REAL-TIME, SELF-LEARNING IDENTIFICATION AND STOCHASTIC OPTIMAL CONTROL OF ADVANCED POWERTRAIN SYSTEMS

by

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy (Mechanical Engineering) in The University of Michigan 2008

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To my wife, Voula, and to my daughter, Georgina
ACKNOWLEDGMENTS

When I came to Ann Arbor, I could never imagine that during the years to come I would have the most wonderful and productive time in my life. I had the chance to have come across a lot of wise and wonderful people. Their guidance and support have been invaluable.

I was extremely fortunate to have two remarkably supportive advisors, Professor Dennis Assanis and Professor Panos Papalambros. They provided friendly warmth, challenges, continuing support throughout my studies while affording me a tremendous amount of freedom and responsibility.

Professor Assanis is the reason that I decided to attend the University of Michigan for graduate school. I had come across his research activities at the Automotive Research Center (ARC) while still undecided about the graduate school I should attend. It took me just seconds to realize that this was the research environment I was looking for. When I met him and expressed my strong interest to join his group, I got impressed by his depth of thought, his openness, and his critical eye. Professor Assanis offered an extraordinary depth of knowledge in advanced powertrain systems, and he was a noble teacher and mentor. I would like to sincerely thank him for giving me the opportunity to join his research group at the University of Michigan.

During the first year of my studies, I had the privilege to meet Professor Papalambros while taking the Design Optimization class. I believe that this meeting had a significant impact in shaping my research interests and professional goals. Professor Papalambros provided continuing advice and developed my sense of the academic community in engineering. He provided challenges and he offered a blinding depth of
knowledge in design optimization. He promoted a respect for rigorous work, and
constantly pushed the boundaries of his expertise while maintaining extraordinary
standards of quality. I would like to sincerely thank him for his invaluable guidance and
support throughout my studies.

In addition to my advisors, many people contributed meaningfully by providing
feedback and perspective that helped define my direction. I would like to thank the
committee members of my dissertation, Professor James Freudenberg, Professor Galip
Ulsoy, and Professor Domitilla Del Vecchio for their valuable feedback and comments
on my dissertation and publications. During my interaction with Professor Freudenberg,
while I was taking his class in linear feedback control systems, he contributed directly to
my understanding in control theory and the related applications in advanced powertrain
systems.

I also owe special thanks to Professor Demosthenis Teneketzis for broadening and
deepening my understanding in stochastic control and centralized stochastic systems. He
provided feedback and excellent references; his classes in stochastic process and
stochastic control along with our numerous interactions were instrumental in enhancing
my knowledge in this area.

I would also like to express my appreciation to a plethora of other individuals,
who spent a considerably amount of time in meeting with me and providing assistance.
Dr. Michael Kokkolaras was always willing to provide and share his knowledge in
optimization while working together in various projects. His feedback in various aspects
of my research activities was always helpful and valuable. Professor Rudy Schmerl
provided a tremendous amount of assistance in enhancing my technical communication
skills. I enjoyed all our meetings and discussions. Professor Zoran Filipi was instrumental
in developing my understanding of modeling and simulation of advanced powertrain
systems. Dr. George Lavoie was always willing to share his knowledge and expertise
while provided helpful feedback on my work. Dr. Aristotelis Babajimopoulos provided
unlimited assistance in any computer related issue. Finally, I would like to thank all my lab-mates and staff, past and present, in Autolab and Optimal Design Laboratory.

This research was supported by the Automotive Research Center (ARC), a U.S. Army Center of Excellence in Modeling and Simulation of Ground Vehicles at the University of Michigan. This support is gratefully acknowledged.

I owe my gratitude to my father, Alexandros, and to my mother, Ioanna, who have been always supportive in any aspect of life. The knowledge that my success will bring to them happiness and pride was an extra motivator for me.

This dissertation is dedicated to my wife, Voula, and to my daughter, Georgina. I would not be able to complete my PhD without the boundless love, support, and patience of my wonderful loving wife. I will always be indebted to her for prioritizing my work and success against her interests and professional goals. Georgina’s smile was a tremendous source of energy for me since she was born. Looking at this little angle always rejuvenated me, and immersed me in new energy and tranquility.
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NOMENCLATURE

The following nomenclature is used consistently in the dissertation.

\( k \) \hspace{1cm} \text{Discrete time steps (decision epochs)}
\( s_k \) \hspace{1cm} \text{System state at time } k
\( y_k \) \hspace{1cm} \text{System output at time } k
\( w_k \) \hspace{1cm} \text{Disturbance at time } k
\( v_k \) \hspace{1cm} \text{Measurement error at time } k
\( a_k \) \hspace{1cm} \text{Control action at time } k
\( S \) \hspace{1cm} \text{State space}
\( A \) \hspace{1cm} \text{Control space}
\( W \) \hspace{1cm} \text{Disturbance space}
\( A(\cdot) \) \hspace{1cm} \text{Feasible action set}
\( f \) \hspace{1cm} \text{Function in the state equation}
\( h \) \hspace{1cm} \text{Function in the observation equation}
\( \pi \) \hspace{1cm} \text{Control policy}
\( \mu \) \hspace{1cm} \text{Control functions}
\( J^\pi \) \hspace{1cm} \text{Cost corresponding to a control policy } \pi
\( z_k \) \hspace{1cm} \text{System observation at time } k
\( P^\pi(\cdot|\cdot) \) \hspace{1cm} \text{Conditional distribution of states for a given control policy } \pi
\( R(\cdot|\cdot) \) \hspace{1cm} \text{State transition cost}
\( P(\cdot,\cdot) \) \hspace{1cm} \text{Transition probability matrix}
\( R(\cdot,\cdot) \) \hspace{1cm} \text{Transition cost matrix}
$M^\theta$  Family of models parameterized by the parameter $\theta$

$\hat{\theta}_k$  Estimation of the parameter at time $k$

$\theta^*$  True parameter

$\Theta$  Parameter set

$T_i$  First entrance time of the state

$T_n$  $n$th entrance time of state

$\mu_i$  Mean recurrence time of state $i$

$\mathcal{S}$  Predictive Optimal Decision-making (POD) domain

$\mathcal{S}_i$  Predictive Representation Node (PRN) for each state $i$

$\bar{R}_i(\cdot|\cdot)$  Predictive Representation Node (PRN) value for each state $i$

$R^i_{PRN}$  Predictive Representation Node (PRN) expected evaluation function for each state $i$

$\mu_\bar{s}_i$  Mean recurrence time of each Predictive Representation Node (PRN)

$\rho$  Vector of the stationary distribution of the chain

$I_C$  Indicator function of a given set $C$

$V$  Number of visits of the chain

$\bar{V}$  Mean number of visits of the chain

$\pi$  Lookahead control policy by the Predictive Optimal Stochastic Control Algorithm (POSCA)

$J$  Accumulated cost incurred by dynamic programming

$\bar{J}$  Accumulated cost incurred by the Predictive Optimal Stochastic Control Algorithm (POSCA)

$\mathcal{J}$  Lookahead cost incurred by the Predictive Optimal Stochastic Control Algorithm (POSCA)

$\Gamma$  Strategic form game

$r$  Player in a strategic form game

$R^r$  Payoff function for each player $r$ in a strategic form game
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_r'$</td>
<td>Set of feasible strategies for each player $r$</td>
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ABSTRACT

REAL-TIME, SELF-LEARNING IDENTIFICATION AND STOCHASTIC OPTIMAL CONTROL OF ADVANCED POWERTRAIN SYSTEMS

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Increasing demand for improving fuel economy and reducing emissions without sacrificing performance has stimulated significant research on and investment in advanced internal combustion engine technologies. These technologies have introduced a number of controllable variables that have enhanced our ability to optimize engine operation. Current engine calibration methods for deriving the optimal values of the controllable variables generate a static tabular relationship between the variables and steady-state operating points or specific driving conditions (e.g., vehicle speed profiles for highway and city driving). These methods, however, seldom guarantee optimal engine operation for common driving habits (e.g., stop-and-go driving, rapid acceleration, or rapid braking). Each individual driving style is different and rarely meets those driving conditions of testing for which the engine has been calibrated to operate optimally.

This dissertation develops the theory and algorithms that succeed in making the engine of a vehicle an autonomous intelligent system capable of learning the optimal values of the controllable variables in real time while the driver drives the vehicle. The engine is treated as a controlled stochastic system, and engine calibration is formulated as
a sequential decision-making problem under uncertainty that addresses the system identification and stochastic control problem simultaneously.

Specifically, the theory for building models suited for sequential decision-making under uncertainty is reviewed. These models formalize the framework in which an intelligent or rational system can select control actions so that a long-term reward is maximized. The theory is extended to portray a real-time computational learning model with which the state estimation and system identification problem can be solved. A lookahead control algorithm is implemented that provides the decision-making mechanism suitable for real-time implementation. The algorithm solves the stochastic control problem by utilizing accumulated data acquired over the learning process of the computational model. The increase of the problem’s dimensionality, when more than one controllable variable is considered, is addressed by a decentralized learning control scheme. This scheme draws from multi-agent learning research in a range of areas, including reinforcement learning and game theory, to coordinate optimal behavior among the controllable variables.

Various case studies, including cart-pole balancing, vehicle cruise-control, and gasoline and diesel engine calibration, were conducted. In the engine calibration problem, the engine was shown to progressively perceive the driver’s driving style and eventually learn its optimal calibration for this driving style.

The theory and algorithms developed in this dissertation may reduce considerably the existing discrepancy between the gas mileage estimate displayed on the vehicle’s window sticker and the actual one. This would allow every driver to realize optimal fuel economy and pollutant emissions as fully as possible with respect to his/her driving habits.