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Design of magnetic flywheel control for performance improvement of fuel cells used in vehicles

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ABSTRACT

Because hydrogen can be extracted naturally and stored for a long time, different types of fuel cells have been developed to generate clean power, particularly for use in vehicles. However, the power demand of a running vehicle leads to unstable and irregular loading of fuel cells. This not only reduces fuel cell lifespan and efficiency but also affects driving safety when the slow output response cannot satisfy an abrupt increase in power demand. Magnetic flywheels with characteristics such as high energy density, high-speed charging ability, and low loss have been extensively used in Formula One cars. This study developed a hybrid powertrain in which a magnetic flywheel system (MFS) is integrated with the fuel cells to solve the aforementioned problems. Moreover, an auto-tuning proportional–integral–derivative (PID) controller based on the controls of a multiple adaptive neuro-fuzzy interference system and particle swarm optimization was designed for MFS control. Furthermore, MATLAB/Simulink simulations considering an FTP-75 urban driving cycle were conducted, and a variability improvement of approximately 27.3% in fuel cell output was achieved.

1. Introduction

Energy modeling is now able to make useful contributions to planning and policy formulation in some areas of application [1]. Several approaches based on the available data were proposed to model transport energy consumption. These approaches can be classified into two clusters: econometric and artificial intelligence ones. The former includes multiple linear regression [2], partial least square regression [3], and time series [4–6] while the later includes artificial neural network [2] and [7], harmony search algorithm [8] and Fuzzy theory [9]. Here, NNs (neural network) and FL (fuzzy logic) systems are among the most powerful algorithms for monitoring data pattern classification in diagnostic tasks [1], [10].

In the automobile industry, the main focus is currently on electric cars. However, the major disadvantage of electric cars is that they must be recharged once every 150 miles. Charging a car at home is easy; however, locating a public charging station when travelling can be difficult.

A fuel cell is less complicated than a conventional gas or diesel engine because it is not subjected to high temperatures, corrosion, or any of the structural drawbacks present in conventional engines. In theory, it can operate efficiently and indefinitely as long as it has a fuel source, and its sole tailpipe emission is water vapor. Currently, fuel cells are considered possible alternative power sources for new automobiles. However, some drawbacks of fuel cells, such as poor transient performance because of slow start-up and slow power response and bidirectional energy flow because of the braking energy regeneration, are yet to be overcome. In addition, the target fuel cell lifetime in the continuous operation mode varies considerably from 5000 h for cars to 20,000 h for buses and 40,000 h for stationary applications. The lifetime of fuel cell in automobile applications is considerably lower than that for stationary applications [11], because such operating conditions as dynamic load cycling, startup/shutdown, and freeze/thaw affect fuel cell performance.

To overcome the aforementioned drawbacks, fuel cells must be integrated with other energy storage devices, such as batteries or supercapacitors; examples of such integration include Toyota fuel cell hybrid vehicles and Honda FCX fuel cell vehicles [12], [13].

With the development of high-strength and light-weight composite materials, power electronics, lithium-ion batteries, bearings, and controls, the magnetic flywheel system (MFS) becomes an

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alternative instead of conventional battery systems for solving energy storage problems. The MFS has several advantages, such as high energy storage density, lower risk of overcharge or discharge, wide operable temperature range, and long lifespan, and is environmentally friendly [14], [15]. In this study, the MFS was used in hybrid powertrains. The fuel cell system offers the base power when driving at a constant speed and the MFS provides additional power during start-up and acceleration and recovers the braking energy. Therefore, the proposed powertrain not only reduces the power rating of fuel cells but also improves the transient performance and energy efficiency of the powertrain.

In the proposed powertrain, when the power demand increases, the fuel cell—through the dc/dc converter, inverter, and ac motor, together with the MFS—powers the vehicle shaft. When the power demand is low, the fuel cell—through the dc/dc converter, inverter, and ac motor—powers the vehicle shaft and directly charges the MFS. When the vehicle brakes are applied, the MFS absorbs the kinetic energy of the vehicle directly without using the aforementioned converter and inverter. Compared with most fuel cell electric vehicles (FCEVs), which are facilitated by batteries and supercapacitors [12], [13], [16], the proposed powertrain is clearly more efficient.

To control the MFS with more flexibility, an autotuning proportional–integral–derivative (PID) controller was designed in this study. Conventional PID controllers have three major shortcomings. First, a formula-based PID design generally necessitates system identification before designing. If the controlled body is a nonlinear system with system coupling or time delay, determining the transfer function is difficult, thus rendering the formulas and principles unusable. The response obtained using the formula-based approach is not optimal, and online instantaneous adjustment cannot be performed because the obtained solution is fixed. Second, a rule-based design typically requires an expert to design the rule base; moreover, it requires a large database. Third, the conventional optimization-based design mainly obtains the optimal solution through offline methods such as genetic algorithms and simulated annealing. Furthermore, the controller cannot be instantaneously adjusted to the optimal status, that is, the optimal control results are obtained by tuning the three gains: proportional gain Kp, integral gain Ki, and derivative gain Kd. For a single-input–single-output system, tuning methods, such as Cohen–Coon and Ziegler–Nichols rules, are usually used [17], [18]. For the nonlinearities of machines, power converter and controller, tuning an electric drive controller is a complex problem. To solve this problem, a modified particle swarm optimization (PSO) algorithm to optimize PID gains was presented.

PSO is a population-based stochastic algorithm for optimization [2], [19]. It is robust in solving continuous nonlinear optimization problems by iteratively attempting to improve a particle solution for a given target. Because optimally tuning the gains of PID controllers is extremely difficult, PID tuning methods by using the PSO algorithm have been successively proposed in recent years [20], [21]. However, some studies [22–24] have indicated that because of the utilization of a linearly decreasing inertia weight, PSO may lack global search ability at the end of a run (a run is defined as the total number of generations of the evolutionary algorithms prior to termination). It may fail to determine the required optima when the problems to be solved are extremely complicated.

The adaptive neuro-fuzzy inference system (ANFIS) design technique using neural networks to tune the fuzzy logic Sugeno model type controllers is crucial [25–27] in learning, tracking, and estimation. Through hybrid learning to determine the optimal distribution of membership functions, the ANFIS is beneficial in constructing the mapping relation between the input and output data without considering system nonlinearities, uncertainties, and complications [10], [27]. Furthermore, in neuro-fuzzy approach the capability of fuzzy-ruled based systems in handling uncertain and noisy data and the learning capability of neural networks are combined to form better estimators [28], [29]. ANFIS, as a hybrid intelligent system that enhances the ability to automatically learn and adapt, has shown significant results in modeling [30–32], predictions [33], [34], and controls [35–37].

In this study, the ANFIS was further extended to the multiple ANFIS (MANFIS) architecture to tune the PID controller, combined with PSO. The control purpose of such a control combination is to improve the global search ability of PSO and obtain online optimal PID gains for system control.

2. Configurations of hybrid powertrains

The fuel cell system has such disadvantages as slow start-up, low power response, and relatively lower efficiency at low and high power output. Developing hybrid powertrains should overcome these problems [38], [39]. In this study, the fuel cell system was controlled to avoid operating in low-efficiency regions and supplied the base power, whereas the MFS offered peak power for rapid acceleration and recovered the braking energy. For hybrid powertrains, a control strategy of the MFS based on a designed fuzzy controller was proposed to manage the power flow, detecting various demands of vehicle load and avoiding fuel cells operating in low-efficiency regions. This implies that the fuel cell provided a close-to-constant output, as shown in Fig. 1. In this study, three types of configurations of the powertrain with the MFS, which is regarded as a tunable energy-storage device, were considered (Fig. 2 (a), (b), and (c)). As shown in Fig. 2 (a), if the vehicle load is larger than the fuel cell output, then the MFS discharges power to the shaft of the vehicle. In this case, the governing equation is

$$P_{FC} + \Delta P_{MFS} = P_v(t) \tag{1}$$

where P_{FC} is the constant output power of the fuel cell, ΔP_{MFS} is the charge/discharge power of the MFS, and $Pv(t)$ is the demand power

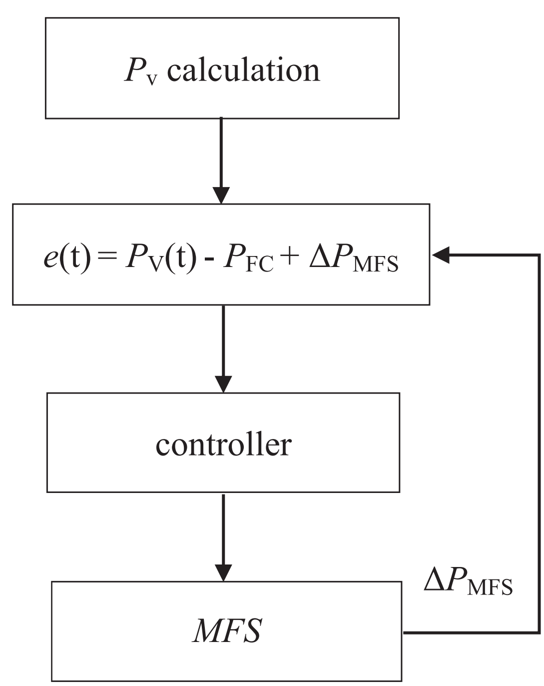

Fig. 1. Illustration of the control design.

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