

Control-Oriented Knock Simulation

James Peyton Jones, Jill M. Spelina, and Jesse Frey
Villanova University

ABSTRACT

Simulation tools are critical to control system development and design. Simulation of knock control systems, however, is complicated both by the stochastic nature of knock, and by the wide range of signal bandwidth and dimensionality within the feedback loop. The aim of this paper is therefore to provide a review, and in some cases an extension, of knock simulation methods from a control-oriented perspective, focusing particularly on the statistical properties of knock intensity and knock events. Deterministic notions of closed-loop performance can be misleading in this context, and recent work using Markov- and Monte-Carlo-based methods is briefly summarized as a means to obtain a more rigorous and complete description of closed-loop behavior. The methods are illustrated using a classical knock controller design.

CITATION: Peyton Jones, J., Spelina, J., and Frey, J., "Control-Oriented Knock Simulation," *SAE Int. J. Engines* 9(2):2016, doi:10.4271/2016-01-0821.

1. INTRODUCTION

The ability to simulate a system or process of interest is integral to control system design, and it enables the closed-loop interaction between the system and controller to be assessed and optimized prior to final implementation in vehicle. In order to be useful, from this control-oriented perspective, such models must be computationally and parametrically efficient, while still able capture the dominant dynamics of the process. Mean value engine models, for example, fulfill this role for many powertrain control development applications [1, 2], though of course much more detailed (and numerically intensive) computational flow dynamics (CFD) type models are available for more fundamental engine *design* work, [3]. Generally, however, these models are deterministic, making them hard to apply in to the knock control case since knock behaves as a random process. The bandwidth of knock signals is also quite high, in order to capture the knock resonant frequencies, so it is not obvious how mean value approaches apply in this case. The aim of this paper is therefore to provide a review, and in some cases an extension, of knock simulation methods from a control-oriented perspective, focusing particularly on the statistical properties of knock intensity and knock events (knock intensities above some specified threshold).

The paper is organized as follows: [Section 2](#) provides a review of knock simulation methods with an extension of these methods for knock intensity and knock events. [Section 3](#) then presents an example of a closed loop knock simulation of a traditional knock controller, and an initial assessment of its performance. However, this assessment is limited to the particular instance of the random process that occurred during the simulation run. Recent work using Markov- and Monte-Carlo-based methods are therefore presented in [Section 4](#) in order to predict the distribution of the closed loop response and provide deeper insight into its performance. The results of applying

these techniques to analyze the behavior of a conventional knock controller are also presented in this section. Finally, brief conclusions are presented in [Section 5](#).

2. KNOCK SIMULATION METHODS

The structure of a typical knock control system is outlined in [Fig. 1](#). The knock process itself is ultimately a spatially and time-dependent phenomenon that occurs during combustion within the cylinder (block #1 of [Fig. 1](#)). One or more knock sensors then translate this process into a knock signal which represents the time history of the combustion as sensed by the transducer (block #2). A knock detection algorithm is then used to reduce this time history, typically to a single scalar knock intensity metric having one value for each cylinder firing (block #3). This knock intensity value is often shown as being fed directly to the knock control system, but it has been argued [4] that it is not possible to control knock intensity directly since knock closely approximates a cyclically independent random process. Instead, some statistical property (such as the rate or probability of knock events) must first be derived from the data (block #4), and then the controller then acts so as to control this property to some user-specified target value (block #5).

To simulate all of the processes outlined in [Fig. 1](#) therefore represents a significant task, particularly in the earlier spatial and time or crank-angle dependent stages. Although the simulation algorithm is clearly different for each of the different blocks (as discussed in more detail below), several different classes of simulation emerge, often reflecting the intent or priorities of the study. These include heavily data-driven models, empirical models, and detailed physically-based models. In the first category, a crude, but sometimes effective technique, for example, is to record the output signal from a real engine over a range of operating conditions, and then to play back the

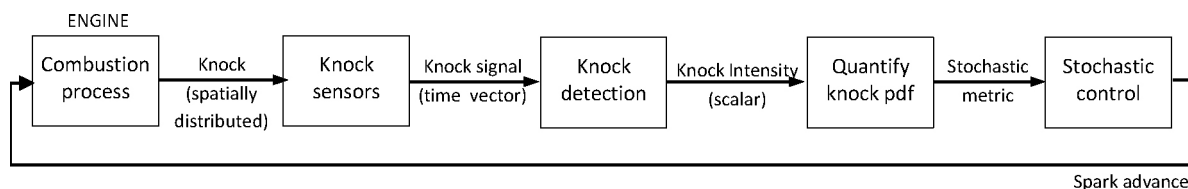


Fig. 1. Structure of a typical knock control system

appropriate data as required during simulation. Though simple, this requires storing a large amount of data, and the results are hard to extrapolate to different engines and operating conditions. A more concise approach is to fit some empirical model to the data, which can then be used to simulate fresh data in a computationally efficient manner. This is often the most useful and practical approach for control system design, but it provides only limited insight into the process. The most detailed simulations therefore attempt to model the physical relationship between input and output, typically enabling the output to be predicted across a broad range of operating conditions and engine configurations, but also resulting in more complex and computationally burdensome models.

Another factor to consider in knock simulation is the extent to which the simulation is stochastic. Combustion, and knocking combustion in particular, varies significantly from cycle to cycle even under nominally static operating conditions. Data-driven simulations capture such cyclic behavior because the data is recorded directly from an engine, (although it should be noted that this behavior might change significantly for a system operating in closed loop). Physical models, however, are typically deterministic unless the model is augmented with some stochastic characterization of the model parameters. Even in cases where cyclically varying responses are obtained, it is important to recognize that a particular cyclic sequence represents just one instance of the possible random sequences that could occur. Truly stochastic simulations, which capture the distribution of the response rather than one random instance, are discussed later in Sections 4 and 5.

2.1. Simulation of Knocking Combustion (Block #1)

Knock is ultimately a spatially and time dependent autoignition phenomenon which depends in a complex manner on many variables, including local temperature, pressure, gas composition, turbulent mixing, gas-wall interaction, chemical kinetics, and chamber geometry. Several authors have therefore sought to capture these dependencies using a full computational fluid dynamics (CFD) model of the process, typically augmenting some variant of the KIVA model for normal combustion [5] with a model for autoignition in the end gas [6, 7, 8, 9, 10]. Although more complex models of autoignition are possible [6], in most cases the Livengood-Wu ‘integral’ model is used to determine knock onset [7]. The principal parameter in this model is the ignition delay, which can be computed from the chemical kinetics, though this is challenging due to the complexity of the process and the uncertainties associated with the reaction rate properties of practical fuels. Reduced chemical kinetic mechanisms, or lookup table based methods help in this regard, and retain the predictive nature of the model [8], but in most cases an Arrhenius type empirical model is used to compute the ignition delay after

fitting the model to experimental data [9, 10]. This is sometimes known as the AnB model to reflect the three parameters, A, n, B, of the Arrhenius relation.

The detailed physical models described above are remarkably effective at describing knocking combustion, including accurate predictions of knock onset timing, knock location, as well as generating the high frequency pressure oscillations that are excited in the cylinder. However, the computational burdens of such studies are considerable, and it is not feasible to use these models to generate data sets of cyclically varying knocking combustion. Indeed, care must be taken in interpreting the results since they reflect the ‘average’ combustion cycle that was used to tune the model rather than the extremes of the cyclic variation that can occur at any fixed operating condition [10].

To reduce the computational burden, a simpler, less detailed modeling approach uses a zero-dimensional, single- or multiple-zone model to characterize the combustion process, where each zone is assumed homogeneous in temperature, pressure, and gas composition. The burn rate is typically modeled empirically using a Wiebe function, and autoignition within the end gases is again modeled using the Livengood-Wu knock onset criteria. As with the more detailed analysis, the ignition delay may be modeled using an empirical Arrhenius relation [11, 12], or using a more detailed chemical kinetic approach [12]. Further simplification has been proposed, where autoignition is modeled using a second Wiebe function, rather than using the ‘integral-knock’ approach [13].

In general, the family of more empirically-based models is reported to be quite effective at predicting knock onset, as well as the effects of compression ratio, air/fuel ratio etc. However, the spatial dimension has been lost, and such models are therefore not able to simulate the high frequency knock resonances that are observed in real data, or the effects of turbulence, variable gas composition and other nonhomogeneities in knocking combustion. Thus while knock onset may be predicted correctly, the knock intensity, knock location and knock oscillations are generally not available. The considerable advantage of these models, however, is their computational efficiency, which also makes feasible the simulation of cyclic variability through random parametric perturbation [12]. Indeed, effects such as turbulent mixing can potentially be reintroduced into the model by treating the zones as stochastic reactors rather than perfectly homogeneous zones [14].

2.2. Simulation of Knocking Time Histories (Block #2)

As discussed above, 3-D CFD-based simulations provide spatial predictions of cylinder pressure at all points within the cylinder. It is relatively straightforward to extract the time history of cylinder

pressure at any given measuring point or virtual sensor location of interest. However, the computational burden of this approach means that it is not feasible to simulate multiple, cyclically varying cycles using this method. The more empirically based zone models are more computationally efficient, but cannot simulate the knock amplitude or resonant oscillations in the pressure time history. The problem is compounded when other types of knock sensor are considered. Production systems, for example, typically employ an accelerometer sensor mounted on the engine block [15], and it is extremely complex to model the multipath vibration response of the block to knocking combustion and other excitation sources. Likewise, although some progress has been made relating the response of ionization sensors to in-cylinder temperature and pressure conditions [16, 17], such models are relatively complex, and are not sufficiently accurate or computationally efficient to predict cycle by cycle responses.

An alternative approach focuses on the prediction of the acoustic resonance frequencies that are excited in the cylinder when knock occurs. These are important because they form the basis of most knock detection strategies, and because they represent a common characteristic in the high frequency content of most knock sensors, regardless of sensor type. The resonant pressure fluctuations can be computed as the sum of various resonant modes whose frequencies are found from the solution of the general wave equation for a cylinder of known dimensions [18]. However, the onset, amplitude, growth and decay of the signal are not predicted from this theory, and in spite of some work trying to model these features [19], the theory is primarily used to help identify resonant frequencies for signal analysis, rather than as a basis for signal simulation.

In practice therefore, it is hard to simulate realistic, cyclically varying knock time histories using physical or empirical models, and this has motivated more data-driven work. In several studies, for example, recorded data is used to test and compare a variety of knock detection metrics, (see Section 2.3), although this hardly qualifies as 'simulation'. A more sophisticated data-driven simulator is described in [20], where signals are selected and replayed from a large database of recorded data. The size of the database is reduced significantly by storing only a statistically representative set of cycles at each operating point and data is selected both according to the simulated operating condition and according to the probability density function of some characteristic of interest. Statistically similar, high bandwidth knocking time histories can therefore be generated with low computational overhead, albeit with large but manageable data storage requirements.

2.3. Simulation of Knock Intensity (Block #3)

As indicated in Fig. 1, the objective of the knock detection strategy (block #3) is to reduce the dimensionality of the knock signal from the time history/waveform generated by the knock sensor to a single scalar knock intensity metric for each cycle. This is necessary because the high frequency nature of the knock signal requires sample rates of the order 15-20 kHz, while the sample rate of the control system as a whole is only once per engine cycle. A wide variety of time, frequency, or time-frequency algorithms have been proposed for the purpose [21, 22, 23, 24, 25, 26, 27, 28]. The majority of these strategies are intended to execute in real time within

the engine control unit, so given the appropriate input knock signal waveforms, it is a simple matter to compute the corresponding knock intensity values. As discussed above, however, it is often difficult to simulate realistic, cyclically varying knock time histories, so this limits the extent to which knock intensities can be simulated directly.

An alternative approach, similar to the data-based simulation of time history traces discussed above, is simply to record knock intensity data from a series of experiments, and to play back the recorded data that most closely corresponds to the current simulation operating conditions. Schmillen et al. [29], for example, use this approach to exercise their control system designs. The disadvantage of this method, however, is that it is only strictly valid for the operating conditions that were tested experimentally, and it is not always clear how to interpolate between these conditions. There is also no guarantee that the closed loop properties of the system will be the same as that observed in the open-loop condition under which the data was recorded.

A more flexible and efficient approach is to characterize the *properties* of knock intensity data, and then to simulate statistically similar data based on this characterization. To a good first approximation, knock intensity has been shown to behave as an independent random process, and is therefore completely described by its probability density function (pdf), or cumulative distribution function (cdf) [30]. If the shape or form of the pdf or cdf is known, then it is straightforward to generate random sequences of knock intensity values that conform to this characteristic. In its simplest form, the shape of the pdf, $f(x)$, or cdf, $F(x)$, can be estimated from experimental data, and stored in lookup tables according to the operating condition of the engine. Figure 2, for example, shows a block diagram of a new knock intensity simulator based on this method. A 2-D lookup table is used to characterize the inverse cumulative density function and its variation with spark advance, based on data gathered from a Ford gasoline V6 engine operating at 1000 rpm. Further details on the experimental data may be found in [30]. The first input, (spark advance), is used to select the appropriate curve from the family of inverse cdf curves that were estimated from this data. The second table input comes from a uniform random number generator source. If U is a uniform random variable on $(0,1)$, then $F^{-1}(U)$ has the distribution $f(x)$, [31]. The output of the lookup table therefore yields knock intensity values that conform to the experimental/stored characteristic.

To validate the simulator, the pdf estimated from 1000 cycles of simulated knock intensity data was compared with that estimated directly from experimental data recorded at a 1000 rpm, and borderline audible knock (BL+0) spark advance. The results, presented in Fig. 3, show close agreement between the two even though the analytical form of the distribution is not known or assumed. Indeed, one advantage of this approach is that it can characterize arbitrarily shaped cumulative density functions, and is therefore able closely to match the statistical properties of the experimental data on which the tables were based. However, it is also necessary to store an entire cdf curve at each operating point of interest. To extend the model across different engine operating conditions, for example, would require a 3-D lookup table and the model therefore becomes increasingly unwieldy.