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Fuzzy Logic based Power-Split Hybrid Propulsion Control System using Digital Twin Assisted Parallel Learning

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Abstract: This paper explores an innovative concept of cyber-physical real-time optimisation, in which a digital twin-assisted parallel learning (DTPL) mechanism is proposed to improve the performance of a fuzzy logic (FL-) based power-split hybrid propulsion control system in terms of stability and energy consumption. This mechanism enables parallel learning between the actual supervisor and its digital twin in real driving situations. If the virtual controller dominates the driving process, the new parameter functions are synchronised to the real controller at the same time. Based on an analysis of the conformation of the hybrid propulsion model and its FL-based control system, a chaos-enhanced accelerated particle swarm optimisation algorithm is applied to the parallel learning of the membership functions. By hardware-in-the-loop testing, the result shows that the DTPL-driven control system leads to better fuel economy. Fuel consumption can be reduced by up to 15% compared to a system using charge sustaining and charge depleting strategy, and by up to 12% compared to a system using FL control strategy over an in-house driving cycle collected from the driving simulator.

Keywords: Digital twin; fuzzy logic control system; hybrid electric propulsion powertrain; online energy management.

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1 Introduction

At present, the increases in emissions caused by traffic growth pose a challenge in terms of reducing CO_2 emissions and improving urban air quality (Wu et al., 2012). Hybridization, as a transformative technical route to full-electric vehicles, is committed to fuel economy as well as emission reductions (Sabri, Danapalasingam and Rahmat, 2016). Relying on the architecture of hybrid powertrains, they can continuously work with over 40% thermal efficiency to enhance engine torque, drivability and fuel-saving required by customers while meeting emission regulations (Lu *et al.*, 2021). When considering the improvement of dynamic performance and energy efficiency for hybrid electric vehicles (HEVs), the optimisations of energy management approaches are often a crucial part as the process of achieving the mentioned goals(Tran *et al.*, 2020).

The energy management supervisory system controls the various kinds of power flow that ensure that the traction system can be operated properly (Ferreira *et al.*, 2008). FL-based control systems provide efficient robustness that allows optimisation of energy management monitoring systems (see Ref. (Khayyam and Bab-hadiashar, 2014)). The electrical chain component evaluation vehicle has been equipped with the probabilistic FLC while its effectiveness has been assessed by modelling (Solano *et al*., 2012) and testing (Harel *et al*., 2013). The evaluation shows that probabilistic FLC (Type II) can be employed on a large scale for performing energy management tasks. Kheirandish et al. (Kheirandish *et al*., 2017) introduce the use of the dynamical fuzzy cognitive networks to account for speculations on the behaviour of fuel cell electric bicycles. However, such a system fails to escape the constraints of human cognition and its achievements also be restricted by previous experience. Tian et al. (Tian *et al*., 2018) introduced a hierarchical control by data-driving that is used for networked HEV energy controlling. The membership function of the neuro-fuzzy reasoning system with adaptive properties is formed from the trained driving data. To reduce the development workload for energy management controllers, Zhou et al. research a transferable representation modelling routine, where two artificial intelligence technologies of deep neural network(Zhou *et al.*, 2021) and Gaussian process regression (Zhou *et al*., 2022) are developed to cooperate with an adaptive neuro-fuzzy inference system for knowledge transfer of the energy management controller. Through the work of Zhou et al.(D. Zhou *et al.*, 2017) and Collotta et al.(Collotta, Pau and Maniscalco, 2017), genetic algorithms and particle swarm optimisation were applied to perform outlier optimisation of FL-based control systems. Caraveo et al.(Caraveo, Valdez and Castillo, 2016) proposed that all of the above systems have the potential to be optimised to a networked model with dynamical fuzzy parameter adaptation.

Optimisation-based control methods are influenced by numerical or analytical optimisation algorithms. Kolmanovsky (Kolmanovsky, 2014) presents the development of the game theories for HEV energy controlling and the specific experimental setup. However, the game theories cannot be extended to more vehicle types as the system elements of other vehicle types cannot be understood in depth (Martinez *et al.*, 2017). Liu et al. (Liu *et al.*, 2017) found that when reinforcement learning technologies were added to a vehicle with hybrid electric tracks, its transitional probability matrix can be derived from the particular driving schedules.

To improve vehicle system adaptability against drivers and pedestrians, Li et al. research two optimal design methods of PHEV energy management system, wherein one takes care of car owners via personalized non-stationary inference (Li *et al.*, 2021) and the other one takes care of pedestrians via pedestrian-aware interactive optimization (Li *et al*, 2021). Deep reinforcement learning (Mnih *et al.*, 2015), was applied by Wu et al. (Wu *et al.*, 2019) for developing a sequential control policy of hybrid electric buses. However, the availability and reliability of such a computationally burdensome algorithm need to be further evaluated in a real-world environment. Ahmadi et al. (Ahmadi, Bathaee and Hosseinpour, 2018) invoked a genetic algorithm to regulate the control parameters of the FLC. The vehicle was significantly improved in terms of performance and fuel economy after precise tuning. Dynamic programming is one of the benching-marking global optimisation algorithms. It explores provably optimal control policies by traversing all states (Silva and Press, 2010) (Zhang and Xiong, 2015). However, precise information about the future driving state is rarely available in practical situations. This leads to dynamic programming and genetic algorithms that cannot handle real-time problems very well (Zeng, Wang and Member, 2017).

Digital twin (DT) is an emerging concept that aims to construct a virtual mirror of a physical entity to emulate its real-world operation performance (Tao and Qi, 2019). Through its access to big data, high-dimensional expensive problems within cyber-physical systems can be better solved. (Zhou *et al.*, 2018) (Lu *et al.*, 2020). Wang et al. (Wang *et al.*, 2020) proposed a novel surrogate modelling approach combining proton physics models and data-driven modelling in the construction of an exchange membrane fuel cell model. Vohra et al. (Vohra *et al.*, 2020) developed an accelerated surrogate model for charting various input variables to live interest quantities to reduce calculated cost and time and achieve efficient multi-physics solved DTs. Through this series of discussions, computational gains can bring great potential value in the generation of training data and the optimisation of new manufacturing process control. However, the development of this technology has been constrained by the lack of clarity on specific applications.

In order to overcome the above research limitations, a new concept for cyber-physical real-time optimisation is proposed, namely DT-assisted parallel learning (DTPL) mechanism, for a fuzzy logic (FL-) based engine powered hybrid propulsion control system. The real controller and its digital twin can learn in parallel under real driving conditions using this mechanism. When the virtual controller dominates the process, the new parameters of its membership functions (MFs) are synchronised to the real controller. The contributions are as follows:

1) A DTPL mechanism is proposed to enhance the stability and energy efficiency of FL-based engine-powered hybrid propulsion control systems.

2) Chaos-enhanced accelerated particle swarm optimisation algorithm is developed to improve the efficiency of the real controller's DT for parallel learning.

3) A condition for synchronisation of controller parameters is designed by using a specific cost function to obtain better fuel economy performance.

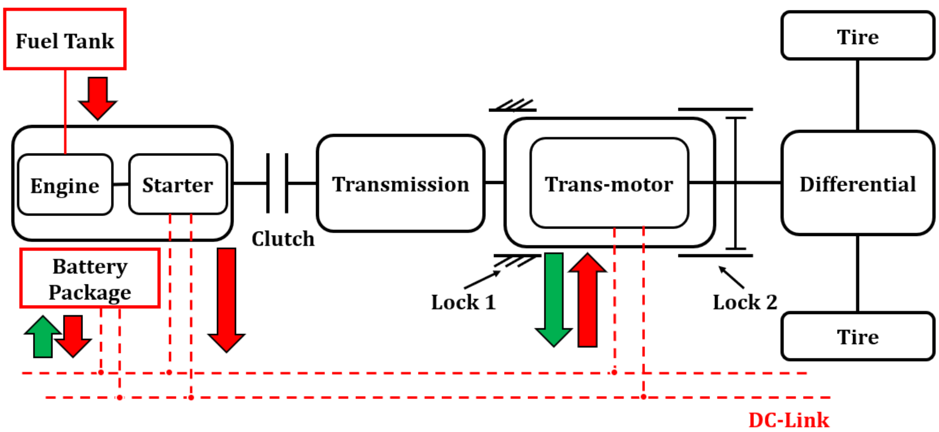
Following the Introduction, a HEV architecture and its FL-based engine-powered hybrid propulsion control system inherited from the previous study (Li, Zhou, He, *et al.*, 2020) (Li, Zhou, Williams, *et al.*, 2020) are briefly described in Section 2. In Section 3, the mechanism of DTPL is explained and the process of parallel learning and real-time evaluation is presented. In Section 4, the HiL experiment and a comparative analysis of different control strategies are carried out. Conclusions are summarised in the final.

2 Engine-powered Hybrid Propulsion Control System

2.1 System Configuration

As shown in Figure 1, the power-split hybrid propulsion powertrain consists of a gasoline engine and an integrated starter-generator (ISG) At the same time, a trans-motor is added to this powertrain. The whole powertrain is provided power by a gasoline-electric mixed contribution. The drives of the electricity and power sources are combined in series and their speeds are allowed to add up (equal torque). Different driving modes can be achieved by the collaboration of a clutch and a lock (Ehsani *et al.*, 2018). The peak power of the trans-motor is $P_{mot^*} = 75$ kW with 270 Nm maximum torque. The peak power of the gasoline engine is $P_{ICE^*} = 63$ kW with 140 Nm peak torque. The peak power of the ISG is $P_{ISG^*} = 32$ kW. The data used are from (Li, Zhou, He, *et al.*, 2020) (Li, Zhou, Williams, *et al.*, 2020).

Figure 1 The propulsion system architecture model



2.2 FL-based Supervisory Controller

Considering the need to enable the vehicle power demand, P_d, to be allocated appropriately, the torque demand, T_d, which measured at the gearbox input and the state of charge, SoC, the one of the battery pack (BP) are combined and paired to form the input quantities to the propulsion control system. The system has two traction modes: purely electric drive mode, $Mode_{EV}$, and FL-based drive mode, $Mode_{FLC}$. The modes are represented as follows:

$$\left.\begin{aligned}\left(T_{mot}, P_{ice}, P_{gen}\right) = Mode_{EV}(P_d, SoC),\ SoC > 0.5,\\ \left(n_{mot}, P_{ice}, P_{gen}\right) = Mode_{FLC}(P_d, SoC),\ SoC \leq 0.5,\end{aligned}\right\} \tag{1}$$

where: T_{mot} is the trans-motor torque; n_{mot} is the trans-motor speed; P_{ice} is the ICE power; and P_{gen} is the ISG power.

In electric mode, the ICE and ISG can be successfully deactivated as the electric traction system can achieve the full amount of torque required. The distribution of power, in this case, is as follows:

$$\left(T_{mot}, P_{ice}, P_{gen}\right) = (T_d, 0, 0). \tag{2}$$

The FLC is used to manage the vehicle energy in fuzzy logic control mode. This allows BP's SoC to safely provide power to drive the vehicle. The standard triangular MFs play a regulatory role in the current fuzzy set containing linguistic terminology. Their membership’s degrees are indicated as a normalised value function in the interval [0, 1]. MFs are classified into three levels, Low (L), Medium (M) and High (H), according to the magnitude of their values. As can be seen in Table 1, the "if A and B, then C and D" strategy is used in the rule base. This means that if the input states are A and B, then the control outputs C and D are determined. The mathematical expression for this policy is:

$$[C \quad D] = (A \times B) \circ R \tag{3}$$

where. "A" represents the fuzzy set of power demand; "B" represents the fuzzy set of SoC; "C" represents the crisp value of the normalised motor speed; "D " represents the crisp value of the normalized ISG power; "R" represents the fuzzy relation matrix of the cross product index of "A" and "B". The formula derivation is under equation (3), using the Sugeno fuzzy set below:

Table 1 Fuzzy logic rule base for decision reasoning

Rule	Demand power	SoC value	Motor speed Ref.	ISG power Ref.
1	L	L	H	H
2	M	L	L	H
3	H	L	L	H
4	L	M	H	M
5	M	M	M	M
6	H	M	L	M
7	L	H	H	L
8	M	H	H	L
9	H	H	M	L

In the inference mechanism, fuzzy sets are generated by a max-min combination. During the defuzzification process, the sets are combined and applied as crisp values for the controller output. The individual membership values are finally output as weighted by the average of the corresponding centres. In the FLC model, the final power distribution is calculated as follows:

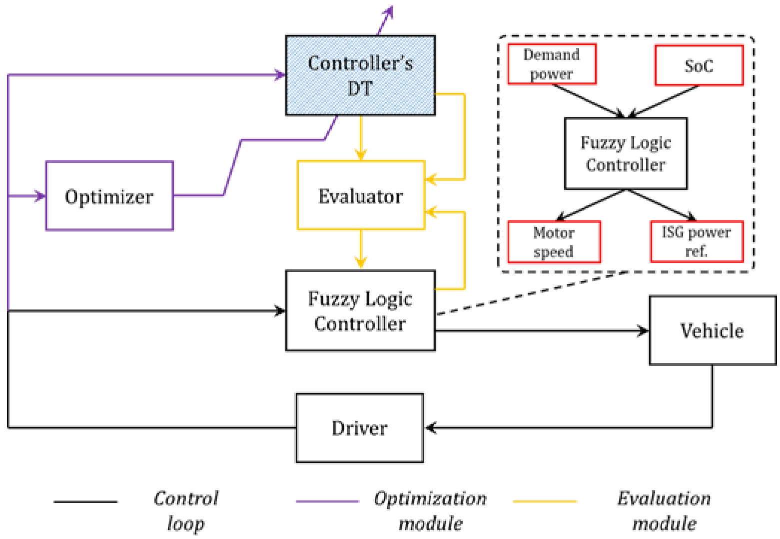
$$\left.\begin{array}{c} n_{mot} = Output_1 \cdot n_{mot}^{*}, \\ P_{gen} = Output_2 \cdot P_{gen}^{*}, \\ T_{mot} = T_d, \\ P_{ice} = \begin{cases} P_d - n_{mot} \cdot T_{mot} - P_{gen}, & P_d \geq 0, \\ -P_{gen}, & P_d < 0, \end{cases} \end{array}\right\} \tag{4}$$

where, n_{mot}^{*} is the maximum speed of the traction motor, and P_{gen}^{*} is the maximum power of the ISG.

3 Digital-Twin-Assisted Parallel Learning

The proposed DT-assisted parallel learning (DTPL) is illustrated in Figure 2. The structure consists of a DT and parallel learning module that is used as a virtual controller and a real-time evaluation module. In the parallel module, the DT has the same FL structure and is trained online with the help of an intelligent swarm optimiser. In the real-time evaluation module, the evaluator evaluates the actual controller competitively with the virtual controller. The aim is to determine whether the DT's parameters are synchronised with the actual controller. In a real driving situation, if a better MF scale parameter is detected in the DT, the evaluator will pass this parameter to the actual controller.

Figure 2 Concept of the DTPL mechanism



3.1 Parallel Learning for the Virtual Controller

The input and output parameters are set to fixed values (a_M, b_L, a_H, c_L, b_H, and c_M) to simplify the operation of the optimisation algorithm. Following this design, 24 MF scalar parameters are formulated to be optimised. The generic particles for each input and output can be presented in the following structure:

$$|a_M \quad b_L \quad a_H \quad c_L \quad b_H \quad c_M| \tag{5}$$

In order to fit the FLC structure, the parameters of the inputs and outputs should obey the following order:

$$\left.\begin{array}{ll} a_L < a_M < a_H, & a_L < b_L < c_H, \\ a_L < a_H < b_M, & b_M < c_L < c_H, \\ b_M < b_H < c_H, & b_M < c_M < c_H. \end{array}\right\} \tag{6}$$

The constraint in equation (6) cannot be ignored when considering iterations of the algorithm. The overall liquid fuel consumption and the SoC of the final BP are the two main constraint targets in this concept. These cost functions are expressed as:

$$\left.\begin{array}{l} J_1 = \frac{1}{\rho_{gaso}} \int \dot{m}_f(t) dt \\ J_2 = \frac{1}{SoC(t_{end})} \end{array}\right\} \tag{7}$$

where, ρ_{gaso} is the density of gasoline (0.77 g/ml); $\dot{m}_f$ is the fuel consumption mass rate (g/s); and t_{end} is the final time of the driving cycle.

In this concept, the weighted sum method (Marler and Arora, 2010) is used to formulate that the swarm-based algorithm is applied to transform the multi-objective into a single-objective and optimise it accordingly. Thus, the minimisation total cost function J can be used to represent an inquiry into optimal energy flow control with constraints. The following equation can be derived.

$$\min J = w \cdot \frac{J_1}{J_1^*} + (1-w) \cdot \frac{J_2}{J_2^*}$$

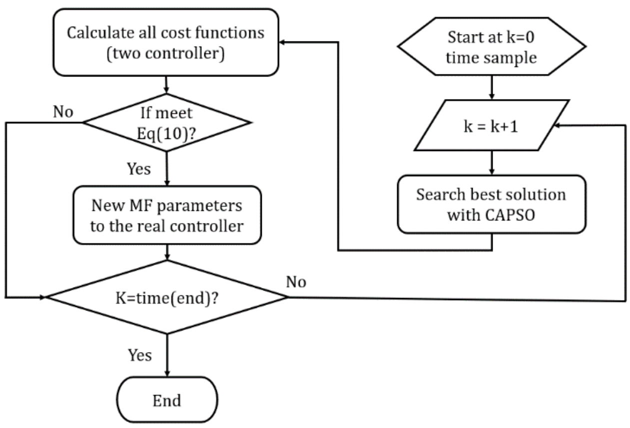
$$s.t. \begin{cases} SoC(k), & 0.8 \geq SoC(k) \geq 0.2 \\ n_{mot}(k), & n_{mot^*} \geq n_{mot}(k) \geq 0 \\ T_{mot}(k), & T_{mot^*} \geq T_{mot}(k) \geq -T_{mot^*} \\ P_{ICE}(k), & P_{ICE^*} \geq P_{ICE}(k) \geq 0 \\ P_{ISG}(k), & 0 \geq P_{ISG}(k) \geq -P_{ISG^*} \end{cases} \tag{8}$$

In Equation (8), w is a weight coefficient; J_1^* and J_2^* are scaling constants for the cost functions, J_1 and J_2. The SoC ensures the life cycle of the battery. Meanwhile, the chaos-enhanced accelerated particle swarm optimisation (CAPSO) algorithm, derived from Animal Swarm (Hossein *et al.*, 2013) is used as an online optimiser for DT here. This algorithm helps to jump out the way of convergence to a partial optimisation by dynamically attracting parameters to create some 'accident like problems in each iteration (Zhou *et al.*, 2017) (Zhou *et al.*, 2018).

3.2 Real-time Evaluation with Fuel Priority

A short-term moving window H was added to assess the fuel-saving performance comparison between FLCs with parallel learning. With H, the competition is deemed fair and equal reference driving curves to existing for parallel learning under the CAPSO algorithm.

Figure 3 Flow chart of the competitive evaluation procedure



The competitive evaluation procedure regarding the selection of a performance controller for the fuel-saving optimisation is shown in Figure 3. The optimiser applies the CAPSO algorithm to select the general optimum for the DT at each time step using the short-term driving curve constrained by the observation window as a reference criterion. The best scalar parameters of the MF are applied to the DT. Thus, The strengths and weaknesses of the two products in terms of fuel-saving optimisation are assessed.

With the effect of the length of the observation window on fuel consumption, the cost function (2 controllers) is derived as:

$$\left.\begin{aligned} csn_{real} &= w \cdot \frac{J_1'}{H \cdot J_1^*} + (1-w) \cdot \left(\frac{J_2'}{H \cdot J_2^*}\right)^2, \\ csn_{virtual} &= w \cdot \frac{J_1''}{H \cdot J_1^*} + (1-w) \cdot \left(\frac{J_2''}{H \cdot J_2^*}\right)^2, \end{aligned}\right\} \tag{9}$$

where H is the length of the observation window; csn_{real} and $csn_{virtual}$ are the cost functions of the two controllers; J_1' and J_2' are the evaluation objects for the execution controller; and J_1'' and J_2'' are the evaluation objects for the trained controller.

The cost function of the actual controller is often considered to be the learning target of another controller in practical situations. The DTPL mechanism derives the cost function of each controller when the conditions are met as follows:

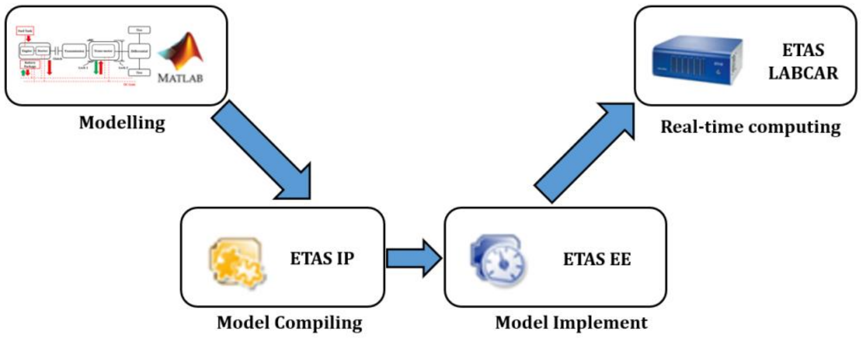
$$\left.\begin{aligned} & csn_{virtual}(k) - csn_{real}(k) < 0, \text{and} \\ & \frac{csn_{virtual}(k) - csn_{real}(k)}{csn_{virtual}(k-1) - csn_{real}(k-1)} < 1. \end{aligned}\right\} \tag{10}$$

where the error and derivative of the cost function greatly influence the final decision for this test. If $csn_{virtual}(k-1) - csn_{real}(k-1) = 0$, then only the first condition of Equation (10) should be met and the MF scalar parameters in the virtual controller are then passed to the real controller. Otherwise, it continues to explore new scalar parameters to provide a solution with more efficient fuel-saving performance to be used at the next time step.

4 Result and Discussion

The working environment for this test was based on industry-standard real-time test equipment purchased by the ETAS Group (ETAS Products, 2018). Figure 4 illustrates the setup flow of the HiL test system. The HEV model and FL control system were obeyed into MATLAB code in the first step. Afterwards, the code is exported to consolidation platforms via the host computer. In the user interface for configuring the HiL system, signal paths are created in the model and hardware. At the same time, the LABCAR simulation target LABCAR-RTPC generates the code. Finally, the entire vehicle system is downloaded to DESK-LABCAR by the ETAS Experimental Environment (EE) under the ethernet protocol.

Figure 4 Hardware-in-the-loop test bench



EE monitors the performance of the vehicle. The recorded results display that the average time taken for the CAPSO algorithm to converge is 0.225 seconds. Given this average time, it is assumed that its capacity can continue to increase and that computational resources will still be available while still meeting the needs of the current version. According to Moore's law, the mechanism of DTPL working on an actual onboard controller for HEVs is expected and affordable.

4.1 Competitive Learning Performance

The MF generates an evaluation of parallel learning as it evolves. This involved the cost function going through 15 iterations. The 100 km test cycle provided by Li et al. (Li, Zhou, *et al.*, 2019) through observing human drivers interaction, wherein a driving simulator and CarMaker software are both used.

Figure 5 Membership function evolution

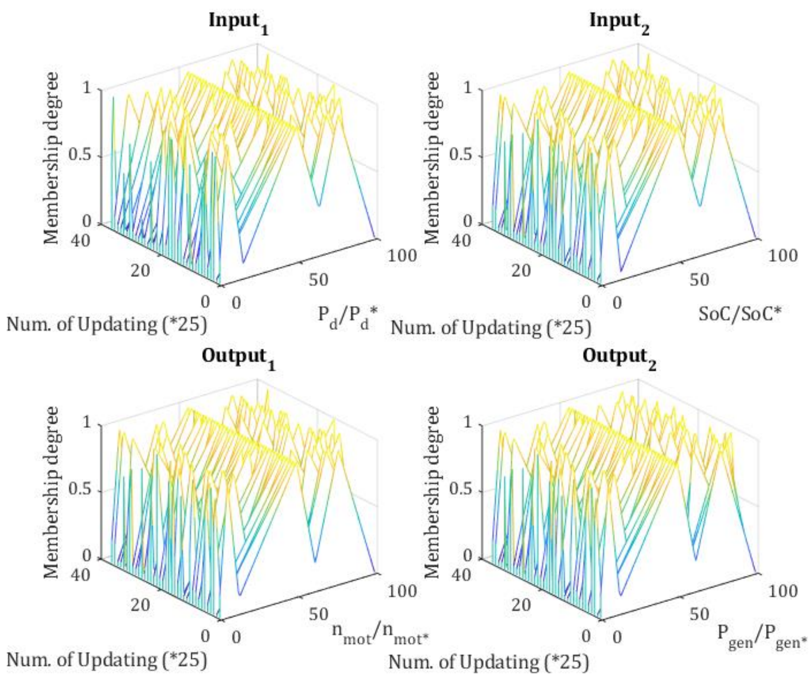
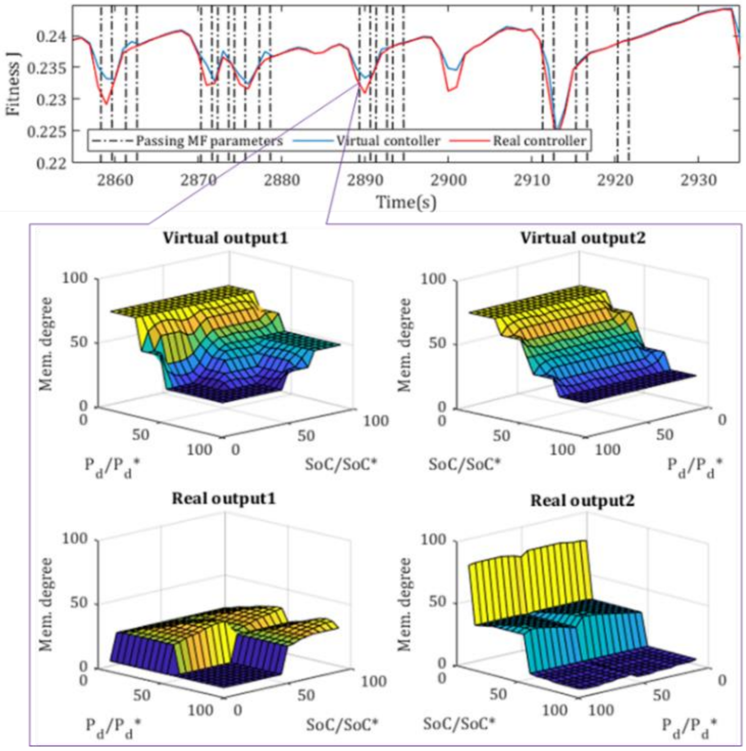


Fig. 5 shows the MF evolution process driven by the CAPSO algorithm for an initial SoC of 0.4 during real-world driving. The MF scalar parameters of the inputs and the outputs have been updated 957 times over the 8000-second driving cycle. The average updating time of the MF scalar parameters is 8.36 seconds which means that the average application time of a set of MF scalar parameters for real-world driving with uncertain driving behaviours is 8.36 seconds.

Figure 6 Real-time performance of two FLCs boosted by the DTPL

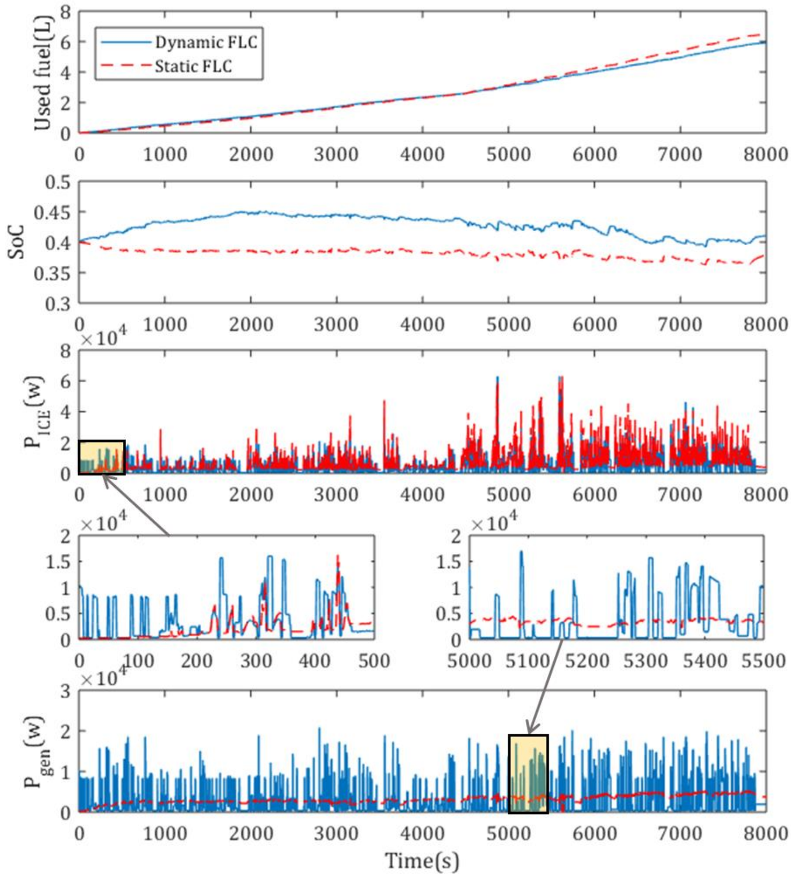


Some of the real-time performance of the two FLCs is shown in Figure 6. The black dashed line represents the time of the MF parameters. As can be seen from the above subplot results, the DT is continuously updated by the DTPL and the parameters tend to pass at prominent spikes. Significant changes in human driving behaviour are the cause of this. The subplot below analyses the evolution of the output between FLCs at 2889s. It can be seen that the DTPL mechanism uses an aggressive output surface geared towards higher fuel economy in place of a correspondingly smooth output surface for most existing driving situations.

4.2 Vehicle Performance Comparison

Figure 7 illustrates a comparative analysis of the hybrid propulsion control system with a conventional control system based on FL. The new mechanism proposed in this paper has lower fuel consumption and a higher SoC value. Driven by it, the ICE initially focuses on compensating the overall power needs to prevent possible risks of a rapid drop in SoC. The ISG also takes on a higher workload than a conventional FL-based control system.

Figure 7 Vehicle performance comparisons at initial SoC=0.4



The vehicle performance under three policies is summarised in Table 2. similar results can be observed for the performances with SoCs of 0.5 and 0.3. The classical rule-based control strategy utilising charge depletion (CD) and charge sustaining (CS) is applied as a benchmark for comparing different FL-based strategies. As the SoC decreases, the space available for system energy to be freely allocated shrinks seriously. Compared to the baseline strategy, an offline optimised FL static system can adaptively adjust the energy allocation but it is not as effective. The new FL dynamic mechanism of the DTPL collaboration, however, allows the selection of a controller with a better cost function to be driven in real-time. The results show that this optimised system has the best performance in terms of fuel-saving. At the same time, it can keep a high SoC value. Considering the rigour of the research, future work will focus on the experimental validation onboard.

Table 2 The vehicle performance with different control policies

Control strategy	Initial SoC	Final SoC	Fuel consumption (L/100km)	Saving (%)
CD/CS	0.5	0.353	6.41	-
Static FLC	0.5	0.379	6.24	2.7%
Dynamic FLC	0.5	0.408	5.44	15.1%
CD/CS	0.4	0.351	6.63	-
Static FLC	0.4	0.379	6.48	2.3%
Dynamic FLC	0.4	0.412	5.88	11.3%
CD/CS	0.3	0.352	6.89	-
Static FLC	0.3	0.379	6.75	2.0%
Dynamic FLC	0.3	0.408	6.26	9.14%

5 Conclusion

This paper proposes a DT-assisted parallel learning (DTPL) mechanism. This mechanism can assist FL-based engine drive control systems with higher fuel-saving efficiency. Rule-based strategies, as well as static FLC strategies, are also used for comparative analysis with the mechanism proposed in this paper. The findings of this study are as follows:

1) Assisted by DT technology, the proposed mechanism can adapt to changes in driving behaviour in real-time while ensuring the effective working of the original FL-based control system.
2) Compared to the conventional two control strategies, the proposed mechanism with dynamic FLCs in this paper can reduce fuel consumption and maintain a high SoC final value under various initial SoC value settings.
3) The FL-based control system under DTPL optimisation can significantly reduce fuel consumption during real-world driving, wherein the fuel consumption performance can be saved by up to 15% compared to conventional CD/CS systems and up to 12% compared to conventional static FL-based systems.

Acknowledge

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