Modeling and Offline Control of Parallel Hybrid Electric Vehicles using MATLAB

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Abstract - Due to strict emission rules and reduction of oil in reserves, hybrid electric vehicles have been upgraded and now a day's given utmost importance. Fuel consumption can be achieved by utilizing the regenerated energy while braking condition. The restrictions involved in the control of HEV's are fuel consumption, emission and drivability without exhausting the battery state of charge at the end of defined driving cycles. As a result of the above mentioned particulars there are many number of power management strategies in literature. This paper presents the handout of these literatures in the view of parallel hybrid electric vehicle modeling and control. As a part of this work susceptible gaps in research are also analyzed.

Keywords - Hybrid electric vehicle; Regenerative braking, optimization of brake energy recovery, Dynamic programming, Optimal control, HEV control,

Vehicle modeling, Parallel HEV, ECMS, Model Predictive Control, GPS

I. INTRODUCTION

The research and development activities in the field of HEV's have gained huge importance due to the lack of oil in reserves and strict emission rules [1-3]. In recent years the industries and scientific community have suggested a collection of creative ideas to overcome this declination. A new view point in the effective solutions comes up with hybrid powertrain architectures. HEV's have found to give effective solution for this problem by proposing a powertrain with additional propulsion system, which consists of an electric motor and an electric battery and it also have a couplet for electric driveline and thermal driveline. The added driveline concedes for greater flaccidity in engine use while safeguarding fulfillment of the power request at the wheels.

On comparing conventional vehicles with HEV's, Hybrid Electric Vehicle offers a lot of advantages. The most popular of such benefits is the opportunity of downsizing the original internal combustion engine although meeting the power demand at the wheels. This advantage is brought about by the ability of the hybrid powertrain to distribute power to the wheels from both the internal combustion engine and the electric motor at the same time, which results in reduction of fuel consumption [4, 5].Due to electric drivelines the regeneration of kinetic energy from the brake system is achieved, which would otherwise be lost to mechanical brakes in conventional

In order to achieve the above mentioned advantages it is necessary for a real time control strategy efficient of coordinating the on-board power sources in order to increase fuel economy and lower emissions. A lot of energy management strategies have been present in previous literatures. This paper presents a complete review of the literatures, focusing in the aspect of parallel hybrid electric vehicle modeling and control. Along with it susceptible research gaps were also identified.

The contributions in this paper are elucidated as follows: HEV configurations, HEV modeling approaches are briefed and importance of every modeling approach was discussed. Then HEV control strategies are reviewed at depth on HEV offline control strategies. This detailed appraisal is aimed at emphasizing the control structure of the reviewed techniques, its novelty, as well as contributions towards the satisfaction of several optimization objectives, which includes but are not limited to: decrease of fuel consumption and emissions, charge sustenance, optimization of braking energy regeneration, and refinement of vehicle drivability. Finally, credulous research gaps within the research area are identified and discussed.

II. HEV CONFIGURATIONS

Nowadays, there are two types of hybrid electric system configurations ("series hybrid" and "parallel hybrid") directly in use by automotive engineers [6,7]. The diverse that isolate HEVs into these divisions lie in the design of the power flow from the sources of energy. Power flow in the series HEV is run down to the transmission over a single path (electrical path) [8]. Parallel HEVs allow power flow through two paths (electrical and mechanical path) from the energy sources to the transmission [8].

III. HEV MODELLING APPROACHES

There exist partially three main stages of computational modeling currently employed in the evolution of HEVs. These stages are:

- Accurate modeling, which is completed through the research and early development stages of the HEV. This kind of modeling centers mainly on single powertrain components such as internal combustion engine and electric motor. This type of modeling is planned at realizing detailed information about explicit characteristics of the module being modeled.

- Software in the loop (SIL) modeling, which is carried out at a later stage of the HEV development cycle, but usually before any hardware production is made. The employment of SIL today has become well liked in HEV control system development.

- Hardware in the loop (HIL) modeling, which is carried out once the construction of controllers has been finished and authenticated. Three typical approaches exist for HEV modeling at the complete modeling stage of the development process: the kinematic or backward approach, the quasi static or forward approach, and the dynamic approach [26].

A. Kinematic Approach

The kinematic approach, as shown in Fig. 1, is a backward methodology where the input variables are the speed of the vehicle and the grade angle of the road. In this technique, the engine speed is decided using simple kinematic relationships preliminary from the wheel revolution speed and the total transmission ratio of the driveline. The tractive torque that should be provided to the wheels to drive the vehicle according to the chosen speed profile can be computed from the main vehicle uniqueness (e.g. vehicle mass, aerodynamic drag and rolling resistance). The computed engine torque and speed is then used near a statistical fuel consumption model to create an immediate fuel expenditure or emissions rate calculation [9]. The kinematic approach believes that the vehicle meets the target performance, so that the vehicle speed is supposedly known a priori; thus enjoying the benefit of accessibility and low computational cost [10]. The backward or kinematic modeling method guards that the driving speed profile will be accurately followed. However, there exists no assurance that the given vehicle will truly be able to meet the preferred speed trace, since the power is straightly calculated from the speed and not ensured against the actual powertrain capabilities. Typically, in simulation, the kinematic approach includes a “fail-safe” attribute which stops the simulation run if the required torque exceeds the maximum torque available (from the electric motor and engine). Another flaw of this modeling technique is its negligence of thermal transient behavior of engines which are noticeable after an engine cold start. The overview of transient conditions as a succession of stationary states limits this modeling method to an option extensive mainly for preliminary estimation of vehicle fuel consumption and emissions [7].

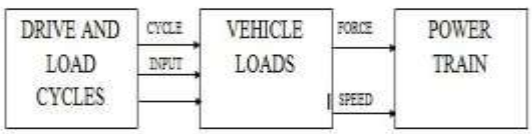

Fig. 1 Information flow in kinematic or backward HEV model[31]

B. Quasi-Static Approach

The quasi-static approach of HEV modeling as shown in Fig. 2 makes use of a driver model, typically a PID which evaluates the target vehicle speed (driving cycle speed), with the actual speed profile of the vehicle and then causes a power demand profile required to imitate the target vehicle speed profile. This power demand profile is created by solving the differential motion equation of the vehicle [10]. Once the propulsion torque and speed of the engine have been established, instant fuel consumption can be approximated using a statistical engine model as already clarified in the kinematic or backward approach. The suitability and accuracy of the quasi-static modeling approach depends very much on the nature of simulation studies to be performed. The quasi-static modeling approach offers rational correctness when it comes to the evaluation of the fuel consumption and NOx of a vehicle equipped with conventional powertrain. For pollutants like smoke, the acceleration transients and related “turbo-lag” phenomena significantly add to the cycle increasing emissions, thus demanding a more detailed engine simulation model which is proficient of properly confining engine transient performance in more detail.

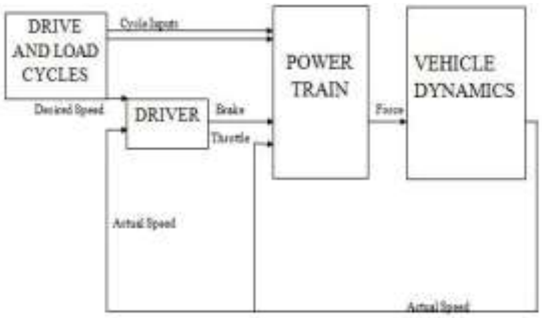

Fig. 2 Information flow in quasi-static powertrain model source[3]

C. Dynamic modeling approach

In the dynamic modeling approach, the internal combustion engine performance during transients is also modeled in addition to the longitudinal vehicle dynamics. The engine transient performance is modeled by means of a detailed one-dimensional fluid dynamic model. For example, the intake and exhaust schemes of the internal combustion engine in the dynamic modeling approach are represented as a network of ducts connected by the junctions that correspond to either physical joints between the ducts, such as area changes or volumes, or subsystems such as the engine cylinder. Solutions to the equations directing the conservation of mass, momentum and energy flow for every element of the system can then be achieved using a finite difference technique. This makes it likely for highly dynamic results such as rapid vehicle accelerations to be suitably and dependable, simulated with sensible accuracy. The achievement of dynamic modeling comes with a enormous time and calculation lumber and as such its demand is often confined to research regions that deal with internal combustion engine progress [11–13].

From a control expansion point of view, the quasi-static approach is favored since it preserves the physical causality of the vehicle system, and lets for the probability of using the similar controller.

IV. HEV CONTROL STRATEGIES

HEVs have been exposed to remarkably get better automotive fuel economy and lessen emissions, at the same time meeting the vehicle power demand, preserving acceptable vehicle performance, and driver-feel [14]. In spite of the HEV design in question, registering the right power split among the energy sources (ICE and electric motor) is decisive to the accomplishment of a improved fuel economy and lower emissions. To this attempt, several power split control policies have been suggested, assessed and utilized to different HEV configurations.

Fig. 3 HEV Control Strategy Classification

Typically, inputs to the power-split controller of HEVs frequently comprise vehicle power demand, vehicle speed or acceleration, battery state of charge, current road load, and on occasion, "intelligent" future traffic circumstances from the Global Positioning System (GPS). The controller outputs signal holds a set of control conclusions which identify whether the HEV should function in any of the following modes:

1. Engine-only mode (ICE operates alone).
2. Assist mode (ICE and electric motor operates).
3. Electric motor-only mode (Electric motor operates alone).
4. Regenerative mode (Electric motor is used for kinetic energy recovery).
5. Trickle charge mode (Engine produces power used in charging the battery).

Minimization of fuel expenditure and release without negotiating of vehicle performance, and battery state of charge are often the key control aims of most HEV control policies. HEV control strategies can be mostly classified into online control strategies and offline control strategies as shown in the control strategy classification chart in Fig. 3. Even though there have been a range of papers and research journals which have contributed to the compilation of evaluations on HEV control strategies, this part of research is permanently moving forward and with the opening of newer methods, there is need for an advanced review. The main purpose of this piece is not only to add to the producing list of assessment discussions but also to decide applicable research gaps in the domain.

V.HEV OFFLINE CONTROL

STRATEGIES

Optimization-based control strategies choose the control signals also by dropping the sum of the objective function over time (global optimization) or by instantly diminishing the objective function (local optimization). The accomplishment of a worldwide optimal control method relies absolutely on the awareness of the whole driving cycle a priori, and since this is usually complicated to choose in real-time, universal optimal procedures are usually referred to as "non-causal", which cannot be pertained in realtime, but are helpful as a control benchmark to which all other causal real-time controllers can be evaluated. Linear programming, dynamic programming, genetic algorithms etc., have been related as global optimization techniques for optimal energy management of HEVs.

Linear programming

Using linear programming, the non-linear fuel consumption model of an HEV is estimated and solved for a global optimal solution [15]. Linear programming has been applied productively to automotive energy organization problems. For example in the study of Kleimaier et al. [16], a convex optimisation technique for the investigation of thrust abilities using linear programming was planned as shown in Fig. 9. Pisuetal. Proposed a stable and robust controller using linear matrix inequalities, to diminish fuel utilization.

Dynamic programming

The dynamic programming technique is a practice formerly developed by Richard Bellman, which aspires to find optimal control policies using a multi-stage choice procedure. As distinct by Bellman: An optimal control policy has the property that no matter what the preceding decision (i.e., controls) has been, the outstanding choices must include an optimal policy with believe to the state resultant from those preceding result [18].

Dynamic programming algorithm is a discrete multi-stage optimization difficulty in which a conclusion based on the optimization standard is selected from a finite number of resulting variables at every time step. Bellman's dynamic programming algorithm can be linked using two methods: the backward recursive technique and the forward dynamic programming technique. In the backward recursive technique, the optimal sequence of control variables is obtained scheduled backwards from the final state and choose it at each time step the path that minimize the cost-to-go (integral cost from that time step up to the final state). By regularity, most dynamic programming problems elucidated using the backward recursive method could be resolved using the forward dynamic programming method. Even though both method do direct to the alike set of optimal control policies for the whole issue, their "by-products" are different. When resolving a problem using the backward dynamic programming method, the by-products gain are the optimal values from each state in every stage to the end; whereas in explaining a problem using forward dynamic programming, the equivalent by-products would be the optimal values from the initial state(s) in the first stage to every state in the residual stages.

Dynamic programming has the settlement of being applied to both linear and non-linear systems as well as forced and forsaken obstruction. It also experience two setbacks: its reliance on prior knowledge of the full driving cycle, and the curse of dimensionality which amplify the computational burden. Accordingly, control consequences from dynamic programming are only obliging as optimal benchmarks for other controllers, or as a base for the growth and improvement of other sub-optimal controllers. In Shen et al. [19], an effort was made to lessen the calculation time of the dynamic programming approach, through the use of a forward search algorithm.

Dynamic programming features extremely in HEV energy management studies [24–36]. In this part, some notable instance of its request on HEVs is reviewed. Brahma et al. [20] applied dynamic programming to attain a real-time optimal split between the ICE and electric motor of a series HEV. They propose that by using the discrete state formulation approach of dynamic programming, computational effectiveness can be further improved. Likewise, Lin et al. [22] establish that optimal control rules could be detached from dynamic programming, and used to near-optimally get used to a rule-based controller. The resulting enhancement in fuel economy for different levels of heuristic controller adjustment is detailed in Table 1, for the UDDSHDV cycle. In another study by Lin et al. [24], a simple approach for extracting heuristic control rules from dynamic programming (based on the ratio of power request to transmission speed) was prepared. Simulation results from this study explained that, by proper analyze of control results from dynamic programming, an enhanced rule-based control policy could be developed. In this study, heuristic control rules were extracted from one driving cycle and used to near-optimally control other driving cycles. Obtained simulation results (Table 2) showed a 50–70% decrease in presentation gap between the optimal controller (DP controller) and the improved rule-based controller. The combination of dynamic programming and rule-based control policies for real-time charge-sustaining control of HEVs, have also been measured in Lin et al. [21,22] and Kum et al. [35]. In Kum et al. [35], the control steps are uttered as follows: dynamic programming is first used to obtain a global optimal solution to the formulate energy management difficulty. Next, battery SOC for the residual trip distance is estimated using the energy-to-distance ratio (EDR). An adaptive supervisory powertrain controller is related consequently, to reduce fuel expenditure and emissions based on consequences from the EDR and catalyst temperature system.

In Perez et al. [37], a finite horizon dynamical optimization problem is devised and solved using dynamic programming, with the objective of preserving battery energy levels within the stipulated range without affecting the battery state of health. Gong et al. [38], investigated two variations of the dynamic programming algorithm (conventional dynamic programming and two-scale dynamic programming) on a charge-depleting plug-in HEV. In the two-scale dynamic programming algorithm, the electric mode of the process is used first for the known trip distance. The rest of the distance is divided into different segments of known length and for each segment; fuel expenditure and SOC level (Fig. 4) are calculated.

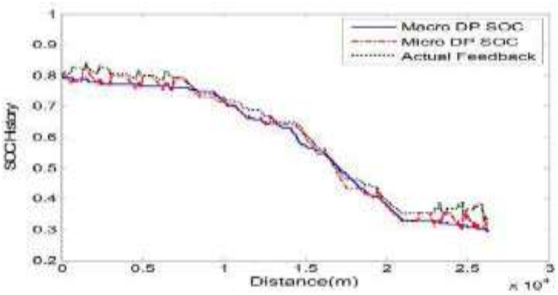

Fig. 4 Trip Segmentation on road segment (source [38])

Table 1 Fuel Economy Comparison over UDDSHDV Cycle(Source [22]

	Fuel Economy (MPG)
Conventional	10.63
Preliminary rule-based	12.56
New shift control	13.02
New power split control	13.17
New recharging control	13.24
Dynamic programming	13.63

Finally, spatial domain optimization is performing to find the optimal solution. Results from this study show that compared to the conventional dynamic programming algorithm which is very computationally expensive, a near-optimal fuel economy (3.7% less than optimal fuel economy) could be achieved using the two-scale dynamic programming algorithm. The two-scale dynamic programming algorithm was further used to develop an efficient on-board control strategy in another study by Gong et al. [23].

Table 2 Fuel Economy and Emissions Evaluation for a Dynamic Programming- Inspired Rule-Based Controller (Source [21])

	FE (mi/gal)	NOx (g/mi)	PM (g/mi)	Performance measure	
				g/mi	Improvement %
a. Results over the WVUSUB cycle (Suburban driving)					
Preliminary rule-based	15.31	4.43	0.36	671.23	0%
New rule-based	14.61	3.02	0.30	582.18	13.27%
DP (Fuel economy & emissions)	15.41	2.78	0.26	526.67	21.54%
b. Results over the WVUNITER driving cycles (Interstate driving)					
Preliminary rule-based	12.84	7.29	0.51	948.83	0%
New rule-based	12.72	6.31	0.49	896.00	5.57%
DP (Fuel economy & emissions)	12.97	6.17	0.44	847.67	10.66%
c. Results over the WVUCITY driving cycles (City driving)					
Preliminary rule-based	16.18	3.87	0.33	621.22	0%
New rule-based	15.09	2.49	0.23	494.12	20.46%
DP (Fuel economy & emissions)	16.63	2.04	0.16	403.58	35.03%

Genetic algorithm

Genetic algorithm (GA) is a heuristic search algorithm for generating solutions to optimization problems. This branch of artificial intelligence is stimulated by Darwin's theory of evolution. In order to obtain an optimal solution to a problem, GA begins with a set of preliminary solutions (chromosomes) called population. The solutions from each population are chosen according to their appropriateness to form new and improved versions. Therefore, the most appropriate solutions have a improved chance of growth than weaker solutions. The process is incessantly repeated in anticipation of the desired optimization conditions are satisfied. Genetic algorithm is a robust and possible global optimization approach with a wide variety of search space, useful for solving complex Engineering optimization problems characterized by non-linear, multimodal, non-convex objective functions. A number of studies have measured genetic algorithm for energy management in HEVs [39–47]. Piccolo et al. [48] applied genetic algorithm to an on-road vehicle with the objective of optimizing an objective function involving fuel consumption and emissions terms. They evaluated their genetic based approach with a conventional gradient based approach, and establish that the genetic optimization approach attained a better reduction in CO emissions, while the HC and NOx emissions stayed unevenly the same (Table 3)

Table 3 Genetic Algorithm Results over an Urban Driving Cycle (Source[48])

	Genetic based	Gradient based	Deviation %
CO(g/km)	4.53	5.18	-12.5
NO_x(g/km)	0.25	0.25	0
HC(g/km)	0.45	0.44	+2.2
Fuel Consumption	6.9	6.8	+1.4

Ippolito et al. [46], combined a fuzzy clustering criterion with genetic algorithm to give back the presentation for the planned energy controller in dynamic and changeable driving conditions. Results from this study as detailed in Table 4 show that the grouping of both policies yield major decrease in computational effort and development in fuel efficiency when compared to the multi objective optimization approach. Wang et al. [60], Poursamad et al.

[51] and Yi et al. [50], used genetic algorithm to tune and optimize a robust real-time implementable fuzzy-logic based HEV control policy. The purpose of genetic algorithm for multi-objective energy management is measured by Huang et al. [45]. In this study, a multi-objective genetic algorithm (MOGA) is used to resolve an optimisation problem for a series HEV. Their consequences show that genetic algorithm is supple and efficiently handles multi-objective optimization problems.

Table 4 Simulation Results: Mos (Multi-Objective Solutions), Db(Data-Base), Dev% (Deviation In Percentile (Source [46])

Driving cycle no.	Monitored parameters	MOS	DB	Dev %
NEDC	HC (g/km)	0.247	0.2485	+0.63%
	CO (g/km)	1.469	1.4642	−0.36%
	NO (g/km)	0.134	0.1337	−0.59%
	Fuel Consumption (Litres/ km*100)	3.593	3.5992	+0.17%
	Final SOC	0.557	0.5584	−0.16%
	CPU Time consumption during the cycle (s) (N-184)	965.86	70.09	−92.74%
FTP	HC (g/km)	0.173	0.1713	−0.75%
	CO (g/km)	0.996	0.8444	−15.2%
	NO (g/km)	0.151	0.1501	−0.6%
	Fuel Consumption (litres/ km*100)	3.963	3.6926	−6.82%
	Final SOC	0.547	0.5219	−4.65%
	CPU Time consumption during the cycle (s) (N=465)	2018.3	287.45	−85.75%
US06	HC (g/km)	0.216	0.217	0.49%
	CO (g/km)	2.048	2.054	0.31%
	NO (g/km)	0.251	0.247	−1.69%
	Fuel Consumption (Liters/ km*100)	5.127	5.165	0.006%
	Final SOC	0.0508	0.5077	0.75%
	CPU Time consumption during the cycle (s) (N=131)	747.75	35.5	−95.23%
HWFET	HC (g/km)	0.163	0.1603	−1.4%
	CO (g/km)	0.913	0.8853	−3.0%
	NO (g/km)	0.143	0.1381	−3.7%
	Fuel Consumption (Liters/ km*100)	3.446	3.142	−0.99%
	Final SOC	0.357	0.5523	−0.86%
	CPU Time consumption during the cycle (s) (N=156)	833.39	52.24	−93.73%

The ICE, motor and battery sizes, in addition to the control policy parameters, were optimized. The effects of the trade-off solution displayed significant enhancements in vehicle performance over the UDDS driving cycle. In Fang et al. [47], the MOGA approach is used to simultaneously optimize the control system and powertrain parameters. Genetic algorithm has also been used to solve an HEV control problem relating the optimization of component masses and the minimization of fuel consumption and emissions [39–43,52]. In Hu et al. [52], the planned approach is a non-dominated sorting genetic algorithm (NSGA).

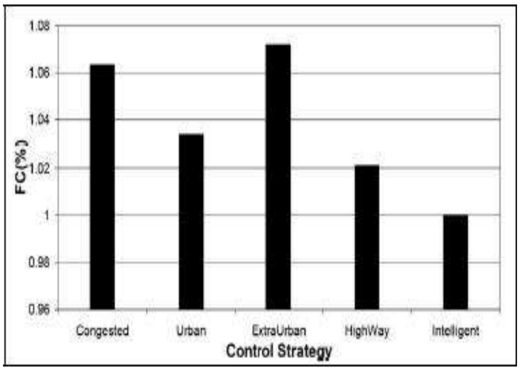

Fig. 5 Fuel consumption obtained from simulation HEV over TEH-CAR driving cycle (source[53])

The NSGA varies from GA only in the way the selection operator works. Crossover and mutation operations remain the same. In a study by Montazeri-Gh et al. [52], a genetic-fuzzy approach is planned to find an optimal region for engine process. First, a hidden Markov model was developed to classify and make out driving patterns from earlier driving practices. Afterwards, predicted driving models were utilized for the optimization of HEV control parameters using a genetic-fuzzy approach. Simulation outcomes from this study show that adaptation to traffic conditions using intelligent genetic-fuzzy approach is very efficient in reducing fuel consumption (Fig. 5).

Particle swarm optimization

Particle swarm optimization (PSO) is a computational method developed by Dr. Eberhart and Dr. Kennedy in 1995 [55,56]. This technique is inspired by the social behavior of bird-flocking, which optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. In PSO, particles move around a search space and are guided by best known positions in the search space, as well as the best known position of the entire swarm. Movement of the swarm particles occurs when improved positions are discovered.

PSO is a meta-heuristic approach, and can investigate very large spaces of candidate solutions. Though non-causal in nature, PSO does not necessitate the optimization problem to be differentiable and as such is very appropriate for optimization problems with some degree of noise or indiscretion. Particle swarm optimization has productively been applied in HEVs. In a study by Huang et al. [57], an better particle swarm optimization approach was used to optimize a multilevel hierarchical control strategy for a parallel HEV. Outcomes from this study show that balanced to a baseline control strategy (PSAT built-in control strategy), the optimal multilevel hierarchical control strategy is able to articulate the engine, electric motor and battery towards operating efficiently in an optimal state. In this way, fuel utilization and releases are simultaneously minimized (Table 5). In Junhong [58], PSO was also successfully applied to solve an HEV energy organization problem involving the simultaneous minimization of fuel utilization and releases.

Table 5 Comparison of a Baseline Control Strategy (PSAT Built-In Control Strategy), With An Optimal Multilevel Hierarchial Control Strategy (Source [57,59])

Control Strategy	Fuel Consumption (L/100 km)	Final SOC (initial SOC-0.7)
Optimal multilevel hierarchial control strategy	6.0921	0.6929
PSAT built-in control strategy	7.1597	0.7557

Wang et al. [60] proposeed a control approach to optimize fuel utilization and emissions in HEVs using PSO.

Through simulation, the predicted PSO strategy is shown to considerably expand fuel economy in high-speed driving cycles (US06), and emissions in middle or low-speed driving cycles (NEDC and MANHATTAN cycle) as detailed in Table 6

Table 6 PSO Simulation Results Over Different Driving Cycles (Source [60])

Control strategy	Fuel economy (mpg)	HC emission (g/mi)	CO emission (g/mi)	NOx emission (g/mi)
a. US06 driving cycle				
Before opt	28.8	0.722	3.422	1.003
Direct	35.4902	0.7026	3.5538	0.9757
PSO	44.9723	0.6680	3.4383	0.8892
b. NEDC driving cycle				
Before opt	39.9	0.756	3.726	0.959
Direct	30.4926	0.6937	1.7738	0.5324
PSO	38.1694	0.6834	2.3926	0.6984
c. MANHATTAN driving cycle				
Before opt	32.7	2.256	11.497	2.613
Direct	34.8820	0.7056	3.5636	0.9829
PSO	32.5624	0.7304	1.9575	0.7098

VI.EXISTING RESEARCH GAPS IN HEV ENERGY MANAGEMENT

As assessed so far, vehicle hybridization poses new challenges in the form of: how to optimally split energy demand in real-time among various challenging power sources. In the case of braking, this respond is clear-cut because while braking, the focal point of the strategy is to maximize energy recovery in the battery by using the motor as much as probable. Easy keys however, prove incompetent when the vehicle power demand is positive. The first step in solving energy managing problems when the vehicle power demand is positive lies in the configuration of an objective function representing the objectives to be minimized (e.g. fuel consumption, emissions). Another characteristic of great significance in solving energy management harms lies in the control of the battery state of charge. This control is employed to evenly keep the battery SOC within safe agreed boundaries to ensure battery durability, and to ensure suitable and convenient utilization of the energy stored in the battery. The resultant energy organization difficulty is a classical constrained optimization problem which has been addressed by a variety of studies. Regardless of the enormous developments in fuel consumption and emissions reported by most studies, the following gaps in control strategies still exist:

1. Rule-based control strategies: Rule-based control strategies are by nature sub-optimal, and unable to give assurance for the execution of integral restraints such as charge sustenance. They also necessitate vigorous tuning to optimize rules for specific driving scenarios. This affects the robustness of the controller, consequently leading to highly sub-optimal online performances. The difficulty is further deteriorated in the lack of route preview information.
2. Dynamic programming: Even though known to yield global optimal solutions to HEV energy management problems, dynamic programming present non-causal results which are non-implementable in real-time, but can be used to create or benchmark sub-optimal controllers. The possibility of receiving useful realtime manage policies from dynamic programming has been extensively explored in literature. Regardless of the research proceeds made, some of the resultant sub-optimal control policies have been established to yield selective performances, which are charge-depleting in highway driving scenarios or charge-hoarding in urban driving scenarios.
3. ECMS: The corresponding expenditure minimization plan is a local optimization approach based on the heuristic concept that the energy used to drive a vehicle over a driving cycle ultimately comes from the engine, and as such the hybrid system just serves as an energy buffer [61]. The resultant controller thus impacts the qualified benefit of both heuristic controllers and optimal controllers. As a affect the ECMS has acknowledged significant quantity of concentration in literature, with several dissimilarities in the form of Adaptive ECMS and Telemetry ECMS being designed. In spite of these research advances, the ECMS technique in its present form is still not capable to guarantee a charge-sustaining optimization performance in real-time. In a study by Silvertsonn et al. [62], the final battery SOC of sub-optimal ECMS strategies were shown to deviate by as much as 20% over standard driving cycles. The consequence shows that the correspondence factor of ECMS strategies are highly responsive and cycle dependent i.e. the optimal correspondence factor for one driving cycle might lead to a poor presentation on another driving cycle.
4. MPC strategy: Owing to better vehicular computational capabilities, and the wide accessibility of partial route preview information, model predictive control (MPC) strategies have gained major attention, as a viable charge-sustaining energy organization approach for HEVs. According to most literatures, future driving information can be expected and included into MPC strategies in two forms:
    a. Directly through real-time navigation systems
    b. Through the clustering based analysis of past recorded driving data.

Though both techniques have been effectively realized in literature, future driving information prediction based on navigation systems, have witnessed a wider appreciation. This is due to the computational burden associated with static and clustering based analysis. In most production vehicles today, the predictive MPC framework is devised using heuristics, which decide when the battery should be charged or discharged accordingly. Consequently, the resultant controller encloses no form of optimization and is not defined to account for charge sustenance. In addition to the prior research gaps, the idea of vehicle speed control is comparatively new and has only been examined by a few researchers . With the research area in its early days, most of the projected vehicle speed control models are overly simplified and often yield non-realizable fuel-optimal speed trajectories. For example, no study to date has been known to consider engine braking effects in the formulation of fuel-optimal vehicle speed trajectories. By ignoring these real-world effects, the resulting speed trajectory is only of academic interest.

VII. CONCLUSION

Due to the view of improved fuel economy and vehicle presentation, HEVs carry on to have the benefit of a wide research attention from academics and industrial researchers alike. With increased government funding and industrial cost optimizations, HEVs are becoming more reasonably priced and reachable than ever. To meet the energy demands of different HEV configurations, several power management strategies have been proposed in literature. This paper presents a comprehensive review of appropriate literatures pertaining to modeling and control of parallel hybrid electric vehicles. HEV control strategies were evaluated at depth on: HEV offline control strategies. This thorough assessment is aimed at highlighting the control structure of the reviewed systems, their innovation, as well as contributions towards the approval of more than a few optimization objectives, which comprises but are not limited to: reduction of fuel utilization and releases, charge sustenance, optimization of braking energy regeneration, and development of vehicle driveability. As part of this article, exploitable research gaps pertaining to rule based control strategies, dynamic programming, the equivalent consumption minimisation strategy (ECMS) and model predictive control (MPC) strategies were recognized. These acknowledged research gaps propose current HEV control policies are still lacking primarily in the aspects of: optimisation of braking energy regeneration and charge sustaining sub-optimal control using partial route preview information and no route preview information. Future studies towards extenuating these research gaps are expected to yield control strategies capable of realising the ultimate charge-sustaining fuel saving potentials of HEVs in real-time.

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