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Designing an optimal fuzzy controller for a fuel cell vehicle considering driving patterns

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Abstract. Design of an optimal fuzzy scheme for a fuel cell/battery vehicle to control the power flow between the main components, i.e. the fuel cell, electric motor, and battery, under various driving conditions, is considered in this paper. For this purpose, firstly, the optimum sizes of the main components are calculated by means of a Particle Swarm Optimization (PSO) algorithm. Subsequently, a Fuzzy Logic Controller (FLC) is devised for the control of the power flow. Finally, the FLC is optimized for various driving patterns and an optimal control scheme, based on PSO application, is proposed for energy management of the Fuel Cell Vehicle (FCV) under various traffic conditions. In each one of the mentioned stages, the same optimization process is conducted by applying a Genetic Algorithm (GA) for comparison with the result of the PSO. The results of the computer simulation are compared over diverse driving conditions. The results give an acceptable indication of progress in fuel economy for various driving patterns, using the proposed optimal fuzzy controller.

1. Introduction

Present-day society has substantial dependence on fossil fuels since they supply power to vehicles, machines and even power stations. The enormous global growth of car production is inexorable due to transformation of the social structure by urbanization. There is no disputing the fact that this growing trend comes with some direct consequences. The overall picture is analogous to a chain of events, since oil assumes a key role in the development of transportation. Air pollution and climate change are major drawbacks associated with burning oil, and vehicles are perceived as potential candidates for its consumption. Global warming, which is one of the most vigorously debated topics on Earth, is attributed to the accumulation of greenhouse gases like carbon dioxide, the product of igniting fossil fuels in the atmosphere. Overall, accomplishing environmental and energy sustainability falls under the direct influence of vehicles and personal transportation [1,2].

Running on petrol and diesel fuel, conventional vehicles are counted as a main contributor to air pollution and carbon dioxide release. Furthermore, there are other exhaust fumes from conventional vehicles, inclusive of carbon monoxide and nitrogen oxides. In short, the drawbacks of conventional vehicles encompass high energy loss, undue detrimental exhaust emissions, and heavy reliance upon a sole fuel source. Conventional vehicles also employ a sole Internal Combustion Engine (ICE) as the power source [3].

Electric vehicles encompass a range of virtues and issues competing against one another. By far, the main benefits gained from electric vehicles are the absence of emissions and high efficiency. It is worth remembering that the positive aspects of electric

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vehicles are attributable to the absence of internal combustion engines. However, high cost, limited driving range and confined charge sustainability are still conceived as worrying drawbacks associated with electric vehicles [4,5].

Hybrid Electric Vehicles (HEVs) are one of the alternatives proposed to address the issues associated with the energy crises and global warming. HEVs, which are comprised of an Internal Combustion Engine (ICE) as the primary power source and an electric motor as the secondary power source, surmount conventional and EVs related challenges, such as high cost and limited driving range, since they need not plug in to charge. Moreover, the fuel consumption of HEVs is greatly decreased in comparison with conventional vehicles. Nevertheless, they still run on fossil fuels [6].

FCVs embrace hybrid vehicles and hydrogen fuel cell technology to elude exhaust emissions and optimize fuel consumption [7]. Fuel cell vehicles are generally viewed as zero emission vehicles, thanks to omission of the combustion process. In FCVs, hydrogen and oxygen are translated into electricity by means of fuel cells. Hence, no tailpipe pollutants are produced in order to propel the vehicle. Water and heat are counted as products of the mentioned reaction. In automotive applications, virtually all the significant manufacturers have declared that plans for commercializing FCVs are on the horizon [8].

In particular, the Proton Exchange Membrane Fuel Cell (PEMFC) is an auspicious candidate for FCVs, owing to its inherent characteristics, which include high power density, higher efficiency and lower temperature operation, in comparison with ICEs [9]. Nevertheless, due to the unsteady power demand of a vehicle during its operation, application of a sole FC system as the power source is not appropriate. As a general rule, combining FC systems with an Energy Storage System (ESS) diminishes cost, enhances performance, and provides fuel economy [10].

Batteries are a prime example of ESS in FCV applications. Among dozens of existing batteries, Lithium-ion batteries are the most promising for applying in FCVs, by virtue of their energy density and power density range [11].

Since FC and battery have diverse dynamic characteristics, an appropriate Energy Management Strategy (EMS) seems to be vital for this system [12,13]. The EMS, preset in the vehicle controller, is to control the power flow between the FC system, the ESS, and the drive train. There are a number of EMSs for FCVs, such as intelligent-based EMSs and optimization-based EMSs. Among intelligent-based EMSs, FLC has a quite suitable performance, as reported in many studies [14-16]. Overall, FLC furnishes firm deduction, from inexact and inexplicit information, about the state of the system in an undemanding way. Classical control demands profound knowledge of a system and accurate equations. In contrast, FLC permits modeling convoluted systems by employing an expert's knowledge and experience. In comparison to regular approaches, FLC presents an appropriate performance in nonlinear systems where acquiring an entire mathematical model is very demanding. Furthermore, another strength ascribed to such a control approach, in comparison with other methods like neural networks, is that it is entirely independent of former data. For the reasons above, it is evident that FLC has a fairly proper configuration for FCVs [17,18].

Utilizing unaided FLC provokes some debates, as follows: Firstly, FLC is designed based on the technical expertise of the designer. Therefore, it cannot succeed in accomplishing higher efficiency under all operating conditions of a complex system like FCV. Secondly, driving patterns, which represent real traffic conditions and have a profound impact on the fuel consumption of the FCV, are not incorporated in the design of the control strategy [19]. From this standpoint, the most important course of action to address these issues is to employ optimization algorithms for modelling an optimal FLC. In this case, the impact of driving patterns on fuel consumption is considered in the control design of the FCV.

There are dozens of algorithms applicable to the optimization process of complex systems. They can fall into diverse categories; for instance, local optimization methods against global ones; a deterministic optimization algorithm versus a stochastic optimization algorithm; or the gradient-based algorithm versus the derivative-free algorithm. The main drawback of local optimization methods is that they do not search the whole design space for finding the answer. Unlike local optimization methods, global optimization algorithms are capable of finding the best optimum answer in FCV applications. Derivative-free and stochastic optimization methods, despite gradient-based and deterministic methods, are not dependent on the derivatives, and can deal with inherent nonlinear or discontinuous systems effectively. The Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are perceived as potential means for vehicular applications, since they are fitted into global, stochastic, derivative-free optimization categories [20].

There are a number of approaches to identify existing situations and project future driving conditions. The main techniques fall into three categories: The Global Positioning System (GPS) or Intelligent Transportation System (ITS)-based method, which acquires several driving features, such as speed, acceleration etc. to implement in different control strategies like dynamic programming [21,22]. Statistic and clustering analysis-based approaches, in which future driving conditions are predicted by scrutinizing former and current driving information [23]. The sentence is not complete. The last category is Markov chain-based technique, which proves helpful for stochastic process prediction.

In this paper, a new optimal fuzzy controller based on the PSO algorithm is suggested to control the power flow between the FCV main components, i.e. Lithium-ion battery, PEMFC, and electric motor. For this purpose, firstly, the optimal sizes of the aforementioned components are determined. A backward/forward simulation approach is then employed to formulate the power flow in the drive train system over various driving conditions. Finally, the optimal controller is implemented. It is worth remembering that the same optimization process is done by utilizing the GA method, and the ultimate outcomes are compared with PSO.

This paper is organized as follows: Section 2 presents a description of the power train system and driving cycles. Section 3 describes the design of the primary FLC and the optimal FLC. Section 4 presents the simulation results. Finally, conclusions are given in Section 5.

2. Modeling and simulation

2.1. Drive train

$A(FC + B)$ architecture is a common structure in FCVs [25]. As shown in Figure 1, in this structure, a battery is regularly connected to the FC system in order to supply additional power for starting the system. Unlike the PEMFC, which is linked to the DC bus by a DC/DC converter, the battery is directly connected to the bus. The total power, provided by the FC and the battery, flows towards the Electric Motor (EM) after passing the DC/AC inverter. The electric motor converts the electric energy into mechanical energy to propel the vehicle or to generate electricity for the purpose of charging the batteries [26].

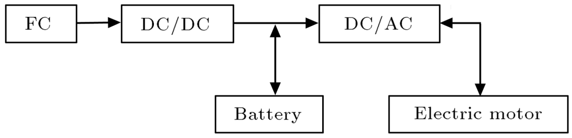

Figure 1. Drive train.

Some of the specifications of the vehicle and its key components are explained in Table 1.

2.2. Driving cycles

It is difficult to precisely describe the driving patterns and speed variations under all traffic conditions. However, some representative driving cycles have been developed to emulate typical traffic environments [27]. Driving cycles are standard vehicle speed versus time profiles developed for testing vehicle exhaust emissions and fuel consumption in a standard laboratory test. In this paper, three diverse driving cycles, the Federal Test Procedure driving cycle (FTP), the Economic

Table 1. Some data regarding the vehicle and its chief components.

Specifications	
Vehicle	Class: Average Model: Saturn SL Total mass: 1380 kg Dimensions (mm): Length: 4478, width: 1717, height: 1285 Transmission type: Automatic, 5-speed
Fuel cell system	Type: PEMFC Model: Based on ANL (Argonne National Laboratory) model Fuel type: Hydrogen Peak efficiency: 60% Maximum output power: 44 kw FC weight: 223 kg Stack and reformer pressure drop: 15 to 30 kPa
Battery	Type: Lithium ion battery Model: Saft (6 Ah) Number of cell: 29 Maximum voltage: 3.9 V
Electric motor	Model: Westinghouse induction electric motor (inverter) Maximum output power: 44 kw Peak efficiency: 92% Weight: 91 kg

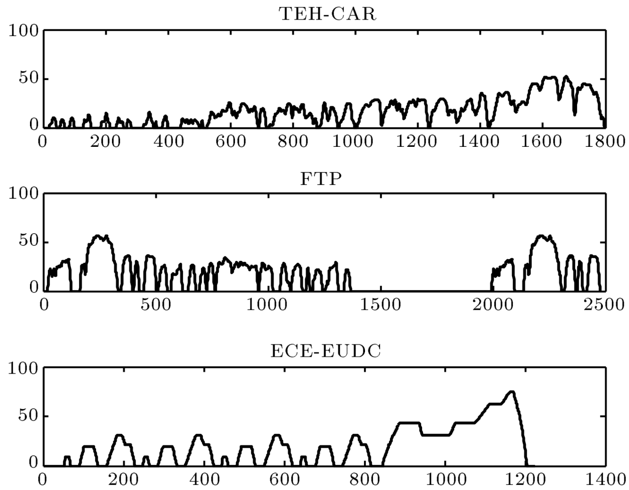

Figure 2. TEH-CAR, FTP, and ECE-EUDC driving cycle.

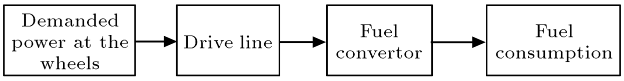

Figure 3. Backward-facing simulation.

Commission for Europe and Extra Urban Driving Cycle (ECE-EUDC) [28], and Tehran city driving cycle (TEH-CAR) [29], are employed in a simulation process. The aforementioned driving cycles, which are employed in this study, are shown in Figure 2.

2.3. Simulation approach

Considering the direction of computation, simulation methods come into two categories, including forward-facing and backward-facing. In the latter, which resembles the standard laboratory emission test, the simulation chain, as shown in Figure 3, starts with the power demand at the wheels and continues until the operating point of the fuel cell, which can be translated to fuel consumption. However, in the first approach, the simulation process commences with the fuel converter coming towards the wheels. In this study, a backward/forward facing simulation procedure is utilized to formulate the power flow.

3. Energy management

3.1. Component sizing

Designing appropriate component sizes, to achieve preferable vehicle performance, plays a significant role in the control design of a FCV. In general, a hybrid power train is composed of electric motors, power electronics converters, energy storage devices, fuel converters, and so on. Thus, the complexity of a hybrid power train is far more convoluted than a conventional one. A parametric design can be utilized to evaluate the size of the main components in hybrid vehicles [30]. In this study, design parameters encompass the maximum power of the fuel converter (fuel cell), the maximum power of the electric motor, and the number of battery modules. As mentioned earlier, among variant global algorithms, GA and PSO seem to be potential candidates for the component sizing process, as they do not converge to the local extrema.

It is worth mentioning that the prime merit of the PSO algorithm is that fewer parameters need to be tuned in comparison to the GA. Furthermore, the equations are more straightforward and some operators, such as crossover, mutation, and selection, are not needed. On account of the mentioned merits, the PSO algorithm is able to converge to optimum at a quite rapid pace, compared to evolutionary algorithms like GA. It should be noted that selecting suitable constants is highly important in gaining a superior performance, while employing PSO.

In this paper, Particle Swarm Optimization (PSO) is utilized for determining the desired component sizes. The PSO is a swarm intelligence technique and an evolutionary algorithm, inspired by the flocking behavior of birds, which was developed by Kennedy and Eberhart [31]. Generally, the PSO algorithm commences searching by a random population, or swarm, of candidate solutions, called particles. These particles go around the search-space, employing some simple formulas, to trace the solutions. While searching the whole space, particles are aware of their own best position and the entire swarm's best position. When particles notice an improvement in positions, they guide the swarm towards it. The process is repeated until achieving a satisfactory solution. The flowchart representing the PSO algorithm is shown in Figure 4.

The velocity of each particle is updated as follows:

$$\begin{aligned} v_i^{n+1} =& k v_i^n + \alpha_1 \mathrm{rand}_1 (pbest_i - p_i^n) \\ &+ \alpha_2 \mathrm{rand}_2 (gbest - p_i^n), \end{aligned} \tag{1}$$

where v_i^{n+1} is the velocity of particle i at iteration $n+1$, k is the weighing factor, α_1 and α_2 are the weighing factors, rand_1 and rand_2 are two random numbers between 0 and 1, p_i^n is the position of particle i at iteration n, $pbest_i$ is the best position of particle i, and $gbest$ is the best position of the swarm.

Similarly, the position is updated as follows:

$$p_i^{n+1} = p_i^n + v_i^{n+1}. \tag{2}$$

As mentioned before, this study attempts to reach fuel economy without sacrificing vehicle performance. Therefore, Partnership for the Next Generation of Vehicle (PNGV) constraints [32] is considered a penalty for the fitness function. The penalty is used to update *pbest* and *gbest* for each particle. For a particle i, the *pbest* value is updated if the penalty of the particle is less than the previous best penalty. The same is

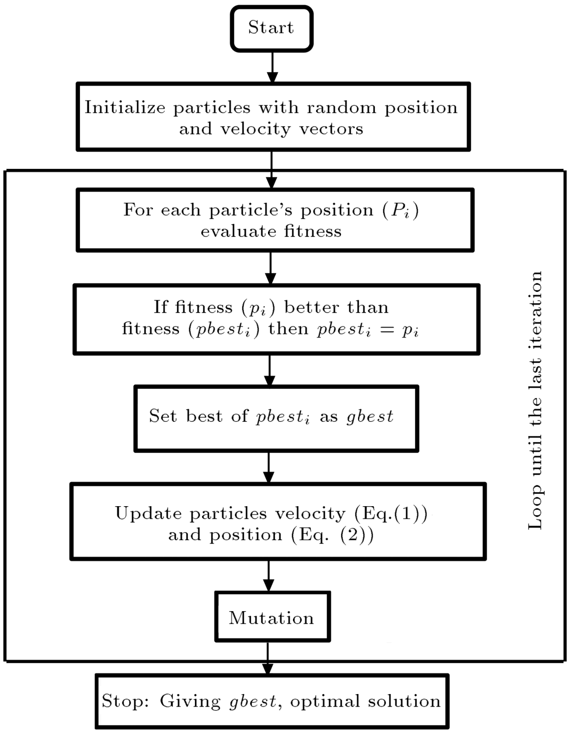

Figure 4. PSO flowchart.

Table 2. Design variables limitations.

Variable bounds	Upper bound	Lower bound
S_{FC}	1.3	0.7
S_{EM}	1.3	0.1
N_{BM}	35	5

done when *gbest* is updated. This makes sure that the objective function is maximized. In addition to the PNGV passenger constraints, some limitations are imposed on design variables, as listed in Table 2.

In this table, S_{FC} is the scaling factor for the fuel converter, S_{EM} is the scaling factor for the electric motor, and N_{BM} is the number of battery modules. In order to employ the PSO algorithm, a fitness function is demanded. Penalty functions are utilized to apply the constraints to the problem. The fitness function is formulated as follows:

$$F(x) = \frac{1}{F_c} - \sum_{i-1}^{N_{\mathrm{con}}} \alpha_i \times C_i(x), \tag{3}$$

where $F(x)$ is the fitness function, F_c is fuel consumption, $C_i(x)$ is the penalty function of the related constraint, and α_i is the amount of punishment for each constraint, attained by trial and error. It should be noted that as a control strategy has no considerable impact on the sizing procedure [33], the component sizing process is done by employing the thermostat control strategy.

3.2. Fuzzy logic controller

In this study, FLC has been employed for the energy management of the system. Several advantages can be counted for this control approach. Firstly, it is based on verbose statements, which provides the capability of integrating the knowledge of an expert into the design procedure. Moreover, it does not need an exact model of the system. It is a key advantage in the FCV, where, in the backward-facing simulation approach, an explicit model of the system is not available. Furthermore, FLC has an inherent robustness which can cope with uncertainties in the control design procedure. The employed controller is a PD FLC, which incorporates the required power and the State Of Charge (SOC) as inputs, and requested power from the FC as the output. Characteristics of the FLC are also as follows: The fuzzy system type is Mamdani, the inference engine is AND (minimum operator) and diffuzification is centroid. The fuzzy system is shown in Figure 5.

Besides, the fuzzy control surface is shown in Figure 6. Each input and output has three MFs, as shown in Figure 7. In Figure 7, the trapezoid MF is used for small, big, low, and high MFs in inputs and output. The triangle MF is employed for Average and Normal MFs in inputs and output. The fuzzy reasoning rules with 9 items are given in Table 3.

3.3. Optimal fuzzy logic controller

In the FLC discussed in the foregoing section, the membership functions are distributed uniformly over

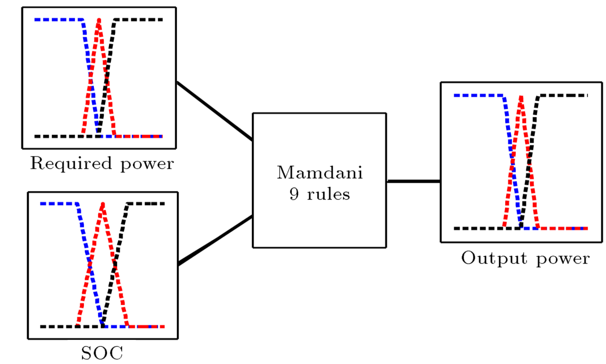

Figure 5. Fuzzy system.

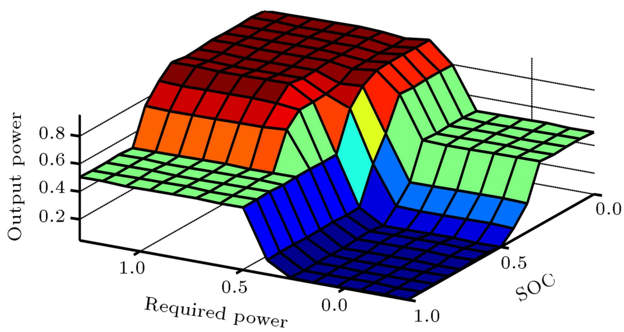

Figure 6. Fuzzy control surface.

Table 3. Fuzzy reasoning rules.

Rules descriptions
If (required power is small) and (SOC is low) then (output power is average)
If (required power is small) and (SOC is normal) then (output power is small)
If (required power is small) and (SOC is high) then (output power is small)
If (required power is average) and (SOC is low) then (output power is big)
If (required power is average) and (SOC is normal) then (output power is average)
If (required power is average) and (SOC is high) then (output power is average)
If (required power is big) and (SOC is low) then (output power is big)
If (required power is big) and (SOC is normal) then (output power is big)
If (required power is big) and (SOC is high) then (output power is average)

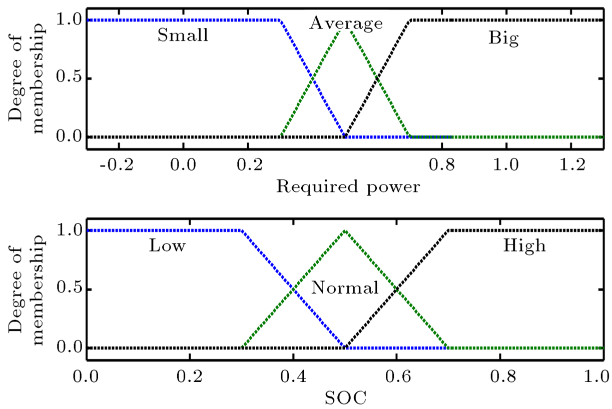

Figure 7. Input membership functions.

the universe of discourse. Therefore, it does not necessarily work optimally over variant driving cycles. In other words, some parameters need to be modified in the FLC, for each driving cycle, in order to achieve optimal fuel consumption in the corresponding traffic condition [34]. In designing a FLC, driving patterns should be taken into consideration because driving habits are dissimilar in different areas. Thus, they may exert a strong influence over operating points of the FC and, consequently, on fuel consumption.

In this section, the application of PSO to create a novel optimal FLC (Fuzzy-PSO) is represented. An optimal fuzzy controller is a FLC in which some parameters are adjusted, concerning the driving pattern, by an optimization algorithm to minimize the fitness function to a feasible extent [35]. In this paper, PSO is exploited as an optimizer. The optimum sized parameters, achieved in Section 3, are utilized as scaling factors of main components. The fitness function is akin to the one described in Eq. (3), in Section 3. However, the design parameters are dissimilar. In this case, the constructing parameters of the input membership functions are considered the optimization parameters. As seen in Figure 7, considering the symmetry of membership functions, which is assumed to be valid even after adjustment, a set of membership functions corresponding to each input can be described

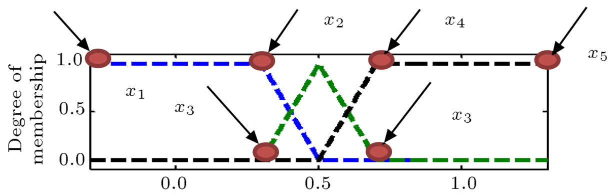

Figure 8. Design variables.

by 5 parameters. Thus, the number of optimization parameters comes to 10. As shown in Figure 8, the first trapezoid MF, for the required power, can be described by three points. The first and second points are considered as x_1 and x_2, and the third point is fixed at 0.5. The triangle MF, for the required power, is viewed as x_3 and depicted by three points. Finally, the second trapezoid MF, for the required power, is specified by three points. The first point is set at 0.5 and the other points, x_4 and x_5, are perceived as design variables.

It should be noted that simulation time is heavily influenced by the number of design variables. Hence, a simple FLC has been employed in this study to decrease computational effort.

4. Simulation study and results analysis

The performance of the proposed optimal controller is assessed via extensive simulations carried out over various driving patterns. In this section, firstly, the sizing results are presented. The performance of the optimal controller, in comparison with the initial fuzzy and thermostat controller, for various driving patterns, is subsequently evaluated. Finally, the results are discussed.

Figures 9 and 10 depict the optimization trend, for the TEH-CAR driving cycle, in the optimization procedure of the component sizes. As seen in these figures, the predefined fitness function increases generation by generation, employing continuous fuel economy improvement, until it reaches a steady level. The optimization process has been conducted for 60 generations and each generation has a population of 70. The same procedure has been done for the other driving

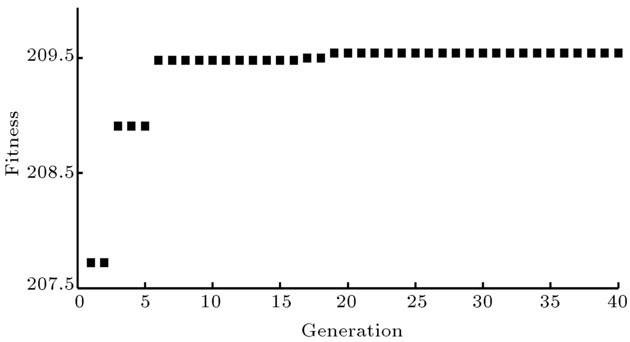

Figure 9. Objective function trends by PSO.

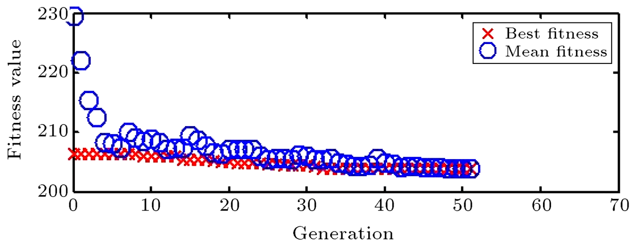

Figure 10. Objective function trends by GA.

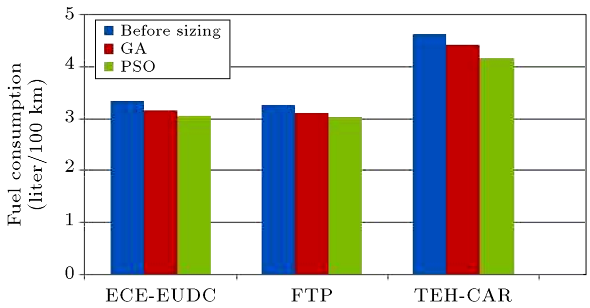

Figure 11. Fuel consumption.

Table 4. Size of main components.

Components	Size	
	GA	PSO
Fuel cell	44 kw	42 kw
Electric motor	44.5 kw	44 kw
Battery module (number)	30	29

cycles. Since the control strategy does not affect the optimization results, the thermostat control strategy has been utilized during the optimization process for all driving cycles. Table 4 provides the size of the main components after optimization.

Figure 11 presents fuel consumption before and after the sizing process at various driving patterns. As seen in this figure, by applying the sizing procedure, fuel consumption has been decreased for all mentioned driving patterns. Employing the optimal sizes acquired from the sizing procedure, the fuzzy controller has been implemented on the fuel cell model. Moreover, the parameters of the fuzzy controller are tuned using the particle swarm optimization approach. Figure 12

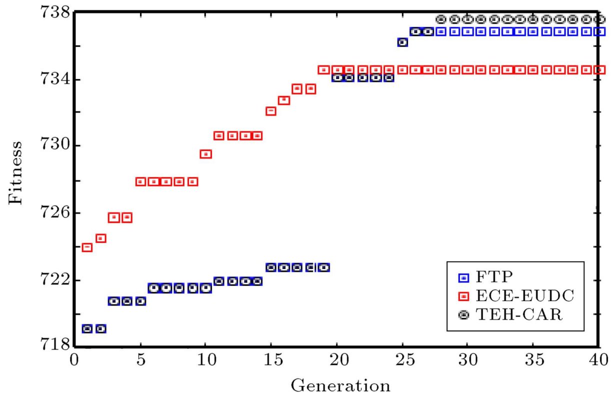

Figure 12. Objective function trend (PSO).

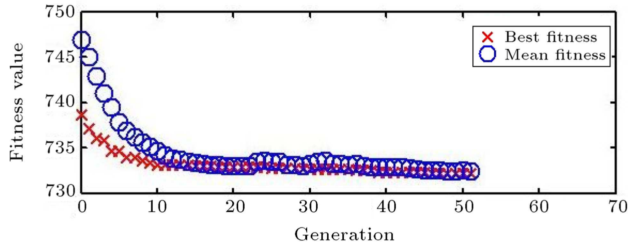

Figure 13. Objective function trend of TEH-CAR driving cycle (GA).

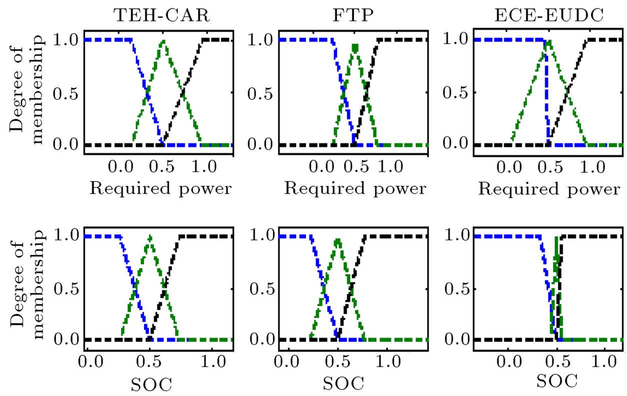

Figure 14. Adjusted MFs.

shows the objective function optimization trend of the fuzzy controller for the three driving cycles. Figure 13 represents the optimization trend of the objective function for the TEH-CAR driving cycle, by means of GA. The same process has been conducted for other driving cycles. Furthermore, Figure 14 presents the optimized MFs of optimal FLC for each driving cycle. As clear from Figure 14, the MFs shapes have been considerably affected by the optimization procedure, illustrating the impact of the driving pattern on optimization of the fuzzy controller.

Comparisons of fuel consumption for the FLC and optimal controller for various driving patterns are shown in Figure 15. According to this figure, reduction of fuel consumption is not the same for diverse driving cycles. Overall, a six point five to seven percent

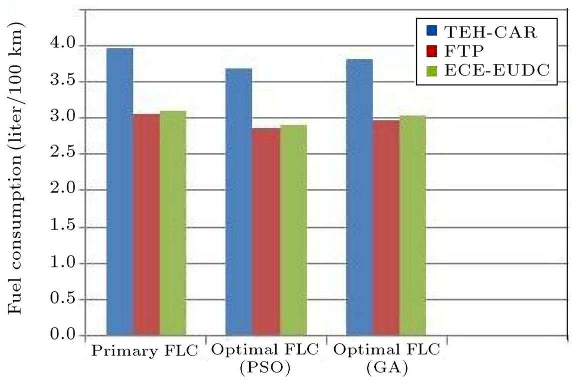

Figure 15. Fuel consumption comparison.

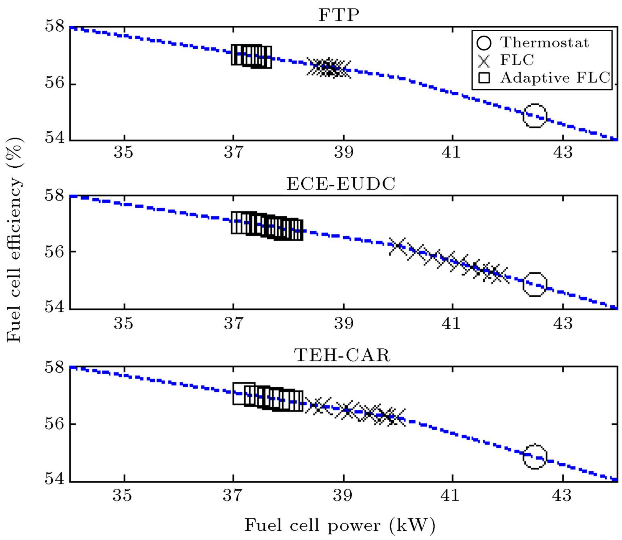

Figure 16. Fuel cell operating point.

progress in fuel consumption is crystal clear, according to a comparison of the fuel consumption of FLC with optimal FLC. According to Figure 15, the performance of PSO is slightly better than GA in this application. The greatest advantage of the PSO algorithm is the rapid pace of convergence in comparison with GA, which results in a reduction of time in completing the optimization process.

In order to analyze the performance of the employed controllers, the operating points of the fuel cell using diverse controllers for various driving patterns have been examined. Figure 16 depicts the operating points of the fuel cell with the thermostat control strategy, FLC, and optimal FLC under various traffic conditions. As seen in this figure, applying optimal FLC to the FCV has a beneficial effect on the operating points of the fuel cell system, since they have moved towards the higher efficiency region. This alteration in the trend of the operating range is in agreement with previous results, where a drop in fuel consumption was reported utilizing the optimal controller.

There are four individual traffic conditions on the inside of the TEH-CAR driving cycle. Since

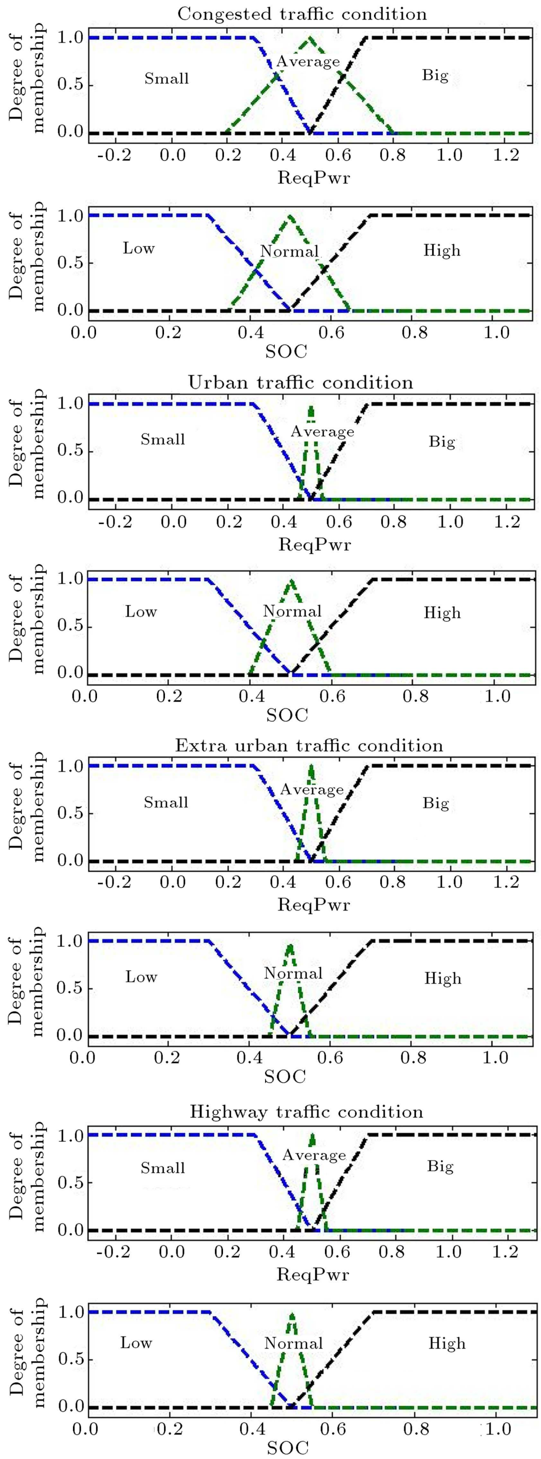

Figure 17. Optimal FLC MFs.

traffic conditions have a considerable influence on the performance and fuel consumption of a vehicle, it should be incorporated into the design of the fuzzy control scheme. For this purpose, at the second stage, an optimal FLC is designed, with regard to different modes in the TEH-CAR driving cycle. The optimal FLC has four modes to embrace each individual traffic condition, as shown in Figure 17.

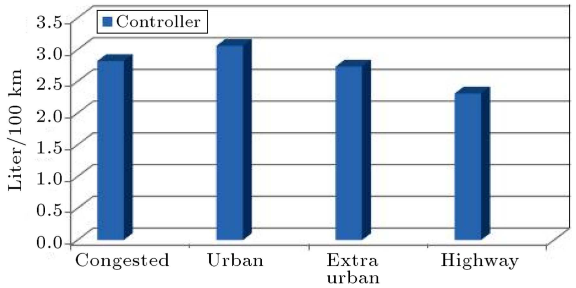

Figure 18. Performance test of the optimal controller.

The performance of the optimal controller is studied. For this purpose, the primary controller is separately optimized for all representative traffic conditions, using a PSO approach. The optimized controller is then applied to all traffic conditions, including its corresponding one. Figure 18 compares fuel consumption for highway traffic conditions with various modes of the controller. As is clear in this figure, the controller, optimized for highway traffic conditions, has the best performance for this traffic condition. The same results have been obtained for other controllers.

According to Figure 18, it is seen that the optimal controller gives a superb performance when confronting all traffic conditions.

5. Conclusion

An optimal FLC for a (FC+B) vehicle, considering the driving pattern, is suggested in this study. The principal purpose is to achieve optimal fuel economy for various driving cycles while maintaining driving performance within a feasible range. For this purpose, the optimum sizes of the main components are calculated using a PSO algorithm. A FLC is then devised to control power flow between key components. Meanwhile, the performance of the PSO algorithm, which is perceived as a newcomer in FCV applications, is compared with GA, in the process of optimization. In order to reach the optimal performance of FLC under various traffic conditions, firstly, an optimal control scheme, based on the PSO algorithm, is proposed for the three driving cycles. Secondly, a four-mode optimal controller is designed to embrace diverse traffic conditions on the inside of the TEH-CAR driving cycle. The results acquired from the simulation stage prove the effectiveness of the proposed controller in tackling various driving patterns in order to attain optimal fuel consumption.

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