

# TOWARDS THE OPTIMAL OPERATION OF AN ORGANIC RANKINE CYCLE UNIT BY MEANS OF MODEL PREDICTIVE CONTROL

Andres Hernandez<sup>1,2\*</sup>, Adriano Desideri<sup>2</sup>, Clara Ionescu<sup>1</sup>, Sylvain Quoilin<sup>2</sup>,  
Vincent Lemort<sup>2</sup>, Robin De Keyser<sup>1</sup>

<sup>1</sup> Ghent University, Department of Electrical energy, Systems and Automation, Ghent, Belgium  
andres.hernandez@ugent.be, claramihaela.ionescu@ugent.be, robain.dekeyser@ugent.be

<sup>2</sup> University of Liège, Aerospace and Mechanical engineering department, Liège, Belgium  
adesideri@ulg.ac.be, squoilin@ulg.ac.be, vincent.lemort@ulg.ac.be

\* Corresponding Author

## ABSTRACT

In this paper the optimal operation of an Organic Rankine Cycle (ORC) unit is investigated both in terms of energy production and safety conditions. Simulations on a validated dynamic model of a real regenerative ORC unit, are used to illustrate the existence of an optimal evaporating temperature which maximizes energy production for some given heat source conditions. This idea is further extended using a perturbation based Extremum Seeking (ES) algorithm to find online the optimal evaporating temperature. Regarding safety conditions we propose the use of the Extended Prediction Self-Adaptive Control (EPSAC) approach to constrained Model Predictive Control (MPC). Since it uses input/output models for prediction, it avoids the need of state estimators, making of it a suitable tool for industrial applications. The performance of the proposed control strategy is compared to PID-like schemes. Results show that EPSAC-MPC is a more effective control strategy as it allows a safer and more efficient operation of the ORC unit, as it can handle constraints in a natural way, operating close to the boundary conditions where power generation is maximized.

## 1. INTRODUCTION

In recent years several studies have underlined the potential of low-grade heat recovery to reduce the amount of worldwide industrial energy consumption (IEA, 2010). The highly fluctuating nature of the heat source makes waste heat recovery (WHR) applications a challenging task. Organic Rankine Cycle (ORC) systems represent the most promising technology for WHR, where the main objectives to optimally operate the system are twofold: 1) keep the cycle in a safe condition and 2) maximize the net output power.

Safe operation of the ORC unit is important as it allows a longer life expectancy in all components. In this regard, an accurate regulation of the superheating represents an important task for the controller. The regulator has to guarantee a minimum value of superheating in order to maximize the efficiency, and to avoid the formation of liquid droplets at expander inlet that can damage the expansion machine (Wei et al., 2007). On the other hand, in order to maximize the output power, the evaporating temperature represents the most relevant controlled variable (Quoilin et al., 2011; Hernandez et al., 2015).

In this contribution we propose a two-layer control structure to guarantee the optimal operation of an ORC unit for waste heat recovery applications: an Extremum Seeking (ES) algorithm to find on-line the optimal evaporating temperature, which is later given as reference to a constrained Model Predictive Controller (MPC).

Extremum Seeking is a well developed research area which addresses the problem of objective value optimization when the objective function, its gradient and optimum value are unknown (Ariyur and

Krstic, 2003). In this study we make use of a perturbation based ES to find the evaporating temperature that maximizes the output power for the case of heat source variations. The performance of the ES algorithm is compared to the correlation obtained directly from the dynamic nonlinear model.

A possible drawback for ES algorithms appears for the case when the extremum causes other variables to violate safety limits. One option to tackle this situation is to design a complex ES algorithm which accounts for constraints as proposed in (De Hann and Guay, 2005). Here, instead we propose to use a simple ES algorithm and let a local controller to deal with constraints, e.g., taking actions for the cases when superheating is below a threshold value. The Extended Prediction Self-Adaptive Control (EPSAC) approach to constrained Model Predictive Control is proposed as local control strategy. Since it uses input/output models for prediction and not state-space models as in other MPC algorithms (Maciejowski, 2002), it avoids the need of state estimators, making of it a suitable tool for industrial applications. The performance of the proposed EPSAC-MPC strategy is compared to the one achieved using PI-like strategies.

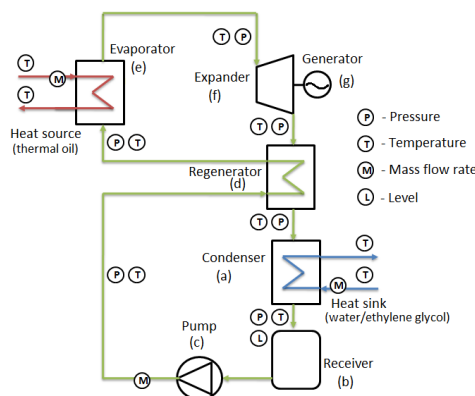
The paper is structured as follows: a description of the ORC process is presented in section 2, followed by a brief description of the adaptive Extremum Seeking algorithm in section 3. Next in section 4 the EPSAC-MPC algorithm is formulated, followed by the discussion of the simulation results in section 5. Finally a conclusion section summarizes the main outcome of this contribution.

## 2. PROCESS DESCRIPTION

This section describes the architecture and main characteristics of the ORC system used for evaluating the performance of the developed control strategies.

### 2.1 The Organic Rankine Cycle System

In order to assess the performance of the different developed control strategies, a dynamic model of the ORC system presented in Fig. 1 has been developed in the Modelica language using existent components from the ThermoCycle library (Quoilin et al., 2014). The developed model is then exported into Simulink/Matlab environment by means of the Functional Mock-Up Interface (FMI) open standard.



**Figure 1: Schematic layout of the pilot plant available at Ghent University, campus Kortrijk (Belgium)**

The system based on a regenerative cycle and solkatherm (SES36) as working fluid, shows a nominal power of 11 *kWe*. The expander is originally a single screw compressor adapted to run in expander mode. It drives an asynchronous generator connected to the electric grid through a four-quadrant inverter, which allows varying the generator rotational speed ( $N_{exp}$ ). During the simulations performed in this paper, the generator rotational speed is kept constant at 3000 *rpm* to emulate an installation directly connected to the grid. The circulating pump ( $N_{pp}$ ) is a vertical variable speed 14-stage centrifugal pump with a maximum pressure of 14 bar and 2.2 *kWe* nominal power.

Starting from the bottom of the scheme it is possible to recognize the liquid receiver (b) installed at the outlet of the condenser (a) where the fluid is collected in saturated liquid condition. From the receiver outlet, the fluid is pumped (c) through the regenerator (d) cold side, and the evaporator (e), where it is heated up to superheated vapor, reaching its maximum temperature at the evaporator outlet. The fluid, after being expanded in the volumetric machine (f), enters the regenerator hot side, and then it flows into the condenser (a) to close the cycle.

## 2.2 Conditions for optimal operation of an ORC unit

In order to optimally operate an ORC unit, two main conditions need to be satisfied: **1)** keep the cycle in a safe condition during operation and **2)** maximize the net output power. Safe operation of the ORC unit is important as it allows a longer life expectancy in all components. In this concern, an accurate regulation of superheating ( $\Delta T_{sh}$ ), is the main priority since a minimum value of superheating has to be guaranteed in order to avoid a wet expansion (i.e., formation of liquid droplets at the expander inlet that can damage the expansion machine). The superheating is defined as:

$$\Delta T_{sh} = T_{exp,su} - T_{sat,ev} \quad (1)$$

where  $T_{exp,su}$  is the temperature measured at the inlet of the expander and  $T_{sat,ev}$  the evaporating temperature, corresponding to the temperature at which the fluid undergoes the phase transition from saturated liquid to saturated vapor at the fixed evaporating pressure  $p_{sat,ev}$ .

$$T_{sat,ev} = f(p_{sat,ev}) \quad (2)$$

where  $f$  corresponds to a function that correlates the pressure for the refrigerant.

In order to maximize the output power the evaporating temperature represents the most relevant control variable (Quoilin et al., 2011), which needs to be adapted depending on the heat source conditions (Hernandez et al., 2015). The main terms to assess the performance of the ORC system are the net output power and the cycle efficiency, which are defined as:

$$\dot{W}_{el,net} = \dot{W}_{exp} - \dot{W}_{pump} \quad (3)$$

$$\eta_{cycle} = \frac{\dot{W}_{el,net}}{\dot{Q}_{in,ORC}} \quad (4)$$

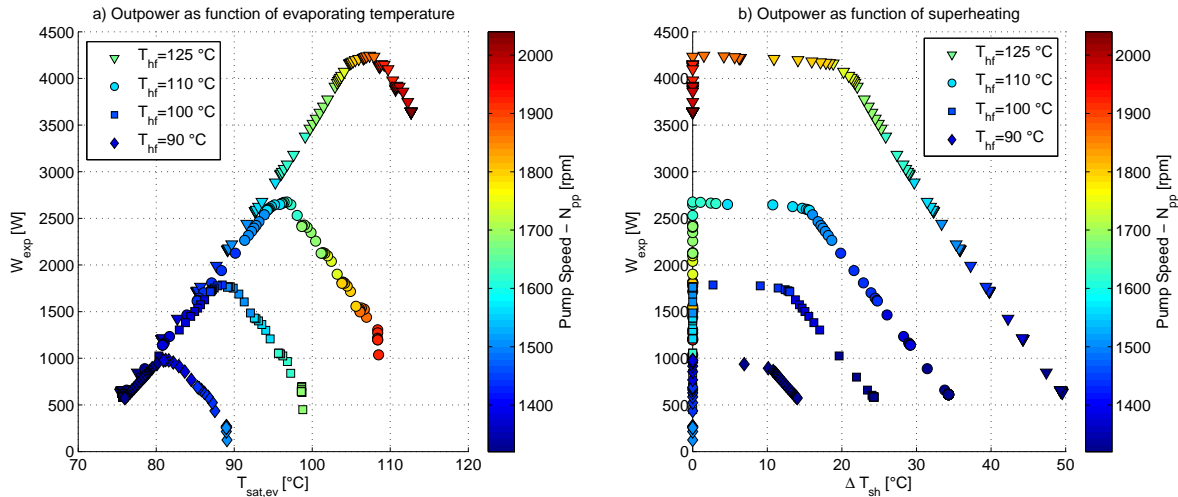
where  $\dot{W}_{exp}$  is the expander electrical power,  $\dot{W}_{pump}$  is the pump electrical power and  $\dot{Q}_{in,ORC}$  is the thermal power supplied to the ORC system in the evaporator.

## 2.3 Optimal evaporating temperature

The developed Modelica dynamic model has been used to gain insight on the system's dynamics, in particular on the relationship between superheating ( $\Delta T_{sh}$ ), evaporating temperature ( $T_{sat,ev}$ ), pump speed ( $N_{pp}$ ) and expander electrical power ( $\dot{W}_{exp}$ ). The simulation consists on decreasing the pump speed  $N_{pp}$  from maximum to minimum in small steps. The same experiment is performed for different heat source conditions, temperature and mass flow, in the ranges  $T_{hf} = \{90, 100, 110, 125\}^\circ\text{C}$  and  $\dot{m}_{hf} = \{0.5, 0.8, 1.0, 1.5\} \text{ kg/s}$ , while temperature and mass flow in the heat sink  $T_{cf}$  and  $\dot{m}_{cf}$  were kept constant at  $15^\circ\text{C}$  and  $4 \text{ kg/s}$ , respectively. The results for the case of  $\dot{m}_{hf} = 1.0 \text{ kg/s}$  are depicted in Fig. 2, where the expander electrical power  $\dot{W}_{exp}$  is represented as a function of  $T_{sat,ev}$  and  $\Delta T_{sh}$ . Fig. 2a shows how, for each heat source condition, the expander output power initially grows for increasing evaporating temperature until it reaches a maximum. This is a consequence of the working fluid mass flow that is circulated in the system, see the pump rotational speed value. As the pump speed increases further, two-phase condition appears at the evaporator outlet and a lower output power is registered. Fig. 2b shows the relation between expander output power and superheating level for the same heat source conditions as in Fig. 2a. The power increases as the level of superheating decreases. Notice also that for values of superheating lower than  $10^\circ\text{C}$  there is not much gain in the output power. Using the current data it is then possible to derive a correlation for the optimal evaporating temperature as a function of the heat source conditions:

$$T_{sat,opt} = -290.915 + 183.33 * \log_{10}(T_{hf}) + 10.636 * \dot{m}_{hf} \quad (5)$$

Equation (5) is valid in the range of  $0.5 \leq \dot{m}_{hf} \leq 1.5 \text{ kg/s}$  and  $90 \leq T_{hf} \leq 125^\circ\text{C}$  given a constant saturation temperature in the condenser of  $p_{sat,cd} = 1.4 \text{ bar}$ .



**Figure 2: Understanding the operation of an ORC unit. Relationship between output power and a) evaporating temperature and b) superheating for four different heat source conditions  $T_{hf} = \{90, 100, 110, 125\} \text{ }^\circ\text{C}$  with  $\dot{m}_{hf} = 1.0 \text{ kg/s}$ .**

### 3. ADAPTIVE OPTIMIZATION

As presented in section 2.3, in order to maximize the output power it is necessary to find the optimal evaporating temperature for some given heat source conditions. If a dynamic model of the system is known, one can then build a correlation which satisfies also safety conditions. However, there are two drawbacks in this approach: first, a validated dynamic model is not always available and second, there will be modeling errors and consequently a biased correlation.

In this contribution we follow a different approach, by using an Extremum Seeking (ES) algorithm to find the optimal evaporating temperature, which maximizes the output power without the need of a model. Extremum Seeking is a well developed field that addresses the problem of objective value optimization when the objective function, its gradient and optimum value are unknown (Ariyur and Krstic, 2003). These techniques are categorized into five main groups: sliding mode ES, neural network ES, approximation based ES, perturbation based ES and adaptive ES. From those the perturbation based ES framework is the most popular method in literature (Ariyur and Krstic, 2003). Since it has proved to be more robust to noise and dynamic effects in the system, thus producing smoother references which decrease the risk of instability (Zhang and Ordonez, 2012).

The control structure here proposed is depicted in Fig. 3. A *perturbation based ES algorithm* is in charge of finding the extremum  $T_{sat,opt}$  that arises from the reference-to-output nonlinear map (i.e.,  $T_{sat,ev}$  to  $\dot{W}_{exp}$ ), while a local feedback controller will keep the system stable at that equilibrium optimal point.

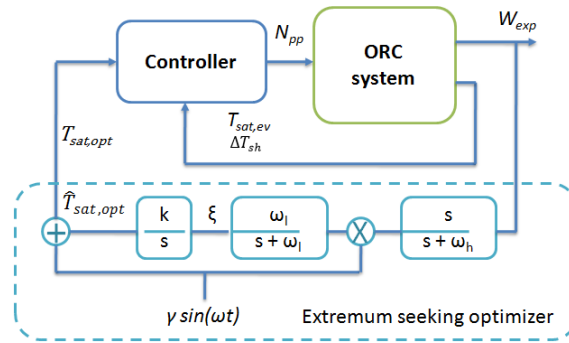
The ES algorithm works as follows: it sends a sine wave to the system as position reference together with an adaptation input:

$$T_{sat,opt} = \gamma \sin(\omega t) + \hat{T}_{sat,opt} \quad (6)$$

with some amplitude  $\gamma$  and modulation frequency  $\omega$ . The adaptation signal  $\hat{T}_{sat,opt}$  shifts the sine wave towards the gradient direction, thus (6) is the modulation phase of the algorithm. The response of the system to this signal is measured in the objective value ( $\dot{W}_{exp}$ ). This output is filtered by a high-pass filter to eliminate the DC component and demodulated by the same sine signal to extract the gradient direction.

$$\zeta = W_{exp} \left( \frac{\omega_l}{s + \omega_l} \right) \left( \frac{s}{s + \omega_h} \right) (\gamma \sin(\omega t)) \quad (7)$$

This information is used to calculate the shift in the sine signal towards the gradient. Next the adaptation



**Figure 3: Perturbation based extremum seeking algorithm applied to the ORC system.**

law is computed:

$$\hat{T}_{sat,opt} = \zeta \frac{k}{s} \quad (8)$$

where  $k$  is a positive constant that specifies the adaptation speed. Since only the DC component of the demodulated signal is needed for gradient calculation, a low pass filter is often used. The amplitude and frequency of the sine wave signal and the cutoff frequencies of the filters are important design parameters. A detailed study of how the design of the perturbation signal affects the performance of the ES algorithm is presented in (Krstic, 2000).

#### 4. MODEL PREDICTIVE CONTROL

A brief introduction to EPSAC algorithm is presented in this section. For a detailed description the reader is referred to (De Keyser, 2003; Hernandez et al., 2015).

##### 4.1 Computing the Predictions

Using EPSAC algorithm, the measured process output can be represented as:

$$y(t) = x(t) + n(t) \quad (9)$$

where  $x(t)$  is the model output which represents the effect of the control input  $u(t)$  and  $n(t)$  represents the effect of the disturbances and modeling errors, all at discrete-time index  $t$ . Model output  $x(t)$  can be described by the generic system dynamic model:

$$x(t) = f[x(t-1), x(t-2), \dots, u(t-1), u(t-2), \dots] \quad (10)$$

Notice that  $x(t)$  represents here the model output, not the state vector. Also important is the fact that  $f$  can be either a *linear* or a *nonlinear* function.

Furthermore, the disturbance  $n(t)$  can be modeled as colored noise through a filter with the transfer function:

$$n(t) = \frac{C(q^{-1})}{D(q^{-1})} e(t) \quad (11)$$

with  $e(t)$  uncorrelated (white) noise with zero-mean and  $C, D$  monic polynomials in the backward shift operator  $q^{-1}$ . The disturbance model must be designed to achieve robustness of the control loop against unmeasured disturbances and modeling errors (Maciejowski, 2002).

A fundamental step in the EPSAC methodology consists of the prediction. Using the generic process model (9), the predicted values of the output are:

$$y(t+k|t) = x(t+k|t) + n(t+k|t) \quad (12)$$

$x(t+k|t)$  and  $n(t+k|t)$  can be predicted by recursion of the process model (10) and by using filtering techniques on the noise model (11), respectively (De Keyser, 2003).

## 4.2 Computing the optimal control action

A key element in linear MPC is the use of base (or free) and optimizing (or forced) response concepts (Camacho and Bordons, 2004). In EPSAC, the future response can be expressed as:

$$y(t+k|t) = y_{base}(t+k|t) + y_{optimize}(t+k|t) \quad (13)$$

The two contributing factors have the following origin:

- $y_{base}(t+k|t)$  is the effect of the past inputs, the apriori defined future base control sequence  $u_{base}(t+k|t)$  and the predicted disturbance  $n(t+k|t)$ .
- $y_{optimize}(t+k|t)$  is the effect of the additions  $\delta u(t+k|t)$  that are optimized and added to  $u_{base}(t+k|t)$ , according to  $\delta u(t+k|t) = u(t+k|t) - u_{base}(t+k|t)$ . The effect of these additions is the discrete time convolution of  $\Delta U = \{\delta u(t|t), \dots, \delta u(t+N_u-1|t)\}$  with the impulse response coefficients of the system (G matrix), where  $N_u$  is the chosen control horizon.

The control  $\Delta U$  is the solution to the following constrained optimization problem:

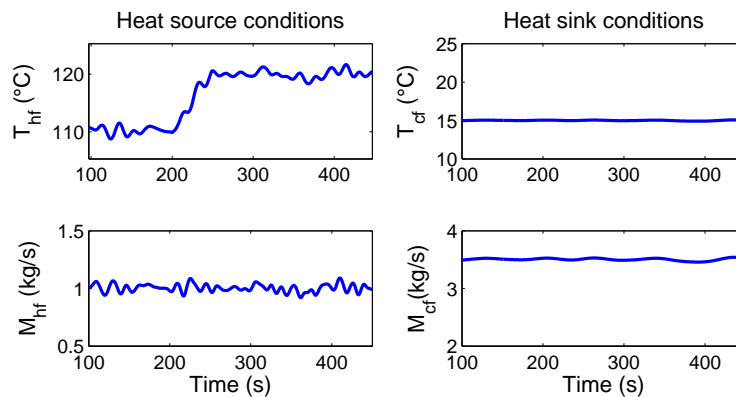
$$\Delta U = \arg \min_{\Delta U \in \mathbb{R}^{N_u}} \sum_{k=N_1}^{N_2} [r(t+k|t) - y(t+k|t)]^2 \quad (14)$$

subject to  $A \cdot \Delta U \leq B$

where  $N_1$  and  $N_2$  are the minimum and maximum prediction horizons,  $N_u$  is the control horizon,  $r(t+k|t)$  is a future setpoint or reference sequence. The various process input and output constraints can all be expressed in terms of  $\Delta U$ , resulting in matrices  $A$ ,  $B$ . Since (14) is quadratic with linear constraints in decision variables  $\Delta U$ , then the minimization problem can be solved by a quadratic programming (QP) algorithm (Maciejowski, 2002; Camacho and Bordons, 2004).

## 5. SIMULATION RESULTS

The developed ES algorithm is tested in simulation using the proposed EPSAC-MPC strategy and two PI-like strategies. The heat source and heat sink profiles of the ORC system are depicted in Fig. 4. The main variation in the heat source is due to an increase in the temperature ( $T_{hf}$ ) from  $110^\circ\text{C}$  to  $120^\circ\text{C}$ . Other heat source and heat sink variables are rather constant with some small variations around the operating point.



**Figure 4: Temperature and mass flow rate of the defined heat source and heat sink.**

### 5.1 Low-order model for prediction

MPC requires of a low-order model suitable for prediction. Following a similar approach as the one performed in (Hernandez et al., 2015), the model has been identified from the manipulated variable: pump

speed ( $N_{pp}$ ) to the evaporating temperature ( $T_{sat,ev}$ ) and superheating ( $\Delta T_{sh}$ ). Notice that the temperature  $T_{hf}$  in the heat source also influences  $T_{sat,ev}$  and  $\Delta T_{sh}$ , thus becoming a measured disturbance. As result we are interested on identifying a system consisting of 2 inputs (one manipulated and one measured disturbance) and 2 outputs.

A linear parametric identification is thus performed in the system using the prediction error minimization method from the data collected using a multisine excitation signal (Ljung, 2007). The identified model presented in (15) is in the form of discrete-time transfer functions for a sampling time  $T_s = 1 s$ .

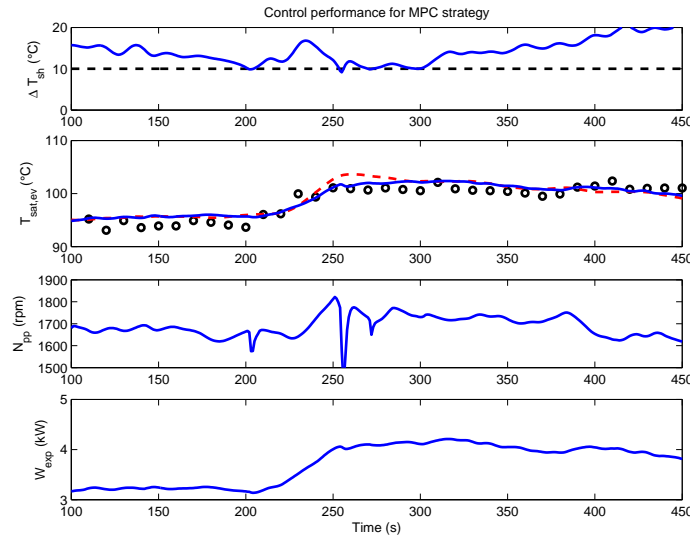
$$\Delta T_{sh}(q) = \frac{-0.063q^{-1}+0.059q^{-2}}{1-2.44q^{-1}+1.955q^{-2}-0.51q^{-3}}N_{pp}(q) + \frac{0.47q^{-1}}{1-0.51q^{-1}}T_{hf}(q) \quad (15a)$$

$$T_{sat,ev}(q) = \frac{0.066q^{-1}-0.063q^{-2}}{1-2.42q^{-1}+1.91q^{-2}-0.49q^{-3}}N_{pp}(q) + \frac{0.0017q^{-11}-0.0017q^{-12}}{1-3.6q^{-1}+4.88q^{-2}-2.95q^{-3}+0.67q^{-4}}T_{hf}(q) \quad (15b)$$

## 5.2 Performance of ES with constrained EPSAC-MPC strategy

The MPC control objective consists in tracking the optimal setpoint generated by the optimizer (Fig. 3), while keeping the superheating above a desired threshold value to guarantee a safe operation. The control strategy must satisfy these conditions using only one degree of freedom (i.e. pump speed  $N_{pp}$ ), while satisfying actuator constraints ( $N_{pp,min} = 1320 rpm$ ;  $N_{pp,max} = 2100 rpm$ ;  $\Delta N_{pp} = 100 rpm$ ) and constraints at the process output ( $\Delta T_{sh,min} = 10^\circ C$ ).

The EPSAC-MPC controller is tuned for horizons  $N_1 = 1$ ,  $N_2 = 15$  and  $N_u = 1$ . While the ES optimizer is tuned for  $k = 1/38$ ,  $\omega_l = 0.02 rad/s$ ,  $\omega_h = 0.1 rad/s$ ,  $\gamma = 0.05$  and  $\omega = 0.06 rad/s$ . Its performance is depicted in Fig. 5.

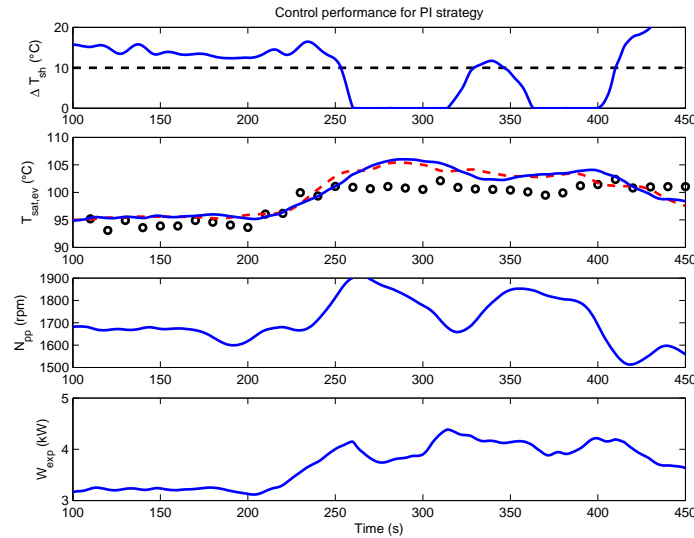


**Figure 5: Control performance of MPC. Dashed-red line represents the ES optimizer while black-circles represents the optimizer obtained from the dynamic model.**

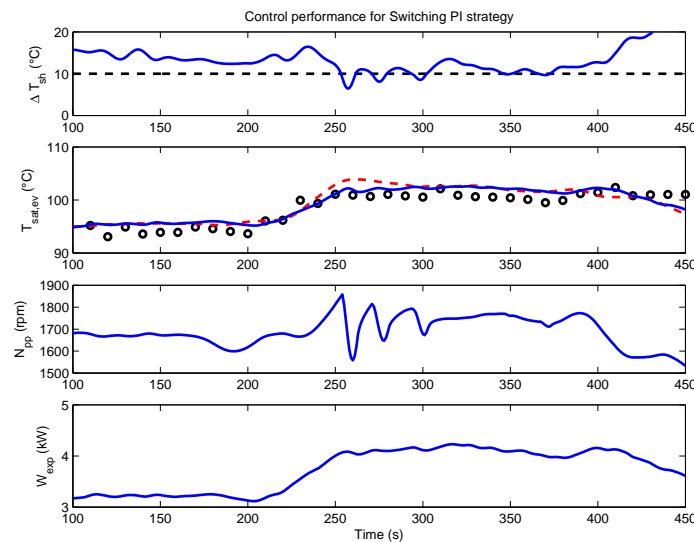
Two important elements must be analyzed from results in Fig. 5. First, two optimal evaporating temperatures are present, one computed using the ES algorithm (dashed red line) and the other (black circles) computed from correlation (5). The ES algorithm is able to adapt properly to the heat source variation, maximizing the output power. Second, it is important to notice that in the time range between 250 and 300 seconds, the controller is not following the setpoint but it rather brings the evaporating temperature closer to the reference computed using correlation (5). This is due to the active constraint in superheating, which causes the controller to take actions in the pump to bring the system in a safer regime (i.e.,  $\Delta T_{sh} > 10^\circ C$ ). Remember that equation (5) was computed to ‘guarantee’ superheating will remain above  $10^\circ C$ .

### 5.3 Performance of ES with PI-like strategies

The EPSAC-MPC strategy is replaced by two PI-like controllers, in order to compare the performance. The first strategy consists on a PI controller used to track the reference given by the ES optimizer. The second strategy consists in using a PI controller to track the optimal evaporating temperature unless superheating goes below the threshold value of  $10^{\circ}\text{C}$ , in which case a second PI controller for superheating with reference at  $(\Delta T_{sh,ref} = 10^{\circ}\text{C})$  is activated, thus bringing the system back into a safer regime.



**Figure 6: Control performance for a PI strategy. Dashed-red line represents the ES optimizer while black-circles represents the optimizer obtained from the dynamic model.**



**Figure 7: Control performance for a switching PI strategy. Dashed-red line represents the ES optimizer while black-circles represents the optimizer obtained from the dynamic model.**

The result for the single PI strategy is depicted in Fig. 6. The ES optimizer (dashed red line) adapts the reference to the local PI controller, finding the point which maximizes the output power. As known from section 2.3 and Fig. 2 this maximum corresponds to zero superheating values. Since this strategy does not supervise superheating, once the controller tracks this reference the system reaches zero superheating, decreasing the generated power  $W_{exp}$  as observed at time 250 to 300 seconds and 350 to 400 seconds.



Next it is evaluated the performance of the switching PI strategy as depicted in Fig. 7. In this case the controller tracks the reference generated by the ES optimizer (dashed red line); but once it detects superheating values below  $10^{\circ}\text{C}$ , the PI controller for superheating becomes active. Thus avoiding that the organic fluid is in two-phase (i.e., gas and liquid phase) which would decrease the performance of the system as observed for the single PI strategy. Although the switching mechanism avoids superheating going to zero, it still reaches values near  $5^{\circ}\text{C}$  and requires of more aggressive control actions which increases power consumption in the pump compared to the EPSAC-MPC. Nevertheless, its simplicity is still remarkable.

#### 5.4 Discussion of the obtained results

Although safety is highly important for Rankine cycles, it is also interesting to look into the net energy produced. Using results from Fig. 5 and Fig. 7, the net output power is calculated using (3). These values of net output power are further integrated over time to obtain the energy produced for each of the control strategies.

Taking the switching PI as a reference (100%), the EPSAC-MPC strategy allows increasing the *net energy production* by 21%. This is due to a better handling of the constraints, thus operating the system closer to the constraint for superheating while requiring a lower control effort (i.e., less power consumption in the pump) as observed in the results during the time from 250 to 300 seconds.

In an industrial context the single PI strategy solely is not safe to be applied, therefore its output power is not computed.

## 6. CONCLUSIONS

In this contribution a two layer control structure to achieve constrained optimal operation of an organic Rankine cycle unit for waste heat recovery applications is proposed. First, an optimizer based on a perturbation based extremum seeking algorithm is designed and implemented, to find the near-to-optimal evaporating temperature which maximizes energy production. Second, a constrained model predictive controller is implemented to track the optimal evaporating temperature given by the optimizer, while keeping the safety limit for superheating. Finally, the performance of the resulting loop is compared to PI control strategies. It is shown that a single PI cannot guarantee safety conditions, therefore a switching PI is proposed, resulting in a safer operation compared to a single PI but less effective compared to model predictive control since it violates safety limit for superheating and produces a lower net output power.

Future work will include the development of a multivariable control strategy by making use of the expander speed, as an additional manipulated variable.

## NOMENCLATURE

ORC	Organic Rankine Cycle	
WHR	Waste Heat Recovery	
MPC	Model Predictive Control	
EPSAC	Extended Prediction Self-Adaptive Control	
PI	Proportional-Integral Control	
ES	Extremum Seeking	
$\dot{m}$	Mass flow rate	(kg/s)
$\dot{W}$	Power	(W)
N	Rotational speed	(rpm)
p	Pressure	(Pa)
T	Temperature	( $^{\circ}\text{C}$ )

Subscript		Greek letter	
el	Electric	$\eta$	Efficiency
ev	Evaporator	$\gamma$	Amplitude perturbation in ES algorithm
exp	Expander	$\alpha$	Time constant reference trajectory in MPC
pp	Pump		

## REFERENCES

- Ariyur, K. and Krstic, M. (2003). *Real-Time optimization by Extremum-Seeking Control*. John Wiley & sons.
- Camacho, E. F. and Bordons, C. (2004). *Model Predictive Control*, volume 405 pages. Springer-Verlag, London,, 2nd edition.
- De Hann, D. and Guay, M. (2005). Extremum-seeking control of state-constrained nonlinear systems. *Automatica*, 41:pp. 1567–1574.
- De Keyser, R. (2003). *Model based Predictive Control for Linear Systems*, chapter invited in UNESCO Encyclopaedia of Life Support Systems (EoLSS). Article contribution 6.43.16.1, Eolss Publishers Co Ltd, Oxford, 35p.
- Hernandez, A., Desideri, A., Ionescu, C., Quoilin, S., Lemort, V., and De Keyser., R. (2015). Experimental study of predictive control strategies for optimal operation of organic rankine cycle systems. In *Proceedings of the European Control Conference (ECC15)*, Linz, Austria.
- IEA (2010). Industrial excess heat recovery technologies & applications. Technical report, Technical report, Industrial Energy-related Technologies and Systems (IETS).
- Krstic, M. (2000). Performance improvement and limitations in extremum seeking control. *systems and control letters*, vol. 39:pp. 313–326.
- Ljung, L. (2007). *System identification: theory for the user*. Prentice-Hall.
- Maciejowski, J. (2002). *Predictive Control: With Constraints*. Pearson Education. Prentice Hall.
- Quoilin, S., Aumann, R., Grill, A., Schuster, A., and Lemort., V. (2011). Dynamic modeling and optimal control strategy for waste heat recovery organic rankine cycles. *Applied Energy*, Vol. 88:2183–2190.
- Quoilin, S., Desideri, A., Wronski, J., Bell, I., and Lemort., V. (2014). Thermocycle: A modelica library for the simulation of thermodynamic systems. In *Proceedings of the 10th International Modelica Conference*, Lund, Sweden.
- Wei, D., Lu, X., Lu, Z., and Gu., J. (2007). Performance analysis and optimization of organic rankine cycle (orc) for waste heat recovery. *J. Energy Conversion and Management*, Vol. 48:1113–1119.
- Zhang, C. and Ordonez, R. (2012). *Extremum-Seeking Control and Applications. A Numerical Optimization-Based Approach*. Advances in Industrial Control. Springer-Verlag.

## ACKNOWLEDGEMENT

The results presented in this paper have been obtained within the frame of the IWT SBO-110006 project The Next Generation Organic Rankine Cycles ([www.orcnext.be](http://www.orcnext.be)), funded by the Institute for the Promotion and Innovation by Science and Technology in Flanders. This financial support is gratefully acknowledged.