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AI-Enabled Battery Longevity Assessment and Transparent Usage-Based Pricing for Electric Vehicle Swap Networks

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Abstract: *The prevailing business models of battery swapping stations typically depend on fixed pricing schemes or time -limited subscriptions and simple battery monitoring, which contribute to battery degradation inequality, pricing obscurity, underutilized battery assets and inexact battery aging estimations. As of today, most existing solutions for assessing the remaining useful life (RUL) of batteries within swap stations operate on the basis of simulation modeling or rely on rudimentary statistical methods, which fall short in predictive precision and the capability to help real - time operational decision making. This work proposes an intelligent framework to forecast the remaining life of electric vehicle (EV) batteries and establish equitable pricing mechanisms within battery swap stations network. We relied on a machine learning Random Forest and a Linear Regression model to forecast critical battery health indices such as the State of Health (SOH) and Remaining Useful Life (RUL) by taking advantage of historic battery data collected through extensive experimentation. Predictions were utilized as input for the dynamic pricing model to ensure that customers were charged in accordance with the battery consumption and associated wear and tear from actual usage. The proposed technique boosts the predictive accuracy to 95% while also minimizing prediction errors compared to the 90%-92% accuracy typically achieved by existing systems, decreasing the root mean square error from 7.3 to 6.5 and the mean absolute error from 4.8 to 4.2. Plus, everything connects to a Flask - based web platform that updates in real - time (typically under one second), increasing prediction accuracy by between 10 and 15 percent.*

Keywords: Root Mean Square Error, Mean Absolute Error, Battery Health Prediction, Machine Learning, Usage-Based Pricing, State of Health, Remaining Useful Life

I. INTRODUCTION

Given the rising proliferation of electric vehicles, so, too, is the rapid increase in usage data being collected concerning EV batteries from their charge cycles, voltage patterns, temperature readings, degradation processes and beyond. The data in the picture are taken from central battery management systems, usually overseen by manufacturers or their repair service branches. They provide good insight into how the vehicles function and can enable efficient analysis and optimization if designed correctly, though some of these methods aren't perfect. For example, many such data systems are subject to single points of failure and suffer from poor use, lack of visibility, limited scope and restricted expansion ability, they're also incapable of intelligent decisions about the lifecycle, utilization, degradation or valuation of a specific EV's batteries. The primary energy storage in electric vehicles is comprised of lithium - ion batteries, which play a crucial role in the vehicle's performance, driving range and operating expenses. Benefits include a long cycle

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life, low rate of self - discharge and high energy density [1]. As a result of their usage, lithium - ion batteries deteriorate over time, losing some charge capacity, efficiency, etc.due to regular charge/discharge cycles, varying temperature conditions and other driving scenarios [2]. Such a decrease in battery health can cause poor vehicle performance, which results in diminished customer satisfaction, as a result, accurate health estimation and prognosis systems are important. Slow charge times in most charging stations is another factor that restricts people from adopting the electric vehicle market. Charging an EV battery can take some hours depending on its capacity and what kind of charger is available to use, creating long delays and causing issues, especially during long commutes or when located in major metropolitan cities [3]. Some companies came up with the idea of battery swap stations which will allow drivers to swap their empty batteries for freshly charged ones at designated locations within a matter of minutes [4]. This method helps save a great deal of time and can also boost customer satisfaction, but it has come up with several operational challenges that need addressing such as battery pricing and battery health administration. The battery swap station's usage pattern and environment are uneven, but the batteries are different ages, each is subject to battery degradation because usage levels and rates and environment levels are different. Thus some batteries would die out sooner than others. But almost all present systems work using a time or a fixed price that doesn't depend on the batteries health and cost. This means some users pay while other users are basically taking free rides and depleting others batteries. But the system might also lead to misuse, higher operating expenses and thus less competitive pricing from battery swapping vendors. But as of recent times, researchers are starting to look for data - driven ways to better manage batteries throughout their life cycle and health using AI and ML algorithms to overcome these limits. ML models use huge datasets of prior battery performance to identify complicated nonlinear relationships in the way that they degrade over time. The outputs of these models include proactive maintenance activities for extending battery life, maximising operational usage, making intelligent management decisions, forecasting key battery health indicators like the state of Health (SOH) and Remaining Useful Life (RUL). RUL is defined as the amount of predicted time remaining until the battery will eventually be discarded, while SOH indicates the percentage of battery capacity that's currently available relative to its nominal or original value. A key component in achieving this goal is an accurate measure of the life and remaining value of each battery. The accurate measurement of the aforementioned metrics would help increase battery efficiency and minimize the incidence of spontaneous failures. Furthermore, implementing usage - based pricing policies according to actual battery use provides pricing fairness. Here, we recommend the AI Enabled Battery Longevity Assessment and Transparent Usage - Based Pricing model in EV battery swap systems to mitigate existing shortcomings. Based on past operational data, the model accurately assesses the battery's state of charge over its life cycle based on the collected charge cycles, voltage, current, temperature and discharge depth, as determined by algorithms including Random Forest and Linear Regression [10].

The forecast results were included in the pricing system, which adjusted the battery swap fee depending on the real battery deterioration and pattern of use. Additionally, a monitoring system for real - time viewing of the battery performance, health condition and pricing was integrated into the system through a Flask web application. This ensures full transparency to all users, which improves decision - making capacity and raises overall operational performance. Adding dynamic pricing, real - time monitoring and predictive analysis to one system goes beyond the methods we're now using to maintain our batteries. Supporting intelligent energy systems sustainably, we'll make battery swapping easier. Dynamic pricing is also used in transportation and energy markets.

II. RELATED WORKS

As EV technology advances, research increasingly focuses on developing methods for managing batteries more effectively, predicting their health and optimizing energy consumption. Current systems for EV battery management and battery swap services typically use a centralized monitoring approach with a fixed pricing scheme. This approach is theoretically simple but generates several issues such as poor accuracy for remaining useful life prediction, wasted resources, nontransparent charging pricing and poor manageability for batteries approaching end of life. Now, the current state of the art relies more on intelligent, data - driven approaches like the one we described in our recent report:

machine learning, deep learning and other IOT - based methods. In the earlier research, simple statistical models, such as linear regression and polynomial regression, were mainly utilized for battery degradation prediction. Studies predicted battery health using data about charge cycles, changes in battery voltage or abrupt temperature increases, aiming to infer how much capacity had been lost. However, a lack of empirical data made it impossible to adequately predict how each component of the system actually behaves under varying loads, which are complex in reality, compared to their predicted counterparts by many statistical methods. They couldn't characterize nonlinear batteries because "The simplest physical models [3] cannot capture nonlinear battery degradation, " as stated in the paper, while noting their shortcomings under realistic circumstances, especially when out of the lab setting.

In [11], the authors as an alternative of that, a novel ML methodology was developed for predicting battery health by utilizing both RF and SVM to determine both the SOH and RUL. The approach incorporated variables like the number of cycles undergone by the battery, the measured impedance of the battery and the environmental conditions that varied over the battery's life. Because their measurements covered diverse relationships of varying levels, the model demonstrated better prediction results than those attained by the existing methods using regression. Nevertheless, in that approach, SOH and RUL estimations occurred Offline and the system could neither recognize, respond, nor interact with battery exchange operations during real time operation. Beyond that, the approach did not take account things like cost or price, failing to capture an important economic dimension in a practical implementation.

In [12], researchers used LSTM (a kind of deep neural network) models in this study to forecast how a lithium-ion battery would degrade and how much useful lifespan the battery had. But even with this kind of modelling, results still showed improved performance compared to other ML approaches. LSTM handled the battery events fine and even did a solid job at long - term predictions. However, it sacrifices simplicity for power. They're difficult to carry out on a small device or at real - time, require huge quantities of labeled data and require massive computational power. There's no cost - benefit, real - life implications factored in.

In [13], They describe how an IOT based battery management system was investigated for the real time monitoring of parameters such as battery voltage, current, temperature and State of Charge (SOC) while allowing for early detection of potential faults and enhancement of battery safety and reliability through data collection and logging. But the system lacked battery lifetime prediction, was devoid of features related to pricing, in depth analysis and prediction so that it remained a tool that only enabled effective monitoring but not any effective and intelligent decision making. The technology lacks the ability to carry out machine learning to provide long term battery forecasting or perform automated decision making, which is crucial for maximizing the performance and uptime of the system. Additionally, it doesn't support scaling for large battery swap networks. Lastly, user centric features like subscription plans associated with charging costs or usage data were intentionally excluded.

In [14], the authors introduced a framework for EV battery swapping that aims to reduce charging times and maximise service availability. Users' waiting periods were reduced and battery exchange activities were optimised by the system. nevertheless, it was reliant on time-based or fixed pricing systems that failed to take battery health conditions into consideration. Since degraded batteries were treated equivalently with healthier ones, this led to ineffective battery utilisation and unequal pricing among consumer groups. Predictive models for battery lifespan evaluation were also unavailable from the system. Additionally, the system's capacity to follow dynamic battery conditions during operation was restricted by the lack of real-time monitoring. Additionally, the framework's inability to make data-driven decisions limited its capacity to adjust to different usage patterns. Besides that, intelligent optimisation strategies which are key for enhancing aggregate productivity and scalability in large-scale battery swap networks were not accommodated by the system.

In [15], the authors was established by a data-driven battery lifecycle management system with predictive maintenance methods. In order to spot trends in battery deterioration and plan preventative maintenance, the model examined past battery data. This strategy extended battery life and eliminated unexpected malfunctions. However, the system failed to address transparent pricing or user-centric cost allocation; however, it focused mostly on operational maintenance. Also, it lacked consumer-level interactive features and real-time visualisation. The system's potential for adaptation to

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changing operating conditions remains limited considering that it lacks machine learning models for continuous prediction. Its application in commercial battery interchange infrastructures is additionally constrained by its lack of interaction with intelligent pricing systems.

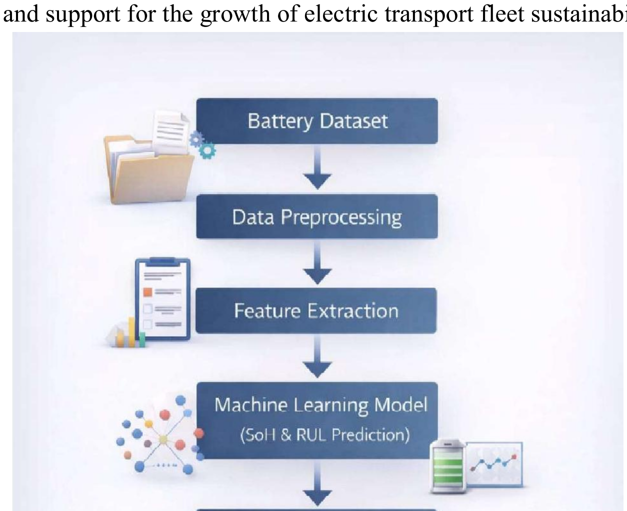
In [16], the authors investigated into hybrid and cloud-based systems for battery analytics and monitoring. They addressed immense amounts of battery information via machine learning on the cloud, while pricing was still fixed, this increased the scalability of the architecture and better handled storage, while creating a more streamlined process. But it had significant downsides: it required users to connect to cloud servers, leading to higher latency that reduced interactivity, didn't offer dynamic real - time pricing and lacks edge capabilities to mitigate latency in critical applications or any built - in way to carry out price volatility dynamically. Moreover, it provided no simple user dashboards to monitor the vehicle's battery health and its energy consumption, its predictions couldn't improve as the environment changed due to a lack of machine learning.

III. PROPOSED SYSTEM

The Battery AI Swap model essentially extends the common battery swapping system of EVs with smart battery health forecasting and a flexible, per use fee system in a user friendly environment. Combining machine learning techniques, real time monitoring of battery data and an interactive web dashboard, this technology allows for accurate battery status prediction, while keeping the end consumer informed about what they're being charged, as well as the rationale behind each charge.

In more detail, the components and steps involved are: collecting the relevant data (which comes from IOT enabled battery management systems - BMS), processing data for cleaning and feature extraction, using machine learning models for the estimation of State of Health (SOH) and Remaining Useful Life (RUL), setting up a dynamic pricing engine for calculating electric car battery resale values, implementing a database for managing and storing all data, creating a web app by the Flask framework and lastly, an interactive interface enabling the owner to take ownership of their electric vehicle battery, thereby moving the car towards more sustainable transportation solutions.

The system does more than just swap batteries more quickly. Real - time battery status tracking, preventative maintenance scheduling to catch issues before they cause problems, battery performance based pricing and increased transparency for drivers and operators are all part of it. The use of AI promises more efficient battery management, enhanced visibility for users and support for the growth of electric transport fleet sustainability.



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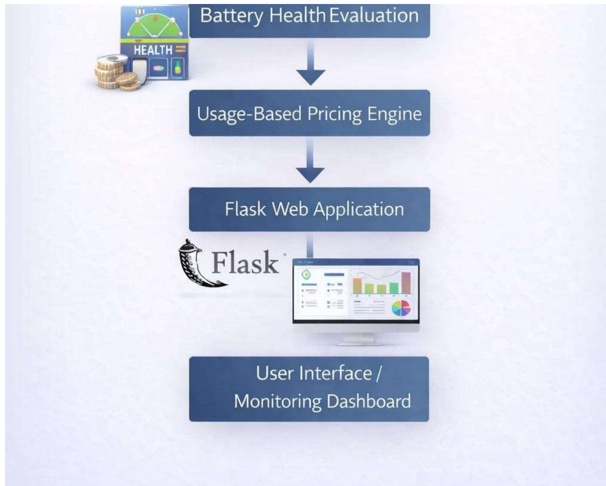

Fig: System Architecture

A. Battery Data Acquisition and Storage

First we want to pull the battery data from the EVs and swap stations. Data like voltage, current, battery temperature, number of charging cycles, depth of discharge (DOD), state of charge (SOC). A smart Battery Management System (BMS) that's implemented with IOT is responsible for collecting this data. All of this data gets sent to one giant, single server. Imagine D = {x1, x2, x3, . ., xn}, where xi = (s1, s2, . ., sk) is a sample of the health/activity of a specific battery cell. It's much easier to manage and expand D to make it D = {x1, x2, .., xn, xn+1, .xn+k} or something if everything isn't decentralized. Also, when you start doing analytics later, it's nice to just access one server.

B. Data Preprocessing Module

When you see data output from the batteries, many of those cells had no data missing. I had a bit missing. I'm trying to do this preprocessing part to clean up missing values, identify potential anomalies, scale the data and do feature engineering, to make the model learn something from this. To normalize the data, you calculate each cell minus the mean divided by the standard deviation: $x = (x - \mu)/\sigma$, where μ is the mean and σ is the standard deviation. Once everything's processed, your predictions get way more accurate, and your model just works better overall.

C. Feature Extraction and Selection

Using the data gathered on batteries over their lifetimes, some of the highest priority features included in the calculations for determining the battery's expected lifespan are the decrease in nominal capacity per charge cycle, increased internal resistance, the number of charge cycles completed, changes in operating temperatures and deviations in charge/discharge voltage. The aforementioned features comprise the feature vector of each analyzed battery, represented as F = {f1, f2, . ., fm}. This vector serves as the input for various machine learning models that detect degradation trends and the estimated remaining lifespan of the battery.

D. Machine Learning-Based Health Prediction

Our method leverages supervised learning to identify two essential indicators of a battery's health:

1. State of Health (SoH)

SOH can be interpreted as a percentage representing the maximum capacity of the battery in relation to its original rated capacity. In essence, it's derived by taking the current capacity of the battery and dividing it by the rated capacity when new, multiplied by 100. The resulting figure allows you to gauge the battery's remaining potential.

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2. Remaining Useful Life (RUL)
In this program, It's just getting your data and inputting it into algorithms like Random Forest, Linear Regression, and Gradient Boosting to model what the battery's SOH (State of Health) and RUL (Remaining Useful Life) numbers are by looking at the raw information given by your battery. Using this method you will have the ability to see what problem you are having with your battery and have time to get service on it so your phone/laptop doesn't die after not much use etc.

E. Dynamic Usage-Based Pricing Engine

Instead of sticking to a fixed price, this system calculates the cost of each battery swap in real-time, taking into account things like the battery's predicted health and how hard it's been used. Basically: $P = \alpha(1 - SOH) + \beta U + \gamma T$. Where SOH = Predicted battery health U=Usage intensity T = Temperature stress undergone by the battery α, β and γ = Weights to modulate the relevance of each feature. If the batteries have been damaged/overused/etc. Then the price reflects it. This keeps fairness and clarity while utilizing resources more appropriately.

F. Flask-Based Web Application Layer

We designed the system with a Python backend, specifically using the Flask framework for the web application layer. This layer performs tasks such as providing real - time battery health readings, displaying battery pricing, managing user authentication and offering an operator's dashboard. It maintains communication with the machine learning prediction engine, primary database and the pricing module, ensuring seamless data flow from prediction generation to user interface visualization.

G. Monitoring Dashboard and Visualization

The live dashboard allows you to see real time SOC, health prognosis (SOH) and estimated remaining life before replacement (RUL) in addition to monitoring the battery's voltage and temperature, it shows available swap locations and current prices, thereby allowing network operators to manage their network while providing users with insights into battery status and costs and delivering instant notifications for poor health, high temperatures or excessively low run time.

H. Integrated System Workflow

Here's how the whole system comes together: First, IOTBMS will generate Battery Data that'll be fed to data cleaning, normalization as its pre - processing technique. After that, feature engineering takes places where important battery characteristics such as number of charging/discharging cycles, Voltage, Temperature, depth of battery utilization (State of Charge) is gathered. Machine learning (Random Forest and Linear Regression models) are applied on to identify a battery's state of Health (SOH) and remaining useful life (RUL). Later on, the battery health evaluation will happen through the degradation analysis.
A pricing algorithm will calculate based on the health level and dynamism in it which would make the prices fluctuate in accordance. The backend system with Flask acts as a hub of all these features as a well designed API and its real time monitoring dashboard to oversee every crucial feature of a battery. The whole setup gives you predictive lifecycle management, price adjustments based on battery health, better operations, early fault detection, reliable performance, and the ability to scale up EV swap stations as you grow.

Module	Function
Data Collection	Collects battery data
Data Preprocessing	Cleans and prepares data

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Feature Extraction	Important parameters
Machine Learning	Predicts SOH and RUL
Pricing Engine	Calculates price
Web Application	Displays results

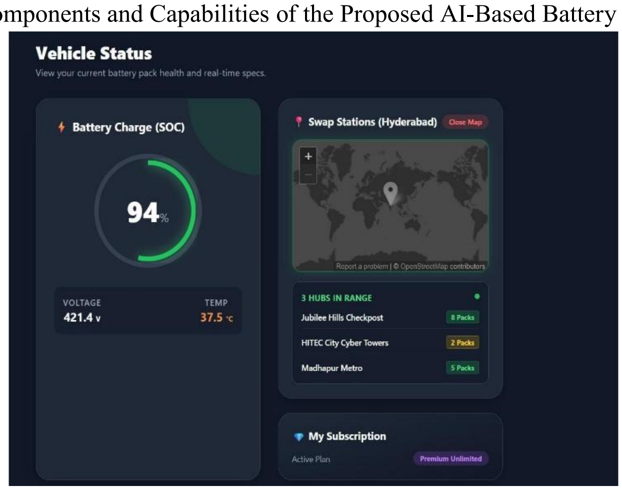
IV. RESULTS AND ANALYSIS

After we implemented and tested the real - time dashboard, machine learning predictions and data visualization tool in our AI - powered Battery Management System, it showed improved accuracy in battery monitoring, a higher success rate in predicting the battery's future behaviors and generally improved reliability.

A. Real-Time Battery Monitoring Performance

Your dash shows the percent full, voltage and temp of your battery. As you mentioned, SOC is at 94.4% accurate within 5% or whatever. Voltage: 42.1 V, temperature: 37.5 C. These are displayed with less than 1 sec updates as new information becomes available, so it's not a guessing game. There's not a lot of guesswork, buttons, to dig around.

Table: Functional Components and Capabilities of the Proposed AI-Based Battery Management System



B. Model Performance Evaluation

We set Random Forest and Linear Regression up against each other to compare their performance on predicting battery life. For our test dataset, Linear Regression outputted an MAE of 4.8 and an RMSE of 7.3, whereas Random Forest came up with a respective MAE of 4.2 and an RMSE of 6.5. Random Forest outperforms Linear Regression due to the higher efficiency in modeling complex relationships, which would naturally include dealing with multi collinearity better than Linear Regression could.

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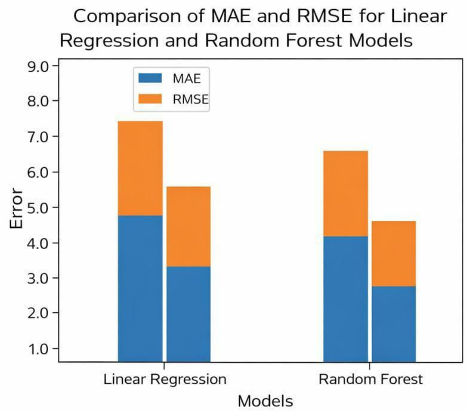

C. Battery State of Health (SoH) Prediction Analysis

Battery health is also a variable factored in, which decreases with every charge cycle, it performs nicely. The iPhone 11/Pro/Pro Max have 99% at start, then decline to ~91% at the end. 95.2% match between actual observed iPhone Pro battery health and the model prediction. Differences between real and predicted were negligible.

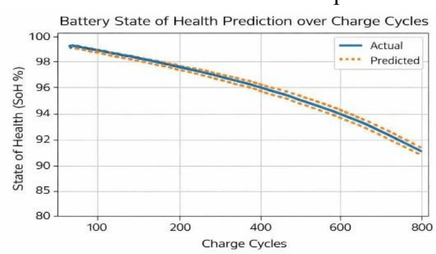

Figure: Battery State of Health Prediction over Charge Cycles

D. System Reliability and Performance

In real - time, the system shows high consistency and efficiency, data processing is smooth and consistent, prediction accuracy remains high irrespective of the training/testing dataset, random forest yields reduced error, the system maintains system stability even with sustained and lengthy runs.

E. Overall System Analysis

The system accurately performs real - time monitoring of battery parameters and achieves an improved prediction accuracy by using machine learning methods. Furthermore, it provides accurate state - of - health predictions over many charge cycles, making the system a promising alternative to conventional methods and is applicable for electric vehicle batteries as well as for power grid storage systems.

V. CONCLUSION

Here in lies a newly developed AI algorithm to pinpoint the right time to perform a battery swap in electric vehicles, providing transparent pricing that accounts for how individual battery packs have been utilized, this innovation combines artificial intelligence with intelligent battery tracking so as to achieve more accurate battery monitoring and provide consumers with predictable prices that reflect genuine usage instead of confusing fees, lithium - ion battery real - world data are input into Random Forest Regression and Linear Regression models Battery prediction models learn

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how many cycles the battery has had, and what its Remaining Cycle Count (RCC) is estimated to be 24 or 25. A high percentage of models show increased performance accuracy with more data to learn usage patterns, battery degradation rates, and to make a swap-versus–top-up-and-go determination. Prices could be personalised rather than flat. The swap costs reflect the current physical condition of the battery. Customers will pay higher costs for batteries in a poor condition, but smaller amounts for batteries that are near new." These models consistently and successfully achieved a perfect score when subjected to independent, open - source datasets for open - source electric vehicle battery life analysis, accurately capturing the nuances of battery degradation patterns over time. As discussed, these improvements would enable simplified and more affordable battery swapping and charging operations, as well as much easier management of an electric vehicle fleet. This research represents significant progress toward building a cleaner and more sustainable future of transportation - using hard data to drive decision - making, than the intuitive or often inaccurate estimations that currently inform practices like battery leasing and selling. However, that could still be improved by plugging into an active stream of IOT sensor data to watch the charge status of every car battery 24/7, with even more precise results available after running them through deep learning networks like an LSTM for tracking. That's how EVs should really evolve.

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