Parameter Co-optimization for Hybrid Electric Vehicles Powertrain System Leveraging V2V/V2I Information

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***Abstract*—A parameter tuning based co-optimization scheme for the hybrid electric vehicles (HEV) powertrain system is designed to maximize the fuel efficiency. The optimization controlled input parameters are chosen based on sensitivity study of powertrain control parameters. The vehicle to vehicle (V2V) and vehicle to infrastructure information is another optimization input, to have the driving conditions taking in to considerations for maximizing fuel efficiency. The catalyst temperature is considered as an additional constraint as the speed to reach light-off temperature should not decrease during optimized operation. Neural network is used to develop a simplified yet equivalent model for the optimization problem model. We have achieved an average of 9.22% fuel savings for a random driving cycle on a Toyota Prius test model.**

***Keywords*— Hybrid Electric Vehicle, Neural Network, Parameter Optimization**

I. Introduction

Hybrid electric vehicle (HEV) combines a conventional internal combustion engine (ICE) with an electric propulsion system. HEV has become a rising trend in the market as it is a solution to achieve a better fuel economy and a better performance than conventional vehicles [1]. Moreover, the emerging Connected Vehicle (CV) techniques [2] has been encouraging researches on developing optimization schemes with Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) knowledge to maximize the fuel efficiency. Such optimal control strategy utilize the traffic information (such as traffic signal and the speed of closed vehicles) as an optimization input and develop on-time optimization scheme.

There has been many optimal power management approaches to maximize the fuel efficiency for the HEVs. Ali et al. in [3] has given a systematic review of the optimal power management. Typical optimal power management strategy can be divided in to the following two categories: *optimization based methods* and *rule based methods*. In this paper, we primarily consider the optimal power management strategy for a Toyota Prius Hybrid, which uses a rule-based power management framework. Thus, this work will develop optimal power management based on rule-based methods.

Rule-based (RB) power management strategy has been the most commonly seen method in the market, which is widely used by commercial vehicle brands. In [4], the authors developed power follower control strategy, which is a well-known strategy within the rule based methods. There has been several approaches on optimal rule-based power management strategies. For example, in [5], the authors developed a non-dominated sorting genetic algorithm-II (NSGA-II) to achieve parameter optimization for the HEVs. In [6], the authors developed a particle swarm optimization strategy of driving torque demand decision. However, in these rearches did not consider V2V/V2I information as an optimization input. In [7], the authors came up with a four levels fuzzy rules based on traffic congestion to optimize fuel consumption. This study uses the traffic information to optimize the operation cost with RB method. However, the application of this method would require some major changes to the existing commercial vehicle control logic.

Despite the optimization approach for rule-based power management, optimization based power management method has also been a research trend recent years. Such method directly minimize the operation cost over time. In [8], the authors used particle swarm optimization (PSO) to deal with the energy management for hybrid electric vehicles. It is known as the first attempt to use PSO for HEV power management, but it has been limited due the off-line implementation. In [9], the authors used neuro-dynamic programming (DP) methods to build controllers and optimize the energy flow. In [10], the authors used DP methods for optimal power management with the use of trip based information.

Developing optimal power management strategy for hybrid electric vehicle has become a raising research trend. From the above discussion, one can see that while rule based power

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management strategy has been widely used in commercial vehicle control, most research which directly implement to commercial vehicles did not consider traffic conditions. To address these outstanding issues, this work develops a parameter co-optimization tuning strategy for the powertrain system in Toyota Prius hybrid 2017. To take traffic condition into consideration, this work consider the future driving condition to be modeled by V2V and V2I information as optimization inputs. The ultimate objective is to design an optimization method which can lead to the solution to optimal parameter tuning of the control system parameters to achieve fuel savings. This paper is the extended work of [11]. In the previous work, the simplified optimization problem is formulated with neural network and the Toyota Prius Hybrid model has been well validated. The *main contributions* of this paper are the followings:

- Define cost and constraints of the optimization problem. Use neural network techniques to establish simple yet equivalent models for the powertrain and the cost function (i.e., the fuel consumption rate) via the first principle powertrain models. This is performed with respect to the driving cycles and the system parameters.
- Design powertrain control parameter tuning strategy based on the solution of the optimization problem. Verify the design with simulations.

The reminder of this paper is organized as follows: Section II defines the optimization problem. Section III introduces the formulation of the optimization problem via developing equivalent neural network models for the system dynamics and the cost function. Section IV solves the optimization problem and derives the control parameter tuning law. Section V contains concluding remarks and discusses the future works.

II. PROBLEM STATEMENT

This section introduces the optimization problem. First the dynamic model of HEV is introduced. Then, the hybrid vehicle dynamic model (powertrain model) used in this work is first introduced. Then, the parameter selection and how V2V/V2I information is characterized as optimization input is introduced. Finally, the objectives of the optimization design are stated.

A. Dynamic Model of HEV

In this paper, the dynamic model of 2017 Toyota hybrid is considered. This model is derived based on previous studies in [12], [13]. The Toyota Hybrid system is built with a planetary gear system is the power split device. The system dynamic equation derived by [12] can be summarized as following

$$(I_s + I_{MG1})\dot{\omega}_{MG1} = FS - T_{MG1} \tag{1}$$

$$(I_c + I_e)\dot{\omega}_e = T_e = FR - FS \tag{2}$$

$$\begin{aligned}(\frac{R_{tire}}{K}m + I_{MG2}K + I_rK)\dot{\omega}_r = (T_{MG2} + FR)K \\ - T_f - mgf_rR_{tire} \\ - 0.5\rho AC_d(\frac{\omega_r}{K})^2R_{tire}^3\end{aligned} \tag{3}$$

$$S\dot{O}C = -V_o - \sqrt{\frac{-V_o^2 - 4P_bR_b}{2R_bQ_{max}}} \tag{4}$$

where T_{MG1}, T_{MG2} and T_e are the torques generated by first and secondary motor/generator sets and the engine; I_r, I_s and I_c are inertia of the ring gear, sun gear, and carrier gear, I_{MG1} and I_{MG2} and I_e are the inertia of the power sources, F represents the internal force on the pinion gears and m is the vehicle mass, T_f is the brake torque, K is the final drive ratio, f_r is the rolling resistance coefficient, and $0.5\rho AC_d$ is the aerodynamic drag resistance, P_b is the battery power, the sign of P_b indicates the charging states of the battery ($P_b < 0$ when battery is charging), V_o is the open circuit battery voltage, R_b is the battery internal resistance and Q_{max} is the battery capacity.

B. Hybrid Vehicle Model Validation

In this research a Matlab/Simulink model is used to represent the dynamic of the powertrain system of a 2017 Toyota prius hybrid. The powertrain model is built based on the previous studies of Toyota Prius hybrid modeling in [12], [13]. The aftertreatment system modeling is realized based on ADVISOR (a MATLAB Simulink based package for aftertreatment systems of different vehicles developed by National Renewable Energy Laboratory, US Department of Energy). Figure 1 shows the integrated model structure. This integrated model is then validated with the measurement (of states in powertrain) collected from several test drives on a Toyota Prius hybrid 2017. The validation of this simulink model has been introduced in the previous work [11].

C. Parameter Selection

The powertrain controller parameters to be tuned in our co-optimization scheme is chosen based on two aspects: (i) the parameter sensitivity to fuel efficiency variation; and (ii) the fuel efficiency saving test on the Toyota Prius hybrid Simulink model. In our previous work [11], we have constructed the sensitivity studies and found the three control parameter which are sensitive to fuel efficiency variation. Testing these parameter in the Simulink model and analyzing the physic meaning of these parameters, the three parameter chosen for the tuning strategy shown in Table I.

TABLE I: Three control parameters selected for parameter tuning.

Parameter Name	Physical Meaning	Nominal Value	Range used
param1	Generator speed controller proportional gain	0.9	[0.5, 1]
param2	Generator speed controller integral gain	0.005	[0.0001, 0.05]
param3	Battery charging controller gain	15000	[13000, 17000]

D. Use of V2V/V2I Information

In this work, we use V2V/V2I information as an optimization input. The objective is to find the influence of future driving condition on the controller parameter to achieve maximum fuel saving, i.e., find the function which represent driving condition and parameter to fuel saving. To this end, we

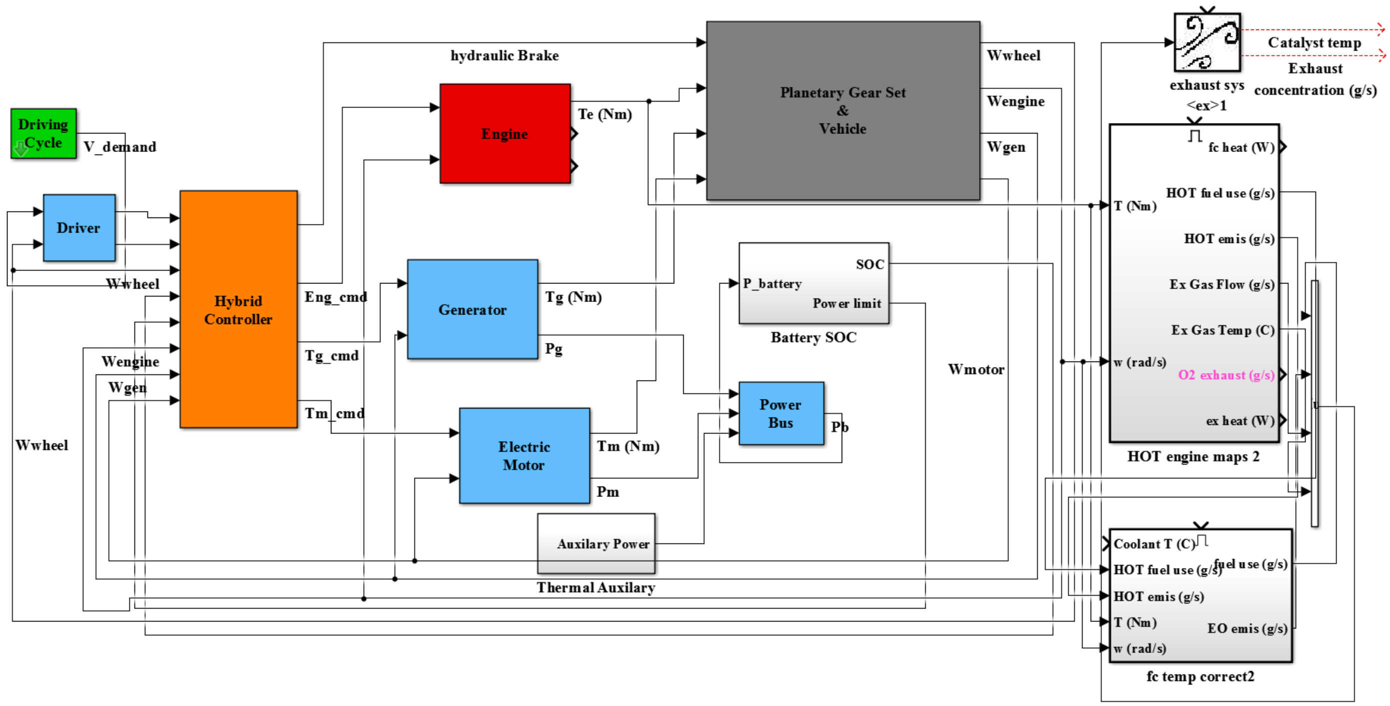


Fig. 1: Integrated HEV Simulink model [11].

need to characterize the real-time signals in to mathematical term to be used in optimization design. The V2I information mainly contains the traffic signal S_T, and the V2V information includes the speed and the acceleration of the preceding vehicle and the left/right front vehicles, denoting $v_p, a_p, v_l, a_l, v_r, a_r$ respectively. In this study, we consider the effect of V2V/V2I information represented by the predicted future vehicle speed v_f, where

$$v_f = W(S_T, v_p, a_p, v_l, a_l, v_r, a_r). \tag{5}$$

E. Control Objectives

To achieve a better fuel saving for the HEVs, the objective of this work is to design a parameter optimal tuning scheme for the powertrain controller parameters chosen in Table I to achieve maximize fuel saving with future driving condition taken into account.

The optimization model is simplified by neural network which is used to capture the characteristic of the real model and eliminates the amount of calculations.

III. Parameter Optimization Design

This section formulates the parameter optimization problem. First the neural network is introduced as a preparation to construct the simplified optimization model. Then the cost function is derived using the neural network. Finally the states constraints to the optimization problem are defined and the optimization design is presented.

A. Optimization Problem Formulation

Cost function. The fuel consumption of the HEV with respect to driving condition and control parameter can be directly derived based on the mathematical model of the HEV powertrain as

$$fuel(t) = \int_0^t f(\theta(\tau), cyc_i(\tau))d\tau, \tag{6}$$

where $\theta(\tau) = [\theta_1(\tau), \theta_2(\tau), \theta_3(\tau)]$ are the three controller parameters at time τ, which is chosen to be tuned in Table I, and $cyc_i(\tau)$ indicates the vehicle speed at time τ. This expression indicates that the amount of fuel consumption in the time period $[0, t]$ can be expressed by all history information of controller parameters and driving cycle in $[0, t]$. Since the fuel consumption curve is a smooth slowly increasing function, equation (6) can be simplified to a discrete-time form as

$$fuel(nT) = \sum_{i=1}^{n} \Delta f_k(\theta(k), cyc(k)), \tag{7}$$

where T is the step size, Δf_k indicates the fuel consumption in the time period $[(k-1)T, kT]$. Equation (8) is the cost function to the parameter optimization problem, denoting

$$J = fuel(nT) = \sum_{i=1}^{n} \Delta f_k(\theta(k), cyc(k)). \tag{8}$$

State constraints. To form the optimization problem, state constraints is needed to represent the powertrain dynamic. The discrete-time state constraint is defined as

$$x(k+1) = g(x(k), \theta(k), cyc(k)), \tag{9}$$

where $x = [T_e, T_g, T_m, \omega_e, \omega_g, \omega_m, SOC]$ indicates the engine, generator, motor torque and speed, and battery state of charge (SOC) respectively.

B. Equvalent Neural Network Model

For the optimization problem formulated in Subsection III-A, the dynamics are captured by the Matlab Simulink model described in Subsection II-B. While one can directly solve the optimization problem based on the first principle model of the Simulink model, the amount of calculation required to solve the optimization problem is significantly large since there exist three interdependent controller parameters to be tuned. Thus, this work come up with a scheme to collect data from the Simulink model to train equivalent neural network models for the cost function and state constraints. Then the optimization problem is solved based on the equivalent neural network model. The detailed neural network training results are shown in our previous work [11].

1) Training Procedure: The training procedure of the optimization model can be concluded with the following steps: (a) Run the Simulink model with different choice of arbitrary controller parameter dynamics in different driving cycles; (b) collect input/output time-series data for cost function and state constraints, where the controller parameter dynamic and future vehicle speed dynamic are also considered as the input time-series data. Note that in training process, since the model is trained with some given driving cycles (the vehicle speed trajectories are known), the future driving condition (future speed information) is directly obtained from the driving cycle information; and (c) train the neural network model with the collected data.

2) Cost functions: The cost function, namely the fuel consumption, defined in (8) can be predicted by a neural network model. The prediction of the cost function is

$$\tilde{J} = \sum_{i=1}^{n} \Delta\tilde{f}_k(\theta(k), cyc(k)), \tag{10}$$

where $\Delta\tilde{f}_i$ is obtained by training the neural network. The neural network expression is given by

$$\Delta\tilde{f}_k = w_{c2}L_1(w_{c1}y_f(k) + b_{c1}) + b_{c2} \tag{11}$$

which indicate a neural network with 1 input layer $y_f(k)$ (note that $y_f(k)$ contains 3+n_f input, where $3+n_f$ indicates the n_f number of driving cycle future step known and three controller parameters), 3 hidden layer (20 neurons), 1 output layer (1 output: fuel consumption), and $w_{c1} \in R^{20\times(3+n_f)}$, $w_{c2} \in R^{20\times1}$ are the weights, $b_{c1} \in R^{20\times1}$, $b_{c2} \in R$ are the biases, L_1 is the activation function, chosen to be 'RELU' function ($x = x\mathbf{1}(x > 0)$).

3) State Constraints: The neural network estimation of the state constraint (9) is given by

$$\tilde{g} = w_{s2}(\tanh(w_{s1}y_s(k) + b_{s1}) + b_{s2}, \tag{12}$$

which indicate a neural network with 1 input layer $y_s(k)$ (note that $y_s(k)$ includes 10+n_f inputs, where the inputs are 7 powertrain states, 3 controller parameters and n_f step of future driving information), 1 hidden layer (20 neurons), 1 output layer (7 output), and $w_{s1} \in R^{20\times(10+n_f)}$, $w_{s2} \in R^{1\times20}$ are the weights, $b_{s1} \in R^{20\times1}$, $b_{s2} \in R^{7\times1}$ are the biases.

C. Equivalent Optimization Problem Description

The equivalent optimization problem is to solve θ to the minimized fuel consumption given by the equivalent cost function

$$\tilde{J} = \sum_{i=1}^{n} \Delta\tilde{f}_k(\theta(k), cyc(k)), \tag{13}$$

and satisfy the following constraint:

$$x(k+1) = \tilde{g}(x(k), \theta(k), cyc(k)) + \epsilon \tag{14}$$

where ϵ is a bounded constant indicates the estimation upper bound for state constraint.

IV. Parameter Tuning Strategy

A. Optimization Problem Solution

This work uses the MATLAB function fmincon to solve the optimization problem with the cost function and the constraints developed in Section 3. Note that cost function which represented by the neural network is not a convex problem, thus, a global minimum of the cost function may not exist. In order to find the minimum, this work propose to essential point for the fmincon function to solve for the local minimum, and find the solution to the optimization problem among all the local minimums.

Parameter Tuning Law. To solve the optimization problem, we should solve θ for

$$\frac{\partial\tilde{J}}{\partial\theta} = 0 \tag{15}$$

$$x(k+1) = \tilde{g}(x(k), \theta(k), cyc(k)) + \epsilon \tag{16}$$

For each time step k, we only need to solve θ for $\tilde{J}_k = \Delta\tilde{f}_k$, which gives the following result

$$\theta_{k+1} = \theta k - w_2 w_1' \frac{\partial L_1}{\partial y_f} cyc(k) \tag{17}$$

$$x(k+1) = \tilde{g}(x(k), \theta(k), cyc(k)) + \epsilon \tag{18}$$

where w_1' is the corresponding weight with $cyc(k)$. The above equation set can be rewritten in the form

$$\theta(k+1) = S(x(k), cyc(k)). \tag{19}$$

This parameter tuning law indicates that after solving the optimization problem, the dynamic of controller parameter will depend on the powertrain states and future driving condition. This result indicates that driving condition will have influence to fuel saving.

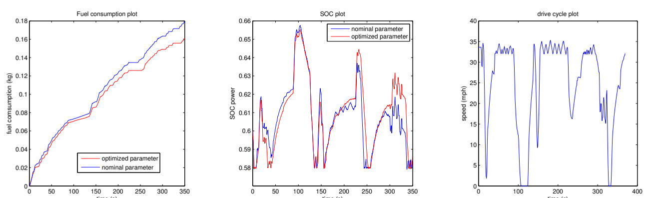
B. Simulation Study

To illustrate how the parameter tuning law is applied to the HEV controller and how future driving information will influence the optimization result, simulation studies are accomplished in this subsection.

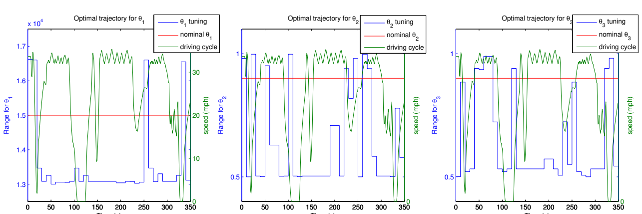
Simulation model. This simulation study is based on the Matlab/Simulink model introduced in Section II-B. First the equivalent optimization model is trained based on the data collected from the Simulink model operating different driving cycles. The training procedure is introduce in Section

III-B. Then, the optimization problem is solved based on the equivalent optimization model, and the parameter tuning law is obtained. In this study, to test the influence of future driving information to fuel saving, we solved the optimization problem with different amount of knowledge in future driving condition.

1) Simulation results: First we consider if two step of future driving information is known, with the step size $T = 2s$, i.e., $cyc(k) = [v(k), v(k+1), v(k+2)]$. Figure 2 shows the optimization results. Figure 2(a) shows the fuel saving, catalyst temperature, battery state of charge (SOC) and the driving cycle information respectively. The blue curves indicates the nominal performance and the red curves shows the optimal performance. From which we can see that fuel saving of 9.93% is achieved. The optimal battery SoC remain similar with nominal SoC, indicating the fuel saving is not from reducing the battery state of charge. Figure 2(b) shows the optimal parameter trajectory of the three controller parameters. The red curves are the nominal controller parameter value, and the blue curves are the optimal parameter trajectory. The greed curves are the driving cycle information. This result shows that the controller parameter varies the most when vehicle speed changes, indicating the relationship between parameter tuning strategy and the future driving condition information.



(a) Optimal system performance



(b) Optimal parameter trajectory

Fig. 2: Optimization result with two future step known.

Influence of future driving condition. To test the influence of future driving cycle information to parameter tuning strategy and fuel savings, similar optimization test is made with different numbers of future step used in the optimization modeling. The optimization performance is similar to Figure 2. Figure 3 shows the fuel saving with different future driving cycle knowledge. One can see that the more future driving information available for optimization modeling, the more fuel saving is achieved. We constructed the similar test for several different driving cycles and found the following pattern: every one step (2 seconds) more future vehicle speed information known, the fuel saving can increase by approximately 0.8%, and this increase will decrease after 8 seconds of future vehicle speed information. Thus, we should use 8 seconds (4 steps) of future speed information for future optimization problem modeling for best results.

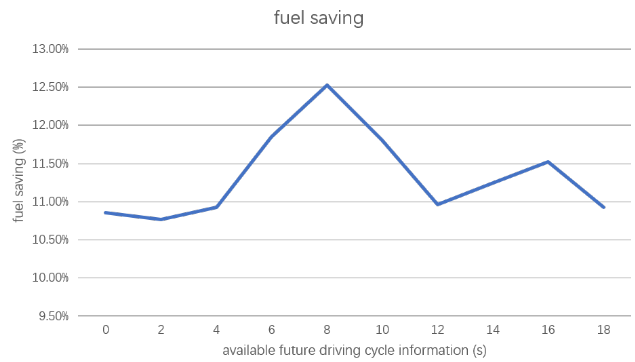


Fig. 3: Fuel saving with different future driving information.

Fuel saving summary. To test the fuel saving of the proposed parameter tuning strategy, we tested our algorithm in 10 different driving cycles and record the fuel savings. An average of 9.22% of fuel saving is achieved with 4 steps of future speed information available. Figure 4 shows the fuel saving of individual driving cycle tested.

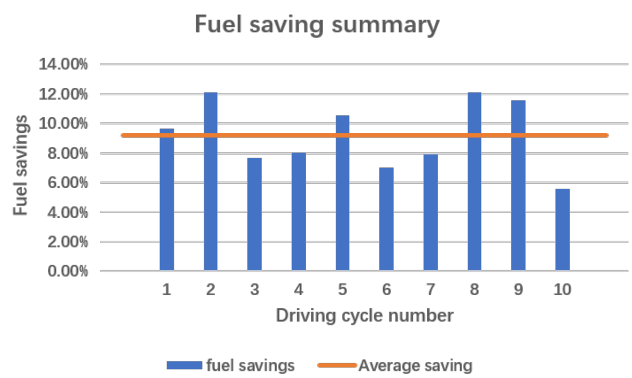


Fig. 4: Fuel saving in 10 driving cycles.

V. Conclusions and Future Work

In this paper, a parameter tuning strategy to optimize the fuel consumption for HEV is designed. First the equivalent optimization model is built using neural network tools. Then the optimization problem is solved and the parameter tuning strategy is obtained. Finally the simulation study is presented to verify the parameter tuning strategy designed in this paper. From the simulation result, we achieved an average of 9.22% fuel saving for different driving cycles. Thus, one can conclude that the designed parameter tuning strategy the desired fuel saving can be achieved.

This paper gives an inspiration on using parameter tuning strategy with V2V/V2I information to achieve fuel saving. This method can be applied for commercial vehicle to save energy. Some future work related to this paper are to test the fuel saving on an actual vehicle.

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