Adaptive energy management strategy for a hybrid vehicle using Energetic Macroscopic Representation

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***Abstract*— The Energetic Macroscopic Representation is used in this paper to model a pre-transmission parallel hybrid electric vehicle and its control and energy management system. Since optimizing energy management onboard is among the key factors in reducing consumption of hybrid vehicles, several strategies are developed in the literature such as instantaneous-optimization rule-based strategies and global-optimization strategies; however, being implemented separately and for different purposes. For instance, rule-based strategies serve for real-time operation, where the global-optimization strategies for benchmarking, as it lacks the ability to be used in real-time control. Hence, the combination of both strategies would result in close-to-optimal energy consumption through a real-time control system. Therefore, a simple adaptive rule-based strategy is presented in this study, based on short-term driving pattern recognition and the global optimization routine of dynamic programming.**

Keywords*— *Energy management strategy, adaptive rule-based control, global optimization control, dynamic programming, powertrain modeling, energetic macroscopic representation.

I. INTRODUCTION

Due to the continuous tightening of legislations on carbon emissions from transport, hybrid electric vehicles (HEV) are presented as the potential solution for fuel savings and emissions reduction of passenger cars on the short-to-medium terms. The rational of combining an internal combustion engine to an electric powertrain is to provide additional options for managing the energy onboard in an optimal way, by offering different driving modes. Thus, the development of these vehicles requires the simulation of both the thermal and electric powertrain systems, which renders HEVs complex to model, as they include interaction between components of different physical nature. Therefore, a rigorous and organized modeling approach based on tracking the energy flow between the powertrain components is highly recommended.

The Energetic Macroscopic Representation (EMR) is an energy-based graphical description, used in this study to organize the powertrain model with its different physical properties, as well as its energy management strategy [1]. Several examples can be consulted in the literature for using EMR in modeling different hybrid and electric vehicles, providing the advantage of a systematic modeling of the powertrain and a simple deduction of its control system [2-4].

The Energy Management Strategy's (EMS) main role in HEVs is to ensure the driver's performance request by adequately splitting the torque between the engine and the electric machine with the minimum energy consumption. The review of the literature shows that EMSs are classified under two main categories, the global optimization EMS and the instantaneous optimization EMS [5, 6]. Global optimization EMS such as Dynamic Programming (DP) ensures the minimum fuel consumption over a predefined route, however cannot be implemented in real-time operations due to the heavy computation time required [7-9]. On another hand, instantaneous optimization EMS (commonly of rule-based (RB) type) ensures a real-time control of the torque-split; however does not ensure the overall minimum fuel consumption over the entire route [10, 11]. The principal author and co-workers presented in [12] a methodology to extract optimal rules for a RB EMS using DP. The suggested RB EMS lead to a close-to-optimal energy consumption for the specific route that was considered in the DP analysis; however, not for other routes. In this paper, an adaptive RB EMS based on the methodology presented in [12] and on a driving pattern recognition (DPR) algorithm is furtherly developed in order to present close-to-optimal energy consumption results for any random route, with no prior knowledge of its driving pattern.

Consequently, the study presents a methodology for an adaptive EMS, combining the advantage of the real-time control of the RB EMS to the global energy minimization of the DP EMS. EMR of the investigated hybrid powertrain configuration is presented in section II, and its adaptive RB EMS based on the DPR and DP in section III. This model serves as a simple demonstration of feasibility and is being used for the development of a further sophisticated adaptive RB EMS.

II. VEHICLE MODELING SETUP

A. Powertrain architecture: pre-transmission parallel hybrid

The vehicle studied corresponds to a front-wheel drive parallel hybrid architecture that combines a monodirectional thermal powertrain to a bidirectional electric powertrain. The thermal powertrain consists of a 1.2 L downsized-turbocharged engine and a 5 gears automated manual gearbox. The electric powertrain consists of a 27 kW motor, a power electronics module and a 6.5 Ah NiMH battery. A pre-transmission parallel hybrid configuration is considered as illustrated in Fig.1, with direct coupling between the engine and the motor, separated by a clutch system in order to reduce the engine drag losses during electric drive mode. The vehicle and components specifications needed for modeling are summarized in Table 1.

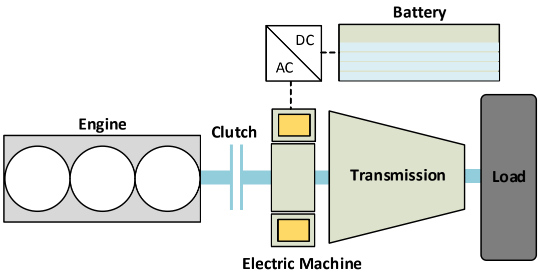

Figure 1 - Pre-transmission parallel hybrid configuration considered in this study.

TABLE 1 - VEHICLE AND COMPONENTS SPECIFICATIONS

Vehicle specifications	Unit	Value
Vehicle Mass	Kg	1560
Frontal area/ Drag coefficient	m^2/-	1.2/0.3
Wheel radius	m	0.32
Gearbox efficiency	-	0.95
Gearbox ratios	-	[3.64 1.95 1.28 0.97 0.77]
Differential ratio	-	3.76
Auxiliaries' consumption	W	294
Battery voltage/capacity	V/Ah	240/6.5

B. Modeling approach: Energetic Macroscopic Representation

The modeling technique used to evaluate and manage the fuel and electrical energy use of the considered vehicle is the Energetic Macroscopic Representation (EMR). EMR is an energy-based graphical modeling methodology, emulating the energy flow between the connected components (called elements) of the powertrain through exchange vectors, based on the principle of action-reaction and integral causality. Consequently, EMR provides the advantage of tracking the instantaneous power exchange between the connected elements, determined by the product of the action and reaction variables (constituting the exchange vector). This allows the energetic representation of the powertrain component systems (energy accumulation, conversion and distribution) similar to their physical behavior [13]. Summary on the EMR synoptic and elements types are presented in appendix A. Further details can be consulted on EMR website [14].

Due to this special energy-based representation, the EMR offers a second major advantage, which consists of the systematic deduction of the powertrain controller's structure, through the simple inversion of the EMR elements forming the powertrain model. The inversion process (called Inversed Based Control (IBC) scheme) follows specific rules where time-independent elements' equations (such as conversion and coupling elements) are directly inverted (emulating the physical inversion of the element), and time-dependent elements' inversion is done through a controller (e.g. PI controller), in order to avoid having a derivative operator and respect the physical integral causality. Note that, the first step in the IBC process is the determination of the tuning path of the EMR model, which consists of the set of input variables that control the powertrain. Then, the IBC control path is realized by inverting the tuning path. The EMR and IBC of the considered powertrain are explained in section II.C.

C. EMR and IBC of the studied powertrain

The EMR representation of the studied powertrain is illustrated in Fig.2. The exchange vectors are highlighted reflecting the instantaneous power exchange between the connected powertrain components. Each component is modeled by its equivalent energetic element: for instance the engine and motor are represented by 'conversion elements', the fuel tank and battery by 'source elements', the torque coupling device between the engine and the motor by a 'coupling element', and the chassis by an 'accumulation element'. Since the focus of this paper is the energy management strategy (EMS), the elements' equations are summarized in Table 2, giving further space for the EMS design.

The IBC scheme of this powertrain is also illustrated in Fig. 2. The tuning path is identified from the EMR model, with three tuning inputs: the reference torques of the engine and the electric machine (T_{ICE_ref} and T_{EM_ref}), and the braking reference force (F_{brake_ref}). In this model, the vehicle velocity ($V_{vehicle}$) is controlled to follow the reference vehicle velocity (V_{ref}) set by the driving cycle. Consequently, the tuning path is constituted by the sequence of variables connecting the tuning inputs T_{ICE_ref}, T_{EM_ref} and F_{brake_ref} to the control output $V_{vehicle}$, as illustrated in Fig. 3. Thus, Fig. 4 illustrates the control path, resulting from the inversion of the tuning path, respecting the integral causality and the inversion rules stated above. The equations of inversion blocks are summarized in Table 2.

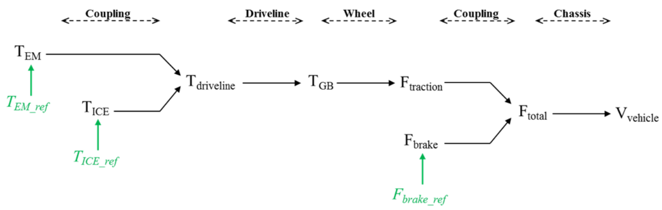

Figure 3: Tuning path of the powertrain.

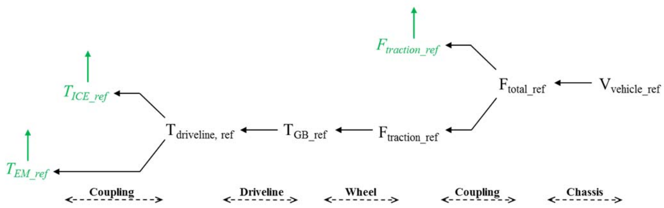

Figure 4: Control path of the powertrain.

III. Energy Management Strategy

Two control levels exist in the vehicle: (1) the components control represented above by the IBC scheme, and (2) the vehicle main control which includes the energy management strategy. The EMS has to ensure several objectives besides the minimization of the energy consumption, such as the emissions minimization, the gear-shifting optimization, the fun-to-drive and comfort, as well as to ensure the driver's performance request on the accelerator and braking pedals. For the purpose of this study, the EMS focus is on the energy consumption minimization only; gear-shifting optimization and emissions minimizations were disregarded.

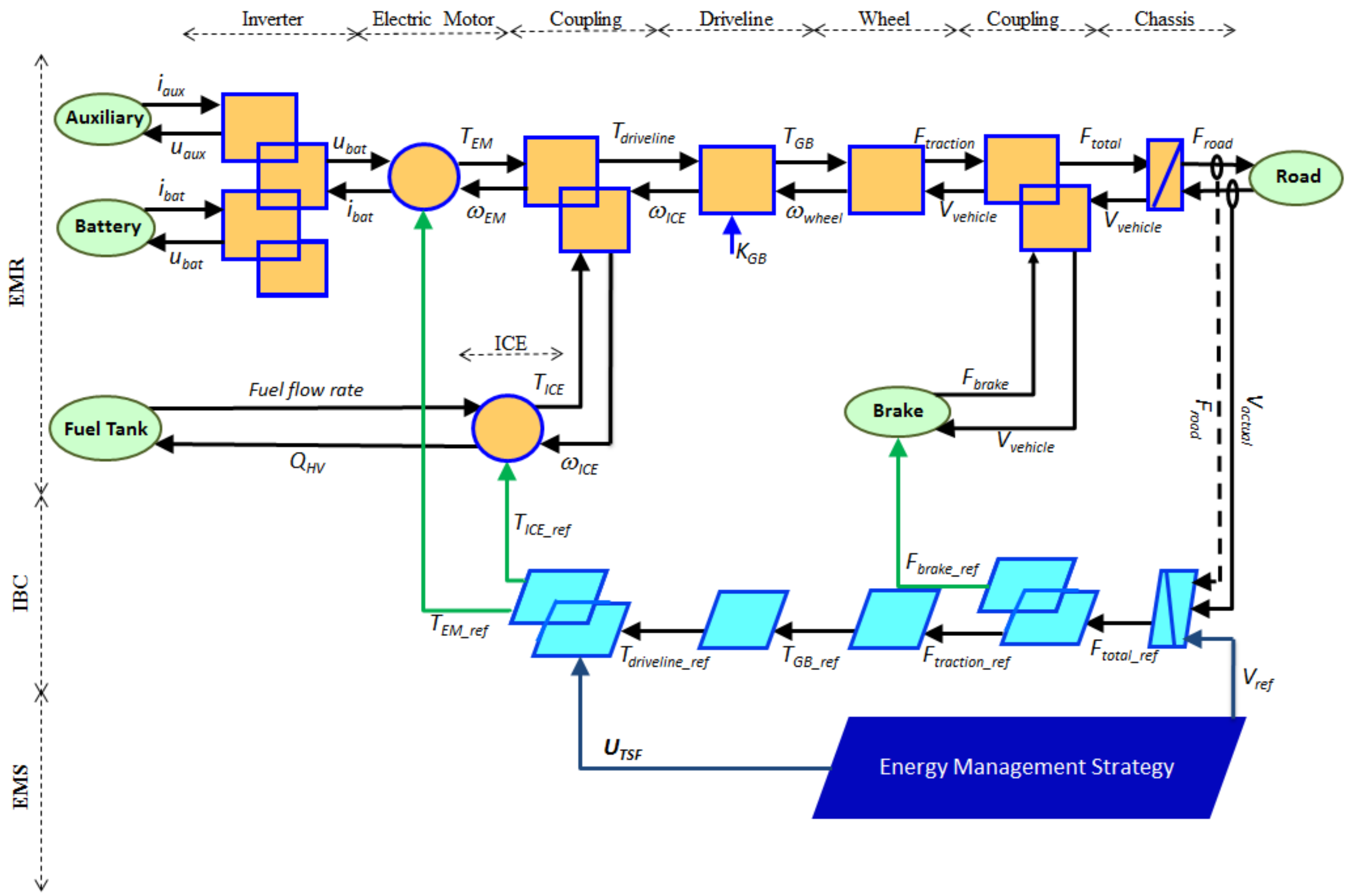

Figure 2 - Energetic Macroscopic Representation and Inversion-Based Control of the studied pre-transmission parallel hybrid powertrain.

TABLE 2: EQUATIONS OF THE POWERTRAIN ELEMENTS AND THEIR CORRESPONDING NEEDED INVERSION BLOCKS.

Elements	Elements Equations	Elements Equations after Inversion
Engine	drag torque: $T_{e0} = \alpha_e \times J_e + T_{friction}$ (1)	No inversion
Electric machine	drag torque: $T_{m0} = \alpha_m \times J_m$ (2)	No inversion
Battery	$I\_bat = I\_mot + I\_aux$ (3) $I_{mot} = \frac{V_{OC}(SOC) - \sqrt{V_{OC}^2(SOC) - 4P_{bat}R(SOC)}}{2R(SOC)}$ (4) $SOC = \frac{\left(C_{ini} + \int_{t_0}^{t} I\,dt\right)}{C_{max}}$ (5)	No inversion
Mechanical Coupling (ICE/EM)	$T_{driveline} = T_{EM} + T_{ICE} + T_{drag}$ (6)	$T_{EM} = \left(T_{driveline\_ref} + T_{drag}\right) \times u_{TSF}$ (7) $T_{ICE} = (T_{driveline\_ref} + T_{drag}) \times (1 - u_{TSF})$ (8)
Transmission System	$T_{GB} = T_{driveline} \times K_{GB} \times \eta_{GB} + T_{GB\_losses}$ (9) $w_{ICE} = w_{wheel} \times K_{GB}$ (10)	$T_{GB\_losses} = T_{driveline\_ref} + \frac{T_{GB\_ref}}{K_{GB}}$ (11) $T_{driveline} = \frac{T_{GB\_ref}}{K_{GB} \times \eta_{GB}}$ (12)
Wheel	$F_{wheel} = \frac{T_{GB}}{R_{wheel}}$ (13) $w_{wheel} = \frac{V_{vehicle}}{R_{wheel}}$ (14)	$T_{GB} = F_{wheel} \times R_{wheel}$ (15)
Chassis *(Time dependent)*	$V_{vehicle} = \int \frac{F_{traction} - F_{road}}{m_{veh}} dt$ (16)	$V_{vehicle}$ is controlled using a Proportional Integrator Controller

In order to minimize the energy consumption, the EMS has to optimally split the torque between the engine and the electric machine (T_{ICE_ref} and T_{EM_ref}). This split ratio is named the torque split factor and denoted (U_{TSF}). A value 1 of U_{TSF} corresponds to electric drive mode, 0 to thermal drive mode and -1 to brake energy recovery mode. Values between 0 and 1 indicate that both the engine and electric machine provide torque for traction, and values between -1 and 0 indicate that the engine provides excess power to drive the vehicle and recharge the battery through the electric machine (operating in generator mode).
During braking mode, F_{brake_ref} – emulating the hydraulic braking force – is generated by the EMS and corresponds to the additional braking force required to decelerate the vehicle only in case the generator cannot meet the total required braking torque. Consequently, this approach overestimates the braking energy recovery, since the hydraulic brakes are always activated on the rear wheels in order to ensure the vehicle stability by braking simultaneously the four tires.

As a result, the EMS communicates to the control inputs (T_{ICE_ref}, T_{EM_ref} and F_{brake_ref}) of the IBC the proper values to ensure the energy consumption minimization, which depends on the value of the torque split factor, as represented in equations (7) and (8). Consequently, the objective of this study is to optimize this torque split factor to ensure minimum fuel consumption throughout the different driving cycles.

The author has suggested in [8] a methodology to generate an optimized rule-based EMS for a specific route (driving cycle) based on the optimal control results obtained from Dynamic Programming optimization. In brief, the methodology consists of (1) running the DP algorithm on a specific route, (2) analyzing the obtained results for identifying the different obtained driving modes on this route, and finally (3) the generation of rules for each of the identified driving mode. Although this approach is suitable for specific recurrent routes such as a repetitive bus route or work-home commute, where the RB EMS is optimized for this specific route; it lacks to provide optimal control of the vehicle for other routes with no prior knowledge of the driving pattern. Hence, this section presents a methodology to design an adaptive EMS which provides close-to-optimal consumption results for a random route.

A. Adaptive RB EMS methodology

Since DP optimization requires the prior knowledge of the route in order to provide the optimal torque-split ratio and minimize the energy consumption by the end of the trip, DP cannot be implemented to manage the energy onboard in real-time. Consequently, as per the methodology presented in [8], DP is used to generate optimized RB EMS for specific predefined routes. Fig. 5 is an illustrative example of an optimized RB EMS for the EUDC driving cycle. The optimal torque-split factor is represented as function of the vehicle load power:

- For negative load power, obviously the brake energy recovery (BER) mode is triggered.
- For load power ranging between 0 and a threshold (P_{EV}), the vehicle is driven in the motor alone mode (EM).
- For load power ranging between (P_{EV}) and (P_{PS}), the vehicle is driven in the power split mode (PS).
- For load power greater than (P_{PS}), the vehicle is driven in thermal mode (ICEM).

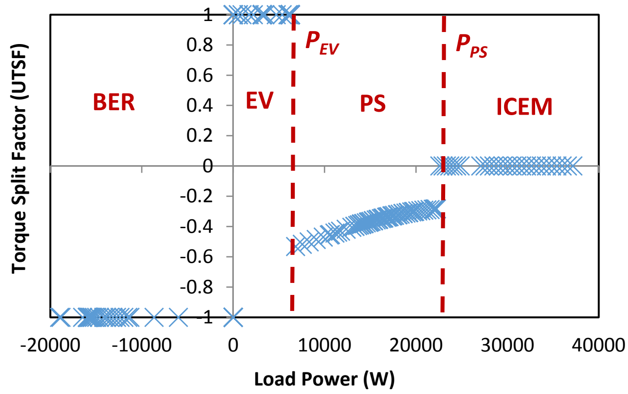

Figure 5 - Optimized Rule-based EMS based on DP optimization results for the EUDC predefined route.

It is noteworthy to mention that the same drive mode structure of Fig. 5 was observed for the DP optimization for other drive cycles; however, with different values of P_{EV} and P_{PS} thresholds, and different torque-split factors under the power-split modes. Hence, the design methodology for the suggested adaptive EMS of this paper consists of the offline creation of a library of optimized RB EMS for several predefined-routes, based on the mentioned above DP analysis, and then to perform a real-time driving pattern recognition (DPR) for a random scheduled route (with no prior knowledge of the whole route) in order to down select the most convenient RB EMS from the library, as illustrated in Fig. 6.

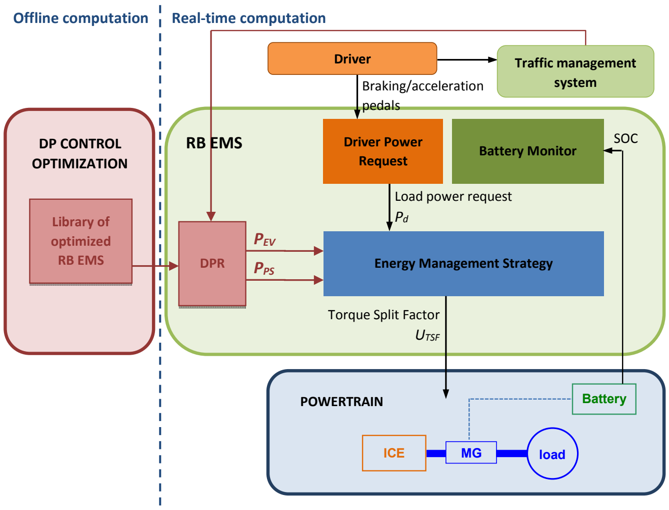

Figure 6: Illustration of the suggested adaptive RB EMS.

B. Driving Pattern Recognition

The DPR process' objective is the identification of the most convenient RB EMS from the offline library for each upcoming 5-driving-seconds. The methodology consists of the prediction of the mean load power for the upcoming 5-driving-seconds (using data from traffic management systems), then the comparison of this value to the mean load power of the offline predefined-routes used in the library. Consequently, the RB EMS of the closest offline predefined-route is down selected, and the corresponding torque-split factor is generated as function of the instantaneous vehicle load power. Note that the load power prediction is limited to a short duration of 5-driving-seconds in order to minimize the load prediction errors compared to real load power. Further analysis on the load power prediction time optimization will be investigated in future work.

IV. RESULTS

As a simple demonstration of feasibility, two cases are considered for analysis:

1. The offline RB EMS library is generated for the UDC and EUDC predefined driving cycles, and the scheduled random route is the NEDC driving cycle.
2. The offline RB EMS library is generated for the UDC, EUDC and NEDC predefined driving cycles, and the scheduled random route is the Japanese 10-15 mode driving cycle.

For the first case, the NEDC is considered as the scheduled random route. Since NEDC is constituted by four repeated UDC (800 seconds) and one EUDC (400 seconds) driving cycles, the designed DPR strategy selected the RB EMS of UDC for the first 800 seconds and then the RB EMS of EUDC for the last 400 seconds. Fig. 7 and 8 compare the obtained battery SOC and fuel consumption results compared to the DP optimal results for NEDC. A fuel consumption difference of 0.2 l/100km is observed (2.16 l/100km for the DP model and 2.36 for the adaptive RB EMS).

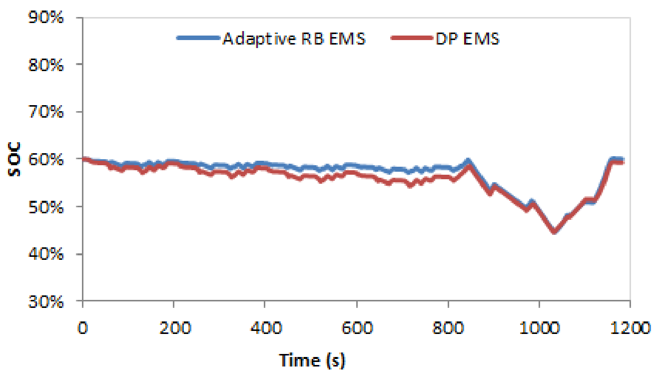

Figure 7: Battery SOC comparison between the suggested adaptive EMS and DP for NEDC.

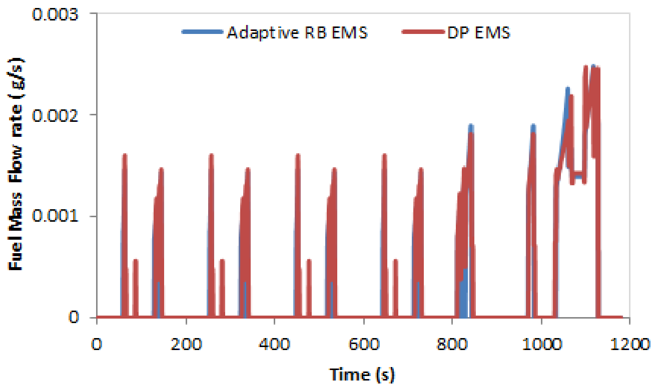

Figure 8: Fuel consumption comparison between the suggested adaptive EMS and DP for NEDC.

For the second case, the Japanese 10-15 mode cycle is considered as the random scheduled route for further validation of the results. Note that UDC, EUDC and NEDC were considered in this case to generate the offline library of optimized RB EMS. Fig. 9 to Fig. 12 illustrate obtained results. The observed vehicle velocity is perfectly controlled and fits with the reference velocity set by the driving cycle. Fig. 10 and 11 compare between the engine and electric machine torques respectively using the adaptive EMS and DP. Very minor torque differences are observed due to the small number of predefined cycles in the offline library, which restricts the DPR selection of control strategy to only the three combinations of rules. Battery SOC comparison is illustrated in Fig. 12; results of adaptive EMS and DP abide by the constraint of having the same start and end SOC values of 60%, as well as similar SOC profiles along the route. Finally, a fuel consumption difference of 0.1 l/100km was observed by the end of the cycle, where the observed DP consumption is 1.90 l/100km and the adaptive EMS consumption 1.99 l/100km.

Note that this approach is subject to further investigation and development, by increasing the number of predefined routes in the offline library of optimized RB EMS, and testing different random scheduled routes such as the WLTP, FTP72 and realistic driving cycles measured through GPS data loggers.

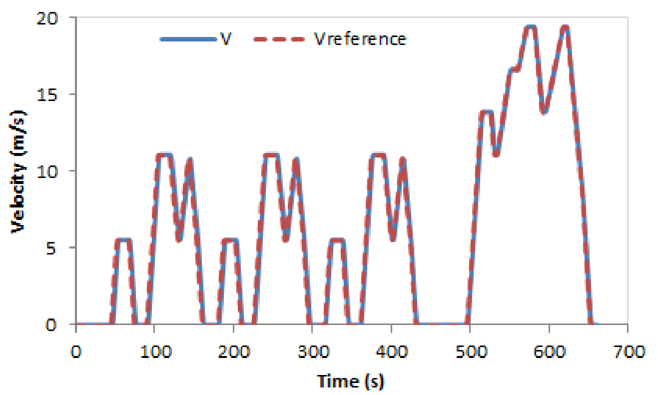

Figure 9: Velocity profile validation using the EMR powertrain model.

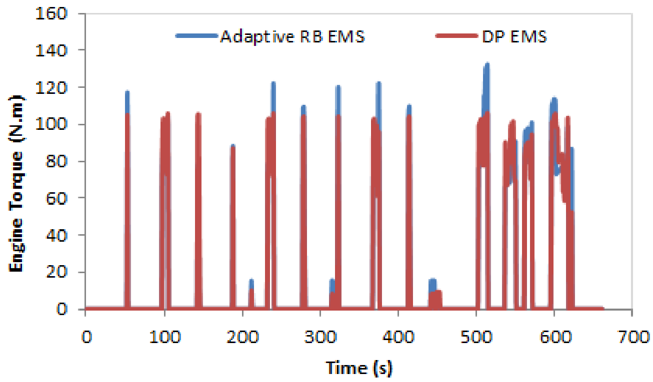

Figure 10: Engine torque comparison between the suggested adaptive EMS and DP for Japanese 10-15 mode.

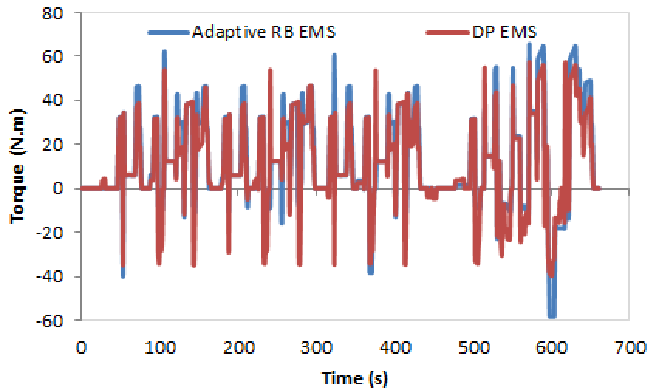

Figure 11: Electric machine torque comparison between the suggested adaptive EMS and DP for Japanese 10-15 mode.

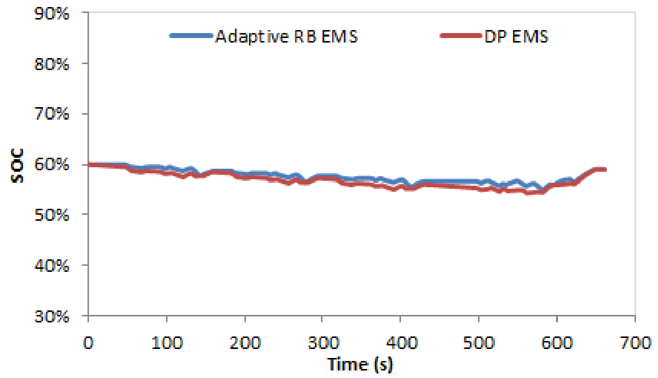

Figure 12: Battery SOC comparison between the suggested adaptive EMS and DP for Japanese 10-15 mode.

V. CONCLUSION

This paper presents a systematic modeling of the powertrain and control of a pre-transmission parallel HEV using EMR. Due to its rigorous energy-based graphical representation, EMR offered two advantages pertaining to modeling this vehicle: (1) tracking the instantaneous power exchange between the connected elements with different physical properties, and (2) the systematic deduction of the powertrain controller's structure, through the simple inversion of the EMR elements forming the powertrain model.

The second contribution of this paper relies on the presentation of a design methodology for an adaptive EMS, combining the advantage of the real-time control of RB EMS to the global energy minimization of DP EMS. The adaptive EMS used a simplified short-term driving pattern recognition process in order to identify the proper torque split factor. Results comparing the suggested adaptive EMS to the DP EMS showed similar components behavior and close energy consumption. This model serves as a simple demonstration of feasibility and is being used for the development of a further optimized adaptive RB EMS.

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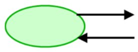
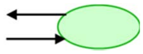
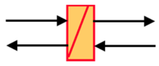
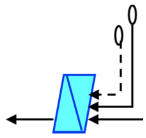
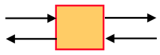
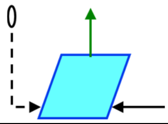
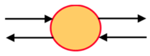
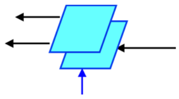
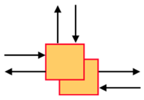
Appendix A: Synoptic of Energetic macroscopic Representation

Energy Source		Sink	
Accumulation Element		Controller	
Mono-Physical Conversion Element		Inversion of conversion element	
Multi-Physical Conversion Element		Inversion of Coupling Element	
Multi-Physical Coupling Element		Strategy Block