MULTIOBJECTIVE OPTIMIZATION FOR ENGINEERING DESIGN

2014

Applications to modeling, control and optimization of processes and systems

CERN (Geneva, 2-3 June 2014)

Summary

- Multiobjective Optimization
- An example: Parameters Identification
- Design concept comparison
- Conclusions

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- Multiobjective Optimization
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MULTIOBJECTIVE OPTIMIZATION

Multiobjective problem – Basics

Problem

Design
Modeling
Control tuning
Management
Production
...

To solve **conflict** between objectives

Security
Performance/Quality
Reliability
Cost
...

Can be formulated as an Optimization Problem

No unique solution

Solution

There is a **set of solutions** with advantages and disadvantages

Usually it is necessary **deciding one** of these solutions

Multiobjective problem – Basics

Three fundamental steps

MO Problem → **Optimization** Pareto approximation → **Decision Making** Selecting one solution

MO Problem	Optimization	Decision Making
Design Concept Objectives Constraints	Algorithms	Preferences

Multiobjective problem – Basics

Decision variables 'xi', (design variables):

X=(x1, x2, x3)

Ex: PID tuning X=(Kc, Ti, Td)

Function 'Ji(X)' evaluates an objective:

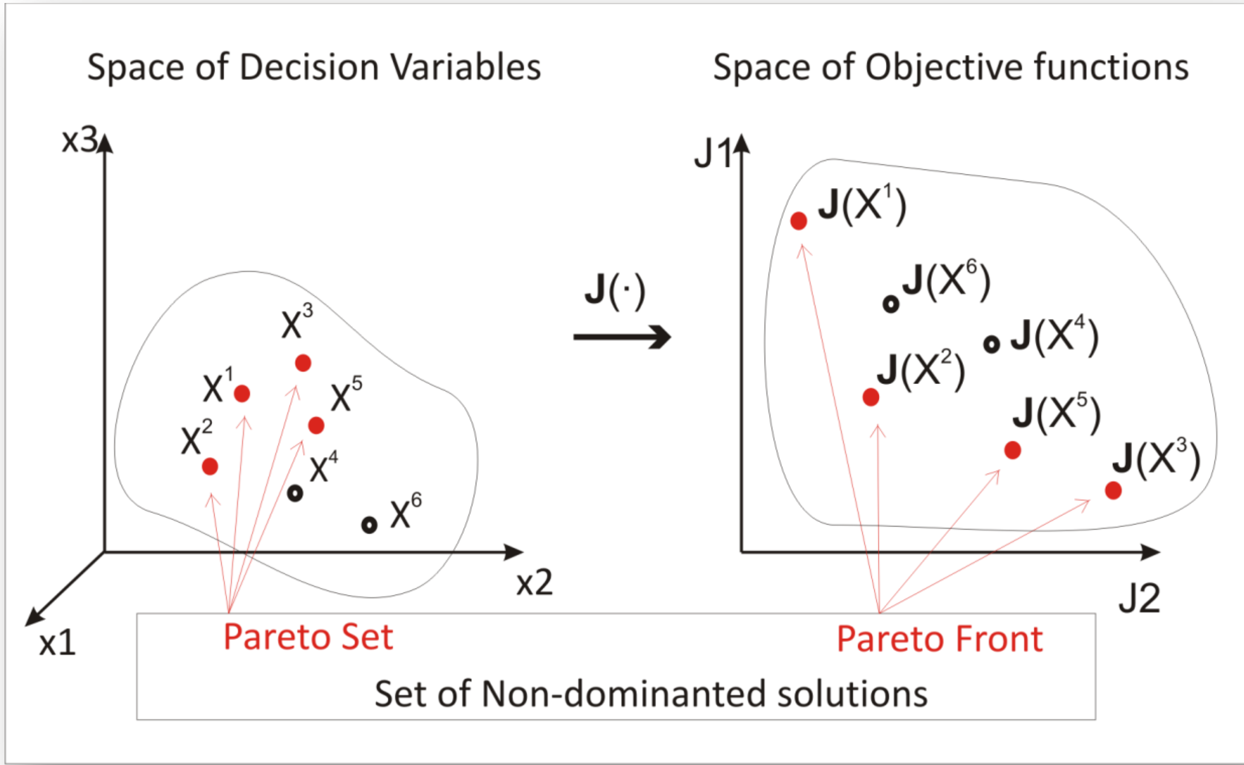
J(X)=(J1(X), J2(X))

Ex: PID tuning
J1= iae
J2= settling time

Constraints :

gi(X)<=lim

Ex: PID tuning
g1=overshoot<= 4%



Problem:
optimize J(X) subject to gi(X)<=lim

Solution:
Set of non-dominated solutions

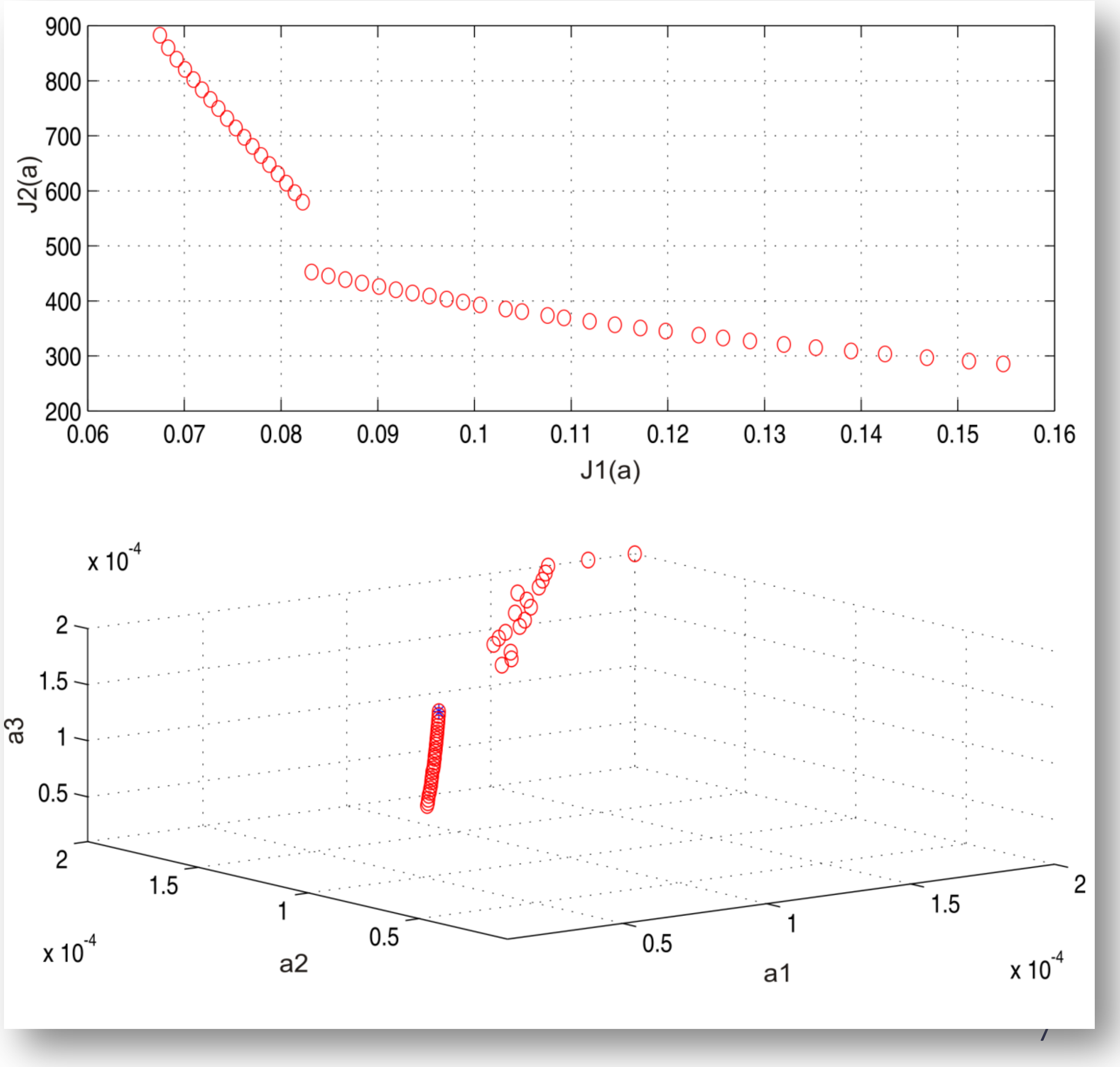
Multiobjective problem – An Example

MO Optimizer

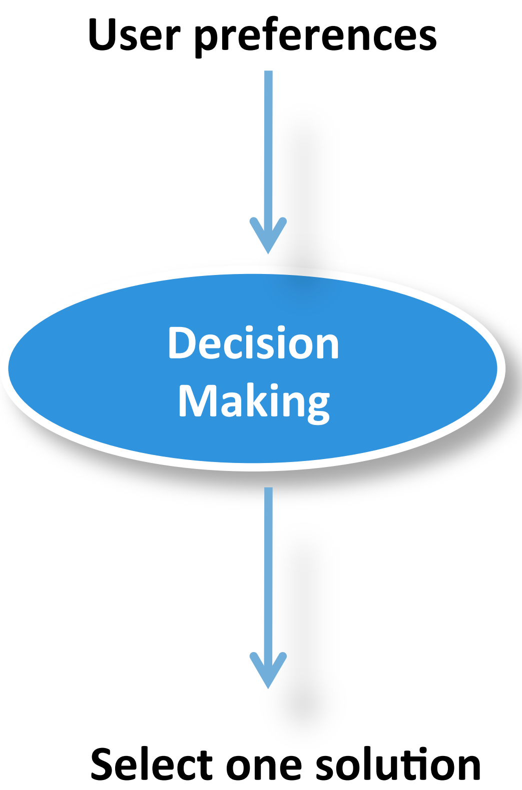
SOLUTION

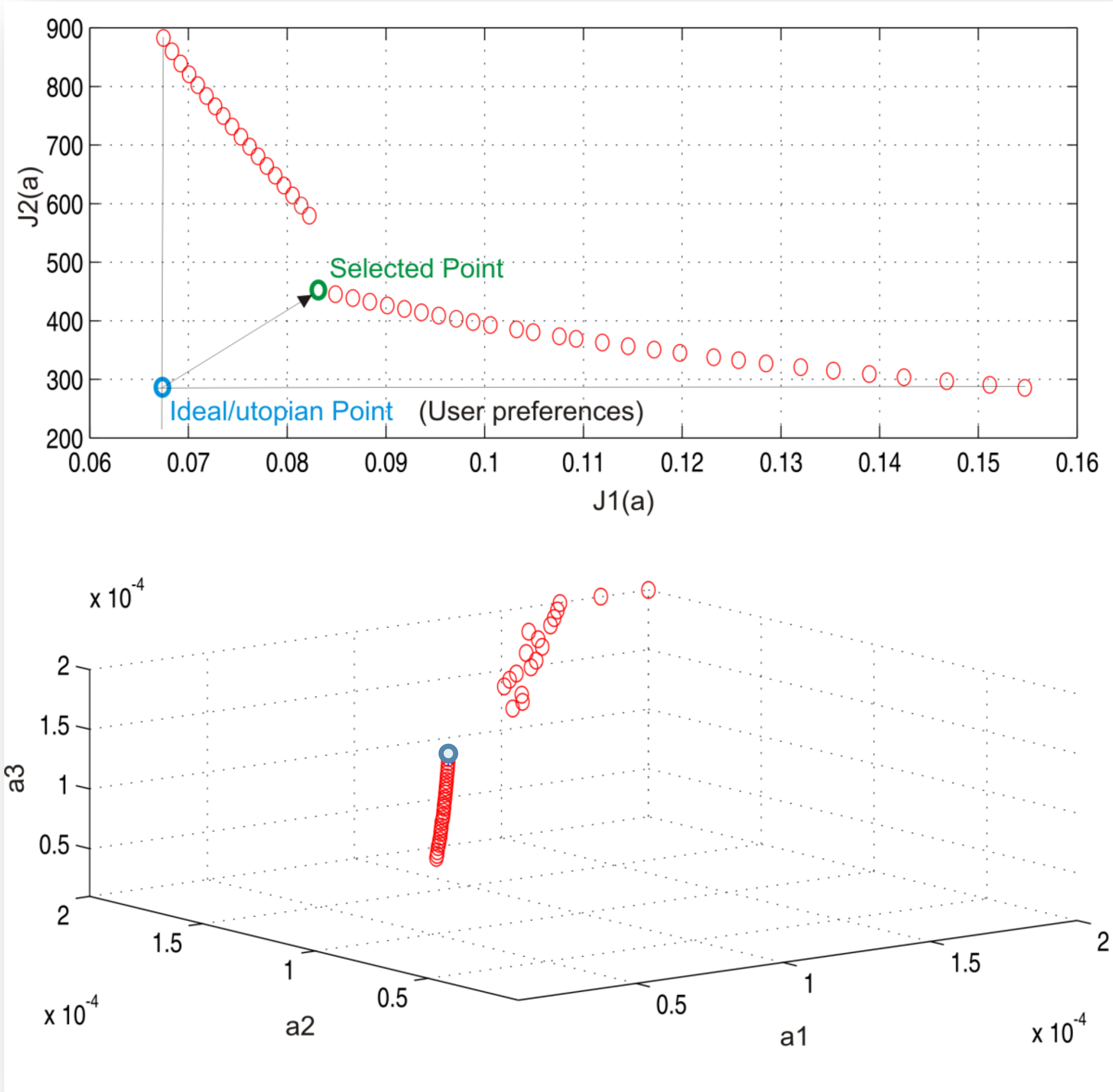
Pareto Front
(Objective Function space)

Pareto Set
(Decision Variables space)

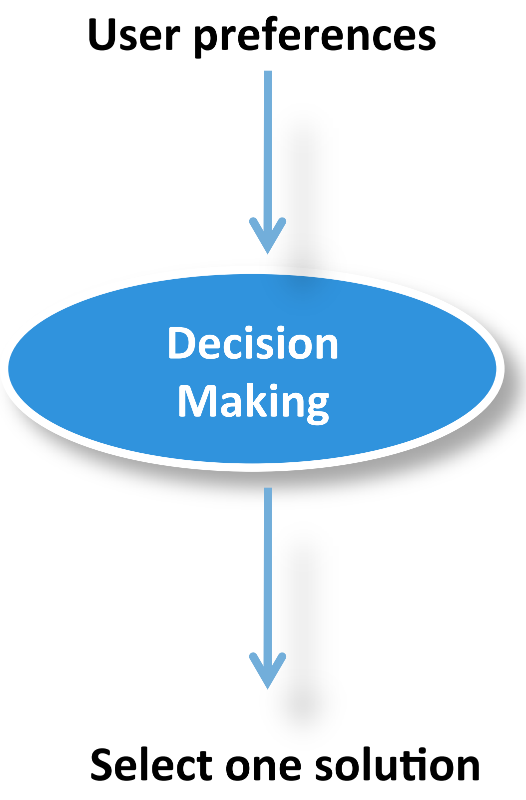


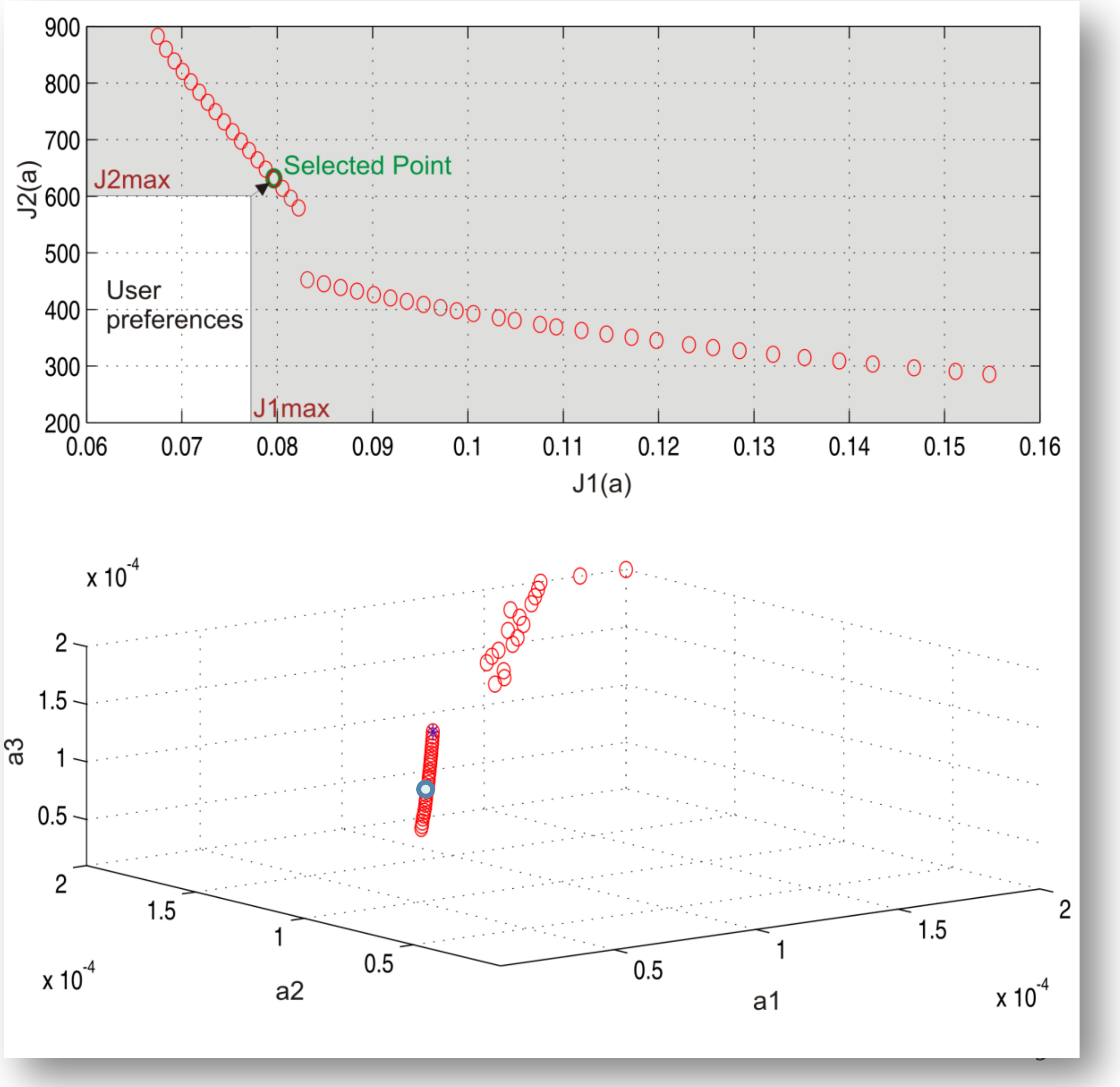
Multiobjective problem – An Example





Multiobjective problem – An Example





Multiobjective Optimization Problem MOP

Required tools

Solution

There is a **set of solutions with advantages and disadvantages**

Usually it is necessary **deciding one** of these solutions

Searching the set of solutions – Multiobjective optimization algorithms

- Many variables and objectives.
- Achieving good approximations
- Non-convex problems
- Linear / Non linear Constraints
- Pertinency
- Low computational cost

Deciding one – Decision Making

- Including preferences
- Decision support systems
- Visualization of high dimensional problems

Multiobjective Optimization Problem MOP

Required tools

Solution

There is a **set of solutions with** advantages and disadvantages

Usually it is necessary **deciding one** of these solutions

Searching the set of solutions – Multiobjective optimization algorithms

- Classical techniques based on aggregation function and NL optimizer:
  - SQP, Interior Point, others
- Evolutionary algorithm:
  - ev-MOGA, sp-MODE, others

Deciding one – Decision Making

- Global physical programming: Including preferences (could be used as aggregation function or for ranking)

-Level Diagrams: Visualization of high dimensional problems

Some of our algorithms and tools are available at File Exchange in matlabcentral.

look for tag: CPOH

Multiobjective Optimization

An example: Parameters Identification

Design concept comparison

Conclusions

AN EXAMPLE:
PROCESS PARAMETERS IDENTIFICATION

Process identification

Dynamical model identification

Dynamical Model

vector of model states

vector of model inputs

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}),$$
$$\hat{\mathbf{y}}(t, \theta) = g(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\theta}),$$

vector of model outputs

vector of model parameters

***The challenge** is to look for the best parameters, such as the model outputs (simulation) were as similar as possible to the real process outputs (experiments).*

Traditional methods try to achieve it by a minimization of a function based on the identification error.

The identification error for the output *j* :

Real outputs

$$\mathbf{e}_j(\boldsymbol{\theta}) = \mathbf{y}_j - \hat{y}_j(\boldsymbol{\theta}).$$

Process identification

Dynamical model identification

With multiobjective formulation, several model quality indicators can be used simultaneously according to designer preferences.

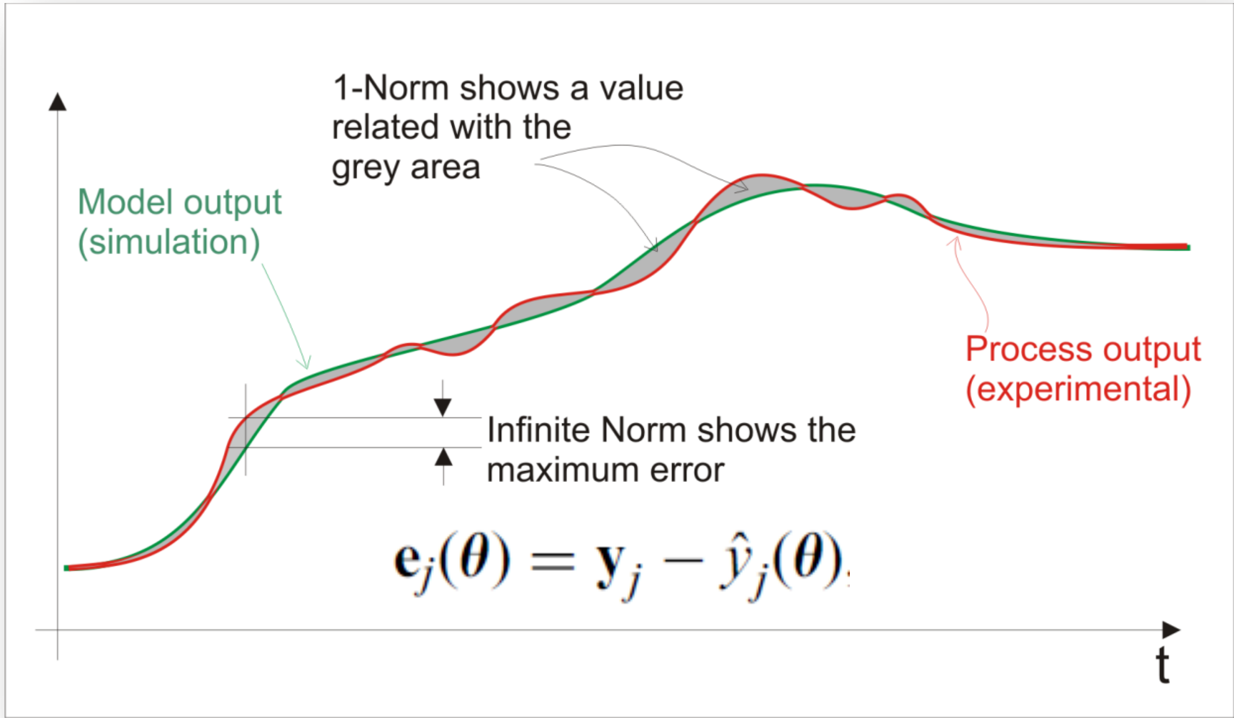
For instance:

- Minimizing average identification error for each output independently.

$$J_k(\theta) = \left\| \boldsymbol{e}_j(\theta) \right\|_1$$

- Minimizing maximum identification error for each output independently.

$$J_l(\theta) = \left\| \boldsymbol{e}_j(\theta) \right\|_\infty$$



Process identification

Think different:

model performance indicators/objectives according to meaningful and understandable designer objectives

Indicators/objectives have to show **properties needed by the users**, not only properties needed by optimization algorithms.

Designer appreciates indicators/objectives with physical units.

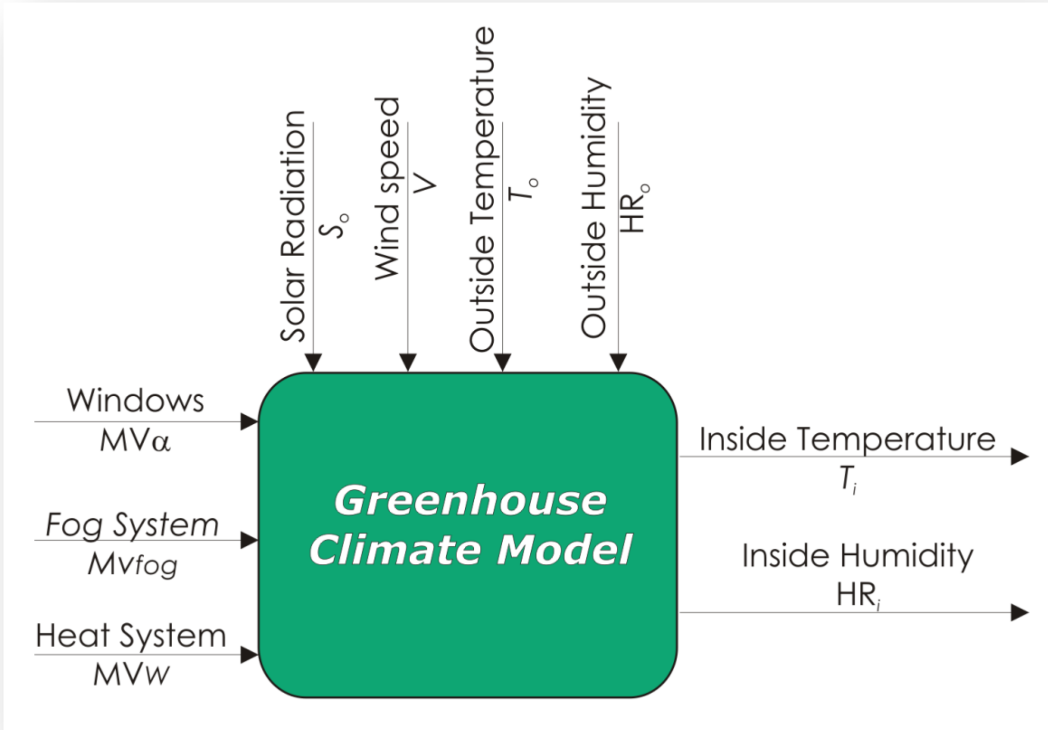
Some alternatives:

- Mean, max and/or standard deviation for absolute error for identification data set.
- Indicators/objectives based on absolute error altering 10% model parameters.
- Indicators/objectives based on deviation for a validation data set
- Indicators/objectives based on normalized error

And much more (designer choice) trying to fulfill designer preferences.

Model identification – An example

Non-linear climatic model for greenhouses based on first principle equations.



Model identification – An example

First principles climate model including biological processes of the crop

$$\rho v_i \frac{\mathrm{d}H_i}{\mathrm{d}t} = F_v + C_{sat}(E + fog),$$

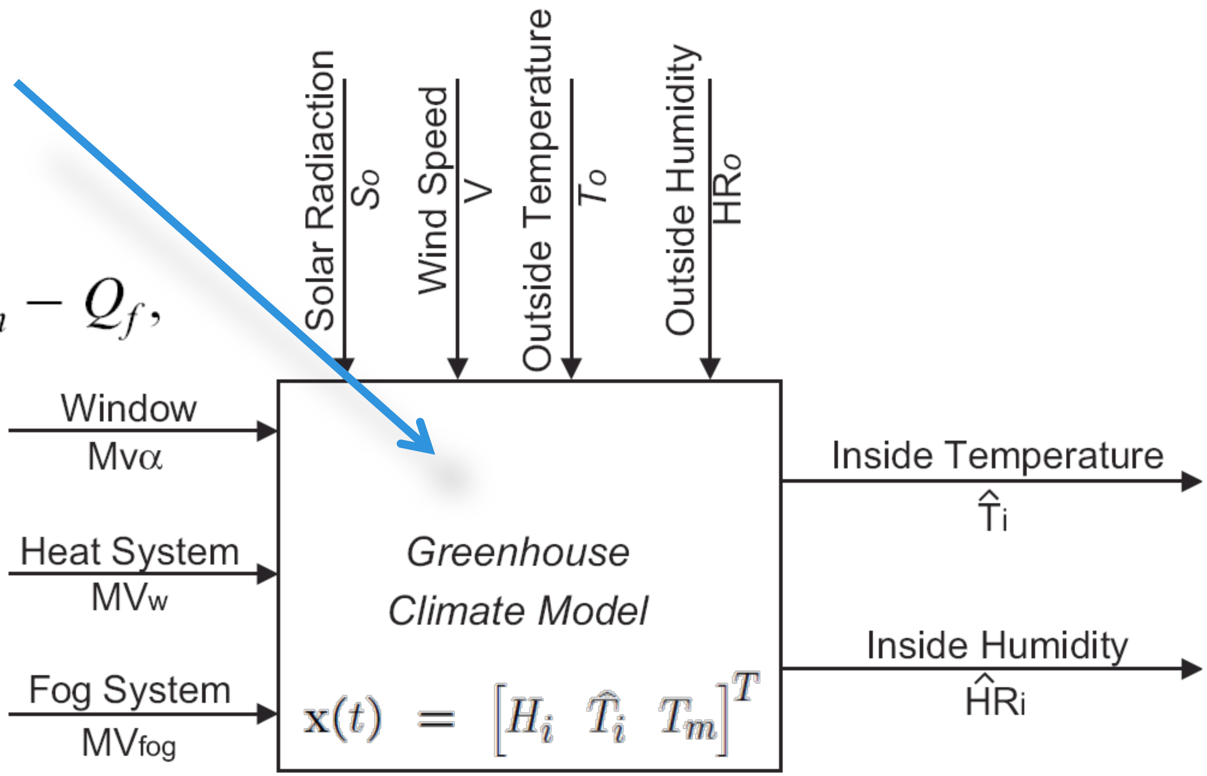
$$v_i \rho c_p \frac{\mathrm{d}\hat{T}_i}{\mathrm{d}t} = Q_s - Q_{cc} + Q_m - Q_v - C_{sat}(Q_e + Q_n) + W,$$

…

…

…

$$A_i C_m \frac{\mathrm{d}T_m}{\mathrm{d}t} = Q_{sm} - Q_m - Q_f,$$



Model identification – An example

Decision variables - Parameters to identify (**θ**)

		min	max	Unidades
θ_1	gws_{max}	0.01	0.03	$m\ s^{-1}$
θ_2	gws_{min}	0.0001	0.005	ms^{-1}
θ_3	k	0.1	0.7	
θ_4	L	0.5	2	$m^2_{hojas}\ m^{-2}_{suelo}$
θ_5	gwb	0.001	0.05	$m\ s^{-1}$
θ_6	τ	0.3	0.9	
θ_7	a	0.0005	0.01	
θ_8	G_o	0.0	0.01	
θ_9	A_c	2	20	
θ_{10}	C_m	1e5	3e5	$J^oC^{-1}m^{-2}$
θ_{11}	h_m	1	20	$W\ m^{-1}\ {}^o\ K^{-1}$
θ_{12}	T_{ref}	10	20	^oC
θ_{13}	α_m	0.01	0.3	
θ_{14}	k_a	0.5	10	$W\ m^{-1}\ {}^o\ K^{-1}$
θ_{15}	fog_{max}	0.001	0.02	$Kg_{H_2O}\ s^{-1}$

15 unknown model parameters

Model identification – An example

Formulated as a Multiobjective problem

Identification errors considered (Temperature and Humidity)

$$e_1(t) = T_i(t) - \hat{T_i}(t,\theta)$$

$$e_2(t) = HR_i(t) - \hat{HR_i}(t,\theta)$$

Measured outputs

Simulated 1st. Principles Model outputs

$$J_1(\theta) = ||\mathrm{e}_1||_1 = \frac{1}{N}\sum_{k=1}^{N} |e_1(t+k)|$$

$$J_2(\theta) = ||\mathrm{e}_2||_1 = \frac{1}{N}\sum_{k=1}^{N} |e_2(t+k)|$$

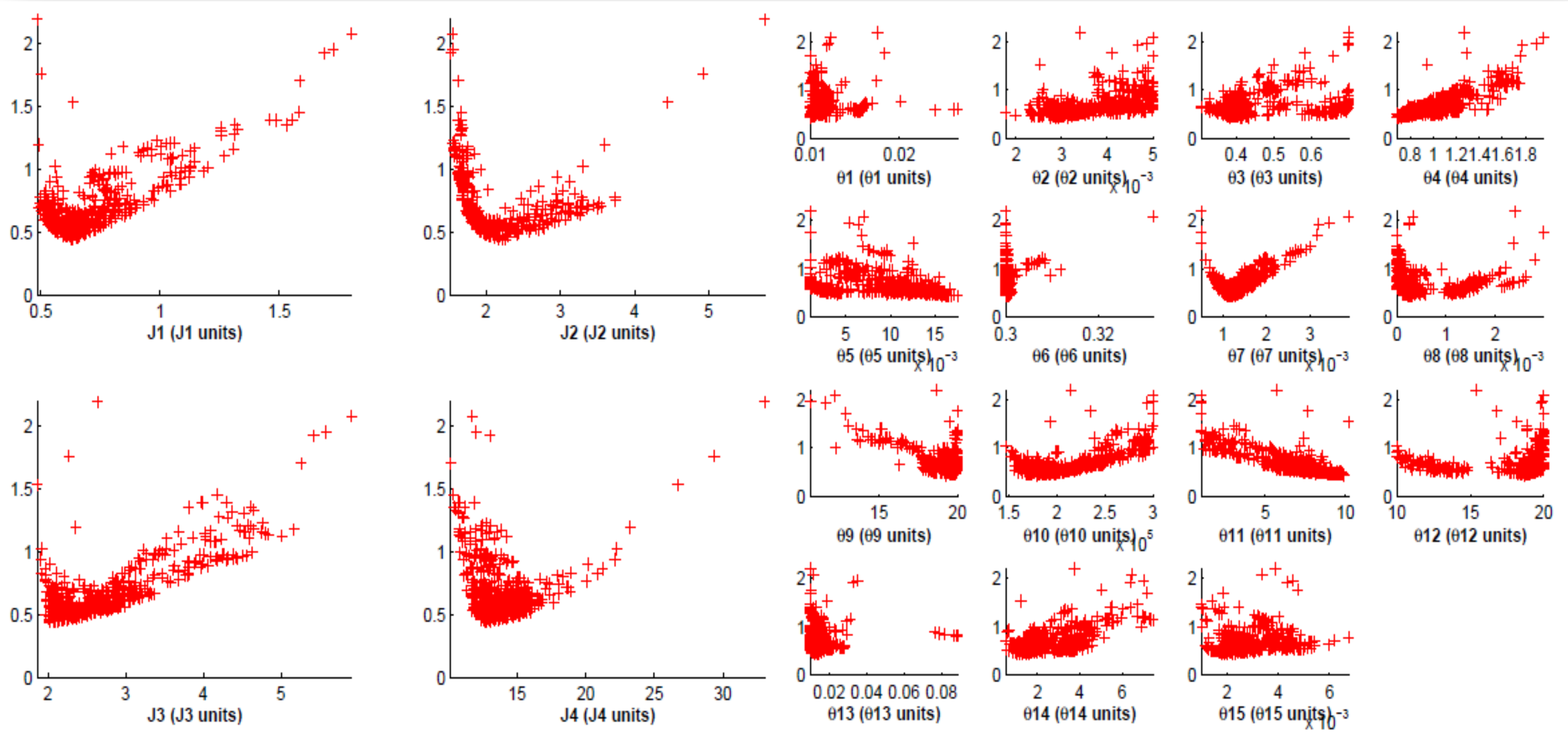
$$J_3(\theta) = ||\mathrm{e}_1||_\infty = \max_{k=1\ldots N} |e_1(t+k)|$$

$$J_4(\theta) = ||\mathrm{e}_1||_\infty = \max_{k=1\ldots N} |e_2(t+k)|$$

Two objectives are considered for each variable:
Mean ident. abs. error (J1, J2)
Maximum ident. abs. error (J3, J4)

Model identification – An example

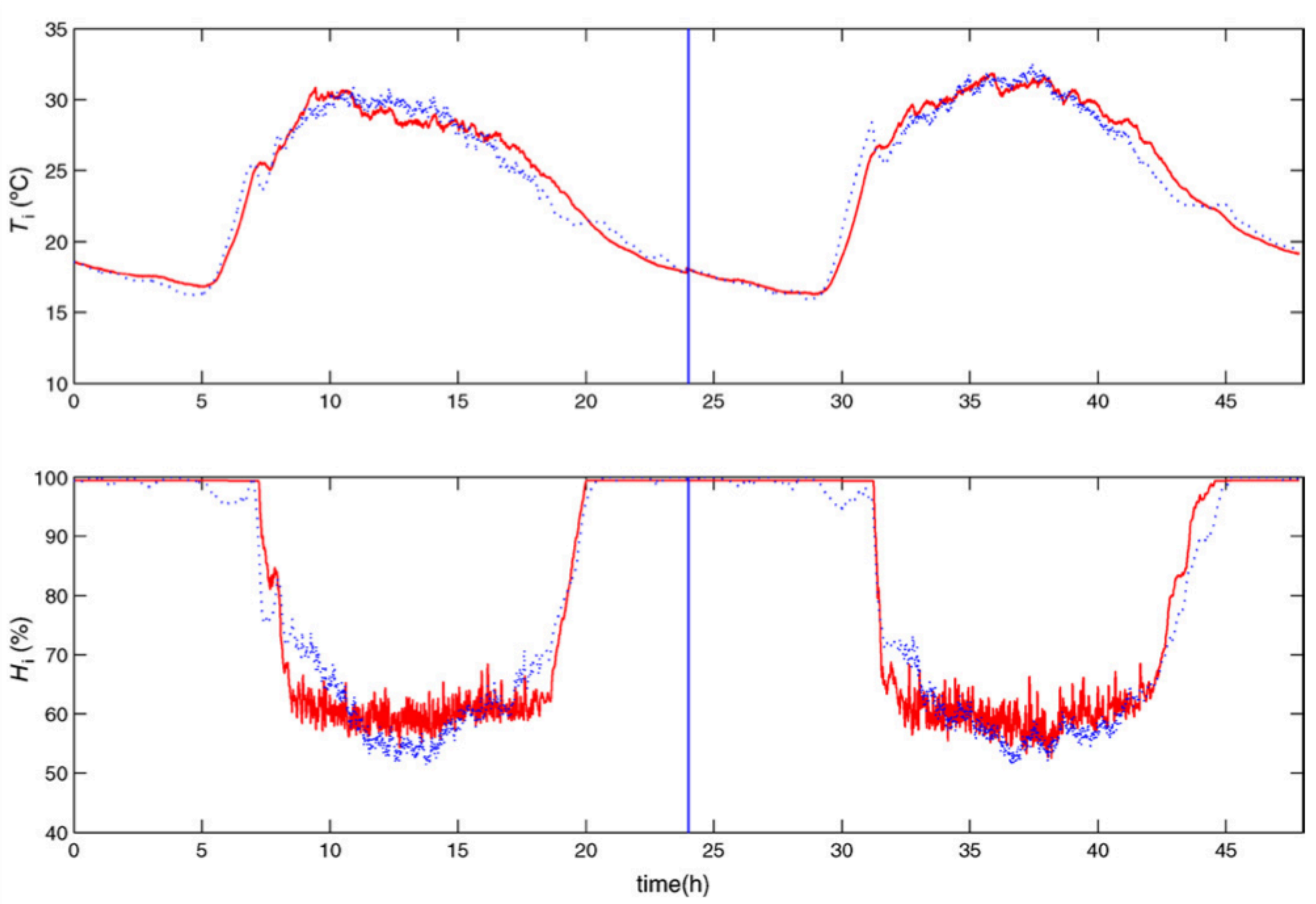
$$\min_{\theta \in D}[J_1, J_2, J_3, J_4]$$ → **Optimal Solutions (best models)**



Objectives Space (Pareto Front) **Decision Var. Space(Pareto Set)**

Model identification – An example

Simple Decision Making process: Choose one model from Pareto Set (i.e. the nearest to the Utopia Point)



Real **Simulated**

Model identification – An example

More advanced Decision Making process:
Choose according to preferences (Global Physical Programming – GPP)

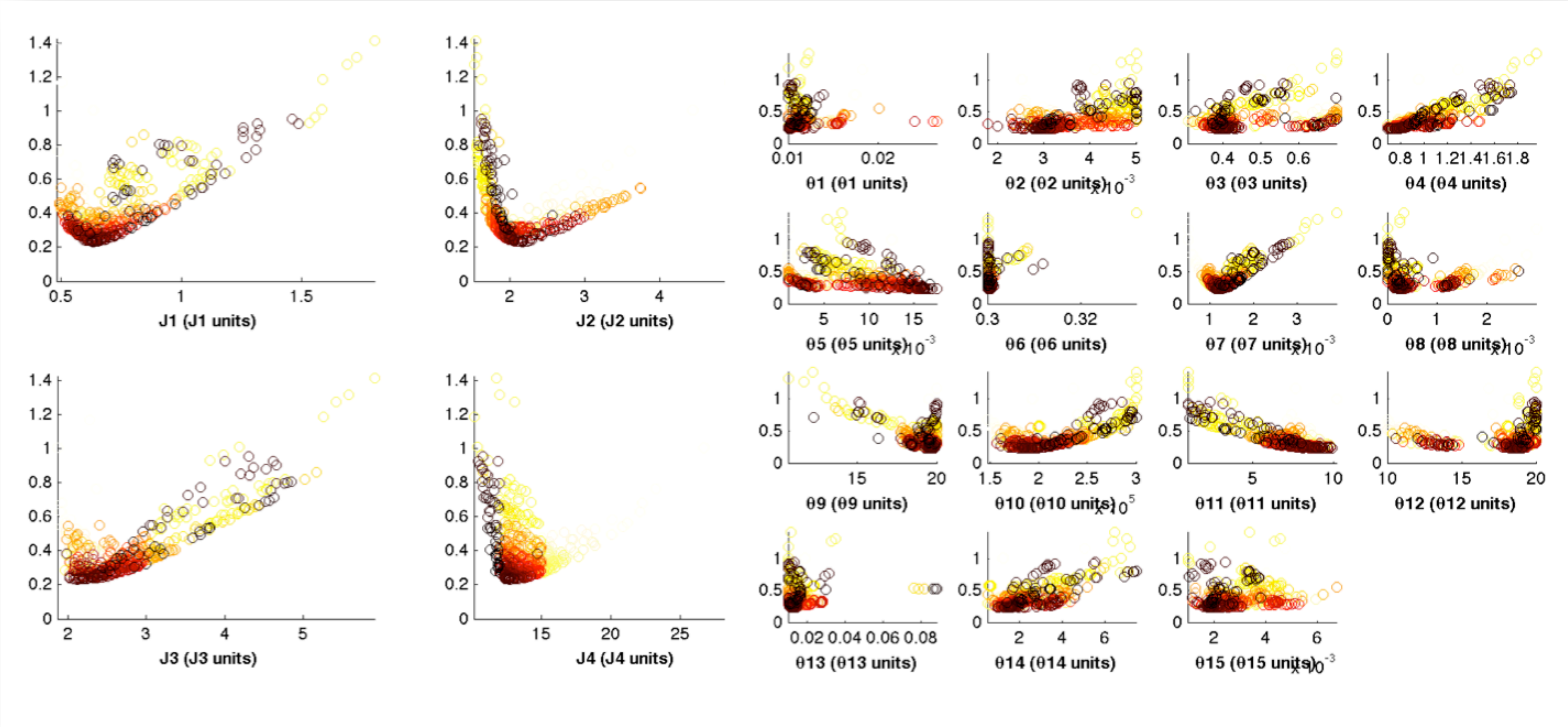
Solutions from the Pareto Front are ranked based on user preferences by means of GPP value. GPP value aggregates information supplied in a table as:

objetive	Range		
	Desirable (D)	Tolerable (T)	Undesirable (U)
$J_1(\theta) = \|\|e_T\|\|_1$	$[0, 1]^oC$	$]1, 3]^oC$	$]3, \infty[^oC$
$J_2(\theta) = \|\|e_T\|\|_\infty$	$[0, 5]^oC$	$]5, 8]^oC$	$]8, \infty[^oC$
$J_3(\theta) = \|\|e_{HR}\|\|_1$	$[0, 5]\%$	$]5, 15]\%$	$]15, \infty[\%$
$J_4(\theta) = \|\|e_{HR}\|\|_\infty$	$[0, 12]\%$	$]12, 25]\%$	$]25, \infty[\%$

Remember that the values in the table are in units of the objectives then they are understandable by the Decision Maker.

Model identification – An example

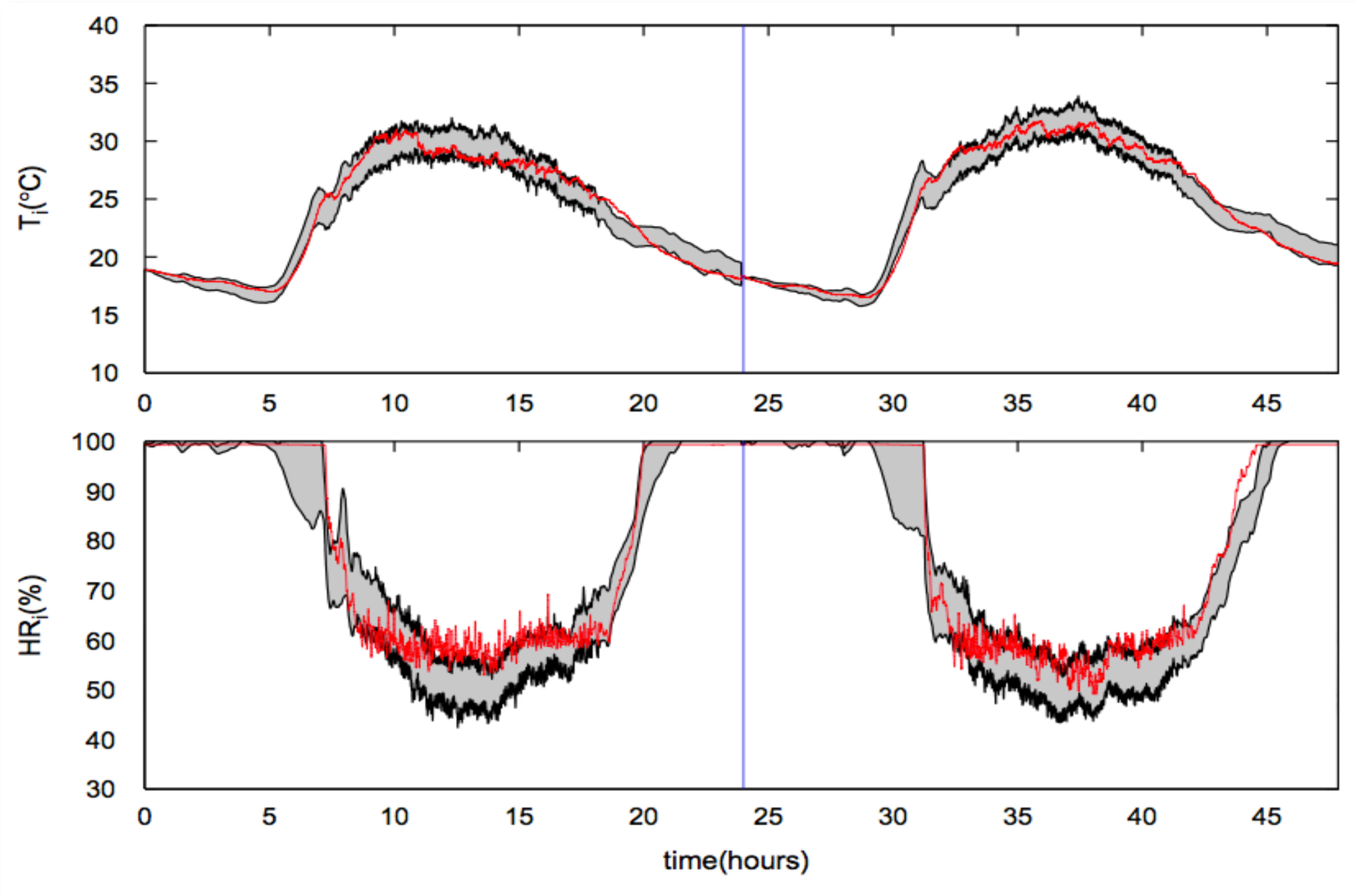
More advanced Decision Making process:
Pareto front and set colored according GPP index



Objectives Space (Pareto Front) **Decision Var. Space(Pareto Set)**

Model identification – An example

More Info available from Pareto set: Envelope obtained



Real

- Multiobjective Optimization
- An example: Parameters Identification
- **Design concept comparison**
- Conclusions

DESIGN CONCEPTS COMPARISON

Design concepts comparison

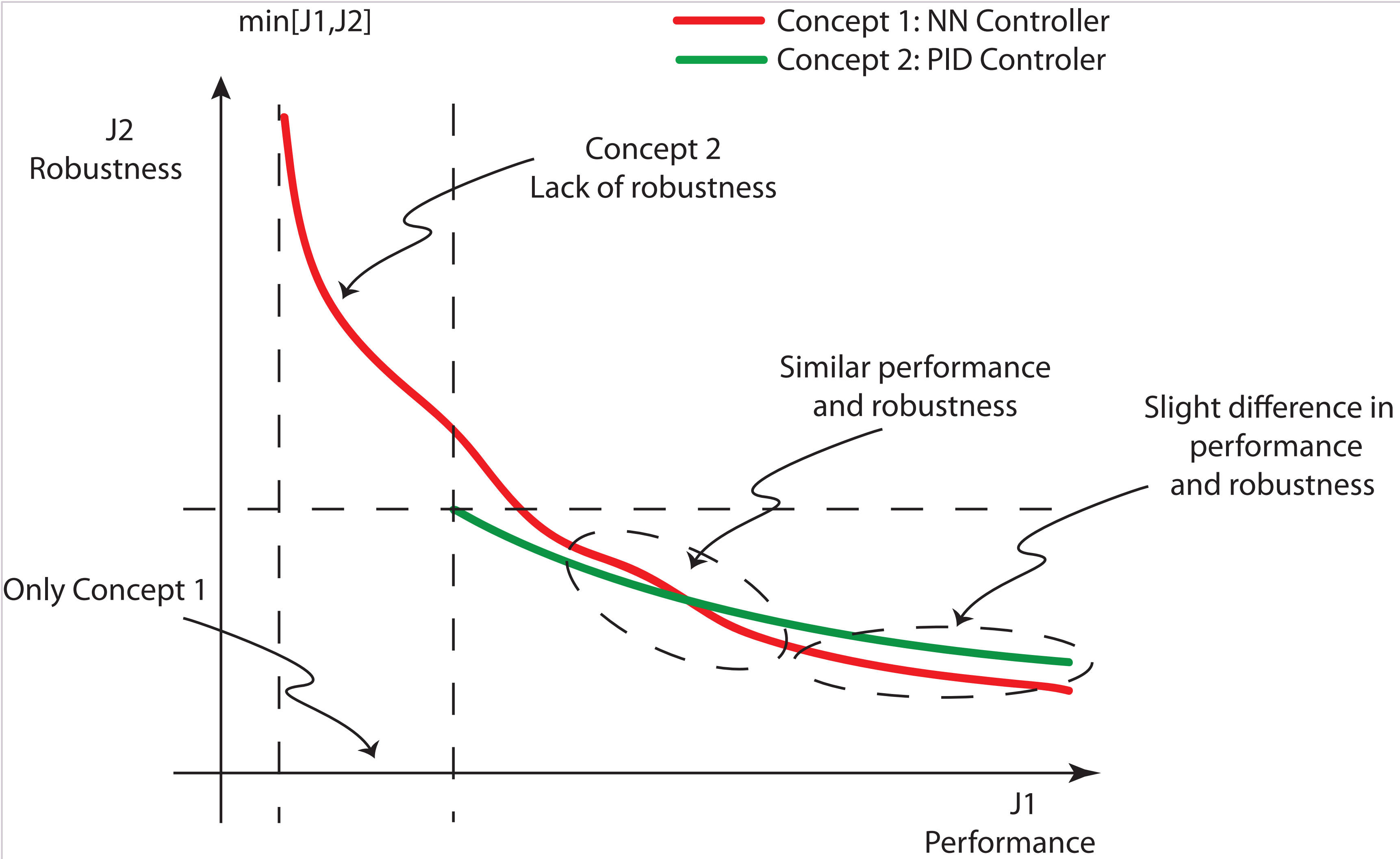
The multiobjective approach can **improve the analysis** of the achievable performance for different design concepts.

Concepts: methodologies/ways to face a design problem

For example:

- Control loop could be designed using PID, state feedback, Fuzzy, etc.
- Dynamical model could be built using first principle, neural network, transfer function, etc.

Design concepts comparison



Multiobjective Optimization
An example: Parameters Identification
Design concept comparison
Conclusions

CONCLUSIONS

Conclusions

Multiobjective Optimization can be used to solve problems in the areas of…

- **Model Identification**
- **Process Control**
- **Engineering Design**

…and much more.

Several tools are already available, for instance:

J .M. Herrero Durá (2006). **Robust identification of non-linear systems by means of evolutionary algorithms.** PhD Thesis – UPV (SPAIN).

Gilberto Reynoso Meza (2014). **Controller Tuning by Means of Evolutionary Multiobjective Optimization: a Holistic Multiobjective Optimization Design Procedure.** PhD Thesis – UPV (SPAIN).

Think different!
Try to getting close to your design preferences

Thank you very much, pleased to answer your questions.

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AN EXAMPLE: ENGINEERING DESIGN

Engineering Design – Sonic Crystals

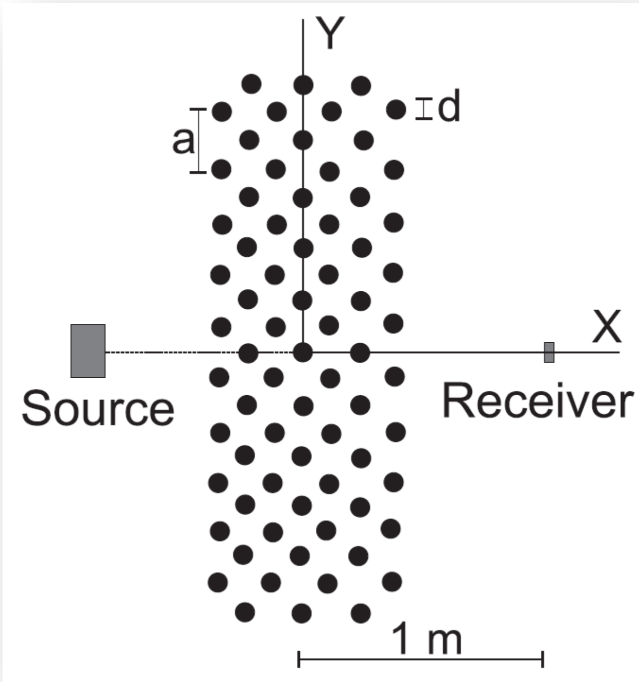
New acoustic materials called **Sonic Crystals - SCs** (periodic distributions of acoustic scatterers) are an alternative to classic acoustic barriers .
2D SCs, formed with isolated cylindrical scatterers made with rigid materials can be used to construct acoustic barriers.

Part of the design of these acoustic barriers can be formulated as a multiobjective optimization problem.

Engineering Design – Sonic Crystals

Multiobjective problem:

Decision variables:
θ is a vector that contains the **information about the space configuration** of the structure.

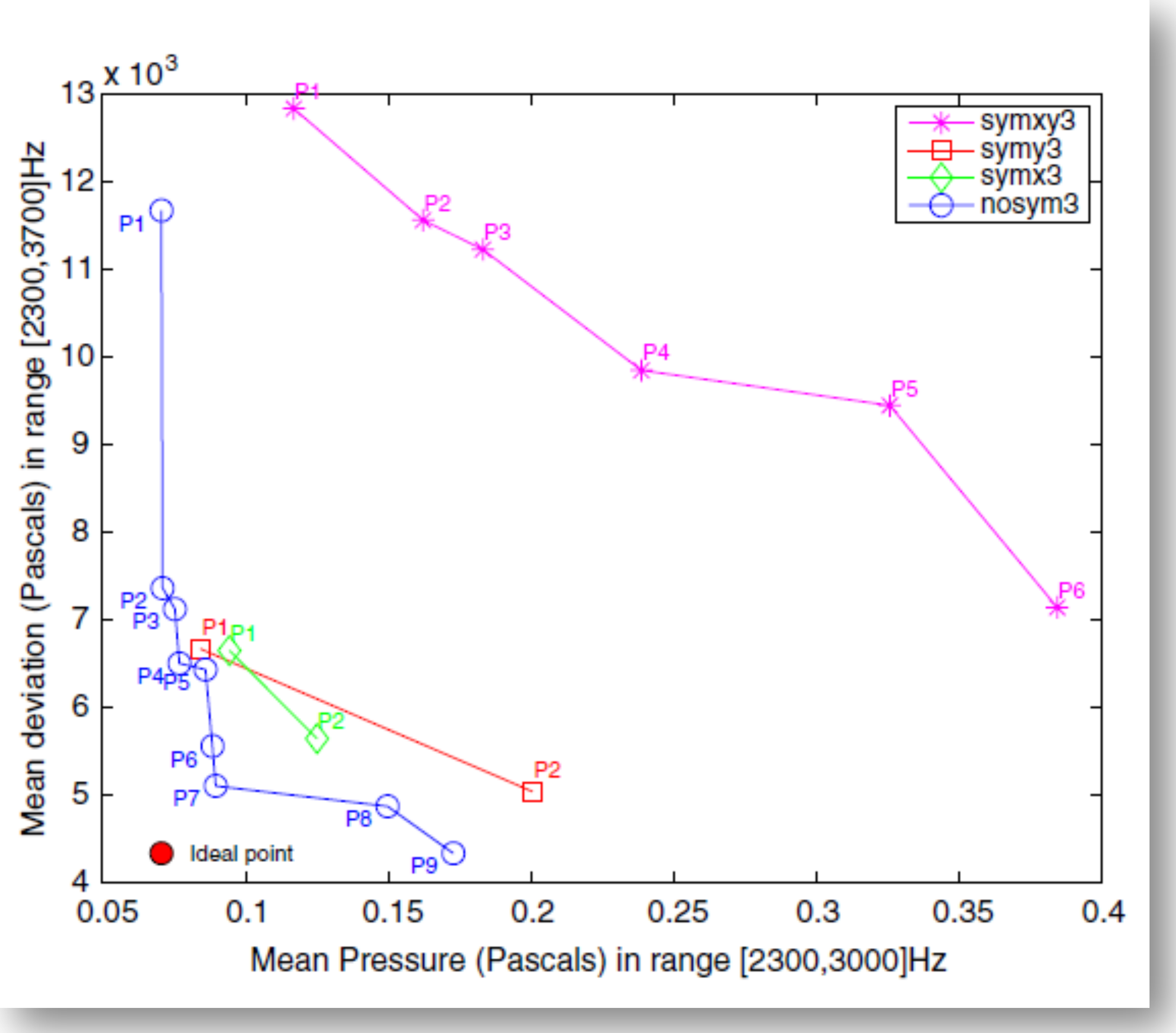


Objectives:
Minimize J1(θ)**,** the **mean pressure (Pa)**
Minimize J2(θ)**,** the **mean deviation (Pa)**
in a range of frequencies

Constraints:
Different type of symmetry around the X axis, Y axis or XY axes (each constraint is proposed as a separate problem).

Engineering Design – Sonic Crystals

Pareto Front for each symmetry



Engineering Design – Sonic Crystals

Solutions of the Pareto Front