGA will be used in the rest of the work.

5. Gain-scheduled PID

$$K(z) = K_P(k) + K_I \frac{T_s}{z-1} + K_D \frac{2z-2}{(T_s+2T_c)z + T_s - 2T_c}$$

where

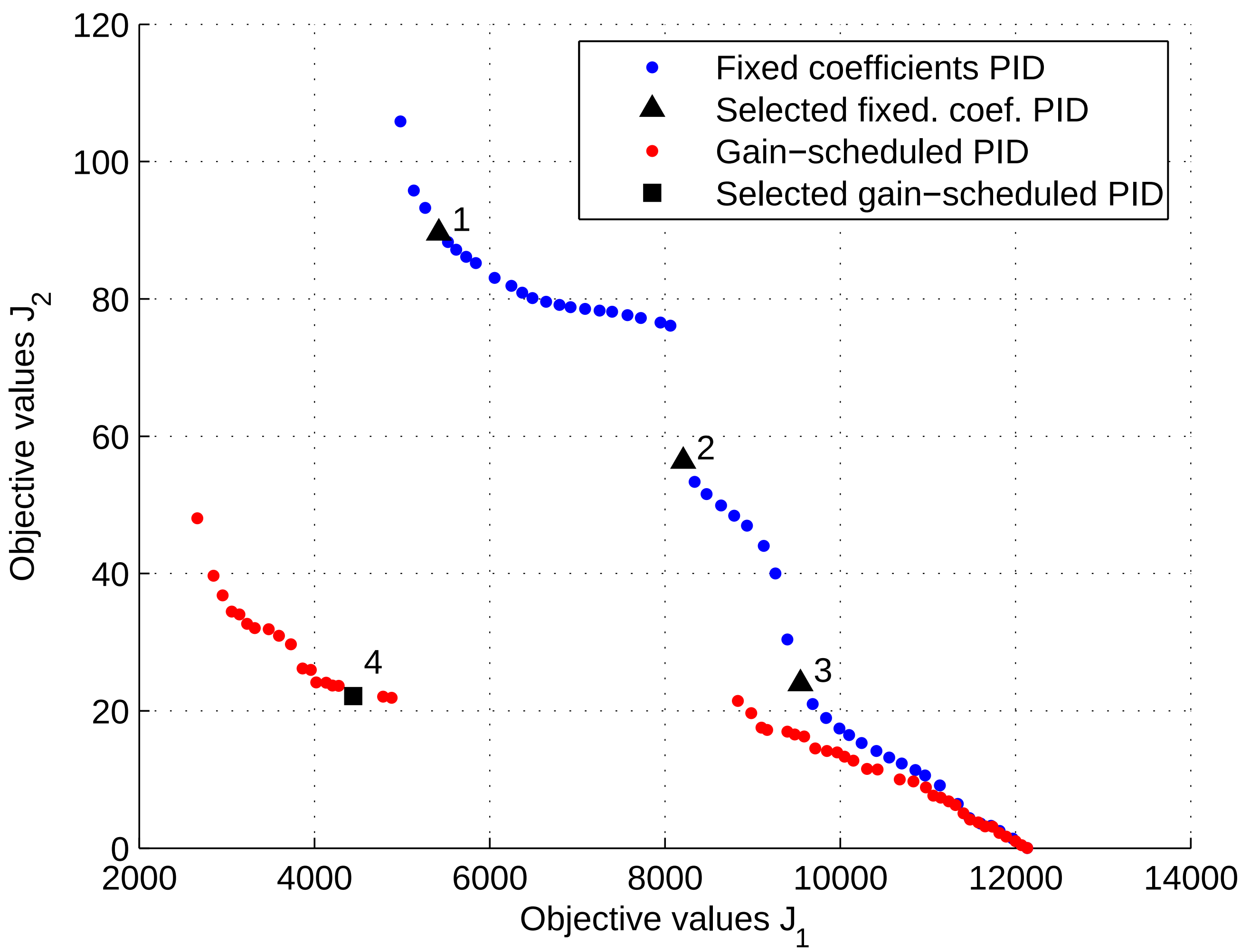
$$K_P(k) = K_{P0} + K_{P1}\varepsilon(k) + K_{P2}\varepsilon^2(k) \tag{5}$$

$$\varepsilon(k) = pH(k) - C_{pH}$$

Total of 6 design parameters: K_{P0}, K_{P1}, K_{P2}, C_{pH}, K_I and K_D.

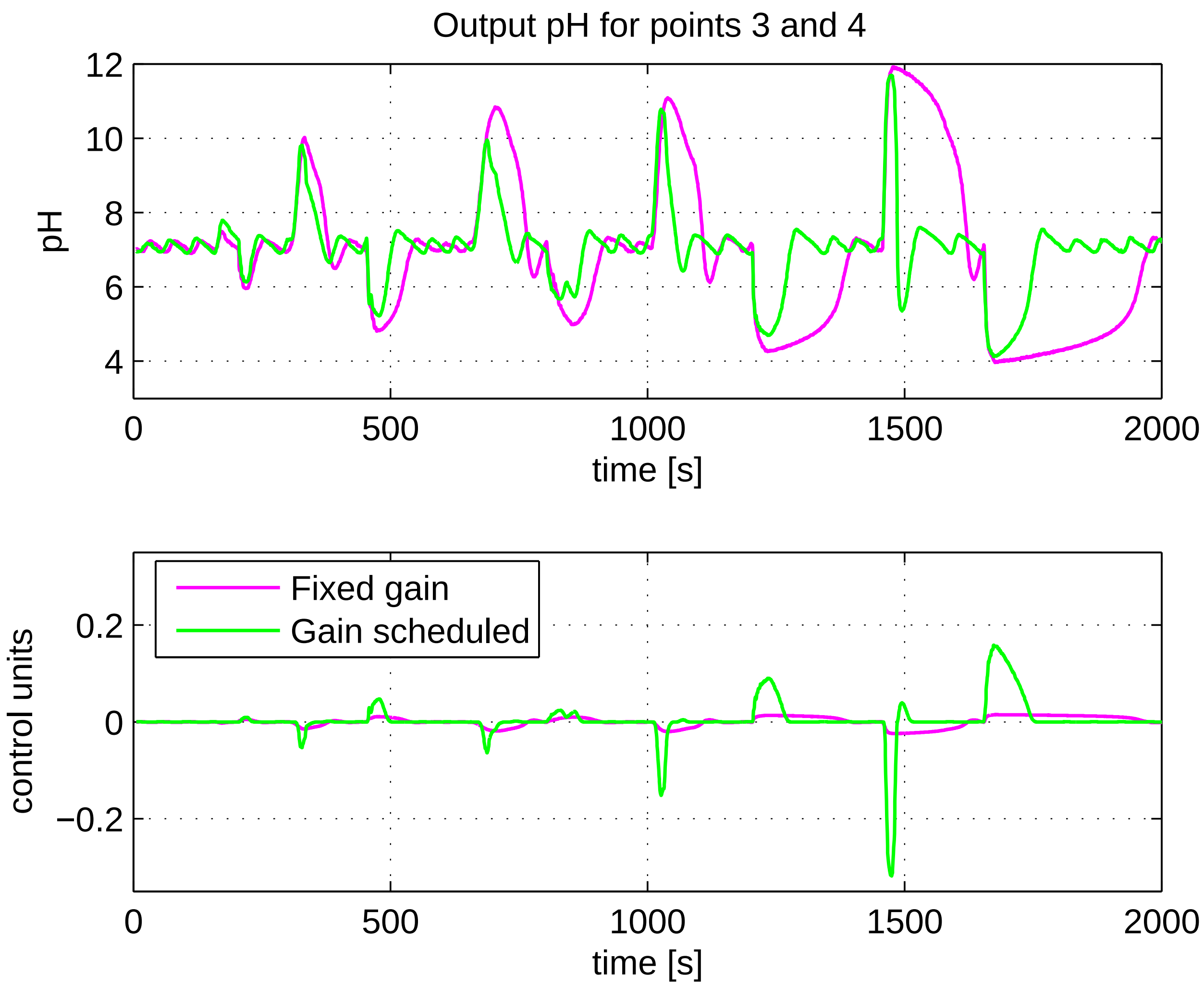
5. Optimization results

Population size = 50; Generations = 200;



5. Experimental results

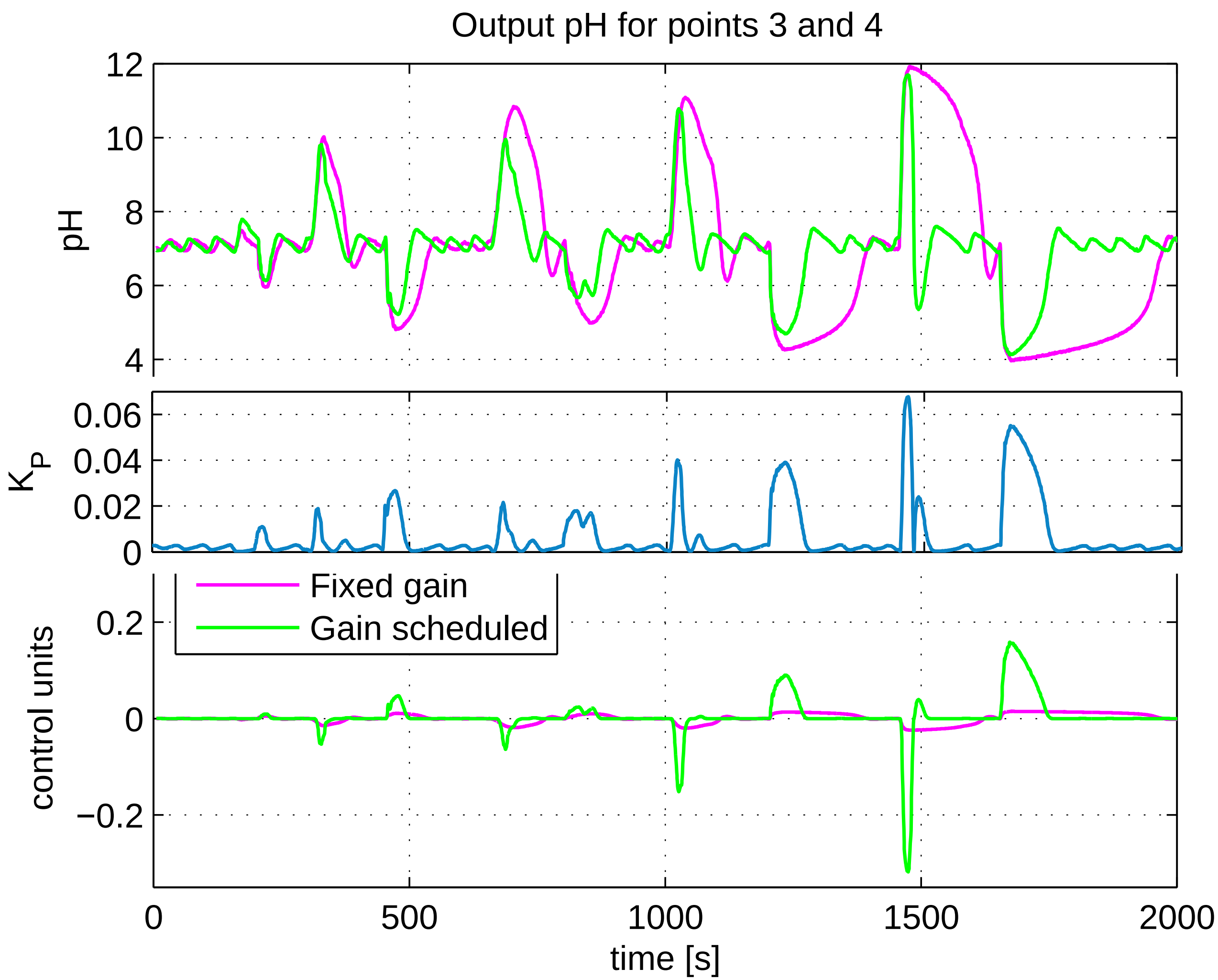
Controller No. 4



$K_{P0} = 5.26 \cdot 10^{-4}$; $K_{P1} = -2.52 \cdot 10^{-3}$; $K_{P2} = 1.25 \cdot 10^{-3}$; $C_{pH} = 8.68$; $K_I = 2.28 \cdot 10^{-8}$; $K_D = 2.62 \cdot 10^{-4}$.

5. Experimental results

Controller No. 4



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6. Summary and Conclusions

- Aggregation to a single objective function and multi-objective optimization are used to design a fixed gain PID for highly nonlinear chemical plant;
- MOGA is shown to be superior in terms of efficiency;
- Gain scheduled PID is designed and is experimentally shown to give better results than fixed gain PID;

Q&A

Thank you for your attention!

Q&A: Model

Experimental data from the plant running in closed-loop operation with varying disturbance signals have been gathered.

During the experiment a proportional controller was used to keep the pH value around 7 and avoid saturation.

The same disturbance signal was used again later in the tuning process.

The data set was then used to train a neural network (NN).

Q&A: Domination and Pareto Optimality

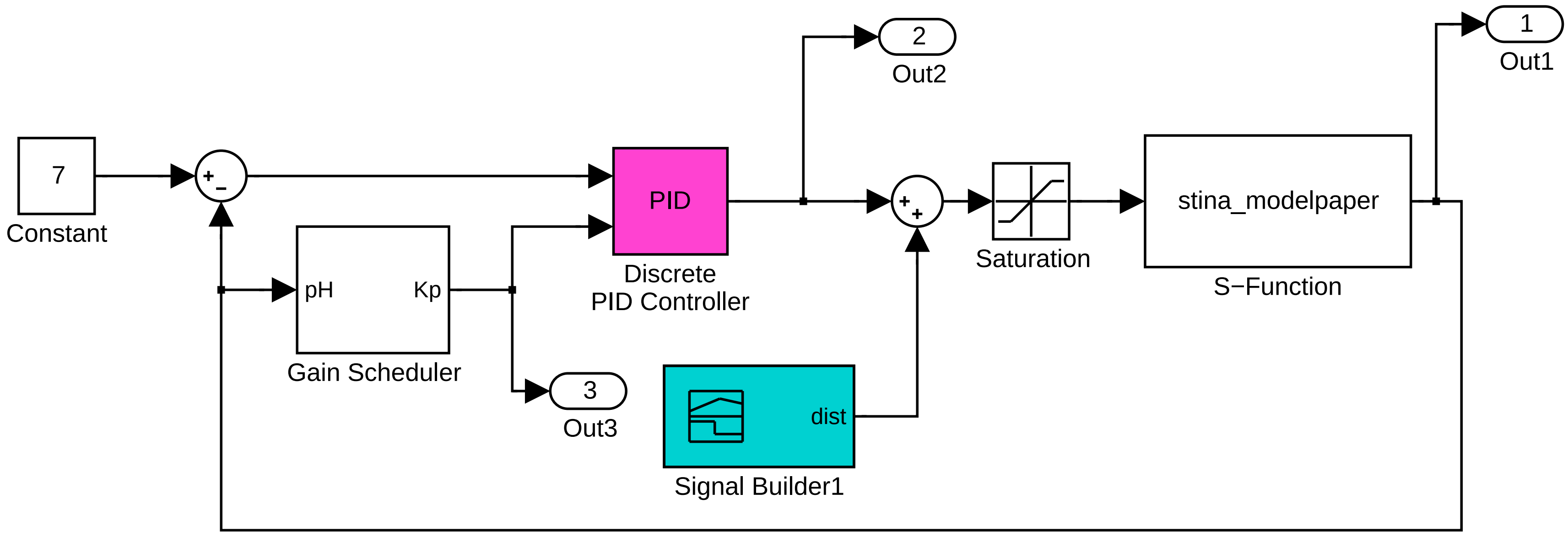
Definition 1 (Domination) *Vector v is said to dominate vector u ($v \succ u$), if and only if v is partially less then u:*

$$\forall i \in \{1, 2, \ldots, n\} : v_i \leq u_i \text{ and } \exists j \in \{1, 2, \ldots, n\} : v_j < u_j \tag{6}$$

Definition 2 (Pareto optimality) *A solution $x \in S$ is a said to be Pareto-optimal solution, if and only if there is no $y \in S$, for which $F(y) = \big(f_1(y), \ldots, f_n(y)\big)$ dominates $F(x) = \big(f_1(x), \ldots, f_n(x)\big)$.*

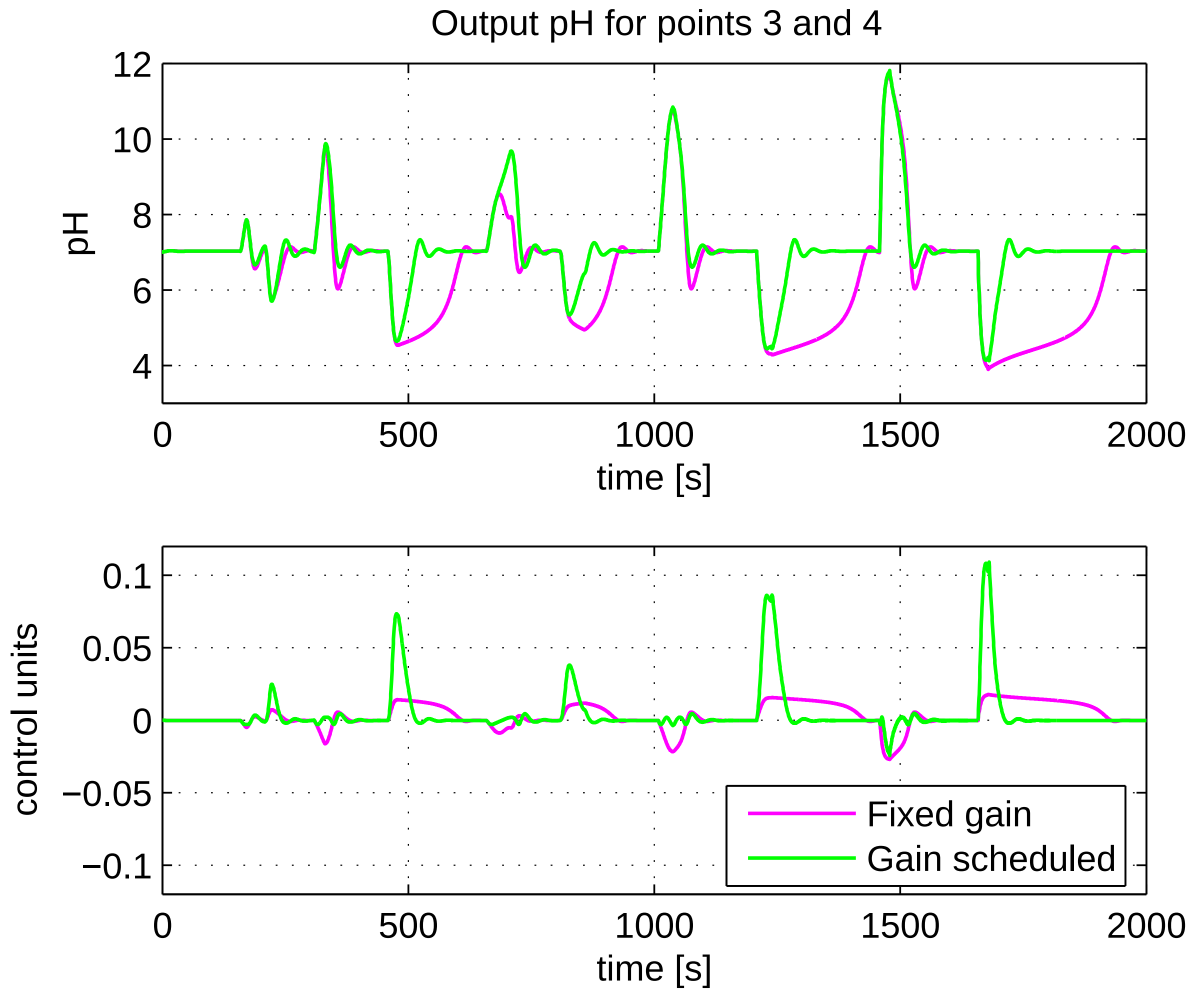
where S is the permitted parameter space.

Q&A: Gain Scheduled PID



Q&A: GS-PID: Simulation results

Controller No. 4



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