A Deep Reinforcement Learning Framework for Optimizing Fuel Economy of Hybrid Electric Vehicles

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Outline

- Motivation
- HEV System Architecture
- DRL Framework of HEV power control
- Experimental Results

Motivation

- Hybrid electric vehicles (HEVs) combine the energy efficiency of electric motor (EMs) and a long driving range of internal combustion engine (ICE)
- The relatively complicated powertrain structures of HEVs necessitate an effective power management policy to determine the power split between ICE and EM

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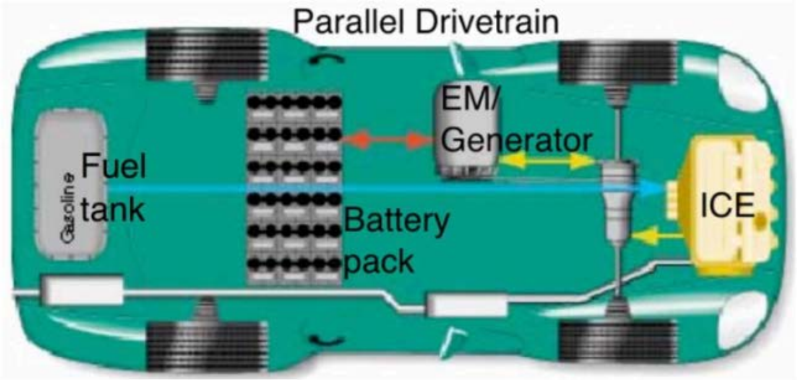
HEV System Architecture

- HEV Components
  - Internal Combustion Engine (ICE)
  - Electric motor (EM)
  - Vehicle Dynamic
  - Powertrain Mechanics
- HEV Control
  - The HEV controller needs to control the operation of the ICE, EM and powertrain to meet the target propulsion

HEV System Architecture -- HEV Components

- Parallel hybrid powertrain
  - ICE and EM propel the vehicle in parallel



- Internal Combustion Engine (ICE)
  - ICE fuel efficiency:

$$\eta_{ICE}(T_{ICE}, \omega_{ICE}) = T_{ICE} \cdot \omega_{ICE} / (\dot{m}_f \cdot D_f)$$

$$\omega_{ICE}^{\min} \leq \omega_{ICE} \leq \omega_{ICE}^{\max},$$
$$0 \leq T_{ICE} \leq T_{ICE}^{\max}(\omega_{ICE}).$$

HEV System Architecture -- HEV Components

- Electric Motor (EM)
  - a motor to propel the vehicle solely or together with ICE
  - a generator to charge the battery pack

$$\eta_{EM}(T_{EM}, \omega_{EM}) = \begin{cases} (T_{EM} \cdot \omega_{EM})/P_{batt} & T_{EM} \geq 0 \\ P_{batt}/(T_{EM} \cdot \omega_{EM}) & T_{EM} < 0 \end{cases}$$

$$0 \leq \omega_{EM} \leq \omega_{EM}^{\max},$$
$$T_{EM}^{\min}(\omega_{EM}) \leq T_{EM} \leq T_{EM}^{\max}(\omega_{EM}).$$

HEV System Architecture -- HEV Components

- Vehicle Dynamics

$$F_{TR} = m \cdot a + F_g + F_R + F_{AD},$$
$$F_g = m \cdot g \cdot \sin\theta,$$
$$F_R = m \cdot g \cdot \cos\theta \cdot C_R,$$
$$F_{AD} = 0.5 \cdot \rho \cdot C_D \cdot A_F \cdot v^2,$$

  - The demanded power for propelling the vehicle:

$$T_{wh} = F_{TR} \cdot r_{wh},$$
$$\omega_{wh} = v / r_{wh}.$$

$$P_{dem} = F_{TR} \cdot v = T_{wh} \cdot \omega_{wh}.$$

HEV System Architecture -- HEV Components

- Powertrain Mechanics
  - The speed and torque of the ICE and EM must satisfy the speed and torque relation:

$$\omega_{wh} = \frac{\omega_{ICE}}{R(j)} = \frac{\omega_{EM}}{R(j) \cdot \rho_{reg}},$$

$$T_{wh} = R(j) \cdot (T_{ICE} + \rho_{reg} \cdot T_{EM} \cdot (\eta_{reg})^{\alpha}) \cdot (\eta_{gb})^{\beta}$$

$$\alpha = \begin{cases} +1 & T_{EM} \geq 0, \\ -1 & T_{EM} < 0. \end{cases}$$

$$\beta = \begin{cases} +1 & T_{ICE} + \rho_{reg} \cdot T_{EM} \cdot (\eta_{reg})^{\alpha} \geq 0, \\ -1 & T_{ICE} + \rho_{reg} \cdot T_{EM} \cdot (\eta_{reg})^{\alpha} < 0. \end{cases}$$

HEV System Architecture -- HEV Control

- The speed and acceleration are determined by the driver
- The HEV controller controls the operation of the ICE, EM and powertrain to meet the target propulsion
- Control Variables:
  - The battery output power
  - The gear ratio
  - The ICE torque
  - The EM torque
- control variables follows the operating principles of HEV components

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DRL Framework

- Basics of DRL
- DRL Formulation
  - State Space
  - Action Space
  - Reward Function
- DRL Procedure
  - Offline DNN Construction
  - Online Deep Q-Learning

DRL Framework -- DRL basics

- Interaction between agent and environment

  - Agent selects actions
  - Environment responds to actions and presents new situations to the agent
  - Environment also gives rise to rewards

DRL Framework -- DRL basics

- value function
  - the expected accumulated reward with discount

$$Q(s,a) = \mathbf{E}\Big[\sum_{k=0}^{\infty} \gamma^k r_k \Big| s_0, a_0\Big]$$

- the reward
  - the negative of the fuel consumption in the time slot

$$r_k = -\dot{m}_f \cdot \Delta T$$

- The DRL agent targets at maximizing the Q value

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DRL Framework -- DRL Formulation

- State Space
  - A finite number of states, each represented by:
    - the propulsion power demand,
    - vehicle speed,
    - charge stored in the battery pack,
    - predicted propulsion power demand for the next time slot

$$S = \left\{ s = [p_{dem}, v, q, pre]^T \,|\, p_{dem} \in P_{dem}, \right.$$
$$\left. v \in V, q \in Q, pre \in \mathrm{P}_{pre} \right\}$$

DRL Framework -- DRL Formulation

- State Space
  - Q is constructed by discretizing the range of charge stored in the battery pack

$$Q = \{q_1, q_2, \cdots, q_N\},$$

$$q_{min} = q_1 < q_2 < \ldots < q_N = q_{max}$$

  - incorporate future driving characteristics (i.e., *pre*) into consideration for more effective representation

$$pre_i \leftarrow (1-\alpha) \cdot pre_{i-1} + \alpha \cdot meas_{i-1}$$

DRL Framework -- DRL Formulation

- Action Space
  - A finite number of actions, each represented by:
    - the discharging current of the battery pack
    - the gear ratio

$$A = \{a = [i, R(j)]^T \,|i \in I, R(j) \in R\}$$

- I : a finite (discretized) number of discharging current values in $[-I_{max}; I_{max}]$

  $i > 0$: discharge the battery pack

  $i < 0$: charge the battery pack

- R contains all allowable gear ratio values
  - Usually 4 or 5 values

DRL Framework -- DRL Formulation

- Reward Function

$$r_k = -\dot{m}_f \cdot \Delta T$$

  - r_k is the reward the agent receives after taking action a_k in state s_k
  - the negative of the fuel consumption in the time slot
- DRL agent targets at maximizing the expected return

$$\Sigma_{k=0}^{\infty} \gamma^k \cdot r_k,$$

  - the discounted sum of rewards

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DRL Framework -- DRL Procedure

- The DRL procedure comprises:
  - an offline DNN construction phase
  - an online deep Q-learning phase

- offline DNN construction
  - derives the Q-value estimate for each state-action pair
  - employ a convolutional neural network as the DNN structure
  - The real world and testing driving cycles are utilized to obtain the Q value estimates for the training of DNN

DRL Framework -- DRL Procedure

- online deep Q-learning phase
  - At each decision epoch, the policy selects
    - the action with the maximum $Q(s_k, a)$ value estimate with probability $1 - \varepsilon$,
    - or a random action with probability ε
  - At the next decision epoch, update Q-value

$$Q(s,a) \leftarrow Q(s,a) + \alpha \cdot e(s,a) \cdot \delta,$$

$$\delta \leftarrow r_{k+1} + \gamma \cdot \max_{a'} Q(s_{k+1}, a') - Q(s_k, a_k).$$

  - $r_k(s_k, a_k)$ is the observed reward
  - α is a coefficient controlling the learning rate
  - γ is the discount rate

DRL Framework -- DRL Procedure

Algorithm 1 The DRL Framework of HEV power control

Offline:

Simulate the control process using an arbitrary but gradually refined policy for enough long time;

Obtain the state transition profile and $Q(s, a)$ value estimates during the process simulation;

Store the state transition profile and $Q(s, a)$ value estimates in experience memory D with capacity N_D;

Train a DNN with features (s, a) and outcomes $Q(s, a)$;

Online:

for each execution sequence **do**

  for each decision epoch t_k **do**

    With probability $1 - \varepsilon$ select the action $a_k = \arg\max_a Q(s_k, a)$, otherwise select an action randomly;

    Perform system control using the chosen action;

    Observe reward $r_k(s_k, a_k)$ during time period $[t_k, t_{k+1})$ and the new state s_{k+1} at the next epoch;

    Store transition set (s_k, a_k, r_k, s_{k+1}) in D;

    Update $Q(s_k, a_k)$ using $\max_{a'} Q(s_{k+1}, a')$ and $r_k(s_k, a_k)$ based on the Q-learning updating rule;

  end for

  Update DNN weight set θ based on the newly updated Q-value estimates in a mini-batch manner;

end for

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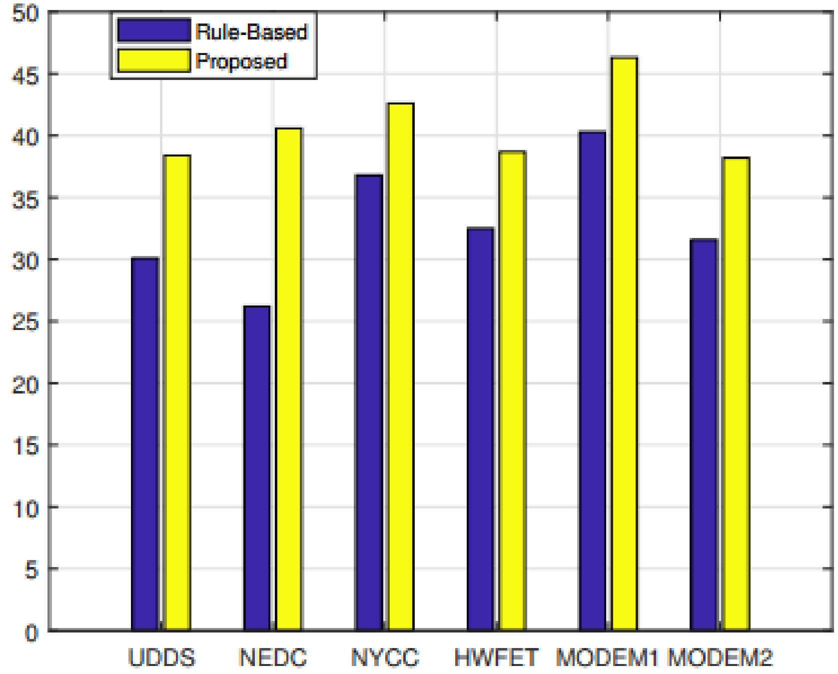
Experimental Results

- based on both real-word and testing driving cycles
- compared with the rule-based policy

Driving cycle	Rule-based	Proposed method	reduction
UDDS	412.3g	303.5g	26.4%
NEDC	319.8g	203.5g	36.4%
NYCC	86.1g	37.6g	56.3%
HWFET	364.0g	201.9g	44.5%
Modem1	228.6g	162.6g	28.9%
Modem2	344.9g	225.6g	34.6%
total	1755.7g	1134.7g	35.4%

Experimental Results

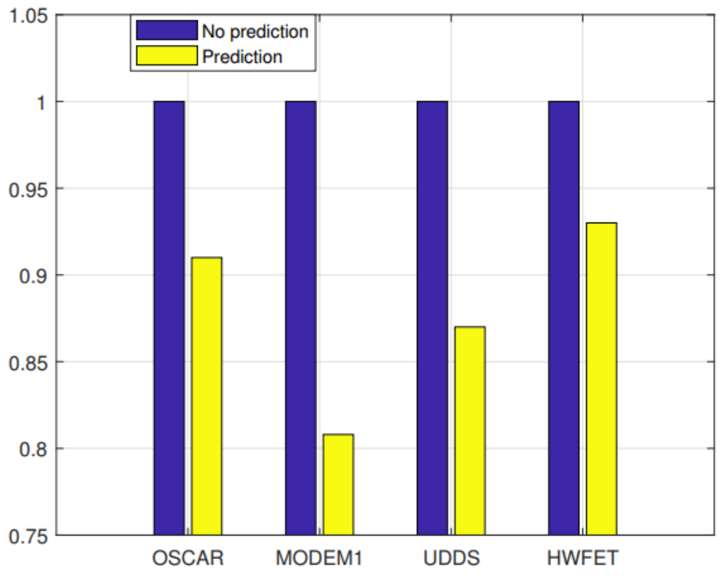
- compared with the rule-based policy

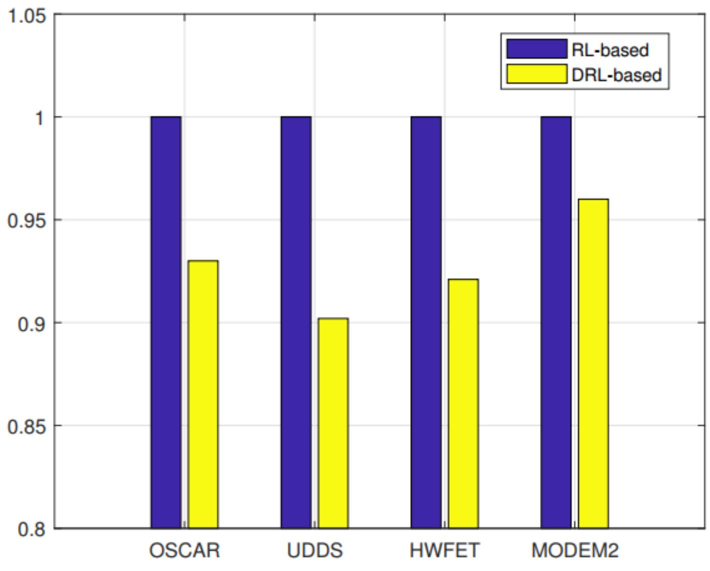


The MPG values achieved by the proposed DRL framework and the rule-based policy

Experimental Results

- compared with the RL-based method
  - employs $TD(\lambda)$ learning algorithm





- Prediction can decreases fuel consumption
- DRL-based power control can achieve better fuel economy than the RL-based framework

Thank You !