

Recent Advances in Knock Analysis, Simulation, and Control

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ABSTRACT

This paper collates and summarizes recent advances in knock analysis, simulation and control. The statistical properties of knock intensity and knock events are reviewed showing in particular that knock intensity behaves as an independent random process, and that knock events conform to a binomial distribution. These properties have a significant impact on knock control and simulation. Traditional and recently proposed cumulative-summation-based and Likelihood-based knock control strategies are reviewed and illustrated in this context. Efficient tools for simulating both specific instances of the closed loop time response, and the evolution of the *distribution* of these responses based on a Markov-like approach, are also briefly reviewed. Finally, it is shown how an optimization of the knock threshold and an associated retuning of the controller parameters can result in significantly improved closed loop performance without any other modification of the control algorithm.

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1. INTRODUCTION

Although knock has been an active topic of research for many years, it remains an important and challenging issue in modern powertrains especially given the trend for heavily turbo-charged, downsized engines. Despite the field's maturity, however, recent work has shown how a more stochastic view of knock control can offer new insights and possibilities for improving controller or simulation performance, [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]. The aim of this paper is to collate and review this material, and to provide a brief tutorial overview of some of the key concepts and principles.

The foundation for this work is presented in [Section 2](#), which describes both the statistical properties of knock intensity data, and of knock event data, - where a knock event is defined as occurring whenever the knock intensity exceeds a given threshold, [5]. These properties have a profound impact on knock control since it is then only possible to control some statistical aspect of the knock process, such as the knock event rate, rather than the knock intensity itself. The application of a knock threshold is also shown to transform the process into binomially distributed event data, which provides a useful theoretical basis for analysis, simulation, and controller design.

A variety of knock event rate controllers are described in [Section 3](#), including recently proposed Cumulative-Summation-based (CumSum) and Likelihood-based controllers [7, 8, 9, 10], as well as the more traditional advance-retard type strategy, [15]. These controllers are classified according to *when* control moves are deemed necessary, as well as how the

magnitude of the control move is determined. In general, the new controllers are less active, only making spark timing adjustments when there is statistical evidence that there is a need to do so, but still responding quickly when the control objective is not being met. This leads to less dispersion in the applied spark angle, and the ability to operate closer to the knock limit without increased risk of knock.

Some of the challenges and tools for performing control-oriented knock simulation are discussed in [Section 4](#). These challenges include the disparate range of dimensionality and sample rate within the physical control loop, the random nature of the knock process itself, and the difficulties in assessing the closed loop performance given the random nature of the excitation. Most control-oriented simulation tools are therefore empirical in nature, and simple tools for generating simulated knock intensity data or knock event data are reviewed and described, [14]. These tools however only simulate individual instances of the knock process. A recently proposed stochastic simulation which yields the probability distribution of the closed loop response is therefore also briefly summarized and illustrated, [14].

A more fundamental conception of the control objective, in [Section 5](#), suggests that closed loop performance can be improved by lowering the knock threshold and controlling the 'weak' knock event rate rather than the more typical 1% 'hard' knock rate. The hard knock rate is controlled implicitly because both hard and weak knock intensities are drawn from the same



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distribution. A strategy for optimizing this threshold is reviewed and simulation results show faster and tighter control, [12, 13]. Brief conclusions follow in [Section 6](#).

2. KNOCK PROCESS CHARACTERIZATION

Although there are a large variety of knock sensors and signal processing algorithms [16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27], the resultant knock intensity values, however obtained, are widely recognized as belonging to some random process, as shown in [Fig. 1](#). A critical property of this process, from a control perspective, is the extent to which it is cyclically correlated, since any such correlations could be exploited to predict and control the forthcoming cycle. This attribute is rarely examined in practice, although hot-spots or high levels of EGR certainly provide mechanisms that could potentially lead to correlated knock events, or even runaway knock. However, recent work analyzing a large database of over 2,300 records, recorded from a Ford V6 gasoline engine, over a wide range of operating speeds, swirl conditions, and engine calibrations, found little evidence of any prior-cycle effect, [5]. The autocorrelation function for a particular knock record, for example, is shown in [Fig. 2](#), and the lag-1 autocorrelation value, although slightly outside the 95% probability interval associated with an independent random process (shown as dashed lines in the figure), is still very low. Similar results were shown to hold across the entire database, and for the cross-correlations evaluated between cylinders, demonstrating that (at least for this data) knock intensities closely approximate an independent random process.

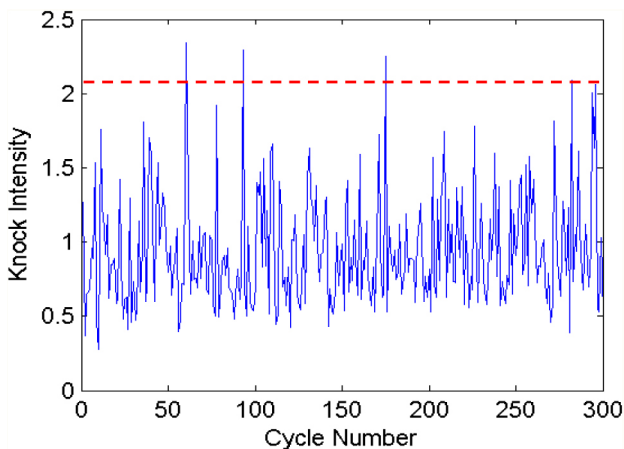


Figure 1. Cyclic variations in knock intensity.

Given this assumption, the knock process is completely characterized by its Probability Density Function (PDF) or Cumulative Distribution Function (CDF), which are readily estimated from the observed knock intensities, [5, 23, 27]. Clearly this distribution changes as a function of engine operating condition. [Figure 3](#), for example shows the evolution of the estimated PDF as a function of the primary manipulated variable, spark advance. The latter is measured relative to the spark angle of BorderLine (BL+0°) audible knock as

determined by an experienced calibration engineer. At more retarded spark conditions eg. BL-4°, the distribution is concentrated at low knock intensities, but as the spark is advanced the distribution broadens and shifts to the right, with a larger portion falling in the undesirable high knock intensity region.

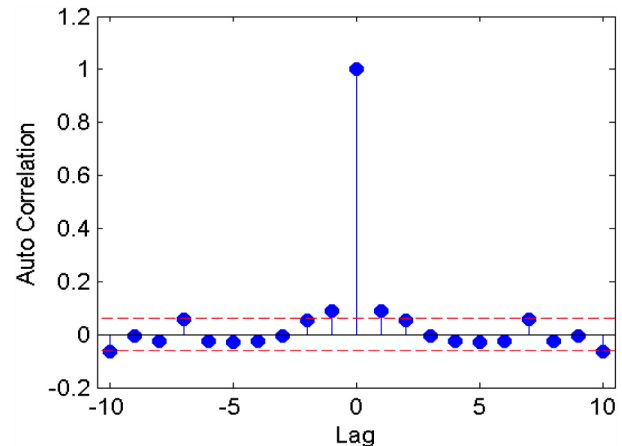


Figure 2. Autocorrelation of knock intensity.

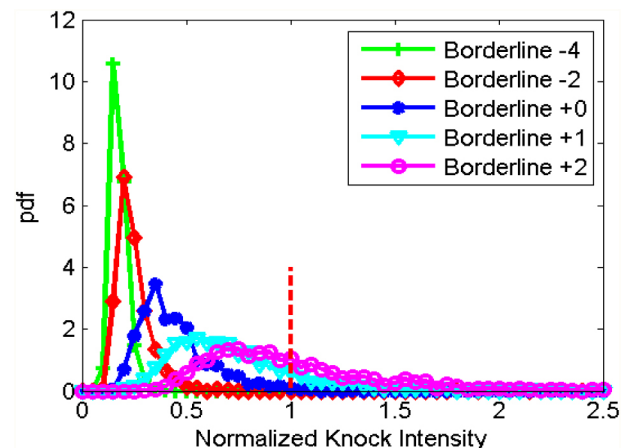


Figure 3. Knock intensity PDF's at different spark advances.

Several authors have sought to characterize these distributions parametrically, using log-normal or gamma function models, [6, 23, 27]. The advantage of this approach is that the entire distribution is modeled in a very concise manner, and any secondary quantities of interest can then be derived analytically, if required, from the parametric model. Lonari et al. take this process further, estimating the parameters of the lognormal model online, and using it to derive a knock factor that is fed to the controller, [27]. Such alternative measures of knock intensity distributions have significant potential, although the use of the knock event rate for feedback remains standard in production controllers at present. Furthermore, although such models appear to fit the data quite well, a visual assessment, or even a more quantitative assessment using the Coefficient of Variation for example, can be slightly misleading. A detailed analysis, using the same database outlined above, actually suggests that the data does not conform to these

models at the 5% significance level, [6]. However, the log-normal model performed better than the gamma function model, and may be sufficient for many practical purposes.

Although the knock intensity PDF provides the most complete characterization of the knock process, most production control systems simply apply a threshold directly to the observed knock intensities (see the dotted line in Fig. 1), and then use the resultant knock event rate for feedback purposes. The choice of threshold level is generally motivated by the desire to detect potentially damaging cycles, or cycles likely to cause NVH issues, so the threshold is typically set such that only a small number, typically 1-4% of cycles classify as knocking under BL+0° spark conditions. While this is a seemingly appropriate choice, other, potentially better, strategies for setting the knock threshold are discussed in Section 5.

The quantification of the knock process using a threshold and associated knock event rate can also be interpreted in terms of the more general PDF distributions of Fig. 3, where the threshold is shown as a dotted line. The knock event rate, or knock probability, then corresponds to the area under the PDF and to the right of this line. As the spark is advanced, and the tail of the distribution expands into the higher knock intensity region, this probability clearly increases, while it decreases if the spark is retarded and the distribution concentrates in the region below the threshold. For a given threshold level, the knock probability therefore varies with spark advance according to the characteristic shown in Fig. 4.

The classification of knock *intensities* into knocking and non-knocking *events* is also important because the resulting knock events are then binomially distributed - in contrast to the raw knock intensity distributions shown in Fig. 3. This provides a strong theoretical foundation for the design or simulation of knock event-based controllers. The probability of observing exactly k knock events in n cycles, for example, is given by

$$P_n(k) = \binom{n}{k} p^k (1-p)^{(n-k)} \quad (1)$$

where the knock probability p at any operating point is defined by the characteristic shown in Fig. 4. It's then straightforward to determine the distribution of the number of knocking cycles observed in 1000 cycles, for example, with $p=0.01$, as shown in Fig. 5, and such results have been shown to be in close agreement with experimental data, [10].

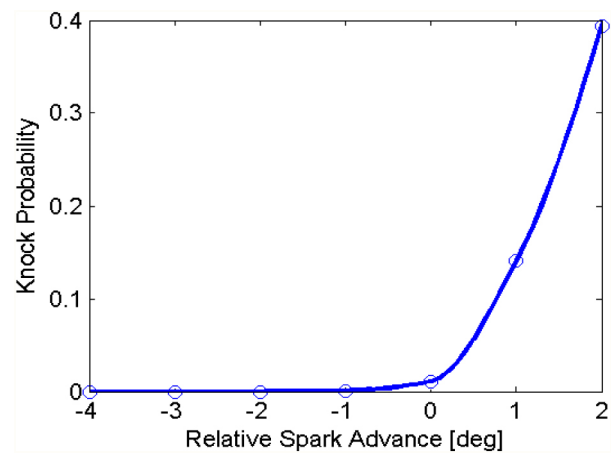


Figure 4. Knock probability as a function of spark advance.

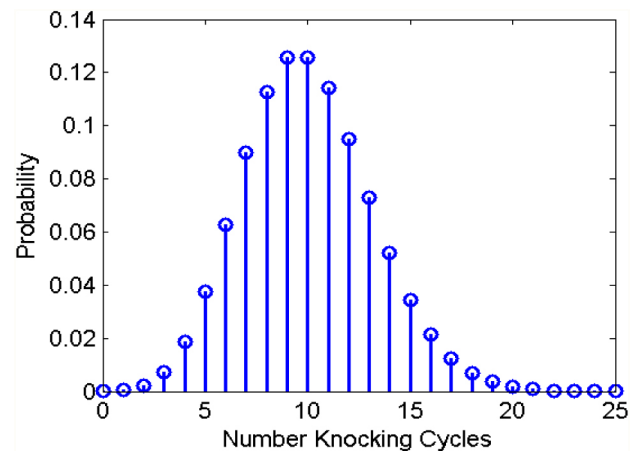


Figure 5. Binomial distribution of the number of knock events observed in 1000 cycles, with $p=0.01$.

3. KNOCK CONTROL

Knock control presents a fundamentally different challenge to that which is normally encountered in the control of dynamic systems. As discussed in the previous section, knock intensity closely approximates an independent random process, and it is therefore not possible to control the outcome of the forthcoming cycle based on observation of the current cycle's knock intensity. This is in strong contrast to the control of deterministic dynamic systems where the error observed in the current cycle is strongly coupled to the response at the next timestep, and can therefore be used for feedback using standard control system design methodologies. These methodologies cannot be used to control knock intensity directly, and instead some form of stochastic control is necessary.

Knock control, in this context, therefore refers more precisely to control of some statistical quantity, such as the knock event rate, rather than control of the knock intensity itself. In this