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A Review of Reinforcement Learning Based EMS for Fuel Cell Based Transportation Vehicles

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Abstract—*In recent years, the transportation industry has been under pressure to address issues such as climate change, local pollution, and noise pollution. When compared with other modes of mass transportation the most recent fuel cell based hybrid electric transportation vehicles are more environmentally friendly since they produce no tailpipe emissions making them more energy efficient than vehicles that are powered by electric, petrol, or diesel engines. When accelerating and braking in fuel cell (FCell) based vehicles require very quick and dynamic responses from the vehicle. As a result, hybrid electric vehicles should be implemented using fuel cell stacks and batteries to provide a balanced dynamic response. In this work, energy management (EM) solutions for FCell hybrid electric vehicle that are capable of self-learning are discussed. An energy management strategy (EMS) that is based on Reinforcement Learning (RL) is being researched for use with the FCell based vehicles in order to ascertain how power is distributed between the two energy sources. The purpose of this work is to provide a review for future FCell transportation technology by discussing various reinforcement learning methods and highlighting their main outcomes. Additionally, the work will highlight the potential benefits that FCell technology may have for the transportation industry in terms of reduced operational costs as well as improved performance. The work will be based on the compilation of information from a wide range of acknowledged sources. In particular, RL approaches known as Q-Learning is utilized in order to maximize battery longevity while simultaneously reducing the amount of fuel that is used. During the procedure a variety of goal functions are modified as necessary so that they are acceptable for Q-learning. Additionally, the difficulties observed in the continuing RL based EMS study are described along with possible solutions that allow possibility for additional research.*
Keywords: *State of Charge, Fuel cell, Reinforcement learning, Transfer learning, Energy management strategy.*

1. INTRODUCTION

The increasing concern about the impact of exhaust emissions on climate change and health has led to a re-evaluation of transportation options. As a result, there is a growing demand for energy efficient and environmentally friendly transportation, which has given rise to innovative solutions such as fuel cell hybrid electric vehicles. Japan, Germany, China and the United States have already implemented fuel cell technology to power vehicles-trains and India is also exploring this technology through several pilot projects due to the significant contribution of the country's transportation emissions by the vehicles-trains. Fuel cell technology has been a reliable source of electricity generation for several decades and converting hydrogen and oxygen into electricity and water with only heat and water being emitted as byproducts[1]. FCell based vehicles use a fuel cell system and battery system for power [2]. The fuel cell system powers the electric motors by converting hydrogen and oxygen into electricity and water. The battery system stores excess and regenerative energy and provides additional power during acceleration and high-power demand situations[3]. FCell based vehicles are constructed from a main power source known as the Fcell system and an energy storage system that may take the form of a battery bank or a bank of supercapacitors (SC) both of which are responsible for supplying power to the load. When there is a demand for power from the load denoted by $P_{demand}(t)$, it may be partially met by the FCell, denoted by $P_{FCELL}(t)$, while the remainder of the power is met by the battery/ultracapacitor denoted by $P_{bat/supercapacitor}(t)$.

$$P_{demand}(t) = P_{Fcell}(t)+P_{bat/supercapacitor}(t) \text{ for all t.} \tag{1}$$

To gain a better understanding of the advantages and disadvantages of FCell based vehicles, it is essential to examine the functions of the energy management storage system in an FCell hybrid vehicle (FCell Hybrid) as listed below [4]:

I. Providing traction power during FCell start-up: FCell output power may be lower than its rated value in cold ambient or cold-start conditions, hence traction power must be provided in these cases. The energy storage system should make up the difference while the FCell heats up and achieves its rated output.

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III. Recapturing energy from regenerative braking: In automobile applications, regenerative braking may recover energy lost at friction brakes, improving hydrogen efficiency. Energy recovered ranges from 4.9 % in a highway cycle to 18% in an urban cycle. FCell Hybrid vehicle have constant loads from radiator fans, electric power steering, brakes, and air conditioning. The ESS may temporarily sustain electrical supplementary loads while the FCELL is turned off using recovered energy.

IV. FCell Hybrid vehicle benefit from FCell start/stop: An energy-management technique may shut down and restart the FCELL while the vehicle is running.

1.1 Need of RL based Energy Management Strategy

An EM strategy is responsible for the equitable sharing of power from multiple energy sources. These emerging technologies such as fuel cells and auxiliary energy source batteries offer the potential to create less carbon-intensive and more environmentally-friendly transportation scenarios.

In the transportation sector, the development of efficient energy management strategies and powertrain architecture is critical for advancing the utilization of novel energy sources. An EMS is essential in reducing energy consumption and emissions for electrified powertrain technologies. Among the most common types of energy management systems are Model predictive control (MPCtrl), Dynamic programming (D_Prog), Rule-based techniques, Equivalent consumption energy management (ECMS). Creating a set of fixed norms for vehicle operation is required for rule-based EMS which is the simplest and least expensive option. D_Prog on the other hand provides globally optimized solutions but it is computationally intensive and requires predefined speed profiles which makes it inappropriate for real-time applications. By reducing optimized domain to cost function ECMS is an effective method that delivers real-time solutions. Despite the fact that ECMS has been studied exhaustively for electrified propulsion systems, its optimization is still far from the global optimum due to single time step optimization. MPCtrl offers multi-step optimization and real-time solutions but its results are model-dependent and based on a local optimum causing the use of reduced order models during analysis in an effort to cut down on processing costs which does a disservice to accuracy.

Reinforcement learning provides an alternative to traditional control techniques for the development of efficient EM strategies for electrified powertrains. Similar to dynamic programming reinforcement learning utilizes the Bellman Equation to obtain a globally optimized solution. It operates by combining instantaneous rewards from the current state with cumulative rewards from the next stage to the episode's conclusion. The RL agent interacts directly with the environment to acquire state, reward, and action information in order to discover decision-making principles that maximize accumulated reward over time. RL algorithms are founded on Markov decision processes and presume that only the current state influences future states. RL-based algorithms provide more accurate optimization results than rule-based techniques while absorbing less computational time and cost and operating online unlike D_Prog techniques. In addition, RL is a model-free operation, eradicating the dependence of ECMS and MPCtrl on reduced order models. RL approximates globally optimal results and performs similarly to D_Prog which makes it a promising strategy for designing efficient and robust EMS for electrified powertrains. Sources [5-8] claim that fuel cell vehicles-locomotives with an energy storage system installed may improve fuel economy by recovering braking energy and lowering peak power requirements. Hybrid power systems that use fuel cells and batteries may help speed up reaction times. Research on fuel cell-based vehicle-train technology goes back to the early 1990s [9]. The first pure fuel cell traction locomotive was built in 2002 [10], while the first fuel cell train with a recovered brake energy system was built in 2006 [11]. Fuel cell vehicles-locomotives have lately been created in several nations like France and China [12].

Many researchers have proposed different energy management strategies such as the streamlining method [13], the force-the-board technique [14], and others to optimize energy distribution. In 2021, China released the first domestically produced hybrid train powered by hydrogen fuel cells (China Daily, 2021). The locomotive's top speed is 80 kilometers per hour and its range is 500 kilometers and it is powered by a Fcell and a battery energy storage system. These include least identical hydrogen consumption [15], fuzzy coherent energy [16], strong PI control [17], dynamic following coefficient, an algorithm based on forward dynamic programming [18], an optimization-based methodology [19], the pontryagin's minimum principle [20], metaheuristic optimisation techniques, fuzzy logic control, and speed trajectory optimisation [21]. However, most of these EMSs are made for low-powered road vehicles which means they might not work with massive, high-powered vehicles or rail vehicles whose power requirements vary over time. Some researchers have proposed fuzzy logic-based EMSs for fuel cell hybrid locomotives [22] but these methods may be too complex and costly for practical implementation.

The Deep reinforcement learning (DRL) based EMS was compared with three other EMSs like rule-based EM startegy, model predictive control EM strategy, and a fuzzy logic EM strategy. The review show that the DRL-based EMS achieved the best performance in terms of hydrogen consumption, fuel cell aging, and battery SOC variation. The DRL-based EMS showed a hydrogen consumption reduction of up to 8.3% and a fuel cell aging reduction of up to 23%. The fuzzy logic EMS showed the worst performance with a hydrogen consumption reduction of only 2.9% and a fuel cell aging reduction of only 5.9%. The DRL-based EMS was also able to maintain the battery SOC within a narrow range, which is important for the longevity of the battery.

Organizing the paper: Section 2 Covers RL methods used in electric powertrains. Section 3 Discuss RL technique-based

EMS. Section 4 Challenges, opportunities, and potential solutions and Section 5 conclude the paper.

2. RL TECHNIQUE

One way to apply RL to FCell hybrid transportation vehicles is to use it to optimize the power split between the Fcell and the battery. The agent could take actions such as adjusting the power output of the Fcell and battery and the reward signal could be based on the energy efficiency of the vehicle as well as other factors such as passenger comfort and safety. Another potential use of RL in Fcell hybrid vehicles is to optimize the charging and discharging of the battery. It is possible that the agent will have to make decisions on when to recharge the battery when to take power from the battery and how much power to drain from the battery in order to do this. In such a scenario, the incentive signal would be decided upon based on the energy efficiency of the vehicle, state of the battery and a number of other criteria such as the level of comfort and security experienced by the passengers. The RL may be able to optimize the functioning of Fcell hybrid vehicles which would lead to increased energy efficiency and decreased operating costs. However, when RL is used in complex control systems like those used in train operations safety and reliability must be carefully considered. Before putting the RL-based control system into use in the actual world it is essential to conduct thorough evaluations and tests of its effectiveness first. A generalized diagram of RL approaches may be shown in Figure 1.

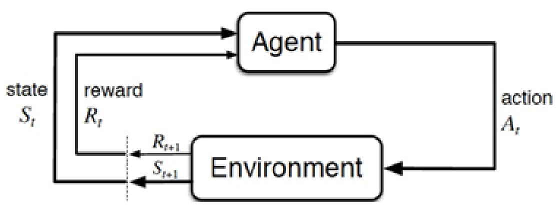

Figure 1: Schematic Diagram of RL Method

In the area of machine learning and AI, reinforcement learning algorithms have seen widespread usage in the development of control approaches that can attain a degree of control comparable to that of a person. There are several different reinforcement learning techniques that can be used to optimize the operation of fuel cell hybrid transportation vehicles.

1. Q-learning: This reinforcement learning method is simple and popular. It requires learning an action-value function that links state action pairings to predicted rewards. Next, the agent can maximise the action-value function. In the context of fuel cell hybrid vehicles, Q learning could be used to optimize the power split between the Fcell and battery or to optimize the charging and discharging of the battery[23].

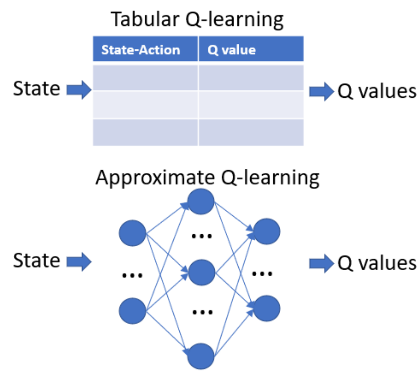

Figure 2: Q learning mechanism

2. **Deep reinforcement learning:** Deep neural networks approach the action-value function. Real-world control issues generally have high-dimensional state and action spaces making this technique valuable. Deep reinforcement learning has optimized wind farms and other renewable energy sources and might optimize fuel cell hybrid vehicles[24].
3. **Actor-critic methods:** Actor-critic methods involve learning both a policy (i.e. a mapping from states to actions) and an action-value function. The policy is optimized using the action-value function as a critic. Actor-critic methods can be more sample efficient than Q-learning and are often used in continuous control problems such as robotic manipulation. In the context of Fcell hybrid vehicles-trains actor-critic methods could be used to learn a policy for the power split between the Fcell and battery or for the charging and discharging of the battery[25].
4. **Model-dependent reinforcement learning:** Model-dependent reinforcement learning involves learning a model of the environment (e.g. a dynamical system model) in addition to learning a policy or action-value function. This can be useful when the environment is complex or uncertain. Model-dependent reinforcement learning has been used to optimize the operation of HVAC systems and other building automation systems, and could potentially be applied to fuel cell hybrid vehicles-trains as well [26].

These are only a few reinforcement learning methods that potentially optimize fuel cell hybrid vehicles-train functioning. The issue, environment, and control system will determine the method.

2.1 Rl Algorithms for various transportation vehicles:

I. Reinforcement learning for HEVs

RL based EMS for Hybrid Electric Vehicles (HEVs) involves the use of RL algorithms to optimize the EM of hybrid electric vehicles. RL agents learn optimal control policies based on the vehicle's operating conditions and driver behavior. The main advantages of RL-based EMS for HEVs include improved fuel economy, reduced emissions, and increased drivability. However, challenges include data quality and quantity, system complexity, safety and reliability, and explainability. Potential solutions include data preprocessing, hierarchical RL, safe RL, and explainable RL. Various RL algorithms have been compared in terms of their performance for HEV energy management with DDPG and PPO being popular choices[27-28].

II. Reinforcement learning for PHEVs

Reinforcement learning has been used in the development of EM systems for plug-in hybrid electric vehicles (PHEVs). The RL algorithm learns an optimal control policy that can dynamically allocate power between the engine, battery, and other components to achieve optimal performance while meeting various constraints such as battery SOC, engine efficiency, and emissions. The RL-based EMS for PHEVs has been shown to improve fuel efficiency and reduce emissions compared to traditional rule-based approaches. The RL algorithm takes into account various factors such as the vehicle's speed, the battery SOC, and the distance to the next charging station to make decisions on power allocation. RL-based EMS can also adapt to changes in driving patterns and environmental conditions to optimize performance in real-time. However, the use of RL in PHEVs EMS faces challenges such as data quality and quantity, system complexity, and safety and reliability concerns. To overcome these challenges, techniques such as data preprocessing, hierarchical RL, and safe RL can be employed. The quality of the data that the RL agent uses may be improved via the use of data preparation by cleaning and filtering any noisy input. Hierarchical RL has the ability to partition a problem into many more manageable subproblems, which makes for more effective learning. It is possible for safe RL to guarantee that the RL agent acts within safe bounds and steers clear of dangerous activities [29-31].

III. Reinforcement learning for HETVs

The use of RL algorithms to optimize the EM of hybrid electric track vehicles is at the center of the reinforcement learning-based EM system for hybrid electric tracked vehicles (HETVs). Taking into consideration the dynamics and the restrictions of the system, RL algorithms are able to learn the best control rules for the HETV system. The complexity of the HETV system, which includes various energy sources and different power flow channels, is one of the issues faced by RL-based EMS for high-efficiency all-terrain vehicles. Internal combustion engines and electric motors are two examples of these types of energy sources. In order to overcome this complexity, RL algorithms like as DDPG and PPO, which learn the best control policies at several levels of abstraction, may be used. Another obstacle is the scarcity of training data derived from the actual world for RL algorithms. Researchers have been making use of simulation environments to test RL algorithms and create training data in order to overcome this difficulty. It is possible that RL-based EMS for HETVs will increase fuel economy, lower emissions, and enhance the overall performance of the HETV system. In the future, research might concentrate on building more sophisticated RL algorithms and include more complicated dynamics and restrictions in RL models [32-33].

IV. Reinforcement learning based EMS for BEVs

The complexity of the system, the availability and quality of data, the safety and dependability of the system, the scalability of the method, and the possibility for creative solutions are some of the most important aspects of RL-based EMS for battery electric vehicles (BEVs). It is also important to consider the specific challenges and opportunities that arise in the context of BEVs, such as the need for efficient charging and energy management to optimize range and battery life. Technical factors to consider include the choice of RL algorithm, the design of the reward function, and the use of techniques such as hierarchical RL and safe RL to improve performance and ensure safety [34-36].

V. Reinforcement learning based EMS for FCELLVs

Reinforcement learning based EM Systems for Fuel Cell Vehicles (FCELLVs) have gained significant attention in recent years. FCELLVs have a unique characteristic where the efficiency of the Fcell stack and other components can be optimized for better energy management. RL-based EMS can take advantage of this feature and learn optimal control policies to enhance the vehicle's energy efficiency. One of the key factors for RL-based EMS in FCELLVs is the selection of appropriate state and action spaces. The state space should capture all relevant information related to the vehicle's energy consumption and the environment, such as battery state of charge, vehicle speed, and road gradient. Similarly, the action space should provide enough flexibility for the controller to adjust the power output of different components to meet the desired power demand while minimizing energy loss. Another critical aspect is the choice of the RL algorithm. Different algorithms, such as Q-learning, SARSA, and actor-critic, have been used for RL-based EMS in FCELLVs. The algorithm should be able to learn optimal control policies in a computationally efficient manner considering the complexity of the FCELLV model. Lastly, the performance evaluation of the RL-based EMS is crucial to ensure that it provides better energy efficiency than traditional rule-based controllers. Simulation and real-world testing can be used to evaluate the RL-based EMS's performance considering various driving scenarios and environmental conditions. Overall, RL-based EMS has the potential to significantly enhance FCELLV energy efficiency and reduce its environmental impact [37-38].

3. RL TECHNIQUES BASED EMS

Reinforcement Learning was used to create an intelligent EMS for a FCell/battery EV [37]. The scientists employed a novel European drive cycle to simulate propulsion load and found that the algorithm enhances battery lifespan and power delivery system efficiency. [40] created another FCELLV RL-based dynamic EMS. This method maintained battery SOC stability while reducing hydrogen consumption better than fuzzy logic-based methods. FCELLVs have RL-based long-term EMS [41]. This research extended the vehicle's two power sources. The simulation results were compared to rule-based techniques and showed that the suggested approach minimized Fcell and Li-ion battery attenuation and satisfied vehicle power demand. FCELLVs with three power sources—Fcell, battery and ultracapacitor use RL [42]. Hierarchical RL approximation global optimization was used to create an intelligent EMS [43]. Simulations showed that the suggested technique can self-learn to adapt to driving style changes. The suggested technique lowered hydrogen usage by 5.8% and Fcell start-stop times by 19.3%. As indicators of status, use the arrival time, the waiting time, the driving time, and the driving distance in [44] in order for deep reinforcement learning to design an ideal route and make pricing advice.

DRL has been used in various transportation applications, such as intelligent transportation systems, autonomous vehicles, traffic management, and energy management. In intelligent transportation systems, DRL has been applied for route planning, traffic signal control, and public transit scheduling. In autonomous vehicles, DRL has been used for decision-making, perception and control. In traffic management DRL has been applied for congestion control, incident detection, and emergency response. In energy management DRL has been used for fuel consumption optimization, battery management and powertrain control. In recent years, DRL has demonstrated impressive performance in beating games like Atari and Go and it has also been utilized in various applications such as robotics, lane-keeping assistance, automated braking, and driverless cars [45-46]. For instance, reference [45] presents a DRL-based EMS for a FCell hybrid electric cars. This EM strategy makes use of a DNN in order to approximate the most effective EMS strategy. The results indicate that the DRL based EM strategy performs noticeably better than the traditional rule-based technique in terms of both the amount of fuel efficiency and the amount of energy that is used. Similar to this [47] propose DRL-based EMS for many different kinds of Fcell-based hybrid electric cars. According to the findings of the simulations the DRL-based EMS that was developed achieves a higher level of performance than the rule-based approach and the other heuristic algorithms. DRL algorithms such as DQN and DDPG have been extensively employed to learn the appropriate EMS policy for a variety of driving situations and circumstances. In general, the study suggests that DRL-based EMS may improve the vehicle's efficiency in both its use of fuel and energy to a significant degree. Deep reinforcement learning often known as DRL is an advanced kind of reinforcement learning that makes use of deep neural networks in order to train a policy that maximizes a reward function. The use of DRL as a method for tackling difficult control issues and managing vast state spaces is becoming more common. Model-based and model-free DRL algorithms are the two distinct classifications that are possible to find. Model-based algorithms are those that need a model of the environment in order to function while model-free algorithms are those that directly learn from the state-action transitions. Deep Q-Networks (DQN), Double Deep Q-Networks (DDQN), Policy Gradient (PG), Actor-Critic (AC), and Deep Deterministic Policy Gradient (DDPG) are some of the prominent DRL algorithms that are employed in transportation research.

4. CHALLENGES, OPPORTUNITIES, AND POTENTIAL SOLUTIONS

I. Challenges

One of the main challenges in RL-based EM strategy for Fcell-based transportation vehicles is the complex dynamics of the fuel cell system. Fuel cells have highly nonlinear and time-varying behavior which makes it difficult to model accurately. This can lead to inaccurate or unstable control decisions made by the RL agent which can negatively impact the performance and safety of the system. Another challenge is the limited availability of data for training the RL agent. Fuel cell systems are relatively new and data on their performance and behavior is limited. Additionally, data from fuel cell systems may be noisy, incomplete, or biased which can affect the performance of the RL agent.

II. Opportunities

Using RL based EM strategy for fuel cell-powered transportation vehicles has the potential to boost system performance and efficiency in a variety of ways. One of the most promising prospects is the chance to improve the efficiency and reduce the operational expenses of the fuel cell system in real time. For instance, the RL agent may figure out how to adjust the fuel cell stack's power output such that it satisfies the vehicle's needs. This would save fuel consumption by preventing unnecessary energy loss. Another opportunity afforded by RL-based EMS is the ability of learning from experience and adapting to new conditions. Dynamic factors such as environmental conditions, load requirements, and other factors may all affect the efficiency of a Fcell system. The system's performance and reliability might be enhanced by RL-based EMS's capacity to learn from these changes and adjust the control strategy accordingly.

III. Potential Solutions

There are a diversity of approaches that may be taken to deal with the difficulties of RL-based EMS for fuel cell-based transportation vehicles and to take use of the possibilities that arise from their use.

Possible solutions include the use of more complex modelling and control techniques like MPCtrl and adaptive control. These methods may improve the RL agent's control precision and consistency by taking into consideration the complex and nonlinear dynamics of the fuel cell system. Data pretreatment methods including signal processing, data cleansing, and outlier identification are another option. By minimizing the effects of noise, missing data, and biases these methods may improve the quality of the data used to train the RL agent. Additionally, transfer learning strategies can be experimented with. To boost the RL agent's learning efficiency and performance, one might use transfer learning, which is moving information from one domain to another. The quantity of data needed to train the RL agent may be decreased by applying what was learned about one fuel cell system to another comparable system.

Table 1: Summary of challenges and solutions

Challenges	Potential Solutions
Complex and nonlinear dynamics of fuel cell system	Use of more complex modelling and control techniques like MPCtrl and adaptive control to improve control precision and consistency. Integration with physical models to improve the accuracy of predictions and control decisions.
Limited availability of data for training the RL agent	Data pretreatment methods including signal processing, data cleansing, and outlier identification to improve the quality of the data used to train the RL agent.
Noisy, incomplete, or biased data	Data pretreatment methods to minimize the effects of noise, missing data, and biases.
Difficulty adapting to new conditions	Use of transfer learning to improve the RL agent learning efficiency and performance by applying what was learned about one fuel cell system to another comparable system. Ensemble learning to improve overall performance by combining multiple RL agents; Human-in-the-loop to incorporate human input and address safety concerns.

5. CONCLUSION

The development of powertrains that are both environmentally friendly and efficient in terms of energy consumption is strongly reliant on the technology of electrified powertrains and energy management systems. fuel cell-based hybrid electric vehicles have the potential to significantly reduce environmental pollution caused by transportation. The quick and dynamic responses required by Fcell-based vehicles during acceleration and braking can be addressed by implementing a hybrid electric system that utilizes fuel cell stacks and batteries. The use of an EM strategy based on reinforcement learning can optimize the distribution of power between multiple energy sources in order to maximize battery longevity and reduce fuel consumption. The potential benefits of FCell technology for the transportation industry include reduced operational costs and improved performance. this review paper highlights the challenges, opportunities, and potential solutions for using reinforcement learning-based EM systems in fuel cell-based transportation vehicles. RL-based EMSs have a number of benefits over rule-based approaches, as well as D_Prog, ECMS, and MPCtrl in terms of the amount of computing time required, the complexity of the models, and the optimality of the results. Despite the complex dynamics and limited availability of data RL-based EMS offers significant potential for improving the performance and efficiency of fuel cell systems through real-time optimization and adaptive learning. Advanced modeling and control techniques, data preprocessing, and transfer learning are some of the potential solutions that can address the challenges and take advantage of the opportunities presented by RL-based EMS for fuel cell-based transportation vehicles. With further research and development RL-based EMS can play a significant role in reducing the environmental impact and improving the overall performance of transportation systems.

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