Robust optimization of an Organic Rankine Cycle for heavy duty engine waste heat recovery

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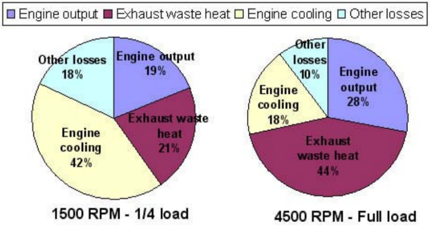
September 14, 2017

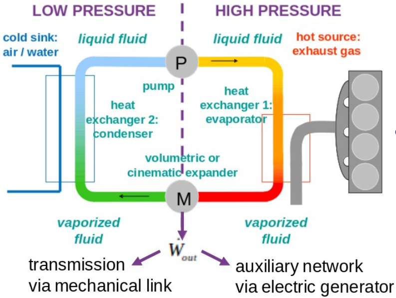
Context: the ORC for WHR applications

- ORC has gained interest in the last years for automotive WHR applications:
  - Only about one-third of the fuel energy is converted into mechanical power on typical driving cycles at full load
  - Low temperature heat released through the radiator and the exhaust gases
- **Small-scale ORC** plants as proposed solutions to recover waste heat:
  - reduction of fuel consumption up to 12% and engine thermal efficiency improvements of 10% (Mack Trucks, Honda, Cummins)
  - no large-scale commercial ORC solutions in the automotive field are available (low robustness to duty driving cycles, small improvements of the engine global efficiency)



Energy balance of a 1.4 l spark ignition engine (El Chammas and Clodic, 2005)

Case study: hybrid Diesel-electric intercity train

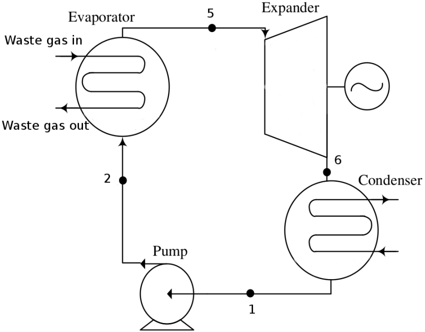


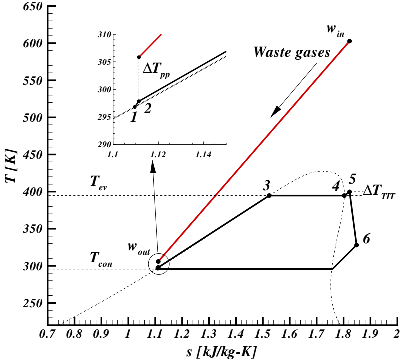
- Issues:
  - Typical intercity train trips have frequent start/stop cycles → very large variation of exhaust gas mass-flow rate and temperature
  - Non-stationary behaviour of the engine combustion process, variability of the exhaust gases chemical composition, aleatory ambient conditions etc.
    → **Non-deterministic ORC performance**
- Need for thermodynamic optimization of ORC subject to randomly variable conditions:
  - Find probability distributions for ORC performance parameters: **Uncertainty Quantification** (UQ) techniques
- Design ORC with stable performance under fluctuating operating conditions:
  - Minimization of the performance variability (seek for **robustness**)
  - Search for the best ORC performance under uncertainty: **Robust Optimization** (RO)

Outlines

- CYCLE CONFIGURATION AND HEAT SOURCE CHARACTERIZATION
- WORKING FLUIDS
- UQ AND SENSITIVITY ANALYSIS
- DETERMINISTIC OPTIMIZATION
- ROBUST OPTIMIZATION
- CONCLUSIONS

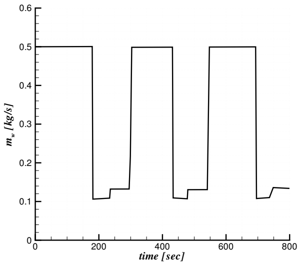
Cycle configuration

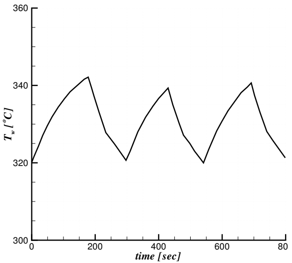


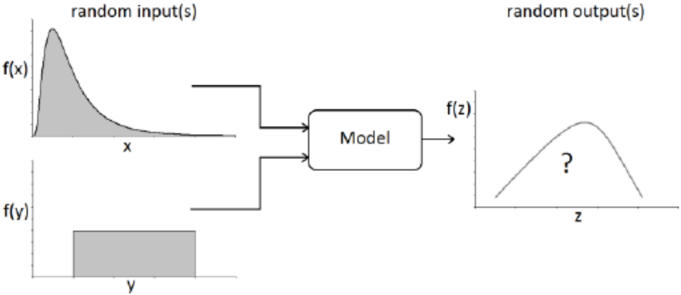


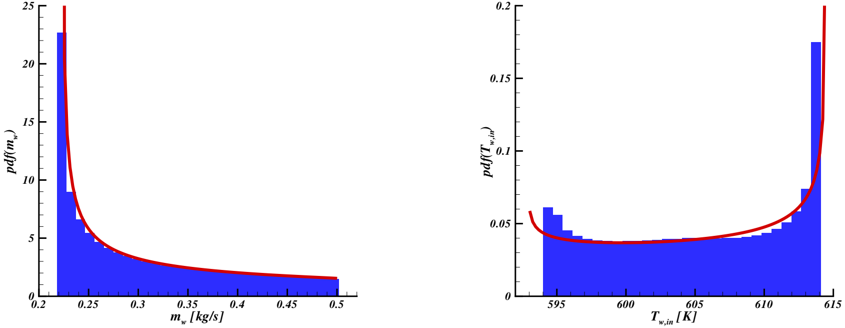
- ORC parameters (model input):
  - T_{amb}, T_{con}, $T_{w,in}$, c_w, $\dot{m}_{w,in}$
  - η_P, η_T
  - p_{ev}, ΔT_{pp}, ΔT_{TIT}
- ORC performance (model output):
  - $\eta_I = W_{net}/Q_{in}$
  - $\eta_{II} = W_{net}/[Q_{in}(1 - \frac{T_0}{T_m})]$
  - $V_r = \frac{V_{t,out}}{V_{t,in}}$
  - $S_T = \frac{\dot{V}_{t,out}^{0.5}}{\Delta H_t^{0.25}}$

Heat source characterization









- The heat source is modelled by means of beta probability density functions (pdfs):

Variable	a	b	loc	scale
$\dot{m}_w$	0.444	1.009	0.222 kg/s	0.284
$\dot{T}_w$	0.847	0.666	592.9 K	21.58

Working fluids

- Six organic fluids, well known in ORC applications, have been selected as candidates for the parametric study
- The complex thermodynamic behaviour is described by multi-parameter equations of state (EOS) based on Helmholtz free-energy, as provided by the open-source library CoolProp

Fluid	Molecular weight (kg/kmol)	p_c (MPa)	T_c (K)
R245fa	134.05	3.651	427.01
R245ca	134.05	3.941	447.57
Novec649	316.04	1.869	441.81
R11	137.37	4.394	471.06
R134a	102.03	4.059	374.21
R113	187.38	3.392	487.21

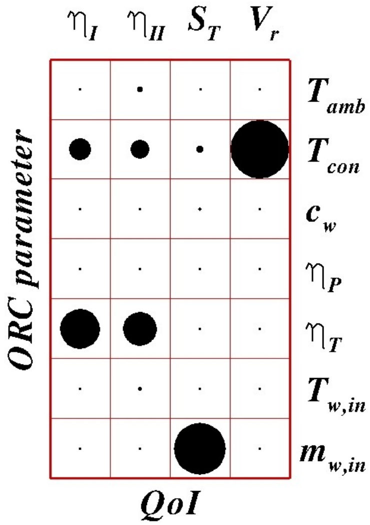
- The main ORC parameters are treated as uncertain → choice of suitable pdfs

Parameter	Distribution	Range
T_{amb} (K)	Uniform	[290-300]
T_{con} (K)	Uniform	[293.15-303.15]
c_w (J/kg-K)	Uniform	[1000-1200]
η_P	Uniform	[0.65-0.75]
η_T	Uniform	[0.75-0.85]
$T_{w,in}$ (K)	Beta	[592-615]
$\dot{m}_{w,in}$ (kg/s)	Beta	[0.1-0.5]

- The uncertainties are propagated through the ORC model by performing a large number of simulations → statistics reconstruction (mean and variance) by means of the **Monte Carlo** method

- Result for the **baseline** ORC configuration ($p_{ev} = 0.545 p_{cr}$, $\Delta T_{pp} = 8\ K$ and $\Delta T_{TIT} = 5\ K$):

Fluid	μ_{η_I}, CoV_{η_I} (%)	$\mu_{\eta_{II}}$, $CoV_{\eta_{II}}$ (%)	μ_{S_T} (m), CoV_{S_T} (%)	μ_{V_r}, CoV_{V_r} (%)
R245fa	0.145, 4.69	0.357, 4.99	0.0186, 14.2	15.8, 10.4
R245ca	0.161, 4.50	0.383, 4.76	0.0206, 14.38	25.4, 10.8
Novec649	0.122, 4.44	0.294, 4.73	0.0392, 14.5	33.3, 12.1
R11	0.187, 4.38	0.436, 4.65	0.0194, 14.12	23.7, 9.66
R134a	0.0878, 6.94	0.238, 7.20	0.0116, 13.80	3.66, 8.69
R113	0.188, 4.23	0.427, 4.47	0.0287, 14.4	47.8, 10.9



- Sensitivity analysis:
  - the main contributions to the total variance of the cycle performances, expressed in terms of first order Sobol' indices $\rightarrow$ **ANOVA**
  - **Circle diagram:**
    QoI $\rightarrow$ Quantity Of Interest

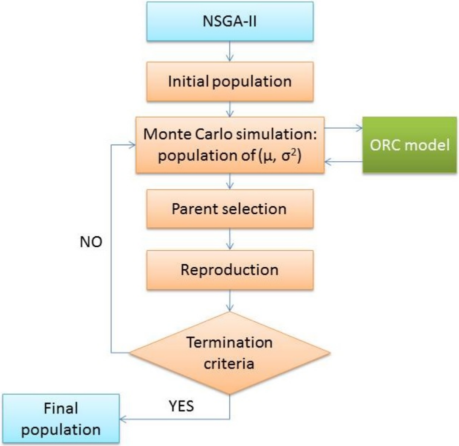
    Circle radius **proportional to the percent contribution** of the parameter to the global variance
- Turbine efficiency is the most influential parameter with respect to η_I and η_{II}
- Condensation temperature is the second most influential parameter

ORC deterministic optimization

- Our goal: find **the cycle parameters** maximizing cycle efficiency!
- Global optimization in the parameter set $\rightarrow$ **Single-objective Genetic Algorithm** (GA)
- Optimization variables (deterministic): $[p_{ev}, \Delta T_{pp}, \Delta T_{TIT}]$
- ORC parameters (deterministic): $T_{amb} = 295\ K$, $\dot{m}_w = 0.4$ kg/s, $T_{w,in} = 610\ K$, $T_{con} = 303\ K$, $c_w = 1100$ J/kg-K, $\eta_P = 0.7$, $\eta_T = 0.8$
- Constraints: $0.4 p_{cr} \leq p_{ev} \leq 0.8 p_{cr}$, $0.1K \leq \Delta T_{TIT} \leq 10K$, $7K \leq \Delta T_{pp} \leq 10K$
- Convergence reached after 11 generations with 40 individuals-per-generation
- Optimal individuals recalculated by **UQ**:

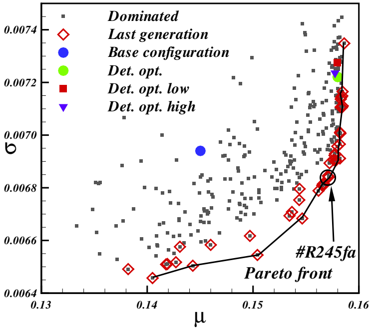
Fluid	μ_{η_I}, CoV_{η_I} (%)	$\mu_{\eta_{II}}$, $CoV_{\eta_{II}}$ (%)	μ_{S_T} (m), CoV_{S_T} (%)	μ_{V_r}, CoV_{V_r} (%)
R245fa	0.158, 4.57	0.441, 5.61	0.0244, 14.3	25.0, 10.4
R245ca	0.171, 4.40	0.524, 5.42	0.0288, 14.4	40.8, 10.8
Novec649	0.129, 4.37	0.393, 5.38	0.0610, 14.6	61.8, 12.1
R11	0.201, 4.27	0.609, 5.24	0.0287, 14.1	37.4, 9.60
R134a	0.108, 5.83	0.328, 6.88	0.0131, 13.8	5.70, 8.59
R113	0.198, 4.16	0.601, 5.12	0.0445, 14.4	76.6, 10.9

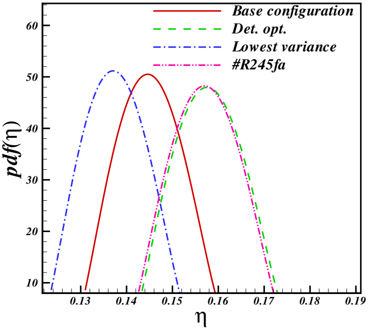
ORC RO optimization



- Our goal: find **the cycle parameters** maximising the **average** cycle efficiency while minimizing its **variance** $\rightarrow$ two-objective optimization problem
- Global optimization in the parameter set $\rightarrow$ **Non-dominated Sorting Genetic Algorithm** (NSGA-II)
- Optimization variables (deterministic): $[p_{ev},\ \Delta T_{pp},\ \Delta T_{TIT}]$
- ORC parameters (**uncertain**): $T_{amb},\ \dot{m}_w,\ T_{w,in},\ T_{con},\ c_w,\ \eta_P,\ \eta_T$
- Constraints:
  $0.4p_{cr} \leq p_{ev} \leq 0.8p_{cr}$
  $0.1K \leq \Delta T_{TIT} \leq 10K$
  $7K \leq \Delta T_{pp} \leq 10K$

ORC RO optimization: results





Case	μ_{η_I}, CoV_{η_I} (%)	$\mu_{\eta_{II}}$, $CoV_{\eta_{II}}$ (%)	μ_{S_T} (m), CoV_{S_T} (%)	μ_{V_r}, CoV_{V_r} (%)
#R245fa	0.157, 4.21	0.375, 4.57	0.0190, 14.01	24.1, 10.3
#R245ca	0.171, 4.26	0.397, 4.49	0.0216, 14.2	40.7, 10.8
#Novec649	0.129, 4.10	0.301, 4.30	0.0458, 13.8	61.4, 11.9
#R11	0.200, 4.07	0.45, 4.25	0.0196, 14.6	35.03, 9.54
#R134a	0.108, 5.53	0.281, 5.92	0.0118, 14.2	5.76, 8.46
#R113	0.198, 3.95	0.436, 4.18	0.0294, 14.5	78.4, 11.01

Conclusions

- Application of **UQ** to ORC for WHR heavy duty applications
- Sensitivity analysis showed that the **expander efficiency** and **the condensing temperature** are the most influential parameters with respect to the thermal and exergetic efficiencies
- Working fluids **R11** and **R113** provide the best performances for this application
  - This behaviour has been observed also after the deterministic optimization, with an improvement in terms of mean values and decrease of variability
- Robust optimization succeeds in reducing performance variability under random variations of the operating conditions
  - The **deterministic solution**, characterized by a high mean efficiency, can be also considered as a **good compromise**
- As future work, more detailed models for the heat exchanger will be considered, allowing to account, e.g., for uncertainties on the geometries and heat exchange coefficients
- Economic cost-functions can also be included in the multi-objective optimization problem

Thank You for the attention!