THE ROLE OF MODERN CONTROL THEORY FOR AUTOMOTIVE ENGINE CONTROL

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ABSTRACT

The purpose of this paper is to discuss the importance of multivariable modern control theory to the design of advanced control systems for future automotive engines. Specific areas include static and dynamic optimization, multivariable stochastic estimation and control, and reliability issues.

MOTIVATION

The purpose of this paper is to discuss the role of modern control and estimation theory (see references [1]*- [17]) in the design of future digital control systems for the automobile engine. The argument will be made that the available tools of modern control theory, which include

(a) static and dynamic optimization
(b) stochastic multivariable control system design
(c) system reliability concepts

will have a major impact in the analysis and synthesis of future automotive engine control systems, provided that a concentrated research effort involving industry, government, and universities is initiated to remove some of the key obstacles before succesful economic and reliable implementations can be developed.

The optimism of the author is based upon the observation that the following ingredients presently exist:

1. Need. Reduction in fuel consumption and emissions is an important, and self-evident, economic and social goal

2. Hardware Technology. Microprocessors are reliable means for the implementation of sophisticated control algorithms.

3. Design Methodology. Generic design methodologies exist for multivariable control problems, that can be adapted and extended to handle the specific problems unique to automotive engine systems.

The major obstacle that has to be overcome is a fundamental understanding of the dynamic cause-and-effect relationships of the key variables of the automobile engine. Such dynamic relations must be obtained from a combination of first principle models and careful experimentation. In particular, these dynamic models must describe by means of stochastic differential equations the quantitative effects of typical engine control variables such as

- throttle
- spark advance angle
- air-fuel ratio
- exhaust gas recirculation (EGR)

upon key output variables such as

- torque
- speed
- fuel consumption
- emissions (NO_x, HC, CO)
- driveability

If adequate dynamic models become available for the engine, catalytic, and transmission systems, then superior multivariable control system designs, implemented via microprocessors, become possible.

In the absence of adequate mathematical models, very little can be done in a systematic manner to design engine control systems, and more important to carry out systematic economic-engineering trade-offs related to sensors, actuators, performance, reliability, and cost.

At the outset I wish to stress that the design of a superior and reliable control system for automotive engines is, in my opinion, a far more complex design problem than that required for most aerospace applications, e.g., the control system for the vehicle . Hence, it represents a true challenge to the state-of-the-art, and the difficulties have to be appreciated by decision-makers, designers, and researchers. Long term commitments of inter-disciplinary resources have to be made. At the present time one can see promising beginnings but the pace and the resource allocation has to be accelerated.

It is equally self-evident, again in my opinion, that the implementation of the projected control systems will be based upon microprocessors. Adaptive closed-loop reliable engine control cannot be accomplished by electromechanical controllers. Such trends are occuring in advanced aerospace systems (e.g. the F-18, cruise missiles, vertical takeoff aircraft, aircraft engines) for which the performance requirements demand the design of closed-loop multivariable control systems which cannot be implemented by conventional electromechanical controllers.

In the remainder of this paper I shall outline certain areas of modern control and estimation theory and their potential impact upon the overall problem of designing superior engine control systems.

*Numbers in brackets designate References at end of paper

STATIC (STEADY STATE) OPTIMIZATION

In static optimization problems all dynamic and stochastic phenomena are ignored. Thus, this represents the "easiest" problem in terms of modelling, and one of the "easier" problems with respect to optimization. It also represents an area in which some work has been already reported (see references [18] - [23]).

To put the problem into perspective define the following variables:

$\underline{u}$:a m-dimensional vector of control variables (e.g. throttle, air-fuel ratio, EGR, spark advance)

$\underline{y}$:a r-dimensional vector of response variables (e.g. torgue, speed, fuel consumption, different emission variables etc.)

$\underline{p}$:a g-dimensional vector of parameters (e.g. engine-specific parameters, catalyst-specific parameters, ambient temperature and humidity etc.)

The steady-state assumption is that the control, response, and parameter vectors are related by means of deterministic algebraic equations which are modelled as a vector equality of the form

$$\underline{y} = \underline{g}(\underline{u},\underline{p}) \qquad (1)$$

This means that given a <u>constant</u> value of the input control variables, $\underline{u}$, and the parameters, $\underline{p}$, one can calculate the response variables, $\underline{y}$, of interest. Such relations, namely the function $\underline{g}(\underline{u},\underline{p})$ can be ontained by steady state engine measurements producing a so-called <u>static engine map</u>.

Constraints upon the physical values of the variables can be modelled as algebraic inequalities of the form

$$\underline{h}(\underline{y},\underline{u},\underline{p}) \leq \underline{0} \qquad (2)$$

In static optimization problems one is interested in minimizing a cost function (or maximizing a utility or payoff function). Let C denote the cost function to be minimized; C must be a <u>scalar</u> although it may depend on several input control variables ($\underline{u}$) response variable ($\underline{y}$), with tradeoff parameters modelled as the components of a vector $\underline{a}$. Thus the cost to be minimized is*

$$C = L(\underline{y},\underline{u},\underline{a}) \qquad (3)$$

The static optimization problem is to find the <u>constant optimal</u> value of the input control variable $\underline{u}$, denoted by $\underline{u}^*$, which minimizes the cost (3) without violating the equality constraints (1) and the inequality constraints (2).

The system-theoretic methodology that one uses is that of constrained multivariable static optimization. There are several algorithms, based upon nonlinear programming variants, that can be used to calculate the optimal solution numerically, mathematically, the solution takes the form

$$\underline{u}^* = \underline{m}(\underline{y},\underline{p},\underline{a}) \qquad (4)$$

*For example

$C = a_1$ (Fuel Consumption)$+a_2(NO_x)+a_3(CH)+a_4(CO)$

which implies that sensor measurements of the response variables ($\underline{y}$), the exogeneous parameters ($\underline{p}$), and for given tradeoff parameters ($\underline{a}$), can be used to calculate the optimal constant control $\underline{u}^*$.

In practice the junction $\underline{m}(\underline{y},\underline{p},\underline{a})$ is computed numerically and stored in the computer memory; to minimize memory requirements a certain amount of interpolation (perhaps using polynomial approximations to the components of the function $\underline{m}(.)$)is possible. This then represents the familiar <u>look-up table</u> concept upon which the majority of the proposed engine electronic engine control systems in the early 1980's depend upon. In a general context this method of control corresponds to the multivariable trimming concept for advanced aerospace vehicles and jet engines or to the set-point determination in process control systems.

There is little doubt that such static problems will be important in the control system design. However, they cannot be expected to work in a satisfactory manner unless additional feedback loops are introduced. For example, there is evidence that the predictive capability of such static engine maps, where the engine is tested in a typical EPA cycle, is limited especially when one wants to predict emission variables. Similarly, it should be stressed that the optimal constant control $\underline{u}^*$ depends on both sensor measurements (which may be noisy) <u>and</u> on the exogeneous parameters ($\underline{p}$); these engine and catalyst parameters may change and such changes would lead to overall degradation, unless the control strategy is augmented to take into account such parameter variations.

To recapitulate: static optimization techniques are <u>necessary but not sufficient</u> for improved automotive engine control. The digital control system must be augmented to compensate for the following factors that are <u>not</u> addressed by the very formulation of the static steady state optimization problems.

(a) Engine, transmission, and catalyst dynamics
(b) Key parameter changes
(c) Availability of economic and reliable sensors
(d) Accuracy of sensor measurements

To address these issues one must examine the stochastic and dynamic issues involved; this necessitates the development of more realistic mathematical models for automotive engine systems.

DYNAMIC OPTIMIZATION

Dynamic optimization represents a very broad field, which since about 1960 has blossomed into several directions, most of them directly important for the automotive engine control problem.

In dynamic optimization one is interested in the implicit time variation of all variables. In addition to the time-varying control variables (denoted by $\underline{u}(t)$) and the response variables (denoted by $\underline{y}(t)$) one must take into account additional energy storage elements, which may include some or all response variables, that define the components of the so-called <u>state vector</u> $\underline{x}(t)$.

The dynamic behavior of the system is described by sets of simultaneous differential equations, in general nonlinear. In such problems, one describes the system to be controlled by a vector differential equation of the form

$$\frac{d}{dt} \underline{x}(t) = \underline{f}\ (\underline{x}(\underline{t}),\ \underline{u}(\underline{t}),\underline{p}) \tag{5}$$

which relates the time evolution of the state variables $\underline{x}(t)$ to the time evolution of the input control variables $\underline{u}(t)$, while $\underline{p}$ is an exogeneous parameter vector. The response variables $\underline{y}(t)$ are related to the state and control variables, $\underline{x}(t)$ and $\underline{u}(t)$ respectively, by means of simultaneous algebraic equations of the form

$$\underline{y}(t) = \underline{g}(\underline{x}(t),\underline{u}(t),\underline{p}) \tag{6}$$

Such dynamic equations capture the cause-and-effects transients, and they represent a detailed mathematical representation of the system.

To the best of the author's knowledge such global nonlinear dynamic models of the engine-transmission-catalyst system are not available. They should be developed; their development would require careful analysis from first principles involving the laws of thermodynamics, physics, and chemistry. Detailed experimentation would be necessary to obtain the numerical values of parameters in the differential equations.

If adequate nonlinear dynamic models of the automotive engine system were available, a wealth of tools from optimal control theory could be employed.

As an example, one could study fundamental problems in the best way of coordinating in a time-varying manner the diverse engine control variables so as to optimize several objective functions that involve tradeoffs between fuel economy, emissions, and driveability. These may be very important in particular in the cold-start regime for which current catalysts are inneffective.

If general dynamic models derived from first principles were available, one could study the possible improvements in overall performance through the introduction of additional control variables in the engine and catalyst.

Such fundamental studies in dynamic optimization and dynamic coordination are very important for understanding both basic limitations and novel techniques for automotive engine control. For complex multivariable systems, it is possible to discover counter intuitive control strategies with significant performance payoffs. The results at first appear counterintuitive because most engineering intuition cannot possibly comprehend the complex dynamic interrelationships and their consequences. Static models and static optimization often mask the performance improvements inherent by the adoption of coordinated dynamic control strategies.

During the past two years initial efforts toward dynamic modelling have taken place, with some very preliminary results based upon dynamic optimization using computer simulations (see references [24] - [26]). Although the results appear encouraging much more fundamental research and experimental verification of the concepts and designs is necessary.

If adequate mathematical models of the engine become available, then current control design methodologies are adequate for designing multivariable control systems. It should be noted that modern control theory designs are based upon time-domain optimization methods, and reliable software for computer-aided multivariable designs are emerging. It should be stressed that the modern control theory designs are not limited to the single-input-output frequency-domain oriented tools normally associated with classical servomechanism theory.

Modern control design methodologies can be used to design dynamic compensators for multivariable systems without decoupling the control loops. This is accomplished by blending time domain dynamic optimization techniques with stochastic estimation methods. Noise in the actuators and in the available sensors is incorporated in modern multivariable designs. Furthermore, modern multivariable control system designs have reasonable robustness properties, which are very desirable because one wishes to make the dynamic performance of the control system as insensitive as possible to engine parameter changes, and guarantee graceful degradation in performance in the presence of non-catastrophic actuator and sensor failures.

During the past two years some exciting general research questions have been posed, and partially answered, about the overall robustness and sensitivity properties of multivariable controllers (see references [27] - [30]). These results have been obtained by blending the time-domain dynamic optimization methods and the frequently domain methods. While these results are still at a general level, their refinement and application to the automotive engine problems should provide valuable insight into the question of obtaining robust engine control system designs.

One way of improving the robustness of a control system is to invest in additional real-time memory and computations so as to estimate, based upon the actual sensor measurements, changes in key parameters and changing the structure of the control system (usually the control gains) based upon this information. This is often referred to as adaptive control (see references [31] and [32] for recent surveys). From the point of view of microprocessor implementation two concepts examined in the context of controlling aircraft utilize parallel bankes of microprocessors to carry out real time identification and control; the first concept [33] uses real-time non-recursive approximate maximum-likelihood identification techniques, while the other [34] utilizes real time hypothesis-testing ideas to determine approximate dynamic models which then are used for control.

The advantage of these adaptive methods is that they utilize linearized models of the system to be controlled in the vicinity of operating conditions (as perhaps determined by the static optimization algorithm). In the context of automotive engine problems linear dynamic models are easier to obtain than global nonlinear models, and such parallel-processing identification and control methods may have some value in the engine control problem. However, very little can be said about the potential value of these techniques in the absence of dynamic models. On the other hand, it is strongly suspected that maximum likelihood methods with suitable modifications for real time control [35] can be incorporated into an adaptive multivariable control system design so as to result in robust designs [36].

FAILURE DETECTION AND MANAGEMENT

If one introduces additional degrees of freedom so as to improve the overall system performance, then one is immediately faced with the problem of requiring additional actuators and sensors. There is no substitute for having a sensor measuring the variable that one wishes to control. However, the relative accuracy of a sensor is an important engineering and economic parameter. Needless to say, in the automotive engine problem the availability and reliability of sensors that measure the emmission variables represents a challengine open problem.

The only way that one can deal with the problem of estimating a variable that one cannot measure is to obtain an estimate of the variable or parameter by correlating other observable quantities. In modern estimation theory there exist systematic techniques for accomplishing such real-time calculations. All these techniques are derivatives and extensions of the Kalman filter and can be implemented by microprocessors; for such problems memory is not a big problem, but real-time computation is (especially with respect to fast multiplications). Effectively a microprocessor implementation of a Kalman filter will have to solve in real-time the differential equations that model the engine dynamics.

The use of Kalman filters in the overall engine problem is further justified from the viewpoint of failure detection and isolation. Consider the problem that one uses a singly redundant sensor A in the control system implementation. If this sensor fails, and such a failure is not detected, then the control system will not perform correctly and in fact it may exhibit instabilities. To detect sensor failure one needs a redundant sensor B, leading to a so-called dually redundant system. However, by comparing the measurements of both A and B one can only conclude that one has failed, but one cannot decide which one; thus, one cannot decide which sensor should drive the control system. Thus, at the sensor hardware level, one needs three sensors A,B,C so that in this triply redundant configuration majority voting can be used to <u>both detect and isolate failures</u>.

In the context of the automotive engine problem the concept of having triply redundant sensors does not appear to be economically feasible. Yet the issue of failure detection and isolation is important if fail-operational strategies are to be adopted. The only way to test whether a particular sensor has failed, is the absence of hardware redundancy, is to obtain independent estimates of the sensed quantity by correlating information available from other sensors. This can be accomplished through Kalman filtering techniques in conjunction with hypothesis testing ideas (see survey reference [37]), provided that adequate dynamic models are available. Thus, one uses microprocessor-based electronics to construct variable estimates, which at the very least provide a systematic basis for failure management. Such concepts have been applied to aerospace problems [38] and they certainly merit attention for automotive engine systems.

The overall dynamic failure management methodology is not complete as yet even from a theoretical point of view (see refs. [39] and [40]). Much of the progress has been driven by aerospace applications. However, the sensor tradeoffs associated with aerospace systems are drastically different than those that will have to be carried out to design a reliable automotive engine control system. Hence, a great deal of directed research has to be carried out in this field, and much of the specifics of the relative complexity of the failure management system will have to await the fundamental understanding of engine dynamic behavior.

CONCLUSIONS

The development of dynamic models for the engine, transmission, and catalytic systems is crucial for the design of digital control systems for superior performance in terms of fuel economy, emissions reduction, driveability, and reliability. Once such models are available many of the existing tools of modern control and estimation theory can be applied to the engine control problem. However, fundamental advances in the theory and methodology associated with robust and reliable control systems for automotive engine control are necessary.

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1. L.S. Pontryagin, et al., "The Mathematical Theory of Optimal Processes", J. Wiley and Sons, Interscience, New York, 1962.
2. M. Athans and P.L. Falb, "Optimal Control", McGraw-Hill Book Co., New York, 1966.
3. E.B. Lee and L. Marcus, "Foundations of Optimal Control Theory", J. Wiley and Sons, New York, 1967.
4. A.E. Bryson and Y.-C. Ho, "Applied Optimal Control", Blaisdell, Waltham, Mass., 1969.
5. R. Bellman, "Dynamic Programming", Princeton University Press, Princeton, N.J., 1957.
6. H. Kwackernaak and R. Sivan, "Linear Optimal Control Systems", J. Wiley and Sons, New York, 1972.
7. B.D.O. Anderson and J.B. Moore, "Linear Optimal Control", Prentice Hall, Englewood Cliffs, N.J., 1971.
8. R.S. Bucy and P.D. Joseph, "Filtering for Stochastic Processes with Applications to Guidance", J. Wiley and Sons, New York, 1962.
9. A.H. Jazwinskii, "Stochastic Processes and Filtering Theory", Academic Press, New York, 1970.
10. A. Gelb, "Applied Optimal Estimation", MIT Press, Cambridge, Mass., 1974.

11. M. Aoki, "Optimization of Stochastic Systems", Academic Press, New York, 1967.
12. K.J. Astrom, "Introduction to Stochastic Control Theory", Academic Press, New York, 1970.
13. H.J. Kushner, "Introduction to Stochastic Control", Holt, Rinehart, and Winston, New York, 1971.
14. A.A. Fel'baum, "Optimal Control Systems", Academic Press, New York, 1967.
15. M. Athans, ed., "Special Issue on Linear Quadratic Gaussian Problem", IEEE Trans. Automat. Contr., Vol. AC-16, (Dec. 1971).
16. T. Kailath, ed. "Special Issue on Time Series Analysis and Identification", IEEE Trans. Auto. Control, Vol. AC-19, (Dec. 1974).
17. M. Athans, ed. "Special Issue on Large Scale Systems and Decentralized Control", IEEE Trans. Auto Control, Vol. AC-23, (April, 1978).
18. L.S. Vora, "Computerized Five Parameter Engine Mapping", GMR-2291-R, G.M. Research Labs, Warren, MI (Feb. 1977).
19. J.F. Cassidy, "A Computerized On-Line Approach to Calculating Optimum Engine Calibrations", GMR-2286, G.M. Research Labs, Warren, MI (Dec. 1976).
20. J.M. Ironside, "On Line Minimization of Fuel Consumption and Exhaust Pollutants", S.M. Thesis, University of Birmingham, U.K. (1973).
21. R. Prabhacker et al, "Optimization of Automotive Engine Efficiency and Emissions" ASME 75 WA/Aut-19, (Dec. 1975).
22. U.S. Dept. of Transportation, "Automobile Engine Control Symposium", Cambridge, Mass., (July 1975)
23. J.F. Cassidy , "Comments on the Engine Control Problem", GMR-2260, G.M. Research Labs, Warren, MI, (Oct. 1976).
24. B.C. Christensen and A.A. Frank, "The Fuel Saving Potential of Cars with Continuously Variable Transmissions and an Optimal Control Algorithm", ASME 75-WA/Aut-20 (Dec. 1975).
25. J.F. Cassidy, W.H. Lee, and M. Athans, "On the Design of Electronic Automotive Engine Controls Using Linear Quadratic Control Theory", Proc. IEEE Conference on Decision and Control, San Diego, CA (Jan. 1979).
26. P.F. Chenea, "Applying Systems Engineering Methods to the Electronic Engine Control Problem", Proc. Convergence, International Conference on Automotive Electronics, Dearborn, Michigan, (Sept. 1978).
27. M.G. Safonov and M. Athans, "Gain and Phase Margins for Multiloop LQG Regulators", IEEE Trans. on Auto. Control, Vol. AC-22 (April 1977).
28. P.K. Wong, G. Stein, and M. Athans, "Structural Reliability and Robustness Properties of Optimal Linear-Quadratic Multivariable Regulators", Proc. IFAC Congress, Helsinki, Finland (June 1978).
29. J.C. Doyle, "Robustness Properties of LQG Regulators", IEEE Trans. on Auto. Control, Vol. AC-23 (Aug. 1978).
30. J.C. Doyle and G. Stein, "Robustness with Observers", to appear.
31. B. Wittenmark, "Stochastic Adaptive Control Methods: A Survey", Int. J. Contr. 21, (1975).
32. M. Athans and P. Varaiya, "A Survey of Adaptive Stochastic Control Methods", in ERDA Report CONF-78067, Systems Engineering for Power: Status and Prospects, L.H. Fink and K. Carlsen, eds., (Oct. 1975).
33. G. Stein, G.L. Hartman, and R.C. Hendrick, "Adaptive Control Laws for F-8 Flight Test", IEEE Trans. Auto. Control, Vol. AC-22, (Oct. 1977).
34. M. Athans et al, "The Stochastic Control of the F8-C Aircraft Using a Multiple Model Adaptive Control Method Part I: Equilibrium Flight", IEEE Trans. Auto. Control, Vol. AC-22, ((ct. 1977).
35. N.R. Sandell, Jr. and K. Yared, "Maximum Likelihood Identification of State Space Models for Linear Dynamical Systems", M.I.T. Electronic Systems Laboratory, Report ESL-R-814, Cambridge, Mass.,(April 1978).
36. M.G. Safonov and M. Athans, "Robustness and Computational Aspects of Nonlinear Stochastic Estimators and Regulators", IEEE Trans. on Auto. Control, Vol. AC-23, (Aug. 1978).
37. A.S. Willsky, "A Survey of Design Methods for Failure Detection in Dynamic Systems", Automatica, Vol. 12, 1976.
38. J.D. Deckert, M.N. Desai, J.J. Deyst, and A.S. Willsky, "A Dual Redundant Sensor Failure Detection Algorithm for the F-8 Aircraft", IEEE Trans. on Auto. Control, Vol. AC-22, (Oct. 1977).
39. J.D. Birdwell and M. Athans, "On the Relationship Between Reliability and Linear Quadratic Optimal Control", Proc. IEEE Conf. on Decision and Control, New Orleans, LA, (Dec. 1977).
40. J.D. Birdwell, "On Reliable Control System Designs", M.I.T. Electronic Systems Laboratory, Report ESL-TH-821, Cambridge, Mass., (May 1978).