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

by

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

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NOMENCLATURE

The following nomenclature is used consistently in the dissertation.

k	Discrete time steps (decision epochs)
s_k	System state at time k
y_k	System output at time k
w_k	Disturbance at time k
v_k	Measurement error at time k
a_k	Control action at time k
$\mathcal{S}$	State space
$\mathcal{A}$	Control space
$\mathcal{W}$	Disturbance space
$A(\cdot)$	Feasible action set
f	Function in the state equation
h	Function in the observation equation
π	Control policy
μ	Control functions
J^{π}	Cost corresponding to a control policy π
z^k	System observation at time k
$P^{\pi}(\cdot \mid \cdot)$	Conditional distribution of states for a given control policy π
$R(\cdot \mid \cdot)$	State transition cost
$\mathbf{P}(\cdot,\cdot)$	Transition probability matrix
$\mathbf{R}(\cdot,\cdot)$	Transition cost matrix

M^{θ}	Family of models parameterized by the parameter θ
$\hat{\theta}_k$	Estimation of the parameter at time k
θ°	True parameter
Θ	Parameter set
T_1	First entrance time of the state
T_n	nth entrance time of state
μ_i	Mean recurrence time of state i
$\tilde{\mathcal{S}}$	Predictive Optimal Decision-making (POD) domain
$\tilde{\mathcal{S}}_i$	Predictive Representation Node (PRN) for each state i
$\bar{R}_i(\cdot \mid \cdot)$	Predictive Representation Node (PRN) value for each state i
R^{i}_{PRN}	Predictive Representation Node (PRN) expected evaluation function for each state i
$\mu_{\tilde{\mathcal{S}}_i}$	Mean recurrence time of each Predictive Representation Node (PRN)
$\boldsymbol{\rho}$	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
$\bar{\pi}$	Lookahead control policy by the Predictive Optimal Stochastic Control Algorithm (POSCA)
J	Accumulated cost incurred by dynamic programming
$\tilde{J}$	Accumulated cost incurred by the Predictive Optimal Stochastic Control Algorithm (POSCA)
$\bar{J}$	Lookahead cost incurred by the Predictive Optimal Stochastic Control Algorithm (POSCA)
Γ	Strategic form game
r	Player in a strategic form game
R^{r}	Payoff function for each player r in a strategic form game

A^r	Set of feasible strategies for each player r
a^r	Strategy for each player r in a strategic form game
R_r'	Mapping of the payoff functions in decentralized learning

ABSTRACT

REAL-TIME, SELF-LEARLING 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.