ABSTRACT: Much progress has been made in the area of electronic engine controls since their introduction in the 1980’s. This progress has included significant improvements in fuel economy and emissions reductions. Nevertheless current ECU’s (Engine Control Units) are much less advanced than those which can be found in the literature.

These advanced controllers are most often model based and include nonlinear estimators, adaptive and neural network systems, sliding mode systems, etc. The purpose of this paper is to review critically some of the more interesting, important and promising advanced systems with a view toward implementing practical model based ECU’s with improved performance.

Keywords: Engine control, Nonlinear control, Estimators

1. INTRODUCTION

As implied by its name, model or observer based control is dependent on using a mathematical model for the design of an engine control system. There are many such models available in the literature, of many different levels of accuracy and complexity. These range from simple (linearized) transfer function models, through fairly complex nonlinear differential equation models to very complex and detailed cycle simulation models.

It is the second type of model which is currently most commonly considered for engine control purposes and will be the subject of the discussion in this paper. Such models are often called Mean Value Engine Models (MVEMs) as they predict engine variables as averages over several or many engine events. As originally conceived, these models are physically based, are very compact and can be constructed for both diesel and spark ignition engines, with and without turbochargers (Hendricks, 1986), (Hendricks, 1989), (Hendricks, et al., 1990), (Hendricks, et al., 1996), (Muller, et al., 1998).

As will become apparent presently, the complexity, accuracy and flexibility of the underlying model has a great influence on the control systems which can be constructed for internal combustion engines. The MVEM based controllers which will be reviewed are of three types: those which are based on analytic functions, measured tables and neural
networks.

2. TWO PHYSICAL, ANALYTICAL MEAN VALUE ENGINE MODELS

In order to establish a framework for the discussion in this paper it is useful to review the defining equations of two typical physical MVEMs. The models which are to be reviewed have recently been detailed in the literature (Fons, et al., 1999), (Hendricks, 2000).

An MVEM for an SI engine contains three important subsystems, the fuelling dynamics, the manifold filling dynamics and the crank shaft speed dynamics. Only the last two systems will be reviewed here as these are the most relevant for model and observer based control systems and are the most physically correct at the current time.

There are two manifold filling models which are relevant for current engine control systems: an isothermal and an adiabatic model.

The isothermal model is derived assuming mass conservation and that the intake manifold temperature is known instantaneously and is equal to the ambient and EGR temperatures. The basic equation of this model including EGR is given by

\[ \dot{p}_i = \frac{\kappa R}{V_i} \left( \dot{m}_i T_i + m_i \dot{T}_i \right) \]

\[ = \frac{RT_i}{V_i} (-m_{ap} + m_{at} + m_{EGR}) \]

\[ = \dot{f}_{Ip}(\alpha, p_i, T_i, n, m_{EGR}) \]  

(1)

where the second equation on the right embodies the assumption that there is no heat transfer and that the intake manifold temperature is constant. This is thus an isothermal model. Obviously since the ambient, intake manifold and EGR temperatures cannot be equal and the intake manifold temperature cannot be measured instantaneously, the isothermal model cannot be accurate, especially for fast throttle transients (Hendricks, 2001).

The throttle and port air mass flows may be expressed as

\[ m_{ap}(n, p_i) = \sqrt{\frac{T_i}{T_a}} \frac{V_d}{120RT_i} (\epsilon_v \cdot p_i)n \]

\[ = s_T \frac{V_d}{120RT_i} (\epsilon_v \cdot p_i)n \]

(2)

where obviously \( s_T = \sqrt{\frac{T_i}{T_a}} \) and

\[ m_{at}(\alpha, p_i) = m_{at1} \frac{p_a}{\sqrt{T_a}} \beta_1(\alpha)\beta_2(p_r) + m_{at0} \]

(3)

where

\[ \beta_1(\alpha) = 1 - \alpha_1 \cos(\alpha) - \alpha_0 \]  

(4a)

\[ p_r = \frac{p_i}{p_a} \]  

(4b)

\[ \beta_2(p_r) = \begin{cases} \sqrt{1 - \left(\frac{p_r - p_c}{1 - p_c}\right)^2}, & \text{if } p_r \geq p_c \\ 1, & \text{if } p_r < p_c \end{cases} \]

(4)

and \( m_{at0}, m_{at1}, \alpha_0, \alpha_1, p_c = 0.4125 \) are constants.

The square root in the port air mass flow (speed-density) equation has been inserted as the standard temperature correction for the volumetric efficiency. Often tables are used for the expressions in equations (2), (3) and (4) in model based engine controllers. Both of the equations above are physically derived and have been confirmed individually directly by experiment (see (Hendricks, et al., 1996) and (Fons, et al., 1999) for more details).

A more correct adiabatic MVEM model for the intake manifold filling dynamics is based on the conservation of mass and energy in the intake manifold and is expressed as the coupled nonlinear differential equations:

\[ \dot{p}_i = \frac{\kappa R}{V_i} \left( \dot{m}_i T_i + m_i \dot{T}_i \right) \]

\[ = \frac{\kappa R}{V_i} (-m_{ap} T_i + m_{at} T_a + m_{EGR} T_{EGR}) \]

\[ = \dot{f}_{Ap}(\alpha, p_i, T_a, T_i, n, m_{EGR}, T_{EGR}) \]

(5)
\[
\dot{T}_i = \frac{RT_i}{p_i V_i} \left[ -m_{ap}(\kappa - 1)T_i + m_{at}(\kappa T_a - T_i) + m_{EGR}(\kappa T_{EGR} - T_i) \right] = f_{AT}(\alpha, p_i, T_a, T_i, n, m_{EGR}, T_{EGR})
\]

(6)

where heat transfer has been neglected.

To complete either of the MVEMs above it is necessary to add the crank shaft speed state equation to either equation (1) or to equations (5) and (6) above. The crank shaft speed state equation can be written as

\[
\dot{n} = -\frac{1}{ln} (P_f + P_p + P_b) + \frac{H_n}{ln} \eta_i m_f(t - \Delta \tau_d) = f_n(p_i, n, \theta, \lambda, m_f)
\]

\[
= \frac{1}{ln} \left[ -\frac{2\pi n}{60} (Q_f + Q_p + Q_b) + H_n \eta_i m_f(t - \Delta \tau_d) \right]
\]

(7)

where the \(Q\)'s are torques and \(\Delta \tau_d\) is the injection-torque time delay.

This equation is here used together with either equation (1) or equations (5) and (6) assuming for the sake of simplicity that there is ideal fuelling of the engine, i.e., that

\[
\dot{m}_f = \frac{\dot{m}_{ap}}{\lambda_{des} L_{eh}}
\]

(8)

where \(\lambda_{des} = 1\) for stoichiometric operation with TWCs (Three Way Catalysts).

In equation (7) the frictional and pumping powers (or torques) are given by regression equations derived from well known physical arguments.

The indicated efficiency is given as a product of four well defined, physically derived functions of the state variables:

\[
\eta_i(n, p_i, \theta, \lambda) = \eta_{in}(n) \cdot \eta_{ip}(p_i) \cdot \eta_\theta(\theta) \cdot \eta_\lambda(\lambda)
\]

(9)

The analytic functions for the component functions in equation (9) can be found in the references (Hendricks, et al., 1996) and (Hendricks, 2000). The model (Matlab Simulink) is also available on the World Wide Web together with the last paper.

The equations above are all physically based thus they are relatively easily calibrated for different engines, for different operating conditions and engine parameter changes due to wear or contamination.

The model equations above are easily understood physically in detail and a number of versions of them exist in the literature, containing more or less concrete descriptions. These models are in general constructed for control purposes and often different controllers are designed for each of them. This makes it possible to split up the description of them in terms of the model types which have been developed.

Analytic models are those which are based on using analytic functions for the MVEM sub-models such as those above. Non-analytic models are those which are based on tables, on neural networks or on fuzzy rule bases. Often mixtures of different types of sub-models are used in the same controller for purposes of simplicity and/or convenience. Thus this distinction is somewhat artificial but is a useful classification for the discussion here.

3. CONTROLLERS USING ANALYTIC MODELS

The first attempt at new controller design usually uses the methodology which is well established in a field at the time of its creation. This is the case for the controllers which are now to be reviewed. These are all ultimately founded on the simulation exercises used to test the first dynamic engine models.

3.1 Direct Nonlinear Engine Controllers

An obvious approach to the design of engine controllers is to use a MVEM model directly to derive various feedback loops which can be established around the engine using available sensors. This section deals with such controllers.

3.1.1 LQR Controllers A well established methodology for the design of multi variable con-
control systems is to use the Linear Quadratic Regulator design technique. The characteristics of such control loops are well known and understood, and they have robustness properties which appear immediately to make them suitable for engine control. Unfortunately this methodology is only useful on linear (or linearized) systems and this means that it is necessary to linearize the engine equations above in order to make a controller.

A well-known attempt at making an LQR regulator was made by (Onder, et al., 1993). This work was based on an isothermal model like that above which was linearized close to idle speed and specialized for combined AFR and engine speed control in a limited speed range. The model was basically semi-physical because engine mapping was employed. In order to obtain the necessary control and input matrices, a fit was made to measured engine data for various engine variables over a limited range and the necessary Jacobian matrices computed.

Fairly good AFR (+/- 5%) and speed control was possible in the region $4^\circ \leq \alpha \leq 8^\circ$ and from idle up to 2000 rpm on an FTP drive cycle using a 3.5 L, 6 cylinder engine. A FTP drive cycle is however a very mild test of an engine controller and somewhat faster throttle angle transients ($<0.1$ sec) should be used to obtain realistic results. Moreover the linearized model found is of a high order, is quite complex and would have to be supplemented with other models at higher loads and crank shaft speeds. Hence it requires a great amount of computational power, much more than is currently available and thus this approach is currently impractical and will probably remain so for some time.

3.1.2. Adaptive Controllers  
Adaptive controllers are an apparently attractive option for engine control because of the initial uncertainty in the modelling parameters and because of the unavoidable parameter drift which must occur during an engine’s operating life. As currently formulated, however, adaptive control theory requires a linear control object and this introduces some of the same problems in such systems as in LQR systems.

Very early attempts were made to do adaptive AFR, engine speed and fuel consumption control. These attempts, though somewhat successful, were hampered by incomplete models which were forced on the authors by the simple linear system models which could be handled at that time by the adaptive control theory and by microprocessors of limited power. Apart from these direct applications of adaptive control, most efforts in this area have concentrated on constructing observers with adaptive means to adjust their internal parameters. This point will be treated later.

3.1.3. Sliding Mode Controllers  
Sliding mode (SM) control is a very attractive proposition for a model based engine control system because it is possible to use it immediately on a well-defined nonlinear system and because, properly applied, it has guaranteed stability and robustness characteristics. Some difficulties do occur because of the inherent system and measurement time delays which exist in internal combustion engines.

An experimental study of a sliding mode controller was reported by (Kaidantzis, et al., 1993a) on an overall lambda control loop for stationary, closed loop and average lambda control. In this paper the performance of a PI controller and a sliding mode controller were compared. The usual sliding mode strategy above was improved by making a careful study of the time delays in the system and a nonlinear fuel film compensator developed at DTU was used. Moreover the control gain was split into two parts (a steady state and a transient part) in order to achieve faster response. The finished controller was tested on a 1.275 L, four cylinder SI engine equipped with a switching lambda sensor, using very aggressive driving scenarios (very large throttle angle inputs and widely varying engine speed). It was found that the lambda variations could be held to within +/- 5% during these tests. The PI lambda controller could achieve an accuracy of not better than +/- 12% for the same test conditions.

More recently the (Choi, et al., 1987) controller above was tested on a 4 cylinder, 2 L engine and reported in (Carnevale, et al., 1995). In this case proper performance was observed and stoichiometry could be maintained to +/-2% using common sensors. Unfortunately the AFR response documented is difficult to compare with that shown in other papers: the bare output of a switching lambda sensor is given instead of an average and only a few transients are shown without the throttle angle input being documented.
3.1.4. **Geometric Controllers** In control system theory, new possibilities for the control of nonlinear systems has recently emerged. As an engine is a well behaved continuous system in the mean value engine picture, these techniques can be immediately applied to engine control.

A rigorous theoretical paper using geometric control was published in 1998 (Xu, et al., 1998). In this paper global feedback linearization is applied to SI engine control using exactly the model above: equations (1) through (7), based on the paper (Hendricks, et al., 1996). This work is of course significantly more relevant to engine control than that based on conventional linearization. It is shown in the paper that the engine model above can be linearized globally and it is not difficult then to construct conventional but effective standard linear controllers for the overall system. This is possible for the fuelling, manifold pressure and crank shaft speed sub-systems.

The simulations show rather good air fuel ratio control but unfortunately without pumping noise and with a sinusoidal throttle input to the system. The control system with the throttle inputs used is not representative of what one can expect in real vehicle operation but the attempt made is interesting. It is fairly obvious however that the computational requirements of such a system will be significant though the response time improvements promised would be useful.

It can be hoped that the geometric control techniques will eventually be tested on a real engine with the unavoidable noise and model inaccuracies which can be expected. Only in this way will the practicality or impracticality of this approach be made apparent.

3.1.5. **Hybrid Controllers** One of the newest developments in model based control system design is the use of hybrid system theory. Hybrid systems are systems which include a number of different kinds of sub-models in the description of a single device, for example an internal combustion engine. This is in contrast to the mean value engine model above which is a system of differential equations with time delays included. Hybrid system theory, like nonlinear system theory is not yet fully developed but some interesting progress has been made.

A recent paper (Balluchi, et al., 2000) describes a hybrid SI engine model which is a combination of finite state machines, discrete event systems and continuous time differential equation sub-systems. Control is accomplished by dividing the system up into a torque tracking outer loop and an intake manifold control as an inner loop. The overall goal of the control system is to provide coordinated control actions which can accomplish a reasonable torque tracking as well as insure optimum use of the catalytic convertor. This is certainly a worthwhile goal and this is one of the first times that the overall control problem has been formulated in this way.

The results of the complex solution of this control problem are presented as a set of simulation plots which show that torque tracking is achieved as well as a reasonably effective use of the catalytic convertor. The torque requirement is selected as a sine wave which is not realistic but it is interesting that an overall control system can be designed to accomplish the design requirements above. It is also interesting that the model can in principle at least describe engine operation down to the individual engine events.

It can be hoped that the authors will continue this work by first using a more physical model, verifying it and then designing a new controller using more realistic control and test inputs.

3.2 **Observer Based Controllers**

Since the emergence of the first verifiably correct mean value engine models in the time frame 1987 to 1990, observer based control systems have dominated engine control applications. The reason for this is that strong emissions legislation and increased performance requirements have made it necessary to make engine controllers with increased accuracy and robustness with respect to engine parameter changes. The availability of powerful microprocessors had enabled this development. This has lead first to the use of open loop observers and then to closed loop observers, often based on what were earlier very advanced control/estimation techniques, only used in the aerospace industry.

Observers can either be open or closed loop types. Open loop observers are dynamic engine models
(MVEMs) which run independent of the engine itself apart from the input. Closed loop here refers to the use of models embedded in a deterministic observer or Kalman filter like structure to filter noise out and to correct approximately for modelling errors. Closed loop here refers to the use of models embedded in a deterministic observer or Kalman filter like structure to filter noise out and to correct approximately for modelling errors. Closed loop observers are a very useful way to obtain a running dynamic picture of what is happening in an internal combustion engine and, if properly, physically derived, it is very easy to understand the way in which they operate and to find construction or programming errors. Closed loop observers can have many different configurations and modes of operation. Several of these will be treated below.

A number of different observers and control strategies have emerged in the literature and the purpose of this section is to sort through them in an attempt to show what has been accomplished in the past and what may be possible in the future.

### 3.2.1. Open Loop, Feedforward Observers

One of the first observer controllers to be put into production is that due to Bosch (Benninger, et al., 1991). It is based on using a discretized version of the isothermal manifold pressure state equation, equation (1), running in parallel with the engine with driving signals which are the throttle angle and crank shaft speed measurements. Later a throttle air mass flow (hot wire or hot film MAF) sensor was also used. The sampling is event based at \( \frac{4 \pi}{n_{\text{cyl}}} \) crank angle intervals.

Because the controller only targets Air/Fuel Ratio (AFR) control, only the manifold pressure state equation is used to estimate, open loop, intake manifold pressure. This estimate is then used to find the port air mass flow via the speed-density relation, equation (2). The functions required in the speed-density equation are used as maps, not functions. The same approach to cylinder air charge estimation is used together with a hot wire MAF sensor in the new Bosch Torque Based ECU (Gerhardt, et al., 1997). An equivalent approach was taken later by Achleiter, et al., 1995, for Siemens. In this case a heated catalyst was used to minimize cold start emissions.

The performance demonstrated by both the Bosch and Siemens controllers seems convincing on the basis of the time responses presented but these are very limited in their extent: only the response to a few simple throttle step functions are shown. In real engine control applications, somewhat more complex throttle inputs are common over a very large operating range. An open question is also how the controllers will work over longer time periods: the mapped functions which are accurate when an engine is new are not those which are accurate after several years of wear and road contamination.

### 3.2.2. Stochastic Optimal Observers (Kalman Filters)

One of the control concepts which is very often used for SI engines is an extended Kalman filter to observe the states of the engine combined with a nonlinear compensator to the fuelling dynamics. Such a controller was first described in papers by (Vesterholm, et al., 1991) and (Hendricks, et al., 1992). This work is based on an early version of the MVEM above (Hendricks, et al., 1990). In fact the observer described is a full state observer: both the intake manifold pressure and the crank shaft speed are estimated in this constant gain extended Kalman filter.

The observer equations are

\[
\dot{p}_i(t) = \frac{RT_i}{V_i} (-m_{ap}(\hat{p}_i, \hat{n}) + m_{at}(\alpha, \hat{p}_i)) + K_{pp}(p_{im} - \hat{p}_i) + K_{pn}(n_m - \hat{n})
\]

and

\[
\dot{n} = f_n(\hat{p}_i, \hat{n}) + K_{np}(p_i - \hat{p}_i) + K_{nn}(n_m - \hat{n})
\]

where the subscript "m" indicates a measurement and where the K’s are Kalman gains. The Kalman gains are found using a noise model for the main disturbance on the measurements and the pumping and torque fluctuations on the states. The observer equations above are integrated in real time using a specially designed integration algorithm.

The observer was tested on a 1.275 L, Central Fuel Injection (CFI), 4 cylinder engine and it was found that AFR deviation from the desired stoichiometric level could be held to less than +/- 5% during very large throttle angle inputs over a large operating range. During these tests, the observer was used together with a specially designed nonlinear compensator for the fuelling dynamics. It was also possible to estimate on-line the load torque using...
the full order observer.

A simplified version of this extended Kalman filter observer, using only the manifold filling state equation has recently been put into production by Delphi. In this ECU the gain matrix has been found using empirically adjusted gains. This makes the Delphi observer a pole placement observer and thus it will be treated in the next section.

A more advanced version of the CFI engine control system described immediately above has been developed and tested on a 1.275 L, Sequential Fuel Injection (SEFI), 4 cylinder engine (Chevalier, et al., 2000). The observer used in this work is a predictive observer which is a true extended Kalman filter, solving on-line a matrix Riccati equation. Included in the observer is the adiabatic MVEM (pressure and temperature state equations), a novel noise suppression algorithm and a nonlinear fuel film compensator. Both manifold pressure and manifold temperature measurements are used in the innovations in the extended Kalman filter.

A drive-by-wire throttle control is used. The performance of this observer is excellent, even for extremely aggressive throttle angle transients and widely varying engine speeds. The overall AFR control performance demonstrated is in worst case +/- 3% over the operating range of the engine. Because of the large amount of calculation involved, the predictive observer is not a practical proposition at the present time. Nevertheless it does contain a number of ideas which can be used in other observers and it does provide a benchmark to which other control systems can be compared.

3.2.3. Pole Placement Observers Kalman filters require a noise picture before the relevant Kalman gains can be generated. Linear and nonlinear observers are however immediately so robust that it is not difficult to just choose a set of gains and simply adjust them to obtain the desired compromise between response (convergence) time, stability, accuracy and noise rejection. This characteristic has been used in at least two well-known papers which will be reviewed below.

As mentioned above, the Delphi production observer controller is based on the isothermal manifold pressure observer equations above with the addition of EGR as in equation (1) (Maloney, et al., 1998). A nonlinear fuel film compensator is also used. This system is called a Pneumatic State Estimator and Thermal State Estimator (PSE & TSE). The state equations of the system are integrated in continuous time as in the precursor to the Delphi work: (Hendricks, et al., 1992). It exhibits good AFR control according the authors and is tolerant of large throttle angle inputs.

Interestingly, even though this observer is designed to work with EGR, it does not use the adiabatic model of equations (5) and (6) above. The temperatures in the engine are estimated using algebraic equations. Clearly this should be done differently as pointed out in (Hendricks, 2001) as an irreversible error is thus incurred, mainly during fast transients. Nevertheless the actual control performance of the PSE & TSE is quite acceptable for most practical purposes and has found a number of uses somewhat beyond its originally conceived purpose: for example the estimation of a number of secondary engine temperatures and pressures for other ECU functions such as diagnostics, etc.

3.2.4. Robust Observers Robust control of engines is of great interest. The reasons for this are the variations of engine parameters which occur due to production tolerances and engine wear. Unfortunately robust control as currently formulated only can be used immediately on linear or linearized systems. Thus it is necessary to carry out a linearization of the engine dynamics before a system can be controlled in this way which implies storing many parameter matrices over a large operating range. Nevertheless it is interesting to see what can be accomplished using such techniques.

A paper on a robust AFR controller was published in 1999 (Vigild, et al., 1999) which attacks this complex problem. The goal of the work is to design an overall lambda control loop which is robust enough to overcome the nonlinearities of the system but which at the same time is fast enough to avoid AFR spikes during fast transient operation.

The starting point of the work is thus in the first case to derive a lambda state equation and then to linearize it. The nonlinearities in the isothermal MVEM and fuel flow dynamics are considered as (relatively large) uncertainties in the variables. Uncertainty in the internal engine variable (such as
the volumetric efficiency) are also considered. The time delays in the engine are approximated using second order Pade approximations and the lambda sensor is modelled as a first order low pass filter.

Use of the standard H-infinity control techniques is then applied to the overall system and a control system gains found: both for the observer and controller. The overall system is then subjected to a \( \mu \) analysis and it is shown that the standard requirements are satisfied: nominal stability, nominal performance, robust stability and robust performance. These are tested using a structured singular value analysis and the results are shown in the paper.

Finally the H-infinity lambda controller was tested on a MultiPoint Injection (MPI), 1.275 L, 4 cylinder engine. When subjected to a series of short rise time throttle angle steps, over a large speed range, the controller was capable of AFR control with an accuracy of +/- 3% over most of the operating range, becoming +/- 6% at the very edges of the design interval. Clearly the controller is not suitable for production applications because of its high order but the possibility of using robust control techniques is interesting.

One of the basic modelling elements used is the isothermal manifold pressure state equation rewritten to make the port air mass flow an independent variable. This equation then includes new variables which are obtained by mapping:

\[
\dot{m}_{\text{ap}} = \frac{1}{\tau_i} \left(-m_{\text{ap}} + m_{ss}(\alpha, n)\right)
\]

where the time constant \( \tau_i \) and the driving function \( m_{ss} \), are obtained by mapping.

This equation is discretized with a sampling time corresponding to 45° crank angle, half of an engine event. Thus the overall system is event rather than time based. A second important element is a simple model of a lambda sensor, modelled as a low pass filter and discretized according to the sample time given above. A time delay of one engine cycle is included in the model to represent the injection/exhaust time delay. The final element of the model is a discretized fuel film dynamic sub-model based on the continuous formulation by (Aquino, 1981) and a corresponding ideal nonlinear fuel film compensator.

In the adaptation scheme, the parameters estimated are the manifold time constant and a bias term added to the driving function in equation (12). The states of the model are fuel puddle mass, equivalence ratio in the cylinder, the equivalence ratio in the exhaust manifold and a bias term \( m_{ab} \) modifying the term \( m_{ss} \) in equation (12).

The adaptive observer scheme above was tested on a 2.2 L, 4 cylinder lean burn engine. For a throttle angle square wave input (constant level, constant amplitude) and widely varying crank shaft speed the air fuel ratio control demonstrated for the controller is very good, +/- 3%. The response for a varying throttle angle at constant engine speed is equally good.

No responses are given when both the throttle angle and engine speed have large and rapid variations. This is unfortunate and is a critical omission as the most difficult test of an engine controller is where all of its variables are excited simultaneously over a large range. In particular this is an important test for adaptive systems as they in general require some time to allow the parameters to change (to adapt) to new operating conditions.

3.2.5. \textit{Adaptive Observers}  

Given the fact that a common problem with model based controllers is that of parameter drift and robustness with respect to production tolerances, observers containing some adaption features are of increasing interest. Another important driver for this development is the desire to decrease the number of sensors on an engine and/or use the observer for OBD applications.

One of the most prominent of the papers presented in this area is (Fekete, et al., 1995). This work has attracted support by Daimler-Chrysler and is being considered for production. These papers describe an adaptive observer based on a model with mapped sub-models and an adaptive scheme to update the parameters of the models. The overall control goals are AFR control and sensor number reduction (no MAP or MAF sensor is used, only a switching lambda sensor). A drive-by-wire throttle is used and the sensors are only sampled when the readings are stable, i.e., the throttle is not moving.
Rapid operating point changes will thus be very difficult to follow for adaptive systems.

3.2.6. Sliding Mode Observers  Sliding mode (SM) observers are a further development of sliding mode controllers and have a form which is close to that of deterministic observers or Kalman filters. The gain in such observers is however higher than in conventional observers but has more or less the same effect (see Kaidantzis, et al., 1993b)). A problem with such observers is that the high gain, neglected time delays and modelling inaccuracy can produce a level of chattering which is greater than the noise in the original system. If boundary layers are introduced to reduce this problem then one has a system with what is basically a conventional observer with an observer gain which is gain scheduled. However newer work on sliding mode observers shows that there are some advantages to be had in using this strategy for AFR control. (Choi, et al., 1998) presents an interesting and apparently useful sliding mode observer controller for the AFR. In principle, what is on offer is a modified sliding mode observer and an open loop (or feedforward) controller. The system is based on the assumption of an ideal model of the fuel supply sub-system and an uncertain air mass flow model. Without going into detail, these assumptions can be used to generate a time dependent observer gain which is less than that which would ordinarily be used to insure that the sliding surface for the observer is always attractive. This leads to a smaller chattering amplitude (about one fifth) of that which could be obtained using conventional sliding mode techniques.

The overall SM, observer based controller has been tested on a 3.8 L, 6 cylinder SI engine with SEFI injection. The tests are conducted over a large speed range with large square wave throttle inputs. A comparison is given between a production ECU, a sliding mode controller and a sliding mode observer based controller at the same operating point with equivalent inputs. It is shown that the lambda control accuracy is +/- 20%, +/- 8% and +/- 3% respectively for the three controllers. This is effectively what can be achieved with somewhat more complex controllers but requires an accurate model as the authors rightly point out in the paper. The effects of large simultaneous throttle angle and large speed changes are not documented in the paper.

4. CONTROLLERS USING NON-ANALYTIC MODELS

Given the difficulties involved in constructing analytic physical models of internal combustion engines, a strong tendency in both mechanical engineering and in particular, control engineering circles, has been to attempt to find an easier modelling strategy for engines. The general availability of very powerful personal- and mini-computers has initiated a tendency to load the modelling task onto fitting routines: for example, regression equations, neural networks and fuzzy set model.

Because of their ability to represent complex functions with good flexibility and detail, neural networks have become popular to model various engine subsystems as black boxes. Such modelling is relatively easy and inexpensive. It can be shown that such a neural network is a universal approximator to an arbitrary input/output function. It is this universal approximation capability for algebraic equations which makes neural networks so attractive as fitting functions.

4.1 Engine Modelling

The mixture of dynamic and algebraic subsystems (see the MVEM equations above) in an IC engine is very difficult to represent in a neural network directly. This has lead to many attempts to represent the physical sub-systems above, equations (1) - (7), as neural networks. In the papers (Winsel, et al., 1998) and (Theuerkauf, et al., 1999) this approach is taken. In these papers the MVEMs are constructed where the engine is divided into its three main subsystems (fueling system, manifold filling and crank shaft dynamics). This division makes it easier to parameterize these sub-models (train them). This is also important because it makes it easier to verify that the neural networks generalize accurately enough for the application at hand.

Another method of modelling engines is to use fuzzy control. Such modelling techniques make it possible use directly the cut-and-try methods which have served the automotive industry so well in the past. While this makes construction of
the model tedious and the analysis difficult (it is for example difficult to analyze, manipulate or differentiate the models), the models can be made to simulate unusual nonphysical behavior which is difficult using conventional optimization techniques.

4.1.1. Virtual Sensing   An important use for neural networks reported in the literature is as virtual or software sensors for various applications. An important application is misfire detection (Wu, et al., 1998). Many other applications of this type may be found in the literature but as this is not directly a subject of this paper, no further work of this type will be mentioned here.

4.2 Non-analytic Controllers

Not too many attempts have been made as yet to construct controllers or observers using non-analytic functions. The reason for this is that the procedure for doing this is not well established. Nevertheless a few controllers have emerged which are worth mentioning here.

4.2.1. Neural Network Controllers   There have not been many papers published using neural networks directly as controllers for engines. There are nevertheless a wealth of possibilities for this because neural networks are very flexible an can in principle be shaped to yield any desired continuous control signal.

In the paper (Winsel, et al., 1999) a neural network is used to adapt the forgetting factor in an adaptive control algorithm for an SI engine. Although the authors use a simulation model instead of real data the paper presents a fairly interesting example of how to use neural networks to optimize the performance of the system. The adaptive algorithm identifies a model describing the relationship between the injection time and the normalized AFR. The adaptive algorithm’s reaction time to speed changes in the system is adjusted by a forgetting factor \( \beta \), \( 0 < \beta < 1 \). The forgetting factor simply weights the last error by \( \beta \), the previous one by \( \beta^2 \) and so on. The authors then observe that a different optimal value for \( \beta \) exists for different operating points of the engine. The optimal value of \( \beta \) depends on several engine states in a complex way that would be difficult to describe physically. A neural network is then trained to output optimal values for \( \beta \) as a function of manifold pressure and engine speed and a so called "transiency" variable. The transiency variable is defined as the difference of the mean of the average manifold pressure of the last seven engine cycles and the actual pressure. The authors do not mention however how the optimal value of \( \beta \) has been found for any given step. They also do not mention the problem of stability. The AFR control demonstrated using the controller is very convincing even though it is a simulation result.

4.2.2. Fuzzy Controllers   Fuzzy control has been applied to an adaptive AFR control system by (Al-Olimat, et al., 2000). This controller is based on simple discrete (event) time sub-models of the fuel flow dynamics and AFR sensor, including a sensor time delay. The sub-model components usually represented as analytic functions or tables are represented in this paper as fuzzy rule bases, each having 27 rules. Adaption is applied for the identification of these functions. A center of gravity defuzzification method is used. The controller is tested by simulation on the model due to (Chang, et al., 1993). These tests are conducted at a single engine speed on a single throttle pulse. The AFR response is satisfactory, with the response around lambda = 1 having errors between about +/- 2%. Because of the number of rules and membership functions which must be constructed, such systems are of limited interest for practical application presently.

5. CONCLUSIONS

A number of different types of AFR controllers have been critically reviewed to determine their suitability for general use. In general those which are formulated as analytic models have been found to be most useful at the current stage of development.

While some direct controllers have reasonable response, observer based controllers are generally acknowledged and are suggested by the review presented here to be the most robust for production applications, in particular those of the closed loop variety. This is due to their relatively large tolerance to modelling errors and hence engine aging. Closed loop observers based on extended Kalman filters, sliding mode observers and deterministic observers fall into this catagory.
Non-analytic engine controllers have been built but are still at a preliminary state in their development. They have shown however some interesting characteristics and it is hoped that their development will continue.

6. NOMENCLATURE

The following symbols are used in this paper:

- \( t \): time (sec)
- \( \alpha \): throttle plate angle (degrees)
- \( n \): engine speed (rpm/1000 or krpm)
- \( m_i \): air mass in intake manifold (kg)
- \( p_a \): ambient pressure (bar)
- \( T_a \): ambient temperature (degrees Kelvin)
- \( p_i \): absolute manifold pressure (bar)
- \( T_i \): intake manifold temperature (degrees Kelvin)
- \( T_{\text{EGR}} \): EGR temperature (degrees Kelvin)
- \( P_f \): engine friction losses (kW)
- \( P_p \): engine pumping losses (kW)
- \( P_b \): engine load power (kW)
- \( H_u \): fuel heating value (kJ/kg)
- \( \eta_i \): indicated efficiency
- \( I \): engine moment of inertia
  \[
  (= I_{\text{ac}} \cdot \left(\frac{\pi}{30}\right)^2 \cdot 1000 \text{rpm})
  \]
- \( I_{\text{ac}} \): actual engine moment of inertia (kg m\(^2\))
- \( m_{at} \): air mass flow past throttle plate (kg/sec)
- \( m_{ap} \): air mass flow into intake port (kg/sec)
- \( m_{\text{EGR}} \): EGR mass flow (kg/sec)
- \( e_v \): volumetric efficiency based on manifold conditions
- \( V_d \): engine displacement (liters)
- \( V_i \): manifold + port passage volume (m\(^3\))
- \( R \): gas constant (here 287 X 10^{-5})
- \( \kappa \): ratio of the specific heats = 1.4 for air
- \( L_{\text{th}} \): stoichiometric air/fuel ratio (14.67)
- \( MAP \): Manifold Absolute Pressure (bar)
- \( MAF \): (throttle) Mass Air Flow
- \( EGR \): Exhaust Gas Recirculation
- \( AFR \): Air/Fuel Ratio

7. REFERENCES


