MPC-Based Optimal Control for Diesel Engine Coupled with Lean NOx Trap System

Fuguo Xu* and Tielong Shen*

Abstract: In this paper, an on-board optimal control problem for diesel engines with lean NOx trap (LNT) is investigated. First, a two-order LNT model based on mass conservation and energy conservation is constructed. Then, the optimal control problem is formulated as a continuous receding horizon problem under dynamical model constraint and discretized into a nonlinear programming problem by using the multiple shooting method. A sequential quadratic programming approach is employed to derive a numerical solution. Finally simulations are conducted under a standard driving cycle and a random driving cycle with comparison to a dynamic programming based control scheme in MATLAB/Simulink platform. Simulation results verify the effectiveness of the proposed control scheme.

Key Words: diesel engine, lean NOx trap, model predictive control, multiple shooting.

1. Introduction

In recent years, the diesel engine has been becoming more popular in light-duty vehicles due to fuel economy than the gasoline engine [1]. However, when facing with stricter government emission regulations, the disadvantage of the diesel engine in NOx emission is a troublesome issue. This problem could not be solved by structural redesign and control strategy of diesel engine itself [2]. One general solution is to concatenate the after-treatment system with exhaust manifold sequentially, mainly including lean NOx trap (LNT) and selective catalytic reduction (SCR).

Comparing to SCR, LNT operating process is only controlled by air-fuel ratio, and hence LNT device occupies less space than SCR in equipment. As is well known, the basic function of LNT is NOx storage in lean engine conditions and NOx purge in rich conditions. In other words, LNT operating mode is determined by air-fuel ratio [3],[4]. Usually, NOx exhausted from engine exhaust manifold is stored as solid phase around the surface of LNT catalyst during NOx storage, and released from the solid phase and converted into N$_2$ as a chemical reaction during NOx purge. In control perspective, developing a model that depicts the chemical reaction of NOx reduction is critical. Many pieces of research have focused on LNT modeling. For example, black-box models are built to describe multiple inputs and multiple outputs (MIMO) behavior for LNT NOx reduction process [5]–[7]. However, the black-box model only concerns outside information of a model so that it could not capture the inner dynamics of LNT NOx reduction. To capture the chemical process of NOx reduction accurately, a physics-based LNT model was developed based on the mass conservation role [8]–[10]. Since LNT temperature is a critical factor that could affect chemical speed, temperature dynamic should be considered in a control-oriented LNT model. Further research on the temperature model can be found in [11],[12], which are based on energy conservation.

Meanwhile, model-based optimization is widely used in practice to achieve better performance in the sense of a pre-specified cost function. For automotive background, if one target is on a given driving route, dynamic programming (DP) is an effective tool to obtain the optimal control law with a model of plant [13]. For the after-treatment system, DP-based optimal control strategy has been used in [14]. Furthermore, Pontryagin’s minimum principle (PMP) is another optimal control theory to solve the above problem by dealing with Hamiltonian [15]. However, both DP and PMP based control schemes could not be implemented in the situation where forward traffic information is unknown, especially for real-time NOx exhaust emission test. An alternative solution is to use a sub-optimal control scheme by employing model predictive control (MPC) with the advantage of real-time receding horizon optimization [16]. Furthermore, to derive the optimal solution during a predictive horizon of MPC, the dynamic-model constraint nonlinear optimal control problem could be converted numerically into a nonlinear programming problem with equality and inequality and then solved by the sequential quadratic programming (SQP) approach. SQP is an effective method to deal with large-scale nonlinear optimization problems iteratively [17],[18].

In the sense of strategies for NOx reduction with minimization of fuel consumption, regeneration timing control is usually conducted, and a trigger is necessary to start NOx purge [7],[9]. However, additional tuning parameter for trigger leads to design complexity and the controllable domain would be limited to improve performance. In our previous work, a feedback control scheme to regulate post fuel injection amount is investigated with the purpose of tracking optimal LNT temperature to maximize storing capacity [19]. Moreover, only temperature dynamics is seen as the state variable for controller design.

In this paper, we investigate further the performance improvement by formulating a nonlinear optimal control problem for a diesel engine with the LNT system and selecting the fuel amount of post injection as a control input. Differently, a two-order LNT dynamic-model is seen as the constraint in the op-
timal control problem. A trade-off between fuel economy and NOx emission is considered in the cost function of the optimal control problem. To derive an optimal solution, a multiple shooting method is employed for converting the optimal control problem into a nonlinear programming problem (NLP), and the NLP is solved by an SQP approach. Finally, a co-simulation platform is built for verifying the proposed control schemes. A standard driving cycle and a random driving cycle generated through traffic scenario software are used as simulation working conditions and a dynamic programming based control scheme is designed for performance comparison.

Remainder sections of this paper are organized as follows. Background of the diesel engine with an LNT system is introduced, and an optimal control problem is formulated for trade-off fuel economy and NOx emission in Section 2. Section 3 mainly develops a two-order LNT model for capturing NOx storage and conservation process. A numerical solution is proposed based on the multiple shooting approach and the sequential quadratic programming algorithm in Section 4. Simulation results with a comparison control scheme are shown in Section 5. The last section gives some conclusions about this paper.

2. Problem Description

The schematic of the diesel engine with an LNT device is shown in Fig. 1. When a driver presses accelerator pedal, demand power is determined. For power satisfaction, common rail injection is used to regulate fuel injection. Since the generation of unhealthy NOx in the diesel engine is uncontrollable, an LNT device is introduced and connected sequentially after engine exhaust manifold to reduce NOx emission.

There are mainly two steps for NOx emission reduction in LNT. The first step is the NOx storage process when air-fuel ratio is higher than one, during which time LNT inlet NOx is stored as the solid phase on the surface of LNT catalyst. The other one is NOx release and conversion. This process occurs only when the engine works in a rich mode with air-fuel ratio less than one. The stored NOx is released as the gas phase quickly and converted into N2 through an oxidation-reduction reaction. LNT has to work in the above two steps periodically since the catalyst capacity is finite. Usually, the engine works in the lean mode for fuel economy, and the active of engine working in rich mode could be implemented by a post fuel injection. To capture the LNT NOx reduction response, an example is given in Fig. 2. The dotted line and black line response LNT represent under logic controller to regulate post injection and without post injection, respectively. There are twice post injection of the logic controller, and air-fuel ratio is less than one only from 30 s to 40 s. During that time, fill ratio of LNT, which is an index to show NOx reduction dynamic, decreases quickly. Moreover, with the logic controller, LNT temperature increases higher than that without fuel injection.

The block diagram of the proposed control system for the diesel engine with LNT is depicted in Fig. 3. The goal is to minimize NOx emission from LNT outlet with as less additional fuel consumption as possible. In this paper, post fuel injection is chosen as the optimal control input. LNT temperature and fill ratio are selected as state variables for optimal control scheme design. For a desired vehicle speed, if the gear ratio is determined, then desired engine operation points (including torque and speed) are also determined. The demand main fuel injection for engine power supply is fixed. Similarly, the exhaust performance of the diesel engine, such as mass flow, air-fuel ratio, exhaust temperature, and NOx mass rate, could be obtained. These variables are seen as disturbance inputs for the LNT system in the design of the optimal control scheme.

With above-mentioned knowledge, during a fixed time interval, the optimal control problem for the minimizing of additional fuel consumption and NOx emission subjects to dynamic-model constraint and inequality constraints of state variables and control input can be written as follows:
where \( t, \Delta t, \) and \( N_p \) are the current time, the sampling time, and the predictive step, respectively. The parameters \( \delta \) and \( \theta \) are weight factors for different purposes; \( \delta \) is used for different attention degree on fuel and NOx emission, and \( \theta \) is used for the balance of order of magnitude. The control input \( u \) denotes fuel consumption rate in this paper. So in the cost function, squares of \( u \) and \( \gamma \) are seen for the purpose of additional fuel consumption consideration and tailpipe NOx emission consideration. In this paper, only fuel economy and emission performance are taken into account, and state variables dynamics are guaranteed within a reasonable region, so there is not a terminal penalty item about state variables in the cost function. Moreover, \( f(\cdot) \) and \( g(\cdot) \) represent the two-order LNT model and NOx emission rate from LNT tailpipe. Concrete expression formula of \( f(\cdot) \) and \( g(\cdot) \) will be given in the next section. The state variables \( x \) are LNT temperature \( T_1 \) and fill ratio \( F_r \). Disturbance inputs \( w = [\dot{m}_{in}, T_{ex}, \lambda_0, m_{NOx}]^T \) denote mass flow, exhaust temperature, air-fuel ratio determined by the main injection, and NOx mass flow, respectively.

### 3. LNT Plant Model

Knowledge of the dynamic process of NOx reduction is critical to capture LNT NOx emission. In this paper, a two-order LNT model is used for optimal control scheme design, which is based on energy and mass conservation [20]. The LNT temperature \( T_1 \) and the fill ratio \( F_r \) are modeled as follows:

\[
\begin{align*}
\frac{dT_1}{dt} &= \frac{c_{pg}\dot{m}_{in}}{c_{mj}}(T_{ex} - T_1) - \frac{k_{A_d}}{c_{mj}(T_1 - T_l^3)} \\
\frac{dF_r}{dt} &= \frac{\alpha_c\dot{m}_{in}}{c_{mj}} - \frac{\dot{m}_{add} \cdot LHV}{c_{mj}},
\end{align*}
\]

where \( c_{lat}, m_{lat}, k_{out}, c_{out}, A_{out}, \) and \( c_{pg} \) denote the LNT specific heat, the LNT mass, the convection coefficient, the radiation coefficient, the LNT outer surface, and the engine exhaust gas specific heat, respectively. LHV denotes low heat value. The parameters \( m_{add} \) and \( T_l \) are the post injection and ambient temperature. Moreover, \( \frac{C_{max}}{C_{max}} \) is the derivative of maximum storage capacity \( C_{max} \), which is calculated by:

\[
C_{max} = C_m \cdot \left( \frac{T_{max}}{T_w} \right)^\gamma,
\]

where \( C_m, T_{max}, \) and \( T_w \) are identified experimentally.

The storage efficiency \( \eta_{stor} \) of Eq. (2) in lean mode is determined through the following exponential equation:

\[
\eta_{stor} = \eta \cdot \frac{e^{\delta(T + b)}}{1 - e^{\delta(T + b)}},
\]

where parameters \( \eta, k, \) and \( b \) are parameters to be identified.

The NOx release rate \( \dot{m}_{rel} \) during the rich mode in Eq. (2) can be calculated by the following equation:

\[
\dot{m}_{rel} = \frac{1 - e^{\delta T}}{1 - e^{T}} (a_d \lambda^3 + b_d \lambda^2 + c_d \lambda + d_d) \cdot C_{max},
\]

where \( \beta, a_d, b_d, c_d, \) and \( d_d \) are determined through an identification method. It is noted that the order of the air-fuel ratio \( \lambda \) is selected as three for better identification performance, which is written in previous work [20]. Actual air-fuel ratio with consideration of additional fuel injection is calculated as:

\[
\lambda = \frac{\dot{m}_{in} \cdot \lambda_0 - \dot{m}_{add}(1 + \lambda_0)}{\dot{m}_{in} + \dot{m}_{add}(1 + \lambda_0)}.
\]

The LNT exhaust emission \( \dot{m}_{out} \) is determined by control input \( \dot{m}_{add} \) and disturbance inputs \( \lambda_0 \) and \( \dot{m}_{out} \), calculated as:

\[
\dot{m}_{out} = \begin{cases} 
\dot{m}_{NOx}(1 - \eta_{stor}) & \text{if } \lambda \geq 1, \\
\dot{m}_{rel}(1 - \eta_{conv}) & \text{if } \lambda < 1.
\end{cases}
\]

The conversion efficiency \( \eta_{conv} \) in Eq. (18) that has a similar relationship between air-fuel ratio \( \lambda \) and the LNT storage rate \( F_r \), which is calculated as:

\[
\eta_{conv} = 1 - e^{\gamma(T - T_l^3)} (a_c \lambda^3 + b_c \lambda^2 + c_c \lambda + d_c),
\]

where \( \gamma, a_c, b_c, c_c, \) and \( d_c \) need to be identified.

Since piecewise functions are hard to be used for continuous-based optimal control algorithms, a sigma function is utilized to make discrete functions continuous, shown as follows:

\[
S(x) = \frac{1}{1 + \exp(-100(x - 1)).
\]

With Eq. (18) and Eq. (20), NOx emission model is rewritten as:

\[
\dot{m}_{out} = S \cdot \dot{m}_{NOx} \cdot (1 - \eta_{stor}) + (1 - S) \cdot \dot{m}_{rel} \cdot (1 - \eta_{conv}).
\]

In summary, with above information, state variables are written as \( x = [x_1, x_2]^T = [T_1, F_r]^T \), control input is written as \( u = \dot{m}_{add} \) and disturbance inputs are written as \( w = [w_1, w_2, w_3, w_4]^T = [\dot{m}_{in}, T_{ex}, \lambda_0, m_{NOx}]^T \). The nonlinear dynamics equation \( f(x, u, w) \) and the output equation \( g(x, u, w) \) are expressed in Eq. (11) and Eq. (12), respectively. They could be found at the bottom of this page.

For controller design purpose, the continuous dynamic and output equations are converted into discrete form by the Euler method, which are written as:

\[
x_{k+1} = f(x_k, u_k, w_k) + \Delta t \cdot x_k,
\]

\[
y_k = g(x_k, u_k, w_k).
\]
where the function $f$ is defined for ease in writing.

Moreover, constraining the artificial degrees of freedom $s$ to physically meaningful values $x$ could be seen as minimizing the distances between solid circles and crosses in Fig. 4. Thus the continuity conditions are imposed as follows:

$$S_{k+1} = x_{k+1} = f_1(x_k, u_k, \Delta t).$$

Simultaneously, the cost function is also numerically computed with $s$. Then, the discrete optimal control problem in Eq. (15) is rewritten as:

$$\min J = \min_{U} \sum_{k=t_k}^{t_k+N_p-1} [(1-\delta)u_k^2 + \delta g^2(x_k, u_k, W_k)]$$

subject to:

$$x_{k+1} = f(x_k, u_k, w_k)\Delta t + x_k,$$

$$y_k = g(x_k, u_k, w_k),$$

$$x_{\min} \leq x_k \leq x_{\max},$$

$$u_{\min} \leq x_k \leq u_{\max},$$

where the control variables are denoted as $U = [u_{t_k}, u_{t_k+1}, \ldots, u_{t_k+N_p-1}]^T$.

It is seen in Eq. (13) that $x_{k+1}$ is dependent on $x_k$ and it would be time-consuming if a single shooting method is used to decouple $x_k$ and $x_{k+1}$ [18]. In this paper, a direct multiple shooting method is employed for decoupling dynamic model constraints between $x_k$ and $x_{k+1}$ by augmenting artificial control inputs $s_k$ [21]. The illustration of the multiple shooting approach is depicted in Fig. 4. The hollow circle denotes initial state variables at step $t_k$. The solid circle and cross denote artificial control inputs $s_k$, and new state variables $x_{k+1}$ obtained from dynamic constraints start with an artificial initial value $s_k$ on each step from $t_k$ to $t_k + N_p - 1$, written as:

$$x_{k+1} = f(x_k, u_k, \Delta t) + x_k = f_1(s_k, u_k, \Delta t),$$

where the function $f_1$ is defined for ease in writing.

5. Simulation Validation and Discussion

The proposed MPC-based control scheme is verified in a simulator built in MATLAB/Simulink. A dynamic programming (DP) algorithm based control scheme is also designed to analyze the performance comparatively. It is noted that the DP-based control scheme is designed with driving cycle information pre-known. However, it is not necessary for the proposed
MPC-based control scheme. In this paper, it is assumed that the disturbances from $t_k + 1$ to $t_k + N_p - 1$ are equal to that at $t_k$. Two driving cycles simulation results are given. One is Worldwide harmonized Light vehicles Test Cycles (WLTC), which is a standard driving cycle to test NOx emission. The other is generated through a traffic scenario simulator, named IPG CarMaker, and it is defined as new route in this paper. In IPG CarMaker, stochastic traffic scenario could be generated with the capability of presetting road, traffic density, traffic flow, and traffic signal. Moreover, there are interfaces between CarMaker and Simulink so that the information could be exchanged bidirectionally. Traffic scenario and the after-treatment system are simulated in CarMaker and Simulink, respectively. The predictive horizon $N_p$ and control horizon $N_c$ are set as 10, and the sampling time $\Delta t$ in the discretization is selected as 1 s in MPC-based control scheme design.

5.1 WLTC Testing

WLTC driving cycle denotes information of vehicle speed versus time. In this validation process, a logical-based controller is used to control the gear number of a gearbox to track driver demand power, which is determined by vehicle speed. As it has been mentioned in the previous section, engine operation points and exhaust performance are also obtained. The simulation results in WLTC under designed control schemes are depicted in Figs. 7 and 8. In Fig. 7, vehicle velocity of WLTC and engine exhaust performance, including air-fuel ratio, exhaust temperature, and NOx mass rate are given. WLTC driving cycle includes low speed and higher vehicle speed to simulate urban traffic scenario with many stops and motorway. Engine exhaust temperature and exhaust NOx mass rate under motorway road seem to be higher than that of urban road. Figure 8 shows LNT temperature, fill ratio, post fuel injection and NOx emission from LNT tailpipe. It could be seen that LNT dynamics under both DP-based and MPC-based control schemes are within the constraints of state variables. Moreover, both amplitude and frequency of fuel consumption rate and NOx emission rate under MPC-based control scheme are higher than those of the DP-based control scheme since a global optimal control scheme is derived from the DP algorithm. Moreover, it could be seen that since higher temperature from LNT inlet, LNT catalyst temperature is also high without post fuel injection, which would lead to fill ratio increase quickly.

5.2 New Route Testing

To verify the universally applicable performance of the MPC-based control scheme, simulations of the MPC-based and DP-based control schemes are conducted under a driving cycle generated stochastically through CarMaker, named new route in this paper. There are six intersections, and the route length is 4158.8 m. There is a driver model in CarMaker so that the gearbox is regulated by an emulated driver to deal with real-world simulated traffic scenario. Only signals of engine speed and engine torque are transmitted into the LNT simulator in Simulink. It is noted that DP-based control scheme obtained for WLTC is also used for new route. Since new route driving cycle time is much less than WLTC, only the first 300 s of the DP-based control scheme for WLTC is used for performance comparison in new route. Simulation results are depicted in Figs. 9, 10, and 11. Figure 9 shows vehicle speed of stochastic driving cycle, air-fuel ratio, engine temperature and LNT inlet NOx emission, respectively. Driver behavior, such as gear ratio, is simulated by the driver of CarMaker in this simulation. In Fig. 10, LNT temperature, fill ratio, post fuel injection rate and outlet NOx emission are given. It is seen that fuel economy and NOx emis-
Fig. 7 Vehicle speed, air-fuel ratio, exhaust temperature and LNT inlet NOx in WLTC.

Fig. 8 Comparison of LNT temperature, fill ratio, post injection and tailpipe NOx under DP and MPC in WLTC.

...mission performances of the DP-based control scheme are worse than those of the MPC-based control scheme. Moreover, the accumulations of fuel consumption and NOx emission in Fig. 11 also show a better universally applicable performance of MPC.

5.3 Different Initial States Testing

Simulation results with different initial fill ratios under the MPC-based control scheme are given in Figs. 12 and 13. It is noted that \( F_{0r} \) represents the initial value of the fill ratio. In Fig. 12, it is seen that there are similar post-injection times for the engine in rich mode to reduce NOx emission, although different initial fill ratios are given. With analyzing Fig. 9, for fuel economy purpose, post injection signals are sent when air-fuel ratio is relatively lower. Figure 13 shows fuel consumption and NOx emission with different initial fill ratio. There is higher maximum capacity for LNT NOx reduction when initial LNT temperature is 300°C. So there are more NOx stored as solid phase for higher fill ratio. Although more fuel is used to reduce NOx emission, outlet NOx emission is still high.

5.4 Artificial Control Input Tracking Testing

To verify the tracking performance of artificial control inputs \( s_k \) to state variable \( x_k \), simulations are conducted with different initial state \( x_0 \). The results of optimal control input vector, which are calculated by SQP algorithm, are given in Figs. 14 and 15. The \( y \) label \( x_1 \) and \( x_2 \) denote the LNT temperature and the fill ratio, respectively. The predictive step is selected as 10. It is seen that the circles could track the crosses well and quickly under situations with different \( x_0 \). Hence the tracking performance is satisfied, and we could use the multiple shooting and the SQP approach to obtain optimal sequence for the MPC control scheme.

5.5 Testing with Different Weight Factors

The weight factor \( \delta \) in the cost function plays an important role in the optimal control problem, which mainly shows the
attention between post fuel injection and NOx emission in this paper. Simulation results under different δ are given in Figs. 16 and 17. Only fuel consider, Both consider, and Only NOx consider denote δ = 0, δ = 0.5, and δ = 1, respectively. Figure 16 shows SQP results for optimal control input vector calculation. Control step is set as 10, which is from step 0 to step 9. For state variables, there are 11 values because of existing of initial states. It could be seen that with different δ, x1 and x2 and optimal control input sequence u are different. However, both circle and triangle have the same control inputs at Np = 0. For MPC, only the first element of obtained control sequence will be used for control. Furthermore, simulation results under a driving cycle are given to verify the different effectiveness of δ, shown in Fig. 17. When NOx emission is considered, the fuel consumption is highest to guarantee the minimization of NOx emission. However, when only fuel consumption is considered in the cost function, there is almost no additional fuel consumption. Because in this case, the LNT temperature and the fill ratio are within the working region during driving cycle time, and post-injection does not start.

6. Conclusion

With fuel economy and NOx emission taking into consideration, a receding horizon form optimal control problem for the diesel engine with an LNT system is formulated with the two-order LNT model as the dynamic constraint. A direct shooting method is used for discretizations of the cost function and dynamic constraint. An optimal solution for post-injection is derived by the sequential quadratic programming al-
algorithm. Simulation results by comparing the DP-based control scheme show the MPC-based control scheme has the universal application in different driving cycles. Moreover, optimal post-injection is usually activated when the air-fuel ratio determined by the main injection, is low for fuel economy saving.

Acknowledgments

The authors would like to thank Honda R&D Co., Ltd. Automobile R&D Center for the help in data supporting.

References

[1] T.V. Johnson: Review of vehicular emissions trends, SAE International Journal of Engines, Vol. 95, pp. 1152–1167, 2015.
[2] K. Joo, W.P. Jin, J. Lee, S.J. Kim, and S. Yoo: A study of LNT and urea SCR on DPF system to meet the stringent exhaust emission regulation, SAE Technical Paper, 2014-01-2810, 2014.
[3] Y. Kim, C. Jung, C.H. Kim, Y.W. Kim, and J.M. Lee: Dynamic modelling and sensitivity analysis integrated LNT-pSCR system, IFAC-Papers OnLine, Vol. 49, No. 7, pp. 326–331, 2016.
[4] Z. Gao, K. Chakravarthy, C. Daw, and J. Conklin: Lean NOx trap modeling for vehicle systems simulations, SAE International Journal of Fuels and Lubricants, 2010-01-0882, 2010.
[5] H. Yang: LNT NOx storage modeling and estimation via NARX, SAE Technical Paper, 2010-01-1937, 2010.
[6] M. Karimshouhtari, C. Novara, and A. Totta: Data-driven model predictive control for lean NOx trap regeneration, IFAC-Papers OnLine, Vol. 50, No. 1, pp. 6004–6009, 2017.
[7] M. Karimshouhtari and C. Novara: Lean NOx trap regeneration control: A data-driven MPC approach, 56th IEEE Conference on Decision and Control, pp. 226–231, 2017.
[8] J. Sun, Y.W. Kim, and L. Wang: Aftertreatment control and adaptation for automotive lean burn engines with HEGO sensors, International Journal of Adaptive Control and Signal Processing, Vol. 18, No. 2, pp. 145–166, 2004.
[9] M. Hsieh, J. Wang, and M. Canova: Two-level nonlinear model predictive control for lean NOx trap regenerations, Journal of Dynamic Systems, Measurement, and Control, Vol. 132, No. 4, pp. 1–13, 2015.
[10] M. Han and B. Lee: Control oriented model of a lean NOx trap for the catalyst regeneration in a 2.2 L direct injection diesel engine, International Journal of Automotive Technology, Vol. 16, No. 3, pp. 371–378, 2015.

Fuguo Xu

He received his M.E degrees from Yanshan University, China, in 2016. He is currently pursuing the Ph.D. degree in the Department of Engineering and Applied Sciences, Sophia University. His research interests include control theory and application in automotive powertrain.

Tielong Shen (Member)

He received the Ph.D. degree in mechanical engineering from Sophia University, Tokyo, Japan, in 1992. He has been a Faculty Member with the Department of Mechanical Engineering, Sophia University, since 1992, where he currently serves as a Professor in the Department of Engineering and Applied Sciences. His research interests include control theory and application in mechanical systems, power systems, and automotive powertrain.