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Energy Management in Fuel Cell Electric Vehicle by Employing AI/ML Techniques

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The increasing significance of climate change, air pollution, and the reduction of fossil fuel reserves has prompted regulatory bodies to enforce stricter regulations in the automotive sector, which accounts for 22% of global CO2 emissions. Battery Electric Vehicles (BEVs) are currently highly favoured as an alternative, while there is a renewed interest in Fuel Cell Hybrid Electric Vehicles (FCHEVs) following a decline in the previous decade. Hybrid Electric Vehicles (HEVs) utilize multiple power sources for propulsion, making Energy Management Strategies (EMS) essential for optimizing power distribution and reducing fuel consumption. Modern EMSs also take into account factors such as the lifespan of fuel cells. Traditionally, EMSs for HEVs were developed using optimal control theory, but there is a flourishing interest in engrossing machine learning techniques to intensify EMS performance. This research paper implies a comprehensive overview of numerous EMSs purposed in the literature, highlighting the transit fronting integration of machine learning and artificial intelligence advancements in EMS evolution. Additionally, it addresses concerns related to the range anxiety and operational lifespan of FCHEVs.
Keywords: EMS, ML techniques, Range Anxiety, Running Useful Life.

1. Introduction

Recently, a significant increase in attention to climate change has been observed by scientists and government officials. The momentum for the implementation of decarbonization policies is gaining traction across various sectors, with a specific focus on the transportation industry, which is renowned for its heavy dependence on fossil fuels. The primary challenge being encountered is the fact that a substantial number of vehicles currently in operation are propelled by Internal Combustion Engines (ICE), resulting in the emission of noxious pollutants such as nitrogen oxides (NOx), carbon monoxide (CO), and unburned hydrocarbons (HC) that pose risks to human health. As reported by the International Energy Agency (IEA), the transportation stratum accounts for 22% of global CO2 emissions, positioning it as the second-largest contributor to climate change following the electricity and heat sector. Notably, passenger cars and trucks are responsible for 74% of the total emissions produced by the transportation industry.

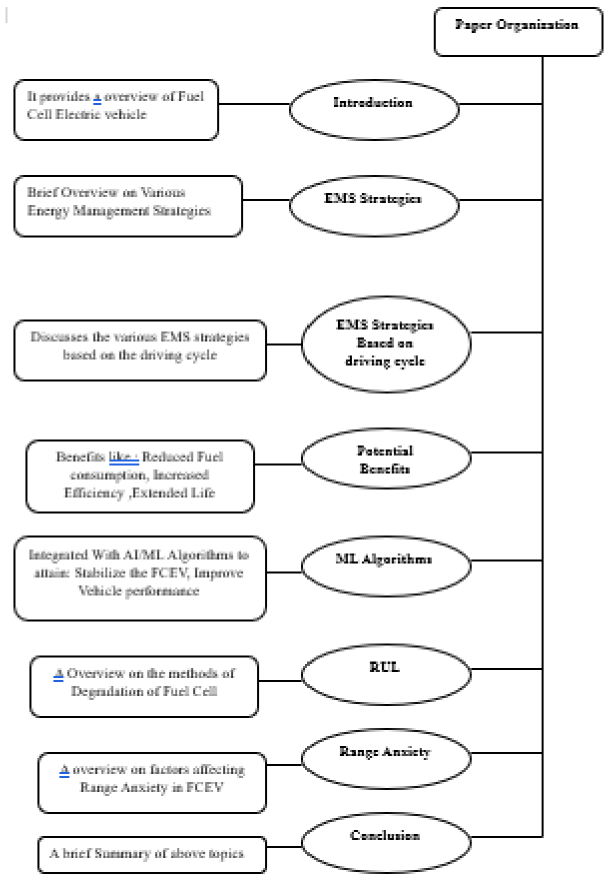
Efforts to decrease emissions from vehicles on the streets are being escalated by officials. For instance, targets have been established by the EU to lower Carbon dioxide emissions from cars by 37.5% and vans by 31% by 2030. Consequently, there exists an obligation to investigate eco-friendly transportation alternatives that produce fewer pollutants and have reduced reliance on oil. [2].

In traditional vehicles lacking hybrid technology, drivers are in charge of managing power distribution through the brake and accelerator pedals, as well as gear selection in manual transmission cars. Yet, in hybrid vehicles, drivers must also consider how to distribute power from various energy sources onboard. This is because hybrid vehicles can capture energy during braking or downhill driving, storing it in a battery for future use to support the primary power source for traction. To oversee this process, hybrid vehicles come equipped with an energy management controller that incline the most efficient dispersal of power between energy sources. The initial even handed of the energy management system is typically to curtail fuel consumption, although other goals like emission reduction, prolonging fuel cell life, or achieving a balance between these aims may also be considered based on the specific application.[3].

The notability of EMSs in maximizing power distribution in Hybrid Electric Vehicles (HEVs) to enhance fuel efficiency and reduce emissions in various driving scenarios is widely recognized [4]. The significant role played by EMSs in improving the environmental impact of HEVs is well acknowledged. An essential aspect of energy management in Fuel Cell Electric Vehicles (FCEVs) involves optimizing the operation of the fuel cell stack, which includes the regulation of hydrogen and oxygen flow to the stack, as well as monitoring the temperature and pressure of the stack to enhance efficiency and durability. Energy management in FCEVs is generally considered a critical and complex component of their operation. Effective control of energy flow among the fuel cell stack, battery pack, and other components enables FCEVs to actualize remarkable levels of efficiency and performance, positioning them as a viable recourse to conventional internal combustion engine vehicles.

Leveraging of artificial intelligence (AI) and machine learning (ML) techniques has been demonstrated to be highly effective in the optimization of energy management for Fuel Cell Electric Vehicles (FCEVs). These sophisticated methodologies facilitate the real-time analysis of extensive data, enabling intelligent decision-making regarding energy allocation and utilization within the vehicle. Through the incorporation of AI and ML algorithms, FCEVs can accustom dynamically to differing driving conditions, traffic patterns, and energy exigency, thereby improving energy efficiency and extending the vehicle's operational range. The incorporation of artificial intelligence and machine learning methodologies into energy management systems for FCEVs not only enhances efficiency and range but also elevates the overall driving experience. Additionally, these methodologies play a crucial role in forecasting future energy needs and optimizing the fuel cell system for peak performance. This technological advancement represents a significant progression in sustainable transportation solutions. [6].

An Overview of Paper Organization



ENERGY MANAGEMENT STRATEGIES :

Efficient management of energy in fuel cell electric vehicles plays a critical role in improving vehicle efficiency and range. This process entails optimizing the utilization of energy stored in the fuel cell system by regulating the flow of energy among the fuel cell, battery, and electric motor to enact exquisite fruition. An important technique involves the utilization of regenerative braking, which captures energy from braking to recharge the battery for future use, thereby enhancing overall efficiency and extending the vehicle's range. Furthermore, the management of power output from the fuel cell system based on driving conditions and energy demands is of utmost importance. This includes the adjustment of the fuel cell's configurations to regulate the vehicle's power requirements and the control of energy transfer amid the fuel cell and battery to ensure a consistent power supply. Effective strategies for energy management are crucial for maximizing efficiency, extending range, and enhancing performance in fuel cell electric vehicles. Manufacturers can guarantee superior performance and driving experience by adeptly overseeing the flow of energy within the vehicle's powertrain.

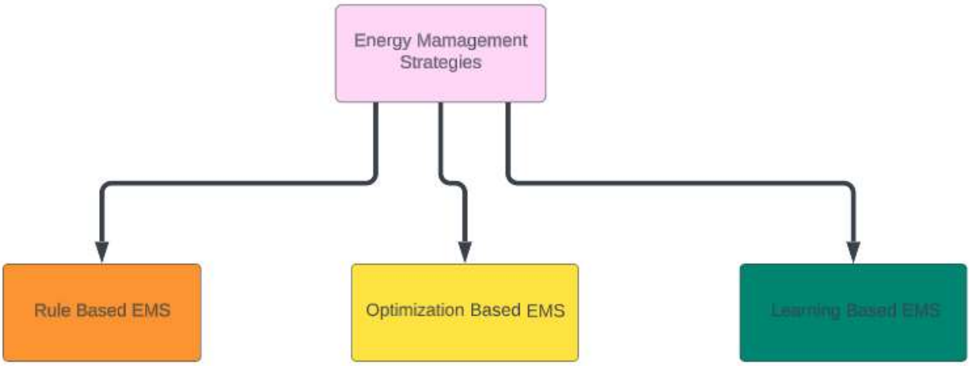


Figure 1: Energy Management Strategies

Rule based EMS

Recent research has seen a shift towards improving the effectiveness of conventional RB control strategies in commercial HEVs, such as EACS, PFCS, and CDCS, through the application of optimization methods [10]. A novel RB EMS concept, referred to as the threshold switching mechanism, has transformed the approach by integrating pre-established power thresholds into operational guidelines to promote efficient HEV operation. In contrast to traditional RB EMS systems that depended solely on battery SOC for threshold setting, this innovative approach takes into account both SOC and engine speed. The efficacy of this approach was evaluated against DP outcomes, which represent the globally optimal solution, and EACS outcomes, which represent a practical solution. Additionally[11], a interpreted iteration of the proffered EMS was formulated for real-time usage and embodied in the correlation. In another investigation, a rule-based EMS was utilized to optimize a fuzzy control system with the objective of enhancing transmission efficiency rather than solely concentrating on consumption reduction.

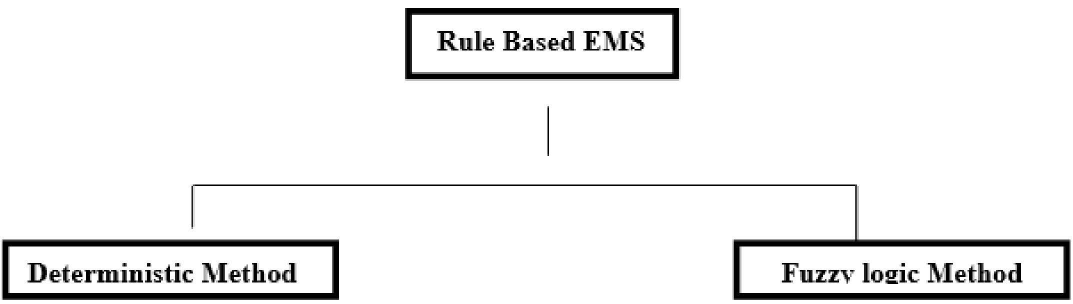


Figure 2.Types of Rule Based EMS

Optimization Based

EMSs based on optimization desire to uncover the most effective control sequence, referred to as the reference power demand, to reduce costs while following dynamic state constraints. These constraints include overall state limitations like SOC and local restrictions such as power, speed, and torque. Cost functions can differ, encompassing elements like fuel consumption, hybridization costs, vehicle payload, and emissions. This research focuses on real-time strategies that can be practically applied. Within this category, strategies like ECMS, MPC, robust control, extreme value search, decoupling curb, pseudo spectral optimal control, and sliding mode are considered. An example is a dynamic EMS with a predictive rate correlated as a mixed-integer optimization problem as presented in [8].

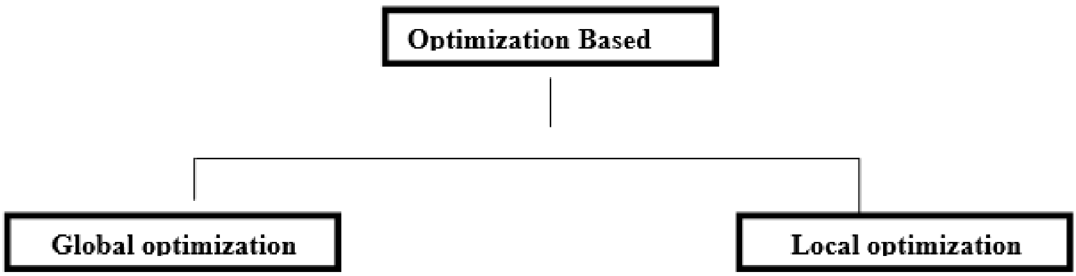


Figure 3.Types of Optimization Based EMS

Learning based EMS

Supervised learning encompasses methodologies that acquire behaviours based on predefined guidelines or labels. Following training with labelled data, supervised learning algorithms can subsequently implement these guidelines on novel data. The main challenge lies in the accurate application of these guidelines to familiar scenarios and the effective extension to unfamiliar data or situations. In order to facilitate the implementation of adaptive fuzzy rule-based strategies for EMSs, supervised learning techniques are utilized and validated. Additionally, a learning vector quantization network is devised for the identification of driving patterns. The identification of driving patterns, which determines the transition between driving modes, is accomplished through the utilization of long short-term memory within a recurrent neural network (RNN). In contradiction to supervised learning, unsupervised learning is employed to unveil structures or patterns in unlabelled data..

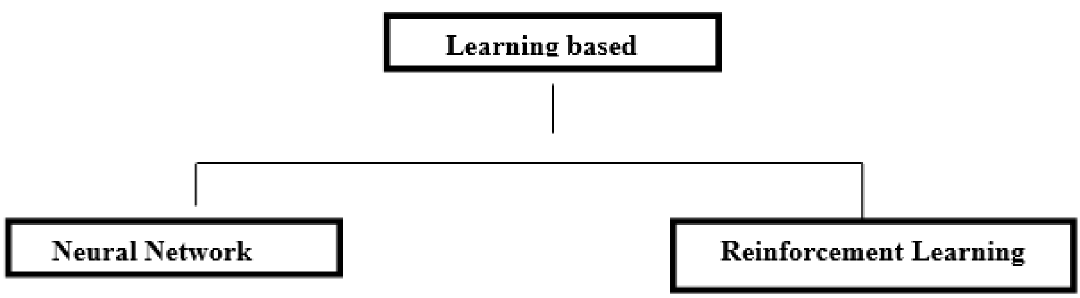


Figure 4.Types of Learning Based EMS

TABLE 1 : VARIOUS ENERGY MANAGEMENT STRATEGIES

REFERENCE	METHOD USED	PARAMETERS OPTIMIZED	ADVANTAGES	LIMITATIONS
Pengli Yu, Mince Li, Yujie Wang,	GA	-hydrogen consumption - Battery SOC range .	- Enhanced fuel economy and prolonged fuel cell longevity.	- Insufficient research on the energy management strategy for hydrogen-powered yard trucks.
Omer Abbaker AM1,2,	Rule based	- fuel economy. - lifetime of the fuel cell.	- Improved fuel economy and power pursuance. - Prolongs fuel cell lifetime and reduces power fluctuation.	- The fuel cell experiences varying levels of stress and power fluctuations due to external factors.
Weiwei Huo, Tianyu Zhao,	- SAC -DRL algorithm -SAC-PL	- Fuel economy, fuel cell degradation, - Instantaneous cost, power constraint embedded in SAC algorithm	- Reduced fuel consumption, extended lifetime, improved training stability. -SAC-PL algorithm speeds up convergence, enhances EMS optimization.	-Minimal details on optimisation of the fuel cells
Walid Touil, Zhongliang Li	MPC	- Battery state of charge range.	-Efficient power conversion -MPC to achieve sustainable battery charging and reduce hydrogen consumption.	- performance of EMS is influenced by accuracy and the length of the control horizon. - Co-designing prediction model and horizon length is necessary for optimization.
Shengya Hou, Hai Yin, Benjamín Pla,	Offline optimization	- The distribution of power is divided between the battery and the fuel cell.	- Energy savings of 8.48-10.71% compared to rule-based strategy. - Performance improvement with increased battery capacity by 0.15-1.66%.	- Significant effort is required for the calibration in the offline phase through the utilization of dynamic programming. - Sub-optimal results in on-board applicability compared to theoretical optimum.
Ahmed Khadhraoui, Tarek Selmi	GA	-hydrogen consumption.	- Improved fuel efficiency and extended fuel cell life. - Real-coded GA outperforms existing rule-based strategy.	- dearth of scrutiny on energy management strategy for hydrogen-fuelled yard truck.
Karem BenChikha, Ali Amamou,	-Online Based	-power distribution optimization. - Battery SOC	- Maintaining high levels of battery state of charge (SOC) helps minimize recharging downtime by efficiently distributing power between the FC and the battery.	- Extant rule-based strategy results are inferior to GA solutions.
Hao Gu, Bifeng Yin,	-Fuzzy logic	- Fuel cell degradation and driving range parameters	- Increased driving range by 4.7% to 5.9% - Reduced fuel cell degradation by 19.8% to 21.4%	- Serious power fluctuations affecting fuel cell durability

Matthieu Matignon, Toufik Azib,	-DP	- Driving pattern and SOC ,FCS size	- optimal offline strategy with under 2% consumption gap.	- high computational cost - Requires prior knowledge of driving cycle. - Not adaptable for real-time operating conditions.
Haoqin Hu, Jiaqi Tan,	-GA	- Battery SOC range	- Enhanced fuel efficiency and extended fuel cell life.	-Not suitable for real time operation.

OPTIMIZATION OF FCEVS BASED ON DIFFERENT DRIVING CYCLE

EMS play a crucial role in optimizing FCEVs based on different driving cycles. Various research papers have proposed innovative EMS approaches to enhance energy efficiency and perpetuate the agedness of fuel cells. FLC has been employed to regulate energy flow bounded by fuel cell and Li-ion battery, ensuring efficient energy distribution under diverse driving conditions[28]. Additionally, strategies combining offline optimization with online algorithms have been developed to achieve optimal control and real-time performance, resulting in energy savings and adaptability to different vehicle configurations[9]. Model predictive control (MPC) has also been explored to enhance EMS performance by considering velocity prediction and control horizon length[54].

Table 2 : Various EMS strategies based on Different driving cycle

References	Method used	Information on driving cycle	Advantages	Disadvantages
Omer Abbaker	-NNOA	- HWFET, UDDS, and WLTP driving schedules evaluated..	-Improved fuel economy and reduce power fluctuation.	- Load stress ,power fluctuation on fuel cell
Sekanina, Zdenek	-Nonlinear autoregressive moving average (NARMA-L2) neuro-controller	-Driving conditions used for EMS evaluation in MATLAB/Simulink model.	-Prolonged lifetime of the fuel cell.	-Extensive driving cycle training requires substantial and representative data sets..
Weiwei Huo, Tianyu Zhao	- SAC - DRL algorithm	- four prevailing vehicle driving cycles. - Dynamic Programming algorithm employed	- Enhancing training stability can lead to reduced fuel consumption -prolonged lifespan of fuel cells.	- Lack of investigation on energy management strategy.
Hai-Bo Yuan	GA	- Total resistance effort (Fr) models advancement force for driving EV..	-efficient power allocation.	- horizon length is necessary for optimization.
Walid Touil, Zhongliang Li	- Prescient MPC, Frozen time MPC, Markov chain MPC.	- Driving cycles used to study prediction impact on EMS performance.	- low hydrogen consumption. - Co-designing prediction model and horizon length enhances EMS performance.	- Prediction accuracy, control horizon length affect EMS performance.
Shengya Hou, Hai Yin, Benjamín Pla	- Offline optimization	- Total resistance effort (Fr) models advancement force for driving EV.	- Enhances the performances of the fuel cell	-Calibrating in the offline phase using dynamic programming may need some effort, but the results may not be as effective when applied on-board compared to the theoretical

				best outcome.
Hao Gu, Bifeng Yin	- Fuzzy control method	- Fr function formula can represent the motorization system's required effort.	-Reduces fuel cell degradation. - The fuzzy control method limits rapid shifts in fuel cell power.	-Significant power shifts are impacting the lastingness of fuel cells. Various limitations, such as fluctuations in fuel cell power and hydrogen consumption, are being observed.
Mostafa Salem, Mahmoud Elnaggar	- Online optimization technique	- No prior knowledge of driving cycle needed for optimization. - Driving cycle not specifically detailed .	- Optimal fuel consumption & powertrain component lifetime management in vehicles. - Real-time strategy without prior knowledge of driving cycle.	- Fuel cells exhibit a sluggish response to changes in energy demand, highlighting the importance of coordinating energy usage in hybrid systems.
Julian Kölbl, A. Ferrara,	- Adaptive EMS -Dynamic predictions of the Remaining Useful Life (RUL) of each stack	- Fr function formula can represent the motorization system's required effort.	- The longevity of multi-fuel cell stack systems has been significantly increased.	- decreased reliability and a limited energy efficient operating range..
Dapai Shi, Shipeng Li	-GA	- BPNN for intelligent recognition of driving cycle	-Enhances fuel economy in PHEV - Improves EMS based on driving cycle prediction.	- Comprehensive driving cycle training necessitates a substantial amount of representative and extensive data on effective velocity sequences.
Matignon Matthieu; Azib Toufik	-Rule based	- Driving cycle prediction integrated into real-time EMS.	- Extended lifetime of fuel cell	- Integration of data processing algorithms for real-time driving conditions.
Jiangtao Fu, Zhumu Fu	- GA	- Real driving cycle evaluation conducted for EMS verification.	- improved fuel economy by 8.8% during real driving cycle.	-Reduced reliability
Adel Oubelaid, Smail Mezani	-fuzzy logic control (FLC)	- Validation is conducted using three common driving cycles: NYCC, WLTP, and UDDS.	- Efficient energy distribution in dual-source electric vehicles under various driving cycles. - Minimize fuel consumption.	- Lack of investigation on energy management strategy
an Sun, Chang Gao Xia	- game theory	- Driving cycle used: WLTP	-extended lifetime. -minimize hydrogen consumption.	- Short lifetime, reduced reliability, and narrow energy

Potential benefits of improving energy management in fuel cell electric vehicle for various applications

Enhancing energy management in fuel cells has the potential to yield several advantages across different applications. One such advantage is the decrease in fuel consumption, which can result in heightened efficiency and an extended driving range [21]. Another advantage is the decrease in hydrogen consumption, which can help in prolonging the lifespan of the fuel cell stack and reducing operational expenses [22]. Furthermore, the optimization of energy management approaches can lead to the minimization of power fluctuations, which can enhance the persistence of the fuel cell and decrease degradation [23]. The exertion of real-time energy management strategies can also enhance the economic performance of powertrain systems, thereby increasing energy-saving capabilities and reducing energy usage [24]. Moreover, taking into account factors like fuel expenses, degradation expenses, and inconsistent fuel cell performance can aid in reducing operational costs and enhancing system efficiency [25]. In summary, the enhancement of energy management in fuel cells can improve performance, boost efficiency, and lower costs across various applications.

Table 3 : POTENTIAL BENEFITS OF IMPROVING ENERGY MANAGEMENT

Reference	Method used	Advantages	Limitations
Heena Mishra, Shashwati Ray,	- Energy management strategy with CDM controllers - Parallel connection of PEM fuel cell and battery sources	- Enhanced performance by coordinating fuel cell and battery energy sources. - Stable system operation under varying load conditions	- The single fuel cell system has limited reliability and operates within a narrow energy-efficient range.
A. Hamlat, M. Sekkour, M.	-ML Techniques	- Minimizes hydrogen consumption in MFCS system by 12%	-reduced reliability
Hao Gu, Bifeng Yin	- Power following strategy - Fuzzy control method	- Drawn out life time of fuel cell	- Significant power variations are impacting the longevity of fuel cells.

ENERGY MANAGEMENT STRATEGIES USING ML ALGORITHMS

The effective management of energy plays a cavillous portrayal in bettering the efficiency of fuel cells utilized in electric vehicles. Recent research has suggested that advanced Artificial Intelligence (AI) and Machine Learning (ML) techniques labouring to achieve this goal. For example, the utilization of reinforcement learning algorithms like Q-learning and Deep Deterministic Policy Gradient (DDPG) has been proposed to enhance energy management systems in fuel cell hybrid vehicles[13]. Furthermore, the incorporation of Deep Reinforcement Learning (DRL) algorithms, such as Soft Actor-Critic (SAC) and SAC-PL, has demonstrated promising outcomes in extending the lifespan of PEMFC stacks and enhancing fuel efficiency in electric vehicles[28]. These strategies driven by AI/ML aim to decrease hydrogen consumption, maintain a stable State of Charge (SOC), and improve overall vehicle performance while reducing environmental impact[3],[4]. Figure 5 illustrates various Energy Management System (EMS) strategies based on ML Algorithms.

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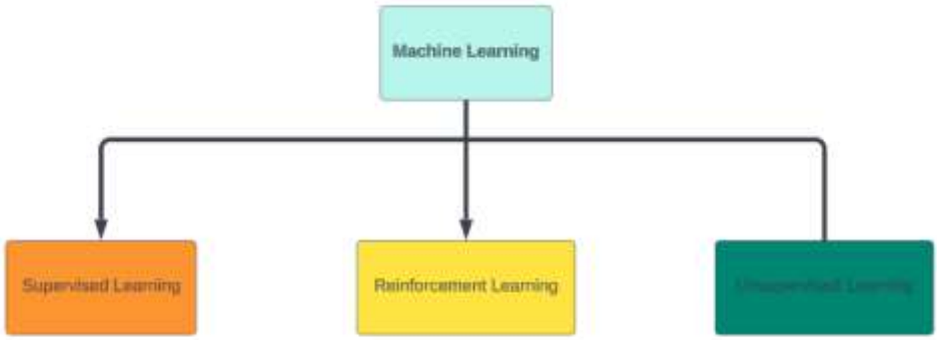

Figure 5: Various ML Algorithms

Table 4: EMS BASED ON ML TECHNIQUES

TYPE	METHOD USED	ADVANTAGES	DISADVANTAGES	AUTHOR
Supervised learning	- Fuzzy reinforcement learning-based	- No pollution, fast charging, high efficiency - Extended lifetime of fuel cells, reduced fuel consumption	- Modelling the complexity of a system can be challenging, especially when the model needs to account for changes over time and uncertain external factors.	Liang Guo; Zhongliang Li
	-Neural network optimization algorithm (NNOA) for tuning membership functions of fuzzy logic controllers (FLCs)	- Reformed fuel economy and power performance. - Prolongs fuel cell lifetime and reduces power wavering .	-The fuel cell experiences load stress and power vacillation.	OMER Abbaker Ahmed, Haoping Wang
	- Offline optimization with dynamic programming	- No pollution, fast charging, high efficiency - Extends lifetime of fuel cells, reduces fuel consumption	- Calibration effort required in the offline phase	Shengya Hou, Hai Yin, Benjamín
	- deep reinforcement learning	- reduces fuel consumption	- Short lifetime, reduced reliability, and narrow energy-efficient	Yang Shen; Fengyan Yi
	- DRL	- Extends lifetime of fuel cells	- Lack of investigation on energy management strategy	Zhumu Fu, Haiyan Wang,
	LSTMN	-fast charging	- Practical Implications are difficult	Hujun Peng; Feifei Li; Zhu Chen
Unsupervised Learning	- TD3 - DDPG	-has higher training efficiency	-reduced reliability	Kunang Li, Chun-Qiang Jia,
	- TD3, DQN, DDPG, DP	-Better rate of hydrogen consumption and system efficiency	-Reduced Lifetime	QinXiang Gao, Tao Lei, Fei Deng,
	- Model-based offline reinforcement learning - Conservative MDP and state regularization techniques	-Enhances performances	- challenges associated with sample inefficiency, risky exploration, and the disparity between simulated environments and actual real-world conditions.	Bo Hu, Yang Xiao, Su Xiang
	- Pontryagin's minimum principle	- reduces hydrogen consumption by 49.9% .	-	Haochen Sun, Fazhan Tao,

	(PMP) method for computing optimal equivalent factor (EF)	- reduces total cost to use by 31.4%.		
	- Optimizing convex programming within the framework of partially observable Markov decision processes.	-enhances efficiency and performance of electric vehicles.	- Decoupling system performance from future power demand prediction accuracy.	Di Shen, Cheng-Chew Lim,
	online optimization technique	- The most efficient strategy for improving performance is to do so even in the absence of prior familiarity with the driving cycle.	- The slow dynamic response exhibited by fuel cells has been identified as a significant challenge in the field of energy systems. - necessity for the coordination of energy within hybrid systems to address this issue effectively.	Mostafa Salem , Mahmoud Elnaggar
	offline RL algorithm	- Address the distributional shift issue in off-policy RL to a significant degree.	- Issues such as inefficiency, safety concerns in exploration, and the disparity between simulated and real-world environments are common challenges faced in reinforcement learning methods.	Bo Hu , Yang Xiao,
Reinforcement learning	- Batch-constrained deep Q-learning (BCQ)	- improves battery SoC stabilization and fuel economy.		Niu Zegong; He Hongwen
	- DDPG algorithm based on actor-critic structure with deep neural networks	- Strategies for effectively managing energy in hybrid electric vehicles.	- Complex and proprietary vehicle models limit broad applicability. - not suitable for general use.	Xinyang Wu, Elisabeth Wedernikow
	- Q-learning algorithm	-better performance, robustness, generality, and modelling difficulty of EMSs.	- DQN lags DP by around 9% in fuel efficiency. - DDPG lags DP by around 4% in fuel efficiency.	Yuxiang Zhang, Rui Ma, Dongdong Zhao

RUNNING USEFUL LIFE OF FCEVS

Estimating the RuL of fuel cells is crucial for energy management in FCEVs [38][41]. Prognostic health management (PHM) techniques are employed to monitor fuel cell degradation and predict RuL[47][52]. Various approaches, including data-driven methods like LSTM [55], as well as algorithms such as the Extended Kalman Filter and the Inverse First Order Reliability Method, have been suggested for RuL estimation. Moreover, adaptive EMS have been devised to enlarge the lifespan of multi-fuel cell stack (MFCS) systems in FCEVs. These strategies optimize power distribution and reduce hydrogen consumption by dynamically predicting the RuL of each stack.

Table 5 : RUL of FCEVs

AUTHOR	METHOD USED	ADVANTAGES	LIMITATIONS
Wenato Bankati, A. Macias,	- Dynamic predictions of RUL	-Extended lifetime and minimize hydrogen consumption.	- limited reliability and a narrow range of energy-efficient operation.
Karem Benca	- LSTM is used for data-based PHM method.	- The method achieves high accuracy in predicting FC voltage degradation and RuL.	-Less operating range
Mohsen Kandidayeni, Ali	- LSTM is used for data-	- Accurate prediction of fuel	-

Amamou	based PHM method.	cell voltage degradation with 88.13% accuracy. - Forecasting of remaining useful life (RuL) with 92.5% accuracy for 135 hours of operation.	
H. Cherragui, Mathieu Bressel,	- Real-time Extended Kalman Filter	- predict RuL of fuel cells. - high accuracy in predicting FC voltage degradation and RUL.	-- Need for energy coordination
Hao Gu, Bifeng Yin,	- Power following strategy - Fuzzy control method	-increases driving range and reduces fuel cell degradation. - The fuzzy control method limits rapid shifts in fuel cell power.	- Serious power fluctuations affecting fuel cell durability
Kevin Davis, John G. Hayes	- Equivalent consumption minimization strategy	-reduced overall consumption and prolonged component lifespan.	- Slow dynamic response of fuel cells
Julian Kölbl, A. Ferrara,	- Adaptive Energy Management Strategy EMS	- extended useful life is achieved through the equivalent consumption minimization strategy, optimizing hydrogen consumption.	- lifespan limited dependability, and operates within a narrow range of energy efficiency.

RANGE ANXIETY

EM in FCEVs is crucial for addressing range anxiety. Various strategies have been proposed to optimize fuel consumption and enhance vehicle performance [40][46][28]. For instance, fuzzy control-based EMS have been developed to augment fuel cell durability and efficiency[18]. Additionally, the integration of battery systems in FCEVs allows for automatic switching between power following and thermostat control methods to maintain optimal energy source system operation[50]. Furthermore, the use of photovoltaic cells and battery banks in hybrid powertrains, along with advanced control techniques like nonlinear autoregressive moving average (NARMA-L2) neuro-controllers, has shown promising results in enhancing system efficiency and stability. These innovative approaches aim to alleviate range anxiety and enhance the overall performance of FCEVs. The factors that contribute to range anxiety include real-world elements that impact the range of an electric vehicle, like traffic conditions, terrain incline, outside temperature, driving speed, and more.

Table 6: RANGE ANXIETY OF FCEVS

AUTHOR	METHOD USED	ADVANTAGES
Wenhao Liu; Jianping Dou	- Real-coded genetic algorithms make use of unvarying mutation and two-point crossover operators. - The penalty method is employed to assure the maintenance of the battery SOC within a specified range.	- Improved fuel efficiency and extended fuel cell life. - Real-coded GA outperforms existing rule-based strategy.
Yangyang Ma, Zhuo Hao,	- Power following control strategy	-High power performance and fuel efficiency
Yoshihiko Takahashi	- Optimum energy management control system	- Range anxiety addressed by optimum energy management control system.
Shengya Hou, Xuan Zuo Liu	- Dynamic Programming	- Minimizes hydrogen consumption - Keeps battery SOC stable
Yang Hui-ce, Zhang Chong	-dynamic programming	- Optimal economy achieved through

		dynamic programming EMS - Superior fuel economy and energy savings demonstrated in simulation results
Hekun Jia, Tang Jiexu,	- Series fuzzy control strategy (SFCS) - Particle swarm optimization (PSO)	- Reduced FCs load changing rate, optimized durability - Increased driving mileage by 11.2% under WLTC conditions
Hamed Farhadi Gharibeh	- Controlling operational modes, managing state machines, and minimizing equivalent consumption are essential for optimizing fuel cell vehicles. - Implementing dynamic power factor strategies is crucial for enhancing energy efficiency in electric motors used in these vehicles.	- reduction in fuel consumption results in an enhancement of the energy efficiency of storage systems.
Ruyang Zhang, Qi Liu	- GA	- Hybrid power system combines fuel cells with secondary charging sources. - Genetic algorithm optimizes EMS for fuel cell vehicles.
Enyong Xu, Wei-Guang Zheng	- MPC	- Widely used in commerce due to its high efficiency and zero pollution.
M. Sellali, Alexandre Ravey	- Dynamic predictions of RUL	- Reduced economic cost up to 50% - Extended lifetime with 50% degradation reduction

2. Conclusion

Efficient management of energy in fuel cell electric vehicles is deemed essential for the enhancement of performance and efficiency. Optimal outcomes can be achieved by vehicle manufacturers through skillful management of the energy flow from the fuel cell to the electric motor and battery, thereby contributing to the extension of the vehicle's range, reduction of emissions, and improvement of the overall driving experience. Key roles in the attainment of these objectives are played by strategies such as regenerative braking, predictive energy management, and intelligent power distribution systems. Further innovation in energy management for fuel cell electric vehicles will be driven by continuous advancements in technology and infrastructure, thereby fostering a transportation solution that is more sustainable and environmentally friendly. The application of techniques based on artificial intelligence and machine learning in energy management for these vehicles has demonstrated significant potential in enhancing energy efficiency and overall performance. These techniques prove to be effective in the prediction of energy consumption, optimization of power distribution, and increase in vehicle range. Through the utilization of real-time data and advanced algorithms, artificial intelligence and machine learning can efficiently manage energy flow within the vehicle, resulting in reduced energy consumption and improved efficiency. The integration of techniques based on artificial intelligence and machine learning in energy management for fuel cell electric vehicles shows promise in significantly enhancing performance and sustainability. Ongoing research and development in this domain will be essential in fully exploiting the capabilities of artificial intelligence and machine learning to optimize energy management for fuel cell electric vehicles.

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