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K-FOLD FUZZY LEARNING FOR IMPLEMENTATION OF DYNAMIC PROGRAMMING RESULTS IN REAL-TIME ENERGY MANAGEMENT OF THE PLUG-IN HYBRID VEHICLE

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ABSTRACT

Plug-in hybrid vehicles will become a major part of urban transportation before 2030. The hybrid powertrain is a micro energy system that needs to be managed to achieve low carbon emission. Dynamic programming is widely adopted to optimize the energy efficiency, but it cannot be directly used for real-time control. This paper proposes a new Global K-fold Fuzzy Learning (GKFL) scheme to implement the offline optimization results in real-time control with adaptive neuro-fuzzy inference system (ANFIS). It aims to obtain an ANFIS network that can robustly achieve the optimum control utility which is defined as a function of the vehicle's energy efficiency and the battery state-of-charge (SoC). The performances of the 2 ANFIS network systems developed by both standard method and the GKFL method respectively are evaluated through experimental studies. GKFL is shown effective in knowledge implementation. Compared to the default solver in the MATLAB ANFIS toolbox, GKFL can increase the control utility of the studied vehicle by 8% in the Worldwide-harmonized Light-duty Testing Cycle.

Keywords: Energy management, Hybrid vehicle, Adaptive neuro-fuzzy inference system, K fold cross validation, Machine learning

1. INTRODUCTION

Plug-in hybrid electric vehicles, as a mainstream ultra-low emission solution, will account for more than 60% of the world vehicular market by 2030 according to predictions from the International Energy Agency [1]. The energy management systems (EMS) control the energy flows between the power units (e.g. engine and battery) within the hybrid vehicle. The optimization of energy efficiency in the EMS is among the most challenging decision-making tasks because of the uncertainties in real-world driving and constraints in operations [2,3].

EMS should be optimized to allow vehicles to comply with the regulations in fuel consumption and emissions. New European Driving Cycle (NEDC) for road vehicles has been replaced by the Worldwide-harmonized Light-duty Testing Cycle (WLTC), where an increasing number of transient operation points are included to evaluate energy efficiency and emissions [4]. New vehicle legislations on examining real-world driving emissions (RDE) have been enforced [5,6].

Although online optimization methods including both model-based [7] and model-free [8] controls have been developed recently, offline optimization of the power management strategy under testing cycles is still an essential procedure to help automakers comply with legislations. Offline optimization determines the optimal control signals that achieve the maximum energy efficiency [9], where dynamic programming (DP) is considered as the benchmark method. However, dynamic programming requires large computational efforts and therefore, is not feasible to be implemented in real-time control directly [10,11].

It is critical to implement the DP results in real-time energy management [12]. The implementation process can be regarded as an optimization problem that determines the optimum parameters in an energy management control model that achieves the minimum mean square error with the DP results.

Meta-heuristic algorithms, e.g. particle swarm optimization (PSO) [13,14] and genetic algorithms (GA) [15,16], have been developed to minimize the mean square errors between model data and testing data. The learning performance heavily depends on the data used in training and validation. Khayyam et al. modelled a fuzzy logic power management controller using 5 groups of data sets, while each set contains 30k data pairs [16]. Xing et al. used 10k data pairs to train recurrent neural networks for driver behavior prediction [17]. Tian et al. used 1120 data sets to train a fuzzy power management controller [18], while each set contains more than 4k data pairs. These papers demonstrated that model learning with a huge amount of data is time-consuming and sometimes may cause overfitting.

Ideally, the optimal vehicle control model should be built using the data collected from a test cycle (e.g. WLTC) [6]. Building precise and robust vehicle control models with the limited data is a challenge, which can be addressed by cross-validation [19]. The K-fold cross-validation is widely used for learning with labelled data [19]. Lv et al. used a five-fold cross-validation to train a neural network for driver intention prediction [20]. Zuo et al developed a five-fold method to train a fuzzy model in solving regression problems [21]. Tivive used a ten-fold method to train a convolutional neural network for pattern recognition [22]. However, using K-fold cross-validation methods for implementation of offline optimization results for power management has not been reported.

This paper proposed a new k-fold fuzzy learning method to implement the dynamic programming results in real-time control. The work is conducted with two main contributions: 1) a global k-fold fuzzy learning (GKFL) scheme is proposed, which incorporates k-fold cross validation for fuzzy modelling; 2) GKFL is incorporated with GA and PSO for optimization of the fuzzy model. The GKFL results are evaluated through experiments.

The rest of the paper is organized as follows: Section 2 describes the energy flow within a PHEV power management system, and Section 3 proposes the GKFL for implementation of offline optimization results. Experimental evaluations of the GKFL are conducted in Section 4. Conclusions are summarized in Section 5.

2. THE HYBRID ELECTRIC POWERTRAIN SYSTEM

2.1 The hybrid electric powertrain

A PHEV with a series topology is studied in this paper, which has two power units to meet the power demand for vehicle operation. The power flows of power units are shown in **Fig. 1**, where P_{dem} is the power demand for vehicle operation; P_{ppu} is the power output from the battery pack; the battery is discharging when $P_{\text{ppu}} > 0$, and is charging when $P_{\text{ppu}} < 0$; P_{apu} is the power output from the engine-generator. The battery package works as the primary power unit of the PHEV. The engine-generator is used as the alternative power unit for maintaining the battery's state-of-charge (SoC) to allow longer driving distance.

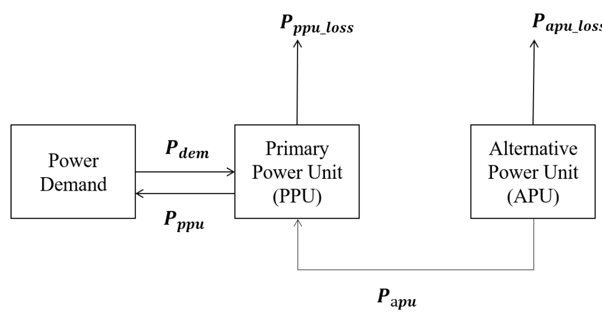

Fig. 1 Power Flow of a Hybrid Powertrain System

From the perspective of energy transmission, the power flow in the PHEV is expressed as

$$P_{\text{dem}}(t) = P_{\text{ppu}}(t) + P_{\text{apu}}(t). \tag{1}$$

The power losses of the battery and the engine-generator can be modelled by:

$$\left.\begin{aligned} P_{\text{ppu\_loss}}(t) &= R_{\text{loss}}(SoC) \cdot I_{\text{batt}}(u_{\text{batt}}(t))^2 \\ P_{\text{apu\_loss}}(t) &= \dot{m}_f\big(u_{egu}(t)\big) \cdot H_f - P_{\text{apu}}(t) \end{aligned}\right\}, \tag{2}$$

where R_{loss} is the battery internal resistance; I_{batt} is the battery current; u_{batt} is the battery control signal; u_{egu} is the engine-generator control signal; $\dot{m}_f$ is the fuel mass flow rate; and H_f is the heat value of the fuel.

Achieving maximum vehicle energy efficiency is the primary objective for power management. The energy efficiency of the PHEV, η, is defined as:

$$\eta = \frac{\sum_{t=t_0}^{t_\tau} P_{\text{dem}}(t)\cdot\Delta t}{\sum_{t=t_0}^{t_\tau} P_{\text{dem}}(t)\cdot\Delta t + \sum_{t=t_0}^{t_\tau} P_{\text{loss}}(t)\cdot\Delta t}, \tag{3}$$

where t_0 and t_t are the start and terminate of a driving cycle; Δt is the sampling time; and $P_{\text{loss}}(t) = P_{\text{ppu\_loss}}(t) + P_{\text{apu\_loss}}(t)$ is the total power loss.

Maintaining the battery SoC is a critical constraint to be followed in power management. The battery SoC at time t_l is calculated by

$$SoC(t_l) = SoC(t_{l-1}) - \frac{I_{\text{batt}}(u_{batt}(t_l))}{Q_{\text{batt}}} \cdot \Delta t, \tag{4}$$

where Q_{batt} and I_{batt} are the battery's capacity and current.

To achieve the maximum vehicle system energy efficiency while maintaining the battery SoC, a control utility function is defined by introducing a penalty in degrading of battery SoC, $\beta \cdot e^{\alpha\cdot(SoC(t)-SoC^{+}-SoC^{-})}$[23], to the denominator of Eq. (3) as

$$\mathcal{U} = \frac{\sum_{t=t_1}^{t_\tau} P_{\text{dem}}(t)\cdot\Delta t}{\sum_{t=t_1}^{t_\tau} P_{\text{dem}}(t)\cdot\Delta t + \sum_{t=t_1}^{t_\tau}(P_{\text{loss}}(t)\cdot\Delta t + \beta\cdot e^{\alpha\cdot(SoC(t)-SoC^{+}-SoC^{-})})}, \tag{5}$$

where SoC^{+} and SoC^{-} are the higher and lower boundary of battery SoC for the hybrid power mode.

2.2 Energy Management with Fuzzy Inference System

Typically, energy management strategy determines the power ratio of the engine-generator $u_{\text{egu}}(t)$ by [7,8,24]:

$$u_{\text{egu}}(t) = \mathcal{M}(P_{\text{dem}}(t), SoC(t), \mathbb{C}) \tag{6}$$

where $\mathcal{M}(\cdot)$ is a nonlinear function that projects the inputs of $P_{\text{dem}}(t)$ and $SoC(t)$ to the relevant control command $u_{\text{egu}}(t)$. $\mathbb{C}$ is a vector of parameters.

An ANFIS $\mathcal{M}(\cdot)$ is developed based on a Takagi-Sugeno model that is easy to be implemented in data-driven learning [25]. It includes one input layer, three hidden layers and one output layer. The input layer collects the battery SoC and power demand from the PHEV with an input vector $\boldsymbol{x} = [SoC(t), P_{\text{dem}}(t)]^{\text{T}}$. The output layer implements the control command $u_{\text{egu}}(t) = y$ based on the computing results from hidden layers. The hidden layers calculate y using $\boldsymbol{x}$.

The first hidden layer fuzzifies the inputs with triangular membership functions, $F_{1,i}$ and $F_{2,i}$, as

$$\left.\begin{aligned} F_{1,i}(x_1, \boldsymbol{v}_{1,i}) &= \max\left(\min\left(\frac{x_1 - \boldsymbol{v}_{1,i}(1)}{\boldsymbol{v}_{1,i}(2)-\boldsymbol{v}_{1,i}(1)} \quad \frac{\boldsymbol{v}_{1,i}(3)-x_1}{\boldsymbol{v}_{1,i}(3)-\boldsymbol{v}_{1,i}(2)}\right), 0\right) \\ F_{2,j}(x_2, \boldsymbol{v}_{2,j}) &= \max\left(\min\left(\frac{x_2 - \boldsymbol{v}_{2,j}(1)}{\boldsymbol{v}_{2,j}(2)-\boldsymbol{v}_{2,j}(1)} \quad \frac{\boldsymbol{v}_{2,j}(3)-x_2}{\boldsymbol{v}_{2,j}(3)-\boldsymbol{v}_{2,j}(2)}\right), 0\right) \end{aligned}\right\} \tag{7}$$

where x_1 and x_2 are the elements in the input vector $\boldsymbol{x}$; $F_{1,i}$ is the i-th membership function for the first input; *n* is the total number of membership functions for the first input; $F_{2,j}$ is the j-th membership function for the second input; *m* is the total number of membership functions for the second input; and $\boldsymbol{v}(k)$, k=1,2,3, is the k-th element of the parameter vector $\boldsymbol{v}$.

The second hidden layer connects the outputs of the input membership functions based on fuzzy rules. Each fuzzy rule applies the following linguistic logic:

$$\text{If } \boldsymbol{x}(1) \text{ is } F_{1,i}(\boldsymbol{x}(1), \boldsymbol{v}_{1,i}) \text{ and } \boldsymbol{x}(2) \text{ is } F_{2,j}(\boldsymbol{x}(2), \boldsymbol{v}_{2,j}),$$
$$\text{then } y \text{ is } L(\boldsymbol{x}, a_{i,j}),$$
$$i = 1,2,\dots,n;\ j = 1,2,\dots,m \tag{8}$$

where $L(\boldsymbol{x}, a_{i,j})$ is the output membership function that is a constant type for this study as in [11]; and $a_{i,j}$ is a scale in an output membership function.

The third hidden layer uses a vector $\boldsymbol{W} = [w_{1.1}, w_{1.2}, \dots, w_{1.n}, w_{2.1}, \dots, w_{2.n}, \dots, w_{m.1}, \dots, w_{m.n}]$ to scale the outputs of fuzzy rules:

$$y = \sum_{j=1}^{m}\sum_{i=1}^{n}\left\{\min\left(F_{1,i}(\cdot), F_{2,j}(\cdot)\right)\cdot L(\boldsymbol{x}, a_{i,j})\cdot w_{i.j}\right\} \tag{9}$$

where $w_{i.j} \in [0,1], i = 1,2,\dots,n, j = 1,2,\dots,m$.

The model parameter vector $\mathbb{C}$ is

$$\mathbb{C} = [\boldsymbol{V}_1, \boldsymbol{V}_2, \boldsymbol{A}, \boldsymbol{W}] \tag{10}$$

where $\boldsymbol{V}_1 = [v_{1,1}, v_{1,2}, \dots v_{1,n}]$ and $\boldsymbol{V}_2 = [v_{2,1}, v_{2,2}, \dots v_{2,m}]$ are the parameter vectors of the inputs membership functions; $\boldsymbol{A}_1 = [a_{1,1}, \dots, a_{1,n}, a_{2,1}, \dots, a_{2,n}, \dots a_{m,n1}, \dots, a_{m,n}]$ is the parameter vector of the output membership functions.

3. GLOBAL K-FOLD FUZZY LEARNING FOR OFFLINE OPTIMISATION RESULT IMPLEMENTATION

The global k-fold fuzzy learning implements k-fold cross-validation in optimization of the parameter vector $\mathbb{C}$. It allows accurate knowledge implementation for real-time control by obtaining an ANFIS model $\boldsymbol{\mathcal{M}}^{\mathbf{kf}}$ that allows the vehicle system to achieve high control utility $\mathcal{U}(\boldsymbol{\mathcal{M}}^{\text{kf}})$ in real-time. This model will be better than the one using the conventional model $\boldsymbol{\mathcal{M}}^{\text{cov}}$ (with default setting in the MATLAB ANFIS Toolbox). Since there lacks research into determining the best κ value for fuzzy learning in energy management control, this paper will investigate fuzzy learning performance with all possible κ values (i.e. $\kappa = 2,3,4,\dots,10$).

A global search method is proposed to determine both the optimal setting κ^* for K-fold fuzzy learning and the optimal online energy management model $\boldsymbol{\mathcal{M}}^{\mathbf{kf}}$. The overall working procedure of the proposed global K-fold fuzzy learning is presented in **Fig. 2**. After the initialization of the K value by setting $\kappa = 2$, a rotational learning process will repeat Steps 1)-4):

1) The offline optimization results $\boldsymbol{D}[\boldsymbol{x}, \boldsymbol{y}]^{\text{T}}$ are randomly divided into κ folds which have the similar size, i.e. $\boldsymbol{D}_1, \boldsymbol{D}_2, \dots, \boldsymbol{D}_{\kappa}$.

2) The parameter vector $\mathbb{C}$ in Fuzzy model $\boldsymbol{\mathcal{M}}(.,.,\mathbb{C})$ is optimized in κ independent rounds, where,

$\boldsymbol{D}^r_{\mathrm{trn}} = [\boldsymbol{D}_1, \boldsymbol{D}_2, \dots, \boldsymbol{D}_{r-1}, \boldsymbol{D}_{r+1}, \dots \boldsymbol{D}_\kappa]$ (r=1,2,..., κ) is for training and $\boldsymbol{D}^r_{\mathrm{tst}} = \boldsymbol{D}_r$ is for testing.

3) $\boldsymbol{\mathcal{M}}^\kappa(.,.,\mathbb{C}^\kappa)$ is selected based on the results from Step 2, which has the minimum cross-validation mean square error (CVMSE),

$$\mathrm{CVMSE}_{(\kappa)} = \frac{1}{\kappa}\cdot\sum_{r=1}^{\kappa}\frac{\sum_{t=1}^{\tau'}\left(\boldsymbol{\mathcal{M}}^r(x^r_{\mathrm{tst}}(t)) - y^r_{\mathrm{tst}}(t)\right)^2}{\tau'} \qquad (11)$$

where $\boldsymbol{\mathcal{M}}^r(x^r_{\mathrm{tst}}(t))$ is the model output using the model learnt from training data $\boldsymbol{D}^r_{\mathrm{trn}}$ during round r; $x^r_{\mathrm{tst}}(t)$ is the model input in testing data $\boldsymbol{D}^r_{\mathrm{tst}}$ during round r; and $y^r_{\mathrm{tst}}(t)$ is the model output in testing data $\boldsymbol{D}^r_{\mathrm{tst}}$ in the round r.

4) $\boldsymbol{\mathcal{M}}^\kappa$ is implemented for real-time control under a given driving cycle. The control utility $\mathcal{U}(\boldsymbol{\mathcal{M}}^\kappa)$ is collected as an indicator to select the optimal result.

Once the termination term is met ($\kappa > 10$), the process stops. Then the optimal setting κ^* is extracted, together with the optimal model $\boldsymbol{\mathcal{M}}^{\mathrm{kf}}$ that satisfies

$$\mathcal{U}(\boldsymbol{\mathcal{M}}^{\mathrm{kf}}) = \mathcal{U}(\boldsymbol{\mathcal{M}}^{\kappa^*}) \geq \mathcal{U}(\boldsymbol{\mathcal{M}}^{\kappa}), \qquad \kappa \in [2,10] \qquad (12)$$

where $\mathcal{U}(\boldsymbol{\mathcal{M}}^{\kappa^*})$ is the CU value that the vehicle achieved under a given driving cycle using the fuzzy model $\boldsymbol{\mathcal{M}}^{\kappa^*}$ that is optimized with $\kappa = \kappa^*$.

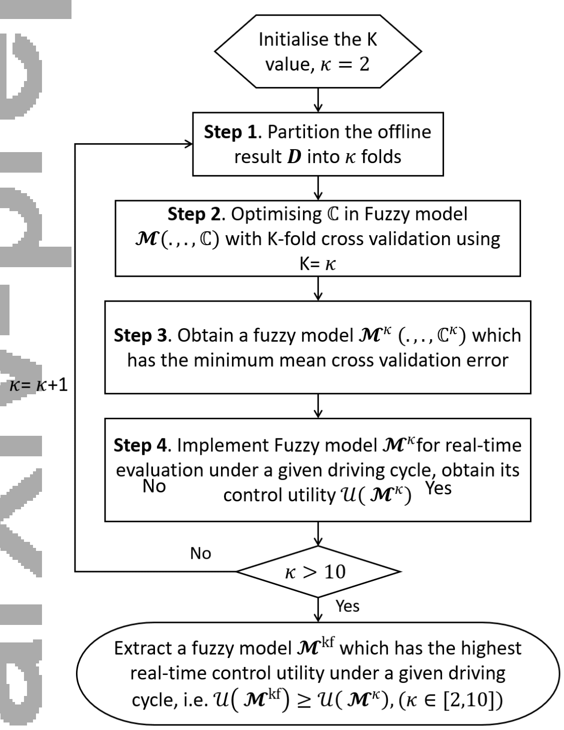

Fig. 2 Procedure of GKFL for implementing the offline optimisation result into real-time control

4. EXPERIMENTAL EVALUATIONS

4.1 Testing vehicle and platform

A plug-in hybrid passenger car, which has a 36.6kW generator powered by a 0.65L engine, a 125kW electric motor, and a 360V/22kWh high-volt battery, were used for experimental evaluations. The vehicle is modelled using the Simulink Powertrain Toolbox based on the dynamometer data. The inputs of the vehicle model are the desired vehicle speed and the power management control signal. The model outputs are the battery SoC, battery voltage/current, fuel mass flow rate. The key parameters are listed in Table I.

Both offline software-in-the-loop (SiL) and online hardware-in-the-loop (HiL) testing platforms were used in experimental evaluations. The SiL test was conducted in MATLAB 2020a on a PC with an i7 CPU and a 16GB RAM. The power control prototypes were developed in Simulink to allow closed-loop control of the PHEV model. A Speedgoat real-time target machine is used for HiL testing, as shown in **Fig. 3**. The control prototype and the real-time vehicle model are compiled in a host PC, downloaded onto the Speedgoat target machine through Ethernet, and physically connected via a CAN bus.

Table I Key Parameters for Vehicle Plant Modelling

Specification	**Value**	**Unit**
Vehicle Mass	1315	kg
Wheel rolling radius	0.35	m
Front Area	2.38	m^2
Drag coefficient	0.30	-
Rolling resistance	0.001	-

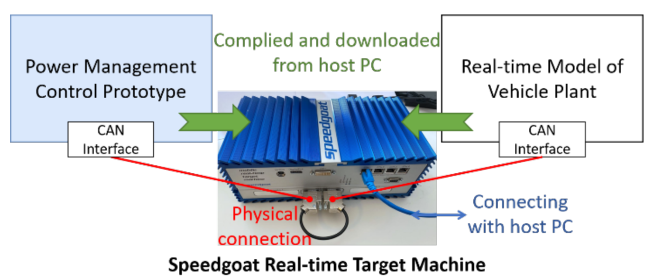

Fig. 3 Online hardware-in-the-loop testing platform

4.2 K-Fold fuzzy learning performance

Experimental evaluation was conducted based on the WLTC which is currently used for vehicle certification in Europe. The benchmark power management strategy under WLTC is obtained by dynamic programming. It is a data set containing 1800 data pairs, where 70% of data is used for learning, and 30% is for verification.

Genetic algorithm (GA) and particle swarm optimization (PSO) algorithms were incorporated with the GKFL. The conventional method (ANFIS toolbox) is selected as the baseline. The results obtained by GA and PSO are compared with the baseline in **Fig. 4** and **Fig. 5**. The mean square error of training data (Train. MSE) is monitored in bule bars, where the MSE with the whole training data set is measured for the conventional method, and the minimum cross-validation mean square is used for evaluation of the GKFL method with different κ values. The models were examined using the verification data to obtain the verification mean square error (Veri. MSE) in red bars. The control utility (CU) was evaluated by deploying the models in real-time control and is shown in yellow lines with markers. The baseline CU value is shown in red dash line as a reference.

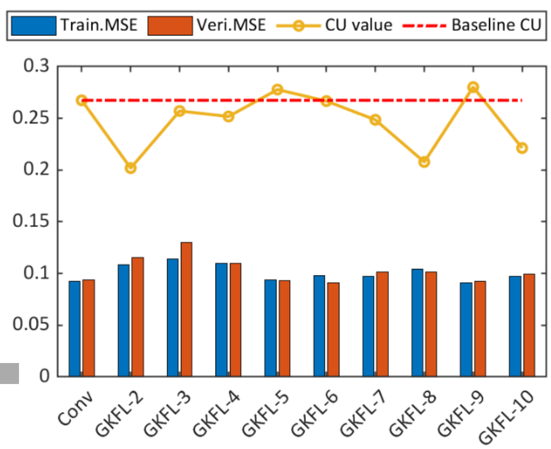

Fig. 4 Learning performance with GA

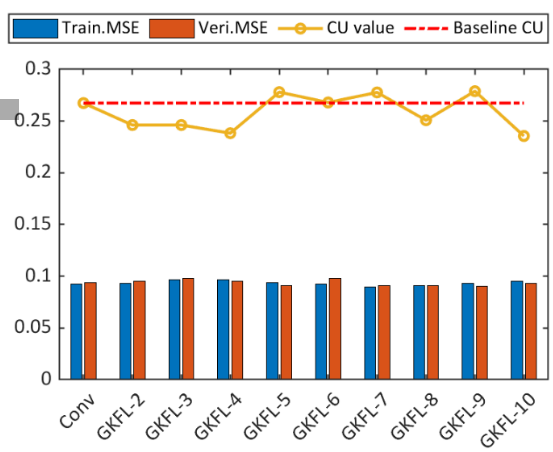

Fig. 5 Learning performance with PSO

The highest CU value is achieved by incorporating GKFL with GA when $\kappa = 9$, however, GKFL is more robust with PSO which achieves higher average CU value in terms of different values of κ. The κ value is very important for GKFL and needed to be chosen very carefully. GKFL achieves higher CU value than the baseline when $\kappa = 5,6,9$ where $\kappa = 5$ is widely used in five-fold cross validation. Another widely used cross-validation method, i.e. ten-fold cross validation, is not as good as expected in GKFL because it achieves lower CU value than the baseline with both GA and PSO.

4.3 Real-time performance

By deploying the model obtained by GKFL-9-GA ($\kappa = 9$, using GA for learning) and the model obtained by Conv-PSO (using PSO for conventional learning) in the Speedgoat real-time target, the real-time performances are obtained (in red and yellow, respectively) and compared with the dynamic programming results (shown in blue dot-dash line) in **Fig.6**. The power management system generates control commands for the engine-generator unit (EGU) as shown in **Fig.6** (b). It is to satisfy the power demand in **Fig.6** (a) while maintaining the battery SoC at a certain level as shown in **Fig.6** (c). It optimizes the vehicle energy efficiency by minimizing fuel consumption. The power management real-time control model obtained by GKFL-9-GA achieves 2.8% lower fuel consumption than using the benchmark strategy, but it achieves 3.4% lower control utility because it has 5.9% less remaining battery SoC. The fuzzy model obtained by GKFL-9-GA achieves the highest control utility compared to other fuzzy learning methods.

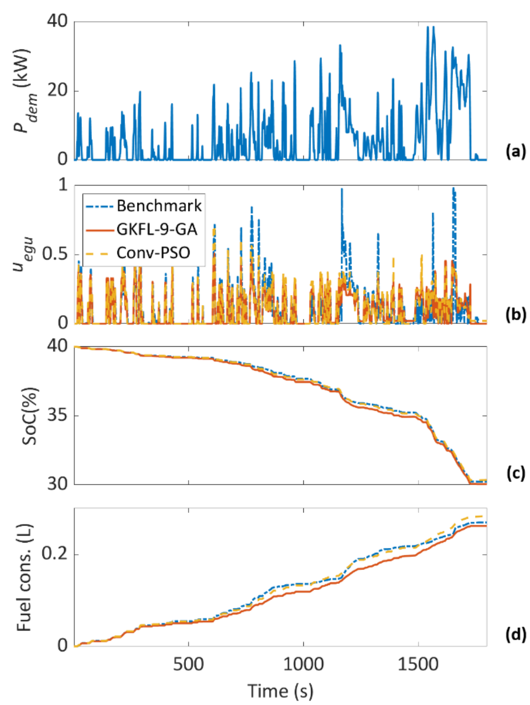

Fig. 6 Real-time performance under WLTC: (a) power demand for vehicle operation; (b) EGU control command; (c) battery SoC; (d) fuel consumptions

5. CONCLUSIONS

This paper proposes a new k-fold fuzzy learning method to implement the dynamic programming results in real-time control. SiL and HiL testing are conducted to evaluate the performance of the GKFL. The conclusions drawn from this work are as follows:

- By incorporating GKFL with GA, the global maximum control utility can be achieved when $\kappa = 9$ which is also the optimum κ value for GKFL with PSO.
- The values of $\kappa = 5,6,9$ are suggested for implementation of the offline optimization result in real-time energy management because GKFLs with these values have achieved higher control utility than the baseline.
- Compared to the default solver in the MATLAB ANFIS toolbox, GKFL can increase the CU of the studied vehicle by 8% in real-time control under WLTC.

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