Fuzzy Logic Based Optimal Power Flow Management in Parallel Hybrid Electric Vehicles

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Abstract—Parallel Hybrid Electric Vehicle powertrain (PHEV), combining an electric motor with an auxiliary power unit, improves vehicle performance and fuel economy, reducing the effects of private cars on air quality in cities. These advantages can be enhanced by using a dedicated control strategy to identify the optimal power flow distribution at each instant of time in the main powerdrive sources as a function of the state of the powerdrive components and the actual driving conditions. In this connection the literature analysis has evidenced as the research efforts in the field of PHEV optimal power flow management should be oriented not only to develop precise and robust control strategies that can improve the vehicle performances, but also to lower the required computational resources making the solution strategy suitable with the vehicle dynamics and allowing, moreover, a cost effective hardware implementation.

To develop this complex activity, fuzzy logic (FL) was used. As demonstrated by the simulation studies developed, FL enables the optimal power flow management problem to be solved by handling its intrinsic non-linearity using rules, membership functions, and the inference process. This results in improved performance, simpler implementation, and reduced design costs compared with rigorous mathematics based approaches.

Index Terms—Hybrid vehicles, power management, energy management systems, fuzzy control, neural control.

I. INTRODUCTION

The minimization of the pollutant emission levels in urban environments is emerging as one of the main challenges of the new millennium.

In this context Hybrid Electric Vehicles (HEVs), which by using different powerdrive configurations are able to integrate an internal combustion engine with an electric powertrain, are desirable because they overcome both the negative environmental impact of conventional cars and the limited range of pure electric vehicles. Consequently, HEVs represent an effective solution to sustaining private mobility [1].

In particular, among the primary configurations adopted for the arrangement of the hybrid powerdrive, the parallel HEV (PHEV) configuration drives the vehicle wheels from two separate power sources, and also drives each component within its optimal efficiency range [2], [3].

Moreover, PHEV offers additional flexibility to enhance road vehicle performances and fuel economy by employing a dedicated control strategy. This function by using the state of the main vehicle’s powerdrive components and the actual driving conditions identifies, at each instant of time, the optimal power flow distribution between the powerdrive sources. This leads to improve the overall environmental impact of the vehicle and at the same time applies a rational use of energy.

Numerous resolution methodologies have been developed in this field. Many of them are based on a static approach that controls vehicle operation starting from a set of thresholds identified by optimising the fuel economy on a fixed drive cycle [4]-[7].

These strategies have been adopted on many commercial vehicles and are optimised for a particular driving cycle and so they exhibit little sensitivity to subtle emissions trade off and limited ability to optimise vehicle performance.

The effort to address these limitations has lead to the development of more advanced control strategies. These start from predictive mathematical models describing the vehicle dynamics, and identify the instantaneous power flows distribution minimizing, by an optimisation procedure, an objective function descriptive of the control goals [8], [9].

Even though these methodologies are effective, they require considerable computing resources and as a result their applicability for real-time applications is reduced. This is mainly caused by the intrinsic complexity of the non linear programming problem providing the optimal solutions which in turn require multiple resolution of the vehicle mathematical model. The large resolution times required to solve this process could be unsuited to the intrinsic vehicle dynamics making effectiveness application of these control strategies very difficult.

Research efforts in this field should therefore not only concentrate on developing precise and robust control strategies to improve vehicle performance, but also on reducing the computational resources required in order to make the optimal power flow management strategy suitable for the vehicle dynamics, making hardware implementation cost effective.

This paper uses Fuzzy Logic (FL) to develop this difficult activity. The proposed FL based methodologies solve the optimal power flow management problem, handling its intrinsic non-linearity by using rules, membership functions (MFs), and the inference process, which result in improved performance, simpler
The vehicle wheels can be driven from two separate power sources, each component can be used within its optimal efficiency range. The use of a consumable fuel energy source allows longer range with a smaller battery pack, while the electric traction enables more efficient drivetrain resulting in high performance and very low emissions.

With regard to the parallel hybrid, the power necessary to drive the vehicle is either provided by an IC engine, an electric motor, or a combination of both of these. The main advantage of the parallel arrangement, whose basic structure is depicted in Fig. 1, is that the engine is able to drive the wheels via direct mechanical coupling of the engine and transmission. This results in:
- The elimination of the losses occurring in both the generator and motor when converting mechanical energy into electricity and vice versa;
- The availability of a “Get You Home” function guarantees the wheels will also be driven when a totally discharged battery or an electric powertrain outage occurs.

However, there is one main disadvantage. Because the speed of the engine depends on the speed of the vehicle, the engine must operate over a wider performance range and this reduces the overall engine efficiency.

All the same, due to it having fewer power conversion stages a PHEV configuration is more efficient than a series HEV with similar components, a result confirmed by the study of the National Renewable Energy Laboratory (NREL) [2].

Moreover, as recent studies show [8], [9] optimising the power flow management results in a further sensible increase in PHEV efficiency. This means the engine and motor can be automated in order to improve the vehicle performances, including when they are used together.

III. ELEMENTS OF POWER FLOW MANAGEMENT IN PHEV

Management of the powerdrive power flows in a PHEV requires a dedicated on board programmable unit which in spite of introducing further complexity compared to a conventional vehicle, is able to offer additional improvement of the overall vehicle environmental impact while at the same time producing rational energy employment.

This can be achieved by designing a suitable control strategy. As a function of the state of the powerdrive components in the main vehicle combined with the actual driving conditions, the optimal power flow distribution amongst the powerdrive sources at each instant of time is identified for the purpose of achieving the following main goals:
- Drive the powerdrive components so that they operate in high efficient regions
- Maintain adequate reserves of energy in the storage devices
- Reduce fuel consumption
- Minimize exhaust emissions from the vehicle
- Achieve these goals without sacrificing road vehicle performance

The pursuit of all the previous goals is hindered by the physical behavior of the ICE. This produces the greatest quantity of CO and HC emissions during the first few minutes of the drive cycle and exhibits poor efficiency when it operates at points characterized by low torque and low velocity. This effect is magnified if the vehicle is cold.
In particular, until the engine and catalyst are fully warmed, fuel mixture preparation is very poor [9].

Obviously fuel economy and the quantity of exhaust emissions generated are also strongly influenced by the driving conditions, and as experimental results show, in particular the levels of emissions generated increase greatly in response to abrupt engine accelerations [8].

Therefore to overcome the previous limiting aspects it is necessary to “hybridize” the vehicle propulsion supplying a proper fraction of the vehicle power demand, defining the powerdrive hybridization degree, by the electric motor. Although it obviously ensures the minimization of exhaust emissions and fuel consumption requirements, a higher degree of hybridization at the same time intensifies use of the electric source which in turn may well cause a reduction in the usable life of the battery pack.

The identification of optimal propulsion hybridization therefore involves the simultaneous satisfaction of multiple conflicting objectives and it consequently requires the definition of a suitable resolution approach aimed at finding a compromise solution.

IV. RELATED WORKS

Analysis of the existing literature shows that the simplest solution to the power flow management problem in a PHEV is to introduce a suitable set of static thresholds that define the narrowest operating window for each power source in accordance with fixed control logic.

In particular, the author of [13] suggest that the static control strategy can be defined by six independent control parameters. These drive the vehicle with a high level of hybridization when the state of battery charge is sufficient and the engine exhibits poor efficiency, as occurs at low vehicle speeds or when torque requirements are low. The vehicle is driven with low level of hybridization when the relative state of charge is low as occurs during the recharging of the battery pack. These parameters are typically identified by employing a dedicated optimization procedure whose purpose is to maximize the vehicle performance during a fixed driving cycle, and also considers the effects of emissions and fuel consumption during the identification procedure [5], [7].

Static power flow management strategies are widely adopted in commercial vehicles and exhibit good levels of robustness. They are particularly suitable for implementation on programmable units. Nevertheless, the main limitation that arises in applying these techniques is that the control strategy implemented is inherently static and therefore it cannot be adapted to the actual state of the vehicle. Moreover, the control parameters optimizing the vehicle performances on a fixed driving cycle are identified, but consequently the performance obtained could deteriorate in different drive conditions.

To overcome these limitations various research activities have recently been developed [8], [9]. They aim to design advanced power flow management strategies for the real-time optimization of fuel economy and pollutant emissions by acquiring a set of observable variables describing the state of the main powerdrive components (such as catalyst temperature, state of battery charge, engine temperature etc.) Such an approach requires the design of a suitable optimization procedure identifying the optimal engine and motor operating point for each vehicle power demand that minimizes a non linear scalar function which is a product of the design objectives. This function is usually described by a weighted sum of the main figures of merit normalized under pre-specified thresholds [8], or, in a more sophisticated approach, by an objective vector [9].

In particular, this real-time optimization procedure requires the development of suitable predictive models describing the vehicle dynamics in order to evaluate a priori the impact of all the possible “guess” power flow configurations on the selected cost function. A rigorous mathematical methodology aimed at minimizing the corresponding non linear cost function is also required.

Using these methodologies means the main intrinsic limitations in the static control strategies can be overcome. However, they require dedicated software procedures which are time consuming and require considerable computing resources for the real time resolution of both the vehicle model and the multiobjective mathematical programming problem which provide the optimal power flow solution.

This limitation becomes critical during the unit prototyping phase where the optimal power flow strategy should be implemented on programmable electronic chips in order to develop field analysis so that the effectiveness and the robustness of the control action can be evaluated.

The previously presented arguments indicate that research efforts in this field should be oriented not only to developing precise control strategies in order to improve the vehicle performance, but also to making them suitable for an effective hardware implementation.

In this context the employment of fuzzy logic based methodologies could play a determining role by contributing to the development of robust, fast and reliable power flow management units.

V. POWER FLOW MANAGEMENT IN HEV USING FUZZY LOGIC BASED METHODOLOGIES

The starting point in the application of a fuzzy logic based methodology for the resolution of an engineering problem is to identify the potential benefits induced by the application of such an approach compared to classical ones. The analysis of the literature presented above concerning the problem under study has shown classical approaches are able to solve the optimal power flow problem with a good degree of accuracy but, on the other hand, require tremendous resources and therefore they may not be applicable for real-time applications.

In this context FL solves the power flow management problem by using rules to handle its intrinsic non-linearity, membership functions, and the inference process, which may result in improved performance, simpler implementation, and reduced design costs.

Moreover, from an implementation point of view, FL is inherently robust since it does not require precise, noise-free inputs, which allows general-purpose sensors to be used and reduces the complexity of the signal acquisition module. All these features allow the overall system complexity and cost to be kept low.
Application of FL to solving the problem under study requires the design of a FUZZY controller. This processes a set of easily measurable variables describing the actual drive condition, the state of both the powerdrive components and the exhaust gas treatment system distributing the instantaneous vehicle power demand between the engine and the motor in order to fulfill the previously described design goals.

Starting from these arguments, the next section describes the main functional steps required to design an FL controller in order to solve the power flow management problem.

A. Design of the FUZZY controller

1) Identification of the input/output variables

The first step in the design of a fuzzy controller is to identify the input and output variables. In this connection, starting from the previous consideration, it is worth to identify as output variable for the FUZZY controller the instantaneous power split between the internal combustion engine and the electric motor described by the degree of hybridization $h$ as:

$$\begin{align*}
    P_{el} &= h P_{req} \\
    P_{ic} &= (1 - h) P_{req}
\end{align*}$$

where $P_{req}$ is the instantaneous vehicle power demand while $P_{el}$ and $P_{ic}$ are the fraction of the power demand supplied from the internal combustion engine and the electric motor respectively.

The identification of the input variables is a little more complicated. In particular, after a preliminary sensitivity analysis, the catalyst temperature was chosen as a variable describing the efficiency state of the exhaust gas treatment system, while the instantaneous vehicle power demand described by the actual speed and the desired acceleration was chosen as the variable describing the driving conditions. Obviously the controller should also supervise the state of charge of the batteries whose signal is therefore also included in the set of input variables.

The overall structure of the proposed FUZZY controller is shown in Fig. 2.

2) Knowledge base acquisition process

Once the design variables have been identified, a suitable control strategy solving the power flow management problem needs to be identified by carrying out a knowledge acquisition process that codifies the knowledge of an expert into a set of fuzzy rules.

In developing this activity, it is possible to take advantage of both linguistic information, that summarise a reasoning process in arriving to a final control action as a set of fuzzy if then rules with imprecise but roughly correct MF, and numerical information, that could derive from experimental data recorded during expert’s operations.

For the problem presented in this paper, a set of suitable linguistic information could be organized by identifying a set of directives codifying suitable resolution strategies as a function of typical powerdrive operating conditions.

This task could be solved by defining a knowledge base structured on a set of fuzzy rules that codify the heuristic resolution methodology defined by the following minimum set of linguistic directives:

- Employ the internal combustion engine in the vehicle traction only when:
  - The battery is sufficiently charged
  - The catalyst temperature is sufficiently high
  - The speed is almost constant
  - The velocity of the vehicle is not extremely low

Using these linguistic directives makes it easy to obtain a set of fuzzy rules having the following structure:

\[
\text{IF (the battery is sufficiently charged) AND (catalyst temperature is PS) AND (acceleration is PO or NE) AND (velocity is PS)} \text{ THEN (h is ZE)}
\]

\[
\text{AND (catalyst temperature is PS) AND (acceleration is ZE) AND (velocity is PM) THEN (h is PS)}
\]

\[
\text{...}
\]

\[
\text{AND (catalyst temperature is PB) AND (acceleration is ZE or PO) AND (velocity is PM) THEN (h is PM)}
\]

\[
\text{AND (catalyst temperature is PB) AND (acceleration is ZE) AND (velocity is PB) THEN (h is PB)}
\]

\[
\text{...}
\]

where NE, ZE, PS and PB define suitable fuzzy sets for each reference variables.

As far as the numerical information, they can be obtained by solving the optimal power flow management problem in various operative conditions using a rigorous mathematical methodology, such as proposed in [9].

As part of the power flow management problem, this methodology solves a multiobjective mathematical programming problem whose purpose is to reach each design objective simultaneously.

Moreover, in accordance with the instantaneous power demand $P_{req}$, the objectives are composed of five important terms:

- the instantaneous HC emissions
- the instantaneous CO emissions
- the instantaneous NOx emissions
- the fuel economy (FC)
- the battery depletion (ASOC)
while the overall problem is to find the power flow distribution between the internal combustion engine ($P_{ice}$) and the electric motor ($P_{el}$) at each moment so that:

$$\min_{\{P_{ice}, P_{el}\} \in \Omega} \begin{pmatrix} HC(P_{ice}, P_{el}, \Gamma), CO(P_{ice}, P_{el}, \Gamma), NOx(P_{ice}, P_{el}, \Gamma), FC(P_{ice}, P_{el}, \Gamma), \\
\Delta SOC(P_{ice}, P_{el}, \Gamma) \end{pmatrix}$$

$$P_{ice}(t) + P_{el}(t) = \text{req}(t)$$

where $\Omega$ is the solution space, and $HC(P_{ice}, P_{el}, \Gamma), CO(P_{ice}, P_{el}, \Gamma), NOx(P_{ice}, P_{el}, \Gamma), FC(P_{ice}, P_{el}, \Gamma),$ and $\Delta SOC(P_{ice}, P_{el}, \Gamma)$ are respectively the estimation of the pollutant emissions, fuel consumption, level of batteries discharge related to the power flow distribution ($P_{ice}, P_{el}$), and the actual powerdrive state described by the vector $\Gamma$.

Since the design objectives conflict with each other, any improvement of one objective can only be achieved at the expense of another. Therefore, the resolution of such a problem has no unique solution and a suitable trade-off between the objectives needs to be identified.

The goal attainment method is particularly suited to solve this problem [14]. It is not subject to any kind of convexity limitations, and it has been shown to be an effective strategy for the solution a large number of complex engineering problems characterized by non linear, multimode, and vectorial objective functions [9].

The formal resolution of the problem (2) for different drive conditions identifies a suitable set of experimental data describing the mathematical solution of the power flow management problem.

The entire set of linguistic and numerical information identified above represents the foundation of the knowledge base that needs to be codified in the fuzzy controller.

### 3) Identification of the controller architecture

The next step in designing the FL controller concerns the identification of the appropriate control architecture. Two different solutions were analysed.

The first is based on a Mamdani architecture and it uses the set of linguistic information to convert heuristic experiences into appropriate fuzzy if/then rules and membership functions according to the previously described principles.

In this context the parameters of the membership functions can be tuned by solving the following non-linear programming problem, as proposed in [4]:

$$\min_{\theta} J(\theta) = w_1 \int h_c(t) dt + w_2 \int c_o(t) dt + w_3 \int n_o(t) dt + w_4 \int s_o(t) dt$$

where $\theta$ is a vector describing the membership functions parameters, $w_1, w_2, w_3, w_4$ are weight factors (that can take either technical aspects or social considerations into account), and all the figures for merits (emissions and battery depletion) are estimated by simulating the vehicle equipped with the corresponding fuzzy controller on a fixed drive cycle and normalized on fixed threshold representing, for example, national norms or standards.

The second approach employs a NEUROFUZZY based architecture that uses the numerical information and dedicated learning algorithms to identify the overall structure and parameters of the corresponding fuzzy controller.

In particular, amongst the possible network architectures, an Adaptive Neuro Fuzzy Inference System (ANFIS) was considered [11]. This topology has been widely applied to solve complex engineering problems, exhibiting high approximation capability especially in identifying the dynamics of non-linear systems [15].

Functionally, the network architecture is equivalent to a Sugeno-Takagi first order fuzzy system [12]. The rules constituting the fuzzy inference system for a two input and one output system have the form:

**Rule 1:** IF $In_1$ is $A_1$ AND $In_2$ is $B_1$ THEN $f_1 = a_1 In_1 + b_1$

$$In_1 + c_1$$

**Rule 2:** IF $In_1$ is $A_2$ AND $In_2$ is $B_2$ THEN $f_2 = a_2 In_1 + b_2$

$$In_1 + c_2$$

where $(In_1, In_2)$ is the input pattern and $f_i$ is the associated rule output. Each rule is characterized by membership functions $A_i$ and $B_i$ for the inputs, and by the coefficients $a_i, b_i$ and $c_i$ for the corresponding crisp output.

In terms of number of fuzzy rules and the optimal set of network parameters describing the membership functions and the crisp output functions used to identify the appropriate network structure, a proper training procedure should be adopted.

For this a hybrid approach based on a combination of the least-squares method and the Levenberg-Marquardt descent method was used [11].

The data set used for the training was obtained by solving the power flow management problem using the previous described goal-attainment based methodology over a standard drive cycle, as schematically reported in Fig. 3. After the network has been trained to mimic the behaviour of the complex multiobjective power flow management unit, it can be employed as a fast control unit in the general vehicle structure, as reported in Fig. 4.
VI. CASE STUDY

In order to evaluate the effectiveness of the proposed methodologies, various simulation studies were performed. Table 1 summarizes the features of the test vehicle used in these studies [4].

The main vehicle performance indicators for different drive cycles can be estimated by using an advanced vehicle simulator developed in Matlab environment [13], [16].

Thanks to the adoption of this simulation tool the design of the two fuzzy controllers could be developed according to the previously described methodologies.

In particular, a 27 rule knowledge base was identified for the Mamdani based fuzzy controller.

The corresponding MFs are characterized by gaussian and sigmoidal profiles, while the respective parameters were identified by solving the optimization problem formalized in (3) using a genetic algorithm as proposed in [4]. In this respect, the Federal Test Procedure drive cycle (FTP) was used as the reference drive cycle to estimate vehicle performances during the optimization process.

The corresponding features of the fuzzy controller, in terms of membership functions and control surfaces, are depicted in Figs. 5 and 6, respectively.

The NEUROFUZZY network was trained to solve the power flow management problem by using a goal attainment based methodology on the Federal Test Procedure drive cycle (FTP). The controller obtained is characterized by the membership functions and the control surfaces depicted in Figs. 7 and 8, respectively.

On the FTP cycle, equipping the test vehicle with the identified FL controllers leads to the dynamical power flow distributions reported in Fig. 9 with the related performances in terms of emission and energy consumption reported in Figs. 10 and 11, respectively. Analysis of the simulation results reveals that the proposed control strategies use intensively the electric motor when the engine is cold or additional power is required considering that the locus of maximum efficiency on internal combustion engine’s torque-speed map does not necessarily correspond to the loci of optimum emission.

In order to evaluate the effectiveness of the proposed fuzzy controllers, simulations were developed so that they could be compared to various other classic approaches. In particular, as references for the comparison, a multiobjective adaptive methodology [9] and a static control strategy with optimized parameters [13] were used. Equipped with such control strategies, the vehicle was then simulated on different cycles in order to evaluate its relative performances in terms of pollutant emissions and fuel consumption. The drive cycles considered included the New European Driving Cycle (NEDC), the Federal Test Procedure (FTP) and the highway fuel economy test (HWFET). The results obtained are summarized in Table II. The value of variables obtained from applying the static control strategy is used as baseline. The analysis of the simulated data shows that both FL controllers exhibit good levels of accuracy in resolving the power flow management problem, with a significant decrease in all the main pollutant emissions entire in the set when compared to the static threshold approach.

As expected, the effectiveness of the static control methodology is only seen in the NEDC cycle, which was adopted in the identification of the optimal setting of its control thresholds. A further consideration worth noting is the observation that the NEUROFUZZY network is able to closely approximate the optimal power flow distribution identified with the multiobjective based methodology. It therefore also exhibits comparable performance in terms of both emissions and fuel consumption for drive cycles sensibly different from the one adopted for the training process. Moreover, although the Mamdani based controller has been designed using weak heuristic knowledge, it exhibits adequate accuracy when compared to the rigorous mathematical solution methodology.
Fig. 5. Membership functions for the input and output variables of the Mamdani based controller.

Fig. 6. Control surfaces of the Mamdani based controller.
Fig. 7. Membership functions for the NEUROFUZZY network input and output variables.

Fig. 8. Control surfaces of the NEUROFUZZY network.

Fig. 9. Power Flow management, (a) Mamdani fuzzy controller, and (b) Neurofuzzy controller.
Finally, further considerations concerning the computational resources required to solve the optimal power flow management problem can be described by adopting the simulation time required to solve the power flow management problem for the test vehicle on the NEDC drive cycle as an index of comparison. The results obtained from a 2Ghz based PC with 1Mb of RAM memory are reported in Tab. III. Compared to the multiobjective resolution methodology, analysis of this data reveals how extremely small the computational resources required by both of the FUZZY strategies are, and are comparable to the computational resources required by the static thresholds based approach. This makes the proposed solutions a suitable trade off between the effectiveness of the formal mathematical methodology and the low complexity of the static threshold based approach currently adopted on commercial vehicles.

These conclusions are also confirmed by the first experimental results obtained by implementing the proposed fuzzy logic based control strategies on a Rabbit 2000™ based microcontroller integrated in an hardware in the loop architecture realized in the Matlab environment by the XPC-Target toolbox.

VII. CONCLUSIONS

This paper proposes the employment of FL in developing a robust, fast, and effective control unit for optimal power flow management in PHEV.

Two design methodologies were analyzed in developing this control unit.

The first one is based on a Mamdani architecture and uses a suitable set of linguistic information to convert heuristic experiences into appropriate fuzzy if/then rules and membership functions.

The second methodology employs numerical information derived from a rigorous resolution of the power flow management problem to train a NEUROFUZZY network that learns the behavior of the complex mathematical resolution methodology.

In both cases the simulation studies developed prove that the problem is solved with a high degree of accuracy and placing little demand on computational resources compared to rigorous mathematical based approaches.

By balancing the potentially conflicting goals of fuel economy and emission reduction, both strategies enable individual emission reduction policies to be implemented and the relative importance of fuel economy and emissions to be rated.

As a result, future research and development will be oriented to implementing the proposed power flow management strategies on hardware in programmable units by integrating them on a laboratory PHEV test bed.

APPENDIX

MATHEMATICAL MODELS OF THE HYBRID ELECTRIC POWERTRAIN

The hybrid electric powertrain has been simulated by a Matlab based Advanced Vehicle Simulator developed at National Renewable Energy Laboratory (NREL) [13], [16]. This tool adopts a backward-facing vehicle simulation strategy since it takes the required speed as an input, and determines what drivetrain torques, speeds, and powers would be required to meet that vehicle speed.

The models adopted are mostly empirical, relying on drivetrain component input/output relationships measured in the laboratory, and quasi-static, using data collected in steady state tests and correcting them for transient effects such as the rotational inertia of drivetrain components. The equations describing the main powerdrive components are briefly reported in the next sections.
Where $t_{\text{cool}_{\text{sp}}}$ and $t_{\text{cool}}$ are the thermostat set point of the coolant and the dynamic coolant temperature, respectively.

These temperatures are derived by solving the thermal dynamic of the main engine components: the cylinder, the engine block, the exterior engine accessories, and the hood of the vehicle. The coolant operates as a thermostat, with a fixed setpoint. Heat is generated by combustion, conducted to the engine block, and removed through forced liquid cooling, conduction, natural convection, and radiation. More details about the equations describing these phenomena could be found in [16].

### B. Exhaust system model

The exhaust system model simulates the engine exhaust after treatment system for the vehicle. It is composed of the exhaust manifold, downpipe, catalytic converter, and muffler. The primary output of the exhaust system model is the tailpipe emissions (HC, CO, NOx, and PM) in g/s, as a function of time. Other outputs include the temperature of various exhaust system components and of the exhaust gas temperature into and out of each system component.

Catalyst conversion efficiencies as a function of temperature are derived experimentally and stored in vectors. These values are dynamically adjusted at high exhaust flow rates (face velocities) and an upper “breakthrough” limit in g/s for each emission component is also considered. The tailpipe emissions are then the product of the fuel converter out emissions and the total effective catalyst efficiency.

Catalyst temperature is calculated using a lumped-capacitance approach. A mass and heat capacity are assigned to both the major converter components and the manifold and downpipe. Heat transfer correlations are used to estimate the convective heat transfer coefficients from the hot exhaust gas to the components, as well as from the components to ambient. Radiative loss to the ambient is also included. Within the converter, the heat of catalysis is estimated based on the g/s of each emission component (HC, CO, NOx, and PM) being catalyzed. This heat adds to the rate of converter warm up.

### C. Energy storage system

The energy storage system is modeled by an equivalent circuit whose experimentally derived parameters are a function of the remaining charge in the reservoir. The equivalent circuit accounts for the circuit parameters of the battery pack, as if it were a perfect open circuit voltage source in series with an internal resistance. The amount of
charge that the ESS can hold is taken as constant, and the battery is subject to a minimum voltage limit. The amount of charge that is required to replenish the battery after discharge is affected by coulombic efficiency. The charging of the battery is limited by a maximum battery voltage. While the battery is treated as a perfect electrical voltage source with a known resistance, the components to which the battery would be connected, such as a motor or a generator, are treated as power sources or sinks. Power delivered by the battery is limited to the maximum that the equivalent circuit can deliver or the maximum that the motor controller can accept, given its minimum voltage requirement.

A simple, single-node lumped-parameter thermal model is adopted to predict the average internal battery temperature and exiting air temperature as a function of time while the vehicle is driven and during soak periods.

D. Electrical motor model
The electrical motor model includes the effects of losses in the motor and controller, rotor inertia, and the motor’s torque speed-dependent torque capability. Power losses are handled as a 2-D lookup table indexed by rotor speed and output torque. The motor’s maximum torque is enforced using a lookup table indexed by rotor speed. Available torque is computed from available power by assuming that the ratio of rotor torque to input (electric) power is the same for the actual/achievable situation as was computed for the request. Rotor speed for the actual/achievable calculations is as computed in the 'request' branch.

A simple thermal model of the motor calculates the temperature of the motor and the thermal power rejected in to the coolant to maintain this temperature. The motor is modeled as a lumped capacity mass with liquid cooling based on a thermostat setpoint. Heat is generated by the motor, and removed through natural and forced convection, radiation to ambient air, and forced liquid cooling [16].

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