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Decentralized Optimal Energy Efficiency Improvement Strategy for Large-Scale Connected HEVs

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Abstract: In this paper, the energy efficiency improvement optimization strategy is explored for large-scale hybrid electric vehicles (HEVs) in a connected environment. Both reducing vehicle speed fluctuation and increasing high efficiency working conditions of HEV powertrain are beneficial for fuel economy improvement. A hierarchical optimization strategy is designed in this paper, where the speed consensus problem is considered in the upper layer and an energy management problem is considered in the lower layer. To deal with optimization of large-scale HEVs, mean field game (MFG) is employed for speed consensus. Meanwhile, model predictive MFG-based control scheme is developed with consideration of distribution predication error caused by the uncertainties of road and traffic. With connection of vehicle to everything (V2X), the real-time distribution can be calculated in the big data center and sent back to individual HEV for model predictive MFG-based controller. Simulations are conducted to show the effectiveness of the proposed strategy.

Keywords: Model predictive mean field game, energy efficiency improvement, HEVs, speed consensus, V2X.

1. INTRODUCTION

Compared to internal combustion engine vehicles, hybrid electric vehicles (HEVs) are gaining increasingly popular when facing with the pressure of sustainable development goals and carbon neutral target around the world. HEVs have the advantage in achieving the carbon emission reduction since there are multiple energy resources, including engine and motor connecting with battery, to propel the vehicle, which makes engine in high efficiency condition more frequently. With the fast development of communication technologies between vehicle to vehicle (V2V) and vehicle to infrastructure (V2I), the potentials in improving fuel economy further for HEVs becomes more realisable than before (Vahidi (2018)).

Under the satisfaction of driver's demand torque, the main work of HEV powertrain control, named as energy management strategy (EMS), is to distribute the torque between engine and motor, where the optimization goal is the energy consumption minimization. There have been a lot research focusing on this issue, starting from the dynamic programming (DP) (Lin (2003)) and Pontryagin's maximum principle (PMP) (Kim (2011)), which are derived from optimal control theory. In DP and PMP based approaches, the optimal solution is obtained under the assumption that the driving cycle is known in advance and the traffic scenario does not change in algorithm application. To deal with this unreasonable assumption and the computation burden of DP, model predictive control (MPC) (or receding horizon control) is widely employed for energy management strategy of HEVs. With the help of V2V and V2I, the future driver behavior learning promotes the energy efficiency further improvement for MPC-based HEV energy optimization. For example, Gaussian process was employed for driving demand torques prediction (Zhang (2020)).

Except for EMS, vehicle speed is also a key factor influencing the fuel economy since an unreasonable speed may lead to the traffic jam and sequently lead to higher energy consumption. In very recently, the jointly optimization of speed planning (or eco-driving) and EMS for connected and automated HEVs has been attracting attention. Moreover, with utilization of vehicle to everything (V2X) information, the energy management strategy design for a group of HEVs in special scenarios becomes popular (Yu (2016); Xu (2021); Wei (2022)). When the proportion of connected and automated HEVs running on the road continues increasing in the future, the optimization of large-scale HEVs will become a problem, especially the computation burden of a centralized controller can not be ignored. To the knowledge of author, there is few research focusing on this topic.

This paper mainly deal with the powertrain efficiency optimization and speed planning for large-scale HEVs by employing mean field game (MFG). MFG is an attractive approach to deal with the large-scale agents by introducing a distribution function to describe the behavior of whole agents and a decentralized controller is derived (Lasry (2007)). In the traditional MFG, a time-dependent open loop optimal solution is derived, which has a natural weakness in the face of uncertainty of future time (Fu (2020)). Moreover, when dealing with the complex nonlinear system, it is hard to derive an analytical solution and it makes the numerical solution time-consuming. Compared to our previous work in (Fu (2020)), the main contribution of this paper is introducing the sense of model predictive (MP) to MFG and applied to the EMS of large-scale HEVs. An MFG problem is solved in the predictive horizon while the real-time distribution is computed remotely and updated back to individual agent. In this way, the proposed MP-MFG based controller has better performance when facing with the uncertainty and computation burden.

The rest of this paper is organized as follows. Section 2 gives the problem description of large-scale vehicles in connected environment to reduce energy consumption. In Section 3, the modelings of HEV powertrain system and energy consumption including fuel consumption and electricity consumption are described. The proposed two-layer optimization strategy is given in Section 4. Simulation results to verify the proposed strategy are given in Section 5. Section 6 makes a conclusion of this paper.

2. PROBLEM DESCRIPTION

When vehicle running in a connected traffic environment, it is possible to communicate with other traffic participants, shown in Fig. 1. The real-time information of individual vehicle, such as vehicle speed, can be sent to big data center through V2I connection; on the other hand, the real-time traffic information, such as traffic density along the route, can be available to individual vehicle to improve the driving safety and fuel economy.

As the number of vehicles running on the route becomes extremely large, it becomes easy to cause a traffic jam due to unsuitable individual running speed. Sequently, the energy consumption of vehicle in this traffic scenario increases since the large-scale vehicles' speeds play an important role in the traffic utilization rate and fuel economy. Reduction of vehicle speed fluctuation and high vehicle speed are beneficial to fuel economy improvement. Meanwhile, the centralized controller that regulates the vehicle speed faces with the computation burden when dealing with large-scale vehicles. On the other hand, the fuel economy can be improved for HEVs by real-time distributing the torques between engine and motor to keep them in high-efficiency condition.

This paper will explore the solutions to above problem by employing the mean field game theory. The designed control scheme based on MFG is decentralized by introducing a distribution function to describe the behavior of whole vehicles and only individual state signal is necessary as feedback signal. In the actual application, there exists the uncertain of the traffic environment, such as rolling coefficient, which leads to the inaccuracy prediction of whole vehicles' behavior by this distribution function. Thank to V2I connection technology, the whole vehicles' state can be sent to big data center and this distribution function can be calculated and sent back to each vehicle through V2I. Through above analysis, a model predictive-MFG (MP-MFG) controller can be developed for speed consensus, where the real-time initial distribution of whole vehicles' speeds is available to the designed controller, shown in Fig. 2. MP-MFG has the advantage in dealing with the uncertainties since only first element of the derived optimal sequence is used as feedback signal and this distribution is updated in the prediction horizon. Meanwhile, with determination of demand driving torque, the torque split optimization between engine and motor is designed to further reduce energy consumption.

As discussed above, the communication signals sending from individual to big data center is the real-time vehicle speed through V2I; the big data center receives speeds of whole vehicles, calculates the updated distribution and broadcasts this updated distribution to whole vehicles by V2I. Thus, the communication burden is small.

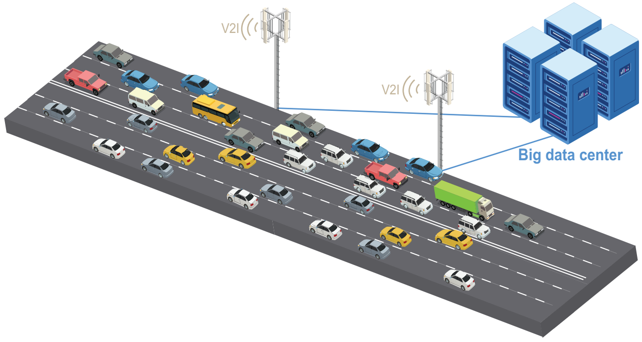

Fig. 1. Large-scale HEVs in connected environment

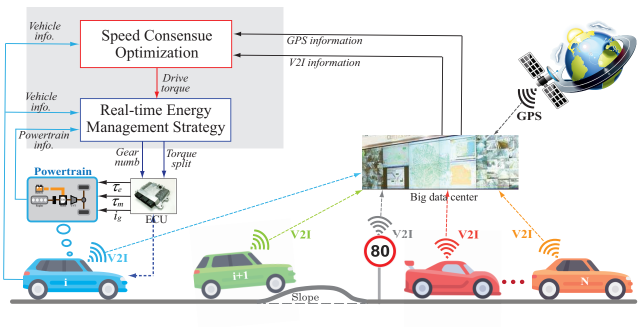

Fig. 2. Framework of proposed hierarchical optimization strategy

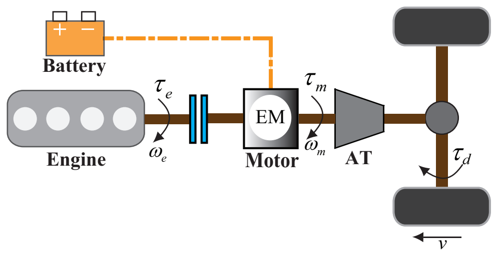

Fig. 3. Powertrain structure of parallel HEV

3. MODELING

3.1 Powertrain Model

Under the assumption that the powertrain structure of each HEV in the connected environment shown in Fig. 1 is identical shown in Fig. 3 and vehicle longitudinal dynamics is described as follows:

$$M\frac{dv}{dt} = \frac{\tau_d}{R_{tire}} - F_{resis}(v), \tag{1}$$

where v is the vehicle velocity. M and R_{tire} denote vehicle mass and tire radius, respectively. The resistance force F_{resis} includes the air resistance, the rolling resistance and gravity resistance, which is expressed as follows:

$$F_{resis}(v) = \frac{1}{2}\rho C_d A v^2 + \mu M g \cos\theta + M g \sin\theta, \tag{2}$$

where ρ, C_d, A, g, μ and θ represent air density, drag coefficient, frontal area, gravitational acceleration, rolling coefficient and slope, respectively.

For a parallel HEV powertrain, the driving torque τ_d shown in (1) in the HEV mode is seen as the summation of the engine torque τ_e and motor torque τ_m

$$\tau_d = i_g i_0 \eta_f (\tau_e + \tau_m), \tag{3}$$

where i_g and i_0 represent gear ratios of automatic transmission and differential gear, and η_f is the transmission efficiency of driveline, it is assumed to be 1 in this paper.

In rotation speed calculation of parallel powertrain, with determination of i_g and v, the engine speed ω_e and the motor speed ω_m in HEV mode are same, which are calculated through following equation:

$$\omega_e = \omega_m = i_g i_0 \frac{v}{R_{tire}}. \tag{4}$$

3.2 Energy Consumption Model

The fuel consumption rate $\dot{m}_f$ of a gasoline engine is described as a map form following the relationship between the engine speed and the engine torque, defined as the brake specific fuel consumption (BSFC), shown in Fig. 4(a). Based on Fig. 4(a), fuel consumption rate $\dot{m}_f$ is fitted in a polynomial form:

$$\begin{aligned}\dot{m}_f &= a_0 + a_1 N_e + a_2\tau_e + a_3 N_e^2 + a_4 N_e \tau_e \\ &+ a_5\tau_e^2 + a_6 N_e^3 + a_7 N_e^2 \tau_e + a_8 N_e \tau_e^2,\end{aligned} \tag{5}$$

where $a_j,\ j \in \{0, 1, ..., 8\}$ are the identified parameters, and $N_e = \frac{30}{\pi}\omega_e$.

The electricity consumption rate $\dot{m}_e$ is seen as the electricity power used in motor to drive the vehicle as follows:

$$\dot{m}_{ele} = \eta_m \tau_m \omega_m, \tag{6}$$

where motor efficiency η_m is described in Fig. 4(b).

3.3 Modeling Rewritten under Torque Split Rate

Based on (3), a torque split rate $\alpha \in [0, 1]$ to distribute the demand driving torque between engine torque and motor torque is introduced, which is defined as

$$\alpha = i_g i_0 \frac{\tau_e}{\tau_d}. \tag{7}$$

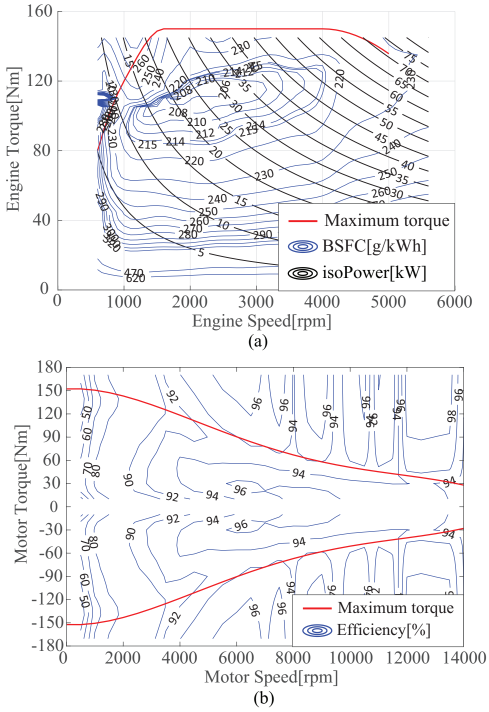

Fig. 4. Map data of the efficiencies of the engine and motor

Then, the motor torque τ_m in HEV mode through τ_d and α is calculated as

$$\tau_m = (1-\alpha)\frac{\tau_d}{i_g i_0}. \tag{8}$$

Sequently, the fuel consumption rate $\dot{m}_f$ and electricity consumption rate $\dot{m}_{ele}$ can be rewritten as follows:

$$\dot{m}_f = b_0 + b_1\alpha + b_2\alpha^2, \tag{9}$$

where parameters $b_k,\ k \in \{1, 2, 3\}$ are as follows

$$\begin{cases} b_0 = a_0 + a_1 N_e + a_3 N_e^2 + a_6 N_e^3, \\ b_1 = a_2\dfrac{\tau_d}{i_g i_0} + a_4\dfrac{N_e\tau_d}{i_g i_0} + a_7\dfrac{N_e^2\tau_d}{i_g i_0}, \\ b_2 = a_5\dfrac{\tau_d^2}{i_g^2 i_0^2} + a_8\dfrac{N_e\tau_d^2}{i_g^2 i_0^2}, \end{cases} \tag{10}$$

and

$$\dot{m}_{ele} = \eta_m \tau_m \omega_m = \eta_m \frac{\tau_d v}{R_{tire}}(1-\alpha). \tag{11}$$

4. UPPER LAYER-SPEED CONSENSUS

4.1 MP-MFG Optimization Problem Formulation

For each vehicle i, it has the same target, including maximizing the traffic utilization, and reducing the energy consumption. With information of start time t_0 and end time t_f, the length of prediction horizon is obtained as $\Delta T = t_f - t_0$. The cost function J is defined as follows:

$$J_i(\tau_{d,i}, \bar{v}) = \int_{t_0}^{t_f} L(v_i(t), \bar{v}(t), \tau_{d,i}(t))\,dt + \Phi(v_i(t_f), v_d), \tag{12}$$

where stage cost L and terminal cost Φ are described as

$$\begin{cases} L(v_i(t), \bar{v}(t), \tau_{d,i}(t)) = \gamma_1 (v_i(t) - \bar{v}(t))^2 + \tau_{d,i}(t)^2, \\ \Phi(v_i(t_f), v_d) = \gamma_2 (v_i(t_f) - v_d)^2, \end{cases} \tag{13}$$

where γ_1 and γ_2 are the weight factors. In L, the first item represents the minimization of tracking of individual vehicle's speed to average speed $\bar{v}$, and the second item represents the minimization of driving torque fluctuation, which is seen as the energy consumption minimization. In Φ, the goal is to achieve target of speed consensus with v_d being the vehicle speed limit on the road.

The minimization of cost function shown in (12) under the constraints is summarized as follows:

$$\min_{\tau_{d,i}} J_i\left(\tau_{d,i}, \bar{v}\right),$$

$$\text{s.t.} \begin{cases} \dfrac{dv_i(t)}{dt} = \dfrac{1}{M}\left(\dfrac{\tau_{d,i}(t)}{R_{tire}} - F_{resis}(v_i)\right), \\ \tau_{d,i,\min} \le \tau_{d,i}(t) \le \tau_{d,i,\max}, \\ v_i(t_0) = v_{i,0}, \\ \bar{v}(t) = \lim\limits_{N\to+\infty} \sum\limits_{i=1}^{N} \dfrac{v_i(t)}{N}, \end{cases} \tag{14}$$

where the state variable is vehicle speed v_i and control input is driving torque $\tau_{d,i}$ for each vehicle.

It is noted that with the dynamic model of vehicle speed, it is possible to predict the future speed within the predictive horizon $[t_0\ t_f]$. Then $\bar{v}$ can be derived for finite vehicles. However, when the number of vehicle becomes very large, calculation of $\bar{v}$ become hard.

4.2 Optimal Solution

When the number of vehicle is very large, an empirical distribution probability density function $m(v,t)$ is introduced to describe the whole vehicles behavior, defined as

$$m(v,t) = \frac{1}{n}\sum_{i=1}^{n} \delta_{v_i=v}, \tag{15}$$

where $\delta_{v_i=v}$ is the indicator function that is equal to 1 if $v_i = v$ and 0 otherwise.

It is noted that the average speed $\bar{v}(t)$ can be calculated through $m(v,t)$. For simplicity, the vehicle index i is omitted in the following parts. Based on the Fokker-Planck (FP) equation, the mean field dynamics of whole vehicles shown in (14) is described as follows:

$$\frac{\partial m(v,t)}{\partial t} = -\frac{\partial}{\partial v}\left(m(v,t)\frac{1}{M}\left(\frac{\tau_d(t)}{R_{tire}} - F_{resis}(v)\right)\right), \tag{16}$$

Based on optimal theory, the Hamiltonian function is written as follows:

$$\begin{aligned} H = &\left(\gamma_1\left(v(t) - \bar{v}(t)\right)^2 + \tau_d^2(t)\right) \\ &+ p\frac{1}{M}\left(\frac{\tau_d(t)}{R_{tire}} - F_{resis}(v)\right). \end{aligned} \tag{17}$$

For optimal solution to minimize Hamiltonian function in Eq. (17) within control input constraints, following equation should be satisfied:

$$\frac{\partial H}{\partial \tau_d} = 2\tau_d(t) + p(t)\frac{1}{MR_{tire}} = 0. \tag{18}$$

Solution τ_d within constraints is calculated as follows:

$$\tau_d(t) = -\frac{1}{2MR_{tire}}p(t). \tag{19}$$

Thus, the actual optimal driving torque τ_d^* with consideration of demand torque boundaries is determined as follows:

$$\tau_d^*(t) = \begin{cases} \tau_{d,\min}, & \text{if} \quad \tau_d(t) \le \tau_{d,\min}, \\ \tau_{d,\max}, & \text{if} \quad \tau_d(t) \ge \tau_{d,\max}, \\ -\dfrac{1}{2MR_{tire}}p(t), & \text{else.} \end{cases} \tag{20}$$

Then, the co-state function p is determined through Hamiltonian function in Eq. (17) as follows:

$$\frac{dp}{dt} = -\frac{\partial H}{\partial v} = -2\gamma_1\left(v(t) - \bar{v}(t)\right) + \frac{\rho C_d A v}{M}. \tag{21}$$

There is a terminal cost $\Phi(v(t_f), t_f)$ in cost function (12), the co-state $p(t)$ in terminal time t_f is calculated as follows:

$$p(t_f) = \frac{\partial \Phi(v_f, t_f)}{\partial v_f} = 2\gamma_2\left(v(t_f) - v_d\right). \tag{22}$$

In summary, the PMP-based optimal condition and FP equation are written as follows:

$$\begin{cases} \tau_d^*(t) = -\dfrac{1}{2MR_{tire}}p(t), \\ \dfrac{dv}{dt} = \dfrac{1}{M}\left(\dfrac{\tau_d(t)}{R_{tire}} - F_{resis}(v)\right), \\ v(t_0) = v_0, \\ \dfrac{dp}{dt} = -2\gamma_1(v(t) - \bar{v}(t)), \\ p(t_f) = 2\gamma_2(v(t_f) - v_d), \\ \dfrac{\partial m(v,t)}{\partial t} = -\dfrac{\partial}{\partial v}\left(m(v,t)(\dfrac{\tau_d}{R_{tire}} + P + Q)\right), \end{cases} \tag{23}$$

where $P = -\frac{1}{2M}\rho C_d A v^2(t)$ and $Q = -\mu g \cos\theta - g\sin\theta$.

Since it is difficult to analytically obtain the optimal control input sequence satisfying the optimal conditions in Eq. (23), two works should be conducted to deal with above condition: 1) how to calculate the partial differential equation; 2)how to obtain the optimal solution. To solve above two problems, a Lax-Friedrichs scheme based numerical solution method is employed to obtain the updated m in the next time step; Newton Raphson method is employed by guessing initial costate to derive the optimal control solution sequence within prediction horizon $[t_0, t_f]$. Then only the first element of this solution sequence is used for the real-time control of large vehicles. The distribution m is updated and used as an initial condition at each time step.

5. LOWER LAYER-POWERTRAIN CONTROL

5.1 Optimization Problem Formulation

The goal of this optimization in HEV powertrain control is to minimize the energy consumption in monetary sense, including gasoline consumption and electricity consumption, thus the cost function in following equation contains two part. Moreover, there exist some constraints that the optimization problem has to follow. It is noted that the battery dynamics is not considered in this optimization since the speed consensus period is short in the upper layer. It is assumed that battery capacity is large enough so that battery state varies very small in the speed consensus time. Thus, a static optimization problem is formulated as

$$\min_{[\alpha, i_g]^T} \left\{ \frac{r_f}{\rho_f} \dot{m}_f(\tau_e, \omega_e) + r_e \dot{m}_{ele}(\tau_m, \omega_m) \right\},$$
$$\text{s.t.} \begin{cases} \tau_e = \alpha \dfrac{\tau_d}{i_g i_0}, \\ \tau_m = (1-\alpha) \dfrac{\tau_d}{i_g i_0}, \\ \alpha_{min} \le \alpha \le \alpha_{max}, \\ \tau_{e,min} \le \tau_e \le \tau_{e,max}, \\ \tau_{m,min} \le \tau_m \le \tau_{m,max}, \end{cases} \tag{24}$$

where r_f and r_e denote prices of fuel and electricity, ρ_f is the fuel conversion factor between grams and liters. The inequalities in (24) represent the physical powertrain constraints, especially the torques of engine and motor.

5.2 Optimal Torque Distribution

Since the gear number of an automatic transmission is limit, it is possible to derive the optimal torque split rate α under a gear number firstly. Then compare with limit optimal split rates, the optimal pair of α and i_g can be derived. For a gear number gn, the total cost rate $\dot{m}_{to}$ is the sum of fuel cost and electricity cost in (9) and (11), written as

$$\begin{aligned} \dot{m}_{to}(gn) &= \frac{r_f}{p_f} \dot{m}_f + r_e \dot{m}_{ele} \\ &= \frac{r_f}{p_f} \left(b_0 + b_1 \alpha + b_2 \alpha^2 \right) + r_e \eta_m \frac{\tau_d v}{R_{tire}} (1-\alpha) \\ &= c_0 + c_1 \alpha + c_2 \alpha^2, \end{aligned} \tag{25}$$

where detail expressions of c_0, c_1 and c_2 are written as

$$\begin{cases} c_0 = \dfrac{r_f}{p_f} b_0 + r_e \eta_m \dfrac{\tau_d v}{R_{tire}}, \\ c_1 = \dfrac{r_f}{p_f} b_1 - r_e \eta_m \dfrac{\tau_d v}{R_{tire}}, \\ c_2 = \dfrac{r_f}{p_f} b_2. \end{cases} \tag{26}$$

Firstly, the optimization without any constraint is considered, and the optimal solution should satisfy following condition in this case:

$$\frac{d\dot{m}_{to}(gn)}{d\alpha} = 2c_2 \alpha + c_1 = 0, \tag{27}$$

then the candidate solution in this case is calculated as

$$\alpha^{tmp}(gn) = -\frac{c_1}{2c_2}. \tag{28}$$

Due to existences of physical torque limitation in HEV powertrain, α is not able to reach its boundary in some cases, the actual $\alpha_{act}(gn)$ is summarized as follows:

$$\begin{cases} \bar{\alpha}_{act}(gn) = \max\left(\alpha_{min}, \dfrac{\tau_{e,min} i_g i_0}{\tau_d}, 1 - \dfrac{\tau_{m,max} i_g i_0}{\tau_d} \right), \\ \underline{\alpha}_{act}(gn) = \min\left(\alpha_{max}, \dfrac{\tau_{e,max} i_g i_0}{\tau_d}, 1 - \dfrac{\tau_{m,min} i_g i_0}{\tau_d} \right). \end{cases} \tag{29}$$

Finally, the actual optimal α^* should one of the candidate solution $\alpha^{tmp}(gn)$ within limitation case, maximum point $\bar{\alpha}_{act}(gn)$ and minimum $\underline{\alpha}_{act}(gn)$, which is determined as

$$\alpha^*(gn) = \arg\min \left\{ \dot{m}_{to}(\alpha^{tmp}), \dot{m}_{to}(\underline{\alpha}_{act}), \dot{m}_{to}(\bar{\alpha}_{act}) \right\}. \tag{30}$$

In summary, the block control diagram of proposed strategy for individual HEV i is shown in Fig. 5. It is noted that whole vehicles in this connected environment send their real-time speed information to big data center through V2I and receives the updated speed distribution from big data center. The driver torque of each vehicle is derived by proposed MP-MFG-based optimization, with only real-time information of itself speed v_i and the updated distribution m, which is obtained from V2I connection. Moreover, for the HEV powertrain, the torque split calculation is conducted by a static optimization algorithm to distribute engine torque and motor torque, which only is dependent on itself speed and the demand driving torque from MF-MFG-based optimization algorithm. Thus, the proposed optimization strategy is decentralized for large-scale vehicle.

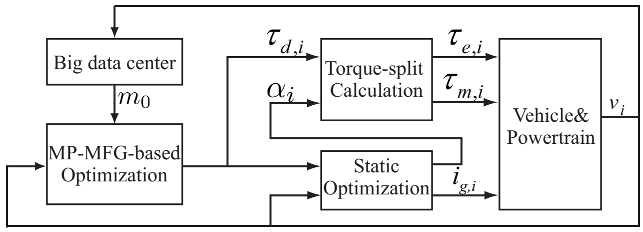

Fig. 5. Block control diagram of proposed strategy for individual HEV i

6. SIMULATION VERIFICATION

6.1 Simulation Condition Setting

To verify the proposed algorithm, a high-density HEV powertrain simulator is built, where the physical parameters used in this paper are listed in Table 1, they are provided by Toyota Motor Corporation, Japan. The parameters used for the proposed algorithm is listed in Table 2. The sampling times of the simulator and control scheme in upper layer are 0.1 s and 1 s, receptively.

Table 1 Specification parameters of the HEVs

Parameters	Symbol	Values
Vehicle mass	M	1138[kg]
Wheel radius	R_w	0.3015[m]
Air density	ρ_{air}	1.2[kg/m^3]
Front area	A	2.239[m^2]
Drag coefficient	C_d	0.32
Rolling resistance	μ	0.022
Differential efficiency	η_f	0.98
Final differential ratio	i_0	3.95
Maximum gear ratio	$i_{g,max}$	3.5
Minimum gear ratio	$i_{g,min}$	0.65

Table 2 Basic parameters of the control scheme

Parameter	Value	Parameter	Value
N	20[-]	t_s	1[sec]
ρ_f	750[g/L]	r_f	165[¥/L]
v_d	100[km/h]	r_e	27[¥/kWh]

6.2 Simulation Results

Simulation results are given in Fig. 6 and Fig. 7. In Fig. 6, the probability distribution densities of vehicle speed, driving torque and energy consumption in monetary sense

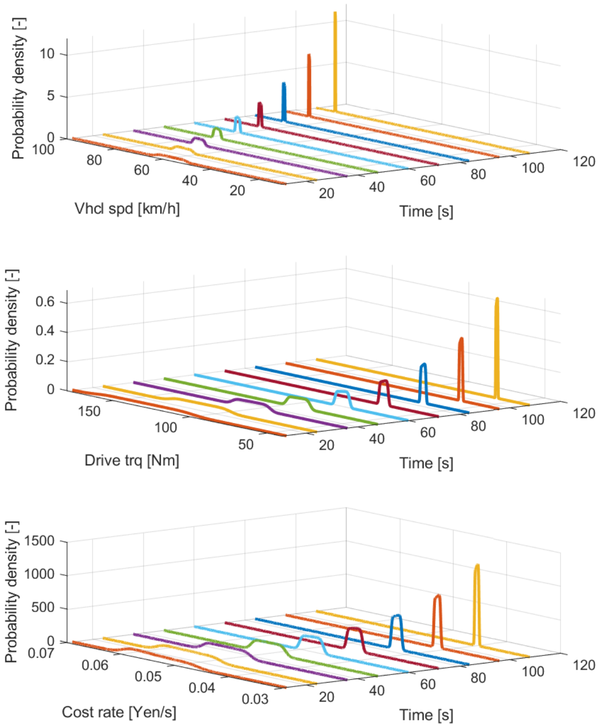

Fig. 6. Distributions of vehicle speed, driving torque and cost rate in different time

of 1000 vehicles are given. It is found that the vehicle speeds are not identical at the initial time, where the probability density is very low; then under the designed control scheme, the distribution density becomes high, which means the vehicle speeds become identical. Similarly, the driving torques become identical finally. Moreover, the cost rate reduces to a small value when time increases.

Fig. 7 shows the the performance comparisons under different scenarios, including different initial speed distributions, different disturbance amplitudes and different weight factors. It is noted that item ηdW_i is added to the actual simulation system to emulate uncertainties in vehicle dynamic function, caused by unknown road condition and the modelling error. dW denotes an independent standard Brownian motion. It is found that vehicle speeds become identical although the initial distributions are different. Similar conclusions can be obtained under different disturbance amplitudes and different weight factors. Meanwhile, it is found that higher γ_1 leads to a faster speed identical behavior for large-scale vehicles.

7. CONCLUSION

A hierarchical energy management strategy is developed for large-scale HEVs to reduce energy consumption in a connected environment. A speed consensus controller is designed by MP-MFG approach and a static optimization strategy is designed for real-time HEV powertrain control. It is found that the MFG-based control scheme in receding horizon sense with utilization of V2X technology can

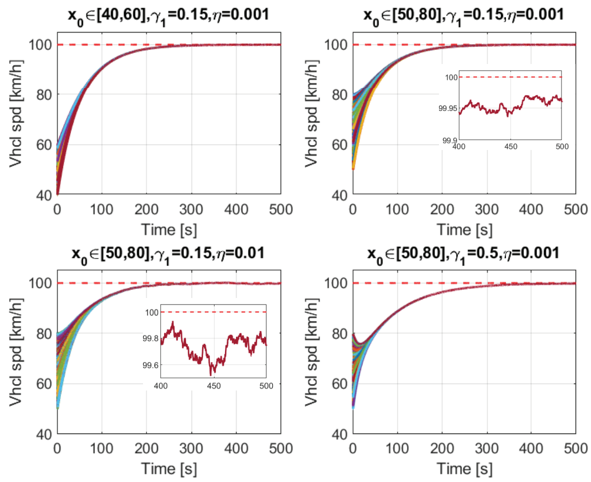

Fig. 7. Vehicle speed comparison under different scenarios

improve the performance in high speed maintaining and the sequent high powertrain efficiency. It is also found that the energy consumption in monetary sense is low when vehicle is in high-speed maintaining mode.

REFERENCES

A. Vahidi and A. Sciarretta. Energy saving potentials of connected and automated vehicles. *Transportation Research Part C: Emerging Technologies*, 95:822–843, 2018.

B. Zhang, J. Zhang, F. Xu, and T. Shen. Optimal control of power-split hybrid electric powertrains with minimization of energy consumption. *Applied Energy*, 266: 114873, 2020.

C. C. Lin, H. Peng, J. W. Grizzle, and J. M. Kang. Power management strategy for a parallel hybrid electric truck. *IEEE Transactions on Control Systems Technology*, 11(6): 839–849, 2003.

F. Xu and T. Shen. Decentralized optimal merging control with optimization of energy consumption for connected hybrid electric vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 2021.DOI:10.1109/TITS.2021.3054903

K. Yu, H. Yang, X. Tan and et al. Model predictive control for hybrid electric vehicle platooning using slope information. *IEEE Transactions on Intelligent Transportation Systems*, 17(7): 1894–1909, 2016.

J. M. Lasry and P. L. Lions. Mean field games. *Japanese Journal of Mathematics*, 2(1): 229–260, 2007.

N. Kim, S. W. Cha, and H. Peng Optimal control of hybrid electric vehicles based on Pontryaginfs minimum principle. *IEEE Transactions on Control Systems Technology*, 19(5): 1279–1287, 2011.

Q. Fu, F. Xu, T. Shen and K. Takai. Distributed optimal energy consumption control of HEVs under MFG-based speed consensus. *Control Theory and Technology*, 18(2): 193–203, 2020.

X. Wei, J. Leng and et al (2022). Co-optimization method of speed planning and energy management for fuel cell vehicles through signalized intersections. *Journal of Power Sources*, 518, 230598, 2022.