

Automotive Engine Tuning Using Least-Squares Support Vector Machines and Evolutionary Optimization

By

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Faculty of Science and Technology
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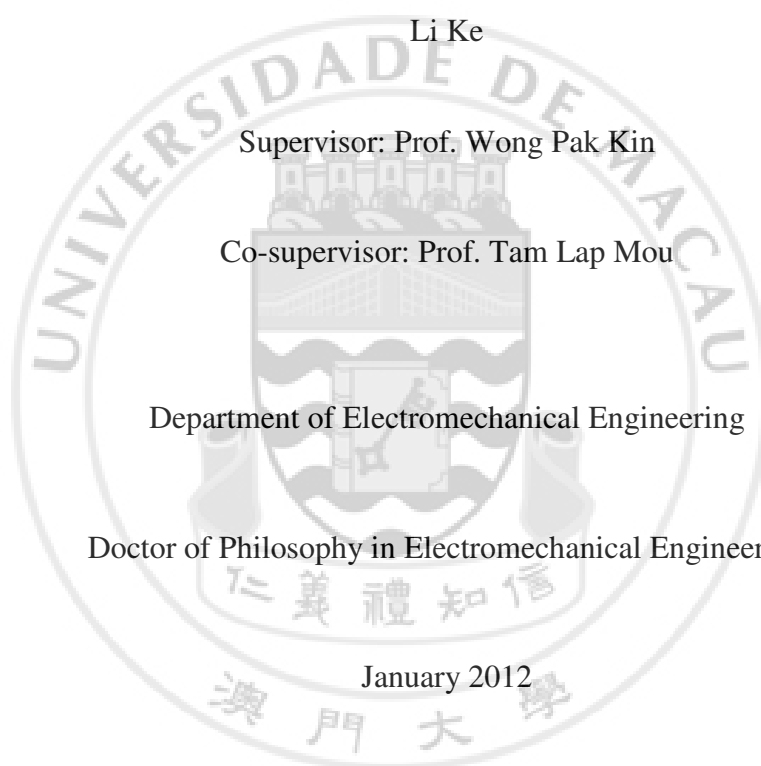
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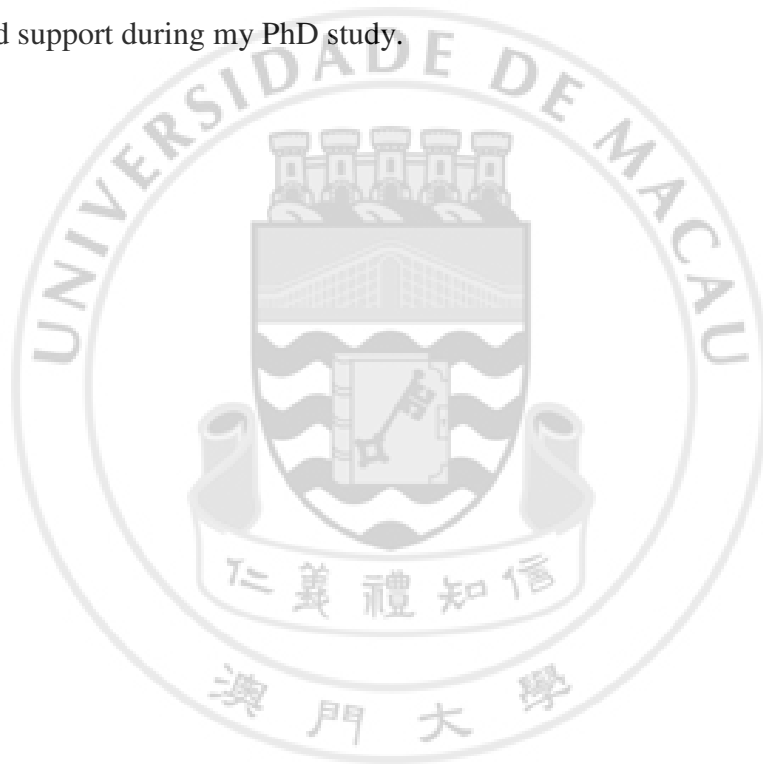




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ABSTRACT

University of Macau

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Modern automotive engines are controlled by electronic control units (ECUs), and the engine performance is significantly affected by the setup of the control parameters in the ECU and the selection of engine parts. Engine tuning is the adjustment or modification of ECU parameters and engine parts to yield optimal performance subject to different user requirements. The current practice of engine tuning relies on the experience of automotive engineers. An engine tuning is usually done by a trial-and-error method. Obviously, the current practice consumes large amounts of time and money. The problem can be solved by developing a mathematical engine model and optimizer for engine setup optimization. This research proposes a novel modeling and optimization approach for engine tuning. In the first phase of the approach, Latin hypercube sampling and multiple-input and multiple-output (MIMO) least-squares support vector machines (LS-SVMs) are proposed to create an engine performance model based on experimental sample data, and then typical deterministic optimization (such as quasi-Newton method) and evolutionary optimization (such as genetic algorithm, and particle swarm

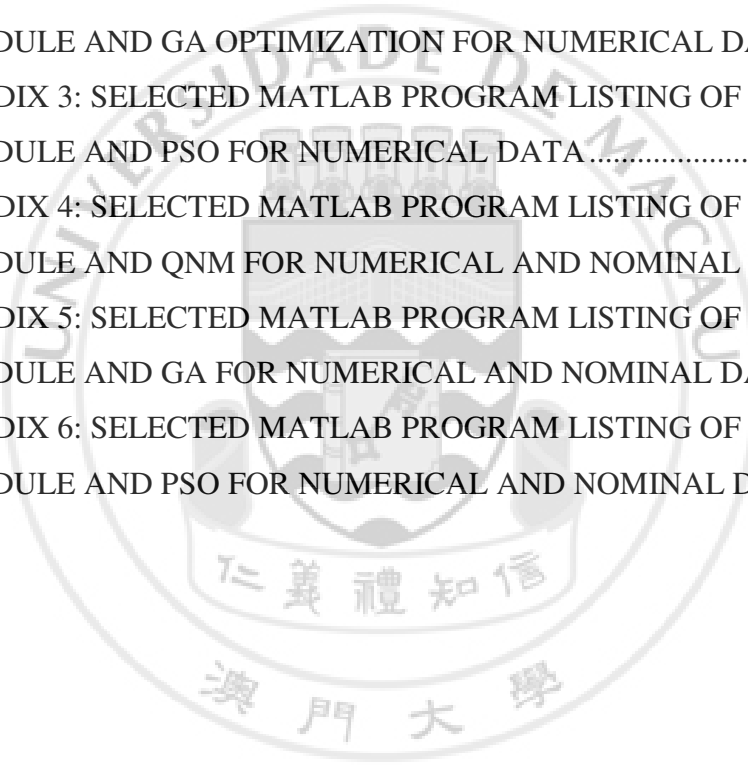
optimization) are applied to the engine model produced to automatically determine the optimal engine performance subject to different user-specific constraints. Both deterministic and evolutionary optimization techniques are examined in sake of comparison purpose. In addition, an equal and fair data pre-processing technique, namely one-of-n remapping and a simple binary code synthesis rule are proposed to handle engine-part selection issue in this research, because engine parts are complicated objects which are usually represented as nominal data. These data are meaningless values in terms of computation. By integrating such a data pre-processing technique with the MIMO LS-SVM modeling framework, engine performance can be simulated under different combinations of engine parts and ECU parameters. Since engine idle-speed control and power performance optimization are typical automotive engine dynamic and static performances, respectively, engine idle-speed control and power performance optimization are selected for case studies to demonstrate the feasibility and efficiency of the novel modeling and optimization approach. Both experimental and simulation results show that the proposed methodology can successfully produce optimal engine setup.

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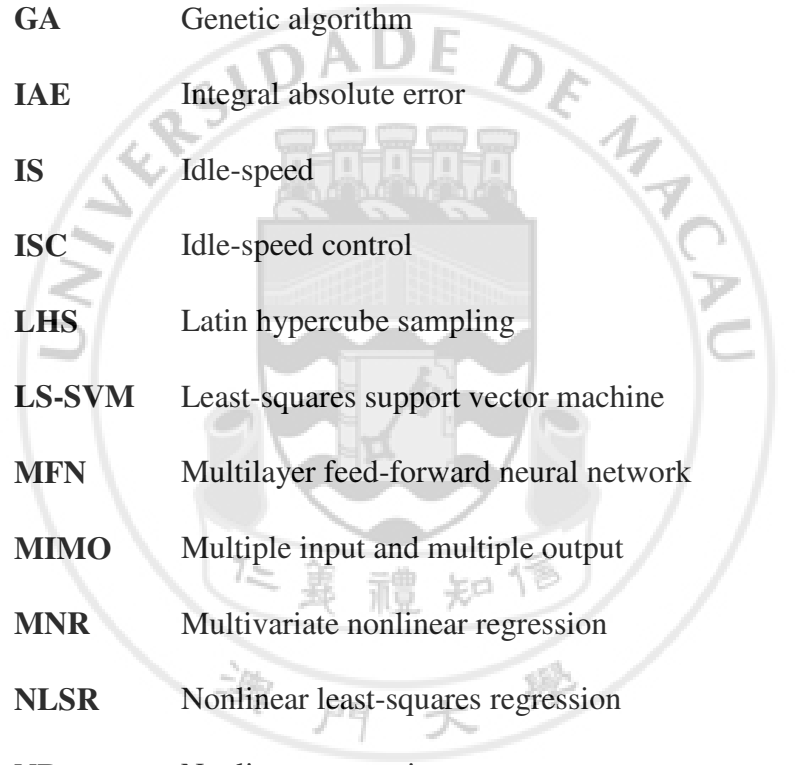
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LIST OF ABBREVIATIONS



BPAV	By-pass air valve
BTDC	Before top dead center
DOE	Design of experiments
ECU	Electronic control unit
GA	Genetic algorithm
IAE	Integral absolute error
IS	Idle-speed
ISC	Idle-speed control
LHS	Latin hypercube sampling
LS-SVM	Least-squares support vector machine
MFN	Multilayer feed-forward neural network
MIMO	Multiple input and multiple output
MNR	Multivariate nonlinear regression
NLSR	Nonlinear least-squares regression
NR	Nonlinear regression
NN	Neural network
PSO	Particle swarm optimization
PID	Proportional-integral-derivative
QNM	Quasi-Newton method
QP	Quadratic programming
RBF	Radial basis function

rpm	Revolutions per minute
RWS	Roulette wheel selection
SVM	Support vector machine

