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A Study on Power Management Strategy of HEV using Dynamic Programming

Heeyun Lee[1], Changbeom Kang[1], Yeong-il Park[2], Suk Won Cha[1]

[1]*Department of Mechanical and Aerospace Engineering, Seoul National University, Daehak-dong, Gwanak-gu, Seoul, Korea, 151-744, leeheeyun@snu.ac.kr*

[2]*Department of Mechanical System Design Engineering, Seoul National University of Science and Technology, Gongrung2-dong, Nowon-gu, Seoul, Korea 139-743*

Summary

For hybrid electric vehicle, it is necessary to control power distribution among multiple power sources to improve fuel economy performance of vehicle. In this paper, power management strategy of hybrid electric vehicle using Dynamic programming is studied. Deterministic dynamic programming could present outstanding fuel economy, while its application as real time control of vehicle is limited. Thus, different kinds of power management strategy using dynamic programming are studied. Stochastic dynamic programming, artificial neural networks and rule-based power management strategy using results from dynamic programming are studied. Simulations using parallel type hybrid electric vehicle model are conducted. Simulation results including fuel economy performance on diverse driving cycles are compared and analysed.

Keywords: HEV(hybrid electric vehicle), Optimization, Power management, Control system.

1 Introduction

In recent decade, Hybrid electric vehicle (HEV) has been studied and developed to improve fuel economy performance and exhaust emission problem of conventional internal engine based vehicle. HEV, consisted of multiple power sources, has more complex structure and intricate control nature and the fuel economy performance of HEV is mainly affected by vehicle's powertrain configuration, components sizing and power management strategy.

The power management strategy of HEV could be said as problem of controlling power distribution among multiple power sources to propel vehicle while satisfying constraints. Different kinds of power management strategy of HEV have been studied [1]. Mainly, it could be classified as two general trends of optimization-based control strategy and rule-based control strategy. Optimization-based control strategy is strategy based on optimization theory and presents outstanding fuel economy performance. In rule-based control strategy, powertrain is controlled based on rule which is made upon heuristics or intuition. Generally optimization-based control strategy shows better fuel economy performance than that of rule-based control strategy, but rule-based control strategy is more applicable into implementation as real time vehicle controller.

Dynamic programming (DP) is one of the optimization-based control strategies presenting outstanding fuel economy performance [2]. DP is well known algorithm that it could solve complex problem by dividing it into simple sub problem and presents it as recursive form. In analysis of HEV, Deterministic dynamic programming (DDP) could be used to find optimal control policy for given vehicle powertrain system with respect to predefined driving cycle. Many researches using DDP have been conducted to find out and evaluate vehicle's optimal fuel economy performance. However even though DDP could suggest global optimal fuel economy performance of HEV, it could not be used as real time implementation of HEV, since DDP requires driving cycle information before the trip and acquired optimal control policy is not effective with respect to other driving cycles. Thus, many researches have been conducted to use DDP for real-time solution. One of them is stochastic dynamic programing (SDP). It is algorithms which could obtain optimal control law by using probabilistic view [3],[4]. Unlike DDP which uses driving cycle information directly, SDP formulated an infinite-horizon stochastic dynamic optimization problem, thus it could be implemented on real time vehicle controller. More simple way is power split ratio (PSR) based control using strong relationship between power distribution ratio of engine and motor with respect to power demand of vehicle, in which PSR line could be optimized using DDP results [2]. On the other hand, supervised learning algorithm such as artificial neural networks (ANNs) could be also used to learn power management strategy from analysis using DDP [5],[6].

In this study, different kinds of algorithms including DDP are studied and simulated on parallel type HEV. DDP is simulated on backward-looking vehicle simulation. For SDP, stochastic dynamic optimization problem is solved for given vehicle system and control policy is simulated on forward-looking vehicle simulation. For PSR based strategy and ANNs based strategy, control policy is extracted from DDP result and it is simulated on forward-looking vehicle simulator. Diverse driving cycle is used for simulation and simulation results are analyzed to compare. The paper is organized as follow. In section 2, vehicle model is described and in section 3, power management strategies are introduced. Simulation results are presented in section 4 and finally conclusion is given in section 5.

2 Vehicle Modelling

In this study, parallel type HEV model is used for simulation. Vehicle parameter and characteristic data is presented in Table 1. The gasoline internal combustion engine data and permanent magnet motor data is used. The energy storage system is a 5.5 Ah Li-ion battery. A steady-state model is used to describe vehicle system. Fuel consumption rate $\dot{m}$ of engine could be represented using steady-state engine map of the engine torque T_{eng} and engine speed ω_{eng} as equation (1)

$$\dot{m} = f(T_{eng}, \omega_{eng}) \qquad (1)$$

Also, the output electric power of battery is mapped from motor torque T_{mot} and motor speed ω_{mot} using 3D look-up table of motor efficiency as equation (2)

$$P_{bat} = g(T_{mot}, \omega_{mot}) \qquad (2)$$

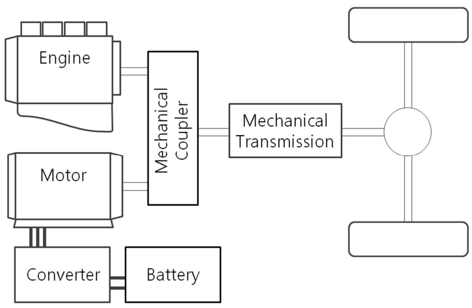

Figure 1: Parallel type HEV

Table 1: Vehicle component specification

Component	Specification
Engine	4 cylinders, 2.2 L 113kw/6000rpm
Electric motor	50kW
Transmission	6 speed AT
Battery	5.5 Ah Li-ion battery
Vehicle weight	1700 kg

3 Power Management Strategy

In this study, different kinds of strategies are studied and simulations using these strategies are conducted for parallel type HEV model. The optimization problem of power management strategy for HEV can be defined as a minimization of total fuel consumption J expressed as equation (3).

$$\mathrm{J} = \sum_{k=0}^{N-1} L\big(x(k), u(k)\big) \qquad (3)$$

where $\mathrm{u}(k)$ is vector of control variable at time k , $\mathrm{x}(k)$ is state variables of the system and $\mathrm{L}(\mathrm{x}(\mathrm{k}), \mathrm{u}(\mathrm{k}))$ represents the instantaneous fuel consumption. In DDP and SDP, they uses similar structure for problem solving, however SDP approaches problem as stochastic view thus driving cycle information needs to be interpreted as probability distribution function and objective cost function is expressed as expectation value. In PSR based strategy and ANNs based strategy, control policy acquired from DDP is used for each strategy to optimize parameters in it.

3.1 Deterministic Dynamic Programming

For DP, optimal problem could be expressed as recursive form of equation (4) and (5).

Step $\mathrm{N}-1$

$$J_{N-1}^{*}(x(N-1) = \min_{u(N-1)}\big[L\big(x(N-1)\big), u\big(x(N-1)\big)\big] \qquad (4)$$

Step k, for $0 < \mathrm{k} < \mathrm{N}-1$

$$J_{k}^{*}\big(x(k)\big) = \min_{u(k)}\big[L(x(k), u(x(k))) + J_{k+1}^{*}\big(x(k+1)\big)\big] \qquad (5)$$

where $J_{k}^{*}(x(k))$ is optimal value function at time k and equation can be solved backward to get optimal control law. In this study, $u(x(k))$ is defined as battery output power which decides power distribution among internal combustion engine and electric motor.

3.2 Stochastic Dynamic Programming

In SDP approach, driving cycle information is presented as probability distribution using Markov chain process. Vehicle speed and power demand is discretized into a finite number of values and represented as probability distribution given as equation (6).

$$\Pr\big(P_{dem,k+1} = p_{dem}^{i}, V_{k+1} = v^{j} \,\big|\, P_{dem,k} = p_{dem}^{l}, V_{k} = v^{m}\big) = p_{lm,ij}$$
$$i, l = 1,2,\ldots, N_p, \qquad j, m = 1,2,\ldots, N_v \qquad (6)$$

where $\sum_{m}^{N_v}\sum_{l=1}^{N_p} p_{lm,ij} = 1$, $p_{lm,ij}$ is probability when power demand p_{dem}^{l} , vehicle speed is v^{m} at time k and power demand p_{dem}^{i} , vehicle speed is v^{j} at time $k+1$.

Then optimization problem of (3) could be presented as infinite horizon problem presented as equation (7).

$$J\ (x_0) = \lim_{N\to\infty} E\{\sum_{k=0}^{N-1} \lambda^{k} c(x_k, \pi(x_k))\} \qquad (7)$$

where c is instantaneous cost and λ is discounted factor. State vector is given as equation (8).

$$x_k = [SOC_k, p_{demand,k}, v_k] \qquad (8)$$

In this study, value iteration method is used to solve infinite horizon problem given as equation (9) and (10).

$$J^{\pi_i}(x_k) = c(x_k, u) + \lambda \sum_{x_{k+1}\in X} P(X_{k+1} = x_{k+1} \mid x_k) J^{\pi_i}(x_{k+1}) \qquad (9)$$

$$J^{\pi_{i+1}}(x_0) = \min_{u}\{c(x_0, u) + \lambda \sum_{x_1\in X} P(X_1 = x_1 \mid x_0) J^{\pi_i}(x_1)\} \qquad (10)$$

As a result of stochastic dynamic optimization, optimal control law could be acquired. Optimal control law presents power split ratio for given battery state of charge(SOC) and power demand and vehicle velocity. The acquired control policy is used for forward-looking vehicle simulation.

3.3 Power Split Ratio based Strategy

PSR based strategy is simple rule-based strategy, in which power split ratio among internal combustion engine and electric motor is decided based on required power. Power split ratio could be defined as equation (11).

$$PSR = \frac{P_{engine}}{P_{required}} \quad (11)$$

where P_{engine} is output power of engine and $P_{required}$ is power demand of vehicle to propel. Operating modes are defined based on power split ratio according to power demand. In this paper, 1-dimensional power split ratio line shown as Figure2 is optimized using result from DDP and applied on forward-looking vehicle simulation.

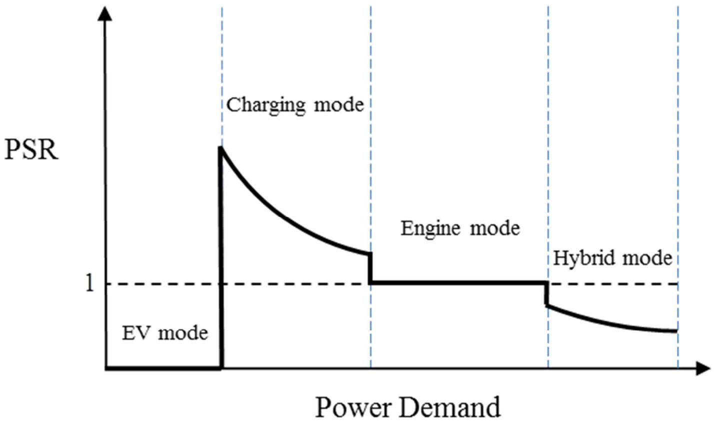

Figure 2: Power split ratio based strategy

3.4 Artificial Neural Networks based Strategy

In recent year, neural networks have been used in control of hybrid electric vehicle thanks to its outstanding function-approximating ability. Neural networks have advantage of learning and generalization for input-output mapping of given system. It could be used for supervised learning by modification of the neural networks' synaptic weights with respect to labelled training samples. In this paper, a two layer feed-forward neural networks is used to fit optimal control policy acquired from DDP analysis. For the net input data, battery SOC, power demand and vehicle velocity are used and the output data is the power split ratio. Levenberg-Marquardt back propagation algorithm is used to train the neural networks. Trained results is presented as 4-dimensional lookup table data as shown in figure3 and applied to forward-looking vehicle simulator to validate its effectiveness.

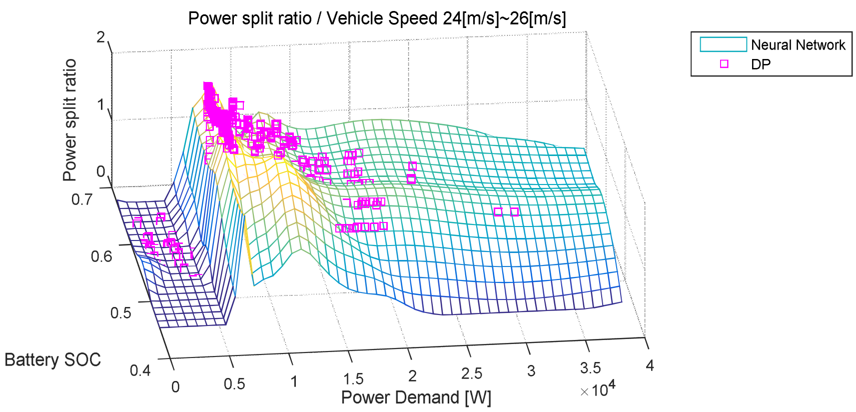

Figure 3: Power split ratio map using artificial neural networks

4 Simulation Result

Vehicle simulations are conducted for diverse driving cycle. Simulation results of DDP and SDP for FTP72 driving cycle are given in figure 4 and simulation results of PSR based strategy and ANNs based strategy are given in figure 5. Fuel economy performances of each power management strategy for diverse driving cycle are given in Table 2. Fuel economy performances for SDP, PSR based strategy and ANNs based strategy are adjusted to compensate battery SOC difference of beginning and end.

Compared to fuel economy performance of DDP, SDP presents decreased fuel economy performance. Since SDP uses driving cycle information as form of probability distribution, fuel economy performance is decreased than that of DDP in which driving cycle profile is used for optimization directly. Simulation results for engine torque and motor torque presents similar results with those of DDP. Battery SOC profile presents more considerable change in DDP than SDP. It implies that DDP could use wide range of battery capacity while SDP need to use relatively narrow range of battery SOC to avoid energy conversion loss due to lack of entire cycle information. However, SDP uses driving cycle information as structure of probability distribution, it shows relatively robust fuel economy performance compared to DDP. In DDP, if driving cycle is changed, optimal control law becomes useless, but in SDP, even if driving cycle is changed, it could presents near optimal fuel economy performance if probability transition matrix has similar distribution. Therefore, SDP could be used as real time implementation of HEV while using non causal property of dynamic programming.

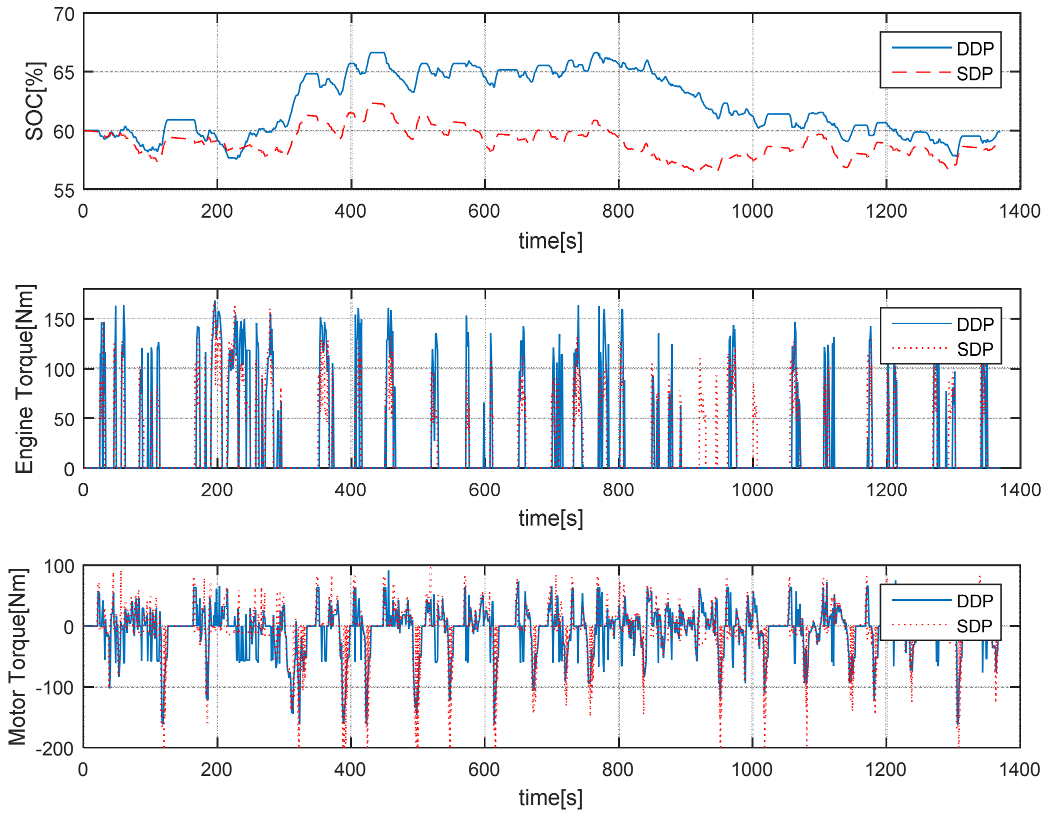

Figure 4: Simulation results of DDP and SDP for FTP72 driving cycle

Table 2: Fuel economy result (km/l) for diverse driving cycle

Strategy \ Driving Cycle	FTP72	FTP75	JN1015	NEDC	HWFET	AVERAGE
Deterministic DP	25.5	25.4	29.1	25.6	27.5	26.6
Stochastic DP	23.0	22.8	24.1	23.8	24.3	23.6
PSR based	22.2	21.9	24.2	23.6	23.4	23.1
ANNs based	23.0	22.9	24.7	23.7	24.5	23.8

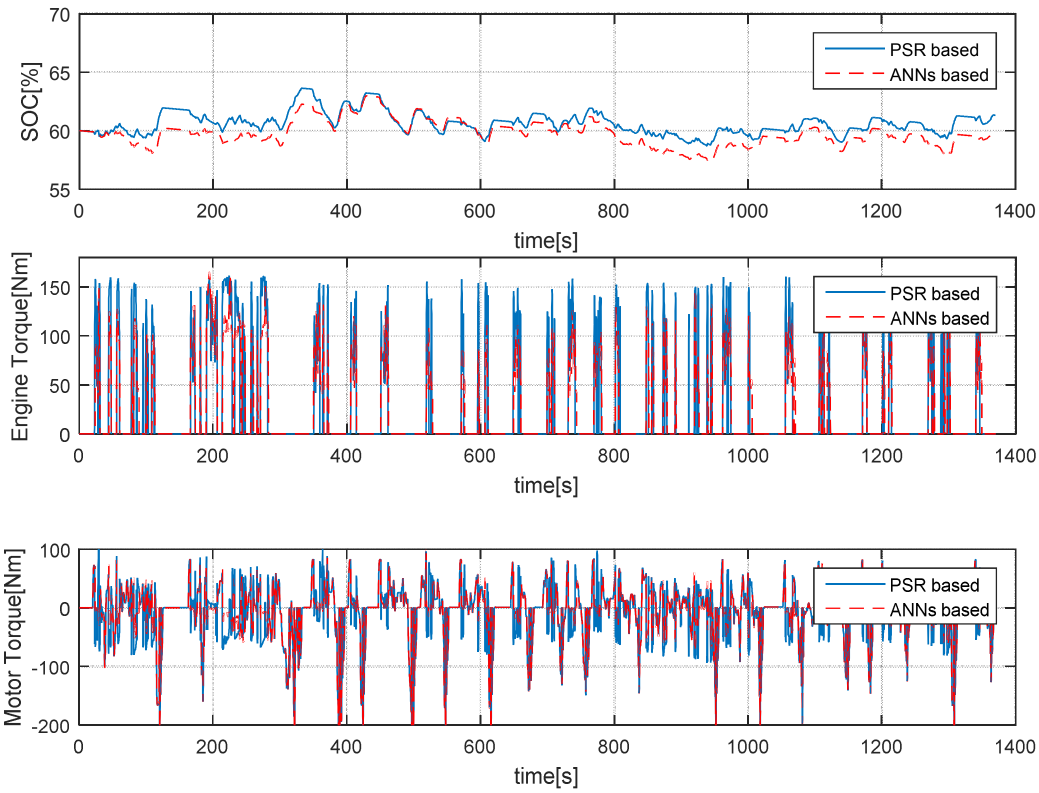

Figure 5: Simulation results of PSR based strategy and ANNs based Strategy for FTP72 driving cycle

In case of PSR based strategy and ANNs based strategy, they also could be used for real time implementation of HEV. They show similar results on engine and electric motor operating each other. However, for fuel economy performance, ANNs based strategy presents better efficiency. ANNs based strategy presents optimal power split ratio learned from DDP results with 4-dimensional lookup table data, thus has more advantage of extracting optimal control law from DDP results compared with PSR based strategy. PSR based strategy shows the lowest fuel economy performance, but it has strong points that control strategy is simple and robust compared with other strategies.

5 Summary

In this study, dynamic programming and several kinds of power management strategies using dynamic programming are studied and simulated. Parallel type HEV is simulated on diverse driving cycle. Backward looking vehicle simulation is conducted for DDP and forward-looking vehicle simulation is conducted for SDP. PSR based strategy and ANNs based strategy are also conducted on forward-looking simulation using optimal control policy extracted from DDP. SDP uses driving cycle information presented as structure of probability distribution according to Markov chain process, while DDP uses driving cycle directly to calculate optimal control. PSR based strategy and ANNs based strategy uses optimal control laws acquired from DDP result. SDP presents decreased fuel economy performance than that of DDP, but shows similar engine and motor operation. Also, SDP does not need to extract optimal control policy once stochastic dynamic optimization conducted, thus it is more applicable as real time vehicle controller. PSR based strategy and ANNs based strategy also could be used as real time vehicle controller. ANNs based strategy presents better fuel economy performance than that of PSR based strategy, but PSR strategy has advantage that it is simple and robust.

Acknowledgments

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