CS 4264 Final Report

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1 Introduction

Hybrid Electric Vehicles (HEVs) have a history dating back much farther than most people would expect. The first HEV was produced in 1899 by Ferdinand Porsche [7]. However, the demand for HEVs shrunk when the automobile assembly line in 1904 meant that gas-powered cars could be produced much faster and for a lower price. Research surrounding HEVs spiked after the Arab oil embargo of 1973 [7], and the Toyota Prius was the first HEV vehicle to truly be successful in a primarily gas-powered market. Recently, acknowledge of the climate crisis, referred to as Climate Change, has encouraged automobile producers and researchers alike to find ways to reduce the burning of fossil fuels, something that is thought to be a primary contributor to Climate Change. In order to get consumers to switch to the cleaner automobile alternative though, HEVs need to have comparable performance to the more common gas-powered car and be reasonably priced. The solve the issues of performance, several researchers have looked into the possibility of using machine learning to create an effective energy management strategy between the gas and electric components of an HEV. In optimizing this energy strategy, gas use can be reduced and overall performance of the HEV can be improved. The goal of this survey is to recognize leaders in this area of research, compare their approaches, and ultimately formulate a recommendation for future work based on the findings of this survey.

2 Field-specific terminology

Acronym	Term	Meaning
ECMS	Equivalent Consumption Minimization Strategy	heuristic method for optimization
AECMS	Adaptive ECMS	ECMS that has updating parameters
ITS	Intelligent Transportation Systems	technology that lets users make smarter use of transportation
HEV	Hybrid Electric Vehicle	vehicle that is powered by electric and chemical energy
	Engine transients	the ON/OFF cycles of the engine's motor
V2V	Vehicle to Vehicle	communication for vehicle speed, etc.
V2I	Vehicle to Infrastructure	communication of lane marking, signs, etc.
ICE	Internal Combustion Engine	traditional method of vehicle powering
EM	Electric Motors	powering of vehicle through electrical energy
	Powertrain control	the system for managing the engine's ignition system
DP	Dynamic Programming	computationally intense optimization method
MPC	Model Predictive Control	method of process control that satisfies constraints while taking the future into account
SOC	State of Charge	charge of a battery relative to its capacity
	Driving cycle	the speed of a vehicle versus time
	Prediction horizon	how far into the future the model can make predictions
PHEV	Plug-in Hybrid Electric Vehicle	HEV that can be recharged with an external power source
EMS	Energy Management System	same idea as Powertrain control
AER	All Electric Range	how far a car can go only on electric power
CS	Charge Sustaining	SOC is maintained on average at a certain level
CD	Charge Depleting	SOC depletes because power solely comes from the EM
DMPC	Direct Model Predictive Control	Method that uses long prediction horizons and is not computationally intense

3 Research Directions

In surveying papers for this report, two main directions for research became clear, each with its own advantages. The first direction was to focus on an offline strategy, which is what Keyser and Crevecoeur [1] did. For an offline strategy, emphasis is placed on maximizing the potential of each of the mechanical parts of the system through the application of physics to create an optimization problem. *Figure 1* serves as an example of such an approach. The second direction, which the majority of the papers fell under, is implementing a real-time strategy. Real-time strategies tend to put more emphasis on things that could effect driving in the present- a person's driving behavior, current driving conditions, or predicting future driving frames based on one that just passed. Many of the papers that went with a real-time strategy employed the use of driving pattern recognition in some form, as shown in *Figure 2*.

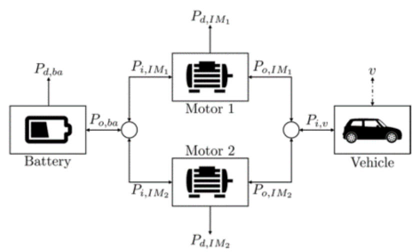


Figure 1: Overview of power flows in a drive train [1]

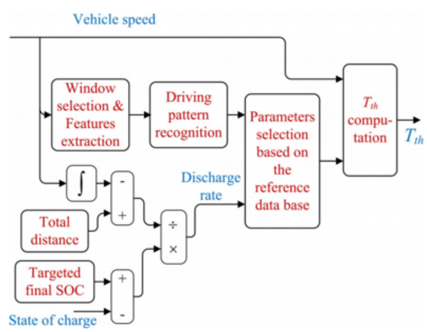


Figure 2: Real-time management of mode transition [3]

4 Research Challenges

A lot of the challenges in this research domain are rooted in the battle between optimal performance and real-life useability. For example, Denis, Dubois, Dube and Desrochers [3] used Dynamic Programming [DP] as the foundation of their machine learning approach, because DP can produce very fuel-efficient results but it cannot be used in real-time. This is due to the fact that DP calculations can take hours for a good computer, hence DP has a very high computational complexity. In addition, there are several methods of powertrain control that can produce optimal results due rely on knowing the full drive cycle (distance, speeds, etc.) ahead of time, which is not realistic. The researchers this paper surveys have each found a unique way of overcoming this hurdle with a different machine learning technique. While these techniques do not require the full drive cycle to be known, they do all require knowing the road grade (incline) and some degree of knowing the driving speed in order to produce good results.

5 Survey of Research Papers

Kazemi, Fallah, Nix, and Wayne [4] had their research published in "IEEE Transactions On Intelligent Vehicles", Vol. 2, No.2, June 2017. Their approach consisted of using PECMS to form three similar methods to be compared with each other. The underlying math of which is made up of a Hamiltonian function, an equivalent factor, modification factor, variable factors, and a cost function. There is also an idealized model proposed using a forward-facing quasi-static method, static maps, and a PI controller for updating the equivalent factor. One of these methods is pictured in Figure 3. Simulations are used to prove the effectiveness of the models. The simulations are based on a high-fidelity model of a hybridized Chevrolet Camaro. There were three scenarios simulated with the high-fidelity model using dynamometer driving schedules developed by the US EPA- urban(UDDS), highway(HWFET), and high acceleration(US06). Additionally, the predictive model was tested with a real-world scenario from the Model Deployment dataset. The results of this team's research is compared to ECMS and ACEMS methods. The advantage over ECMS is that they do not need to know the full drive cycle to choose the equivalent factor and hence can update in real-time. The advantage over ACEMS is that PECMS was shown through simulations to decrease the number of engine ON/OFF cycles and improve fuel economy. They also are able to reduce computational complexity with heir model, which allows calculations as fast as every 15 seconds.

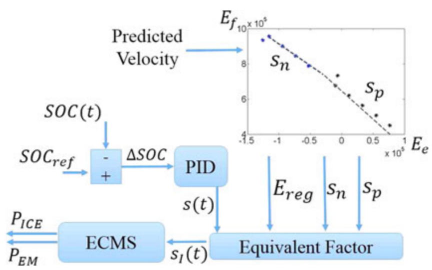
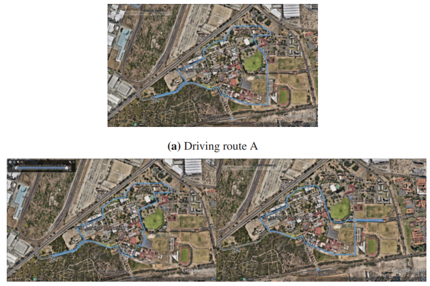


Figure 3: Schematic of method 3 [4]

Denis, Dubois, Dube and Desrochers [3] had their work in the "International Journal of Intelligent Transportation Systems Research", Volume 12, September 2014. The machine learning strategy is built with a DP foundation, from which a Genetic Algorithm is built upon for real-time calculations. K-Nearest Neighbor with 20 neighbors and the Mahalanobis distance is then used as a driving pattern recognition module for real-time analysis based on a past frame of the current driving cycle. To select the length of the frame and perform model validation K-fold cross validation is used. Simulations were done for many cases to validate the model. However, the main focus of the paper is the real-life deployment test done with a three-wheel PHEV in urban and freeway settings. In comparison to a straight rule-based strategy, this group's blended strategy is able to minimize fuel consumption much more efficiently.

Keyser and Crevecoeur [1] presented their research as part of the 2019 IEEE/ASME International Conference on Advanced Intelligent Mechatronics Hong Kong, China, July 8-12, 2019. This research uses an offline power-split optimization strategy built through Q-Learning, a Markov Transition Model, and the Bellman Optimality Principle. They also test an extension of their model by adding a value function. This work is a continuation of their previous work [2], which they use as justification for their use of a dual-drive system and origin of a lot of their parameters and underlying dynamic models. This paper demonstrates performance with simulations that draw from a database of real-world GPS data. This paper compares the performance of their model with DP, for which their model is shown to be within %1 of the optimal value with a much lower computational demand. Additionally, their model is compared to standard DMPC strategies without Q-learning, for which their model showed lower energy consumption per kilo-watt-hour.

Shen, Lim, and Shi [6] presented at International Conference on Machine Learning and Cybernetics (ICMLC), Kobe, Japan, in 2019. Their Energy Management System is built using Predictive State Representation (PSR) by learning past driver's driving behavior. The spectral learning algorithm was used for the learning component. A matrix of parameters is formed, and Singular Value Decomposition (SVD) is performed on it. A fuel-cell hybrid vehicle was used for real life tests around a campus. These routes are pictured in Figure 4. Various routes were taken and repeated for testing. This is one of the few truly real-life tests and the results are impressive. Tests showed that the PSR model had better performance with less predictive error than a Markov-chain based prediction model. Comparisons between PSR and the Markov-chain model are shown in Figure 5. This is thought to be the case because this group's model takes the driver's driving behavior into account.

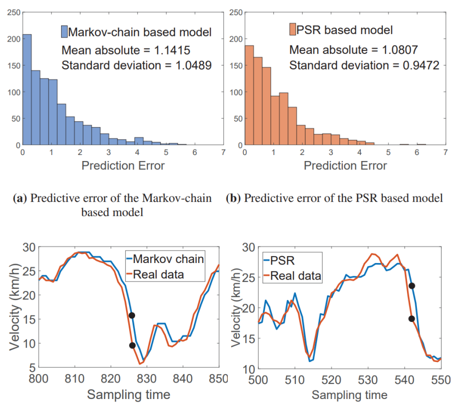


(a) Driving route A

(b) Driving route B

(c) Driving route C

Figure 4: Driving experiments for model training and performance verification [6]



(a) Predictive error of the Markov-chain based model

(b) Predictive error of the PSR based model

(c) Tracking trajectory in the section that includes maximum predictive error - Markov-chain based model

(d) Tracking trajectory in the section that includes maximum predictive error - PSR based model

Figure 5: Performance comparison between models, driving route B [6]

Oncken and Chen [5] had their research in "IEEE Transactions on Vehicular Technology", vol. 69, no. 8., 2020. In terms of the model, Non-linear MPC (NMPC) is used for optimization of the powertrain torque split and engine speed. A separate implementation method of NMPC is used for each mode of the PHEV. The model has been tested in simulations built on real-world driving cycle data, and also tested in real driving tests with an MTU test vehicle. Their model implementation showed a 1-4% of energy savings in comparison to the PHEV's baseline energy usage. They compare themselves to EMCS, demonstrating that their performance is better because of the added Connected and Automated Vehicle (CAV) technology to improve predictions

6 Conclusion

In conclusion, there were two main directions of research: offline and real-time, with real-time solutions being the more popular option with a focus on road conditions and driving patterns dictating the optimization of the Energy Management System. However, a number of different machine learning techniques were used including Q-learning, KNN, and Singular Value Decomposition. In surveying all of these methods, they all seem to have fairly similar high-efficiency results. However, the biggest differentiate between them is how much information the optimization methods were supplied and how many assumptions were made. None of the research surveyed here discussed tests on inclines or heavy traffic. However, Oncken and Chen [5] did experiment with incorporating CAV technology, which could allow for those more complex factors to be taken into consideration. This brings me to my recommendation for future researches. As HEV and CAV technology advances, emphasis should be placed on testing the two together along with a blended machine learning strategy where the benefits of computationally complex calculations be done when offline and be supplemented with faster real-time calculations while driving. In this way we combine an increase of information with the benefits of both research directions. With the gaining popularity of HEVs we are sure to see great advances in this field in the future.

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