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A Study on Look-ahead Control and Energy Management Strategies in Hybrid Electric Vehicles

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***Abstract*—Fuel efficiency in a hybrid electric vehicle requires a fine balance between usage of combustion engine and battery power. Information about the geometry of the road and traffic ahead can have a great impact on optimized control and the power split between the main parts of a hybrid electric vehicle. This paper provides a survey on the existing methods of control and energy management emphasizing on those that consider the look-ahead road situation and trajectory information. Then it presents the future trends in the control and energy management of hybrid electric vehicles.**

I. Introduction

THE fuel economy in hybrid electric vehicles (HEV) is realized through the recovery of the potential energy from regenerative breaking, efficient work of the combustion engine, electric machine (EM), transmission and battery [1]. Also, driving behavior, driving pattern, and road topology affect the fuel consumption of a vehicle. From the standpoint of energy management and optimal control of energy flow in HEVs, the knowledge about disturbances relating to driving route, traffic and road geometry can help develop a suitable strategy. Such a strategy, known as look-ahead control or energy management, can help improve the fuel economy of HEVs.

Look-ahead control is a "predictive control scheme with additional knowledge about some of the future disturbances on the road topography ahead of the vehicle" [2]. Developing a control algorithm, using look-ahead information, allows HEV to plan how and when to use the stored energy in the battery and also recharge it. It is reported that using a prediction horizon of 500 m improves the fuel consumption by 15% [3]. Therefore, in some studies, road situation ahead and also driving pattern have come to consideration. However, this is a new concept in HEVs' control and energy management. This paper aims to show the drawbacks and advantages of some existing energy management studies and then survey the impact of trajectory specifications on HEVs' control and energy management.

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A. Series HEVs

The simplest hybrid topology is series. It acts like an electric vehicle with an on-board generator as a battery charger. A schematic of a series HEV is shown in Fig. 1. While driving is at slow speeds, the controller draws power from the battery to drive the EM. In this case, the vehicle acts like a pure electric car. During acceleration, the combustion engine drives the generator to compensate the power being drawn from the battery. The generator provides power to run the EM, and if necessary, additional power may be drawn from the generator to recharge the battery. Energy from regenerative braking is converted into electricity and stored in the battery. Since ICE is not coupled to the wheels, it operates in a narrow region at near optimum efficiency [7]. This eliminates the need for a complicated clutch and multi-speed transmission, increasing fuel economy and decreasing emission in comparison with a conventional vehicle.

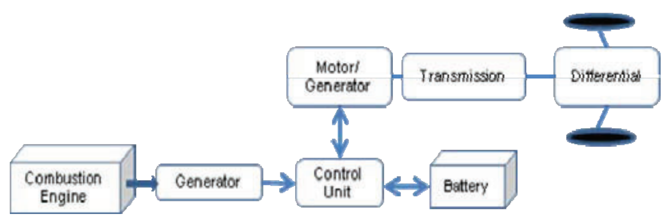

Fig. 1. Schematic of a series HEV.

However, there are two stage of energy conversion during power flow to the wheels, ICE/generator and battery/motor causing the loss of energy. This issue is considered as a drawback for series HEVs and makes them more suitable for city driving.

B. Parallel HEVs

In the parallel hybrid topology, ICE is capable of producing force that is mechanically linked to the transmission. This approach eliminates the generator needed in the series HEVs. In parallel HEVs, there are many ways to configure the transmission system. When ICE is on, the controller divides energy between the propulsion and the energy storage system. The split of energy between the two is determined by the speed and driving pattern. For example, under acceleration, more power is allocated to the drivetrain than to the energy storage system. During periods of idle or low speeds, more power is allocated to the batteries than the

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propulsion. When ICE is off, the parallel hybrid can run like a pure electric vehicle. The batteries can also provide additional power to the transmission when ICE is unable to produce enough energy to run auxiliary systems such as the air conditioner and heater. Fig. 2 shows a schematic of a parallel HEV.

Similar to series HEVs, energy can be saved during regenerating breaking. The significant advantage of parallel topology in comparison with series topology is that less energy is wasted during conversion stages. However, the transmission system in a parallel HEV is more complex than a series one. In the city driving, efficiency is less than series type because the engine operates inefficiently in stop-and-go.

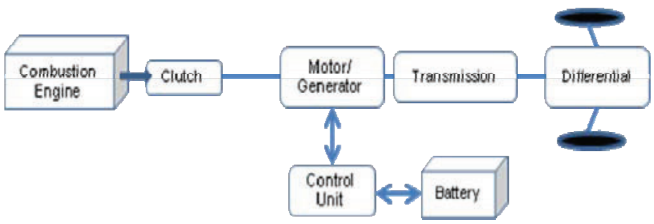

Fig. 2. Schematic of a parallel HEV.

C. Series-Parallel HEVs

This type combines the advantages and complications of both series and parallel HEVs. By combination of the two designs, the engine can both drive the transmissions directly (as in a parallel HEV) and be effectively disconnected from it (as in a series HEV). Fig. 3 shows a schematic of a series-parallel HEV.

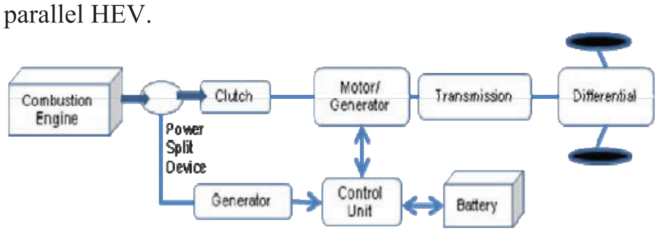

Fig. 3. Schematic of a series-parallel HEV.

In this configuration, the engine can often operate at near optimum efficiency. At lower speeds, the vehicle operates as a series vehicle, while at high speeds, where the series hybrid is less efficient, it acts like a parallel one. Because the system needs a generator, a larger storage system, and a complicated power flow control system, it has a higher cost than the other two types. However, the series-parallel HEV has the potential to perform better than each of the two other systems alone.

II. Energy Management Methods in HEVs

In many studies, energy management in HEVs has been performed by appropriate division of power/energy, efficiency of engine, motor and state of charge of battery. Minimizing fuel consumption depends on suitable powertrain design. An optimal design is composed of configuration and component design. To obtain high overall efficiency, not only the drivetrain configuration and its component need to be power efficient, but also the components need to be compatible in size and type. Considering a suitable powertrain design, to achieve overall efficiency, all components need to be controlled and managed to work in their efficient regions.

Control in HEVs can be divided in two levels: higher level supervisory control and lower level component control. Supervisory controller provides suitable inputs for component controllers. Component controllers send control signals to final elements to attain fuel consumption optimization, minimization of emission, improvement of power train performance, drivability, and safety. In this study, we focus only on energy managements and fuel economy issues.

There exist several control strategies to optimise fuel economy. These include rule-based, fuzzy logic, Deterministic Engine Optimal Operating Line (OOL), Line Quadratic Regulator (LQR), neural network, genetic algorithm, and optimal control. These strategies can be classified into two groups: rule-based and optimization approaches [8].

Engine optimal operating line [9] is considered as the joining point from a sequence intersection of the constant engine power lines with the maximum efficiency contours or minimum fuel consumption. This curve can be considered as the base of the desired value in control system to obtain highest efficiency or minimum fuel consumption. Therefore, in many rule based applications the curve is used to obtain fuel economy or lower emission [10]. However, with the constraints in real situation such as state of charge of battery (SOC), considering drivability and performance, operation point may shift away from the fuel economy condition line.

Joen et al. [11] used the linear quadratic method in which a parallel HEV is simplified to a linear, time-invariant (LTI) system. The control was based on the known reference velocity of the trajectory. However, the assumption of linearity in such a system and the need to know the velocity in advance reduces the appeal of this method.

Dynamic programming (DP) is a global optimization method [12]. In this method, an optimal solution is found by dividing the given driving profile into many segments. For every path between the decision stages, there is a cost. A cost function consists of weighted engine and EM power is considered. First, the optimal solution for the last segment is solved and then in a backward recursive way the calculation moves one step back to obtain the optimal solution for this segment. This computational method will be done segment by segment towards the first stage until the optimal solution is found.

DP has been used in several existing approaches. Perez et al. [13] defined a supervisory control to manage the power in a series HEV. The strategy of the supervisory control is defined to minimize the fuel consumption. They abstracted the series HEV with two sources of energy, fuel tank and electrical storage supply. By power flow relations and related constraints, two functions are defined. Using DP, subject to minimizing the fuel consumption in a time interval, one of functions is solved and the optimal power split between engine power and buffer power for a predefined driving cycle is obtained.

Paganelli et al. [14] introduced chare-sustaining operation. A formulation based on converting the use of the EM into equivalent fuel consumption was performed. This equivalent fuel consumption was added to the mass flow consumed by the engine. A minimization problem due to the rate of fuel consumption of engine, and equivalent fuel rate of EM (positive and negative) was defined. This method was used in the supervisory controller to adjust the instantaneous power split between ICE and the EM to minimize the equivalent fuel consumption. Finding the equivalent fuel consumption of the battery and EM needed all the components in the power flow root from tank to EM. This was not however considered in the reported work.

Jalil et al. [15] defined a rule-based control strategy based on the engineering knowledge. This strategy is formed by splitting the power demand between the engine and the battery, considering vehicle conditions such as SOC. This strategy is expressed in if-then rules form. Rule-based control is the foundation of the fuzzy logic [16] which "translates linguistic representation of control inputs into numerical representation with membership function in the fuzzification and defuzzification process". The knowledge of expert in controlling the process is expressed in the form of rules. This approach has been utilized in many studies.

Schouten et al. [17] proposed a fuzzy-logic control system in order to optimize the fuel consumption in a parallel HEV. The method is based on the efficiency optimization of the essential parts of the vehicle including ICE, EM, and battery. An efficiency map for a generic compression-ignition direct injection (CIDI) engine in the speed-torque is used. Considering SOC, the outputs of the controller track the work of the components (IEC and motor/generator) so that, they work on the efficiency curve. Accordingly, the power-split strategy through fuzzy rules is formulated to manage the possible ways of power. The model was simulated in PSAT software. The operating points for ICE and EM were closed to the optimal curve.

A combination of fuzzy logic and an optimization method is known as adaptive fuzzy rule based. Poursamad and Montazeri [18] proposed a genetic-fuzzy control strategy to determine how to distribute the driver's required torque between the ICE and EM. At first, a fuzzy logic controller (FLC) is designed, the rules are determined, and through a genetic algorithm (GA) the defined parameters (membership functions) are tuned. In their model, they applied a cost function whose target values were minimized fuel consumption (FC) and exhaust emissions (HC, CO, and NO_xs). The values were weighted, and based on the level of importance; they were assigned in the cost function. ADVISOR software was used to simulate the model. The tuning process was performed over three driving cycles: TEH-CAR (Tehran car driving cycle), FTP (in the US), and NEDC (European Community). The results for FC and emissions, in three cycles, before and after tuning were listed. Comparing the values of the objective function, outputs of tuned FLC for the TEH-CAR cycle was less than the non tuned one. However, there was an increase in the CO emission after tuning.

III. Look-ahead Approach

Rajagopalan and Washington [19] used traffic information (speed limits on the road and topological data) from GPS over an entire trip. They used a fuzzy logic controller to determine the torque split between ICE and EM based on efficiency and emission.

Johannesson et al. [20] improved the DP approach. They modeled vehicle travelled in a specific route on collected data. The route was divided into discrete intervals. The speed in the end of each interval was modeled by a "Markova Chains". The control optimization was done by DP. Based on the access level to the route information, three types of optimal controllers were assessed. Controller with the highest access level to the future power demand was considered as an ideal controller.

Ichikawa et al. [21] presented a novel method in order to predict the pattern of a commuting trajectory based on the past information. The main reason to consider this road was to simplify the prediction of the future driving pattern. In term of individual characteristics like stop-and-go information and velocity profile, the driving pattern was divided into separate categories. Clustering algorithm was used to solve the difficulties of the large amount of data collection in every driving cycle. Moreover, they used velocity-distance instead of velocity-time.

Salman et al. [22] solved an optimization problem in which fuel mass and SOC were state variables, and power from engine-to-battery/motor-to-battery were control parameters. Accordingly, system equations, cost function and constraint were obstructed and the optimization problem from current time, to the horizon was solved. They showed that there was a considerable improvement in the fuel consumption when the algorithm used future driving cycle and terrain information.

Hajimiri and Salmasi [23] introduced a FLC to manage the power flow in the series HEV. The base of the strategy resembled that of a conventional power flow FLC, but further inputs, such as the difference between existing elevation of vehicle and future elevation, present speed and predictive speed, were added. It was assumed that this information was available via GPS. Based on future state of vehicle, related to traffic and elevation positions, some rules were added to a conventional FLC. The model was assessed in ADVISOR software. The simulation showed that the fuel consumption and emissions decreased in comparison with conventional FLC. Meanwhile, a control block related to increasing the state of health of battery was appended to the model. The simulation in this state gave poorer results. This implied that there was a tradeoff between the state of health of battery and fuel economy.

Gong et al. [24] applied DP in a plug-in HEV. Because of the higher capacity of the battery in this kind of vehicles, fuel economy was subject to operation in electric mode only for longer distances. In the destination, the charge of battery reached the minimum possible level, and then in the parking duration it could recharge via plug-in. The methodology of energy management was similar to a conventional HEV, and was based on power split management with considering SOC of battery in a numerical DP approach.

IV. Discussions

In the DP approaches, driving conditions have to be known in advance. This assumption is not practical in real situation. Because of the complexity, calculations in both DP and stochastic DP are time intensive, so their application to real-time systems is limited. However, since they provide the global optimality, they can be used as a benchmark for comparison with other optimization algorithms. Since fuzzy logic and rule based methods rely on expert knowledge, they cannot therefore provide an optimal solution. However, these two methods can model a nonlinear and time-varying system; they can provide a suboptimal fuel economy.

In Schouten et al. [17] method, we cannot conclude that the rules and membership functions are in their optimal state and they are defined based on the knowledge of the designer. Therefore, they do not have an optimization stage in their model. The presented analytical method by Perez et al [13] gives a sub optimized solution because the optimal control was not solved for electric part. Also, the complexity of the problem depends on the discrete steps. Increasing these steps result in an increase in the computation time. Also, the developed solution is only an off-line one.

The model by Jonnesson et al. [20] is evaluated by comparing the fuel consumption for three types of vehicles, position dependent, position invariant and ideal with highest access to the level of future power demand. For generalization, the evaluation is repeated for hybrid vehicles with different characteristics. The results show that the fuel consumption in ideal state is less than 6-9%.

The obtained optimal parameters in Poursamad and Montazeri work [18] for three tested driving cycles were different. It shows that the driving cycle affects the optimization process. In addition, optimization of fuel consumption depends on the road condition that was not considered in the model.

To some extent, Ishicawa et al. [21] by using the information of commuting trajectory in advance have been successful to achieve fuel economy. Clustering algorithm was used to solve the difficulties of the large amount of data collection of trajectory. The patterns of roads have been obstructed, but usage of these patterns has been referred to the future works. Also, the affects of route pattern on energy management system have not been evaluated. Moreover, this method for unknown route and long road because the large amount of data and the huge number of clusters is not feasible.

Hajimiri and Salmasi [23] in their paper show that implementation of information about vehicle trajectory and traffic ahead relatively can improve the energy consumption and emissions. However, in their model there is a lack of membership function and rules optimizer to obstruct optimal rules and membership functions.

The most important contribution of Gong et al. [24] was trip modeling. For the case study a sport HEV is simulated. Simulation is done with three energy management approaches, DP-based charge-depletion control, rule-base control, and depletion sustenance control. A simulation was carried out for a conventional sport HEV as a benchmark. Simulation results for a “Trip-Model based driving cycle” were considerably better than the other tried cycles. The comparison between the implemented control methods was performed. Consequently, the DP charge-depletion energy management strategy showed better results.

V. Conclusion

From the reviewed studies, we can conclude that there is a significant potential to improve the performance and efficiency of HEVs. Fuel consumption can be reduced if real traffic conditions are used. Intelligent transportation is formed by using road information. Investigation on road or driving cycle information and applying them in control strategy has a considerable impact on fuel consumption and decreasing emissions. GPS can provide information about the real location of a vehicle. On the other hand, GIS can give information about the travelling route in advance. Radar can determine the distance from the vehicle ahead. By equipping HEVs with more sensors, more real time information about the travelling route can be obtained. Combination of these data and data from the road sensors can improve efficiency. However, intelligent transportation and an optimal-trip-based control strategy can be considered as a novel issue in future HEVs studies. It is in its early stages of investigation and the trend can continue toward development a real-time optimization control and energy management in both aspects, theoretical and practical.

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REFERENCES

[1] S. S. Williamson, and A. Emadi, "Comparative assessment of hybrid electric and fuel cell vehicles based on comprehensive well-to-wheels efficiency analysis," IEEE Transactions on Vehicular Technology, vol. 54, no. 3, pp. 856-862, 2005.

[2] E. HellstrÃom, M. Ivarsson, J.Ã…slund et al., "Look-ahead control for heavy trucks to minimize trip time and fuel consumption," Control Engineering Practice, vol. 17, no. 2, pp. 245-254, 2009.

[3] X. Wei, "Modeling and control of a hybrid electric drivetrain for optimum fuel economy, performance and driveability," 2004.

[4] "College of the Desert,RV. 0," December 2001.

[5] C. C. Chan, "Overview of electric vehicle technology," Proceedings of the IEEE, vol. 81, no. 9, pp. 1202-1213, 1993.

[6] A. Emadi, K. Rajashekara, S. S. Williamson et al., "Topological overview of hybrid electric and fuel cell vehicular power system architectures and configurations," IEEE Transactions on Vehicular Technology, vol. 54, no. 3, pp. 763-770, 2005.

[7] J. M. Miller, P. R. Nicastri, and S. Zarei, ""The automobile power supply in the 21st century"," Proc. Power Systems World Conf. Expo., 1998.

[8] F. R. Salmasi, "Control strategies for hybrid electric vehicles: Evolution, classification, comparison, and future trends," IEEE Trans. Veh. Technol, vol. 56, no. 5, pp. 2393-2404, 2007.

[9] T. Mayer, and D. Schroeder, "Robust control of a parallel hybrid drivetrain with a CVT," Robust Control of a Parallel Hybrid Drivetrain with a CVT, 1996.

[10] B. M. Baumann, G. Washington, B. C. Glenn et al., "Mechatronic design and control of hybrid electric vehicles," IEEE/ASME Transactions on Mechatronics, vol. 5, no. 1, pp. 58-72, 2000.

[11] S. I. Jeon, K. B. Kim, S. T. Jo et al., "Driving simulation of a parallel hybrid electric vehicle using receding horizon control." pp. 1180-1185.

[12] A. Brahma, Y. Guezennec, and G. Rizzoni, "Optimal energy management in series hybrid electric vehicles." pp. 60-64.

[13] L. V. Perez, and E. A. Pilotta, "Optimal power split in a hybrid electric vehicle using direct transcription of an optimal control problem," Mathematics and Computers in Simulation, vol. 79, no. 6, pp. 1959-1970, 2009.

[14] G. Paganelli, M. Tateno, A. Brahma et al., "Control development for a hybrid-electric sport-utility vehicle: Strategy, implementation and field test results," 2001 American Control Conference. pp. 5064-5069.

[15] N. Jalil, N. A. Kheir, and M. Salman, "Rule-based energy management strategy for a series hybrid vehicle," Proceedings of the 1997 American Control Conference. Part 3 (of 6). pp. 689-693.

[16] M. Amiri, V. Esfahanian, M. R. Hairi-Yazdi et al., "Feed-forward modelling and fuzzy logic based control strategy for powertrain efficiency improvement in a parallel hybrid electric vehicle," Mathematical and Computer Modelling of Dynamical Systems, vol. 15, no. 2, pp. 191-207, 2009.

[17] N. J. Schouten, M. A. Salman, and N. A. Kheir, "Energy management strategies for parallel hybrid vehicles using fuzzy logic," Control Engineering Practice, vol. 11, no. 2, pp. 171-177, 2003.

[18] A. Poursamad, and M. Montazeri, "Design of genetic-fuzzy control strategy for parallel hybrid electric vehicles," Control Engineering Practice, vol. 16, no. 7, pp. 861-873, 2008.

[19] A. Rajagopalan, and G.Washington, "Intelligent control of hybrid electric vehicles using GPS information," Future Car Congress, 2002.

[20] L. Johannesson, M. Ã…sbogÃ¥rd, and B. Egardt, "Assessing the potential of predictive control for hybrid vehicle powertrainsusing stochastic dynamic programming," 8th International IEEE Conference on Intelligent Transportation Systems. pp. 366-371.

[21] S. Ichikawa, Y. Yokoi, S. Doki et al., "Novel energy management system for hybrid electric vehicles utilizing car navigation over a commuting route," 2004 IEEE Intelligent Vehicles Symposium. pp. 161-166.

[22] M. Salman, M. F. Chang, and J. S. Chen, "Predictive energy management strategies for hybrid vehicles," 2005 IEEE Vehicle Power and Propulsion Conference, VPPC. pp. 21-25.

[23] M. H. Hajimiri, and F. R. Salmasi, "A Predictive and Battery Protective Control Strategy for Series HEV," Asian Electric Vehicle, vol. 6, No. 2, December, 2008.

[24] Q. Gong, Y. Li, and Z. R. Peng, "Trip-based optimal power management of plug-in hybrid electric vehicles," IEEE Transactions on Vehicular Technology, vol. 57, no. 6, pp. 3393-3401, 2008.