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Engine cylinder pressure reconstruction using crank kinematics and recurrently-trained neural networks

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ABSTRACT

A recurrent non-linear autoregressive with exogenous input (NARX) neural network is proposed, and a suitable fully-recurrent training methodology is adapted and tuned, for reconstructing cylinder pressure in multi-cylinder IC engines using measured crank kinematics. This type of indirect sensing is important for cost effective closed-loop combustion control and for On-Board Diagnostics. The challenge addressed is to accurately predict cylinder pressure traces within the cycle under generalisation conditions: i.e. using data not previously seen by the network during training. This involves direct construction and calibration of a suitable inverse crank dynamic model, which owing to singular behaviour at top-dead-centre (TDC), has proved difficult via physical model construction, calibration, and inversion. The NARX architecture is specialised and adapted to cylinder pressure reconstruction, using a fully-recurrent training methodology which is needed because the alternatives are too slow and unreliable for practical network training on production engines. The fully-recurrent Robust Adaptive Gradient Descent (RAGD) algorithm, is tuned initially using synthesised crank kinematics, and then tested on real engine data to assess the reconstruction capability. Real data is obtained from a 1.125 l, 3-cylinder, in-line, direct injection spark ignition (DISI) engine involving synchronised measurements of crank kinematics and cylinder pressure across a range of steady-state speed and load conditions. The paper shows that a RAGD-trained NARX network using both crank velocity and crank acceleration as input information, provides fast and robust training. By using the optimum epoch identified during RAGD training, acceptably accurate cylinder pressures, and especially accurate location-of-peak-pressure, can be reconstructed robustly under generalisation conditions, making it the most practical NARX configuration and recurrent training methodology for use on production engines.

1. Introduction

Knowledge of the cylinder pressure traces arising in an internal combustion (IC) engine can provide crucial information for feedback control of combustion to improve thermal efficiency, reduce CO_2 emissions, and to reduce harmful emissions. Multi-cylinder gasoline engines in particular have, between cycles and cylinders, significant variability in part-load volumetric efficiency and in-cylinder air motion during part-throttled operation. It is well known that the ability to control fuel

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injection and ignition-timing in order to balance this variability, can dramatically improve efficiency, i.e. using spark timing to phase the non-knocking combustion at light load closer to maximum efficiency [1], or to a lesser extent, by allowing closer operation to the knock limit [2]. In addition, certain features required for On Board Diagnostics could also be improved were pressure traces available for misfire detection, and for in-vehicle calibration by using the cylinder pressure trace for torque estimation [3]. Previous approaches using other on-board sensors, include the use of engine block vibration [4,5], crank kinematics [6,7], and spark ignition ionisation current [8].

The use of in-cylinder pressure transducers is common under test conditions, but still relatively rare on production engines, owing to cost and durability issues. Indirect cylinder pressure reconstruction, by processing information from existing sensors performing other functions, can provide an attractive low-cost alternative to pressure traces for combustion control on production engines. For example, crank position sensors, and knock sensors (i.e. accelerometers), are now fitted as standard on gasoline engines, and have proven durability and acceptable cost. In attempting to reconstruct cylinder pressure using indirectly-sensed information, a causal mathematical model is assumed, linking cylinder pressure to the sensor output. The challenge then, for indirect reconstruction, is either to construct the causal model and then invert it, or to construct an inverse model directly, and then calibrate it. The hope is that when the inverse model is fed with the corresponding sensor signal, the output is precisely the required cylinder pressure.

Various indirect reconstruction methods have been attempted over the past 20 years. These fall broadly into four categories: i) via inverted physical crank dynamic models, ii) via inverted engine block vibration or acoustic transfer functions, iii) via Artificial Neural Networks (ANNs), trained as a non-parametric inverse model to handle previously unseen (generalisation) data, or iv) using spark plug ionisation current (for SI engines) which exploits the effect of combustion by building a relationship to cylinder pressure.

The first three approaches ultimately involve construction of a non-linear relationship between the measured response and the corresponding cylinder pressure. Since the converse (causal) relationship, between cylinder pressure and measured response, is generally amplitude and frequency dependent (i.e. a function of speed and load), constructing the inverse model is very problematic. This is one reason why neural networks are particularly attractive because they provide a powerful and efficient approach to nonlinear system identification. The use of spark plug ionisation current has yet to be fully verified.

One of the difficulties with indirect reconstruction is that the sensed signal may be heavily influenced by sources other than cylinder pressure. For example reconstruction via crank acceleration assumes that the gas pressure acting on the piston crown drives the slider-crank, causing acceleration of the crankshaft. Crank acceleration is however also a function of crank angle, speed, instantaneous inertia, and friction. At certain engine speeds, torsional vibration may also be significant. Similarly, the use of vibration and acoustic signals assume that combustion pressure excites engine-block or cylinder-head vibration, which can be measured directly using accelerometers positioned on the block or head (such as used for knock control). However, engine block vibration can be caused by piston slap, intake and exhaust valve events, and fuel injector actuation. Fortunately these events occur at crank angles well separated from the combustion event for the cylinder under consideration, except in 4-stroke engines with more than four cylinders, there may be problematic overlap.

Early contributions to indirect reconstruction via crank kinematics include using an electrical analogue crank dynamics model to link crank speed fluctuation to indicated torque [9], where the method was verified on a 1.5 l gasoline I4 engine with speeds ranging from 1500 to 3500 rpm. Ten years later, a radial basis function (RBF) network proposed in [10], was applied in [11] using data from a 2.5 l I4 diesel engine at 39 test points, between 1000 rpm and 2600 rpm at 20 N m, to show that P_{max} could often be reconstructed within 5%, and θ_{max} within $\pm 2°$. Use of crank speed and position in [12], exploited a second-order sliding-mode differentiator to estimate instantaneous indicated torque including friction, and was shown using a Simulink model for a 2 l I4 gasoline engine, to obtain P_{max} within 5%. A model was combined with a single pressure measurement in [7] to reconstruct pressure on the other cylinders of an I4 DISI engine, showing accuracy within 5–10% in P_{max}, and $\pm 5°$ on θ_{max}. RBFs trained by recursive hybrid learning of crank or block response data, were used in [13] to predict P_{max} to within 2.9%, and θ_{max} within $\pm 1.5°$ on a 9 l 6-cylinder diesel engine at 39 conditions with speeds varying between 800 rpm and 2000 rpm, from 10% to 90% full load. A NARX ANN was trained in [14] using crank acceleration and fully-recurrent training via the Back-Propagation Through Time (BPTT) algorithm and the Extended Kalman Filter (EKF), to reconstruct P_{max} within 2% for an I3 DISI engine at 1500 rpm and 25.5 N m. BPTT training was found to be unacceptably slow, and the nominally much faster EKF training was still too slow. Moreover recurrently-trained networks were found to occasionally go seriously unstable. An ANN fed with crank speed (at 1800 rpm), motored-engine pressures, and spark advance, was tested in [15] using a heat-release model for cylinder pressure, to give results of 5–10% accuracy on $P_{max.}$ Crank speed for a four-cylinder Diesel engine was also used in [16] to exploit sliding-mode observer predictions of P_{max} within 2% and θ_{max} within $\pm 2°$. A physical torque model by contrast was used in [17] and tested on a 2-l 4 cylinder diesel engine at 1500 rpm to produce $P_{max.}$ within the range 2.3–11.2% and θ_{max} within $-0.4°$ to 4.4°. Finally an ANN was used in [18] driven by crank speed and acceleration from a single cylinder turbocharged gasoline engine with speeds between 1000 and 2000 rpm to produce P_{max} predictions within 4–8%.

Turning attention to indirect cylinder pressure reconstruction using vibration signals the inverse filter concept was extended in [19] for linear system convolution, where Frequency Response Function (FRF) averaging and time-domain Cepstral smoothing was also proposed to reduce the influence of FRF variability, creating a method which they applied to data taken from a single cylinder 4-stroke diesel running full load at 2400 rpm. Vibration signals were processed in [20] using data from a 2-cylinder 4-stroke diesel engine by transforming to the frequency domain and excluding data above 15 kHz then using a Radial Basis Function neural network. Optimal inverse linear filter and averaging using engine condition