MODEL PREDICTIVE CONTROL FOR ORGANIC RANKINE CYCLE SYSTEMS ON HEAVY-DUTY TRUCKS: CONTROLLER TUNING AND OPTIMIZATION

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ABSTRACT

The organic Rankine cycle power system is an emerging technology, which is able to recover the waste heat from the diesel engine of heavy-duty trucks and thus increase the overall engine efficiency. One of the major technical challenges for the integration of the organic Rankine cycle unit on-board trucks are the broad and rapid fluctuations of the available waste heat, caused by the unsteady driving conditions of the truck. Model predictive control has shown to be a powerful tool to ensure safe operation and optimal performance of the organic Rankine cycle unit on-board trucks. This paper presents a novel systematic method for the tuning of model predictive controllers based on a multi-objective optimization routine using a fourth-order reduced linear model. The objectives of the optimization are the settling time due to a step change of the exhaust gas mass flow rate and the cumulative controller effort due to measurement noise. The results suggest that a trade-off exists between the two objectives. Among the controller design parameters, the input rate weight has the largest influence on the controller performance. Interestingly, the simplified optimization procedure based on the reduced-order linear model of the organic Rankine cycle unit can provide key information about the controller performance based on a more complex nonlinear model of the organic Rankine cycle unit when subjected to a realistic waste heat profile. It is found that the settling time due to a step change of the exhaust gas mass flow rate is a good indicator of the absolute mean square tracking error over the profile, and it should not exceed 15 s for an absolute mean square tracking error below 2 K. On the other hand, the cumulative controller effort due to measurement noise is strongly correlated to the cumulative controller effort over the profile, and it should stay below 0.5 %/s for a cumulative controller effort over the whole profile below 2 %/s. The presented method is a powerful tool to help the control designer to find the optimal design parameters of model predictive controllers in a systematic way, in contrast to the time-consuming, experience-based trial and error methods.

1 INTRODUCTION

More than 50 % of the fuel energy consumed by the diesel engines of heavy-duty trucks is released unused to the environment in the form of low to medium temperature waste heat, thus contributing to high fuel consumption and carbon dioxide emissions (Lion *et al.*, 2017). Especially in the last two decades, researchers have focused on the organic Rankine cycle (ORC) technology as a solution to recover the waste heat available from the truck diesel engines (Xu *et al.*, 2019). One of the main challenges for the waste heat recovery are the large and rapid fluctuations of the mass flow rate and temperature of the waste heat caused by the unsteady driving conditions of the truck. In order to cope with these, increasing efforts have been dedicated to the development of suitable control strategies for the ORC unit (Xu *et al.*, 2019). In particular, the control of the ORC unit has the unique tasks of ensuring safe operation while maximizing the net power output. Imran *et al.* (2020) reviewed the various control concepts suggested in literature, including conventional proportional-integral (PI) and proportional-integral-derivative (PID) controllers, feedback/feedforward schemes, linear quadratic control, non-

Gaussian control, dynamic programming and model predictive control (MPC).

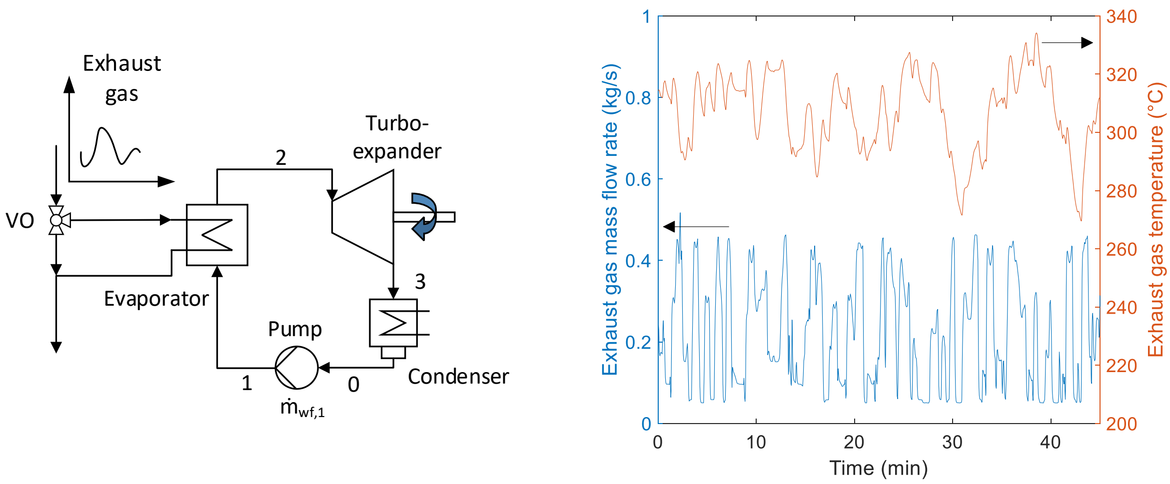
Several works suggest that MPC is a very powerful tool to ensure safe operation of the ORC unit and maximize its net power output, especially in comparison to traditional PID controllers. Among its advantages, MPC can easily handle multi-variable systems, systematically account for plant mismatches and inherently deal with system constraints, which are crucial features to ensure operational and safety limits. Feru *et al.* (2014) compared a conventional PI controller with linear and nonlinear MPC and concluded that the MPC concepts could lead to 15 % more recovered thermal energy over a cold-start World Harmonized Transient Cycle than the conventional PI control strategy. Grelet *et al.* (2015) developed an explicit-model multi-model MPC formulation based on first-order-plus-time-delay models. The controller scheme could achieve good tracking performance when subjected to step changes in the set point. Hernandez *et al.* (2016) developed a perturbation-based extremum-seeking algorithm coupled to a low-level MPC and compared the performance with two PI control schemes. The net electrical energy produced with the MPC was 12 % higher than that of the PI controllers. Koppauer *et al.* (2018) developed a gain-scheduled MPC formulation coupled with an Extended Kalman Filter for state estimation. The solution showed good set point tracking capabilities and good robustness against model uncertainties. Given the nonlinear nature that characterizes the dynamic behavior of ORC systems, other authors focused on nonlinear MPC options. Although gains in performance can be achieved, nonlinear MPCs require higher development costs and computational effort than the linear MPCs (Liu *et al.*, 2017; Petr *et al.*, 2015; Rathod *et al.*, 2019).

The aforementioned works highlight the potential of the MPC concepts to control ORC power systems subjected to highly transient conditions, minimizing the deviations of the controlled variable from the desired set point and guaranteeing safe operation. However, in previous works the tuning of the MPC design parameters were only based on trial and error procedures, potentially leading to suboptimal solutions and instability issues. In contrast to previous works, this paper focuses on the optimization of the MPC design parameters, thus allowing for the exploitation of the full potential of the MPC solution. A novel systematic method is presented for the tuning of model predictive controllers based on a multi-objective optimization routine written in MATLAB®/Simulink® (Mathworks®, 2019) using a fourth-order reduced linear model. The analysis evaluates the MPC design not only in terms of disturbance rejection capabilities, but also in terms of cumulative controller effort and sensitivity to measurement noise, ensuring at the same time sufficient stability margins. The results of the optimization are numerically tested on a nonlinear model of an ORC unit subjected to a realistic waste heat profile from the tailpipe exhaust gas of a heavy-duty truck provided by a truck manufacturer.

The case study is presented in section 2, while section 3 presents the model development used for the MPC design. Section 4 describes the multi-objective optimization routine, followed by the results in section 5 and the conclusions in section 6.

2 CASE STUDY

The investigated system is a subcritical ORC unit without recuperator, whose heat source is the available waste heat in the exhaust gas of a 450-hp 13L turbocharged diesel engine of a heavy-duty truck. The plant layout is shown in Figure 1a. The pump forwards the working fluid from liquid state at state 0 to the evaporator inlet at state 1. In this component, the working fluid is preheated, vaporized and superheated to state 2 by receiving heat from the engine exhaust gas. The vapor at state 2 expands in a turbo-expander generating mechanical power. The turbine exhaust vapor at state 3 is then condensed back to liquid state (state 0) by rejecting heat to a cooling medium. Two actuators control the operation of the ORC system: i) the mass flow rate of the pump $\dot{m}_{wf,1}$ (or, in practice, its rotational speed) is manipulated to control the degree of superheating at turbine inlet $SH_{wf,2}$, and ii) a bypass valve opening VO on the exhaust gas stream (0: fully closed, 1: fully open) limits the turbine inlet pressure $p_{wf,2}$ to assure a pressure limit of 35 bar, thus preventing supercritical operation and excessive stress on the materials. The ORC unit uses R245fa as working fluid, due to its low flammability and high thermal degradation temperature of 300 ºC (Macchi and Astolfi, 2017).



(a) (b)

Figure 1: (a) Layout of the ORC unit and (b) mass flow rate and temperature of the exhaust gas

The time profile of the engine exhaust gas is shown in Figure 1b; the raw data may be found in Pili *et al.*, (2021). The mass flow rate of the engine exhaust gas fluctuates very rapidly between 0.05 kg/s and 0.517 kg/s, whereas the temperature varies more slowly between 270 ºC and 334 ºC because of the dampening effect of the exhaust gas after-treatment system (selective catalytic reactor).

The design of the ORC unit is based on a steady-state thermodynamic optimization using the approximate time-weighted average of the exhaust gas mass flow rate and temperature (0.25 kg/s and 320 ºC). The objective function of the thermodynamic optimization (to be maximized) was the net power output. The optimization assumed the isentropic efficiencies for the turbine and the pump to be 85 % and 75 %, respectively. The optimization led to the following nominal operating point for the ORC unit: a turbine inlet pressure $p_{wf,2}$ of 29.0 bar, a degree of superheating $SH_{wf,2}$ of 28.9 K, a condensation pressure $p_{wf,0}$ of 4.2 bar, a mass flow rate $\dot{m}_{wf,1}$ of 0.187 kg/s, a turbine mechanical power output of 6.8 kW and a nominal net mechanical power output of 6.1 kW. Based on the thermodynamic design, the ORC evaporator was designed to estimate its heat transfer area (13.6 m^2), mass (42 kg) and volume (0.052 m^3), together with the nominal heat transfer coefficients of the working fluid and the exhaust gas. This information was then used to develop a dynamic model of the high pressure part of the ORC unit, which includes the evaporator (fin-and-tube type), the pump and the turbine. The evaporator was discretized in the dynamic model by using 15 finite volume cells. The evaporator and the dynamic models used in this work were previously described and verified by the authors in a previous work (Pili *et al.*, 2021). Since the dynamics of the ORC unit are mainly governed by the heat exchangers, the turbine and the pump were modelled at steady-state (Imran et al. 2020). Given the fact that ORC turbines typically work in sonic conditions, the turbine part-load characteristics was defined by the Stodola equation corrected for real gases (Capra and Martelli, 2015):

$$\dot{m}_{wf,2} = k_T \frac{p_{wf,2}}{\sqrt{\gamma_{wf,2}\, Z_{wf,2} T_{wf,3}}} \tag{1}$$

where $\dot{m}_{wf,2}$ is the mass flow rate of the working fluid, $p_{wf,2}$ the pressure, $\gamma_{wf,2}$ the ratio of the specific heats, $Z_{wf,2}$ the compressibility factor and $T_{wf,2}$ the temperature at turbine inlet. The constant k_T = 0.128 kg/s $\cdot K^{0.5}$/kPa was determined from the design conditions. The isentropic efficiencies of the turbine and the pump (positive-displacement type) were corrected at part-load according to (Vetter, 2014) and (Bauer, 2016). To simplify the control problem, the condenser was modelled by assuming constant temperature and pressure of the working fluid, which is commonly done to simplify the complexity of the control problem (Koppauer et al., 2018; Seitz et al., 2018). Despite the model simplification, the MPC can handle variations in condensation conditions as an unmeasured disturbance and, hence, it can compensate for its influence on the controlled variable.

3 MODEL DEVELOPMENT AND ORDER REDUCTION

The control strategy is based on two separate controllers: i) a single-input-single-output (SISO) MPC that has the most complex task of keeping of the degree of superheating $SH_{wf,2}$ close to the desired set point SH^{SP} by rejecting the fluctuations of the mass flow rate and temperature of the exhaust gas, and ii) a SISO proportional controller that limits the pressure $p_{wf,2}$ to the maximum value of 35 bar. The MPC acts on the mass flow rate of the pump $\dot{m}_{wf,1}$, while the proportional controller manipulates the opening of the exhaust bypass valve VO. The latter was tuned by using the Controller Design Toolbox from MATLAB® (Mathworks®, 2019), leading to a proportional gain of -0.0036 kPa^{-1}. The MPC design requires a dynamic model of the high-pressure part of the ORC system, which can be described by the following SISO nonlinear model with two measured disturbances:

$$\begin{aligned} \dot{x} &= f(x, \dot{m}_{wf,1}, d) \\ SH_{wf,2} &= g(x, \dot{m}_{wf,1}, d) \end{aligned} \tag{2}$$

where x is a vector of 47 states, f is the state function, and g is the output function. The measured disturbance vector d consists of the actual mass flow rate (i.e. the non-bypassed portion) and the inlet temperature of the exhaust gas. Subsequently, the nonlinear system in equation (2) is linearized around the steady-state nominal point $(x^*, \dot{m}^*_{wf,1}, d^*)$. The linear state-space model preserves the 47 states of the original nonlinear model in equation (2). This high number of states can lead to excessive computational time for a real-time implementation of the MPC. To prevent this, the order of the model is reduced. By subjecting the dynamic system to a 5 % step in mass flow rate of the pump $\dot{m}_{wf,1}$, it was found that four states are sufficient to limit the maximum deviation in degree of superheating $SH_{wf,2}$ to 0.1 %. The reduction of the linearized system was carried out by using the 'balred' command of the Control System Toolbox from MATLAB® (Mathworks®, 2019). Next, the model is converted to a discrete-time model by using a zero-order hold with a sample time period of 0.5 s.

4 PARAMETER TUNING VIA MULTI-OBJECTIVE OPTIMIZATION

The fourth-order discrete-time linear system model presented in the previous section was used to tune the MPC parameters via multi-objective optimization. The MPC formulation used in the work is available in the Model Predictive Control Toolbox from MATLAB® (Mathworks®, 2019). The controller objective function J and the constraint on the controller output are defined as follows:

$$\begin{aligned} J(\lambda, N_p, N_c) &= \sum_{i=1}^{N_p} \left\{ \frac{1}{SH^{ref}} \left[SH^{SP} - SH_{wf,2}(i) \right] \right\}^2 + \lambda^2 \sum_{i=1}^{N_c} \left\{ \frac{1}{\dot{m}^{ref}_{wf,1}} \left[\Delta \dot{m}_{wf,1}(i) \right] \right\}^2 \\ \dot{m}_{wf,1,min} &\leq \dot{m}_{wf,1}(i) \leq \dot{m}_{wf,1,max} \quad i = 1, \dots, N_c \end{aligned} \tag{3}$$

where SH^{ref} = 20 K is a scaling factor for the degree of superheating, $\dot{m}^{ref}_{wf,1}$=0.2 kg/s is a scaling factor for the pump mass flow rate and $\dot{m}_{wf,1,min}$ and $\dot{m}_{wf,1,max}$ correspond to 20 % and 120 % of the nominal mass flow rate of the ORC pump. The tuning parameters are the input rate weight λ, the prediction horizon N_p and the control horizon N_c. A high value of the input rate weight λ penalizes changes in pump mass flow rate with respect to deviations of the degree of superheating from the desired set point, and vice versa. A high number of the prediction horizons include more time steps in the future when minimizing the deviation of the degree of superheating $SH_{wf,2}$ from the set point SH^{SP}, and vice versa. The control horizon defines the number of changes for the pump mass flow rate $\Delta\dot{m}_{wf,1}$ in the future. In the time steps $i > N_c$, the pump mass flow rate does not change anymore, i.e. $\Delta\dot{m}_{wf,1}(i > N_c) = 0$. The sample time of the MPC corresponds to the sample time of the dynamic model (0.5 s). For the multi-objective optimization, the unconstrained MPC formulation with the objective function J in equation (3) was used. In other words, the constraint on the pump mass flow rate was not included in the MPC formulation. In this way, the MPC can be written explicitly as a linear time-invariant system having as inputs the measured degree of superheating $SH_{wf,2}$ and the measured disturbance vector d, while the output is the mass flow rate of the pump for the next time step $\dot{m}_{wf,1}(i=1)$.

The explicit MPC system acting on the reduced-order linear model described in section 3 is used by the multi-objective optimization to find the optimal tuning parameters. The genetic algorithm of the Global Optimization Toolbox from MATLAB® (Mathworks®, 2019) is able to handle a combination of real (such as the input rate weight λ) and integer decision variables (such as the prediction horizon N_p and the control horizons N_c) and was, therefore, used as optimization algorithm. The settings for the algorithm are: i) a population size of 100, ii) 500 generations, and iii) a stall generation limit of 200. The input rate weight λ can vary between 0.01 and 60, prediction horizon N_p between 5 and 30, and the control horizon N_c between 1 and 10. The two objectives of the multi-objective optimization routine are the following: i) the settling time of the degree of superheating $t_{S,SH,wf2}$ due to a 1 % step change in the mass flow rate of the exhaust gas, which quantifies the disturbance rejection capabilities of the controller and needs to be minimized, and ii) the cumulative controller effort Q_{noise} when white noise of variance 0.01 K^2 is added to $SH_{wf,2}$ before the measurement is fed back to the MPC, which quantifies the sensitivity of the MPC to measurement noise and needs to be minimized as well. The settling time is the time required by the controller error to fall below 2 % of the peak value, while the controller cumulative effort is defined as:

$$Q = \frac{1}{\left|\dot{m}_{wf,1,max} - \dot{m}_{wf,1,min}\right|} \frac{1}{\Delta t} \int_0^{\Delta t} \left| \frac{\Delta \dot{m}_{wf,1}}{\Delta t} \right| dt \tag{4}$$

where t is the time, Δt the overall time period of the simulation. The variance of the measurement noise is based on the experimental results reported in Pili *et al.* (2020). A low value of the settling time $t_{S,SH,wf,2}$ ensures rapid rejection of the waste heat fluctuations, but it can also imply a high sensitivity to measurement noise, i.e. a high Q_{noise}, potentially leading to an excessive control action and reduced lifetime of the ORC pump and its automation system. For this reason, a trade-off between the two objectives needs to be considered. Furthermore, in order to ensure sufficient stability margins, two constraints are included to the multi-objective optimization: only solutions having a disc gain margin above 2, and a disc phase margin above 45 ^{o} are accepted (Seiler *et al.*, 2020). These margins should ensure sufficient stability, also for operating points far from the nominal point.

5 RESULTS

The multi-objective optimization results in the Pareto front of optimal solutions depicted in Figure 2a. It is important to highlight that Figures 2a to 2d do not show the results of a sensitivity analysis but show the solutions of the multi-objective optimization problem, and therefore represent an optimal tuning of the controller parameters. The results in Figure 2a suggest that a trade-off between the two objectives is required: low settling times $t_{S,SH,wf2}$ imply high Q_{noise} and vice versa. The settling time $t_{S,SH,wf2}$ is below 10 s for a cumulative controller effort above 0.3 %/s, although $t_{S,SH,wf2}$ increases considerably to more than 100 s for a cumulative controller effort below 0.1 %/s. The decision variable that has the largest impact on the settling time $t_{S,SH,wf,2}$ and the cumulative controller effort Q_{noise} is the input rate weight λ, as shown by Figure 2b. A higher λ implies a larger penalty on variations of the pump mass flow rate $\Delta\dot{m}_{wf,1}$, and therefore, the controller becomes more gentle, taking more time to reach the desired set point (larger $t_{S,SH,wf2}$). At the same time, a more gentle reaction of the controller corresponds to a lower cumulative controller effort Q_{noise}. The prediction and the control horizons do not show a clear impact on the settling time and the cumulative controller effort, but the optimization still suggests an optimum range of selection (see Figures 2c and 2d). The prediction horizon N_p varies in the range 10-17 for most of the points, but it is higher than 24 for points having a settling time $t_{S,SH,wf2}$ of more than 30 s. No clear trend between N_p and Q_{noise} is found. The control horizon N_c is in the range of 7-9 for most of the optimal points having a settling time $t_{S,SH,wf2}$ below 30 s, but it drops to 4 for higher $t_{S,SH,wf2}$. Analogously for the prediction horizon N_p, no clear trend is found between N_c and Q_{noise}.

In a next step, the MPC design Pareto-front optimal solutions were tested on the nonlinear model of the high pressure part of the ORC unit described by equation (2), subjected with the realistic waste heat profile in Figure 1b. The mass flow rate of the pump $\dot{m}_{wf,1}$ was constrained between 20 % and 120 % of the nominal value during the simulation. The response of the nonlinear system in equation (2) is assessed according to two quantities: i) the absolute root mean square tracking error (ARMSTE), quantifying the deviations between the degree of superheating $SH_{wf,2}$ and the set point SH^{SP}, and ii) the cumulative controller effort of the pump controller Q over the waste heat profile, see equation (4). The goal is to achieve the minimum ARMSTE as well as the minimum Q to reach good disturbance rejection while ensuring long lifetime of the pump. The results, plotted in Figure 3a, indicate that there is a trade-off between the cumulative controller effort Q and the absolute root mean square tracking error ARMSTE over the profile analogously to the Pareto-front optimal solutions shown in Fig. 2a. The cumulative controller effort increases considerably from 1.1 %/s for an ARMSTE of about 6 K to more than 4 %/s for an ARMSTE below 2 K. Analogously to the results of the multi-objective optimization, the input rate weight λ has the largest impact on the simulation performance, as indicated in Figure 3b. On the one hand, a low λ leads to a low ARMSTE because the controller can react very quickly to the waste heat fluctuations, although this leads to the highest cumulative controller efforts Q. By increasing λ up to 55, Q drops to 1 %/s while the ARMSTE increases to 10 K. Importantly, it can be seen in Figures 3c and 3d that there is a direct correlation between the settling time to a disturbance step $t_{S,SH,wf2}$ and the ARMSTE over the profile, as well as between the cumulative controller effort to noise Q_{noise} and over the profile Q. This means that the considerations based on the reduced-order model and only based

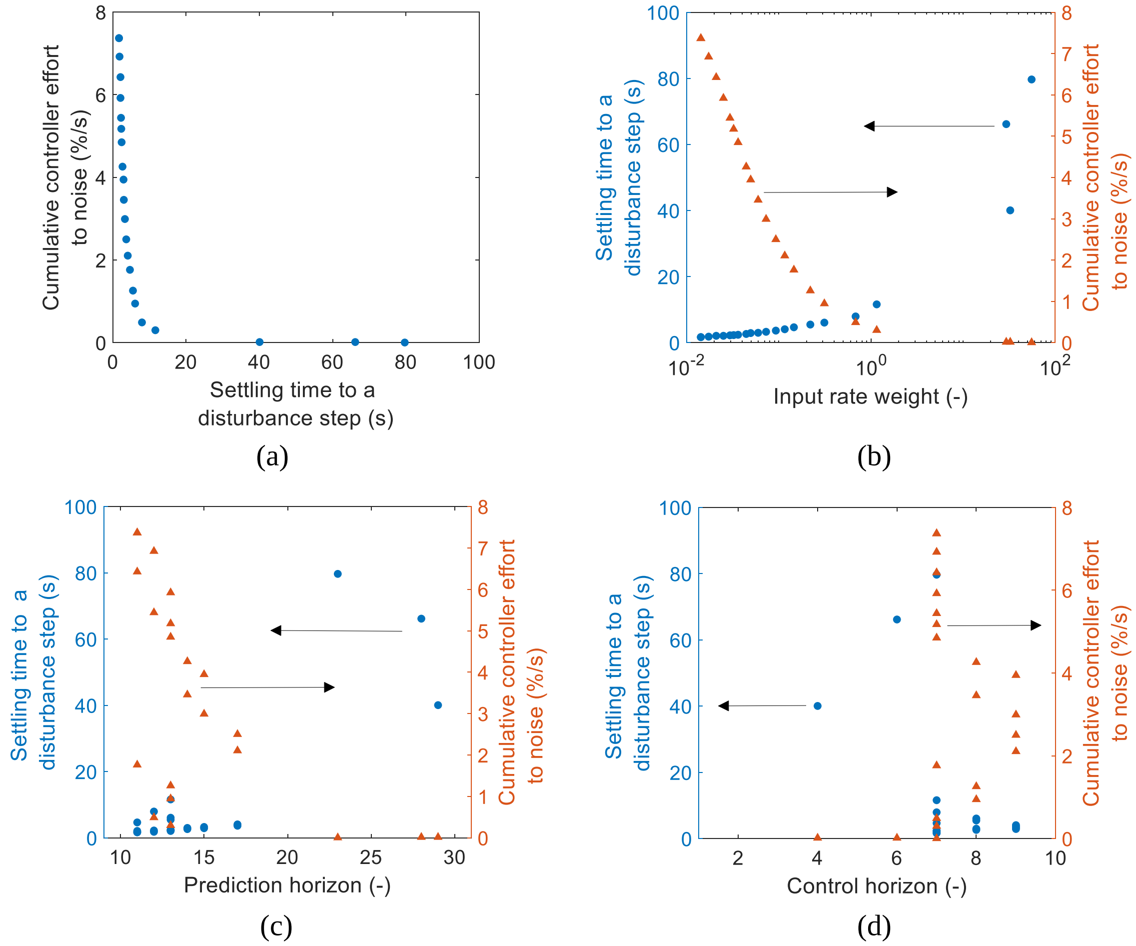


Figure 2: (a) Pareto-front optimal solutions, and influence of the optimal decision variables on the objective functions: (b) input rate weight, (c) prediction horizon, and (d) control horizon

on a disturbance step change and measurement noise on the degree of superheating already provide important information about the controller performance over the profile. This allow saving significant time and computational effort for the controller tuning. For an ARMSTE below 2 K, the settling time $t_{S,SH,wf2}$ should not exceed 15 s, while for Q below 2 %/s, Q_{noise} should be below 0.5 %/s.

6 CONCLUSIONS

This work presented a multi-objective optimization of the design parameters of a model predictive controller, based on a fourth-order linear model of an organic Rankine cycle unit recovering the waste heat available in the exhaust gas of a heavy-duty truck. The performance of the optimal solutions was tested on a nonlinear model of the high pressure part of the organic Rankine cycle unit and on a realistic waste heat profile. The optimization results suggest that there is a trade-off between the settling time due to a step change in exhaust gas mass flow rate and the cumulative controller effort due to measurement noise. Additionally, the results indicate that the input rate weight has the largest influence on the controller performance, while the optimal prediction and control horizons should be in the range 10-17 and 7-9, respectively, for most of the optimal points. It was found that a direct relationship exists between the settling time to a disturbance step and the absolute root mean square tracking error over the profile. Also, the cumulative controller effort over the profile increases for higher cumulative controller effort due to measurement noise. Because of these dependencies, the trade-off between the settling time to a disturbance step change and the cumulative controller effort to noise can be mapped into a trade-off between the absolute root mean square tracking error and the cumulative controller effort over the profile. Thus, the multi-objective optimization presented in the paper can be used to

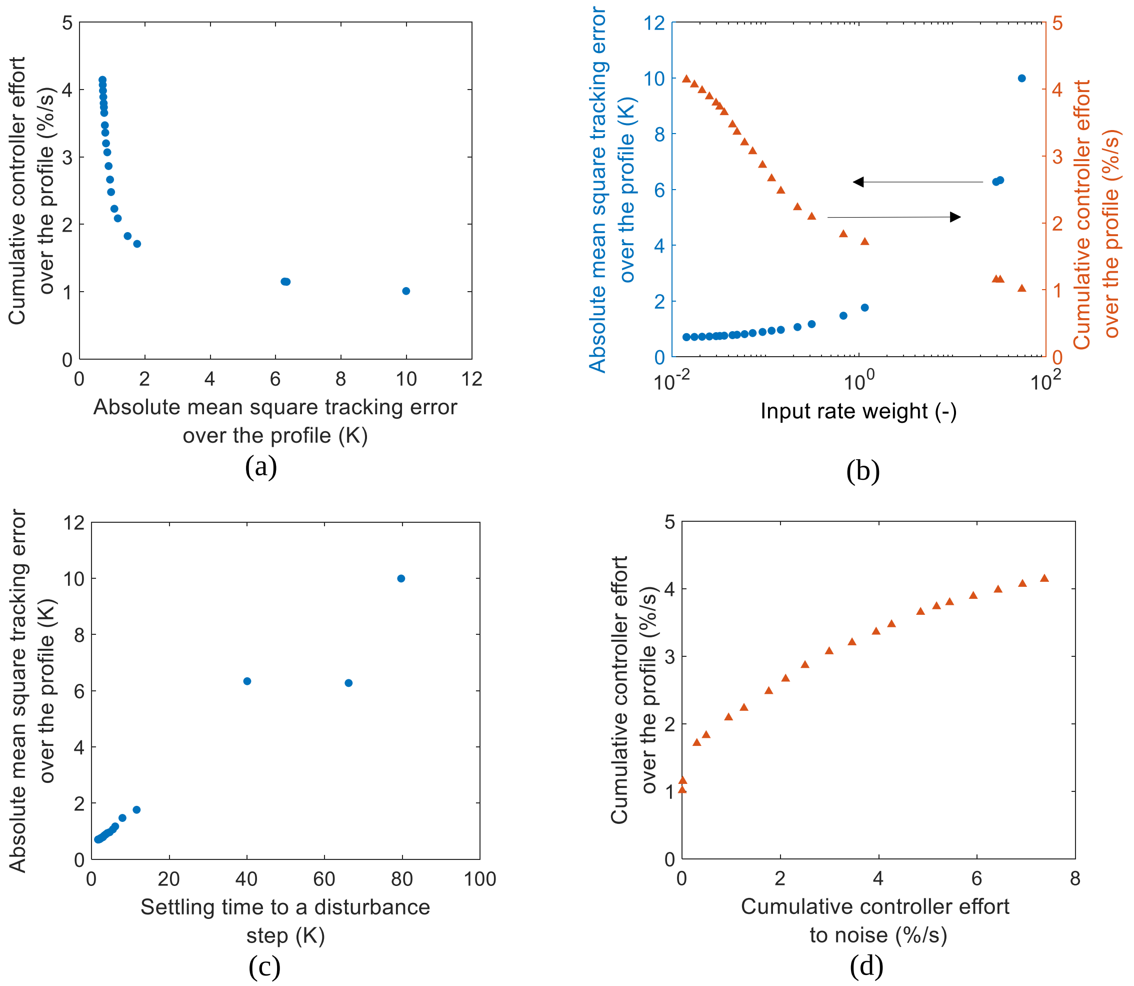


Figure 3: (a) Cumulative controller effort and ARMSTE over the profile, (b) influence of the input rate weight, (c) ARMSTE as a function of the settling time to a disturbance step, and (d) cumulative controller effort over the profile vs cumulative controller effort to noise

identify the optimal model predictive controller parameters, considerably lowering the computational effort compared with that of an optimization based on the more complex nonlinear model. The presented method is a powerful tool to tune the design parameters of model predictive controllers in a more systematic and effective way compared with time-consuming, experience-based trial and error methods. Future work will evaluate the tuning of the controller parameters also in terms of net power output and the economic performance of the organic Rankine cycle unit will be evaluated.

NOMENCLATURE

Symbols

d	disturbance vector	(-)	N_p	prediction horizon	(-)
f	state function	(-)	p	pressure	(bar)
g	output function	(-)	Q	cumulative controller effort	(%/s)
i	counter variable	(-)	SH	degree of superheating	(K)
J	cost function	(-)	x	state vector	(-)
$\dot{m}$	mass flow rate	(kg/s)	Δ	variation	(-)
N_c	cost horizon	(-)	λ	input rate weight	(-)

Subscript and superscripts

$\dot{}$	time derivative	p	participants
*	steady state (operating point)	SP	set point
n	nights	wf	working fluid

Abbreviations

ARMSTE	absolute mean square tracking error	PI	proportional-integral (controller)
MPC	model predictive control	PID	proportional-integral-derivative
ORC	organic Rankine cycle	SISO	single-input-single-output (system)

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