Nonlinear Model Predictive Engine Airpath Control with Dual-Loop Exhaust Gas Recirculation and Variable Nozzle Turbocharger

Abstract—The control of engine airpath is a constrained multi-objective tracking problem. Multiple control variables including Exhaust Gas Recirculation (EGR) and Variable Nozzle Turbocharger (VNT) valve positions are simultaneously adjusted to accommodate fast, slow and coupled nonlinear airpath dynamics. This work proposes a Nonlinear Model Predictive Controller (NMPC) that exploits a convex and multi-rate prediction model for the real-time airpath control of a compression ignition engine equipped with dual-loop EGR and VNT. The benefits of the approach is verified using simulation study against a EURO 6 production-line controller and Hardware-in-the-Loop (HiL) implementation using a 480MHz processor that is comparable to nominal engine control units. The NMPC demonstrates improved control performances including reduced tracking error for intake manifold pressure, oxygen concentration and torque by 12.23%, 21.45% and 26.99%, respectively, as well as a 0.98% fuel economy improvement than the production-line controller. These benefits hold even with simulated 5% and 10% sensor noises, under one set of objective weightings over the Worldwide harmonized Light vehicles Test Cycles (WLTC). The HiL implementation of the NMPC shows the average and maximum computational time of 1.80 ms and 2.94 ms, respectively, across the WLTC, which are below the required 10 ms control interval.

I. INTRODUCTION

Regulations of vehicles including passenger cars (conventional and hybrids), trucks, trains and marine vessels restrain engines tailpipe emissions and fuel consumption [1]. A variety of methods including but not limited to (i) carbon neutral (electro-fuels) and low to zero carbon fuels [2], (ii) novel insulation and coating materials to reduce engine heat losses [3, 4], (iii) high thermodynamic efficiency engine cycles such as Atkinson [5], (iv) waste exhaust heat energy recovery [6] and (v) low temperature combustion strategies such as reactivity controlled compression ignition [7] have been successfully investigated to reduce emissions (including CO2) and fuel consumption for internal combustion engines. The significant emission saving provided by the aforementioned methods can be further improved by control methods exploiting modern engine features. The focus of this work is on designing such control methods exploiting the use of VNT and dual-loop EGR to reduce emissions for smaller engine sizes compared to conventional engines. VNT builds up the intake manifold pressure by recovering part of the otherwise waste energy from the exhaust gas, hence allowing comparable torque and power with smaller-size and hence more efficient engines [8]. EGR lowers in-cylinder oxygen concentration and local peak combustion temperature by diluting the combustion charge to reduce the generation of NOx emissions [9]. However, EGR could increase soot emissions, known as the NOx-soot trade-off, as well as adversely affecting torque tracking during aggressive accelerations [10].

Dual-loop EGR systems combine a High Pressure (HP) and an additional Low Pressure (LP) EGR route. The HP EGR route connects the exhaust and intake manifold, whilst the LP EGR connects the downstream of the Exhaust Aftertreatment System (EATS) and the air intake. Compared to HP EGR, LP EGR delivers a more homogeneously mixed charge at a higher volumetric efficiency due to cooler recirculating gas. Using LP EGR also reduces the amount of HP EGR and hence lowers the pressure drop upstream of the turbocharger. However, LP EGR takes longer to respond and recirculates gases with more condensed water that could reduce the lifespan of the compressor [11]. The optimal split between the HP and LP loops depends on the engine operating condition [12].

The joint use of dual-loop EGR and VNT actuators affects the pressure at the intake manifold and the oxygen concentration inside the cylinders, resulting in a multi-variable control problem. The controller must also consider different operating constraints, such as preventing VNT from choking.
and surging, whilst delivering sufficient mass of oxygen to meet the torque demand.

Different methods have been adopted to solve the engine airpath control problem. Feedback controllers including PI/PID, H-∞ [13] and sliding mode control [14] are combined with feed-forward controllers to improve the transient performance and robustness by exploiting inverse models of the system. In practice, accurate nonlinear inverse models are challenging to implement resulting in the use of lookup tables to accommodate the system nonlinearities. This results in controllers that require significant tuning and calibration to achieve optimal transient performance whilst operating under constraints. By contrast, Model Predictive Control (MPC) [15] systematically considers the constrained multi-variable system in its control formulation. Initially, due to the computational complexity associated with MPC and limited processing power and memory of automotive Electronic Control Unit (ECU), real-time implementations were only possible with linear models. Nonlinearities had to be accommodated by adopting either a gain-scheduled filter applied to the output of the controller [16] or piece-wise linear prediction models and switch between their associated MPCs [17–19]. The latter required an extensive analysis of the system to partition its operating areas into different variable dependent operating zones, and handling of the control discontinuities among the zones.

Adaptive control strategy can be used but online model parameter estimation requires a fast converging and real-time feasible approach in order to react to a rapidly changing engine load. Using perturbation based stochastic approximation strategy and PID, [20] shows moderate computational footprint at the cost of a degraded performance against one of the tracking objectives compared to a production controller. Adaptive airpath control strategy with the approach of MPC has not been reported.

Direct use of nonlinear models within the MPC formulation can overcome issues associated with discontinuities resulting from model switching and reduce the calibration work to identify the operating zones. The construction of nonlinear models can introduce non-convexity to the control problem which significantly increases computational costs without guaranteeing convergence and adversely affects solution quality. Data-driven modelling with move-blocking [21] and specialised constraint handling [22] have been adopted to reduce processing time. Experimental study of a tracking NMPC [23] shows a worst case of 0.72 ms but requires a powerful 2.6 GHz processor. A less powerful 800 MHz processors was used by [24] for set point regulation NMPC with a worst case execution time of 1.8 ms. A 480 MHz processor, which is still powerful in terms of automotive ECU, was used to demonstrate a parameterised airpath NMPC [25] with computational time between 6.5 ms and 10 ms. The parameterisation in [25] reduces the degree of freedom of the resulting optimisation problem but the computational time is still high. Whilst some NMPC controllers have demonstrated promising computation time, existing controllers have not considered the coupled control of HP, LP and EGR which adds to the complexity and computational cost of the control problem. The embedded execution of engine control ideally should use a fraction of the designated execution interval in order for the ECU to process other tasks of different priorities and execution rates [26]. None of the previous studies reported execution time on a processor comparable to ECU whilst achieving less than half of the designated control interval. This undermines their practicality for production uses.

This work addresses the research gaps in the airpath control of engines, i.e., lack of coupled NMPC of dual-loop EGR with real-time results on processor comparable to actual ECUs, by the following contributions:

1) Developed an NMPC control strategy for the airpath of engines with dual-loop EGR and VNT, which improves the tracking errors of boost pressure and in-cylinder oxygen concentration by 12.23% and 21.45%, respectively, and the fuel economy by 0.98% compared to the benchmark EURO 6 production-line controller.

2) Proposed and demonstrated the benefits of convex and multi-rate prediction models for real-time airpath NMPC. The controller employs process dependent prediction step lengths. A standard interval of 0.01 s is used to predict in-cylinder oxygen concentration whilst a longer 0.1 s prediction interval is used for boost pressure.

3) Demonstrated on a HiL the real-time implementation of the proposed NMPC control strategy which considers HP and LP EGRs. The entire engine control software shows a worst case computational time of 2.94 ms achieved on a 480MHz processor, comparable to an automotive ECU.

The remainder of the paper is organised as follows: Section II describes the engine used for this work, along with its production-line controller and a convex multi-rate model of the airpath dynamics. Section III presents the design of the proposed tracking controller. Section IV describes the online implementation of the proposed NMPC on a HiL setup, including the solver and instruments. Section V compares the simulation and experimental results, generated by a desktop computer and the HiL setup, to the ones of the production-line controller. Finally, Section VI concludes the paper and suggests future works.

II. System Description & Modelling

Fig.1 illustrates the target engine used for this work. It is a two litre EURO-6 Compression Ignition (CI) engine equipped with VNT and dual-loop EGR. The available measurements from the engine to the controller include pressure and temperature of the intake manifold, engine speed and coolant temperature. The experimentally validated model of the engine in [27, 28] and the corresponding production-line controller in [27, 29], provided by FEV GmbH, were adopted in this work.

The engine model, referred to as plant model hereafter, is physics-based with empirically determined parameters stored in Look-up Tables (LUTs). The production-line controller includes the control of injection (common rail pressure, injection timing & mass), EATS, and airpath. On actual ECUs, injection control are typically calculated at fixed crank angle interval, and EATS control typically runs at slower sampling interval than the engine control. For simplification, the provided production-line controller runs at a fixed rate of 0.01 s for
this study. The plant model follows a mean value approach and runs at the same fixed rate of 0.01 s. The airpath control of the production-line controller translates a target of engine-out NOx emission to set points of cylinder oxygen and boost pressure, which are then tracked by a combination of feed-forward and PI controllers.

This paper proposes a NMPC that utilises a prediction model of the airpath with the following states:

1) Dynamic states $x = [p_2, x_O]^T$ where $p_2, x_O$ are boost pressure and cylinder oxygen concentration in kPa and mol/mol, respectively.

2) Intermediate states $p_{\text{loss}}, m_{\text{cyl}}$, which represent the pumping loss in kPa and the mass of cylinder charge in milligrams, respectively.

3) Controls $u = [u_h, u_l, u_v]^T$ where $u_h, u_l, u_v$ are desired valve positions in percentage for HP EGR, LP EGR, and VNT, respectively. The corresponding actual valve positions are $\tilde{u} = [\tilde{u}_h, \tilde{u}_l, \tilde{u}_v]^T$.

4) Operating parameters $\rho = [n_c, \text{bmep}, T_{\text{co}}, T_2]^T$ representing engine speed (rpm), Brake Mean Effective Pressure (BMEP) (bar) and the coolant and intake manifold temperature (K), respectively.

The dynamics of boost pressure and in-cylinder oxygen concentration have distinct time scales. Using step changes of VNT and HP EGR, it takes up to, respectively, 4 and 0.1 s for boost pressure and in-cylinder oxygen to settle. Compared to the control interval of 0.01 s, boost pressure presents much slower dynamics than the in-cylinder oxygen. Fig. 2 presents the auto-correlation of boost pressure and in-cylinder oxygen concentration. It reveals the correlation of the current value of the dynamic state with respect to its previous values, taking account of changes in both control and operating parameters. The oxygen concentration has much shorter time lag than the boost pressure for each threshold of correlation. Based on the identified slow and fast dynamics, this work adopts a long and short prediction interval, which are 0.1 s and 0.01 s for boost pressure and in-cylinder oxygen concentration, respectively. A 0.01 s prediction interval for in-cylinder oxygen concentration equals to the control interval. A 0.1 s prediction interval for boost pressure allows a trade-off to maximise prediction length whilst maintaining the Coefficient of Determination ($R^2_f$) of its prediction accuracy to be greater than 80.

The resulting prediction models are represented in generalised form $f(\cdot)$:

\[
\begin{align*}
\tilde{u}_{k+1} &= t_s T u_{k+1} + (I - t_sT) u_k \\
p_{2,k+10} &= f(p_{2,k}, x_{O,k}) + f(u_{v,k}; \rho) \\
x_{O,k+1} &= f(p_{2,k}, x_{O,k}) + f(u; \rho) \\
p_{\text{loss},k} &= f(p_{2,k}, \tilde{u}_k; \rho) \\
m_{\text{cyl},k} &= f(p_{2,k}; \rho) \\
\lambda_{O,k} &= \frac{(m_{\text{cyl,k}} x_{O,k} M_{\text{air}})}{m_{\text{fuel}} M_{\text{O2}}}
\end{align*}
\]

where (1), (2) and (3) govern the dynamics of actuator valves, boost pressure and in-cylinder oxygen, respectively. Pumping loss and cylinder mass intake are modelled in (4) and (5), respectively. The sampling time, $t_s$, is 10 ms. Diagonal matrix $T$ contains the time constants for the HP EGR, LP EGR and VNT. $\lambda_{O}$ is the fraction of Oxygen Fuel Ratio (OFR) over its stoichiometric value $\text{OFR}_{\text{stoich}}$. $M_{\text{O2}}, M_{\text{air}}$ represent the molar mass of oxygen and air, and have constant values of 32 g/mol and 28.97 g/mol, respectively.

The functions $f(\cdot)$ are the multi-parametric polynomials introduced in [30]. The model is identified to be convex, which allows the solver to quickly find the global optimum. The convexity is guaranteed by enforcing the coefficients of the polynomials to be positive. Since the states and controls are non-negative by their physical meaning, the positive coefficients result in a Hessian matrix with non-negative elements. This allows the Hessian matrix to be positive semi-definite. The convex models are pruned iteratively and verified against the WLTC data set generated using the production-line controller. The identification process uses a bounded value least square algorithm and is described with more details in [30]. Table I summarises the resulting model accuracy over WLTC.

### III. Controller Design

The primary objective of the developed NMPC strategy is to track the set points of boost pressure and in-cylinder oxygen.
TABLE I
ACCURACY AND NUMBER OF POLYNOMIAL TERMS FOR THE IDENTIFIED MODEL.

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE [kPa]</th>
<th>NRMSE</th>
<th>$R^2$</th>
<th>Number of Polynomial Terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_i$</td>
<td>10.76</td>
<td>0.56</td>
<td>83.17</td>
<td>13</td>
</tr>
<tr>
<td>$x_O$ [mol/mol]</td>
<td>0.01</td>
<td>0.53</td>
<td>75.84</td>
<td>19</td>
</tr>
<tr>
<td>$p_{loss}$ [kPa]</td>
<td>8.07</td>
<td>0.55</td>
<td>71.45</td>
<td>28</td>
</tr>
<tr>
<td>$m_{cyl}$ [mg]</td>
<td>10.03</td>
<td>0.92</td>
<td>99.65</td>
<td>4</td>
</tr>
</tbody>
</table>

*() indicates a model with 0.1 s prediction interval whilst the rest are of 0.01 s.

Fig. 3. Controller diagram including the airpath NMPC. The fuel controller is provided from the production-line controller to deliver the required torque.

The value of $u_{v, e ff}$ depends on the operating condition of the VNT and may be read from system specific LUT from manufacturer or derived from experiments.

The resulting Optimal Control Problem (OCP) is formulated as follows:

$$\{ u \}^* = \arg \min_u J(x, u, \rho)$$

$$s.t. \begin{cases} (1), (4), (5), (4), (6) \\ p_{2,k+i} = p_{2,k}, i \in \{0, 1, ..., 9\} \\ u_{v,k+i} = u_{v,k}, i \in \{1, ..., 9\} \\ I_{p2,k+i} = I_{p2,k} - t_s(p_{2,k} - p_{2,sp}) \end{cases}$$

$$I_{o2,k+1} = I_{o2,k} - t_s(x_{O,k} - x_{O,sp})$$

where $I_{p2}, I_{o2}$ are the tracking error integral of the boost pressure and oxygen concentration, respectively, to eliminate steady state tracking errors. The boost pressure is initialised from the sensor reading. Since the boost pressure is predicted every ten prediction steps, the intermediate values are held at zeroth order in (7c). The in-cylinder oxygen concentration is estimated with an existing estimator within the production-line controller based on LUTs. The operating parameters $\rho$ are assumed to be time-invariant throughout the prediction horizon due to their small variance compared to the prediction horizon of 0.1 s. The control horizon is assumed equal to the prediction horizon $n_p$. The vector $\{ u \}$ contains decision variables $[u_{h, 1}, u_{h, 2}, ..., u_{i, 1}, u_{i, 2}, ..., u_{v, 1}, u_{v, 1+10}, ...]^T$. $[u_{h, 0}, u_{l, 0}, u_{v, 0}]^T$ are controls applied at last control interval.

The objective function $J$ and stage cost function $L$ are defined as follows:

$$J := \sum_{i=1}^{n_p} L_i$$

$$L_i := \zeta \times \{(N_{\hat{x}} x_i)^T Q (N_{\hat{x}} x_i) + (N_{\hat{u}} u_i)^T R_1 (N_{\hat{u}} u_i) + (N_{\Delta u} \Delta u_i)^T R_2 (N_{\Delta u} \Delta u_i) + \alpha(n_{\text{ploss}})^2\}$$

where

$$Q \succeq 0; R_1 \succ 0; R_2 \succ 0$$

$$N_{\hat{x}} \succeq 0; N_{\hat{u}} \succeq 0; N_{\Delta u} \succeq 0$$

$$\bar{x}_i = x_i - \begin{bmatrix} p_{2,sp} \\ X_{O,sp} \end{bmatrix} - \begin{bmatrix} K_{1,p2} & 0 \\ 0 & K_{1,o2} \end{bmatrix} \begin{bmatrix} I_{p2,i} \\ I_{o2,i} \end{bmatrix}$$

$$\bar{u}_i = u_i - \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\Delta u_i = u_i - u_{i-1}$$

$K_{1,p2}, K_{1,o2}$ are integral gains; $x_i, u_i$ are state and control vectors defined as $[p_{2,i}, x_{O,i}]^T, [u_{h,i}, u_{l,i}, u_{v,i}]^T$ respectively. Diagonal matrices $N_{\hat{x}}, N_{\hat{u}}, N_{\Delta u}$, and scalar $n_{\text{ploss}}$ are positive normalisation factors to scale $\bar{x}, \bar{u}, \Delta u$ and $p_{\text{loss}}$ to unit value. $Q, R_1, R_2$ are diagonal weighting matrices, $\alpha$ is the weighting scalar for the pumping loss term.
Having formulated the control problem, the next section discusses the online implementation of the controller.

IV. ONLINE IMPLEMENTATION OF THE CONTROLLERS

The developed NMPC is evaluated by a simulation study and HiL implementation. The simulation study uses a desktop computer of Intel Xeon E5-1620 CPU (3.60 GHz), 12GB RAM and Win10 Operating System (OS). The HiL implementation uses a dSPACE® SCALEXIO system [32] and the A80Q7 evaluation board [33], as shown in Fig 4. The A80Q7 board is equipped with eight ARM® cores including four Cortex-A15 (1200 MHz) and four Cortex-A7 cores (480 MHz). However, only one of the A7 cores is used to evaluate the developed controller to make it comparable to ECU.

A developed proprietary solver for the NMPC strategy uses exact-Newton method. The solver runs with a fixed number of six iterations to offers the best trade-off between performance and real-time computational requirements. The equality and inequality constraints are converted to barrier functions described in [30]. The solver routine is written in MATLAB® and uses the embedded code® for the HiL implementation.

When implemented on HiL, the A80Q7 board executes the entire engine control software of the production-line controller including fuel injection, common rail, EATS, and airpath. The airpath control software is then replaced by the developed NMPC and tested subsequently. All signals are represented with 1 byte and transmitted on Controller Area Network (CAN) bus at a rate of 1000 kbit/s due to lack of analogue and digital IOs. There are 20 feedback signals and 8 control signals, carried by three receive (RX) and one transmit (TX) CAN packets. The host computer logs the states of the engine, whilst the A80Q7 board logs the computational time. The control software runs as a single thread on a Cortex-A7 core that is free from other tasks.

Both simulation and HiL use WLTC with warm engine start. WLTC comprises four duty parts, namely light (L), medium (M), heavy (H) and extra-heavy (EH). The prediction horizon of the developed NMPC is set to 10 steps. This requires one prediction of boost pressure and nine predictions of the in-cylinder oxygen due to a different prediction interval adopted for the two dynamics. The values of \( u_{\text{v,eff}}, K_{i,j}, N_{i,j}, n_{\text{ploss}} \) are set to constant values throughout the WLTC, but can be adjusted at run-time to further improve performance for future works. Table II illustrates values of the weightings \( Q, R_1 \) and \( R_2 \) in (8), as well as some of the parameters of the OCP. The matrix element is noted in the form of \( (\cdot)_{ij} \), where \( i, j \) stands for the row and column indices, respectively.

V. SIMULATION AND HIJ RESULTS

The proposed NMPC is evaluated against the production-line controller using both simulation studies and HiL. The results are given in terms of percentage improvements, where positive values demonstrate benefits. The feedback signals include engine speed, intake manifold temperature & pressure, coolant temperature and an estimation of the fuel mass injection. Sensors used on a real engine are corrupted by noise and have finite accuracy. For example temperature sensors are accurate to within 0.5% [34]. To simulate noise and sensor accuracy, a zero-mean Gaussian noise, proportional to the range of the signal observed over the WLTC, is added to each feedback signals. To ensure that the controller can operate under the worst case scenario, 5% and 10% noise level are simulated. The proposed NMPC performances are evaluated against the following criteria: tracking Root Mean Square Error (RMSE) of boost pressure and cylinder oxygen, torque tracking RMSE and mean Brake Specific Fuel Consumption (BSFC).

Table III compares the performance of NMPC against the production-line controller for different duty parts of the WLTC and for three levels of additive measurement noise. The proposed NMPC achieves better tracking of set points and torque whilst still offering better fuel economy when there is no additive noise. The benefits of the proposed NMPC degrade moderately with a 5% Gaussian noise and even with a 10% noise, the NMPC still achieves better performance in all criteria than the production-line controller.

The tracking performance of the two controllers differs mainly during transients (see Fig. 5). The NMPC performs better than production-line controller against variations of engine speed and demanded torque since it can exploit and predict the impact of process dynamics. Fig 6 shows the time series from simulation (left) and HiL (right). The set points for each controller differ slightly since they operate at different conditions including temperature and BMEP. The NMPC shows more accurate tracking of oxygen concentration...
TABLE III

<table>
<thead>
<tr>
<th>Percentage Improvement by NMPC against Production-line Controller</th>
</tr>
</thead>
<tbody>
<tr>
<td>WLTC</td>
</tr>
<tr>
<td>L</td>
</tr>
<tr>
<td>M</td>
</tr>
<tr>
<td>H</td>
</tr>
<tr>
<td>EH</td>
</tr>
<tr>
<td>Total</td>
</tr>
</tbody>
</table>

Gaussian Noise Variance = 5% × Value Range of Feedback Signal

| WLTC | Percentage Improvement by NMPC against Production-line Controller |
|---------------------------------------------------------------|
| L | 9.99 | 9.20 | 0.21 | 16.16 |
| M | 10.54 | 18.33 | 0.37 | 24.99 |
| H | 10.02 | 22.65 | 0.79 | 39.92 |
| EH | 7.18 | -4.14 | 1.19 | 19.27 |
| Total | 8.53 | 14.43 | 0.76 | 26.29 |

Gaussian Noise Variance = 10% × Value Range of Feedback Signal

| WLTC | Percentage Improvement by NMPC against Production-line Controller |
|---------------------------------------------------------------|
| L | 8.07 | 7.98 | 0.60 | 23.64 |

During transients (282-285, 1026-1032 s) than the production-line controller. During these transients, the demanded torque follows a rapid rise-and-fall sequence. With an increasing torque requirement, the PI control of production-line controller shows similar trend than the NMPC in reducing in-cylinder oxygen concentration. However, the performance gap increases when the torque demand falls rapidly, accompanying the rise of oxygen concentration set point. The NMPC quickly reacts and shows minimal undershoots due to its consideration of process dynamics and outperforms the PI control used by production-line controller. To overcome the undershoots, the PI controller would require additional features such as a carefully verified adaptive gain scheduler. The approach of NMPC, in contrast, allows better performance for less calibration effort under these transient circumstances.

The NMPC displays a tracking offset of oxygen during steadier periods (293-302, 1043-1048 s). This offset originates from model-plant mismatch and can be reduced with improved process modelling at the costs of increased controller execution time and/or a greater value of the integral gain. Using a greater integral gain across the WLTC degrades the overall tracking performance and reduces the benefits associated with the ability of NMPC to account for process dynamics. The value of the integral gain may be operating point or transient extent dependent and is an area of future work.

Meanwhile, the NMPC shows better tracking of torque, at the peaks of torque increment, than the production-line controller. This corresponds to better vehicle driveability and constraint satisfaction of (7k) (see Fig 6 (g)). The simultaneous improvements of torque tracking and lambda limit satisfaction are direct results of the better set points tracking which correspond to better fulfilment of desired operating conditions.

In Fig 6 (f), the NMPC slightly reduces the pumping loss when the boost pressure peaks (283, 1026-1032 s) and when the engine torque reduces (1037, 1043 s) implying that NMPC discovers and operates at set points promoting better tracking for lower energy losses. As a result, the approach of optimal control allows the engine to operate at higher efficiency, leading to better fuel economy. The benefits of reduced pumping loss is further illustrated by the calculated turbocharger compressor operating points in Fig 7. The NMPC and production-line controller share a similar operating region without any choking or surging of the turbocharger. During heavier duties (H, EH parts), the NMPC operates the turbocharger closer to the diagonal line which implies higher compressor efficiency. This allows the NMPC to achieve desired boost pressure at better fuel economy, as reflected by the mean BSFC in Table III.

The NMPC achieves greater tracking advantage on HiL implementation (see Table IV) than desktop simulation whilst the production-line controller achieves better torque tracking. The results between simulation and HiL differ because of an un-modelled communication latency caused by the asynchronous implementation of CAN read/write between the host and A80Q7 board. Comparing the results of Table IV with Table III shows that this latency has a minor impact on the tracking performance variations. However, the latency results in a delay in the estimation of cylinder mass of charge...
Fig. 6. Time series data from desktop simulation and HiL implementation. The proposed NMPC shows better tracking of oxygen concentration during transients (282-285, 1026-1032 s). The NMPC also shows better satisfaction of the lambda limit (g), than the production-line controller.

Fig. 7. Operating points of the compressor for each duty part of the WLTC. NMPC controls the VNT to operate in similar area to that of the production-line controller. In H and EH duty parts, the NMPC operates the compressor with tighter distribution to the diagonal line that corresponds to higher compressor efficiency whilst fulfilling the tracking objectives.

and hence in fuel adjustment. This significantly affects the production-line controller as it records both a higher number and higher severity of lambda limit violations (see Fig 6 (g) right half, 286, 1033, 1042 s) as demanded torque increases rapidly. By contrast, the NMPC performs consistently from desktop simulation to HiL in respecting the lambda limit. The NMPC considers the lambda limit in its OCP and demonstrates robustness and desirable performance against communication delays. However, note that practical implementation of these controllers adopts analogue or digital IOs which would significantly reduce the communication delay compared to the current implementation.

The real-time performance and computational requirements of the proposed NMPC are evaluated using an ARM Cortex-A7 embedded processor running at 480 MHz, which has a comparable clocking rate to that of an ECU. Table V compares the execution time of the proposed NMPC against the production-line controller. The worst case execution time was 2.94 ms which is lower than the 10 ms sampling time adopted in industry to control the dynamics of the airpath of engines. This demonstrates the ability of the developed NMPC to be used on production ECUs.

The execution efficiency of the NMPC is compared to
existing NMPC works. Using hardware of 480MHz, [25] reported a worst case of 10 ms on a EU4 engine and did not offer a comparison with respect to a reference or production-line controller. [23] approximated its computing time to a worst case execution time of 3.89 ms for a 480 MHz processor. Compared to [23], this work additionally considers the LP EGR but does not incorporate a separate feed-forward design to compensate for fast change of dynamics. Finally, the developed NMPC considers more objectives including tracking and fuel economy than the NMPC in [24] that optimises a single objective of engine efficiency. The NMPC developed in this work has demonstrated one of the lowest computing time on a processor comparable to automotive ECU, whilst considering the simultaneous use of HP and LP EGR. Unlike previous works, this work compares the NMPC tracking performance directly against a EURO 6 production-line controller over WLTC, and demonstrates the practicality of adopting NMPC for production uses.

The use of convex and multi-rate prediction models achieves better control performance than the production-line controller under sensor noises and real-time feasibility. The NMPC was shown to be able to accommodate up to 10% sensor noise, making it a practical solution. Additionally, compared to the conventional approach that requires operation zone partitioning and corresponding calibration, the NMPC used one single set of data-driven nonlinear models and one set of weighting values over the WLTC. During HiL implementation, the un-modelled CAN communication latency negatively affected the control performance. However, the NMPC was still able to achieve competitive tracking and fuel economy advantage at costs of degraded torque tracking. This communication latency, however, will be minimised on vehicle implementation where signals transmit via analogue and digital channels.

Future works include an in-vehicle experiment using a production ECU and the development of adaptive integral gains to improve further tracking performance.

### TABLE IV

<table>
<thead>
<tr>
<th>Percentage Improvement by NMPC against Production-line Controller</th>
<th>WLTC Part</th>
<th>P2 tracking</th>
<th>xO tracking</th>
<th>Mean BSFC</th>
<th>Torque Tracking</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>12.90</td>
<td>15.93</td>
<td>0.75</td>
<td>-8.22</td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>11.22</td>
<td>22.13</td>
<td>0.47</td>
<td>-5.75</td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>13.48</td>
<td>28.34</td>
<td>1.01</td>
<td>-3.95</td>
<td></td>
</tr>
<tr>
<td>EH</td>
<td>10.73</td>
<td>11.89</td>
<td>1.36</td>
<td>-11.69</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>12.23</td>
<td>21.45</td>
<td>0.98</td>
<td>-7.28</td>
<td></td>
</tr>
</tbody>
</table>

### TABLE V

<table>
<thead>
<tr>
<th>Included Airpath Controller</th>
<th>Production-Line Airpath Controller</th>
<th>NMPC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best Case (ms)</td>
<td>0.51</td>
<td>1.33</td>
</tr>
<tr>
<td>Worst Case (ms)</td>
<td>1.82</td>
<td>2.94</td>
</tr>
<tr>
<td>Median (ms)</td>
<td>0.66</td>
<td>1.74</td>
</tr>
<tr>
<td>Mode (ms)</td>
<td>0.65</td>
<td>1.73</td>
</tr>
<tr>
<td>Average (ms)</td>
<td>0.66</td>
<td>1.80</td>
</tr>
<tr>
<td>Standard Deviation (ms)</td>
<td>0.04</td>
<td>0.23</td>
</tr>
</tbody>
</table>

### VI. CONCLUSIONS & FUTURE WORK

This work has presented a NMPC for the tracking control of the airpath for a EURO 6 CI engine. The NMPC tracks the set points of boost pressure and cylinder oxygen concentration whilst minimising pumping loss using dual-loop EGR and VNT, sampled at 10 ms. The developed NMPC was benchmarked against a production-line controller, using both simulation study and HiL. The simulation results showed improved fuel economy, torque tracking, boost pressure and in-cylinder oxygen tracking by 0.89%, 26.99%, 10.14% and 17.93%, respectively. Using a 480MHz processor that is comparable to an automotive ECU, the NMPC achieves a worst-case computing time of 2.94 ms over WLTC.

REFERENCES


