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Optimal Control Strategy for the Next Generation Range Extended Electric Bus

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Abstract

Electric and Hybrid-Electric buses have become a major vehicle platform for demonstrating the advantages and capabilities of electrification in heavy duty vehicles. This type of vehicle can be powered from several different sources that each have several unique operating characteristics and performance requirements that necessitate novel solutions. In this paper, a novel optimal control strategy based on the next generation range-extended electric bus (REEB) has been developed. Control strategies play an essential role in realizing the full potential of electric buses and through careful implementation can increase their effectiveness at displacing conventional internal-combustion powered buses and thus, reducing global fuel consumption and emissions. Initially, a control-oriented powertrain model was developed in Matlab/Simulink. A new control strategy was devised for a series-hybrid baseline vehicle based on an equivalent consumption minimization strategy (ECMS) to govern the powertrain when operating in different modes. Due to the high impact the drive cycle has on the equivalent factor (EF) in an ECMS, an offline optimization process is performed to further increase the effect of the ECMS on various driving routes. Particle swarm optimization (PSO) was applied to the offline control model, generating the most appropriate EF values for different driving routes. The optimization of the EF values, the implementation of the new control strategy and the control execution process are described here in detail. Finally, the proposed control strategy is demonstrated in the simulation environment by analysing its performance with those of a simple rule-based strategy and a dynamic programming based global optimisation strategy. Comparison of results suggests the superior performance of the proposed method in fuel economy optimization versus the rule-based control method and the similarities to the dynamic programming based control method.

Introduction

The on-going conflicts among social development, environment and natural resources require technical evolutions from industry [1]. In automotive fields, a surge in electric powertrain technology has successfully attenuated serious social issues by improving fuel economy and reducing (or eliminating) tailpipe emissions [2]. The advanced new techniques are widely applied not only in passenger vehicles but also in commercial vehicles. From the micro hybridization to full hybridization and full electrification, buses have shown huge potential in energy saving and exhaust emission reduction in urban zones [3]. While fully electric bus and fuel cell bus architectures have been emerging in commercial market, hybrid technologies with high electrification degree will still dominate bus

sector through to 2035 due to the improper performance of full electric buses in achievable ranges, component availability, reliability and cost [4].

The range extended electric bus (REEB), as an anagenesis of traditional hybrid buses (HEBs), demonstrate better economy improvements, exhaust emission reductions and mileage. This performance enhancement is achieved through larger capacity batteries and optimized internal combustion engines, and employing optimal control strategies. In contrast with the optimized components, the control strategies play more essential role than in traditional hybrid vehicles. Generally, the control strategies govern the distribution of the tractive power demand between the engine and battery reasonably without reducing the drivability [5]. To fully realize the benefits of the REEB, optimal, but robust control strategies need to be developed and implemented. Typical considerations in the development of the control strategy for the REEB configuration should include:

- How to optimally distribute power between power sources to maximize efficiency;
- How to maximize the energy recovery and regenerative opportunities during braking;
- How to balance the drivability and fuel economy considerations in the design of the new powertrains.

In recent years, increasingly sophisticated control strategies have been investigated with aims of improving fuel economy. These control methods can be divided into three types: the rule based methods, the global optimized methods, and the instantaneous optimized methods [6]. The rule based methods, for instance, fuzzy logic [7], can be applied in real time but the control effect is typically far from optimal. The global optimized methods, including techniques such as Dynamic Programming (DP) [8], can offer the most optimal power distribution results but requires prior knowledge of the driving cycle which prevents its use in real-time applications. Some instantaneous approaches, like the equivalent consumption minimization strategy (ECMS), can not only provide optimal control results that are close to global optimized methods [9], but also be applied in real time with less burden computation and without requirement for the global driving profiles.

However, the primary performance limit of ECMS arises from the equivalent factor (EF), which is used to convert the electrical energy usage into an equivalent fuel consumption, and changes according to current and future energy depletion. To remove the barrier on ECMS application in real time, adaptive ECMS (A-ECMS) has been developed [10]. The core idea of the A-ECMS is to tune the

equivalent factor according to identified road condition, such as city urban, expressway, etc. It is considered that various road conditions can be, to a certain degree, correlated with the energy depletion. Methods such as neural networks [11] and support vector machine [12] have been used to explore the link between road conditions and energy depletion rates. However, most road identification methods have not offered strong performance in real time applications. From this perspective, the bus sector offers an interesting opportunity for practical application of ECMS. As the routes serviced are known ahead of time, REEBs provide an interesting opportunity to achieve enhanced performance of ECMS in real time. The fuel economy of REEBs implemented with ECMS has the potential to be significantly improved with carefully optimized EF values according to the given operation routes.

The current work presents an optimal control strategy which has been developed and implemented on both single and double deck next generation REEB topologies. The novel control strategy has been developed and implemented based on the ECMS. The EF values under different battery state-of-charges (SOCs) are optimized by particle swarm optimization (PSO) method according to the specific operation route. The algorithm to achieve optimal power management is discussed, and the power distribution strategy is developed and integrated into novel control strategies.

The remainder of this paper is organized as follows. The driving cycle model of REEB is introduced in Section 2. Section 3 presents the newly developed control strategy. Section 4 discusses the simulation results and comparatively validates the performance of the raised strategy, followed by the main conclusions drawn in Section 5.

Driving Cycle Model Development

Figure 1. Configuration of REEB

Configuration of the developed REEB is shown in Fig.1. As is shown in Fig.1, the electric motor itself provides the tractive power to meet various driving requirement. The battery pack, together with the auxiliary power unit (APU), provides the demanded tractive energy. In braking mode, the battery pack also stores the recycled braking energy from motor. The APU also consists of a diesel engine and a generator. The diesel engine is connected directly to the generator for the purposes of electricity production. The component details are given in

Table 1.

Table 1. Detailed parameters of each components

Engine	Displacement	4.5 L
	Maximum Power	134 kW
Motor/ Generator	Maximum Power	160 kW
	Maximum Torque	2500Nm
	Maximum Speed	3500 rpm
Battery	Type	Lithium-Nickel
	Capacity	84.79 kWh
	Nominal Voltage	642.4 V

The tractive force demanded by the driver is transmitted to wheels to overcome driving resistance. Therefore, power balance equation can be written as follows:

$$P_{req} = \frac{v}{\eta_t} \left(\frac{Gf \cos \alpha}{3600} + \frac{Gs \sin \alpha}{3600} + \frac{C_d A v^2}{76140} + \frac{\xi m a}{3600} \right) \quad (1)$$

where P_{req} is the required tractive power; G, α, f are the gravity, gradient and rolling resistance factor, respectively; C_d, A, v are the aerodynamic drag factor, frontal area and vehicle speed, respectively; a is the acceleration; ξ, η_t, m are the correction coefficient of rotating mass, transmission efficiency, vehicle mass, respectively.

At wheels, torque balance equation can be written as:

$$F_t = \frac{T_{em} i_{fd} \eta_t}{R_{wh}} \quad (2)$$

where T_{em} is the electric motor torque, i_{fd} is the final drive ratio, and R_{wh} is the wheel radius.

The engine model in this study is a static model, in which an efficiency map is acquired from a benchmark test. The engine performance can be described as:

$$\eta_{eng}(T_{eng}, n_{eng}) = \frac{T_{eng} \omega_{eng}}{Q_{lhv} \dot{m}_f} \quad (3)$$

where η_{eng} denotes the engine net efficiency, ω_{eng} means the rotating speed of engine, Q_{lhv} represents the fuel lower heating value, and $\dot{m}_f$ expresses the fuel consumption rate. Fig. 2 illustrates the engine map for this paper.

Figure 2. Engine map for the study

Both the electric motor and generator are part of a permanent magnet synchronous motor. As the optimization target in this paper is the fuel economy, the dynamic behaviors of motors are neglected. For the permanent magnet synchronous motor with tractive and generator mode, the relationship between torque and power can be written as:

$$P_{em} = \begin{cases} \frac{T_{em}\omega_{em}}{\eta_{mot}} & T_{em} > 0 \\ T_{em}\omega_{em}\eta_{gen} & T_{em} \leq 0 \end{cases} \quad (4)$$

where ω_{em} is the angular speed of electric motor; P_{em} is the power of electric motor; η_{mot} and η_{gen} are the efficiency in tractive mode and generator mode, respectively.

A single equivalent circuit model is employed to describe the battery performance with neglect of temperature and aging effect. The simple equivalent circuit model can be expressed as:

$$SOC = -\frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_{int}P_{batt}}}{2R_{int}Q_{batt}} \quad (5)$$

where SOC is the battery SOC, V_{oc} is the open circuit voltage of battery, R_{int} is the internal resistance of battery, P_{batt} is the battery power, and Q_{batt} is the battery capacity.

Control Strategy Design Based on ECMS

General Framework of the Developed Optimal Control Strategy

The general framework of the newly developed control strategy is illustrated in Fig.3. As is clearly shown, ECMS is responsible for managing the energy distribution between APU and battery pack instantaneously. PSO is employed in offline optimization, optimizes EF values under different battery SOC's for the given REEB operation routes. The method proposed here successfully integrates the advantages of the global optimization method with those of

instantaneous method, fully considering the impacts on the control strategy from environment. Through this hybridized approach control method, route based optimal control results can be derived.

Figure 3. General framework of the developed optimal control strategy.

Novel Optimal Control Strategy and Implementation

Instead of employing an optimal strategy to select operational modes while distributing energy, this paper employs threshold rules to facilitate the mode switch control, and ECMS to manage the energy flow between the APU and battery. This integrated strategy avoids the improper which can be caused by insufficient optimization constraints. Fig.4 shows implementation of the new control strategy, in which some threshold rules have been preset to control the switch in operational mode. In the online optimal control stage, model switch control and energy management are completed successively. There are two tractive operation modes in the REEB: pure electric mode and hybrid mode. The switch between two modes is mainly determined by the preset battery SOC minimum value. If the current battery SOC is less than the preset value, the REEB will switch into hybrid mode from pure electric mode. When the REEB operates in hybrid mode, the battery SOC would be controlled to vary within a limited range from the preset minimum value to maximum value. Battery pack provides the required tractive energy in pure electric mode, while the APU and battery together provide the tractive energy in hybrid mode. The mode of operation is switched according to the preset threshold rules.

After the appropriate operation mode is determined, the corresponding energy management is applied. In the pure electric vehicle mode, all the required tractive energy is from battery pack. Alternatively, the required energy can be distributed to the APU and battery pack by ECMS. In this paper, some minor modifications are made to the ECMS algorithm to implement an ECMS look-up table with the optimized EF values instead of applying the algorithm directly into controller, which reduces the online calculation time dramatically. The details of the improved ECMS will be described in following section. By inputting the requested tractive power and current battery SOC, the optimal ECMS look-up table will output the demanded APU power. With the distributed APU power, engine operation point can be searched.

According to the previous literature study [6-10], the impact of the rule-based control strategy can be further improved through

optimization of the preset thresholds. Moreover, Musado et al. [10] have suggested that the performance of ECMS could be significantly improved with carefully tuning of the EF values. In this work, particle swarm optimization (PSO) has been used to assist with parameter optimization. PSO is well acknowledged as a method for undertaking parameter optimization methods for problems such as this [13]. PSO can undertake fast global searching which can be easily applied without complex parameter tuning [13]. The mode switch thresholds and EF values in ECMS are all optimized according to the provided driving cycle data.

engine operation point can be acquired through interpolation among points locate on the optimal brake-specific fuel consumption (BSFC) line. As a final step, interpolation is used again to get the demand engine torque and engine speed required.

Specific Requirement on Control Strategy from Bus Operation Route

In the bus daily operation, there is specific, known requirements from operation routes. Schools and hospitals are located on the bus

Figure 4. Implementation of the optimal control strategy.

Figure 5. Engine operation searching process.

Fig.5 presents the searching process of engine operation points according to the power distribution order. After obtaining distributed APU power, engine power can be calculated with consideration of efficiency between generator and diesel engine. The corresponding

operation route, and there are increasing demands for buses to operate in pure electric mode in these areas to reducing noise and emissions. Based on this specific requirement, REEB operation route can be divided into HEV Zones, Approach Zones and ZE (zero

emission) Zones. The divided zones on operation route are illustrated in Fig.6. In the HEV Zone, REEB operates with control strategies that are similar with HEV vehicles. In the Approach Zone, forced charge is activated. If the battery SOC is below the charging threshold, the engine/generator will be controlled to a higher power level to allow the battery to be charged in preparation for entry to the ZE zone. This charging mode will ensure the battery will have sufficient energy to complete the ZE zone in zero emission running mode. In ZE Zone, the pure electric mode is enabled. This will cause the engine to switch off and the vehicle will run using battery energy only. The battery state of charge on entry to the ZE zone will be such that the ZE portion of the route can be completed in ZE mode.

in this study is that keep engine operate in fixed optimal operation point to charge battery. In Normal Mode and Forced Mode, there are pure electric mode and hybrid mode.

ECMS for the REEB

The optimal control problem in this paper is formulated as:

$$J = \int_{t_1}^{t_2} m_f(u(t), x(t), t) dt$$

Figure 6. Illustration on different operation zones on bus routes.

Figure 7. Illustration on full model switch control logic.

The extended mode switch control logic is shown in Fig.7. There are two main modes in the extended mode switch control logic: Normal Mode and Forced Mode. Normal Mode corresponds to vehicle operation in HEV zone without any forced orders, while Forced Mode corresponds to vehicle operation in Approach Zone and ZE Zone with forced orders to charge battery and govern battery discharge alone for pure electric driving. The forced charge strategy

where J is integral performance index, t_1 and t_2 are time variables, u is the control variable, and x is state variable. (6)

As the objective of control strategy of the REEB in this case is to improve fuel economy, the control variable is the power-split ratio

between APU and battery pack and the state variable is battery SOC. To fulfill the optimal control, several constraints should be satisfied:

$$\begin{cases} SOC_{min} \leq SOC(t) \leq SOC_{max} \\ P_{batt_min} \leq P_{batt}(t) \leq P_{batt_max} \\ T_{eng_min} \leq T_{eng}(t) \leq T_{eng_max} \\ \omega_{eng_min} \leq \omega_{eng}(t) \leq \omega_{eng_max} \\ T_{em_min} \leq T_{em}(t) \leq T_{em_max} \\ \omega_{em_min} \leq \omega_{em}(t) \leq \omega_{em_max} \end{cases} \quad (7)$$

where max and min is the maximum and minimum value, respectively, ω_{eng} is the angular speed of engine.

The ECMS tries to realize the optimization target by selecting the optimal power combinations that minimize total equivalent fuel consumption instantaneously [14]. The general expression of ECMS can be expressed as:

$$\begin{cases} \dot{m}_{eqv}(t) = \dot{m}_f(t) + \dot{m}_{ress}(t) \\ \dot{m}_f(t) = \frac{P_{eng}(t)}{\eta_{eng}(t)Q_{lhv}} = \frac{P_{req}(t)u}{\eta_{eng}(t)Q_{lhv}} \\ \dot{m}_{ress}(t) = \frac{s}{Q_{lhv}} P_{batt}(t) = \frac{s}{Q_{lhv}} P_{req}(t)(1-u) \end{cases} \quad (8)$$

where $\dot{m}_{eqv}$ is instantaneous total equivalent fuel consumption (g/s), $\dot{m}_{ress}$ is equivalent fuel consumption transformed from electricity consumption (g/s), s is EF, P_{eng} is engine power

A mathematical expression for the optimal control variable u^* can be written as:

$$u^* = \operatorname{argmin} \left[\frac{P_{req}(t)u}{\eta_{eng}(t)Q_{lhv}} + \frac{s}{Q_{lhv}} P_{req}(t)(1-u) \right] \quad (9)$$

EF, generally acknowledged in previous work, plays an essential role in ECMS application [15]. The EF reflects the chain of efficiencies associated with the transformation of fuel into electrical energy which is influenced by variation of driving conditions. Therefore, performance of ECMS in REEB could be improved with the carefully optimizing on EF values under different battery SOC's according to the given operation routes. As is described in the previous section, PSO is employed to optimized EF values under a number of different driving cycles. The process of EF optimization by PSO is described in the following section. To avoid large computational burden when implementing the ECMS, this calculation is undertaken offline. For the optimized EF values under different battery SOC's, optimal engine powers corresponding to discrete total power requirement and battery SOC's are acquired by Eqn.8 and Eqn.9, forming specific look-up tables for different driving cycles. The look-up tables for power distribution are installed into the controller to realize optimal energy management in real time. The constructed look-up table is shown in Fig.4 and Fig.5.

PSO for EF Optimization in ECMS

PSO is one of widely accepted global optimization tool based on iterative evolution [16]. Particles in PSO, as solutions of optimal control problem, constitute the swarm. The shape of the swarm updates in every iteration as each particle searches for its new position with a particular velocity [17]. The position seeking is performed according to the global optimal position ($gBest$) and individual history optimal position ($pBest$) of each particle.

Basic attribute of each particle in PSO includes position X , velocity V and fitness function value. The position of i th particle can be expressed as:

$$X_i(k) = [a_i(k), b_i(k)] \quad (10)$$

where a and b are optimization targets, k denotes iteration step. The velocity that particle updates position can be written as:

$$V_i(k+1) = w_p V_i(k) + c_1 r_1 (pBest_i(k) - X_i(k)) + c_2 r_2 (gBest(k) - X_i(k)) \quad (11)$$

where w_p is inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are random values. The updated particle position can be expressed as:

$$X_i(k+1) = X_i(k) + V_i(k) \quad (12)$$

In Eqn.11, global optimal position and individual history optimal position can be calculated as:

$$\begin{cases} pBest_i(k) = X_i(u^*) | [J(X_i(u^*)) \leq JX_i(u)] \forall u \in (1, k) \\ gBest(k) = X_j(k) | [J(X_j(k)) \leq JX_\gamma(k)] \forall \gamma \in (i - \gamma, i + \gamma) \end{cases} \quad (13)$$

where γ defines neighboring boundary of each particle, J is the fitness function.

In Eqn.13, $w_p V_i(k)$ signifies current state of particle; $c_1 r_1 (pBest_i(k) - X_i(k))$ represents self-cognition to current state of particle; $c_2 r_2 (gBest(k) - X_i(k))$ describes self-adjustment of particle according to neighborhood. All three parts govern particle updating cooperatively, making sure that particle searches optimal solution along the most beneficial direction.

In EF optimization by PSO, an initial group of EF values corresponding to different battery SOC's is given. The optimization range (maximum and minimum value) of each EF value is prescribed. The fitness function, F , can be expressed as:

$$F = \int \dot{m}_{eqv}(t) dt$$

The inequality constraints in the PSO are the same as those shown in Eqn.7. Based on the given drive cycle data, the PSO is run iteratively to acquire an optimal EF sequence under different battery SOC. The process of PSO implementation is provide in Table 2.

Table 2 Computational procedure of PSO

Step	Content
1	Condition initializing. Setting scale of swarm, boundary conditions for each particle, initial positions and velocities of particles, maximum number of iterations;
2	The initial calculation. For each particle $i, i=1,2, \dots, m$, calculating fitness function values J_i ; position of each particle is the initial $pBest_i$; position that particle holds best fitness function value in initial calculation is marked as $gBest$;
3	Iteration. From the second iteration step, for each particle $i, i=1,2, \dots, m$, velocity and position is updated by Eqn.31; calculating fitness function values J_i , determining individual history optimal position and globally optimal position by Eqn.31;
4	Optimization ending. When number of iterations reaches the maximum value, the optimization procedure ends, and the last particle position is selected as the optimal solution;

Results and Evaluation

Figure 8. Bus operation route in Brighton, UK.

The control strategy proposed in the previous section has been evaluated on a simulation based on a driving cycle derived from a real bus operation route in Brighton, UK which contains elements of proposed zero emission driving. The operation route is shown in

Fig.8. The test drive cycle is 20.053 km long and travel time is 8239 s. The bus travel routes are described by R1-R2-R3-R2-R1. The operational mode is developed to force zero emission in certain segments of the route, and a comparison is undertaken here to demonstrate the difference between the baseline ‘normal’ mode, and the forced mode. The hybrid mode on the vehicle is only activated when the battery SOC is low, or by forced order. Four groups of simulation results are shown in Fig.9-Fig.12 which cover high and low battery SOC with and without forced control orders. The proposed control strategy (ECMS with PSO) is compared with an equivalent rule-based control strategy (power tracking) and DP. The ECMS with PSO and rule-based strategy share the same forced charge strategy.

Fig. 9 illustrates the performance when the battery SOC is high with the forced control orders. As is shown in Fig.8, there is a forced charge order during 1000-1500s and a forced EV order during 1500-2200s. Comparison in velocity profiles demonstrates that the general driving cycle model which has been developed in this work can accurately replicate the dynamic performance of the real vehicle. In this example, even though battery SOC is high, the engine starts to operate after receiving forced charge order to charge battery for future pure electric driving. Due to the same charge strategy in forced charge mode, engine speed and battery SOC curves by two strategies are same.

Fig.10 compares results with a scenario when the battery SOC is low but supplied with the same control orders. The battery SOC is designed to target a value of 0.3 to 0.5 if the battery SOC was lower than preset minimum values (0.3). In Fig.10, the initial battery SOC is 0.28, so both the ECMS with PSO and rule based strategy demand that the engine operates to charge battery in the HEV Zone. However, the engine operates in higher efficiency when controlled by the ECMS with PSO. In particular, engine speeds determined by the ECMS with PSO are typically ~1700 rpm while those determined by the rule based strategy are all around 1200 rpm. For this configuration engine operation points located around 1700 rpm can achieve better fuel economy than 1200 rpm according to the engine map shown in Fig.2. The better engine operation points identified by the ECMS with PSO contributes to a more optimal fuel economy than that determined by the rule based strategy. After receiving forced control orders, both ECMS with PSO and rule based control strategy direct the engine to charge the battery with same strategy and then operate in pure electric mode.

Fig.11 and Fig.12 present the results without any control orders in the high and low battery SOC state, which can be used to further analysis the performance of the proposed method. When the battery SOC is high, both the ECMS with PSO and rule based strategy operate the REEB in pure electric mode, and there is limited difference between the observed performances. Consequently, the battery SOC and engine speed curves are largely identical. However, once the battery SOC is lower than the preset minimum value, as is the case in Fig. 12, the two control strategies force the engine to charge the battery and output tractive power in normal mode. According to the results in Fig.12, engine operating frequency determined by the ECMS with PSO is lower than that by rule based strategy. Similarly, the engine operation points identified by the ECMS with PSO are located in higher efficiency fields than those by rule based strategy. The reduced engine operating time and high engine efficiency points determined by the ECMS with PSO improves total fuel economy of REEB.

Figure 9. Simulation results in high battery SOC with forced control orders.

Figure 10. Simulation results in low battery SOC with forced control orders.

Figure 11. Simulation results in high battery SOC without forced control orders.

Figure 12. Simulation results in low battery SOC without forced control orders.

Figure 13. Cumulative frequency of engine fuel consumption rate by different methods.

Through comparison of the simulation results, it is clear that the newly developed strategy can contribute to overall better fuel economy. Through the forced order, the vehicle can switch into forced pure electric mode and forced charge mode at the desired points within the driving cycle. It is noteworthy that battery SOC profiles obtained from the ECMS with PSO and rule-based strategy are quite similar when battery SOC is high at the start of the driving cycle, as in both instances the controllers will opt for a pure electric operational mode. When battery SOC is low at the start of the driving cycle, there are differences in the maximum battery SOC achieved by the two strategies. After optimizing thresholds by PSO, the state of charge of the battery is typically at a higher level, resulting in overall improvements in fuel economy.

Through the comparative study between ECMS with PSO and rule based strategies with and without control orders, it can be concluded that the proposed method offers significant advantages over conventional rule based strategies. To highlight these performance gains more clearly, performance of the proposed method in hybrid mode is also compared with DP. Fig. 13 illustrates the engine fuel consumption characteristics over the proposed driving cycle as determined by the three different methods. Smaller normalized fuel consumption rate means better fuel economy. Among the three control strategies, the rule based control strategy has widest range of fuel consumption rate frequency distribution, and overall trend of the ECMS with PSO is more closed to that by DP. The frequency distributions of DP and ECMS with PSO are centralized to low fuel consumption rates, enhancing fuel economy of REEB. As the DP strategy can interrogate every possible solution in global range to identify globally optimal results, it is not surprising that this is identified as the best performing of the three strategies. However, even though the ECMS with PSO strategy is locally optimizing the control policy without considering the impact on whole driving cycle, the PSO based EF optimization increases the probability of identifying a close to optimal result. Hence, the performance of ECMS with tuned EF obtained is quite close to that of the DP strategy. Without any well-directed optimization, performance of rule based control strategy is worse than that by DP or ECMS with PSO,

demonstrated by the wide spread of normalized fuel consumption in Fig. 13. Fuel consumption results in Table 3 also support this analysis. The provided fuel economy is the total equivalent fuel consumption, including the equivalent fuel consumption from electric energy consumption by Eqn. 8. Negative electric energy consumption relates to the battery charging. As the DP is not viable for real-time application, the proposed methodology provides an excellent compromise solution with potential real-time applicability. According to the results listed in Table 3, DP and ECMS with PSO can ensure that the APU and motor operate in high efficiency zones, resulting in overall less energy consumption. On the contrary, the rule based strategy without any optimization cannot guarantee that the APU and motor operate in high efficiency zones all the time, lead to increased energy consumption as a result

Table 3. Comparison in fuel economy among different methods

Strategy	Drive Cycle Energy (kWh)	Electric Energy (kWh)	APU Energy (kWh)	Fuel Economy (MPG)	Fuel Economy Improvement (%)
DP	22.17	-9.14	31.31	16.11	19.63%
ECMS with PSO	22.17	-9.89	32.06	15.71	16.62%
Rule Based Strategy	22.17	-13.18	35.35	13.47	-

Conclusions

The current study has successfully demonstrated the viability of a raised optimal control strategy for REEB, showing competitive

performance when compared with conventional rule-based strategies and DP. The raised optimal control strategy takes advantage of the ability of ECMS and develops a real-time application which is appropriate for application in bus control strategy development. The PSO has been used to optimize EF values under different battery SOC in ECMS on the fixed operation route, successfully removing the barrier to ECMS implementation. Simulation results reinforce the superior performance of the raised strategy in details.

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