EXPLICIT MULTI-MODEL PREDICTIVE CONTROL OF A WASTE HEAT RANKINE BASED SYSTEM FOR HEAVY DUTY TRUCKS

Vincent GRELET[1,2,3], Pascal DUFOUR[2], Madiha NADRI[2], Vincent LEMORT [3] and Thomas REICHE[1]

[1]Volvo Group Trucks Technology Advanced Technology and Research, 1 avenue Henri Germain, 69800 Saint Priest, France
[2]Université de Lyon, Lyon F-69003, Université Lyon 1, CNRS UMR 5007, Laboratory of Process Control and Chemical Engineering (LAGEP), Villeurbanne 69100, France
[3]LABOTHAP, University of Liege, Campus du Sart Tilman Bat. B49 B4000 Liege, Belgium

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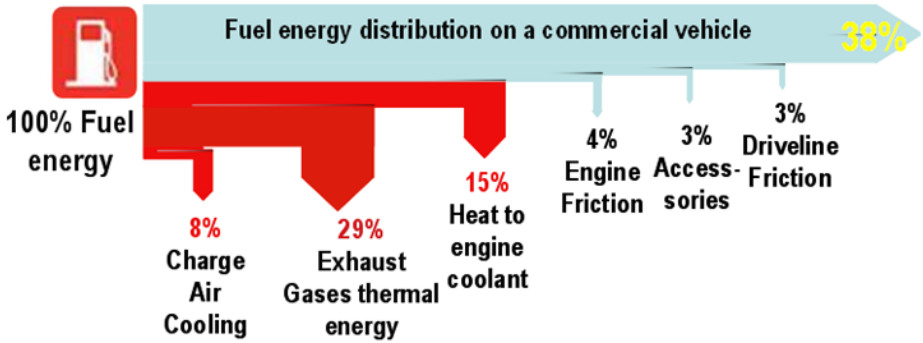
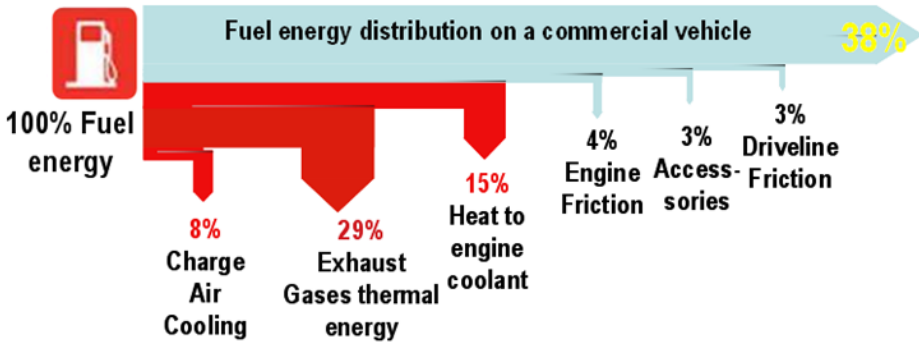
Context and motivations

- In nowadays heavy duty engines, a major part of the chemical energy contained in the fuel is released to the ambient through heat.



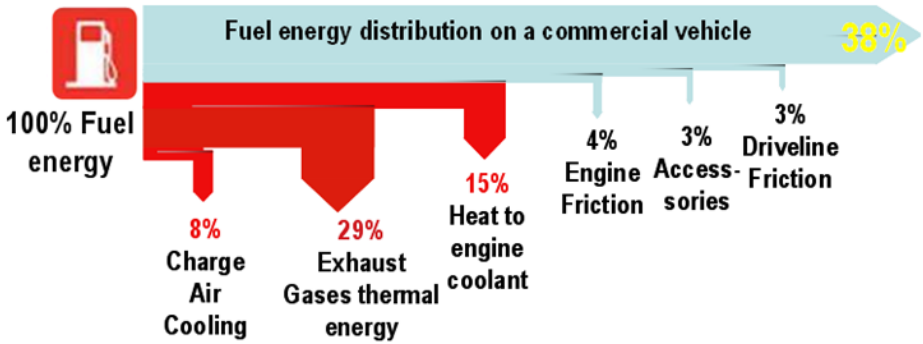
Context and motivations

- In nowadays heavy duty engines, a major part of the chemical energy contained in the fuel is released to the ambient through heat.
- Waste heat recovery based on the Rankine cycle is a promising technique to increase fuel efficiency.



Context and motivations

- In nowadays heavy duty engines, a major part of the chemical energy contained in the fuel is released to the ambient through heat.
- Waste heat recovery based on the Rankine cycle is a promising technique to increase fuel efficiency.
- Dynamic models needed for concept optimization, fuel economy evaluation and control algorithm development.



Rankine process

- Liquid compression ($1 \rightarrow 2$) from condensing to evaporating pressure by means of the pump power $\dot{W}_{in}$.
- Preheating ($2 \rightarrow 3a$), vaporization ($3a \rightarrow 3b$) and superheating ($3b \rightarrow 3c$) by means of the input heat power $\dot{Q}_{in}$.
- Vapor expansion ($3c \rightarrow 4$) from evaporating to condensing pressure creating power $\dot{W}_{out}$ on the expander shaft.
- Condensation ($4 \rightarrow 1$) releasing heat $\dot{Q}_{out}$ in the heat sink.

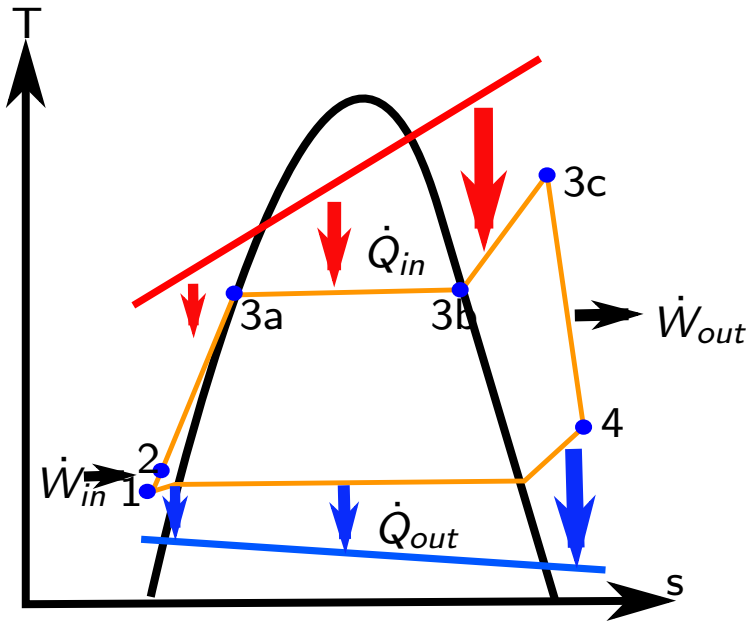
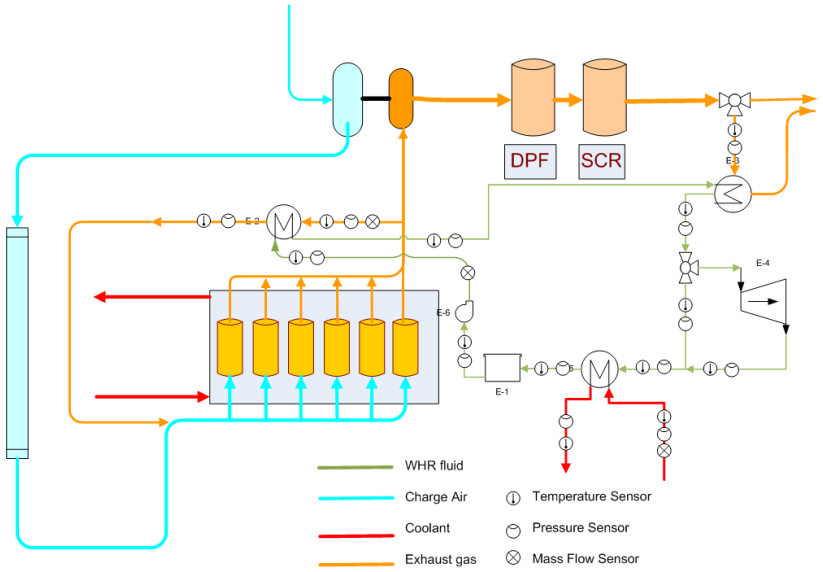


Figure: Temperature-entropy diagram of the Rankine cycle

Studied system and controller objective

- Recover heat from both EGR and exhaust in a serial configuration.
- Working fluid: water ethanol mixture.
- Focus on the control of the working fluid superheat at the expansion machine inlet.
- Even more critical when using a kinetic expander.
- Control issue: Reduce the deviation of the superheat around its set point to have safe and efficient operation.



Nonlinear evaporator detailed model

Model representation

$$\dot{x}_i = f_i\left(x_i, u\right), \tag{1}$$

$$u^T = \begin{bmatrix} \dot{m}_{f_0} & P_{f_0} & h_{f_0} & \dot{m}_{g_L} & T_{g_L} \end{bmatrix}, \; x_i^T = \begin{bmatrix} \dot{m}_{f_i} & h_{f_i} & T_{w_{int_i}} & T_{g_i} & T_{w_{ext_i}} \end{bmatrix} \tag{2}$$

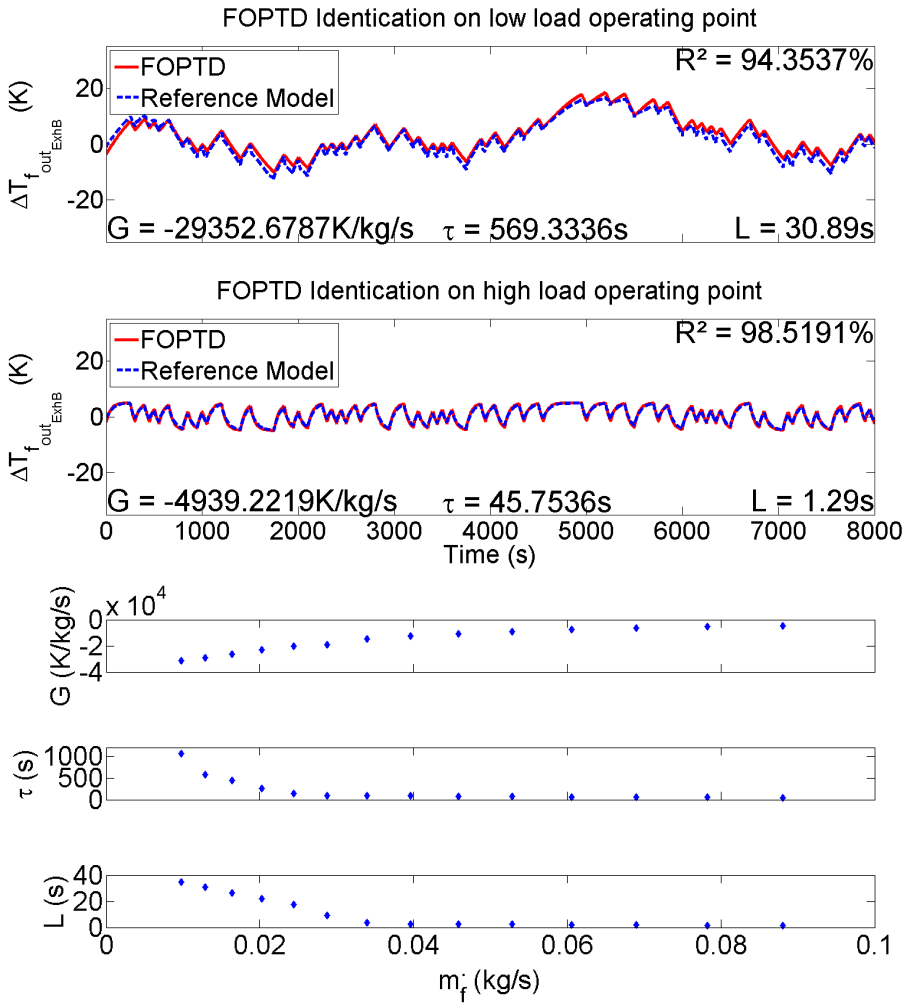
$$f_i(x_i, u) = \begin{bmatrix} \dfrac{\dot{m}_{f_{i-1}} \dfrac{h_{f_{i-1}}}{\rho_{f_{i-1}}} \dfrac{\partial \rho_{f_{i-1}}}{\partial h_{f_{i-1}}} + \dfrac{1}{\rho_{f_{i-1}}} \dfrac{\partial \rho_{f_{i-1}}}{\partial h_{f_{i-1}}} \alpha_{f_i} A_{exch_{int_f}} \left(T_{f_i} - T_{w_{int_i}}\right)}{1 - \dfrac{h_{f_i}}{\rho_{f_i}} \dfrac{\partial \rho_{f_i}}{\partial h_{f_i}}} - \dot{m}_{f_i} \\ \dfrac{\left(\dot{m}_{f_{i-1}} h_{f_{i-1}} - \dot{m}_{f_i} h_{f_i}\right) - \alpha_{f_i} A_{exch_{int_f}} \left(T_{f_i} - T_{w_{int_i}}\right)}{\rho_{f_i} V_f} \\ \dfrac{\alpha_{f_i} A_{exch_{int_f}} \left(T_{f_i} - T_{w_{int_i}}\right) + \alpha_g A_{exch_{int_g}} \left(T_{g_i} - T_{w_{int_i}}\right)}{\rho_{w_{int}} V_{w_{int}}} \\ \dfrac{\dot{m}_g c_{p_g}(T_{g_i})\left(T_{g_{i-1}} - T_{g_i}\right) - \alpha_g \left[A_{exch_{int_g}} \left(T^*_{g_i} - T_{w_{int_i}}\right) - A_{exch_{ext_g}} \left(T_{g_i} - T_{w_{ext_i}}\right)\right]}{\rho_{g_i} V_g c_{p_g}\left(T_{g_i}\right)} \\ \dfrac{\alpha_{amb} A_{exch_{ext_{amb}}} \left(T_{amb} - T_{w_{ext_i}}\right) + \alpha_g A_{exch_{ext_g}} \left(T_{g_i} - T_{w_{ext_i}}\right)}{\rho_{w_{ext}} V_{w_{ext}}} \end{bmatrix}$$

Identification

- Dynamic relation between u (working fluid mass flow) and y (working fluid superheat) can be described around an operating point by a first order plus time delay (FOPTD) model:

$$\frac{y(s)}{u(s)} = \frac{G}{1+\tau s} e^{-Ls}, \qquad (3)$$

- High variation in FOPTD parameters shows high nonlinearity.
- Linear time invariant controller will hardly achieve the control objective with good performance under transient driving cycle.



Piecewise linear approach

- Multi linear model approach consists into identifying a bank of N linear models and combine them by means of a weighting scheme.
- Global model output is (at time t_k):

$$y_k = \sum_{i=1}^{N} y_{i,k} W_{i,k} \tag{4}$$

- Key design issues are : 1/ the selection of the good model(s) in the bank. 2/ linear models mixing.
- Modeling error of the i^{th} model at the current time t_k is defined by:

$$\epsilon_{i,k} = y_{p,k} - y_{i,k}. \tag{5}$$

Weighting scheme

Bayesian recursive scheme

$$p_{i,k} = \frac{\exp(-\frac{1}{2}\epsilon_{i,k} K \epsilon_{i,k}^T p_{i,k-1})}{\sum_{m=1}^{N} (\exp(-\frac{1}{2}\epsilon_{m,k} K \epsilon_{m,k}^T p_{m,k-1})} \quad (6)$$

$$W_{i,k} = \begin{cases} \frac{p_{i,k}}{\sum_{m=1}^{N} p_{m,k}} & \text{for } p_{i,k} > \delta \\ 0 & \text{for } p_{i,k} < \delta \end{cases} \quad (7)$$

where K is a vector and δ a scalar.

New proposed scheme

$$\tilde{\epsilon}_{i,k} = \frac{\epsilon_{i,k}^2}{\sum_{m=1}^{N} \epsilon_{m,k}^2} \quad (8)$$

$$X_{i,k} = (1 - \tilde{\epsilon}_{i,k}) \prod_{j \neq i, j=1}^{j=N} \tilde{\epsilon}_{j,k} \quad (9)$$

$$\tilde{X}_{i,k} = \frac{X_{i,k}}{\sum_{m=1}^{N} X_{m,k}} \quad (10)$$

$$W_{i,k} = \frac{1}{1 + Ts} \tilde{X}_{i,k} \quad (11)$$

where T is a scalar.

Optimization problem

Model Predictive Control cost function for set-point tracking

$$\begin{cases} \min\limits_{u_{inf} \leq u_k \leq u_{sup}} J(u_k) &= \int\limits_{t_k}^{t_k+t_p} (y_p(t) - y^{sp})^2 + w_u \Delta u_k^2 \, dt, \\ \Delta u_k &= u_k - u_{k-1}, \end{cases} \tag{12}$$

where w_u is a scaling factor and a penalty weight.

Modeling error

$$e_k = y_{p,k} - y_k. \tag{13}$$

Output prediction $y_p(t)$ in (12) can be written based on the N models and feedback:

$$y_p(t) = y(t) + e_k. \tag{14}$$

Output response of a FOPTD model

$$y_i(t) = y_{p,k} e^{\frac{-(t-t_k)}{\tau_i}} + \int_{t_k}^{t} (e^{\frac{-(t-s)}{\tau_i}} \frac{G_i}{\tau_i} u(s - L_i)) ds. \tag{15}$$

MMPC framework

Integration intervals

A model response (15) can be developed as:

$$y_i(t) = y_{p,k} e^{\frac{-(t-t_k)}{\tau_i}} + \frac{G_i}{\tau_i} e^{\frac{-t}{\tau_i}} \int_{t_k}^{t} (e^{\frac{s}{\tau_i}} u(s - L_i)) ds, \tag{16}$$

Based on the time delay L_i, let us define:

$$\begin{cases} \lambda_i &= max(a_i \in \mathbb{N} | a_i \leq \frac{L_i}{T_s}) \\ \Delta L_i &= L_i - \lambda_i T_s, \in \mathbb{R}^+. \end{cases} \tag{17}$$

Integration in (16) is done by parts, where the $\lambda_i + 2$ time intervals are:

s	$s - L_i$	$u(s - L_i)$
$t_k \rightarrow t_k + \Delta L_i$	$t_k - L_i \rightarrow t_{k-\lambda_i}$	$u(t_{k-\lambda_i-1})$
$t_k + \Delta L_i \rightarrow t_k + \Delta L_i + T_s$	$t_{k-\lambda_i} \rightarrow t_{k-\lambda_i+1}$	$u(t_{k-\lambda_i})$
$\dots$	$\dots$	$\dots$
$t_k + \Delta L_i + (\lambda_i - j)T_s \rightarrow t_k + \Delta L_i + (\lambda_i - j + 1)T_s$	$t_{k-j} \rightarrow t_{k-j+1}$	$u(t_{k-j})$
$\dots$	$\dots$	$\dots$
$t_k + \Delta L_i + (\lambda_i - 1)T_s \rightarrow t_k + L_i$	$t_{k-1} \rightarrow t_k$	$u(t_{k-1})$
$t_k + L_i \rightarrow t$	$t_k \rightarrow t - L_i$	$u(t_k) = u_k$

MMPC framework

Explicit MMPC formulation

Once integrated, (16) is a linear expression in the optimization argument u_k:

$$\begin{aligned} y_i(t) = y_{p,k} f_{1i}(\tau_i, t_k, t) + f_{2i}(T_s, G_i, \tau_i, \Delta L_i, \lambda_i, t_k, t, u(past)) \\ + u_k f_{3i}(G_i, \tau_i, L_i, t_k, t), \end{aligned} \tag{18}$$

where the $f_.$ may be explicitly defined offline and updated online at each time t_k. Hence the initial cost function is:

$$J(u_k) = \int_{t_k}^{t_k+t_p} \left(\left(\sum_{i=1}^{N} \left(w_{i,k} y_i(t) \right) + e_k - y_k^{sp} \right)^2 + w_u \Delta u_k^2 \right) dt \tag{19}$$

where the prediction horizon $t_p = max(t_{pi})\ \forall i$ may be tuned as:

$$\begin{cases} t_{pi} = \gamma_p * \tau_i + L_i;\ \gamma_p \in \mathbb{R}^+, \\ \text{e.g.: } \gamma_p = 1 \text{ (63\% of the dynamics is predicted)} \\ \text{or } \gamma_p = 3 \text{ (95\% of the dynamics is predicted).} \end{cases} \tag{20}$$

MMPC framework

Explicit MMPC formulation

Based on the step response series (16) of the N linear FOPTD models:

$$\begin{array}{l} J(u_k) = \beta_{2,k}(N, G_i, \tau_i, L_i, t_p, w_u, w_{i,k})u_k^2 \\ +\beta_{1,k}(N, T_s, G_i, \tau_i, L_i, t_p, \Delta L_i, \lambda_i, w_u, y_{p,k}, y_k^{sp}, e_k, u(past), w_{i,k})u_k \\ +\beta_{0,k}(N, T_s, G_i, \tau_i, L_i, t_p, \Delta L_i, \lambda_i, w_u, y_{p,k}, y_k^{sp}, e_k, u(past), w_{i,k}), \end{array} \tag{21}$$

Minimization of (21) obtained with the first order optimality at each t_k:

$$\frac{\partial J}{\partial u_k} = 0 \quad \text{at } u_k = u_k^{min}. \tag{22}$$

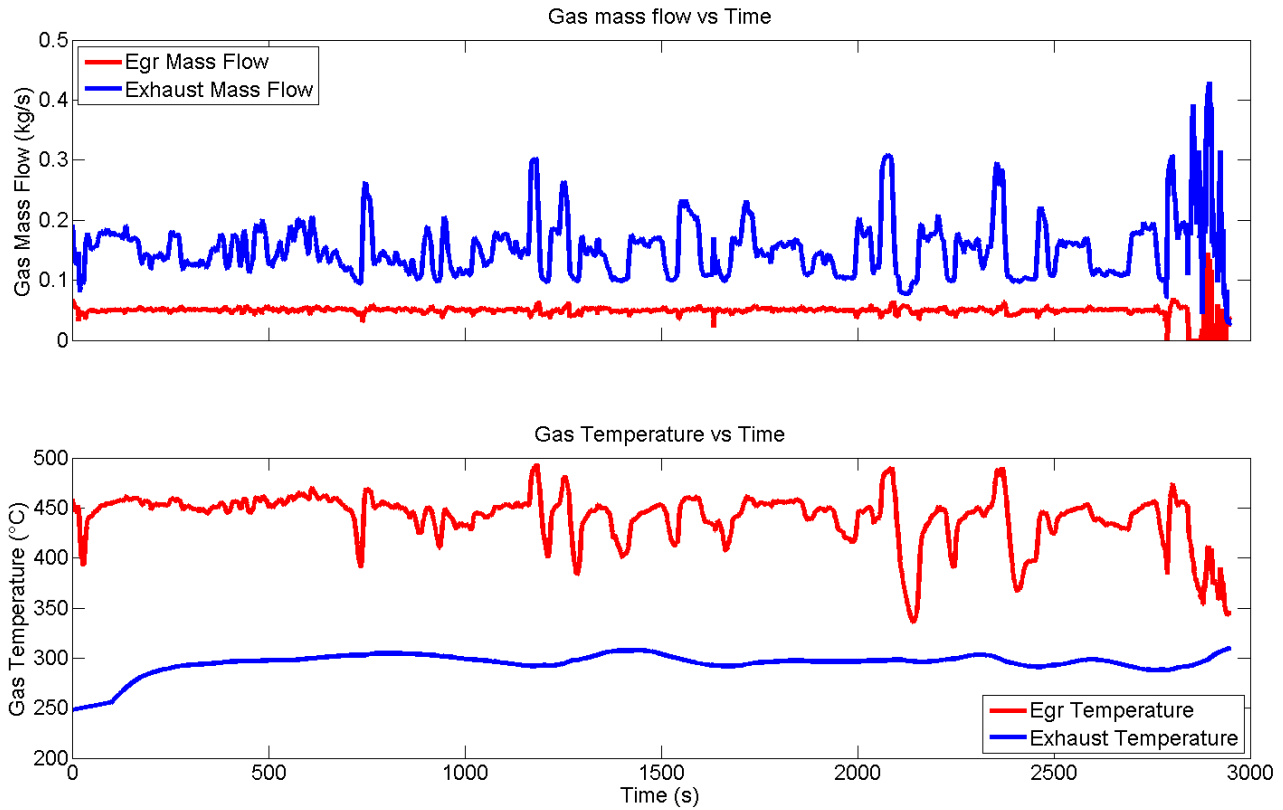
Calculation of u_k^{min} is then straightforward:

$$u_k^{min} = \frac{-\beta_{1,k}}{2\beta_{2,k}} \tag{23}$$

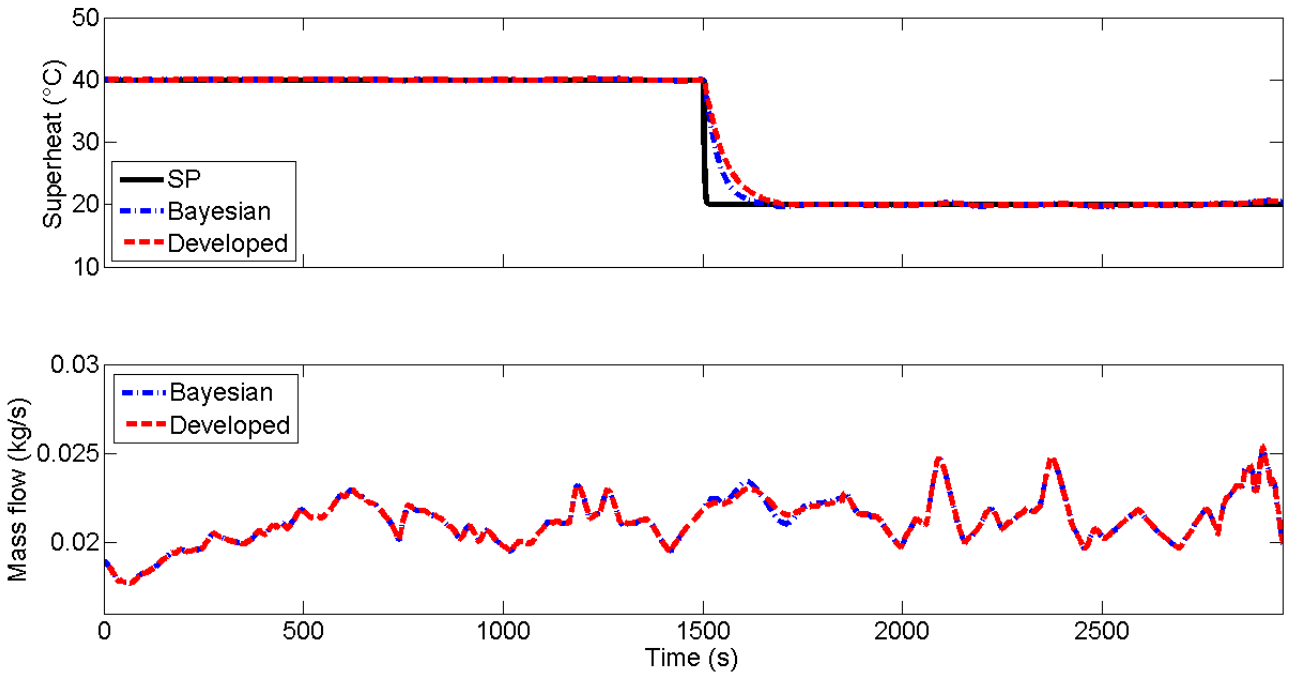
which leads to the explicit formulation of the solution $u_k^\star$:

$$\begin{cases} \text{if} \quad u_{inf} \leq u_k^{min} \leq u_{sup} : \; u_k^\star = u_k^{min} \\ \text{if} \quad u_k^{min} \leq u_{inf} : \; u_k^\star = u_{inf} \\ \text{if} \quad u_{sup} \leq u_k^{min} : \; u_k^\star = u_{sup}. \end{cases} \tag{24}$$

Input disturbances



Tracking error and manipulated variable



Conclusion and next steps

Conclusion

- New modeling weighting scheme based on a piecewise linear approach has been developed and validated.
- New scheme has less tuning parameters than the Bayesian scheme.
- Explicit MMPC strategy for Rankine cycle based heat recovery system is presented.
- MMPC is compliant with classical automotive integration constraints (i.e., basic CPU and fast sampling time).

Next steps

- Experimental validation.
- Robustness study.

Contacts and discussion

Authors

- Vincent GRELET: greletv@live.com
- Pascal DUFOUR: dufour@lagep.univ-lyon1.fr
- Madiha NADRI: nadri@lagep.univ-lyon1.fr
- Vincent LEMORT: vincent.lemort@ulg.ac.be
- Thomas REICHE: thomas.reiche@volvo.com

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β_i expressions

$$\beta_{1,k} = \sum_{i=1}^{N} \left[\beta'_{1,k} + \beta''_{1,k} + \beta'''_{1,k} + \beta''''_{1,k} \right] - 2 w_u u_{k-1} t_p, \tag{25}$$

$$\beta'_{1,k} = -G_i \tau_i {w_{i,k}}^2 y_{p,k} \left(e^{\frac{L_i}{\tau_i}} + 2 e^{-\frac{t_p}{\tau_i}} - e^{\frac{L_i - 2 t_p}{\tau_i}} - 2 \right) \tag{26}$$

$$\beta''_{1,k} = -{G_i}^2 \tau_i u(t_{k-\lambda_i-1}) {w_{i,k}}^2 e^{-\frac{2 t_p}{\tau_i}} \left(e^{\frac{\Delta L_i}{\tau_i}} - 1 \right) \left(e^{\frac{t_p}{\tau_i}} - 1 \right) \ldots$$
$$\left(e^{\frac{L_i}{\tau_i}} - 2 e^{\frac{t_p}{\tau_i}} + e^{\frac{L_i + t_p}{\tau_i}} \right) \tag{27}$$

β_i expressions

$$\beta_{1,k}^{'''} = \sum_{j=1}^{\lambda_i} {G_i}^2 \tau_i \, u(t_{k-j}) \, {w_{i,k}}^2 \, e^{\frac{\Delta L_i - t_p - j\, T_s + \lambda_i \, T_s}{\tau_i}} \left(e^{\frac{T_s}{\tau_i}} - 1\right) \left(e^{\frac{L_i - t_p}{\tau_i}} - 2\right) \ldots$$

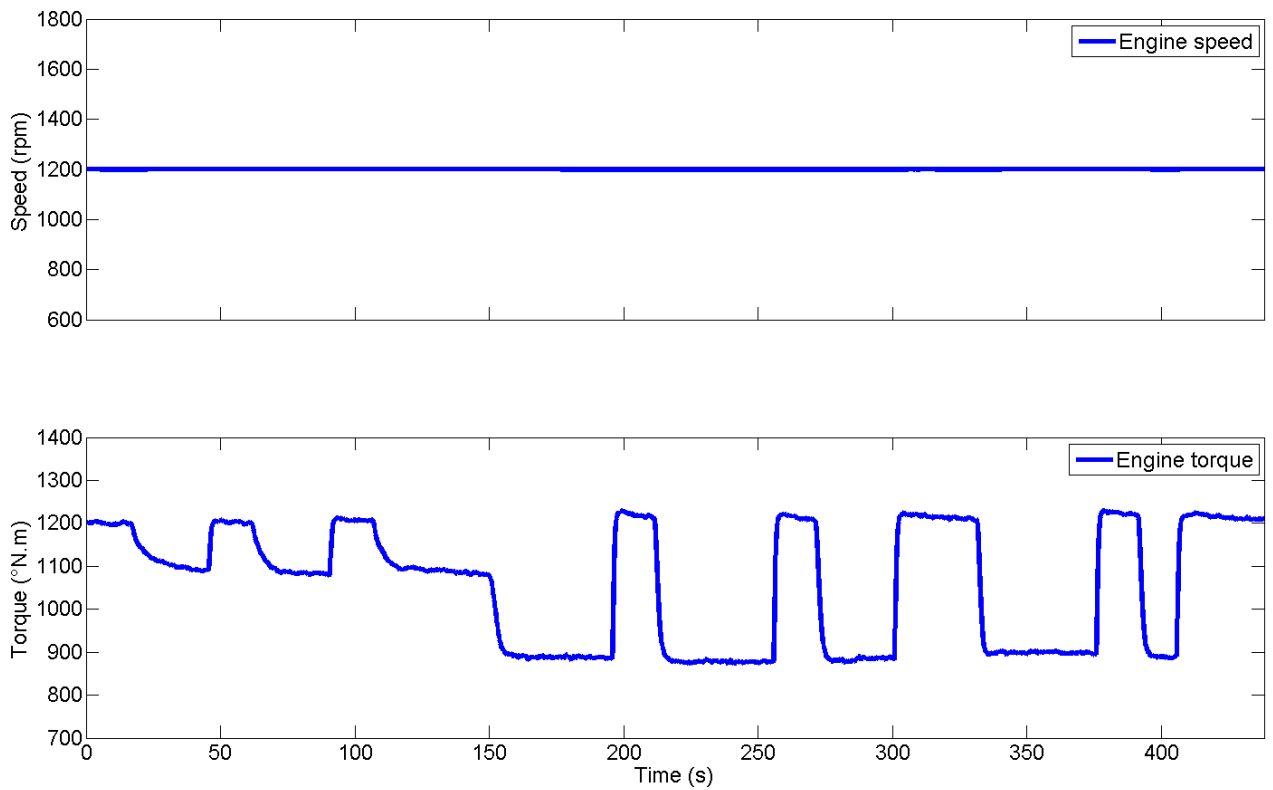
$$- {G_i}^2 \tau_i \, u(t_{k-j}) \, {w_{i,k}}^2 \, e^{\frac{\Delta L_i - j\, T_s + \lambda_i \, T_s}{\tau_i}} \left(e^{\frac{L_i}{\tau_i}} - 2\right) \left(e^{\frac{T_s}{\tau_i}} - 1\right) \quad (28)$$

$$\beta_{1,k}^{''''} = 2 \, G_i \, w_{i,k} \left(e_k - y^{SP}\right) \left(t_p + \tau_i \, e^{\frac{L_i - t_p}{\tau_i}} - \tau_i \, e^{\frac{L_i}{\tau_i}}\right) \quad (29)$$

$$\beta_{2,k} = \frac{{G_i}^2 \, {w_{i,k}}^2 \left(2\, t_p + 4\, \tau_i \, e^{\frac{L_i - t_p}{\tau_i}} - \tau_i \, e^{\frac{2\, L_i - 2\, t_p}{\tau_i}} - 4\, \tau_i \, e^{\frac{L_i}{\tau_i}} + \tau_i \, e^{\frac{2\, L_i}{\tau_i}}\right)}{2} + w_u \, t_p \quad (30)$$

Input disturbances

Engine speed and torque



Tracking error and manipulated variable

Developed weighting scheme