Simultaneous control of NO_x, soot and fuel economy of a dies engine with dual-loop EGR and VNT using economic MPC

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Highlights

Simultaneous and Direct Control of the VNT and Dual-loop EGR to Optimise NO_x, Soot and Fuel Economy with Economic MPC

Zihao Liu, Arash M. Dizgah, Jose M. Herreros, Joschka Schaub, Olivier Haas

- Novel economic model predictive controller design for engine airpath management.
- Simultaneously optimise NO_x, Soot and fuel economy.
- Determine optimal set points online on transient basis.
- Outperform production controller in emission and fuel economy.

Simultaneous and Direct Control of the VNT and Dual-loop EGR to Optimise NO_x, Soot and Fuel Economy with Economic MPC

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ABSTRACT

This paper proposes a nonlinear economic model predictive control (eMPC) strategy for the airpath management of engines with dual-loop exhaust gas recirculation (EGR) and variable nozzle turbocharger (VNT). The controller directly controls the VNT and dual-loop EGR valves to simultaneously minimise NO_x, Soot and pumping loss. The novelty of this management strategy is to use a merged controller to replace a conventional combination of supervisory and tracking controllers, as well as eliminating the offline determination of the intake manifold pressure and cylinder oxygen concentration set points. The eMPC computes the set points online based on the engine operating condition, state feedback and the weightings of each economic objective, namely NO_x, Soot and fuel economy. The eMPC is simulated with an experimentally validated EURO 6 2L four-cylinder engine model. The performance of the eMPC is compared to a proprietary benchmark controller over Worldwide harmonised Light Vehicle Test Cycle (WLTC). Compared to the benchmark controller, the eMPC demonstrates NO_x and Soot emission reductions as well as improved torque tracking and fuel economy.

1. Introduction

Legislation calling for cleaner engines with better fuel economy motivates significant emission reductions. Engine downsizing with variable nozzle turbocharger (VNT) and dual-loop exhaust gas recirculation (EGR) has improved fuel economy and reduced emissions including NO_x and Soot [18]. VNT adjusts its nozzle position to respond quickly to higher boost pressure demand at lower engine speed which results in a higher specific efficiency compared to a fixed geometry turbocharger (FGT) [27]. Increasing EGR reduces NO_x emission by lowering cylinder peak combustion temperature and oxygen concentration [18]. However, increasing EGR also generates more Soot leading to the need to find an appropriate trade-off between reducing NO_x or reducing Soot [19]. Dual-loop EGR supplements the conventional high pressure (HP) EGR with the incorporation of a low pressure (LP) route which comes from downstream of the diesel particulate filter (DPF) and joins the air intake upstream of the compressor. The filtered LP EGR further reduces Soot formation at higher engine loads [6]. It also results in more appropriately cooled and homogeneous mixture of exhaust and fresh air whilst preserving higher pressure differential for the VNT, compared to the HP EGR. However, LP EGR has slower dynamics and could contain condensed water that could damage the compressor [24]. Controlling the dual-loop EGR is usually implemented via a split ratio/index that is operating point specific. The split ratio aims to achieve optimal emission trade-off and fuel economy [23].

The downsized engine airpath presents strongly coupled nonlinear dynamics between multiple inputs and multiple outputs (MIMO) as well as physical constraints such as VNT choking and surging limits. Whilst the system to be controlled is complex, the controller is required to operate under 20 milliseconds to accommodate the fast dynamics [10, 12, 17, 5]. Conventional control strategies for the engine airpath track the intake manifold (boost) pressure and oxygen concentration (or EGR rate) set points. The set points are determined offline, specific to the engine operating point, which is normally defined by engine speed and torque.

This set point tracking strategy can be implemented with feed-forward controllers [14, 7] and PI/PID controllers [31, 8]. Industry solutions for airpath control commonly combine both feed-forward and PI/PID controllers [9]. Feed-forward allows the direct use of nonlinear physical and/or empirical models but are usually determined on a steady-state basis. Using PI/PID for MIMO systems require specific design and tuning approach to accommodate coupled dynamics and constraints. Robust control including nonlinear Lyapunov based [29] and switched linear H_∞ [21] control directly considers the coupled dynamics whilst the state constraints are not explicitly handled. Model predictive control (MPC) is considered promising since it systematically accounts for both model dynamics and state constraints. However, MPC demands significantly more online computation which limits its production use. Linear MPC [30], experimentally validated in [4], uses 192 linear models and reports good tracking and constraint handling ability at 20 ms sampling time. The linear MPC in [26] uses 12 models and enforces constraints over average emission that are modelled in static maps. Nonlinear MPC (NMPC) uses fewer models,

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by taking into account nonlinearities in the system, but is more computationally challenging. NMPC with polynomial models combined with a variety of constraint handling strategies has been shown to be solvable in real time [11]. Approximating NMPC control law with an artificial neural network also offers computationally feasible alternatives [20].

MPC offers a systematic framework for constrained nonlinear tracking control problem as well as supervisory control. Economic MPC (eMPC) optimises directly high-level performance indices with an economic objective function [25]. In the airpath control application, eMPC can directly minimise the set points calibration criteria including emissions and fuel consumption whilst ensuring driveability. This results in a supervisory eMPC that decides the set points online to be tracked by an inner controller [9]. This design has two systematic advantages. First, online set points calculations, considering model dynamics, results in better transient performance than adopting set points calibrated offline at steady-state. Second, future controller developments become simpler and flexible as the calibration policy can be changed simply via eMPC objective weightings during runtime. This simplifies the time consuming calibration process and iterative updating of LUTs. The eMPC in [17] defined the boost pressure and EGR rate to maximise engine efficiency whilst constraining NOx emission. However, it did not explicitly optimise NOx and Soot whose trade-off is critical during calibration. Moreover, coupling their eMPC with an inner tracking MPC requires solving two separate optimisation problems online and is practically challenging to implement. A supervisory eMPC in [15] computes a NOx set point that maximises exhaust thermal power and fuel economy for a long horizon. Both aforementioned implementations created supervisory eMPC with resulting set points being tracked by independent inner controllers. This paper presents a nonlinear eMPC with the following contributions:

1. Different to [17, 15], it directly minimises NOx, Soot and fuel consumption without needing another inner controller;
2. The optimisation of NOx, Soot and fuel economy are computed online on a transient basis as opposed to conventional calibration done offline at steady-state;
3. Its performance is evaluated over the WLTC against an EURO 6 production engine controller, implemented with an experimentally validated engine model provided by FEV GmbH.

The remainder of the paper is organised as follows. **Section II** describes the EURO 6 engine configuration and the prediction model for the eMPC. **Section III** formulates the economic optimal control problem that simultaneously minimises NOx, Soot and fuel consumption. **Section IV** describes the controller implementation using condensing and the handling of inequality constraints. **Section V** presents the simulation results of the eMPC's performance, compared against the benchmark controller over WLTC. Finally, **sec-**

Figure 1: An illustration of the EURO 6 engine studied in this research which is a 2L four-cylinder turbocharged engine with dual-loop EGR and VNT. The LP EGR routes from downstream DPF to upstream of the compressor. A pressure & temperature sensor is installed at the intake manifold.

tion VI concludes this paper and suggests areas of future work.

2. System Modelling

The target engine is an EURO 6 compliant, 4-cylinder, 2L compression ignition engine. The schematic representation of the engine air path is given in Fig 1. The intake manifold pressure & temperature sensor, coolant temperature sensor and engine speed sensor provide feedback to the airpath controller. The intake manifold pressure, temperature and the estimated oxygen concentration are used to predict emission and pumping losses. The coolant temperature is used in prediction mode to consider engine temperature, e.g. cold or warm engine start. Both HP and LP EGR are intercooled. The target engine plant model is a grey-box model with physics. The model parameters are determined empirically and parametric to operating conditions stored in LUTs. These LUTs are experimentally calibrated and validated by FEV GmbH. The prediction model for eMPC includes control valves dynamics, engine dynamics and emissions. The predicted valve dynamics replicates the plant model valve dynamics as a first order filter. The engine dynamics and emissions are modelled with multi-parametric polynomials that are identified with a data-driven method. The model states and parameters are:

1. three control inputs, $\mathbf{u} = [u_h, u_l, u_v]^T$ representing the desired HP EGR, LP EGR and VNT valve position percentage, respectively.
2. three dynamic actuator states, $\tilde{\mathbf{u}} = [\tilde{u}_h, \tilde{u}_l, \tilde{u}_v]^T$ denoting the actual valve position for HP EGR, LP EGR and VNT, respectively.
3. two dynamic states, $\mathbf{x} = [p_2, x_o]^T$ comprised of intake manifold (boost) pressure p_2 in kPa and cylinder oxygen concentration x_o as the molar mass fraction.
4. four algebraic states: the cylinder mass intake m_{cyl} [g] used to model the oxygen fuel ratio; the cylinder NOx [parts-per million (ppm)] and Soot concentration after combustion [kg/kg], denoted by x_{nox} and x_{soot} ,

respectively; the engine pumping loss, p_{loss} , defined as the pressure difference between exhaust and intake manifold in kPa. The last three states are conveniently grouped in the output states vector $\mathbf{y} = [x_{nox}, x_{soot}, p_{loss}]^T$.

5. four parameters grouped within the vector $\boldsymbol{\rho} = [n_e, bmep, T_{co}, T_2]^T$, representing engine speed n_e [rpm], brake mean effective pressure $bmep$ [bar], coolant temperature T_{co} [K], intake-manifold temperature T_2 [K], respectively and the fuel mass [milligram (mg)] injection per stroke m_{fuel} for all cylinders.

The variables in the following sections use subscript h, l, v to represent HP, LP EGR and VNT respectively. t_s denotes sampling time and $\mathbf{I}$ is an identity matrix of size 3×3 .

2.1. Valve and Engine Dynamics

The actuator valves are modelled in discrete time as:

$$\tilde{\mathbf{u}}_{k+1} = t_s \mathbf{T} \mathbf{u}_{k+1} + (\mathbf{I} - t_s \mathbf{T}) \tilde{\mathbf{u}}_k \quad (1)$$

where $\mathbf{T} = \text{diag}(t_h, t_l, t_v)$ is a diagonal matrix embedding the time constants of each valve. The resulting valve dynamic states $\tilde{\mathbf{u}}$ are the actual valve positions under the desired position input $\mathbf{u}$.

The dynamic models for intake manifold pressure p_2 and oxygen concentration x_O are:

$$p_{2,k+1} = f_{2,p2}(p_{2,k}, x_{O,k}) + f_{3,p2}(\tilde{\mathbf{u}}_k; \boldsymbol{\rho}) \quad (2a)$$

$$x_{O,k+1} = f_{2,O}(p_{2,k}, x_{O,k}) + f_{2,O}(\tilde{\mathbf{u}}_k; \boldsymbol{\rho}) \quad (2b)$$

The function of the form $f_d(\cdot)$ is a multi-parametric polynomial that is the span of any number of input elements multiplied up to the order d plus a constant term. For example, for $\mathbf{a} = [a_1, a_2]^T$, $d = 2$, $f_d(\mathbf{a})$ is given by:

$$f_d(\mathbf{a}) = \boldsymbol{\theta}_d^T \Phi_d(\mathbf{a}) \quad (3a)$$

where

$$\Phi_d(\mathbf{a}) = [1, a_1, a_2, a_1 a_2, a_1^2, a_2^2]^T \quad (4a)$$

with $\boldsymbol{\theta}_d$ being a vector of real valued coefficients to be identified.

The first part of each model $f_d(p_{2,k}, x_{O,k})$ in (2) introduces a quadratic relation between the two dynamic states. The subsequent polynomial $f_d(\tilde{\mathbf{u}}_k; \boldsymbol{\rho})$ contains the predicted valve position and the operating conditions.

2.2. Engine Emission, Pumping Loss and Cylinder Mass Intake

The NOx and Soot emissions are modelled with their cylinder concentration after combustion. They are modelled algebraically as the exponential of multi-parametric polynomials (4a) in (5a), (5b). The same multi-parametric polynomials are used to model pumping loss (5c) and cylinder mass intake (5d).

$$x_{nox,k} = \exp(f_{2,nox}(p_{2,k}, x_{O,k}; \boldsymbol{\rho})) \quad (5a)$$

Table 1

Accuracy of the developed prediction model measured by RMSE, normalised RMSE (NRMSE), and coefficient of determination R_T^2 with respect to an experimentally validated model

Model	Unit	Negative / Total Polynomial Terms	RMSE	NRMSE	R_T^2
p_2	kPa	7/29	6.94	0.72	0.94
x_O	mol/mol	10/26	0.01	0.45	0.79
$\log(x_{nox})$	log(ppm)	5/33	0.22	0.73	0.95
$\log(x_{soot})$	log(g/g)	5/43	0.77	0.59	0.85
p_{loss}	kPa	2/27	8.07	0.55	0.71
m_{cyl}	mg	0/4	10.04	0.92	0.99

$$x_{soot,k} = \exp(f_{2,soot}(p_{2,k}, x_{O,k}; \boldsymbol{\rho})) \quad (5b)$$

$$p_{loss,k} = f_{2,ploss}(p_{2,k}, \tilde{\mathbf{u}}_k; \boldsymbol{\rho}) \quad (5c)$$

$$m_{cyl,k} = f_{2,mcyl}(p_{2,k}; \boldsymbol{\rho}) \quad (5d)$$

The emissions are modelled as concentration whereas the control objective is to minimise emission mass, which is the product of the cylinder mass or volume and the concentration. A positive correlation between pumping loss and cylinder mass suggests that reducing pumping loss reduces cylinder mass and hence emission mass. To ensure a sufficient amount of oxygen mass is available for combustion to meet the torque demand, a minimum stoichiometric oxygen fuel ratio is enforced when formulating the control problem.

2.3. Identification of the Prediction Model

The system is identified with artificially generated data and is validated with the WLTC simulation data using the benchmark controller. Both modelling and validation data have warm engine start. The identification data are generated by simulating the plant model's responses to specifically designed inputs signals for n_e , $bmep$ and $\mathbf{u}$. These input signals are created by applying a sequence of random numbers, following a uniform probability, within the nominal range of each input signal. Each randomly generated input is held constant over a time interval suitable for the system to settle, namely 8 seconds for n_e , $bmep$ and 4 seconds for $\mathbf{u}$. A separate fuel injection controller is provided to meet the requested $bmep$.

The model is then repeatedly identified with a pruning procedure by solving a bounded value least square problem using the MATLAB® command `quadprog`. The pruning of the model deletes iteratively the least statistically significant polynomial term until the model reaches the desired trade-off between accuracy and complexity. The desired trade-off requires the coefficient of determination R_T^2 to be greater than 0.70. Further accuracy improvement is assessed numerically for each model leveraging model complexity. The resulting model complexity and goodness of fit is summarised in Table 1.

2.4. Convexity of the Prediction Model

Non-convex optimisation problems can result in sub-optimum solution, poor convergence and premature solver termination. Ideally, the convexity of the models can be guaranteed by enforcing all polynomial coefficients to be positive during system identification. Since other model inputs (including engine speed, torque, valve positions) are inherently non-negative due to their physical meanings, the cost function has positive second order derivatives within the Hessian matrix. An Hessian matrix comprising only positive elements will be positive definite, resulting in an easily solvable convex problem.

During practical implementation, some polynomial coefficients, when allowed to have very small negative value, have been found to considerably improve the prediction model accuracy. The small negative values are required to be greater than -1, so that during states evolution, any multiplication resulting in negative value has a decaying magnitude towards 0. Allowing these negative polynomial coefficients is decided on a case by case basis. The resulting number of negative coefficients are counted in Table 1. Although they improved the model accuracy, their presence negatively affects the convexity and gives rise of non-positive definite (NPD) Hessian matrix. Treatment of the NPD Hessian matrix is discussed in section IV.

3. Economic MPC

The control objective of the eMPC is to simultaneously minimise NOx, Soot and brake specific fuel consumption (*bsfc*). The fuel consumption is minimised via minimising pumping loss. Lower pumping loss results in a higher engine mechanical efficiency, hence improved fuel economy. This differs from the work in [17] which modifies fuel injection to maximise engine efficiency. An independent feed-forward fuel controller is used in this work to calculate the fuel mass injection m_{fuel} based on the driver's torque request as illustrated in Fig. 2. The plant engine model provides sensor feedback on $[n_e, p_2, T_{co}, T_2]$. These feedback along with fuel mass injection m_{fuel} , are checked against LUTs to estimate the delivered torque $bmepe_{st}$ and cylinder oxygen concentration $x_{O,est}$. The eMPC utilises the feedback estimation to compute the optimal control action that minimises its economic objective function.

The OCP is formulated as follow. The subscript *mea* and *est* indicate measured and estimated signal respectively. The stoichiometric oxygen fuel ratio (OFR) by mass OFR_{stoich} , the oxygen molar mass M_{o_2} and the air molar mass M_{air} are constants defined numerically as 3.35, 32 g/mol, 28.97 g/mol respectively. λ_O is the ratio between OFR and OFR_{stoich} shown in (6c). Its inverse (6g) is used for inequality constraint since m_{fuel} may result in a zero valued denominator.

$$\{u\}^* = \arg \min_{u \in \mathbb{U}} \sum_{i=1}^{n_p} L_i(y_i, u_i; \rho) \quad (6a)$$

Figure 2: An illustration of the control loop including the eMPC, an independent fuel controller and the engine. The eMPC manipulates the HP, LP EGR and VNT valves (u_h, u_l, u_v). The fuel controller is feed-forward to control fuel mass injection (m_{fuel}). m_{fuel} is used by the eMPC to enforce sufficient oxygen mass by λ_O limit. The state feedback from the engine include engine speed (n_e), intake manifold pressure (p_2), temperature (T_2) and coolant temperature (T_{co}). The brake engine torque ($bmepe_{st}$) and cylinder oxygen concentration ($x_{O,est}$) are estimated from LUTs.

$$s.t. \quad (1), (2), (5) \quad (6b)$$

$$\lambda_{O,k} = \frac{(m_{cyl,k} x_{O,k} \frac{M_{o_2}}{M_{air}})}{m_{fuel} OFR_{stoich}} \quad (6c)$$

$$p_{2,0} = p_{2,mea}, x_{O,0} = x_{O,est}, \tilde{u}_0 = \tilde{u}_{mea} \quad (6d)$$

$$u_{min} \leq u \leq u_{max} \quad (6e)$$

$$x_{min} \leq x \leq x_{max} \quad (6f)$$

$$(\lambda_{O,k})^{-1} \leq 1 \quad (6g)$$

$$k \in \{0, 1, \dots, n_p - 1\}$$

Where $y_i = [x_{nox,i}, x_{soot,i}, p_{loss,i}]^T$ are the output states, $x = [p_{2,i}, x_{O,i}]^T$ are the dynamic states, $u = [u_{h,i}, u_{l,i}, u_{v,i}]^T$ are the manipulated variables, and $\rho = [n_e, bmepe, T_{co}, T_2]^T$ are the parameters. The stage cost function L_i is defined as:

$$\begin{aligned} L_i := & (N_y y_i)^T Q (N_y y_i) \\ & + (N_{u_E} u_{E,i})^T R_1 (N_{u_E} u_{E,i}) \\ & + (N_{\Delta u} \Delta u_i)^T R_2 (N_{\Delta u} \Delta u_i) \end{aligned} \quad (7)$$

where $Q, R_1, R_2 \in \mathbb{R}_+^{3 \times 3}$ are diagonal matrices of non-negative weightings. The control energy vector is defined as $u_E = u - [0, 0, u_{v,eff}]^T$ with $u_{v,eff}$ being the most efficient VNT valve position which is operating condition specific. Δu is the control variation written as $(u_i - u_{i-1})$. Diagonal matrices $N_y, N_{u_E}, N_{\Delta u} \in \mathbb{R}_+^{3 \times 3}$ contains the normalisation factors to scale each control objective to unit value. Their values are decided based on the maximal value of the term observed over the WLTC with an exception of the Soot concentration. The Soot concentration exhibits significant transient behaviour and is normalised by a value that is larger than 85% of the measured values.

Remark 1. *OFR or its equivalent, has been modelled in [17, 30]. The OFR is used to ensure that the fuel combustion process has sufficient oxygen and to suppress Soot spikes known*

as stoichiometric and Soot limit, respectively. The stoichiometric limit is addressed by enforcing oxygen fuel ratio to be greater than the stoichiometric value. The Soot limit varies upon operating condition and typically requires OFR to be slightly higher than the stoichiometric value. In the cost function design, the soot limit is considered via the weighting between NOx and Soot which automatically adjusts the oxygen concentration to attenuate Soot spike. An upper limit is applied to the oxygen concentration to ensure a feasible optimal trajectory, since its value is physically capped by its ambient concentration.

Remark 2. Dual-loop EGR control with MPC in [3] tracks the target EGR mass flow for each EGR loop. The EGR mass delivered by the HP and LP route is calculated from the EGR split [22]. The proposed cost function design enables the optimal split to be calibrated offline and implemented in the eMPC by adjusting each EGR valve control energy weighting. However, the construction of the eMPC allows an automatic search of optimal EGR split online. This can be done by assigning equal weighting to both HP and LP EGR valve control energy penalty. Such equal weighting is implemented and shown in *section V*.

Remark 3. Box constraints of the VNT valve position are used to prevent turbocharger from choking and surging. Additionally, the cost function encourages an efficient valve position by penalising the $(u_v - u_{v,eff})^2$ term where $u_{v,eff}$ is the most efficient valve position of the VNT.

Remark 4. Since NOx, Soot are directly modelled, constraints can be applied to limit the instantaneous engine-out NOx and Soot mass. A moving window with average emission limits can also be devised.

4. Implementation of the Developed eMPC

Before being solved online, a technique known as "condensing" is used to convert dynamic and algebraic states into functions of control inputs $\mathbf{u}$ hence eliminating equality constraints. This reduces the decision variables to the controls and results in a denser but smaller Hessian matrix. The use of condensing is shown to reduce computational time in [28] for an OCP of similar size. Following condensing, the inequality constraints are converted into exterior penalties. The penalties use exponential functions that are tuned offline. The tuning results in penalties matched to the magnitude of the state and each cost function term's unit value. Using fixed exterior penalty could result in minor bound violation with an exponentially increasing penalty. However, it mitigates the computational overheads in the case where inequality constraints are iteratively tightened online using the interior point method [2]. The exterior point penalty has been shown effective in handling inequalities in [11] and has therefore been adopted in this work.

Having condensed the problem and applied exterior point penalties, the Jacobian and Hessian of the cost function are analytically computed via the algorithmic differentiation tool CasADi [1]. A custom routine written in MATLAB® is

used to solve the unconstrained problem online. The solver routine implements the exact Newton's method with a line search strategy [2]. During implementation, the treatment of non-positive definite (NPD) Hessian matrix is critical. The NPD Hessian matrix is also ill-conditioned. This results in a difficult linear system to solve and may result in premature solver termination or local optimum. The combined computational effort to examine and modify the Hessian matrix motivates a switching strategy that resorts to the gradient descent method described in [16]. The first detection of NPD matrix leads to a switch from exact Newton to gradient descent method. The first order method has slower convergence but allows fast iterations with reasonable descent for real-time application. Having described the eMPC controller implementation, the next section demonstrates its performance against a production controller using a validated EURO 6 engine model.

5. Simulation Results & Discussion

The eMPC is simulated with an experimentally validated engine model on a desktop computer (Intel Xeon E5-1620 CPU, 3.60 GHz clock rate, 12 GB RAM memory with a 64-bit Windows 10 operating system (OS)). The eMPC runs with 10 steps prediction and control horizon. It is compared against an EURO 6 compliant model-based benchmark controller using the WLTC. The benchmark controller accepts an engine-out NOx emission set point calibrated and stored in LUT. The NOx set point translates into the cylinder oxygen concentration and boost pressure targets to be tracked by its inner PI and feed-forward controllers, respectively. Both controllers run at 10 ms with a warm engine start.

The WLTC comprises light (L), medium (M), heavy (H) and extra-heavy (EH) duty cycles. The engine speed and torque are taken from WLTC test data from a vehicle equipped with the target engine. The controller's performance is evaluated for each WLTC part against 6 criteria, namely brake specific NOx emission, Soot emission, engine out NOx, Soot mass, brake specific fuel consumption (*bsfc*) and torque tracking root mean square error (RMSE). The torque tracking between the two controllers is different depending on their violation of the stoichiometric oxygen fuel ratio or Soot limit. The fuel controller works reactively to cut excessive fuel injection upon violation which causes torque tracking infeasibility. During idling, both controllers use zero EGR so that the emissions are identical. This is because idling may not be representative in realistic driving due to start-stop strategies, for example. The resulting overall emission therefore compares the two controllers during engine transient operation. This is done in eMPC by setting both upper and lower limit to 0 for the EGR valves. Throughout the WLTC, eMPC uses 4 sets of weighting values $\mathbf{Q}, \mathbf{R}_1, \mathbf{R}_2$ tuned for each WLTC part; all other parameters ($u_{v,eff}, \mathbf{N}_y, \mathbf{N}_{uE}, \mathbf{N}_{\Delta u}$) remain constant. The values are normalised for confidentiality.

The performance improvements offered by the eMPC are summarised in Table 2. The eMPC has demonstrated better

Table 2

The improvement (%) by eMPC against the benchmark controller calculated for each WLTC section (L: Light; M: Medium; H: High; EH: Extra-High Duties).

Test Cycle Part	Percentage Improvement (%)					Torque Tracking RMSE
	NOx Mass	Soot Mass	BS NOx	BS Soot	Mean BSFC	
L	11.11	8.01	11.43	8.34	1.96	12.16
M	1.51	0.47	2.12	1.09	0.99	25.76
H	3.23	4.12	3.99	4.87	1.91	33.18
EH	1.99	1.98	1.94	1.91	0.73	9.75
Total	4.18	3.28	4.51	3.62	1.24	20.64

Figure 3: A graphical representation of Table. 2 evaluating both controllers by each performance criteria. Data is normalised for the whole WLTC.

performance in all aspects compared to the benchmark controller, including NOx emissions, Soot emissions, fuel economy and torque tracking. Additionally, brake specific emissions are presented to give an unbiased statistic to torque tracking (engine brake power) variation. The absolute magnitude of torque tracking RMSE are within 8 Nm. The trade-off between NOx, Soot is adjusted by the cost function weightings. They are firstly tuned to have a similar trade-off to the benchmark controller before a finer tuning. Selecting cost function weightings that favour better fuel economy results in deterioration in both NOx and Soot. The best improvement was achieved in the light duty part since it has the least variance in engine speed and torque as well as the highest estimated model accuracy. In the extra-heavy duty part, the use of a single set of weighting across the large engine speed and torque variance may have limited further performance advantage. This highlights that the selection of the controller weightings should be based on online identification of the engine operating conditions as opposed to determining weightings based on different sections of the drive cycle. The overall performance advantage by eMPC is also presented in a radar chart in Fig. 3.

Fig. 4 (a) and (b) show how eMPC gains advantage in terms of cumulative NOx and Soot emission mass respectively.

Figure 4: A comparison between the eMPC and the benchmark controller by the cumulative engine-out (a) NOx , (b) Soot mass; (c) cumulative fuel mass injected; and (d) cumulative stage cost function. The stage cost function is defined in (7), calculated with measured signal value. A lower value indicates more optimal performance according to the weighted objective function. *Red dotted lines (· ·) separates each WLTC section.

The eMPC gains emission mass consistently lower than the benchmark controller. The cumulative fuel mass in (c) shows very minor differences and indicates very little torque tracking variation. The overall performance is evaluated by the stage cost function calculated with the measured signal values. A lower value indicates a better performance as defined by the weighted cost function, which considers both emissions and pumping loss reduction. The stage cost function is cumulatively summed in (d), showing that the eMPC has outperformed the benchmark controller according to the defined economic stage cost function.

Fig. 5 shows the time series signals with selected time periods for each WLTC part. Fig. 5 (a) shows the engine speed and demanded torque. (b) and (c) show the oxygen concentration and boost pressure facilitated by each controller, respectively. The resulting engine-out NOx and Soot emission mass are shown in (d) and (e), respectively. Engine motoring can be observed during 170-190s. During motoring, the benchmark controller closes both EGR. The eMPC, however, keeps both EGR valves open. This is due to the valve variation penalty which aims to reduce large and frequent valve variations. Under the same engine speed and similar torque, the two controllers' choice of oxygen concentration and boost pressure are the dominating factors to the generation of NOx and Soot whilst fuel economy depends on the boost pressure. The eMPC shows less aggressive boost pressure response resulting in less pumping loss but potential torque tracking infeasibility. The eMPC overcomes the torque tracking issue with a higher choice of oxygen concentration as shown at time 610s. When the benchmark controller has high boost pressure and low oxygen concentration to facilitate a feasible OFR for the fuel request,

Figure 5: Simulation results of a selected period from each WLTC duty cycle including (a) the engine speed and torque (dashed line); the (b) oxygen concentration and (c) boost pressure realised by each controller; the instantaneous engine out (d) NOx and (e) Soot mass; (f) the pumping loss, i.e. pressure difference between exhaust and intake manifold; (g) the λ defined in (6c) whose inverse is constrained to be no greater than 1; and finally, the valve positions of (i) HP EGR, (j) LP EGR and (k) VNT.

the eMPC chooses a much lower boost pressure and higher oxygen concentration. This results in a similar amount of oxygen mass and none of the controller violates the lambda limit shown in (g). The eMPC hence achieves lower pumping loss and an emission trade-off with higher Soot but lower NOx. Slightly before 610s, as the torque demand increases, the benchmark controller recovers the oxygen concentration to a higher value whereas the eMPC remained at a lower value. The eMPC avoids the NOx spike for a negligible Soot increase compared to the benchmark controller, resulting in a better overall NOx-Soot trade-off which is also observed at 1065s and 1500s.

The violation of λ limit as shown in Fig.5 (g) has occurred to

Figure 6: Operating points of the VNT compressor for each WLTC section. The eMPC operates the VNT at a similar region to that of the benchmark controller without violation of choke and surge boundary.

Figure 7: The operational details of the controllers over WLTC including: (a) the execution time of the eMPC and benchmark controller on a desktop computer with Xeon E5 1620 processor of 3.6 GHz clock rate, running on Windows 10 OS; (b) the iteration count of the solver; (c) the flag indicating the occurrence of the NPD Hessian matrix (1=true) for the eMPC.

Table 3

Measured and predicted execution time of each controller. The desktop PC runs at approximately 1100 MIPS as measured by evaluating Hessian MEX function of known number of instructions. Infineon Aurix runs at 600 MIPS according to its data-sheet [13].

Controller	Estimated Number of Instructions	Measured PC Execution Time (ms)	Predicted Aurix ECU Execution Time (ms)
eMPC	4,392,074	3.47	7.32
Benchmark Controller	825,000	0.8	1.38

the benchmark controller a few times while none happened to the eMPC in the selected time periods. The lambda limit enforced by the exterior penalty in eMPC allows minor violation. This violation is physically possible since building up the cylinder mass could take longer than 1 second which is much slower than the rapidly increasing torque request and also exceeds the controller's prediction horizon. As a result, the controller cannot guarantee sufficient oxygen mass. In order to facilitate maximal possible cylinder oxygen mass when λ^{-1} approaches 1, the eMPC actuates VNT sharply whilst closing all EGR to maximise oxygen concentration. Taking such control demonstrated better torque tracking than

the benchmark controller.

Fig. 6 shows the VNT's compressor operating points. The eMPC operates the compressor at a similar range compared to the benchmark controller. All VNT operating points were simultaneously checked against its model based VNT limit and reported no surge and choke boundary violation. During the H and EH parts, eMPC operated the VNT with higher compressor pressure ratio but overall less mass intake.

Both eMPC and benchmark controller are executed and timed in Simulink® in rapid accelerator mode. The worst and mean computing time for the eMPC shown in Fig. 7 (a) are 3.47 and 1.13 ms respectively. The benchmark controller consistently operates around 0.8 ms. The iteration count for the eMPC solver is shown in (b). The maximum number of iterations allowed for the exact Newton's and gradient descent method are 6 and 10, respectively. The occurrences of NPD Hessian matrix accounts for 17.9% cases throughout the WLTC as shown in (c). A further estimation of the controller's execution time on an Infineon Aurix [13] ECU is shown in Table. 3. The Infineon Aurix is an high specification ECU used for automotive application and has processing power at over 600 million instructions per second (MIPS). The execution time is predicted based on the estimated number of instructions from each controller which is deducted based on the known number of instructions and evaluation time of the Jacobian and Hessian calculation on the desktop computer. The eMPC is predicted to have a worst case 7.32 ms execution time on Infineon Aurix, which makes it promising for production use whilst requiring a relatively high-end ECU.

6. Conclusion

This paper proposes a novel eMPC design for engine airpath control which simultaneously minimises NO_x, Soot and fuel consumption. The design differs to conventional control in that set points are no longer determined offline at steady-state, but rather, computed online with internally predicted dynamics. This design has a potential to simplify conventional controller development since only a number of objective weightings are to be decided, in comparison to calibrating a set of LUTs. However, determining the rule that defines the eMPC objective weightings could be a challenging task and is not studied in this work.

The eMPC was implemented, using simulation, on an experimentally validated proprietary model. Its performance is compared to an industrial standard benchmark controller combining PI and feed-forward control. The eMPC outperforms the benchmark controller in NO_x, Soot mass and fuel economy throughout the WLTC with a worst computing time of 3.47 ms against 0.8 ms of the benchmark controller on a desktop computer. Its worst execution time on an Infineon Aurix ECU is predicted to be 7.32 ms based on known MIPS and estimated number of instructions of the controller.

Future work include the development of an operating point

dependent weighting scheme as well as validation on a hardware-in-loop test bench with an ECU.

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