Performance evaluation of MPC for Waste Heat Recovery applications using organic Rankine cycle systems ⋆

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Abstract: Organic Rankine Cycle (ORC) technology has demonstrated to be a suitable tool for recovering waste heat at low temperatures. The fluctuating nature of the waste heat source (varying temperature and mass flow) makes of waste heat recovery applications a challenging task. In this contribution Model Predictive Control (MPC) and more classical PID-like controllers are investigated, where special attention is paid to the analysis of the control performance for heat source profiles coming from different applications. A dynamic model of a real regenerative ORC unit equipped with a single screw expander developed in the Modelica language is used to test and compare the PID and MPC based control strategies. Results show that for low amplitude variations PID and MPC can perform equally good, but in case of large variations MPC is a more effective control strategy as it allows a safer and more efficient operation, operating close to the boundary conditions where production is maximized.

Keywords: Model Predictive control, Renewable energy systems, Process control, organic Rankine Cycle.

1. INTRODUCTION

Reducing the world-wide industrial energy consumption is a major concern in order to ensure guarantee a sustainable development. Despite all efforts to achieve a more efficient production, waste heat losses are still an important concern. An attractive technology able to recover heat at low temperatures is the Organic Rankine Cycle (ORC) system.

ORC power units stand out for their reliability and cost-effectiveness Verneau (1979),Angelino et al. (1984). Replacing the water by an organic compound opened new challenges, regarding the cycle design, selection of the fluid, modeling, simulation and control design Sun and Li. (2011); Colonna and Van Putten. (2007). Such thermodynamic units are designed to operate around certain steady-state conditions, however due to the highly fluctuating nature of the heat source, they are forced to operate at part-load conditions. Control design plays an essential role to enable a safe and optimal performance of the ORC unit. Safe operation is achieved by an accurate regulation of the superheating, since it is already recognized that low values for superheating maximize the cycle efficiency Hernandez et al. (2014) and avoid the formation of liquid droplets at expander inlet that can damage the expansion machine Wei et al. (2007).

Most of the current studies are restricted to guarantee safety conditions by regulating the superheating (see Grelet et al. (2015) and the references therein), but little attention has been paid to the performance of the power unit in terms of energy production. In order to maximize the output power the evaporating temperature is usually considered as the most relevant controlled variable Quoilin et al. (2011). In Feru et al. (2014), the modeling and control of a waste heat recovery system for a Euro-VI heavy-duty truck engine was achieved through the use of a switching model predictive control strategy to guarantee safe operation of the WHR system and to maximize output power. Also in the automotive field, the problem of maximizing the power produced by an ORC waste heat recovery system on board a diesel-electric railcar is tackled using dynamic real-time optimization Peralez et al. (2015). In Hernandez et al. (2015), an experimental study is conducted using an 11 kW_{el} pilot plant, showing that the constrained Model Predictive Control (MPC) outperforms PID based strategies, as it allows to accurately regulate the evaporating temperature with a lower control effort while keeping the superheating in a safer operating range.

In this study we investigate the performance of MPC and PID based strategies to optimally recover waste heat through ORC technology. Using existent components from the ThermoCycle library Quoilin et al. (2014), a dynamic model of an ORC system is built for simulation purposes. The model dynamics

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are coherent with those observed on real systems as presented in Desideri et al. (2014), where the dynamic models is experimentally validated using a low-capacity (11 kWe) waste heat recovery unit equipped with a single screw expander. Using the developed dynamic model, insight on the system dynamics and optimal operation is achieved, resulting in the development of a real-time optimizer to compute the optimal evaporating temperature which maximizes the power generation. The controller's task is to track the optimal set-point generated by the optimizer while ensuring a minimum superheating value for safely operation.

The paper is structured as follows. Section 2 introduces the architecture and main characteristics of the ORC system. Next, in section 3 the Extended Prediction Self-Adaptive (EPSAC) approach to MPC used in this study is briefly described. A low-order model suitable for prediction is then developed using parametric identification as described in section 4. The control structure, design and tuning of the proposed PID and MPC based strategies is described in section 5, followed by the simulation results in section 6. 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 Thermo Cycle 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.

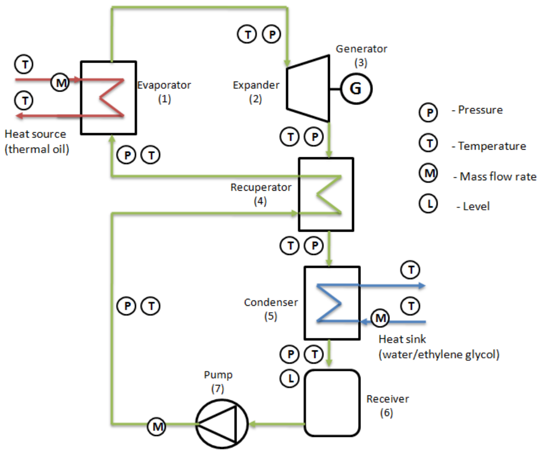

Fig. 1. Schematic layout of the pilot plant available at Ghent University, campus Kortrijk (Belgium)

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.

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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: **i)** keep the cycle in a safe condition during operation and **ii)** 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 (ΔT_{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:

$$\Delta T_{sh} = T_{exp,in} - T_{sat,ev} \tag{1}$$

where $T_{exp,in}$ 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 $p_{sat,ev}$.

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:

$$\dot{W}_{el,net} = \dot{W}_{exp} - \dot{W}_{pump} \tag{2}$$

$$\eta_{cycle} = \frac{\dot{W}_{el,net}}{\dot{Q}_{in,ORC}} \tag{3}$$

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

Previous studies have demonstrated the existence of an optimal evaporating temperature which maximizes the output power for a given heat source conditions, where a real-time optimizer (RTO) can be built using a steady-state model Quoilin et al.

(2011) or by means of extremum-seeking algorithm Hernandez et al. (2016). In this paper the first approach is chosen, thus leading to the following correlation used in the RTO:

$$T_{sat,opt} = -290.915 + 183.33 * log_{10}(T_{hf}) + 10.636 * \dot{m}_{hf} \quad (4)$$

Equation (4) is valid in the range of $0.5 \leq \dot{m}_{hf} \leq 1.5\,\mathrm{kg/s}$ and $90 \leq T_{hf} \leq 125\,^{\circ}\mathrm{C}$ given a constant saturation temperature in the condenser of $p_{sat,cd} = 1.4\,\mathrm{bar}$.

3. 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).

3.1 Computing the Predictions

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

$$y(t) = x(t) + n(t) \quad (5)$$

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:

$$x(t) = f\,[x(t-1), x(t-2), \ldots, u(t-1), u(t-2), \ldots] \quad (6)$$

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:

$$n(t) = \frac{C(q^{-1})}{D(q^{-1})}e(t) \quad (7)$$

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 (5), the predicted values of the output are:

$$y(t+k|t) = x(t+k|t) + n(t+k|t) \quad (8)$$

$x(t+k|t)$ and $n(t+k|t)$ can be predicted by recursion of the process model (6) and by using filtering techniques on the noise model (7), respectively De Keyser (2003).

3.2 Computing the optimal control action

A key element in linear MPC is the use of base (or free) and optimizing (or forced) response concepts Maciejowski. (2002). In EPSAC, the future response can be expressed as:

$$y(t+k|t) = y_{base}(t+k|t) + y_{optimize}(t+k|t) \quad (9)$$

The two contributing factors have the following origin:

- $y_{base}(t+k|t)$ is the effect of the past inputs, the a priori 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 $\Delta U = \{\delta u(t|t), \ldots, \delta u(t+N_u-1|t)\}$ with the impulse response coefficients of the system (G matrix), where N_u is the chosen control horizon.

The control ΔU is the solution to the following constrained optimization problem:

$$\Delta U = arg \min_{\Delta U \in \mathbb{R}^{N_u}} \sum_{k=N_1}^{N_2} [r(t+k|t) - y(t+k|t)]^2 \quad (10)$$
$$subject\,to\,|M.\Delta U \leq N$$

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 set-point or reference sequence. The various process input and output constraints can all be expressed in terms of ΔU, resulting in matrices M, N. Since (10) is quadratic with linear constraints in decision variables ΔU, then the minimization problem can be solved by a quadratic programming (QP) algorithm Maciejowski. (2002).

4. SYSTEM IDENTIFICATION

A trade-off between complexity of the model and prediction accuracy has to be made, in order to ensure the correct performance of the MPC strategy. In this work we have chosen a pragmatic approach by performing a parametric identification based on experimental data recorded in the available setup.

The model has been identified from the manipulated variable, pump speed (N_{pp}) to the evaporating temperature ($T_{sat,ev}$) and superheating (ΔT_{sh}). The identification has been performed using a multisine excitation signal and the prediction error method (pem) Ljung (2007). The sampling time $T_s = 1\,\mathrm{s}$ has been chosen according to the fastest dynamics of the system.

It is important to notice that in practice it is also possible to measure the temperature and mass flow rate of the heat source (T_{hf}) and ($\dot{m}_{hf}$), making possible to use them as measured disturbances. Therefore, models from these variables to evaporating temperature ($T_{sat,ev}$) and superheating (ΔT_{sh}) are also built. The nominal operating conditions of the system are presented in table 1.

Table 1. Nominal operating conditions considered for the Identification Procedure

Parameter	*Description*	*Value*	*Unit*
N_{pp}	Pump rotational speed	1680	rpm
N_{exp}	Expander rotational speed	3000	rpm
$T_{sat,ev}$	Evaporating temperature	100	$^{\circ}C$
ΔT_{sh}	Superheating	20	$^{\circ}C$
T_{hf}	Temperature hot fluid	120	$^{\circ}C$
$\dot{m}_{hf}$	Mass flow rate hot fluid	1.0	kg/s
T_{cf}	Temperature cold fluid	15	$^{\circ}C$
$\dot{m}_{cf}$	Mass flow rate cold fluid	3.0	kg/s
$\dot{W}_{el,net}$	Net output power	11	kW
η_{cycle}	Cycle efficiency	6	%

The identified model is presented in (11) in the form of discrete-time transfer functions using the backwards shift operator q^{-1}.

$$\frac{\Delta T_{sh}(t)}{N_{pp}(t)} = \frac{-0.063q^{-1}+0.059q^{-2}}{1-2.44q^{-1}+1.955q^{-2}-0.51q^{-3}} \quad (11a)$$

$$\frac{\Delta T_{sh}(t)}{T_{hf}(t)} = \frac{0.47q^{-1}}{1-0.51q^{-1}} \quad (11b)$$

$$\frac{\Delta T_{sh}(t)}{m_{hf}(t)} = \frac{-2.98q^{-1}+4.29q^{-2}-1.31q^{-3}}{1-1.35q^{-1}-0.11q^{-2}+0.46q^{-3}} \quad (11c)$$

$$\frac{T_{sat}(t)}{N_{pp}(t)} = \frac{0.066q^{-1}-0.063q^{-2}}{1-2.42q^{-1}+1.91q^{-2}-0.49q^{-3}} \quad (11d)$$

$$\frac{T_{sat}(t)}{T_{hf}(t)} = \frac{0.0017q^{-11}-0.0017q^{-12}}{1-3.6q^{-1}+4.88q^{-2}-2.95q^{-3}+0.67q^{-4}} \quad (11e)$$

$$\frac{T_{sat}(t)}{m_{hf}(t)} = \frac{2.43q^{-1}-6.16q^{-2}+5.33q^{-3}-1.6q^{-4}}{1-2.93q^{-1}+3.12q^{-2}-1.42q^{-3}+0.23q^{-4}} \quad (11f)$$

5. CONTROL STRUCTURE AND TUNING

In this section the control structure and tuning procedure of the proposed strategies are discussed.

Three control strategies are developed in order to control the ORC unit, two based on PID and one based on MPC. In all strategies we make use of the real-time optimizer (RTO) to compute, as a function of the varying heat source conditions, the optimal evaporating temperature $T_{sat,opt}$ which will be used as reference to the controller, as illustrated in Fig. 2.

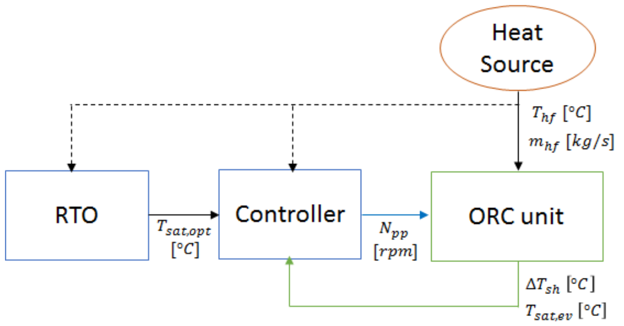

Fig. 2. Control structure of the proposed closed loop including the real-time optimizer (RTO).

An important element on the control design are the physical constraints and the safety conditions of the system. For which, the controller is required to respect the input (pump speed) and output (superheating) constraints, summarized in table 2.

Table 2. Operation constraints of the ORC unit

Variable	*max*	*min*	Δ
Pump Speed N_{pp}	1320 rpm	2100 rpm	60 rpm/s
Superheating ΔT_{sh}	–	10 °C	-

5.1 PI strategy

This strategy is based on a PI controller which is used to track the optimal evaporating temperature $T_{sat,opt}$. The PI controller is tuned using the transfer function which relates the speed in the pump to the evaporating temperature (11) for the following design specifications: settling time $T_{set} = 60$ s, overshoot percent $OS\% = 0$ and robustness $R_o = 0.7$, obtaining the PI parameters:

$$PI_{T_{sat,ev}} = K_p\left(1+\frac{1}{T_i s}\right) = 0.189\left(1+\frac{1}{1.7813\,s}\right) \quad (12)$$

During the implementation phase the clamping anti-reset windup scheme is used to clip the control action into the permissible range of the pump (table 2).

5.2 Switching PIs

In order to improve the performance of the PI strategy, essentially to what refers to safety conditions, an override control (here called switching PI strategy) is implemented. In this strategy the $PI_{T_{sat,ev}}$ controller is used to follow the optimal evaporating temperature set-point unless that superheating value goes below a threshold value $\Delta T_{sh} < 10°C$, in which case another PI controller for superheating $PI_{DT_{sh}}$, is used with set-point at $\Delta T_{sh,ref} = 10°C$, in order to bring the system back to a safe stage.

While the PI controller for the evaporating temperature is the same used on the basic PI strategy (12), the PI controller for superheating is tuned using the transfer function which relates the speed of the pump to the superheating found in (11), for the following design specifications: settling time $T_{set} = 60s$, overshoot percent $OS\% = 0$ and robustness $R_o = 0.7$, the following PI parameters are obtained:

$$PI_{\Delta T_{sh}} = K_p\left(1+\frac{1}{T_i s}\right) = -1.1\left(1+\frac{1}{0.98\,s}\right) \quad (13)$$

5.3 MPC-EPSAC

In this strategy a constrained MPC-EPSAC controller is implemented to track the optimal evaporating temperature $T_{sat,opt}$, while ensuring superheating will remain above 10 °C.

In MPC, a balance between acceptable control effort and acceptable control error can be obtained via many tuning parameters (e.g., the reference trajectory design parameter α; the prediction horizon N_2 and the control horizon design parameter N_u). Closed loop performance is designed using the N_2 parameter, whereas larger values provide a more conservative and robust control. The control horizon N_u is used to structure the future control scenario, reducing the degrees of freedom from N_2 to N_u. Structuring leads to simplified calculations and has generally a positive effect on robustness. The design parameter α in the reference trajectory can vary in the range of: $0 \leq \alpha \leq 1$. A value of α closer to 1 means a smoother variation of the set-point and hence a less aggressive control action.

A trade-off between closed loop speed and robustness has been obtained for $N_2 = 15$, $N_u = 1$ and $\alpha = 0.5$. The main goal is to achieve a response without overshoot $OS\% = 0$ and settling time of about 60 s. Another important element in the design of the controller is the choice of the disturbance model (7), during this study the 'default' filter $C(q^{-1}) = 1$ and $D(q^{-1}) = 1-q^{-1}$ has been chosen leading to zero steady-state error Maciejowski. (2002). Notice that this filter choice acts like the integral action for PID controllers.

6. SIMULATION RESULTS AND DISCUSSION

The present study focuses on investigating which are the advantages of using advanced controllers such as MPC compared to PID-like strategies for the optimal operation of an ORC system in waste heat recovery applications. The control strategy task is to accurately regulate the evaporating temperature (given by the RTO), in order to maximize the energy production, while avoiding formation of liquid droplets that could damage the expander by ensuring an small amount of superheating ΔT_{sh}. Thus in this study we will focus on answering two questions:

- which are the heat source conditions which represent the main challenge for any controller? and

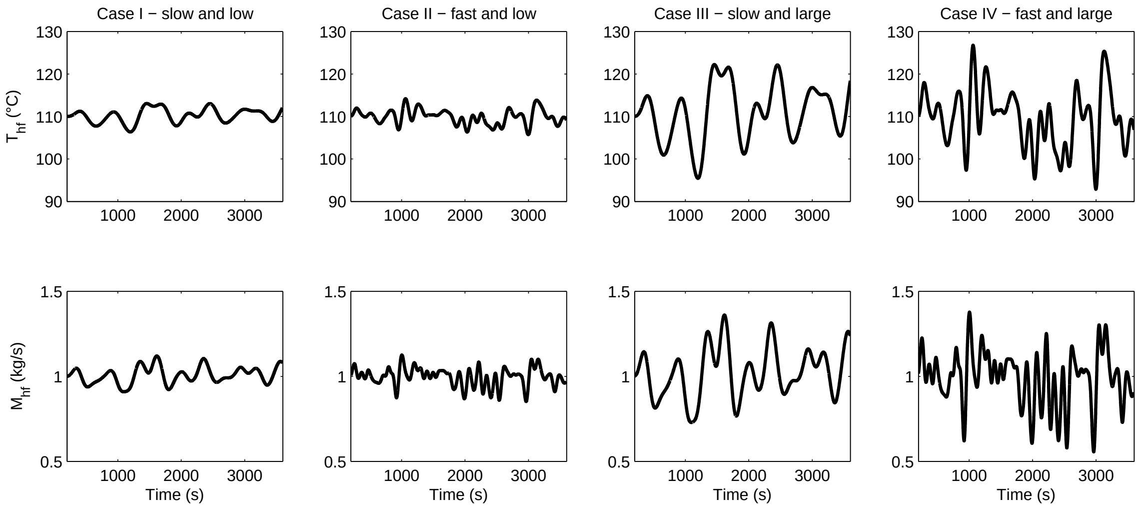

Fig. 3. Heat source profiles due to temperature T_{hf} and mass flow rate m_{hf} variations. Case I: slow and low amplitude variations. Case II: fast and low amplitude variations. Case III: slow and large amplitude variations. Case IV: fast and large amplitude variations.

- which controller produces the highest output power while keeping the safety conditions?

In order to answer those questions, we introduce four different scenarios depicted in figure 3, in which the controllers will be tested. The heat source variations are due to the combination of slow, fast, low or large transitions in temperature T_{hf} and mass-flow-rate m_{hf}:

- Case I: slow and low amplitude transitions. $T_{hf} = \pm 5\,^{\circ}\mathrm{C}$ and $\dot{m}_{hf} = \pm 0.1\,\mathrm{kg/s}$
- Case II: fast and low amplitude transitions. $T_{hf} = \pm 5\,^{\circ}\mathrm{C}$ and $\dot{m}_{hf} = \pm 0.1\,\mathrm{kg/s}$
- Case III: slow and large amplitude transitions. $T_{hf} = \pm 15\,^{\circ}\mathrm{C}$ and $\dot{m}_{hf} = \pm 0.3\,\mathrm{kg/s}$
- Case IV: fast and large amplitude transitions. $T_{hf} = \pm 18\,^{\circ}\mathrm{C}$ and $\dot{m}_{hf} = \pm 0.4\,\mathrm{kg/s}$

The three strategies tested for cases I and II (not shown here) result on good closed-loop performance, i.e., the difference in terms of tracking capabilities and control effort is negligible. During those heat source conditions the controllers are able to track correctly the quick transitions, meaning that the controllers have a high enough bandwidth and superheating remains into the desired limits.

Large amplitude variations in the heat source cause sudden drops in the superheating value, as depicted in Fig. 4 at time instant 1350 s. The switching mechanism avoids the superheating to decrease dramatically compared to the PI strategy, nevertheless, it still undergoes the threshold value of 10 °C. For the case of MPC, the most important element to highlight is the fact that this control strategy always respects the hard-output-constraint of $\Delta T_{sh} > 10\,^{\circ}\mathrm{C}$. Because it uses a model for prediction, it is able to better compensate possible sudden drops in the superheating, thus resulting in a higher net output power and higher life expectancy of the actuator, both due to the smoother control effort (i.e., lower pump speed N_{pp} variations).

Previous observations are more evident when analyzing the results for case IV, (i.e., fast and large amplitude variations), where sudden drops in the superheating value are observed at time instants 1038 s, 1350 s, 2080 s, 2664 s and 3080 s as depicted in Fig. 5.

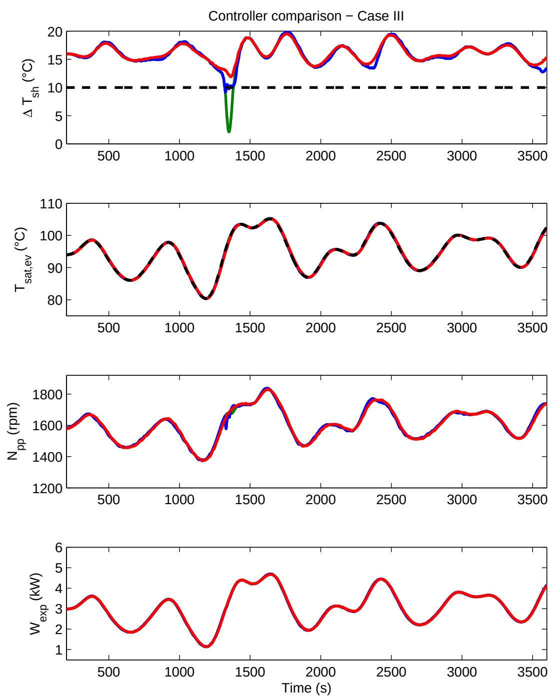

Fig. 4. Controllers comparison for Case III. Solid green- PI strategy; solid blue- Switching PI and solid red- represents MPC-EPSAC strategy.

The simulation results obtained suggest that MPC outperforms the PI based strategies for the case of large amplitude variations in the heat source. Hence, resulting in a desirable strategy regarding safety conditions. In a real industrial context, using a single PI would be an unsafe and therefore unusable strategy. Instead, the switching PI (in solid blue line) regulate

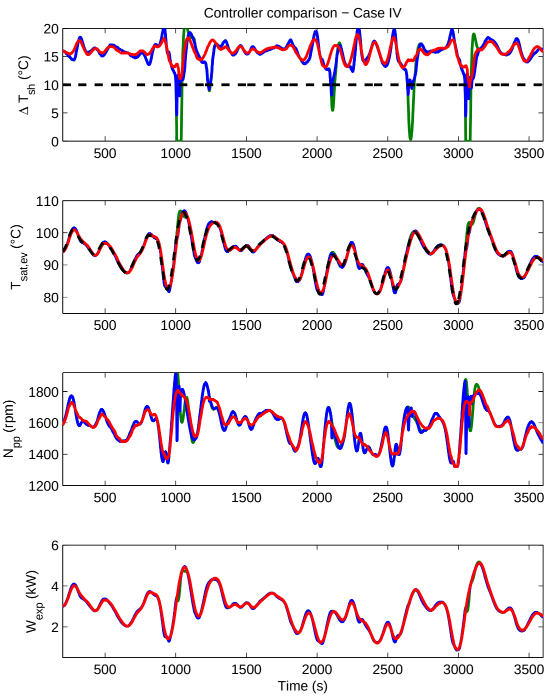

Fig. 5. Controllers comparison for Case IV. Solid green- PI strategy; solid blue- Switching PI and solid red- represents MPC-EPSAC strategy.

both evaporating temperature and superheating, thus enabling a safer operation while keeping smooth transition between the controllers. However, there is no direct control on how much can superheating decrease, as observed in for cases III and IV where superheating values close to 5 °C were observed.

7. CONCLUSION

In the present contribution three different PI and MPC based strategies have been designed and tested in simulation, with the goal of optimizing the working conditions of an ORC unit for WHR applications.

Results suggest that large amplitude variations in the waste heat source (e.g. cases III and IV), represent the most challenging situation for control design. Hence, implementation of advanced controllers such as MPC is highly recommended as it generates the same or higher net electrical output power compared to PID-based strategies while offering a safer operation. This is achieved by more accurately regulating the optimal evaporating temperature generated by the optimizer, while keeping the superheating at safe values, resulting also in a higher efficiency of the system. On the other hand, for the case of low amplitude variations (e.g. cases I and II), PID-like strategies might offer a satisfactory performance.

Future work includes adding more degrees of freedom by manipulating the expander speed, or by acting on the mass flow rate and/or temperature of the heat sink.

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