EVALUATING THE QUALITY OF STEADY-STATE MULTIVARIATE EXPERIMENTAL DATA IN VARIOUS ORC EXPERIMENTAL SETUPS

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September 15th 2017

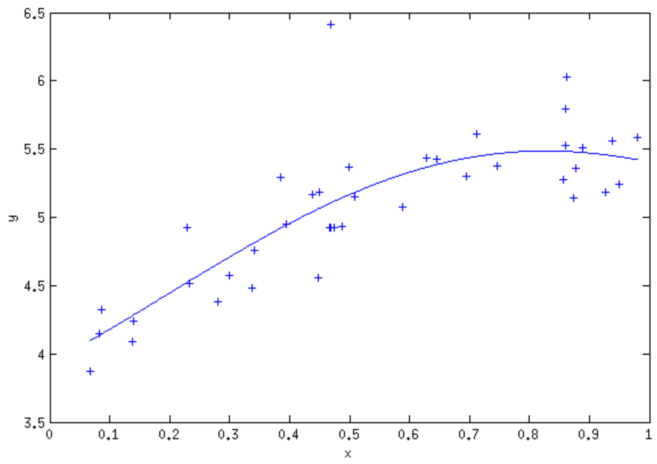
ORC 2017 Conference

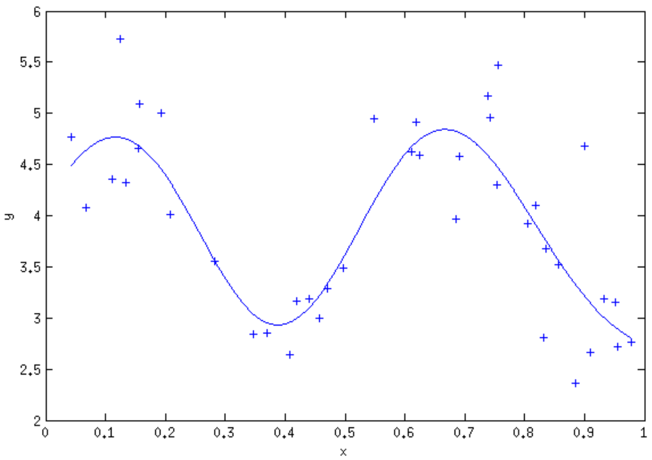
Introduction

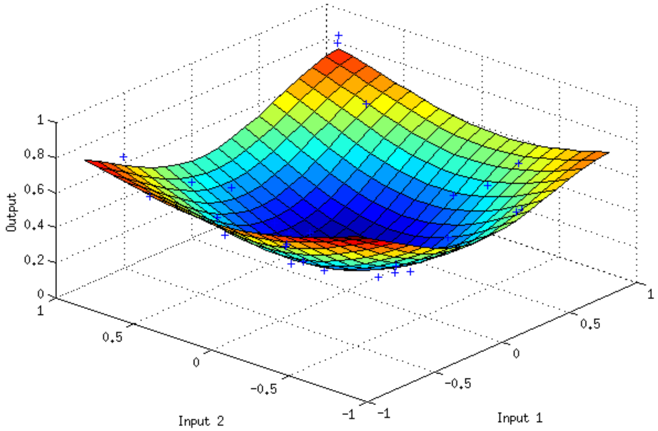
Quality of experimental data

- ✓ High quality data is required for the development, the calibration and the validation of models
- ✓ Different types of models:
  - ✓ Deterministic models
  - ✓ Semi-empirical models
  - ✓ Empirical models
- ✓ Experimental data is subject to many measurements errors, test bench malfunctions, operator misuse or misinterpretation, etc.
- ✓ Special focus on **multidimensional inputs**
- ✓ Goal of this work: provide an **open-source tool** to assess the quality of experimental data and its « explainability »
- ✓ Several key questions to be answered

Question 1:
"Most likely" shape of the function explaining the data?

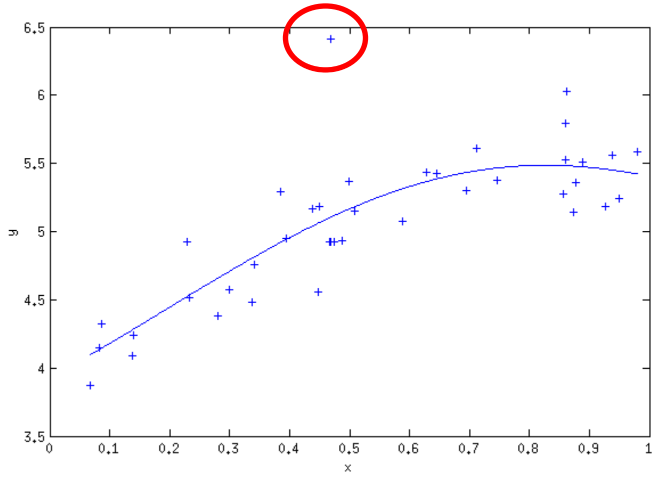


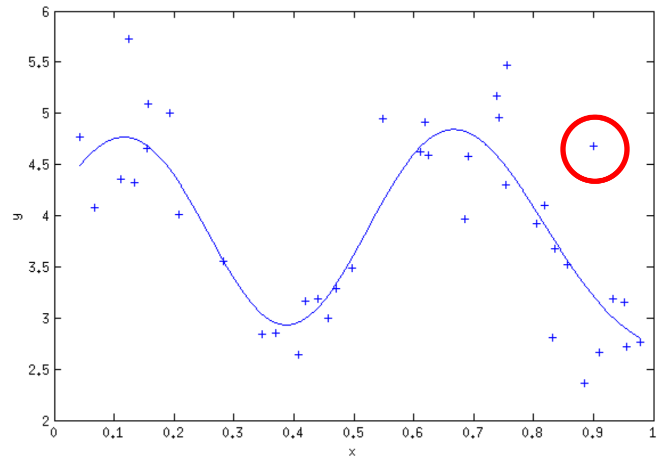


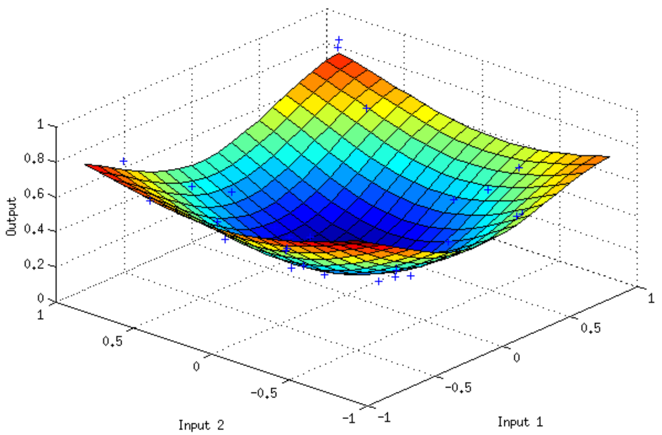


Question 2:

Repeatability and detection of outliers







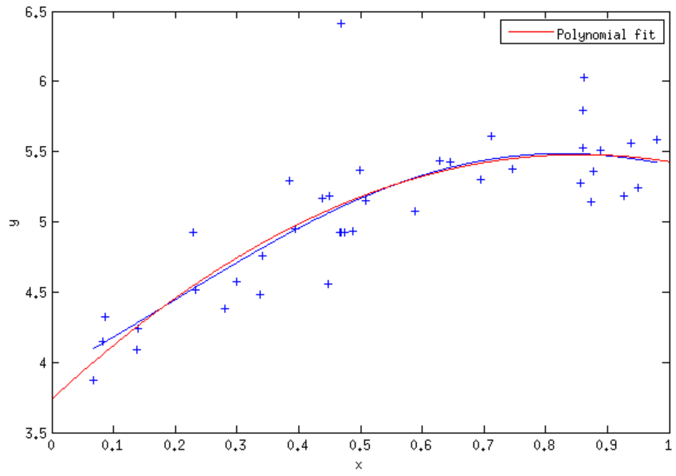
Additional questions:

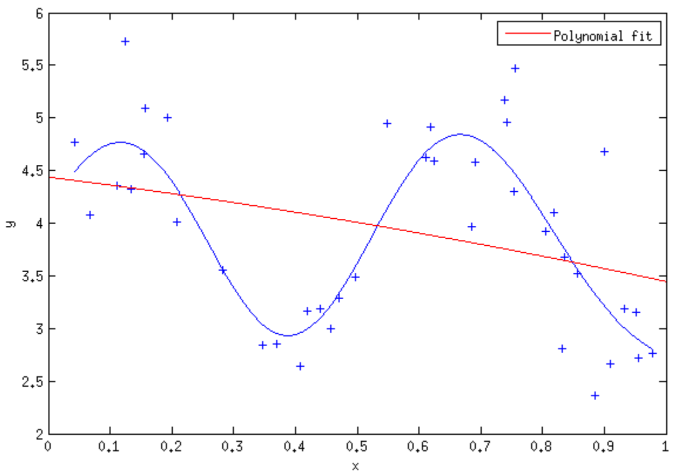
- *Best explanatory variables?*
  - Goal: explain the data with the smallest possible set of input variables
- *Data accuracy / noise level?*
  - Goal: determine experimentally what it the data accuracy => what would be the best accuracy a model could reach with this data
  - Necessity to de-noise the data

Data analysis:

Use of Gaussian Process regressions / Kriging interpolation

Gaussian process regression





- Traditional regression (e.g. based on least-squares):
  - Use of parametric functions
  - Function is defined *a-priori*
- Gaussian process regression:
  - Probabilistic distribution of the function with respect to the data points
  - Instead of the definition of a parametric function, definition of a **Covariance Matrix**
- Bayesian formulation:

$$p(f|y) = \frac{p(y|f)p(f)}{p(y)}$$

- Covariance functions (kernel):

$$K(x, x') = \sigma_0{}^2 \exp\left[-\frac{1}{2}\left(\frac{x - x'}{\lambda}\right)^2\right]$$

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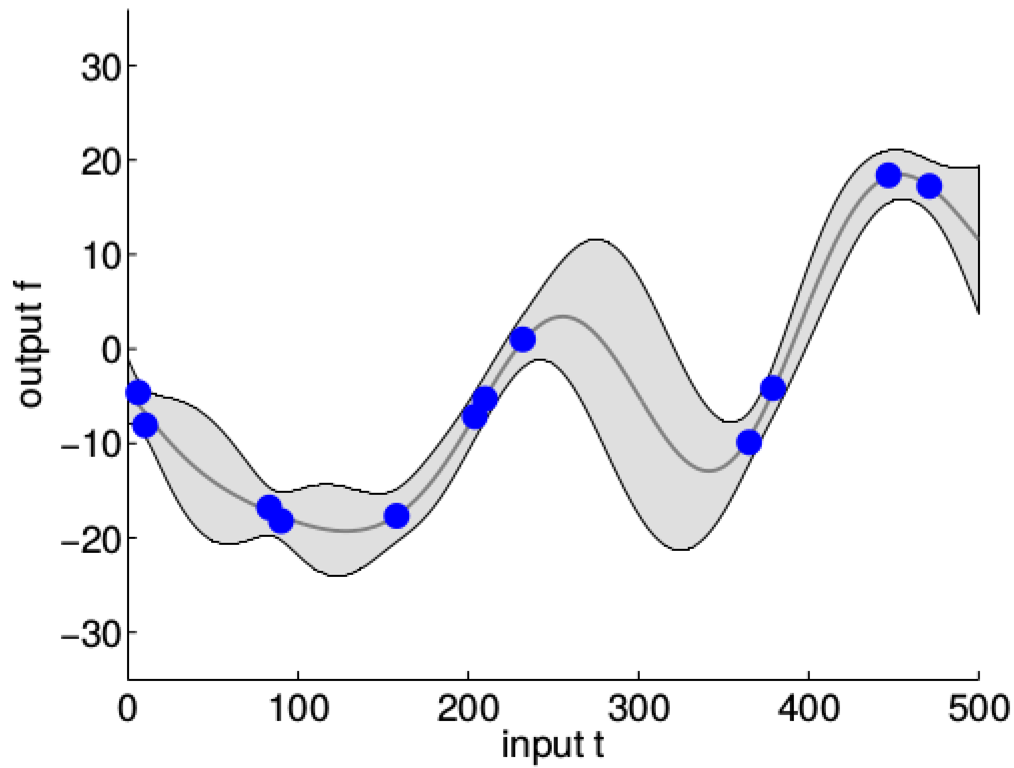
Gaussian process

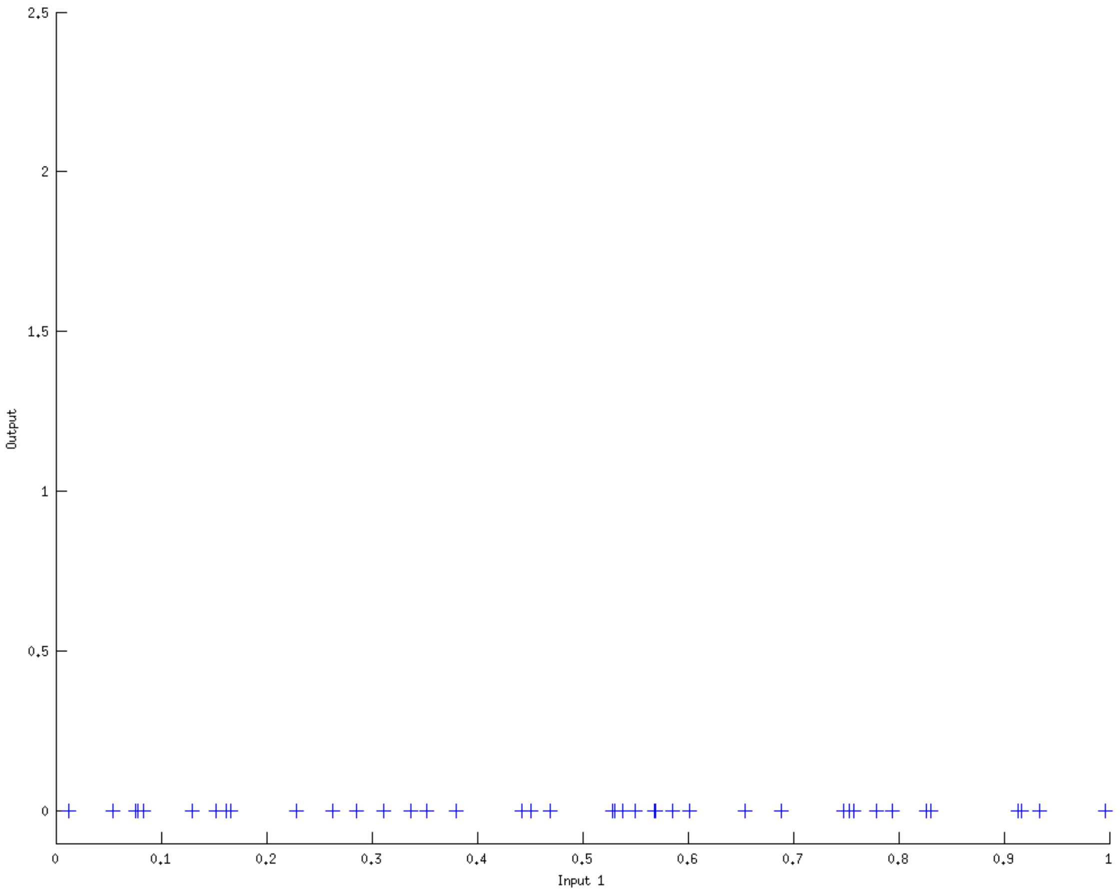
1. Definition of a GP prior
2. Use Baysian inference to update the probability distribution

$$p(f|y) = \frac{p(y|f)p(f)}{p(y)}$$

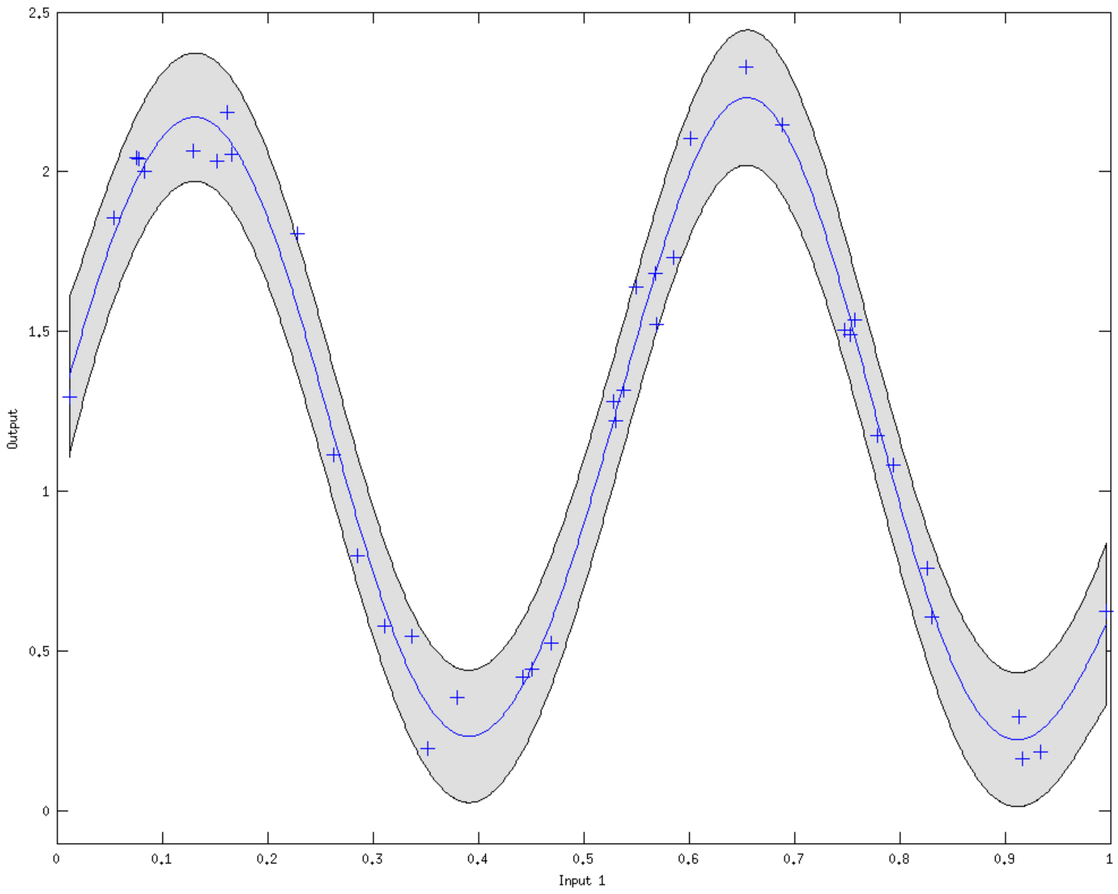


Source: John P. Cunningham, Gaussian Processes for Machine Learning, MLSS 2012

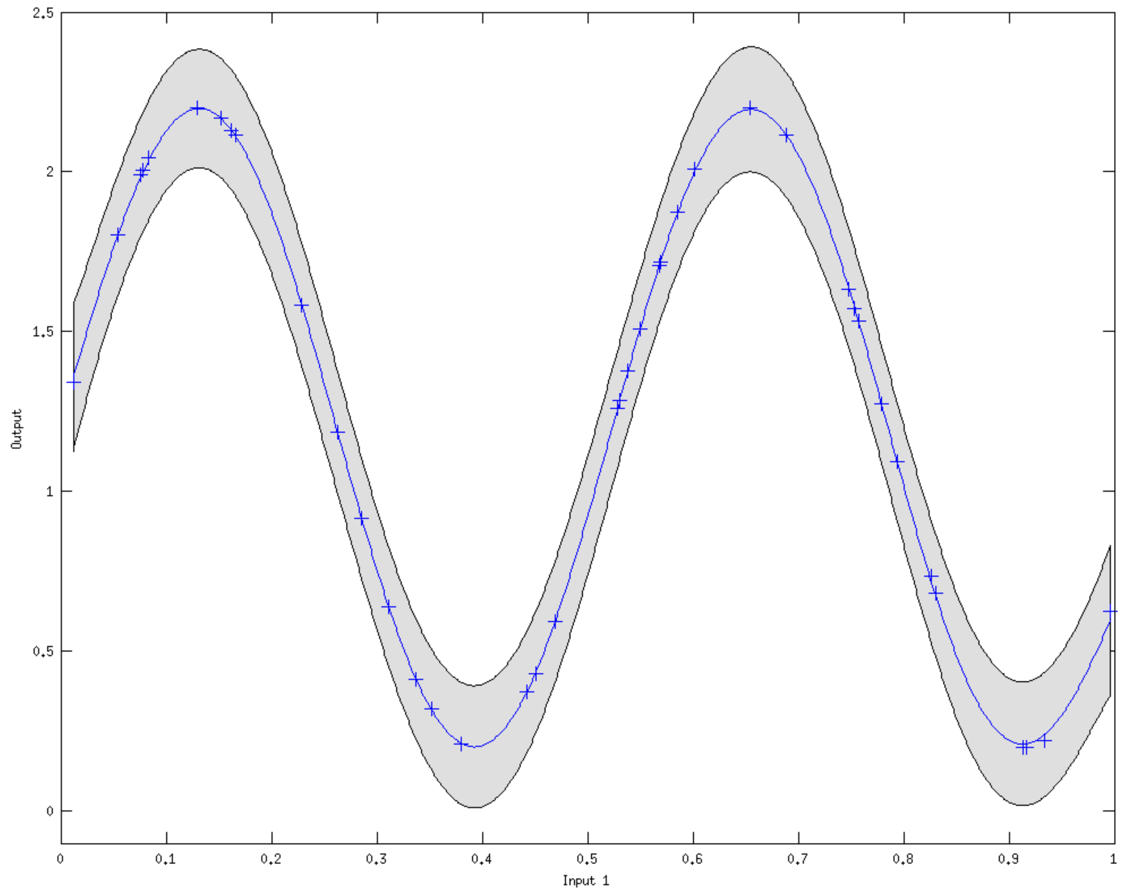
Gaussian process:
Regression



Gaussian process:
Effect of outliers



Gaussian process:
Effect of noise



Selection of the length scales

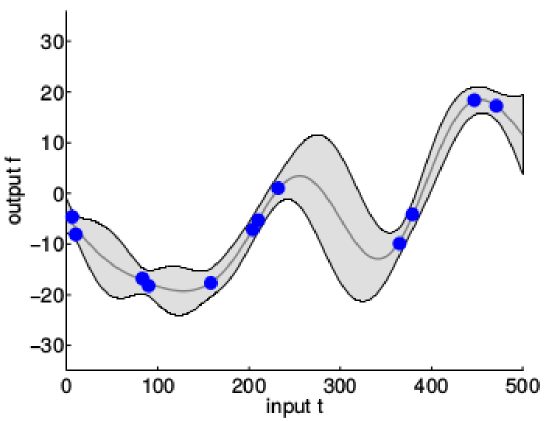
Preventing overfitting

Unidimensional Gaussian Process regression:

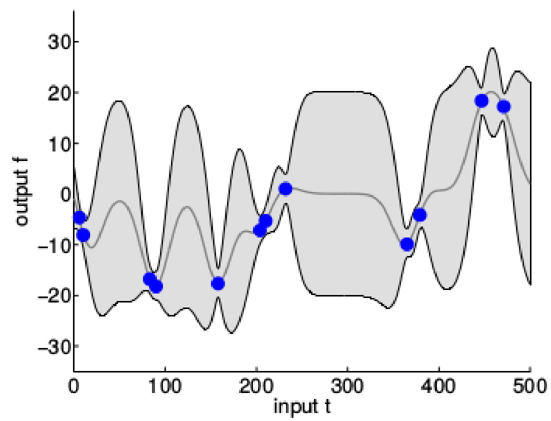
Use of a SE kernel:

$$f \sim \mathcal{GP}(0, k_{ff}), \text{ where } k_{ff}(t_i, t_j) = \sigma_f^2 \exp\left\{-\frac{1}{2\ell^2}(t_i - t_j)^2\right\}$$

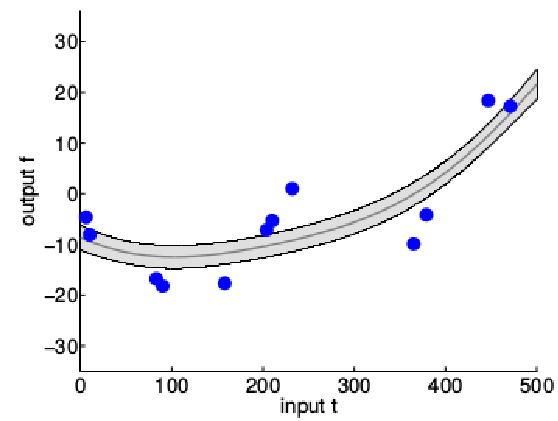
l=50: just right



l=15: Overfitting



l=150: Underfitting



Source: John P. Cunningham, Gaussian Processes for Machine Learning, MLSS 2012

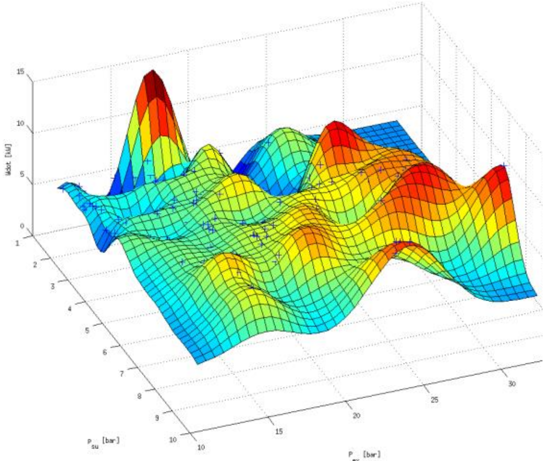
Selection of the length scales

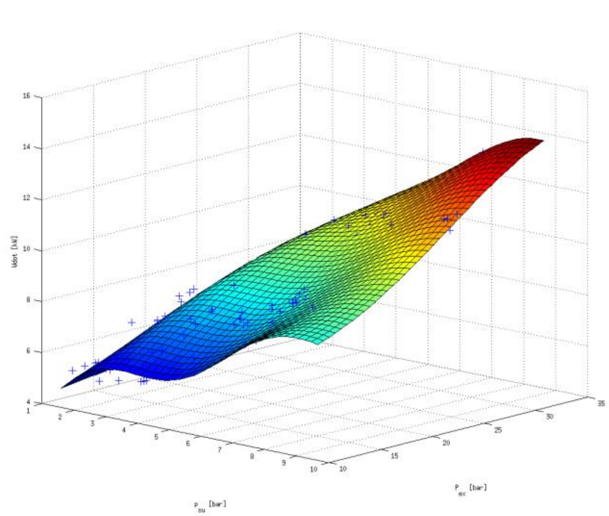
Preventing overfitting

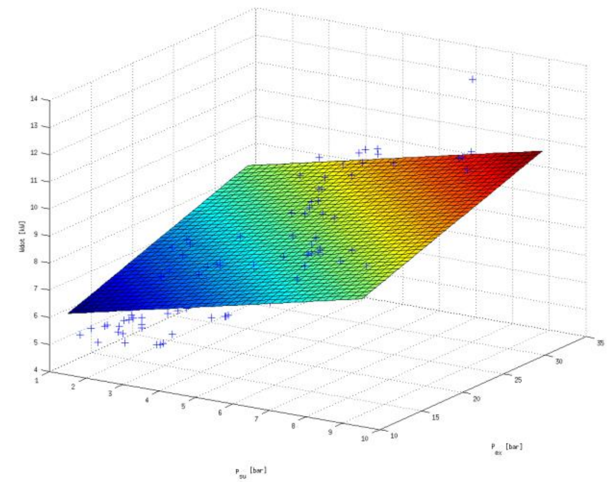
Multidimensional Gaussian Process regression:

Use of an SE ARD Kernel:

$$k_{ff}(x^{(i)}, x^{(j)}) = \sigma_f^2 \exp\left\{ -\sum_d \frac{1}{2\ell_d^2}(x_d^{(i)} - x_d^{(j)})^2 \right\}$$







➡ The hyperparameters l_d must be optimized to avoir under/over fitting

Selection of the length scales
Preventing overfitting

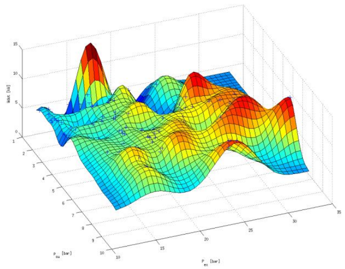
Three-step process:

1. Optimize the parameters (l1,l2,l3,…) to maximize the marginal likelihood

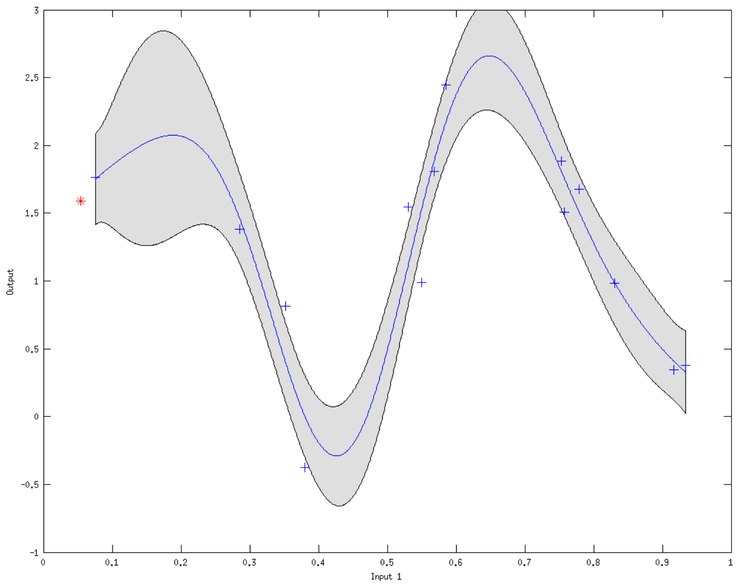
$$p(y) = \int p(y|f)p(f)df$$

2. Computation of the mean average error in Cross-Validation / Training

3. Visual verification:



Cross-validation, good fit:



Mean relative error:

MRE with all points:	2.7%
MRE in cross-validation:	7.6%

Selection of the length scales

Preventing overfitting

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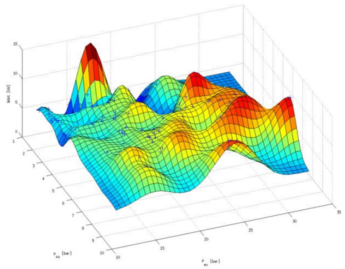
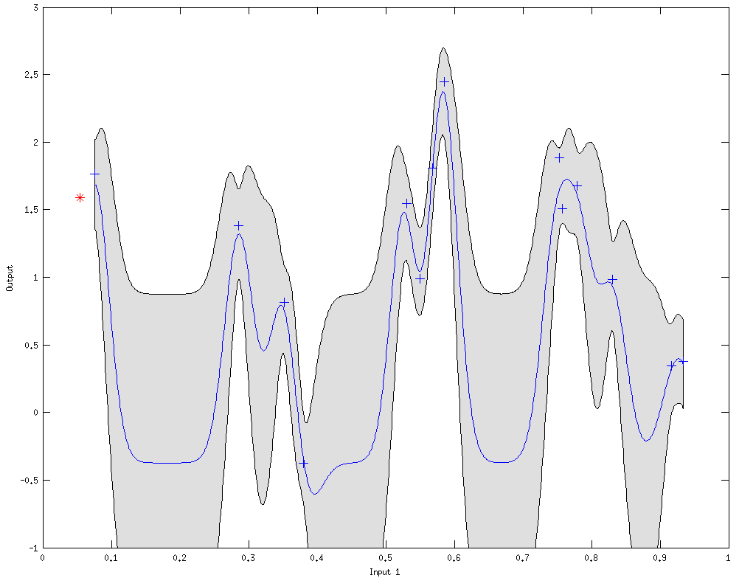


Cross-validation, overfit:



Mean relative error:

MRE with all points:	1.1%
MRE in cross-validation:	18.5%

Examples of experimental test rig

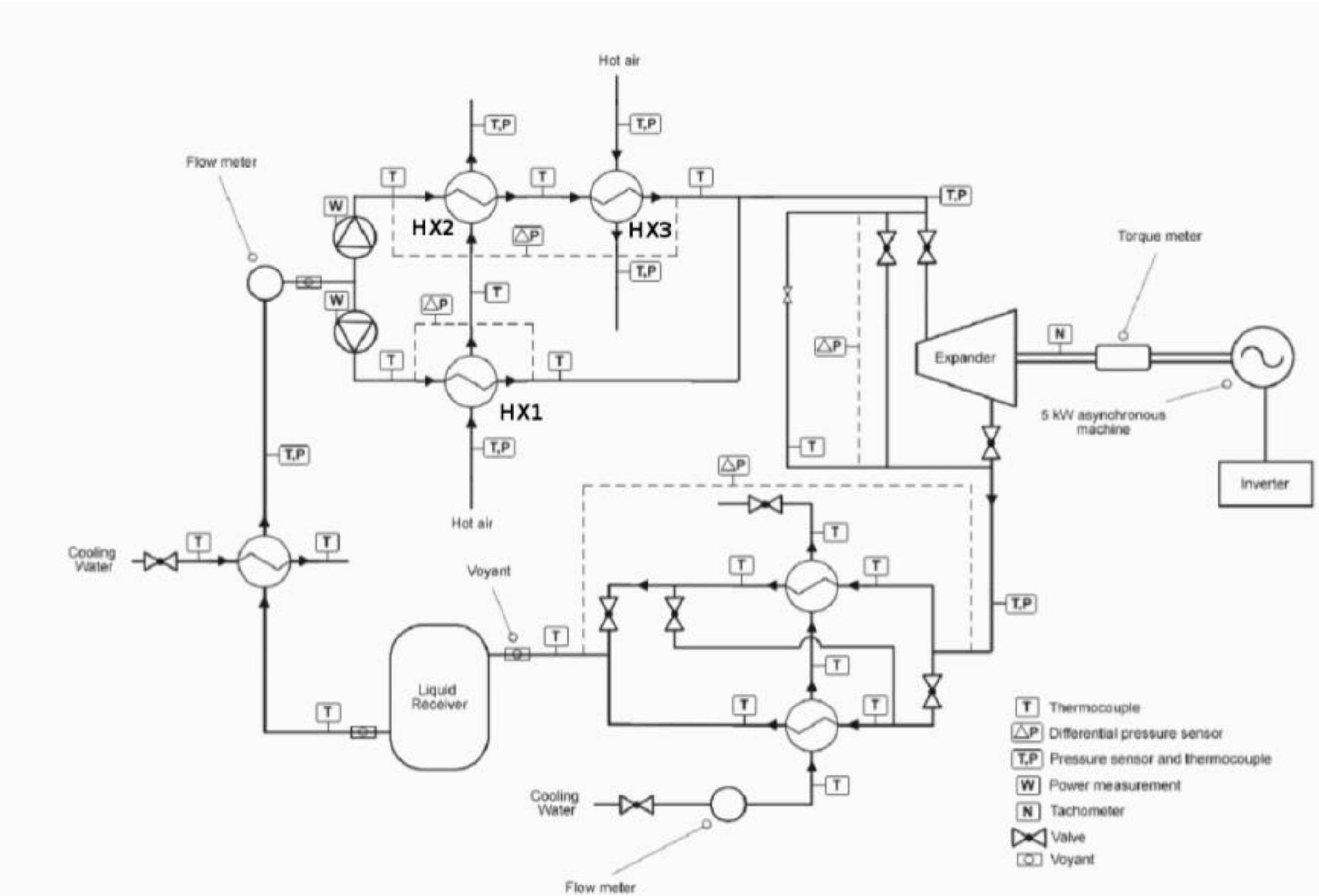
Experimental setups

Open-drive scroll compressor

- Converted into an expander
- Built in volumetric ratio : 3.94
- Absence of lubrication
- Not tight

Experimental setups

Open-drive scroll compressor

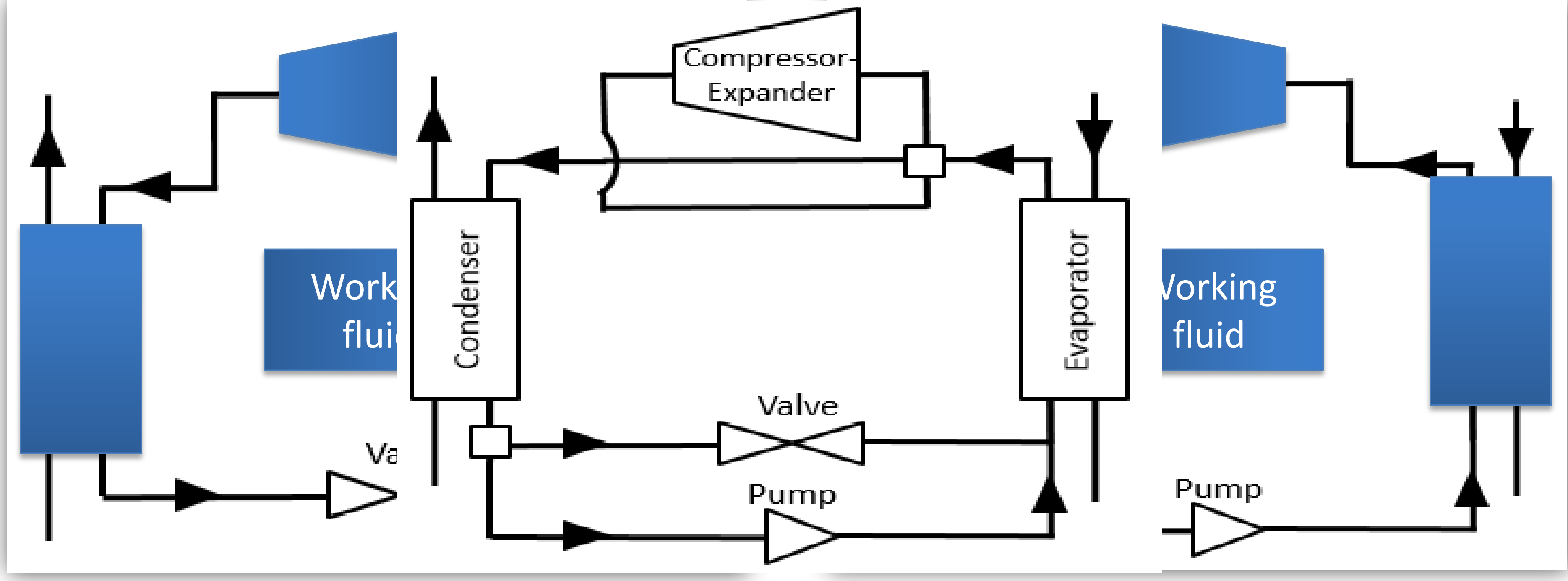


$$\varepsilon_s = \frac{\dot{W}_{sh}}{\dot{M}_r \cdot (h_{su,\exp} - h_{ex,\exp,s})}$$

Experimental setups

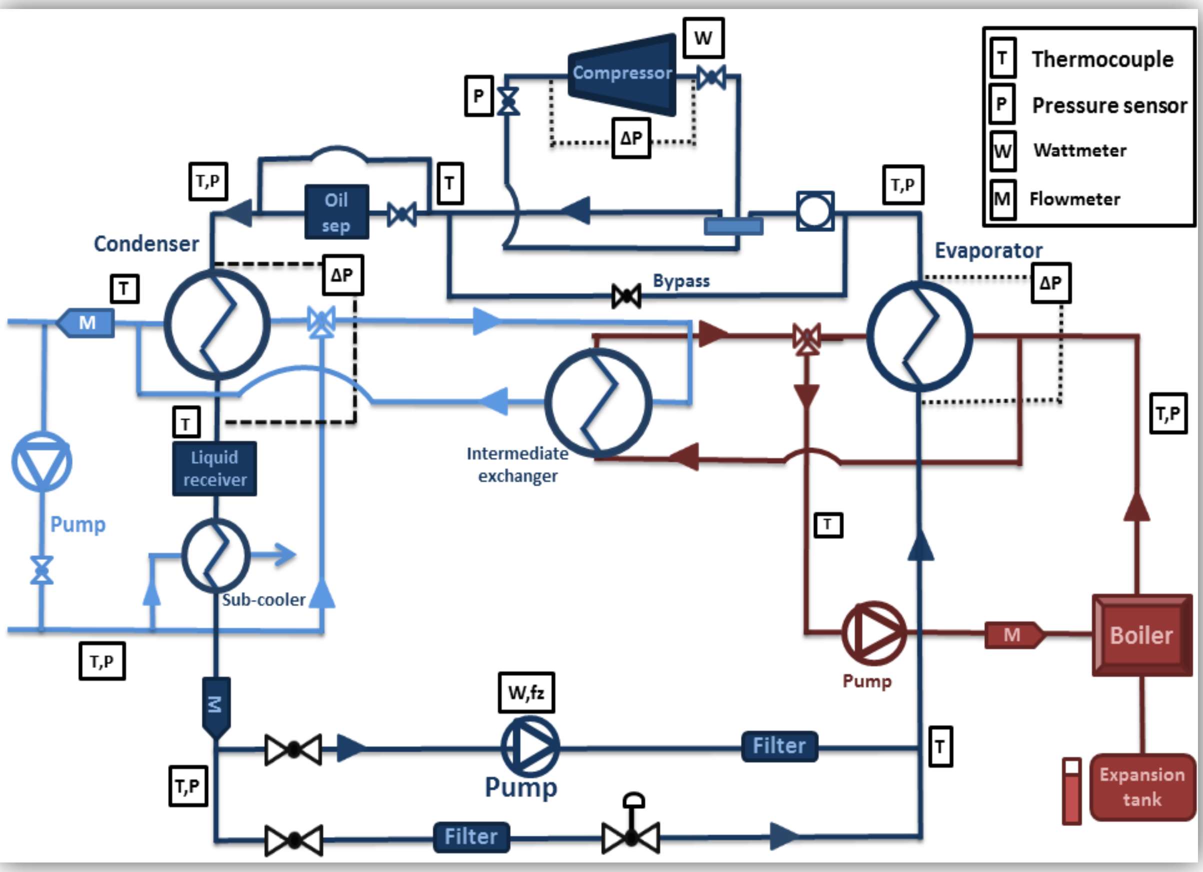
Reversible HP/ORC unit

Heat Pump → ORC → Reversible HP/ORC



Experimental investigations

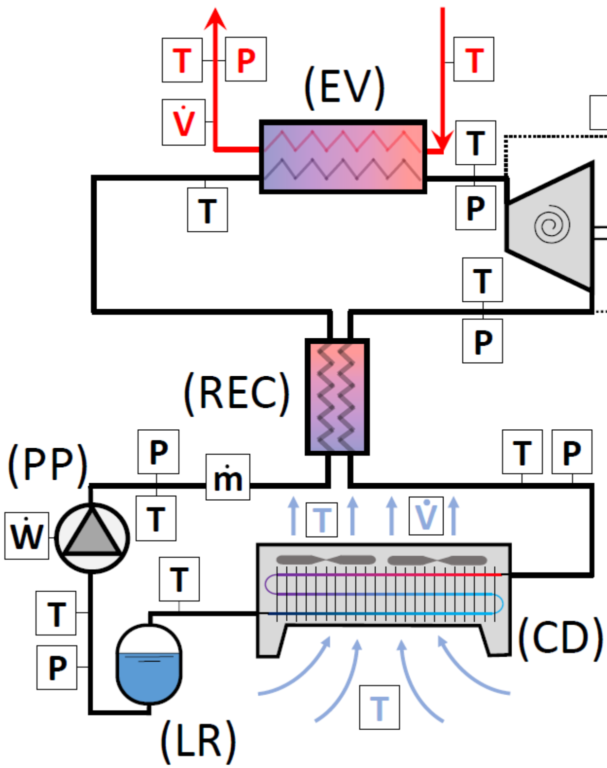
Reversible HP/ORC unit



$$\eta_{ORC} = \frac{W_{exp,el} - W_{pump,el}}{\dot{Q}_{ev}}$$

Experimental investigations

Sun2Power unit



P : pressure sensor - **T** : thermocouple - **$\dot{m}$** : mass flow meter
$\dot{W}$: power meter - **$\dot{V}$** : volumetric flow meter

Sun2Power unit:

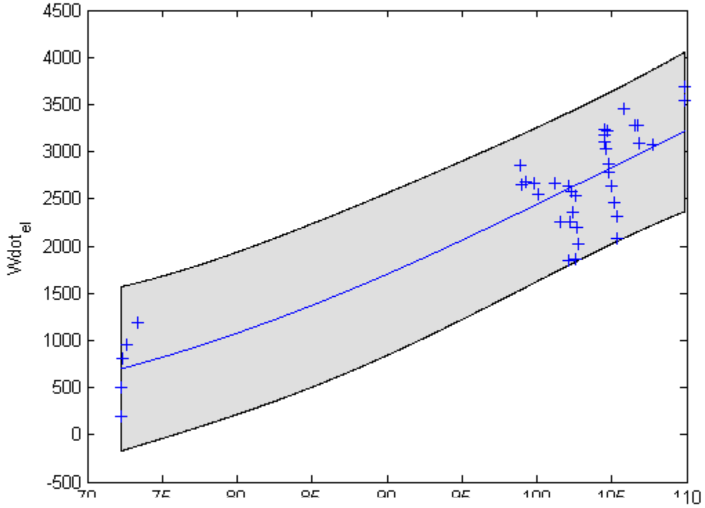
- 2kWe recuperative ORC
- R245fa as working fluid
- Scroll expander + diaphragm pump
- <u>Two BPHEXs (EV + REC)</u>
- <u>One fin coil air-cooled condenser</u>

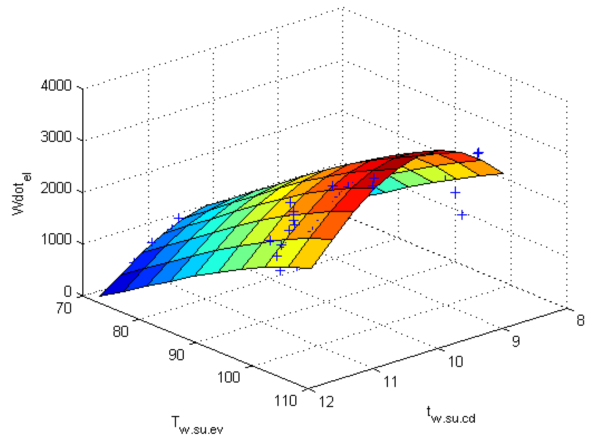
Reference database:

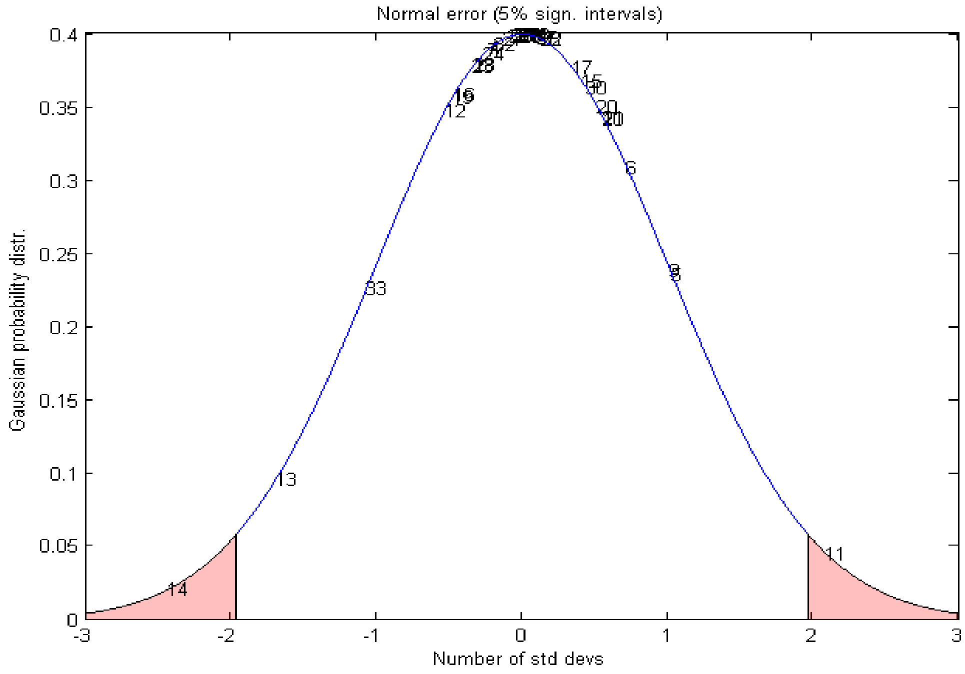
- Experimental measurements
- Complete range of conditions (40 pts)

Outlier detection

Example with the HP/ORC test rig

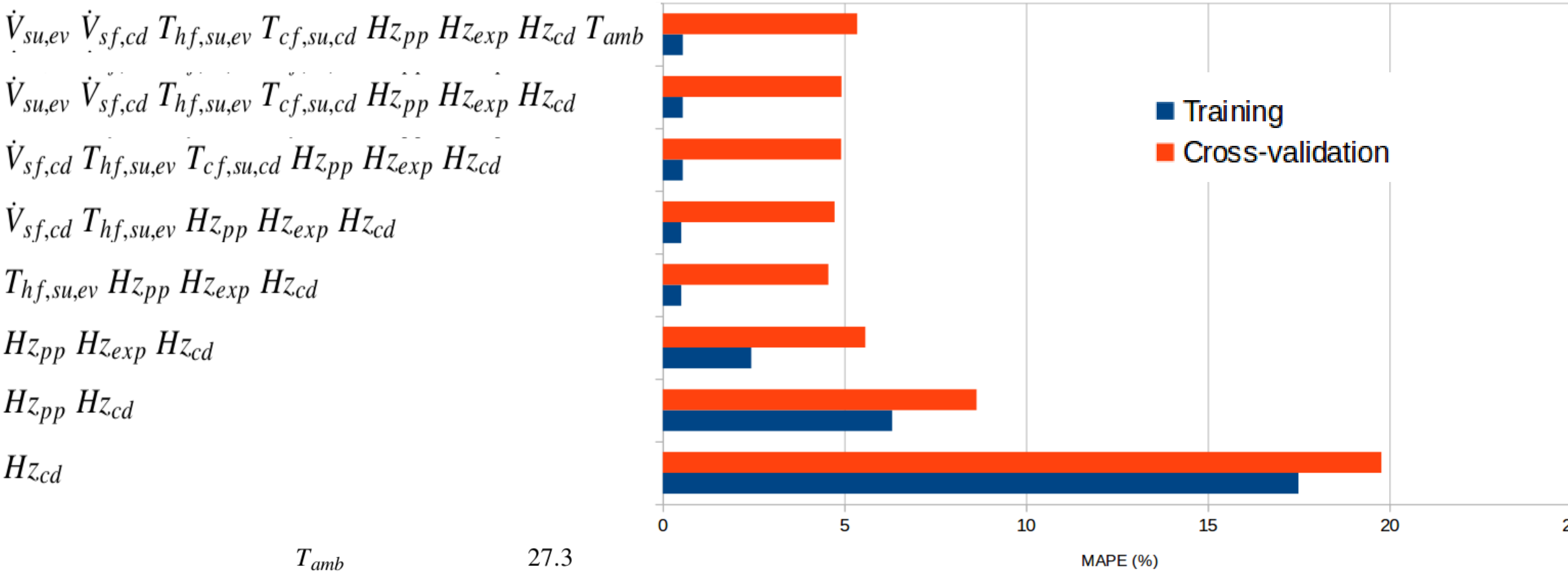






Feature selection

Example with the Sun2power test rig



Lengthscales:

T_{amb}	27.3
$\dot{V}_{su,ev}$	528
$T_{cf,su,cd}$	27.3
$\dot{V}_{sf,cd}$	11.5
$T_{hf,su,ev}$	1.95
Hz_{exp}	1.15
Hz_{pp}	1.31
Hz_{cd}	0.32

Relevant input variable

Summary

Table 2. Inputs variables of the three considered processes

HP/ORC		Sun2Power		Expander	
Heat source flow rate:	$\dot{M}_{su,ev}[kg/s]$	Heat source flow rate:	$\dot{V}_{su,ev}[kg/s]$	Inlet pressure:	$P_{su}[Pa]$
Heat sink flow rate:	$\dot{M}_{sf,cd}[kg/s]$	Heat sink flow rate:	$\dot{V}_{sf,cd}[kg/s]$	Outlet pressure:	$P_{ex}[Pa]$
Heat source temperature	$T_{hf,su,ev}[K]$	Heat source temperature	$T_{hf,su,ev}[K]$	Rotating speed:	$N_{rot}[rpm]$
Heat sink temperature	$T_{cf,su,cd}[K]$	Heat sink temperature	$T_{cf,su,cd}[K]$	Inlet temperature:	$T_{su}[K]$
Pump speed:	$N_{pp}[rpm]$	Expander Rotating speed:	$Hz_{pp}[s^{-1}]$	Ambient temperature:	$T_{amb}[K]$
		Expander Rotating speed:	$Hz_{exp}[s^{-1}]$		
		Condenser fan speed:	$Hz_{cd}[s^{-1}]$		
		Ambient temperature:	$T_{amb}[K]$		

Predicted variable: Power output
2 outliers
MAPE, GP: 1,92%
MAPE, physical model: 2.45 %

Predicted variable: Power output
No outlier
MAPE, GP: 4.56%
MAPE, physical model: 8.12 %

Predicted variable: Power output
2 outliers
MAPE, GP: 0.99%
MAPE, physical model: 1.94 %

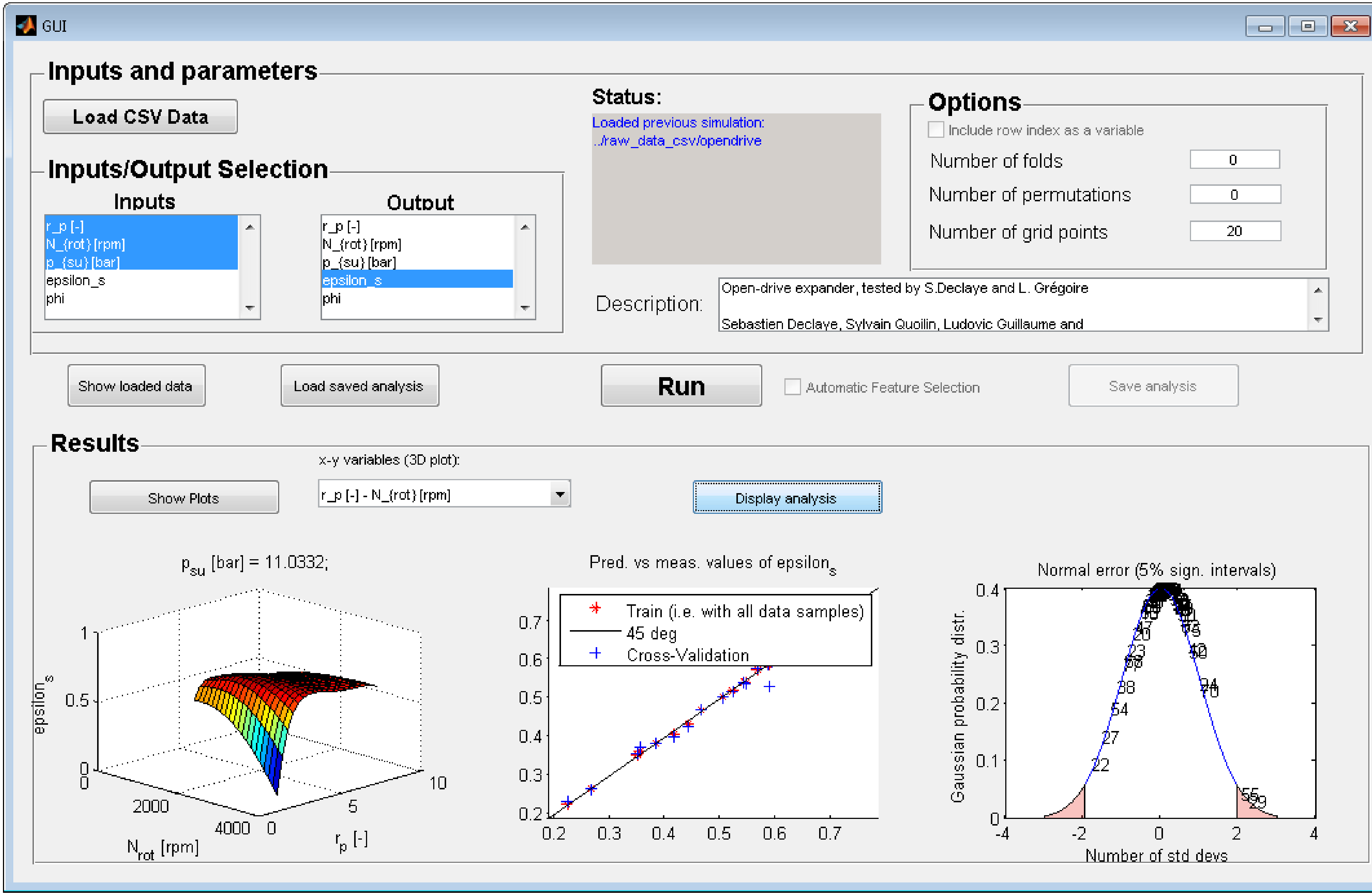
Conclusions

Starting from three ORC-related datasets, the proposed framework allowed us to:

- ✓ Perform non-linear, non-parametric regression
- ✓ Detect doubtful data points (outliers)
- ✓ Select the relevant input variables for the process to model (feature selection)
- ✓ Plot the effect of each relevant input variable by keeping the others constant (response surface)
- ✓ Evaluate the noise level in the data (i.e. the maximum model accuracy)
- ✓ Compare the "quality" of various datasets

The GPExp tool:

- ✓ Open-source
- ✓ Easy to download and run in Matlab
- ✓ Graphical user interface (GUI)
- ✓ External contributions and improvements are welcome



Download GPExp:

https://github.com/squoilin/GPExp

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