

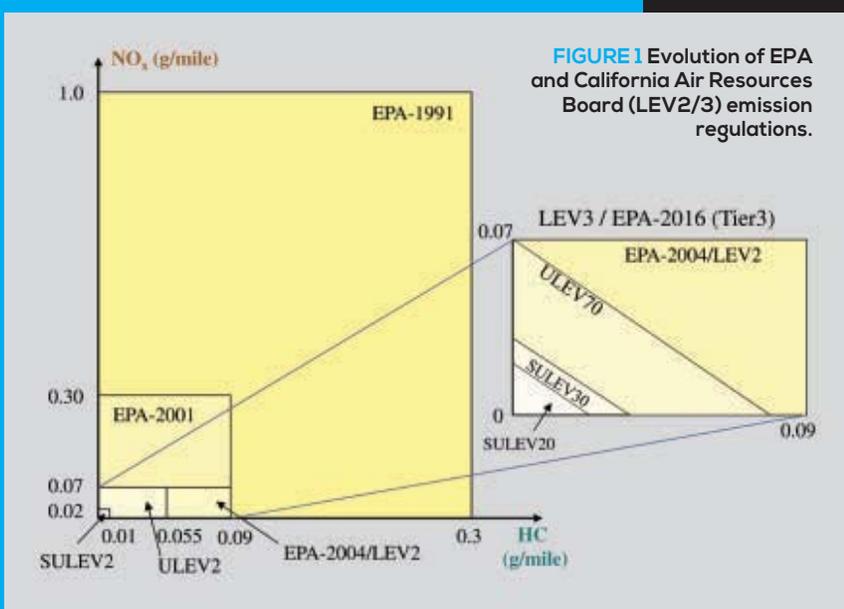
GASOLINE ENGINE AND AFTERTREATMENT MODELING AND CONTROL

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Gasoline or, more precisely, spark ignition engines power a large majority of personal vehicles sold worldwide. A major task for the automakers is to provide good drivability and fuel economy while meeting increasingly stringent emission requirements. A sample of such requirements for oxides of nitrogen (NO_x) and non-methane hydrocarbons (HC), shown in Fig. 1, illustrates their evolution from 1991 to the most recent LEV3 (California) and Tier 3 (EPA) regulations. LEV3 standards require that the average fleet emissions reach SULEV30 (Bin 30) with the catalyst aged up to 150,000 miles.

Achieving such low emissions requires a significant reduction in cold start emissions and employment of catalytic converters to reduce tailpipe emissions once the engine is warmed up. The catalysts are loaded with precious metals – typically platinum, palladium, and rhodium. They achieve very high conversion efficiencies – exceeding 99% – but



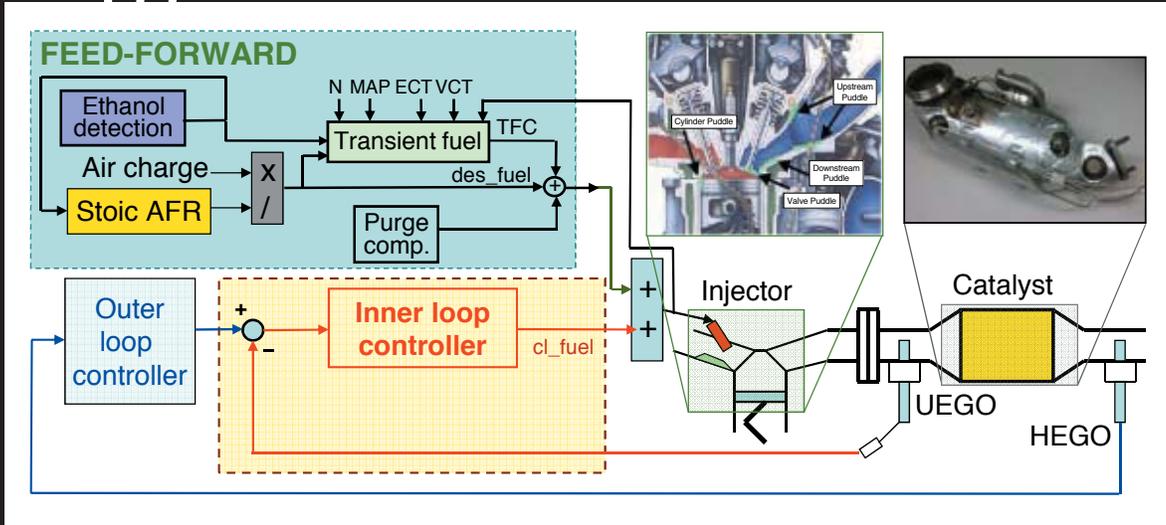


FIGURE 2 The block diagram of the air-fuel ratio regulation system in a gasoline vehicle.

only if the engine is operated very close to stoichiometry that corresponds to the air-fuel ratio (AFR) of about 14.6 for gasoline and of 9 for ethanol. Short deviations from stoichiometry can be tolerated because added cerium oxide can store and release oxygen and for a while compensate the deviations. However, a sustained deviation of as little as 0.1% can cause a manifold increase in emissions.

Maintaining AFR at stoichiometry requires a very elaborate control system. A block diagram, shown in **Figure 2**, illustrates such a system consisting of a feedforward part (air-charge estimation, ethanol detection, transient fuel compensation, etc.); the inner AFR loop from the wide range, universal exhaust gas oxygen (UEGO) sensor; and the outer loop from the narrow range heated exhaust gas oxygen (HEGO) sensor. The inserts with engine drawing and a photograph of an automotive catalyst are included to remind the reader that the actual hardware is much more complex than what the block diagram representation suggests.

Design of a control system component requires that an appropriate model be developed. The models considered range from very simple low-order, linear for the inner loop to a partial-differential-equation (PDE) based model for the catalyst. In general, feedback controllers tolerate and even benefit from simpler models. Feedforward control, estimation, diagnostics, and failure mode management require more elaborate models.

INNER LOOP MODELING AND CONTROL

A conventional method to suppress disturbances and regulate AFR to stoichiometry is to use a gain scheduled Proportional-Integral (PI) controller in the inner (UEGO) AFR loop. If one wants to go beyond PI, a model is needed. The standard model for this system is a first order filter with delay where the filter time constant and the delay are functions of engine speed (N) and the normalized air-charge called load. Despite the very complex physical processes that take place from the injection of fuel until the AFR is measured at the sensor, this simple model captures the system behavior very well. Once this model is calibrated, one could design controllers with delay compensation ranging from the Smith

Predictor [1] to Model Reduction. Delay compensation allows a higher bandwidth and better rejection of disturbances that perturb AFR from stoichiometry. The improvement in AFR regulation accuracy measured experimentally in an emissions lab is shown in **Figure 3**. In a set of comparison tests conducted on two vehicles, the improved AFR regulation achieved by delay compensation resulted in 20% better emissions and 2.3% better fuel economy on average.

OUTER LOOP MODELING

Getting an approximately stoichiometric AFR into the catalyst plays only a part in achieving low emissions. The catalyst oxygen storage has to be maintained close to its optimal operating point too. In general, it is not clear how to assure this, as the oxygen

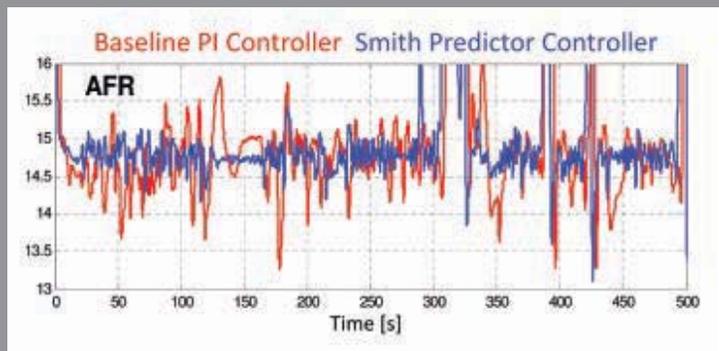


FIGURE 3 The AFR regulation during the first 500 seconds of the US FTP (emissions) cycle. The lean excursions that start after 280 seconds are due to intentional fuel shut off during deceleration.

storage, with varying distribution along the catalyst length (assuming radial symmetry), cannot be measured. The only measurement related to catalyst operation comes from the voltage of the downstream HEGO sensor as shown in **Figure 2**. The HEGO sensor serves other purposes, such as correcting potential UEGO sensor bias, but here we are concentrating on catalyst operation. Whether one wants to estimate the state of oxygen storage or detect an aged catalyst, a reasonably representative model of the catalyst that can be executed in real time in a Powertrain Control Module (PCM) is needed. For a feedback control design, a simple nonlinear integrator model is often considered. For the other tasks, a more elaborate model is needed. In particular, we consider models that have axially distributed oxygen storage and track oxygen O₂, carbon monoxide CO, and hydrogen H₂ components separately. The latter allows the water-to-gas shift

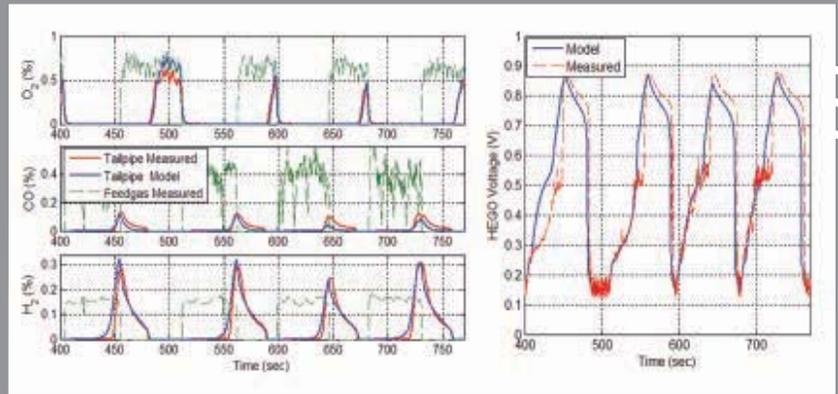
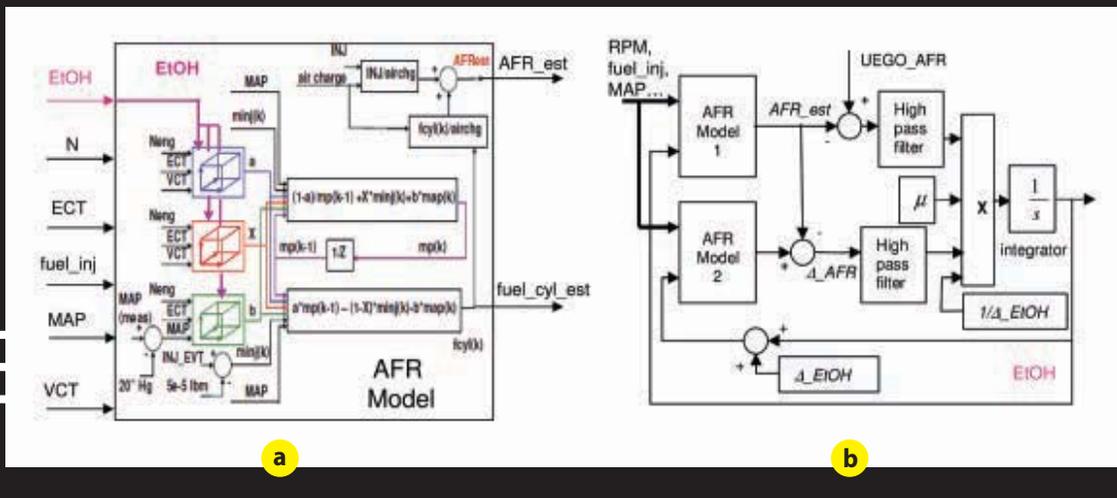


FIGURE 4 Comparison of tailpipe measured and modeled values for the three constituents (left) and comparison of measured and modeled HEGO voltages (right).

discretization, thus improving the chronometric impact by a factor of about 60, with essentially the same (moderate) memory use for the same set of parameters. These parameters have a clear physical meaning, but to get a good match to experimental measurements they are identified using the Particle Swarm Optimization (PSO) method. A few other methods we tried did not produce good results. The match of the measured data - O₂, CO, H₂ concentrations and HEGO voltage – to those

FIGURE 5
a) Transient fuel compensation including a wall wetting model
b) Twin-model ethanol detection.



effect to be captured, which is of interest because the HEGO sensor voltage reacts preferentially to H₂ compared to CO. The standard first principle model that tracks these three components and the oxygen storage cannot be propagated in real time in a PCM. Instead, after introducing reasonable simplifying assumptions, one can solve the resulting linear PDE [2]. We found that propagating the PDE solution instead of the PDE allows greater flexibility in selecting time and space

obtained by the model fed with the feed-gas (engine-out) concentrations of the components is shown in **Figure 4**. The PSO identification takes a couple of hours on a workstation. If the parameters were to be identified using the original PDE model, it would take days – so the faster model has a benefit beyond execution in real time on a PCM.

ETHANOL DETECTION FROM AN ELABORATE WALL-WETTING MODEL

Flex fuel vehicles (FFV) in the US are designed to operate on any blend of gasoline and ethanol (EtOH) ranging from 0% (E0) to 85% ethanol (E85). In Brazil, the allowed ethanol blends range from 22% to 100%. Presence of ethanol changes a number of fuel characteristics: the stoichiometric AFR changes from 14.6 for E0 to 9 for E100; octane

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number for ethanol is much higher, heat of vaporization is much higher, and ethanol is much less volatile at colder temperatures. For these reasons, it is important to have a good measurement or estimate of the ethanol percent. Benefits and drawbacks of a dedicated ethanol sensor are clear – good accuracy (about 5%) versus cost and complexity.

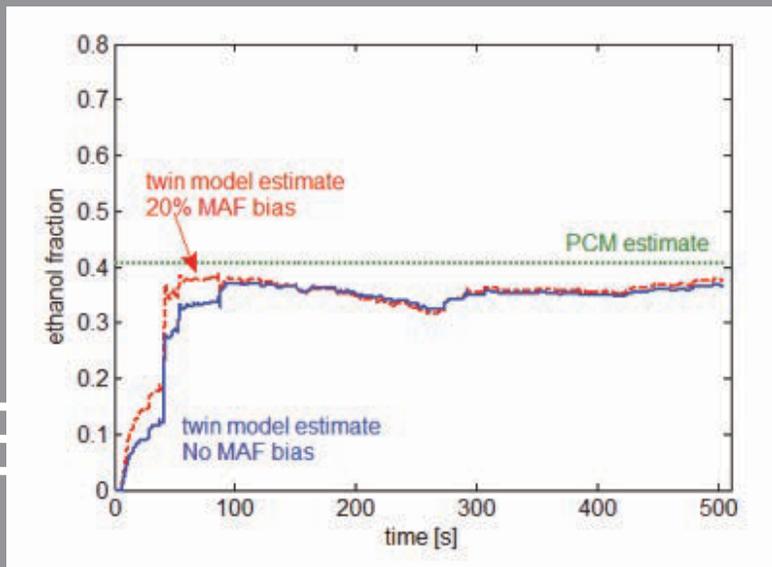


FIGURE 6 Comparison of ethanol percent estimate with no sensor bias and with 20% mass air flow sensor bias.

Without the sensor, in production FFVs, ethanol content is estimated by comparing the measured AFR to the one computed from the estimates of inducted air and injected fuel. The drawback of this approach is that any bias or inaccuracy in the air sensor or fuel injectors is magnified by a factor of about 2 because of the dependence of stoichiometric point on ethanol percent mentioned above. That is, a 10% error/bias in air or fuel results in about 20% error in ethanol estimate. One way to alleviate this problem is to use fuel volatility as an indicator of ethanol content. This brings us to the complex model of wall wetting.

In port fuel injected vehicles during cold engine operation, fuel tends to build puddles on port walls (wall wetting). As the engine warms up, the puddles slowly dissipate. The buildup and dissipation has to be compensated because, otherwise, the engine would run lean during tip-ins, stumble or even stall, while rich tip-outs would affect emissions. Engine control systems contain an elaborate transient fuel compensation that relies on a wall-wetting model. A representation of such a model, shown in **Figure 5a**, illustrates complex dependence of wall wetting on engine speed N , coolant temperature ECT , manifold pressure MAP , variable valve timing VCT , fuel injected, as well as ethanol percent. The entries in the multitude of look-up tables are calibrated through an elaborate and time consuming process. Note that the wall-wetting model in **Figure 5a** also produces an estimate of the AFR. Without changing or recalibrating this model, the two copies of it can be used in the “twin-model” estimator shown in **Figure 5b**. The pair of identical models are fed with a slightly offset ethanol percent, producing an AFR estimate as well as an AFR sensitivity to ethanol. Combining the two signals in an adaptive system results in an ethanol

estimate that (locally) converges to the actual value provided that the wall wetting model is reasonably accurate [3]. The main advantage over the stoichiometric based method is that, thanks to the pair of high pass filters shown in **Figure 5b**, the estimate is almost completely insensitive to the air sensor or injector bias as shown in **Figure 6**. The blue trace shows the estimate with no bias while the red trace shows one with 20% mass air flow (MAF) sensor bias. The same error would have shifted the ethanol estimate from the stoichiometry based method to either 0% or 80% depending on the sign of the error.

CONCLUSION

A few salient points about modeling for control: Selection of the control method and the plant model are inseparable. Often, the simplest possible model turns out to work well for a given purpose. Complex nonlinear or PDE models are difficult to calibrate and design controls for, but we are not giving up on them – a lot can be learned while developing a model. Complex models already exist in the engine controller (e.g. wall-wetting model) and could be exploited. ■

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