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Assessment of Uncertainty Quantification Methods with Application to the Design of ORC

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Context

The Organic Rankine Cycle (ORC) is a viable technology for the exploitation of renewable energies like concentrated solar power, geothermal power, biomass or waste heat recovery. In these applications, it usually outperforms classic steam cycles for its simplicity, the lower operational costs and the higher thermodynamic efficiency.

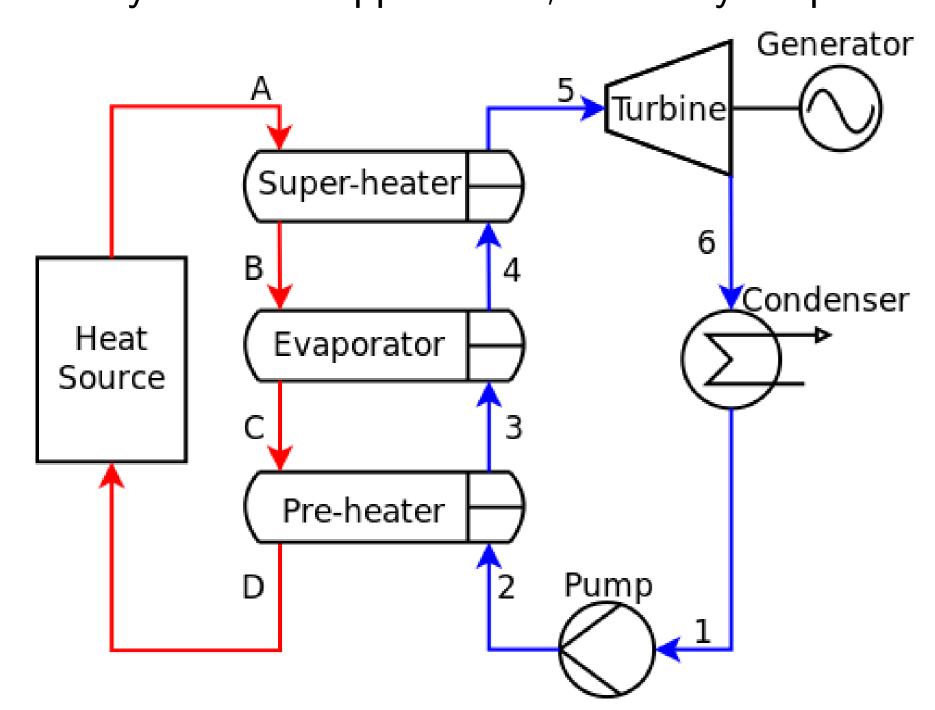


Figure 1: ORC schematic representation

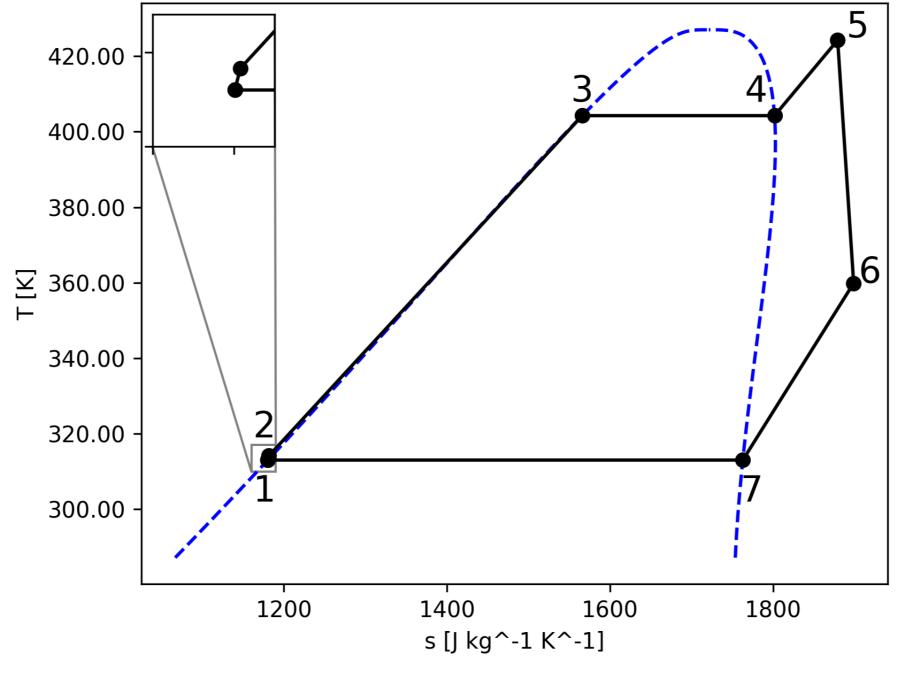


Figure 2: ORC on Ts thermodynamic chart

= temperature

Main ORC parameters

- ▶ Temperature at the Condenser $T_{con} = T_1 = T_7$
- ▶ Pressure at the Evaporator $P_{eva} = P_2 = P_3 = P_4 = P_5$
- Turbine isentropic efficiency $\eta_t = \frac{Turbine Real Work}{Turbine Ideal Work}$
- Superheating $\Delta T_{sh} = T_5 T_4$
- Pump Ideal Work ightharpoonup Pump isentropic efficiency $\eta_p =$ Pump Real Work
- ► ORC working fluid: R245fa

The **Bayesian framework** is a powerful tool for dealing with uncertain data.

The quantity of interest $\mathbf{y}(\boldsymbol{\xi})$ depends on a vector of uncertain variables $\boldsymbol{\xi}$.

Thermodynamic properties of the working fluid are computed by using an advanced equation of state based on the Helmholtz free energy formulation, available through the thermodynamic library Coolprop [1].

As a drawback, due to the aleatory of the heat source, to the properties of the organic fluids and to the need for reducing manufacturing costs, ORCs are by nature subject to several forms of uncertainty.

Uncertain parameters

5 uncertain parameters are considered, all varying with uniform distribution.

	T_{con}	P_{eva}	η_{t}	ΔT_{sh}	$\eta_{ m p}$
Lower Bound	288 K	1.8E+06 Pa	75%	1.0 K	70%
Upper Bound	315 K	2.3E+06 Pa	90%	16.0 K	85%

Quantity of Interest (QoI)

= enthalpy

Kriging 16 samples

ORC Efficiency
$$\eta_{ORC} = \frac{W}{Q_{in}} = \frac{h_5(P_5, T_5) - h_6(P_6, s_6)}{h_5(P_5, T_5) - h_2(P_2, T_2)}$$

(1)

**Note of the image of the imag

= pressure

► Bayesian Kriging (BK) [2].

► Gradient Enhanced Bayesian CoKriging (CK) [3].

Surrogate Models for Uncertainty Propagation

The latter is an enhancement of Kriging using also the information about gradient on data as covariables.

Posterior = $p(\mathbf{y}|\mathbf{y}^*) = \frac{Sampling\ Distribution\ X\ Prior}{Marginal\ Distribution} = \frac{p(\mathbf{y}^*|\mathbf{y})\ p(\mathbf{y})}{p(\mathbf{y}^*|\boldsymbol{\xi})}$

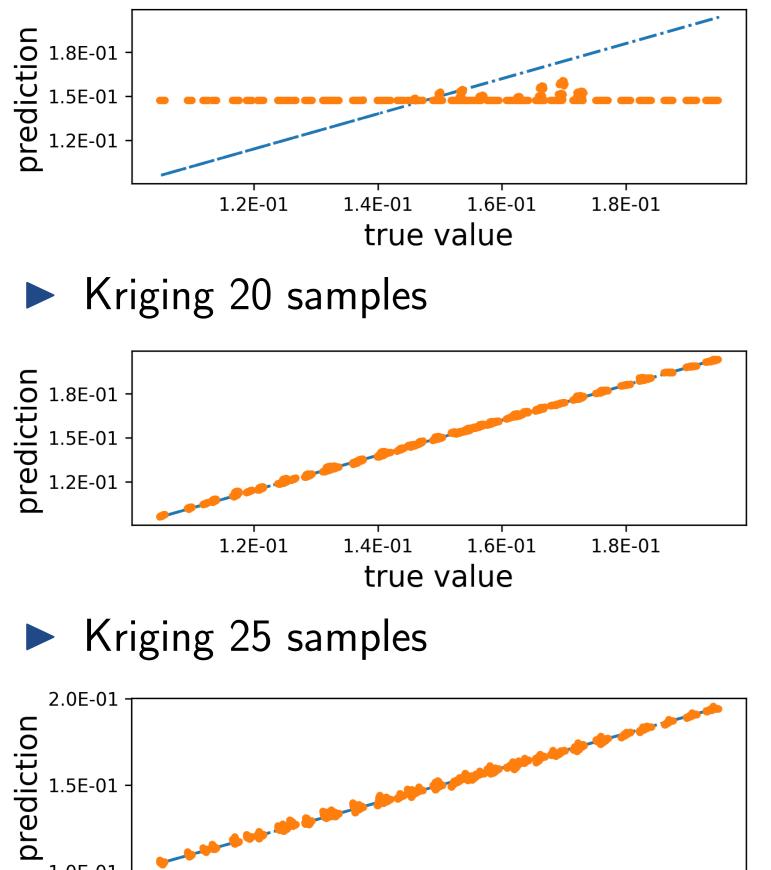
In this work surrogate models are used to relate the Qol to the uncertain input.

The gradient of the Qol w.r.t. the inputs $\frac{\partial \mathbf{y}}{\partial \mathbf{x}}$ is evaluated analytically from Eq.1.

Benchmark of surrogate models

 \triangleright s = entropy

The response surfaces of **BK** and **CK** are constructed by using several **experimental** designs with different numbers of samples of the 5 uncertain parameters (Latin Hypercube). The surfaces are then evaluated on a full factorial grid of 5⁵ points in order to get the predicted values, which are compared to the exact ones (from Eq.1).



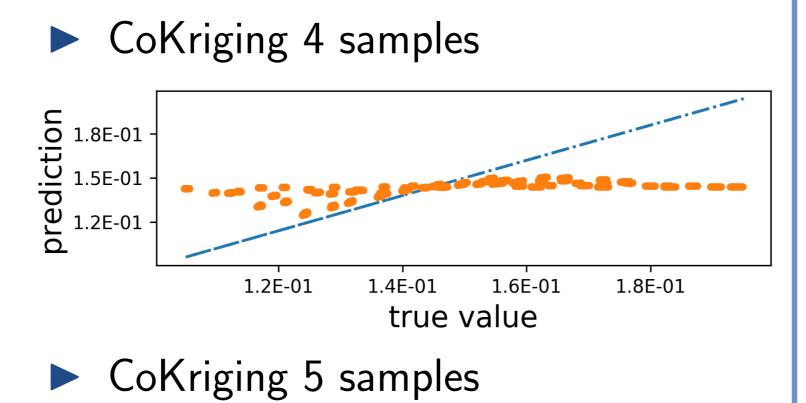
1.4E-01

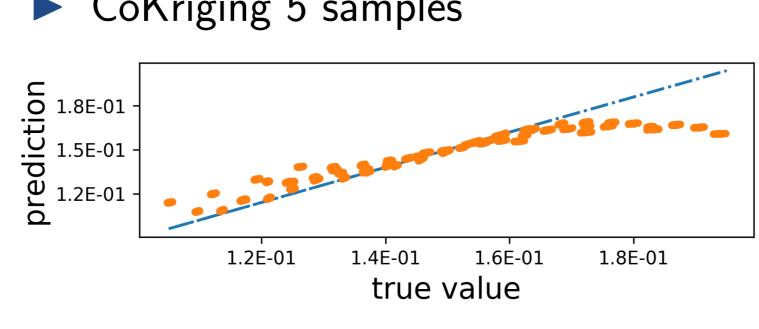
1.2E-01

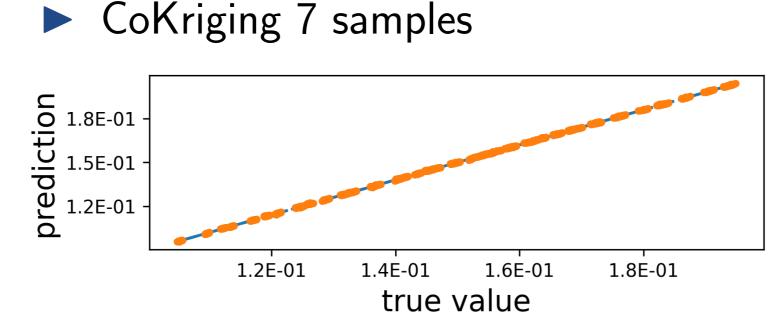
1.6E-01

true value

1.8E-01

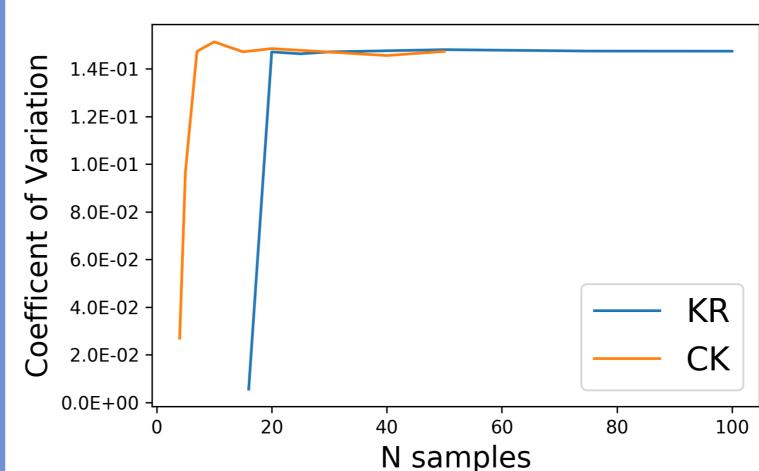






Statistics

For both surrogate models the convergence is verified by monitoring the trend of the average value of the coefficient of variation on the response surface w.r.t. the number of samples in the experimental design.

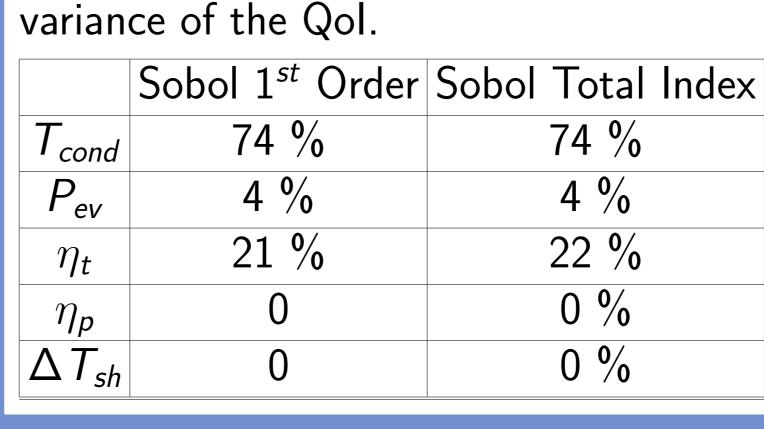


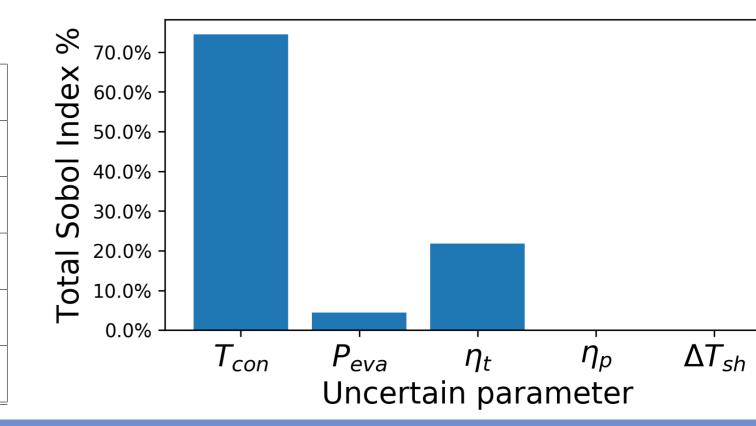
Global Sensitivity Analysis

Method	N samples	μ	σ^2
BK	50	0.148	4.80E-04
CK	10	0.147	4.97E-04

- Computational time for BK:
 - $N_{sample-BK} t_{CPU-ORC} + t_{BK}$
- **►** Computational time for CK: $N_{sample-CK}$ $t_{CPU-ORC} + \alpha_{der} + t_{CK}$

An **ANOVA** decomposition is carried out to identify the greatest contribution to the





Next steps

Extension of CK to surrogate modelling of ORC turbines with CFD simulations.

Reference

- [1] Bell, Wronski, Quoilin, Lemort: Pure and pseudo-pure fluid thermophysical property evaluation and the open-source thermophysical property library Coolprop. Ind. Eng. Chem. Res. 53(6). (2014)
- [2] Wikle, Berliner: A Bayesian tutorial for data assimilation. Physica D: Nonlinear Phenomena, 230(1). (2007)
- [3] De Baar, Dwight, Bijl: Improvements to gradient-enhanced Kriging using a Bayesian interpretation. Int. Journ. for Uncertainty Quantification. 4 (3). (2014)