

Model-Based Optimal Combustion Phasing Control Strategy for Spark Ignition Engines

Qilun Zhu and Robert Prucka
Clemson University

Shu Wang, Michael Prucka, and Hussein Dourra
FCA US LLC

ABSTRACT

Combustion phasing of Spark Ignition (SI) engines is traditionally regulated with map-based spark timing (SPKT) control. The calibration time and effort of this feed forward SPKT control strategy becomes less favorable as the number of engine control actuators increases. This paper proposes a model based combustion phasing control frame work. The feed forward control law is obtained by real time numerical optimization utilizing a high-fidelity combustion model that is based on flame entrainment theory. An optimization routine identifies the SPKT which phases the combustion close to the target without violating combustion constraints of knock and excessive cycle-by-cycle covariance of indicated mean effective pressure (COV of IMEP). Cylinder pressure sensors are utilized to enable feedback control of combustion phasing. An Extended Kalman Filter (EKF) is applied to reject sensor noise and combustion variation from the cylinder pressure signal. The proposed combustion phasing frame work is validated with real-time dynamometer tests using a rapid-prototype engine control system. Test results indicate the SPKT control system is able to track the combustion phasing target (CA50) with a RMSE of 3.8 crank angle degrees without violating combustion constraints under both steady state and transient operating conditions. Furthermore, the successful execution of this SPKT control strategy using a rapid-prototype engine controller demonstrates the computational efficiency of the proposed system.

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INTRODUCTION

Controlling spark timing (SPKT) to achieve optimal combustion phasing without violating the constraints is critical for SI engine efficiency improvement while maintaining stable operation. Calibration time and effort of empirical map-based feed forward SPKT control has become an important limiting factor to further increasing the number of control degrees of freedom of modern SI engines. Model based engine controllers that can easily adapt to different engine designs are becoming favorable as the cost of calibration increases and the online computation load shrinks with the development of faster micro-processors. This paper introduces a model based optimal combustion phasing control structure. The desired feed forward SPKT is computed using a numerical nonlinear programming method with high-fidelity models of combustion phasing, knock and COV of IMEP. A cylinder pressure sensor is employed to estimate the combustion phasing in real time with techniques based on an Extended Kalman Filter (EKF). This information is utilized to generate a modified SPKT, and corrects for the modeling errors in the feed forward SPKT computation.

Many control oriented combustion phasing models have been proposed to estimate the combustion phasing [1]-[5]. These methods were proven to be reasonably accurate with acceptable complexity

for online computation. The combustion phasing models can be categorized into Wiebe Function based models [1][2] and simplified flame entrainment models [3][4][5]. The flame entrainment models have improved fidelity due to their physics-based nature. The prediction of cylinder pressure, temperature, turbulence intensity and laminar flame speed is necessary for the integration of accurate knock and combustion stability models. However, the flame entrainment models often require numerical integration in the crank angle domain. Although these models can be computationally efficient so they can be carried out one or more times within one engine cycle, the ODE structure makes them difficult to invert. Therefore, using them to compute SPKT directly with a given combustion phasing target is difficult.

Since flame entrainment combustion models are constructed to be computationally efficient, iterative numerical optimization methods can be applied to search for the optimal SPKT that generates the desired combustion phasing. Before the existence of control oriented combustion models, optimization routines for SPKT were researched in the context of Extreme Seeking (ES) control [6]-[12]. ES control is an important class of adaptive optimal controllers that consists of model identification and optimization processes [12]-[18]. The optimization process searches for the minimum value of a specific

cost function. The cost functions were often defined as fuel consumption [6][7][11], torque output [10][12], or combustion phasing [9] when the ES approach was applied for SPKT control. It has been observed from several previous researchers that the cost function of SPKT can be approximated with a quadratic function while the engine operating conditions are fixed. However, if the engine operating condition changes ES methods must update this quadratic dependency using online identification methods from real-time measurement feedback. The coefficients of quadratic dependence are estimated iteratively with Recursive Least Square (RLS) methods [18]. RLS algorithms can be altered with forgetting factors and exponential weighting to accelerate this identification process [8]. Regardless of the quadratic dependence assumption, nonparametric ES algorithms [15] have been applied to control SPKT for flex-fuel engines [6]. This method requires the constant addition of SPKT perturbations to identify the Jacobian of the cost function with respect to SPKT.

This research presents a numerical optimization technique that is similar to the ES approach, finding the optimal SPKT with a flame entrainment combustion model. The proposed “virtual” ES approach is augmented with a function to handle knock and combustion variation constraints explicitly. There are several control-oriented knock and combustion variation models developed by previous researchers that can be integrated with the proposed optimal SPKT control as constraints functions. Previous researchers have proposed that knock can be predicted by integrating the Arrhenius function output for the end gases [19][20]. Covariance (COV) of IMEP is commonly considered as an indicator of cycle-by-cycle combustion variability. Researchers have illustrated that the stability of turbulent combustion can be correlated to the time scale ratio between turbulence motion and flame propagation [21][22]. Lee et al. [23] suggested that the COV of IMEP has strong correlation with combustion phasing, differentiating the modeling of COV of IMEP from traditional combustion stability research. Finally, regression models of COV of IMEP have been proposed [24][25].

Control oriented combustion models are expected to be inaccurate for some engine operating conditions, considering limitations of computational complexity and calibration effort for real-time implementation. These inaccuracies can be corrected with feedback control and model adaptation, both of which require accurate measurement (or estimation) of combustion phasing. Cylinder pressure sensors can be utilized to compute combustion phasing [26][27]. However, the results of this computation are corrupted with sensor noise and real cycle-by-cycle combustion variation. While low pass filtering can be applied to reduce the magnitude of measurement noise during steady state situations, this technique may not provide responsive estimation of combustion phasing during transient situations. An Extended Kalman Filter (EKF) based approach is proposed for this application [28]. Similar approaches were applied to estimate the combustion phasing of HCCI engines [29][30]. However, methods to improve steady state performance are required for SI engine applications due to the lack of cycle-to-cycle interactions. Finally, the weighting of the EKF is updated for each engine cycle considering the output of the combustion stability model.

This paper is organized as follows. The experimental setup and engine configuration are first introduced. Then the overall model based optimal SPKT control structure is described. The next section briefly introduces the control oriented combustion phasing, knock and COV of IMEP models. The RLS polynomial method to obtain the optimal SPKT and EKF based combustion phasing estimation is then detailed. Experimental results of the proposed SPKT control strategy are then discussed. Finally, conclusions are drawn and the contribution of this research work is described.

EXPERIMENTAL SETUP

The data in this research was recorded using a port fuel injected 3.6L spark-ignition V-6 engine connected to an AC dynamometer. The test engine was controlled using an ETAS ES910 system overriding the stock ECU. AVL Concerto software was used to process the data that were acquired during each experiment. Each cylinder of one engine bank was instrumented with passage-mounted AVL GH12D piezoelectric cylinder pressure sensors. The sensors were located in the cylinder head to maximize accuracy according to Patterson and Davis [31], and were equipped with flame guards to minimize thermal shock errors. The cylinder pressure measurement was sent to a Cylinder Pressure Development Controller (CPDC) unit to compute CA50 and IMEP [27]. Communication between the CPDC and ES910 was established via a CAN communications link. A summary of engine geometry is given in Table 1.

Table 1. Engine Parameters

Fuel	Gasoline (87 Pump Octane)
Compression Ratio	10.2
Bore	96 mm
Stroke	83 mm
Connecting Rod Length	156.5 mm
Intake Valve Diameter	39 mm
Exhaust Valve Diameter	30 mm

STRUCTURE OF MODEL BASED OPTIMAL SPKT CONTROL STRATEGY

The proposed model based optimal control structure includes a feed forward SPKT determination, feedback correction and u/S_L adaption to account for long term modeling error. Figure 1 shows the block diagram of the complete model based optimal SPKT control strategy.

The initial CA50 target is from an upper level engine controller. The upper level controller is often the engine torque management system that coordinates air-path dynamics and combustion phasing. It usually has a slow update frequency, making it difficult to be integrated with accurate knock and combustion variability constraints. If the given combustion phasing (CA50) target violates the knock or combustion variability constraints the sub-level combustion phasing controller needs find a feasible target that is close to the original target (and corresponding SPKT). This modified target (delayed by one engine cycle) is sent to a Proportional Integral (PI) controller as a tracking reference.



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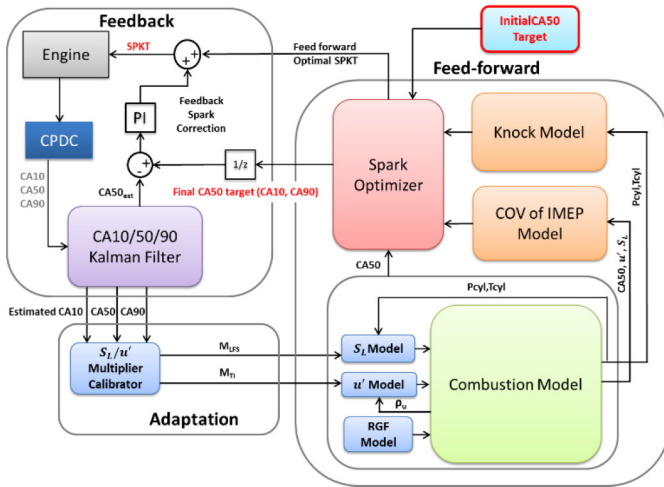


Figure 1. Block diagram of the proposed model based optimal SPKT control structure for SI engines.

The measured combustion phasing (from the cylinder pressure sensors and the CPDC) is conditioned with an EKF based estimator to suppress the noise power. The estimated combustion phasing measurement is sent to the PI controller and model adaptation algorithm. The combustion model is adapted to correct long term errors by modifying S_L and u' models to match the observed and predicted combustion phasing [32]. The adaptation function of the proposed SPKT control is outside the scope of this paper since it is not experimentally validated together with the complete model based optimal SPKT control structure.

CONTROL ORIENTED COMBUSTION MODELS

Combustion phasing is modeled by a quasi-dimensional flame entrainment combustion model. The combustion model was originally proposed by *Blizard and Keck* [33] and then refined by *Tabaczynski et al* [34]. This turbulent flame entrainment based combustion model assumes that the fresh mixture at the flame front is; (1) entrained into small eddies, and then (2) burned up in a characteristic time. Based on these assumptions, the flame entrainment and eddy burn up processes are described as the following ODEs:

$$\frac{dm_e}{dt} = \rho_{unburned} A_{flame} (u' + S_L) \quad (1)$$

$$\frac{dm_b}{dt} = \frac{m_e - m_b}{\tau} + \rho_{unburned} A_{flame} S_L \quad (2)$$

Equation (1) describes the unburned mass entrainment rate at the flame front. It is assumed the flame propagates through unburned charge along Kolmogorov scale vortices entraining turbulent eddies. The unburned mass entrainment rate is determined by unburned mixture density, flame front area, laminar flame speed and turbulence intensity. After unburned mixture entrainment, mass burn-up occurs

at a rate described by Equation (2). Burn-up occurs at a characteristic time, τ , which is defined as the time to travel the eddy diameter at the laminar flame speed. The eddy size is assumed to be Taylor micro scale (λ) [35]. The combustion process is simulated with the numerical integration of equations (1) and (2).

The turbulence intensity u' is computed based on rapid distortion theory [36]:

$$u' = u'_{ini} \left(\frac{\rho}{\rho_{ini}} \right)^{\frac{1}{3}} \quad (3)$$

Where:

u'_{ini} is the turbulence intensity at the initiation of combustion.

ρ_{ini} is the density of the mixture at the initiation of combustion.

The laminar flame speed can be estimated with fuel properties, unburned gas temperature, T_u , cylinder pressure, P_{cyl} , and residual gas fraction, x_b , according to Equation (4) [37]

$$S_L = S_{L,0} \left(\frac{T_u}{T_{ini}} \right)^{\alpha} \left(\frac{P_{cyl}}{P_{ini}} \right)^{\beta} (1 - 2.06x_b^{0.77}) \quad (4)$$

Where:

$S_{L,0}$, α and β are constants related to fuel properties

T_{ini} and P_{ini} are the reference temperature and pressure, which are selected as ambient conditions.

This research uses a modified version of the semi-empirical residual gas mass (RGM) model developed by *Fox* [38]. The Fox model separates RGM into two parts; 1) trapped residual at exhaust valve closing (EVC) due to un-swept cylinder volume, and 2) exhaust gas backflow into the cylinder and intake runner during the valve overlap period. The terms ΔP_{exh} and ΔP_m are added to account for wave tuning dynamics missing in the original Fox model, as shown in Equation (5). The details of residual gas fraction computation can be found at [39].

$$RGM = C_1 \frac{P_{exh}}{RT_{exh}} V_c + C_2 \sqrt{\frac{P_{exh}}{RT_{exh}} ((P_{exh} + \Delta P_{exh}) - (P_m + \Delta P_m))} A_{flow} \frac{OLV}{\omega_e} \quad (5)$$

Where:

$P_{exh} \approx 110 \text{ kPa}$ is the exhaust pressure.

C_1 , C_2 are calibration factors.

ω_e is engine speed.