Machine Learning for Autonomous Vehicle Energy Management and Optimization

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1. Introduction to Autonomous Vehicles and Energy Management

Reinforcement learning is a machine learning (ML) method under debate due to handling the optimal energy management strategy in the connected hybrid electric vehicles (CHEVs). Within the recent few years, a pronounced amount of studies has been presented to explain EMSs based on reinforcement and predictive learning methods. The primary intent of the RL-based methods is to develop an oversight virtual inspector for setting the optimal energy management strategy. These approaches are capable of updating the anticipated energy management strategies with real-time data and models. Various approaches have been introduced in recent years to model the energy consumption and the EV driving agents emulate using reinforcement learning strategies. EVs are a promising transportation solution to reduce pollutants and other greenhouse gases associated with the traditional internal combustion engine vehicles. They incorporate numerous advantages such as controllability, high efficiency, and energy renewal and hence have been an acute focus of attention in the automotive industry.

[1] [2] [3]The need to reduce the effect of vehicular transportation on the environment and the growing requirement for energy efficiency in the automotive industry is at its highest levels today. The present situation of growing global warming has made the car manufacturing companies obligated to build energy-efficient cars and commit themselves to environmental safety policies. However, energy efficiency and reducing greenhouse gas emissions in fossil energy-using vehicles lead to the development of new technologies like electric vehicles (EVs). Taking benefit of electric power either partially or fully introduces a unique opportunity to handle the energy consumption more smartly compared to the traditional vehicle. The primary intent in the optimization and management of the electric vehicle's energy system is to optimize its operational or even curtailed costs as to propose a comprehensive approach.

1.1. Overview of Autonomous Vehicles

As [4] and [5] have touched upon, to improve safety and provide a safer environment and to provide decision-making insights into the vehicles, vehicles carry an onboard fusion platform for the vehicle data. With advances in onboard computational comparing, architectures, and computational power, and with advances in the sensor's data fusion algorithms, vehicles can have a very accurate view of their perceptual world. The problem of understanding and decoding actions of other traffic participants, prediction of future actions and understanding the committed path of traffic participants becomes pertinent for long term behavior prediction and trajectory planning. These models prove to be essential for a successful and safe inception and continuation of autonomous vehicle systems on roads.

[3] An EV is a type of autonomous vehicle that uses onboard embedded systems such as sensors, GPS, cameras, and other subsystems to navigate itself in a controlled environment without human intervention. Conversely, off-road autonomous vehicles are those that run in an open space and are designed for outdoor navigation. These vehicles use a combination of LiDAR, cameras, GNSS, INS, Radar, and other systems for their trajectory planning and localization. Other types of autonomous vehicles include vehicles used for underground mining. Key enabling technologies to develop autonomous vehicles are high-fidelity environment perception, sensor accuracy, delay, and accuracy of the actuators, computational power, integration, communication, robustness, redundancy, and machine learning and data-driven algorithms.

2. Fundamentals of Energy Management in Autonomous Vehicles

Volvo has announced that it is opening a new business unit, Volvo Autonomous Solutions, which will accelerate the development, commercialisation and sales of autonomous transport solutions to provide increased customer value. The section also explores the various differences and the common but unexplored problems in the electric vehicle platform, such as range estimation, energy management and fuel economy. Keeping high resolution map with the exact localization of the vehicle is the thumb rule to perform any kind of automated task. This is feasible and is widely achieved by Google Waymo and BMW using sensors based, as well as the map based localization and by the Nodian bys using perception state extended Kalman filter based kinematic model estimation. This will be a very important study to carry around in eco – friendly society or system as we will get better fuel economy and performance [6].

[7] This section examines the principle of energy management in AVs in some detail. The basic layout of this section has been divided into various points based on the topic considered within it. The various points are—state of charge (SOC) and state of energy (SOE) energy demand, battery performance and aging, and energy management strategies. In addition, the various barriers and constraints associated with energy management in AVs and the importance of energy management in AVs are considered. For the ease of readers, a graphical representation of energy flow within AVs and the first principles governing the operation of a battery in AVs is provided, respectively in Fig. 2.1 and Fig. 2.2. Keeping power consumption at a minimum is crucial for hybrid and electric vehicles (HEV/EVs) as it directly impacts vehicle range. Research is focused on increasing fuel economy for HEV/EVs with autonomous features, such as integrating advanced driver assistance systems (ADAS) and optimizing sensor suites. Design and simulation tools such as AVL CRUISE, HEVC and CarSim are largely used in the automotive industries considering various driving factors such as high way, city tracking, grade ability and temperature which are very useful for energy security and environmental concern practices. Of – line simulation tools available for specific CB (charge sustenance) – HMM (histograms of Markov Models), DRB (Dynamic in-rank Balancing), DFREIT (Desired Future which can behave as Pre-Driven Road Information and Traffic), EMMA (Energy Management for Multi platform and hybrid electric Exercise HEV) and MTIEH (Modified Time-Invariant Equivalent Hybrid) model are used for future non - Markovian driving cycle.

2.1. Energy Sources and Consumption

Electric vehicle energy needs and consumption models have developed rapidly over the past few years and we now have the chance to understand these areas of vehicle study better [8]. Electrification (which includes gasoline–electric, hybrid, and all-electric powertrains) has received substantial attention, although it is still a small share of the overall vehicle energy requirements, as was recently recognized by the International Energy Agency (IEA). In this respect, optimal energy management has become the most critical consideration affecting the performance of EVs in terms of range and energy efficiency [9] . An electrified powertrain's energy consumption largely increases as a real-time operable vehicle's driving style changes.

In order for EVs to optimize fuel consumption, several intricate energy management systems that include power-split, energy recuperation, and traction-control strategies are proposed. As compared to classic petrol vehicles, energy needs are the principal design constraints in electrified vehicles and are significantly affected by vehicle performance. Energy-saving has been crucial for electric vehicles due to the greater importance of speed reduction events. Apart from the primitive vehicle compartment, these vehicles also use various on-board electrical accessories which results in an average increase of 1 kW of energy use. In order to maximize the contribution of renewables in these electrified configurations, multi-objective optimization for driving on extreme multisource and/or multiphase trajectories was considered. This was studied over discrete automotive uses (ACT Urban and NEDC2) and sources from renewable origin (50% electricity and 100% hydrogen). Renewable energies used at their maximum value allowed to reach respective emission reduction rates that were 15% for electricity and 32% for hydrogen co-associated with 13% and 18% respectively of additional renewable delivered autonomy [10].

3. Machine Learning Techniques for Energy Optimization

Machine Learning (ML) is a bright set of algorithms for autonomous optimizations in the modern industrial scenario. ML has attracted attention in the auto industry for different areas [11]. In particular, in Level 4-5 vehicles, long hill gradients and irregular traffic can certainly make an unexpected variation in energy consumption which affects total vehicle driving range. In a undesirable vehicle test scenario, energy consumption can increase by up to 20% compared to realistic cycle-driving conditions. In the past days, many Japanese vehicles, such as the Honda CR-X Hybrid and Toyota Prius, have previously been testing rule-based energy control systems which were generally efficient, though not flexible for variable cycle driving, but simulation and real drive can support it in this track. In 2018, a data interpretation test was used to accurately predict the energy consumption of a Prius in two different driving tests, about 1% better than the Road and Hybrid System Simulator which was the other conventional rule-based controller. A Pumped-Storage Hydroelectric (PSH) System stores energy when the demand for electricity is low by using a reversible pump that moves water from a low reservoir to a high one, acting like a water battery 24 When demand peaks, the water is be pumped back to the lower reservoir allowing the turbines to generate electricity. The energy stored in PSHs is converted to electricity with an efficiency of nearly 80–90% without any greenhouse gas emissions. In operation, maximum power is preferred in optimal generation cost and minimum emissions. RL-based machine learning algorithms considering varying energy prices have been proposed for the trade-off between maximum generator profits and maximum stored energy [12].

3.1. Supervised Learning Algorithms

Almost all the real-time power generation data are measured and characterized in kWh or kW for PV systems, with such figures not always consistent with real-time novel sensors activity. As a data-driven technique, based on household smart appliances consumption data, predicting advanced Multilayer Perceptron (MLP) and Support Vector Machine (SVM) methods are applied for energy predictions. For large-scale energy predictions, SVM, Extreme Learning Machines (ELM), and Nature-Inspired Optimization Algorithms have their individual feature selections, while reinforcement learning meshes with Time series analyses to materialize in real-time forecasting strategies for the novel energy evolution scenarios. Radial Basis Neural Networks (RBFNN), integrating enhanced Particle Swarm Optimization (PSO) and Differential Evolution (DE) methods, effectively construct a linkage energy forecast model. Redundant methods have also been confirmed valid for providing realistic predictions for procedural purging of highly inaccurate and extraneous datasets.

Reports and research have predicted that, in the coming years, the need for optimizing energy consumption strategies of electric vehicles will surpass the need for handling trajectory planning and control schemes [13]. Automobiles have witnessed modifications for serving as electric vehicles. Gradually, electric mobility continues to become familiar among various modes of transport. While designing future smart transportation systems, necessity arises to consider battery electric vehicle (BEV) as a platform for flexible driving options [14]. Prospective owners and interested parties are apprehensive for buying and using electric vehicles. Apart from frequent recharging on public roads, auto consumers are demanding proximate parking with hassle-free charging options [15]. Predictions about future traffic patterns and logical deductions, compilation of energy data obtained from portable energy meters (e.g. Current Cost CT) and intelligent energy management systems (IEMS) in the smart home environment are becoming relevant research domains. Domestic energy-related studies can be deployed to recognize situation-aware usage patterns and to consistently supervise power usage activities.

4. Challenges and Opportunities in Autonomous Vehicle Energy Management

Autonomous vehicles can provide a feasible solution to greatly improve energy conservation when pow- ered by electrical energy in comparison to traditional vehicles. However, challenges and issues, such a higher degree of freedom in vehicle energy management and stronger nonlinear- ity in vehicle powertrain dynamics, are high barriers to smooth progress in energy management and optimization [16]. In order to effectively ar- range powertrain energy states and control power distribution in autonomous vehicles with great energy-saving potential, it is important to fully learn vehicle dynamics, driver behavior and future road information. Therefore, it is feasible and effective to utilize the AI-based energy management and optimization algorithms.

Light-duty vehicles are the source of about 20% of greenhouse gas emissions globally, due mainly to their fuel consumption [17]. An effective strategy to significantly reduce greenhouse gas emissions is to improve the energy efficiency of vehicle operation by making innovations on energy sys- tems and management strategies. Thus, much research has been conducted to improve these two components. In order to effectively improve energy conservation during driving, much research has been conducted to develop electric vehicles and to explore vehicle kinetic energy regeneration, which can be released, stored, and controlled. With the rapid development of artificial intelligence technology, research using AI algorithms including control algorithms and optimization algorithms, as well as reinforcement learning algorithms, for energy management is gaining increasing attention from researchers [11].

4.1. Environmental Impact and Sustainability

Machine Learning for Autonomous Vehicle (AV) Energy Management and Optimization [18]. Under 'Environmental Impact and Sustainability' (specifically summarized in Fig. 12), we elaborate further on the environmental implications of energy management in AVs, thus highlighting the configurations, tracks, and drives for the latter concerning energy efficiency and the strategies to optimize the overall fuel economy, representing the adversarial intersection of energy management and environment [12]. Owing to the need for a paradigm shift in energy management to not only account for passenger comfort and road safety, but to also consider environmental sustainability and operational security of the vehicle in the context of an AV, the importance of these concerns depends on two significant compromisable constraints: battery consumption and the vehicle's torque converter (VESAS' natural frequency). Thus, this is addressed using real-time environmental models, which can be embedded into an advanced driver assistance system ('ADAS') function, that exposes these performance margins in the resulting longitudinal speed guidelines, in the drive for energy optimization. Turning the attention towards deriving the real benefit of self-driving cars, an alternate prospective future 'zero emissions' mobility scenario is discussed, wherein a part of the overall global energy requirement is served by the electrical power, and the operational energy of the vehicles is continuously and indefinitely supplied by the renewable source of solar power coupled to their panels [19].

5. Case Studies and Applications

In this work, we presented a type II review of machine learning applications and future prospects for EV energy management for the electric vehicles and the V2G cases. The latter social benefit has been already studied at Chicago and at Bordeaux ev-strength testsbeds. The future use of e-platforms in V2X/V2X/N4A (EC, decarbonization, digitization, V2H, V2X etc.) pilot smart cities of the ACT:AI/PULSE like 5th Asia Generation and the EC Lighthouse projects/transformative safety, see. In the light of the current work, however, further research should focus on developing better algorithms for vehicle condition control and for the optimal operational planning of hybrid vehicles when tied to a heterogeneous and multi-agent infrastructure. In future, the piloting towards self-learning cyber-vehicle systems requires further research, as well. The V2X case is important due to further grid-tied security reasons and the digitization economic benefits of the two-way connected devices of the new global vehicle fleets [20].

Electric vehicles (EVs), as possible future scenario to replace combustion cars, have unique features including high recharging demand, the need of stationary energy storage to avoid peak generation, default operating patterns, and on-board energy storage in power format. Data-driven modelling and machine learning (ML) increasingly proved useful to solve optimization and fault detection problems in EVs and their management. Additionally, the certification of the EVs with more realistic driving missions in the type approval procedure will involve a general increase of the on-board energy binder with consequences for life cycle costs and battery technologies. The generalization, which is the main advantage of the parametric models decrease, is a serious issue on the edge of established knowledge. The increase of the hybrid-electric vehicles requires new management strategies to onboard the grid and to increase the energy efficiency of on-road resources [21]. It is evident that machine learning and AI, or even sophisticated load management, improves the existing energy management system (EMS) of the vehicles/vehicle to grid (V2G) assets. Machine learning systems, which are broadly applied in vehicle component pointing, electric consumption shaping/reduction, and in grid stabilization initiatives, could positively affect the (semi-)autonomous EVs and the EV battery management during the V2X ecosystem operations.

5.1. Real-World Implementations

It is important to notice that, in addition to the vehicle energy management, potential implementation of machine learning in real-world automotive power electronics systems includes condition monitoring and fault diagnosis. A supervised approach based on Support Vector Machines (SVM) using four features (soft switching, Phase Voltage unbalance, ripple current and ISRP index) has been developed for the identification of inter-turn faults in Permanent Magnet Synchronous Motors functioning in a PMSM/Fault Tolerant Machine (FTM) configuration. An unsupervised approach to inter-turn faults identification is also available in literature: a Convolutional Neural Network was tested on real-life data and compared in terms of the classification accuracy against an SVM-based model [4].

A model for the efficient dispatch of electric vehicle powertrains has been developed: power split has been completed to optimally balance the use of the combustion engine and the electric machine. In addition, a model-based reinforcement learning agent has been introduced to derive fuel-optimal control strategies and to simulate the performance of the learned policies. This allowed demonstrating substantial benefits with respect to the conventional power demand control laws in terms of the overall quality of operation [22].

6. Future Directions and Emerging Technologies

In addition, from various trends and outlooks in self-driving cars and their potential impact on our future societies, we can discern that a distinct mass deployment of autonomous vehicles on the means of transportation is on the way, facing difficulties like energy and environment sustainability. Energy consumption is a critical and predominant element in the cost evaluation of electric vehicles in the context of limiting range. AI is regarded as a revolutionary shift in computer science, computer engineering, and information sciences, where machine learning constitutes one of the major fields. In this connection, attempts have been made in this chapter to provide a general, almost comprehensive review of AI applications and mostly machine learning implementation in energy-efficient autonomous vehicles since energy is the main focus presented in this chapter [9].

It is really important to underline that up until now, we have taken a careful systems approach to the problem of energy management in autonomous vehicles. As such, we have considered a diverse range of components that can have a bearing on energy management and usage. This includes not just the conventional components such as the powertrain, (including the propulsion system and its associated drivetrain and power converters) and the interaction with the electrical grid, but also the sensors and perception systems as well as the computation and communication infrastructure, which will necessarily be energy-intensive components of self-driving vehicles [4] [16]. The problem is further compounded when any of these components have a non-stationary time variable, for example, the motion of the vehicle, the varying quality of the network access, or environmental factors. A natural way to design an optimal, or near-optimal, control strategy in the context of these complicating factors is to model the problem of energy management in terms of a Markov decision process and apply a suitable reinforcement learning framework to tackle the optimization problem.

6.1. Advancements in Battery Technology

Recent examples of the utilization of the energy management system with machine learning in a wide range of researches are, e.g., prediction of SOH of a lithium-ion battery [23], evaluation of radiation effects on batteries, building thermal load prediction during electrical heat storage in lithium-ion batteries, and optimization of WECS for reducing grid power fluctuation in an isolated power system. From the battery material point of view concerning recent publications, as of now, the first report to our knowledge which aims to clarify the relationship between formulation of the anode cylinder and capacity of a battery has been reported by Shan et al. In the report, a battery model with an electrolyte-filled anode cylinder is assumed, and volume of the active material and electrolyte access from a window of the cylinder to the negative electrode based on the configuration of the anode cylinder are successfully established. We report that it is pointed out as thin and thick battery performance behaviors that there is about 80% capacity rate decrease from thin battery to thick battery behavior in the range of electrode window width of 1-10 mm.

The advancements in battery technology have been obtained mainly in the field of battery materials [24]. In recent years, with the development of new technologies, e.g., supercapacitors and lithium-sulfur batteries, battery technology of light weight, high efficiency, and long life have been focused on [25]. Hybrid energy technology between listed fuels and battery/ultracapacitors is one of the examples of advanced technologies for battery technology. The optimal exchange interaction between engine speed and battery/ultracapacitor-discharge voltage has been dealt with to evaluate the optimal performance of the HEV by optimization algorithm in our previous research; the subject was presented at the 38th Int. Conf. on Vehicle System Dynamics, Identification and Anomalies Indianapolis, Indiana, USA in August 2014. On the other hand, research and development of the predictive energy management system at the laboratory level are rather difficult for battery material researches.

7. Concusion

[26]The electric energy management strategy in connected and autonomous vehicles has a substantial impact not only on the electric vehicle performances, such as as the energy consumption, but also on the overall autonomy. In this context, the control strategy, and especially the power and energy planning software, the Energy Management Strategy (EMS), plays a fundamental role. The goal of this work is to investigate the potential to optimize the fuel cell and ultracapacitor energy request of an electrically driven and connected autonomous vehicle formulated as an Energy Management System under the hypothesis of the availability of Local Dynamic Map (LDM) and infrastructure-to-vehicle communication for coping with the energy request optimization of the autonomous vehicle. In the base scenario, the energy consumption profile predicted along the route is shared with an external DataManager (DM) it's assumed operated by the municipality, that can optimize for the vehicle Domande power ultracapacitor bank and the fuel cell energy request as a function of the data available on the energy requests and consumptions of the vehicles in the LDM the algorithm chosen to solve the energetic request optimization at the utility is the reinforcement learning strategy, and concerning Deep Reinforcement Learning scenarios, the Q-Learning and a Double Deep Q-Network reinforcement learning, are then extend to an Off-policy scenario to better perform when dealing with energy for the previously mentioned grid battery, instead of being fixed [27].

[28]This chapter addresses the design of an efficient energy management system for pure electrically driven, and the so-called dual-mode hybrid-electric connected autonomous

vehicles (CAVs). To this aim, as a first step, a Static probability of occupancy based fully connected feed-forward (SO-FF) neural network is used to deduce that the average velocity, road slope and acceleration/ deceleration the vehicle is subjected to, are the most relevant indicators to convert historical vehicle speed profile into its energy consumption profile. Then, the demand power, and hence energy, is optimally distributed between the two power sourcesâ??the power grid and the primary fuel cellâ??always guaranteeing that the fuel cell is never operated too far away high efficient zone associated with its stack best point conditions. Furthermore, an ultralow solar power source, sized on the basis of a practical five day autonomy target, is added as an additional secondary energy source, to absorb, or contribute, all possible excess, or chain, and electrical energy while also contributing to reduce the fuel cell sudden part load points (SPLP) risk of failure. A digital model of the entire system is then validated under typical driving conditions. Given that the powertrain and energy management have a non-negligible impact on the vehicle performances, an efficient optimization procedure for the machine learning model and energy management system is proposed in an attempt to exploit the considerable degrees of freedom offered by a powertrain composed of a fuel cell stack, an ultracapacitor bank, and an ultra-purple solar panel, estimated to supply up to 80% of the energy autonomously.

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