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

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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)**
CYCLE CONFIGURATION AND HEAT SOURCE CHARACTERIZATION

WORKING FLUIDS

UQ AND SENSITIVITY ANALYSIS

DETERMINISTIC OPTIMIZATION

ROBUST OPTIMIZATION

CONCLUSIONS
- **ORC parameters (model input):**
  - $T_{amb}$, $T_{con}$, $T_{w,in}$, $c_w$, $\dot{m}_{w,in}$
  - $\eta_P$, $\eta_T$
  - $p_{ev}$, $\Delta T_{pp}$, $\Delta T_{TIT}$

- **ORC performance (model output):**
  - $\eta_l = \frac{W_{net}}{Q_{in}}$
  - $\eta_{ll} = \frac{W_{net}}{[Q_{in}(1 - \frac{T_0}{T_m})]}$
  - $V_r = \frac{V_{t,out}}{V_{t,in}}$
  - $S_T = \frac{\nu_{0.5, out}}{\Delta H_{0.25}}$
The heat source is modelled by means of beta probability density functions (pdfs):

<table>
<thead>
<tr>
<th>Variable</th>
<th>a</th>
<th>b</th>
<th>loc</th>
<th>scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\dot{m}_w$</td>
<td>0.444</td>
<td>1.009</td>
<td>0.222 kg/s</td>
<td>0.284</td>
</tr>
<tr>
<td>$\dot{T}_w$</td>
<td>0.847</td>
<td>0.666</td>
<td>592.9 K</td>
<td>21.58</td>
</tr>
</tbody>
</table>
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.

<table>
<thead>
<tr>
<th>Fluid</th>
<th>Molecular weight (kg/kmol)</th>
<th>$p_c$ (MPa)</th>
<th>$T_c$ (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R245fa</td>
<td>134.05</td>
<td>3.651</td>
<td>427.01</td>
</tr>
<tr>
<td>R245ca</td>
<td>134.05</td>
<td>3.941</td>
<td>447.57</td>
</tr>
<tr>
<td>Novec649</td>
<td>316.04</td>
<td>1.869</td>
<td>441.81</td>
</tr>
<tr>
<td>R11</td>
<td>137.37</td>
<td>4.394</td>
<td>471.06</td>
</tr>
<tr>
<td>R134a</td>
<td>102.03</td>
<td>4.059</td>
<td>374.21</td>
</tr>
<tr>
<td>R113</td>
<td>187.38</td>
<td>3.392</td>
<td>487.21</td>
</tr>
</tbody>
</table>
ORC sensitivity analysis

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

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Distribution</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{amb}$ (K)</td>
<td>Uniform</td>
<td>[290-300]</td>
</tr>
<tr>
<td>$T_{con}$ (K)</td>
<td>Uniform</td>
<td>[293.15-303.15]</td>
</tr>
<tr>
<td>$c_w$ (J/kg-K)</td>
<td>Uniform</td>
<td>[1000-1200]</td>
</tr>
<tr>
<td>$\eta_P$</td>
<td>Uniform</td>
<td>[0.65-0.75]</td>
</tr>
<tr>
<td>$\eta_T$</td>
<td>Uniform</td>
<td>[0.75-0.85]</td>
</tr>
<tr>
<td>$T_{w,in}$ (K)</td>
<td>Beta</td>
<td>[592-615]</td>
</tr>
<tr>
<td>$\dot{m}_{w,in}$ (kg/s)</td>
<td>Beta</td>
<td>[0.1-0.5]</td>
</tr>
</tbody>
</table>

- 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 ($p_{ev} = 0.545p_{cr}$, $\Delta T_{pp} = 8$ K and $\Delta T_{TIT} = 5$ K):

<table>
<thead>
<tr>
<th>Fluid</th>
<th>$\mu_{\eta_I}$, CoV$_{\eta_I}$ (%)</th>
<th>$\mu_{\eta_{III}}$, CoV$<em>{\eta</em>{III}}$ (%)</th>
<th>$\mu_S$ (m), CoV$_S$ (%)</th>
<th>$\mu_{V_r}$, CoV$_{V_r}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R245fa</td>
<td>0.145, 4.69</td>
<td>0.357, 4.99</td>
<td>0.0186, 14.2</td>
<td>15.8, 10.4</td>
</tr>
<tr>
<td>R245ca</td>
<td>0.161, 4.50</td>
<td>0.383, 4.76</td>
<td>0.0206, 14.38</td>
<td>25.4, 10.8</td>
</tr>
<tr>
<td>Novec649</td>
<td>0.122, 4.44</td>
<td>0.294, 4.73</td>
<td>0.0392, 14.5</td>
<td>33.3, 12.1</td>
</tr>
<tr>
<td>R11</td>
<td>0.187, 4.38</td>
<td>0.436, 4.65</td>
<td>0.0194, 14.12</td>
<td>23.7, 9.66</td>
</tr>
<tr>
<td>R134a</td>
<td>0.0878, 6.94</td>
<td>0.238, 7.20</td>
<td>0.0116, 13.80</td>
<td>3.66, 8.69</td>
</tr>
<tr>
<td>R113</td>
<td>0.188, 4.23</td>
<td>0.427, 4.47</td>
<td>0.0287, 14.4</td>
<td>47.8, 10.9</td>
</tr>
</tbody>
</table>
**Sensitivity analysis:**
- The main contributions to the total variance of the cycle performances, expressed in terms of first order Sobol’ indices → **ANOVA**

**Circle diagram:**
QoI → 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 $\eta_I$ and $\eta_{II}$
- Condensation temperature is the second most influential parameter
Our goal: find the cycle parameters maximizing cycle efficiency!

Global optimization in the parameter set → Single-objective Genetic Algorithm (GA)

Optimization variables (deterministic): $[p_{ev}, \Delta T_{pp}, \Delta T_{TIT}]$

ORC parameters (deterministic): $T_{amb} = 295 \, K$, $\dot{m}_w = 0.4 \, \text{kg/s}$, $T_{w,in} = 610 \, K$, $T_{con} = 303 \, K$, $c_w = 1100 \, \text{J/kg-K}$, $\eta_P = 0.7$, $\eta_T = 0.8$

Constraints: $0.4p_{cr} \leq p_{ev} \leq 0.8p_{cr}$, $0.1K \leq \Delta T_{TIT} \leq 10K$, $7K \leq \Delta T_{pp} \leq 10K$

Convergence reached after 11 generations with 40 individuals-per-generation

Optimal individuals recalculated by UQ:

<table>
<thead>
<tr>
<th>Fluid</th>
<th>$\mu_{\eta_I}, \text{CoV}_{\eta_I} (%)$</th>
<th>$\mu_{\eta_{II}}, \text{CoV}<em>{\eta</em>{II}} (%)$</th>
<th>$\mu_{S_T} (m), \text{CoV}_{S_T} (%)$</th>
<th>$\mu_{V_r}, \text{CoV}_{V_r} (%)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>R245fa</td>
<td>0.158, 4.57</td>
<td>0.441, 5.61</td>
<td>0.0244, 14.3</td>
<td>25.0, 10.4</td>
</tr>
<tr>
<td>R245ca</td>
<td>0.171, 4.40</td>
<td>0.524, 5.42</td>
<td>0.0288, 14.4</td>
<td>40.8, 10.8</td>
</tr>
<tr>
<td>Novec649</td>
<td>0.129, 4.37</td>
<td>0.393, 5.38</td>
<td>0.0610, 14.6</td>
<td>61.8, 12.1</td>
</tr>
<tr>
<td>R11</td>
<td>0.201, 4.27</td>
<td>0.609, 5.24</td>
<td>0.0287, 14.1</td>
<td>37.4, 9.60</td>
</tr>
<tr>
<td>R134a</td>
<td>0.108, 5.83</td>
<td>0.328, 6.88</td>
<td>0.0131, 13.8</td>
<td>5.70, 8.59</td>
</tr>
<tr>
<td>R113</td>
<td>0.198, 4.16</td>
<td>0.601, 5.12</td>
<td>0.0445, 14.4</td>
<td>76.6, 10.9</td>
</tr>
</tbody>
</table>
Our goal: find the cycle parameters maximising the average cycle efficiency while minimizing its variance → two-objective optimization problem

Global optimization in the parameter set → 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

### Pareto front

- Dominated
- Last generation
- Base configuration
- Det. opt.
- Det. opt. low
- Det. opt. high

**#R245fa**

### pdf(η)

<table>
<thead>
<tr>
<th>Case</th>
<th>$\mu_{\eta_I}$, CoV$_{\eta_I}$ (%)</th>
<th>$\mu_{\eta_{II}}$, CoV$<em>{\eta</em>{II}}$ (%)</th>
<th>$\mu_{S_T}$ (m), CoV$_{S_T}$ (%)</th>
<th>$\mu_{V_r}$, CoV$_{V_r}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#R245fa</td>
<td>0.157, 4.21</td>
<td>0.375, 4.57</td>
<td>0.0190, 14.01</td>
<td>24.1, 10.3</td>
</tr>
<tr>
<td>#R245ca</td>
<td>0.171, 4.26</td>
<td>0.397, 4.49</td>
<td>0.0216, 14.2</td>
<td>40.7, 10.8</td>
</tr>
<tr>
<td>Novec649</td>
<td>0.129, 4.10</td>
<td>0.301, 4.30</td>
<td>0.0458, 13.8</td>
<td>61.4, 11.9</td>
</tr>
<tr>
<td>#R11</td>
<td>0.200, 4.07</td>
<td>0.45, 4.25</td>
<td>0.0196, 14.6</td>
<td>35.03, 9.54</td>
</tr>
<tr>
<td>#R134a</td>
<td>0.108, 5.53</td>
<td>0.281, 5.92</td>
<td>0.0118, 14.2</td>
<td>5.76, 8.46</td>
</tr>
<tr>
<td>#R113</td>
<td>0.198, 3.95</td>
<td>0.436, 4.18</td>
<td>0.0294, 14.5</td>
<td>78.4, 11.01</td>
</tr>
</tbody>
</table>
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!