Adaptive Energy Management of Hybrid and Plug-in Hybrid Electric Vehicles Using Artificial Intelligence

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This report summarizes the studies done during the fall 2007 semester. It includes the literature review, and research done on the subject of the Ph.D. dissertation.

Ph.D. Research Subject

Since the oil crises of the 1970's, fuel economy has been one of the dominant issues in automotive industry. Therefore, a lot of research work has been focused on finding more efficient methods for transportation. One approach is provided by the concept of electric vehicles (EV) as compared with the internal combustion engines (ICE), electric machines are much more efficient. Moreover, electric machines are emissions free which means that they are environmentally friendly. Against all benefits, the problem with EVs is in the energy storage systems. In electrical systems, the energy is mostly stored in batteries, where drive range is an issue. They are required to recharge often and the charging times are long. To solve this energy storage problem, hybrid electric vehicles (HEV) are proposed as a practical solution. HEVs are the vehicles which are using both ICE and electric machines as energy transformation medium and again a battery to store the extra energy from the regenerative breaking or ICE. Hence, they enjoy the benefits of both electric and conventional vehicles. In general, hybrid systems can be commanded by splitting the required power between the electric machine and ICE to meet the specific needs like fuel consumption, efficiency, performance, and emissions. This power splitting scenario, which is the key point of hybridization, is in fact the control strategy or energy management of the hybrid automobile. Performance of the system, therefore, depends on the control strategy which needs to be robust (independent from uncertainties and always be stable) and reliable. Moreover, in order to improve the system, the control strategy should be adaptive to track the demand changes from the driver or drive cycle for optimization purposes. To compensate all this needs an adaptive artificial intelligent (neural networks and fuzzy logics) supervisory control system is proposed in this Ph.D. research for energy management of hybrid and plug-in hybrid electric vehicles.

Research on Hybrid Control Strategies

In general, a hybrid control strategy design depends on two main points. First one is the physical topology (series, parallel, or parallel-series) and second one is the performance index or cost function.

The three main topologies of hybrid drive trains depend on the connection of ICE to the electric propulsion system. In series connection, ICE is not connected to the drive train, instead ICE is connected to an electrical generator. This means that the power of the ICE is converted to the electrical energy and it is stored in battery, which is connected to the generator by a charging circuit. The required propulsion power is then taken from the electric machine by a power electronic inverter, which is connected to the battery. The main control strategy is to control the ICE in such a way that it will perform the hybridization need and keep the state of charge (SOC) of the battery is a specific range. For breaking, the electric machine can be controlled to harvest some of the breaking energy to charge the battery keeping SOC at a safe level. This is regenerative breaking. In parallel HEV topology, the ICE is connected to the drive train and the electric machine by a mechanical torque/speed coupler. A battery is also connected to the electric machine. This means that the required propulsion power can be spitted by controlling the power of the electric machine and ICE. Most of the control strategies for parallel HEVs are based on load leveling principle, which means that the main propulsion power source is the ICE and the electric machine is an assisting source giving or taking the difference power at the drive train. Such controller performs the load leveling to achieve the required performance from the hybrid system and to keep the SOC of the battery at safe levels. The general control strategy for a parallel HEV can be summarized as follows [1]:

(1) When the speed of the vehicle is small, ICE stops and electric motor gives the driving power required which avoids higher fuel consumption and worse emission (It is assumed that SOC is sufficient).
(2) When the speed of the vehicle high enough, electric motor stops, ICE starts and gives the driving power required. Currently, ICE works along optimum curve depending on the cost function.
(3) If the power required is larger than ICE can give, ICE and electric motor work together and electric motor takes additional required power from the battery (It is assumed that SOC is sufficient).
(4) If SOC of the battery drops under the safe level, ICE would supply both the energy required for traveling and extra power to charge the battery through electric motor (electric motor is at generator mode).
(5) In brake state, energy floats from vehicle body to drive train. Electric motor works as a generator and transforms braking energy to electricity to charge the battery.

Parallel series HEV (Toyoya Prius) topology is the combination of series and parallel HEV topologies. In this topology like in series topology, there is a generator, an ICE and an electric motor. Each of these three components is connected mechanically to others by a planetary gear set. This gear set can also be viewed as a power split device that splits the required power between the three components. From the viewpoint of the electrical path (series hybrid), the portion of the power from the engine to the generator can be converted into the electric energy. Then the electric motor draws the electric power provided by the battery and the generator to propel the vehicle. From the viewpoint of the mechanical path (parallel hybrid), another portion of the power from the engine to the carrier to the ring gear to counter shaft can be used to drive the vehicle without energy transformation [2].

Performance index or cost function is the mathematical descriptions for different requirements of hybridization. This function is generally a quadratic function of any of SOC, fuel consumption, emission or torque at drive train. The weighting coefficients, in cost function, are selected according to hybridization destinies. The cost functions are selected to be quadratic, because a quadratic function has only one minimum point which is always the global one. Therefore, when an offline mathematical optimization is performed, the solution is the optimum (there is not semi-optimal solutions). One of the problems of offline optimization by cost function is the optimization is performed for a given parameter set. If the parameters of the system changes during the process, the solution is not optimum. Therefore some control systems use engine maps instead of cost functions.

There many control strategies like optimal control [3] [2] [4] [5] [6], discrete time events approaches [7], fuzzy logic controller [8] [9] [10] [1] [11] [12], and neural networks [13]. There are also combinations of these control strategies like neuro-fuzzy control [10] and fuzzy discrete event control [14].

For optimal control scheme controller is optimized according to cost function of the system. Therefore optimal control strategies are nearly perfect, but the optimal controllers are sensitive to parameter changes and also to measurement noise. Any small measurement problem may cause stability problems. To perform the optimization process, all the dynamic and static behaviors of the system components are taken under consideration. This makes the calculations hard to solve and sometimes impossible for complex problems. Therefore calculations are usually simplified by introducing assumptions which means that the solution is optimum only under the assumptions. On the other hand discrete time events approach is simple and more robust. System behaviors are divided into discrete events. Each event is connected to the other one by a certain rules. If the rule is performed, system moves from one state to another. The problem is that it can only serve a partial optimum solution because discrete event systems work in binary (on-off) mode and the performance depends on the resolution of the rules. To solve this problem discrete event approach can be combined with another strategy like shown in [14]. Artificial intelligence control methods are another approach for energy management problem. Most popular one is the fuzzy logic control. Fuzzy logic control has a nonlinear structure that can match with the nonlinear structure of the power split problem. Compared with other method fuzzy logic has more robust structure and it serves more flexibility to optimization. The problem with fuzzy logic is the optimization and mathematical manipulation of defuzzification system. The defuzzification process consumes memory and time in controller. Compared to fuzzy logic, neural network has better characteristic on means of optimization. Neural network systems have the ability to be train online or offline, but online training consumes memory in a controller. This trainability characteristic makes neural networks as a good candidate for adaptive energy management system.

The inputs to the controller are also important. The inputs should be measurable or predictable inputs. For example road load which is the required propulsion power cannot be input for control system, because road load depends on the slope of the road, rolling resistance (depends on the tire pressure and speed), drag forces (depends on the shape of the car and vehicle speed) and also the traction power required for acceleration (depends on the mass of the car, friction coefficient between tire and road).

To achieve a superior performance, an adaptive neural network system is proposed as the energy management system. The inputs are the SOC, the engine speed, and the power demand from the driver (positive for acceleration and negative for deceleration). The outputs will be the reference values for the ICE and electric machine.

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