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Hybrid Digital Twin based Model Predictive Control for Optimal charging of Lithium-Ion Battery to Enhance SOH

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Abstract- Sophisticated control schemes play a crucial role in enhancing the State-of-Health (SOH) of Lithium-ion (Li-ion) batteries by generating an optimal charging profile with operating constraints such as charging time and battery lifespan. However, the development of model-based control strategies with constraints for highly critical systems like battery is challenging due to its complex behavior. In this paper, a hybrid digital twin-based Model Predictive Control (MPC) is proposed to generate an optimal charging profile for a 3.6V, 18Ah $LiFePO_4$ battery. The hybrid digital twin is developed by combining physics-based Electro-Thermal Model (ETM) and linear regression model. The optimal control problem is formulated by imposing constraints on input current and batteries internal states and MPC is designed. The demonstrated simulation results show the performance of the proposed control scheme by satisfying the objective function of minimizing charging time and battery temperature to enhance SOH of battery.

Keyword:- SOH, Hybrid digital twin, MPC, Electro-thermal model, Constraints

I. INTRODUCTION

Recent years the electric vehicle industry is rapidly evolving with customer confidence and uptake predictions with government subsidies and incentives. Global automakers are making huge investments in battery facilities due to the high demand of Electric vehicles (EVs). Due to the high energy, power density, long life cycle and low rate of self-discharge Lithium ion (Li-ion) batteries have become one of the most opted battery technologies in EVs [1,2]. However, the productive utilization of Li-ion batteries in EVs is looking for efficient charging strategies [3,4].

Battery modelling is pivotal in estimating state-of-charge, driving range estimation, designing safe and optimal charging strategies, etc. Much work has already been reported with various modelling approaches such as electrical equivalent circuit models, mathematical models, electrochemical models etc. These individual models are simple, fast for dynamic estimations but limited to only the electrical/ chemical/ thermal characteristics. Few recent works have been reported in integrated electro-thermal model (I-ETM), electro- chemical models (ECM) etc. An empirical model [5] was also proposed to represent the effect of state –of-health (SOH), state-of-charge (SOC), and temperature on the equivalent circuit model (ECM) parameters. Model Predictive Control (MPC) utilizes the model to predict the system behavior and will generate an optimal trajectory to minimize the cost function proposed to generate the charging strategy.

To address the challenge in modelling the battery [6], a hybrid model is proposed by integrating physics based coupled electro-thermal model (ETM) [7] with the dataset collected by conducting the real-time experiment on Li-Ion battery. This model has been used as the digital-twin of a real Li-ion battery after validation.

Major limitations of traditional charging methods and various optimized strategies for enhancing battery performance have been reviewed [8]. Further, hybrid digital twin based MPC has not been reported in the literature for optimal charging. The main objective of this work to generate optimal charging profile based on MPC control by minimizing charging time and battery temperature to enhance SOH of battery.

The main contribution of this paper includes

i) Collection of Real time battery parameters namely voltage, current and temperature from LiFePO4 by conducting experiments.
ii) Development of hybrid digital twin by identifying the parameters of Electro thermal model from Real-time experimental data.
iii) Design of multi-objective model predictive controller (MPC) for optimal charging.

The rest of the paper is organized as follows: - Section 2 presents methodology for optimal charging. Results are discussed in Section 3 and conclusion is given in Section 4.

II. PROPOSED METHODOLOGY FOR OPTIMAL CHARGING

Fig.1 shows the schematic diagram of the proposed methodology. It is composed of three components i) Real-time data collection from Li-ion battery, ii) Hybrid digital twin of Li-ion battery and iii) Multi-objective MPC.

A. REAL-TIME DATA COLLECTION

The data are obtained from real-time LiFePO4 with following specification: -

1. Cell Voltage : 2.5-3.65 V
2. Battery Type : Li-ion battery (LiFePO4)
3. Battery Energy : 57.6Wh
4. Battery Capacity : 18 Ah

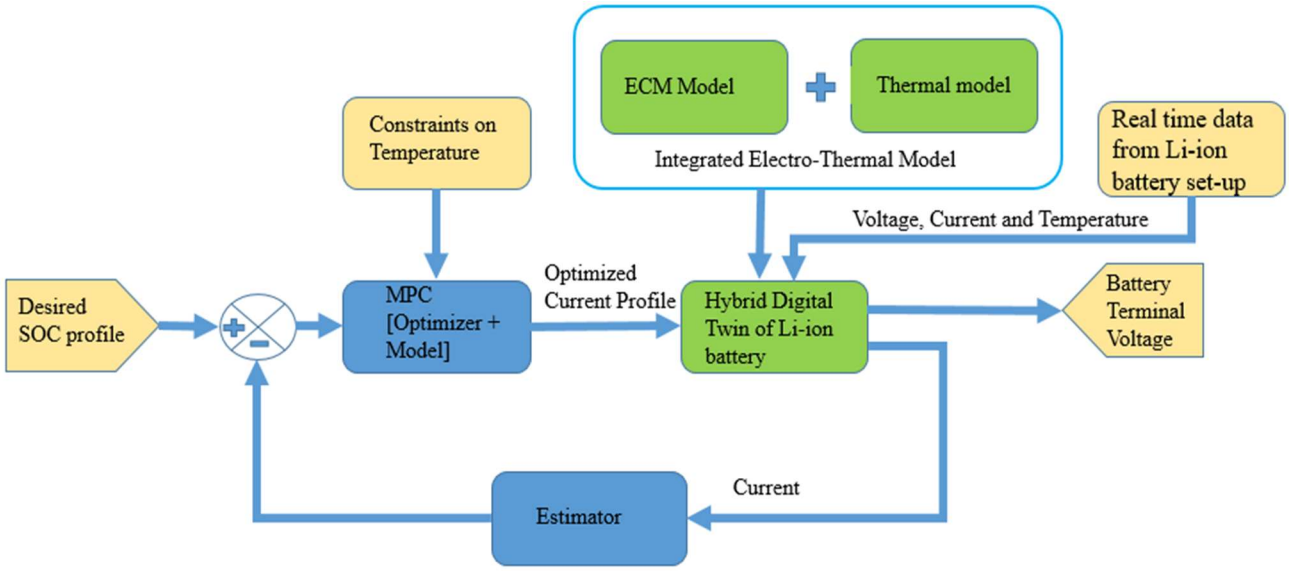


Fig 1. Block diagram of the proposed methodology

HYBRID DIGITAL TWIN

ECM Model

Thevenin ECM [9] depicted in Fig. 2 is modelled to capture the electrical behaviours of the battery. The ECM model consists of an internal resistance and a parallel resistance capacitance (RC) combination. Kirchoff's voltage and current laws are used to derive the governing equations.

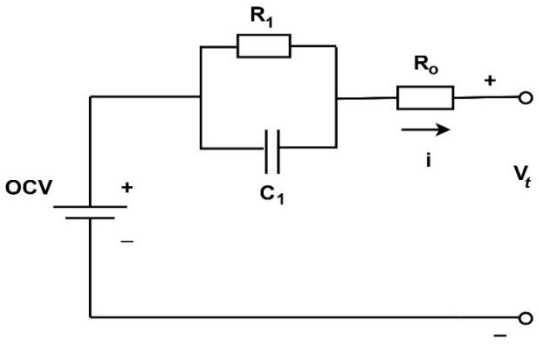


Fig. 2. RC network -Equivalent circuit model of battery

Voltage Calculation

Series voltage can be calculated by Eq. (1)

$$V_s = IR_0 \quad (1)$$

where Ro is the internal impedance of the cell. By using the s-domain the parallel network voltage can be given by Eq (2-3):

$$V_1 = \left(\frac{1}{s}\right)\left(\frac{I}{C_1} - \frac{V}{R_1 C_1}\right) \quad (2)$$

$$V_t = OCV - V_1 - V_s \quad (3)$$

where the parallel RC network (R_1 and C_1) is used to represent the transient behavior of the battery. V_t represents the battery terminal voltage, I is the battery current, OCV is the open circuit voltage of the battery which are functions of temperature and SOC.

SOC Calculation

The SOC can be estimated by the means of the coulomb counting method. The equation is given in Eq.4

$$SOC = SOC_0 - \int \frac{I \times 100}{\alpha^U \times 3600} dt \quad (4)$$

Here the SOC_0 represents the initial $\boldsymbol{SOC}$, $\boldsymbol{\alpha^U}$ is usable capacity [3] and currently represented by I.

OCV from SOC

OCV is obtained as a function of SOC with the help of a curve fitting tool using the experimental table data [1] and is shown in Fig. 3.

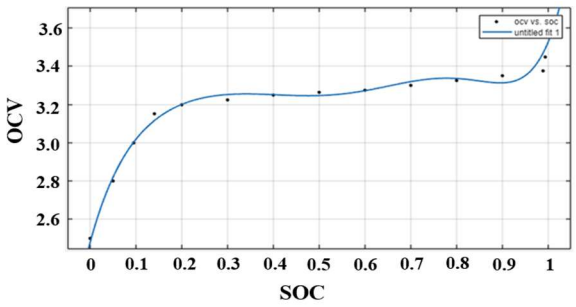


Fig. 3. Li-ion Battery- SOC and OCV characteristics

ECM Model Parameterization

The Hybrid Pulse Power Characterization (HPPC) test is a battery performance test method proposed by the

Freedom battery test manual for power assist hybrid electric vehicles. Through the experiments effective identification of model parameters can be performed. The ECM parameters [10] are estimated using this at different SOC values and temperatures.

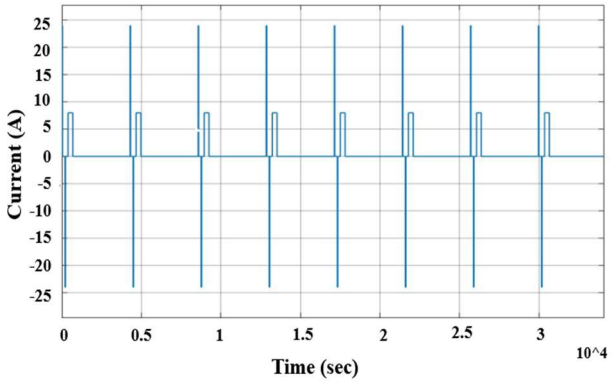


Fig. 4. Li-ion Battery: HPPC current profile

Fig. 4 represents the HPPC current profile when the battery is subjected to a peak charging pulse for 10 seconds, peak discharge for another 10 seconds, actual discharge pulse for T seconds and then a rest period of 3600 seconds.

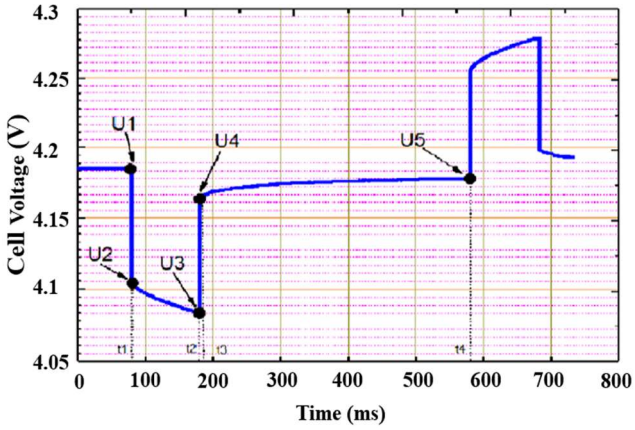


Fig 5. Li-ion Battery- HPPC Test: Voltage profile

The voltage profile obtained for a single cycle of HPPC current profile is depicted in Fig 5. From the points in the above profile the ECM model parameters [10] can be calculated by the following Eqs (5-8),

$$R_o = \frac{(U_1 - U_2) + (U_4 - U_3)}{2I} \tag{5}$$

$$\tau = \frac{t_3 - t_4}{\ln\left(\frac{U_1 - U_5}{U_1 - U_4}\right)} \tag{6}$$

$$R_p = \frac{U_1 - U_3 - R_0 I}{I\left(1 - e^{-\frac{t_2 - t_1}{\tau}}\right)} \tag{7}$$

$$C_p = \frac{\tau}{R_p} \tag{8}$$

where U_n is the voltage at point n at time t_n, I represent the current magnitude.

Thermal Model

Heat Q is generated as the byproduct of the chemical reactions inside the battery. The thermal model uses the heat generated by the ECM model to calculate the cell core (T_c) and surface temperature (T_s) and is represented by Eq (9)

$$Q = I(V_{OCV} - V_T) \tag{9}$$

where Q is the heat generated, V_{ocv} and V_t represent the open circuit voltage and terminal voltage respectively. To model the heat exchange between surface and core of the battery, a heat conduction resistance R_c is used. The convection resistance R_u is to model the convective cooling whose value depends on coolant flow rate, type and pack geometry. T_f represent ambient temperature.

The Eqs (10-12) can be developed based on energy conservation principles.

$$C_c \frac{dT_c}{dt} = Q + \frac{T_s - T_c}{R_c} \tag{10}$$

$$C_s \frac{dT_s}{dt} = \frac{T_f - T_s}{R_u} - \frac{T_s - T_c}{R_c} \tag{11}$$

$$T_m = \frac{T_s + T_c}{2} \tag{12}$$

Here, T_m represents the average temperature, C_c and C_s means core capacity and surface capacity respectively.

Thermal Model Parameterization

A parametric model represented with Eqs. (13-21) reported by [10] is taken for linear regression, where Z is the observation is the regressor which contains measured signals.

Observation:

$$Z = s^2 T_s(s) \tag{13}$$

Regression:

$$\phi = \left[Q(s),\ T_f(s) - T_s(s),\ sT_s(s)\right]^T \tag{14}$$

Parameters:

$$\theta = [\alpha,\ \beta,\ \gamma]^T \quad (15)$$

And the lumped physical parameters [Lin et al (2014)] are

$$\alpha = \frac{1}{C_c C_s R_c} \quad (16)$$

$$\beta = \frac{1}{C_c C_s R_c R_u} \quad (17)$$

$$\gamma = -\frac{C_c R_u + C_s R_u + C_c R_c}{C_c C_s R_c R_u} \quad (18)$$

The Recursive least square (RLS) algorithm is used to identify the parameters [5]. After the identification of the lumped parameter, one parameter which is C_s is assumed and the other three parameters are obtained using the following relation.

$$\widehat{R_u} = \frac{\hat{\alpha}}{\hat{\beta}} \quad (19)$$

$$\widehat{C_c} = -\frac{\hat{\gamma} C_s \widehat{R_u} + \hat{\alpha} C_s{}^2 \widehat{R_u} + 1}{\hat{\alpha} \widehat{R_u} C_s} \quad (20)$$

$$\widehat{R_c} = \frac{1}{\hat{\alpha} C_s \widehat{C_c}} \quad (21)$$

TABLE I. Thermal Model Parameters

C_c (JK^{-1})	C_s (JK^{-1})	R_c (KW^{-1})	R_u (KW^{-1})
62.7	4.5	1.94	3.19

The pre-calculated thermal model parameters are specified in Table I.

Hybrid digital twin

The parameters of the electrical model which is the internal resistance R_0, the parallel resistance and capacitance R_1 and C_1 are all dependent on the SOH [2, 11], SOC, and temperature of the battery. Hence an empirical model [5] is used to represent the relation between them. It is found that within the operating range the relationship is found to be linear and monotonic functions. Hence a first order model was used to find the coefficients of the empirical model using linear fitting. The equation for the empirical model is given in Eq.22,

$$X = b_o + b_1 SOH + b_2 T + b_3 SOC \quad (22)$$

Here X represents any of the parameters of the ECM model. The look up tables given [5] are used to linearly fit the model using the built-in function in MATLAB.

The coefficients for each parameter are identified accordingly and given in Table II. Similarly, the values of the parameters can be estimated at any SOH, SOC, and temperature.

TABLE II. PARAMETERS AFTER FITTING

X	b_0	b_1	b_2	b_3
R_0	10432.8	-4838.27	-114.66	-1.32
R_1	13615.4	-6808.80	-87.53	-37.10
C_1	-11116.6	18045.76	237.42	40.14

III. MULTI-OBJECTIVE MPC

A) MULTI-OBJECTIVE MPC DESIGN

MPC is an optimization technique in which the calculated control actions minimize a cost function for a constrained dynamical system over a finite, receding horizon. With the electro thermal model developed above a charging control [12] strategy is formulated. To optimize battery charging performance, it is important to consider the trade-off between charging time and temperature rise. The battery charging time (Bct) and temperature rise (Btr) are defined in Eq.23-24:

$$\min J_{Bct}(K_{ct}, I) = ts * \left(K_{ct} + \frac{1-(SoC(K_{ct}))}{I}\right) \quad (23)$$

$$\min J_{Btr}(T_s, T_c) = ts * \sum_{i=0}^{K_{ct}} (T_s(i) + T_c(i)) \quad (24)$$

Here, K_{ct} ,$SoC(K_{ct})$, T_s and T_c are evaluated at the time the battery is charged from its initial state to the desired state. K_{ct} is the charging time, $SoC(K_{ct})$, represents the SOC at time K_{ct}, I is the charging current, T_s is the surface temperature, and T_c is the core temperature, with a sampling period of 1 second. The overall fitness function is calculated using a weighted sum approach represented by Eq.25

$$J_{char} = W_{Bct} * J_{Bct} + W_{Btr} * J_{Btr} \quad (25)$$

Where W_{Bct} and W_{Btr} are the weighting factors for charging time and temperature rise, respectively, and $W_{Bct} + W_{Btr} = 1$.–The MPC aims to reduce the error between reference and prediction by means of penalizing the current. The model is imported and linearized before tuning. Here for state estimation, the in-built Kalman filter [13] in the MPC toolbox in MATLAB is used.

a) Constraints and Tuning

Keeping the battery at a moderate temperature range will help to maintain its capacity and prolong its life. Another way to prolong battery life is to avoid deep discharging and overcharging. Deep discharging, which occurs when the battery is drained to a very low level, can cause irreversible damage to the battery. Similarly, overcharging the battery can also cause damage and reduce its capacity. Hence constraints are imposed to keep the operation at physically allowable limits and to maintain the battery life.

$$SoC_{min} = 0 \quad SoC_{max} = 100$$

$$I_{min} = -54\,A \quad I_{max} = +54\,A$$

The constraints imposed on the current also keep the temperature within limits. The maximum temperature of the battery model lies below 45° C generally except the initial peak. The bounds and range can be changed according to the application and environment. A longer prediction horizon means a larger domain of attraction around the desired point however increases the computational efforts. Optimal tuning parameters used are shown in Table III.

TABLE III. MPC TUNING PARAMETERS

Sample time (sec)	1
Prediction Horizon	30
Control Horizon	15

The weights for the input and output are also varied and selected such that the controller output is close to the reference given.

IV. RESULTS AND DISCUSSION

A). REAL TIME VALIDATION OF LI-ION BATTERY

The model developed is tested with HPPC current profile with peak charge, discharge pulse and actual charge pulse. Fig. 6 shows the comparison of results obtained from experiment and simulation.

B). REFERENCE SELECTION

Table 4 shows the data obtained by simulating the model using the specified C rate of pulse width 7500/4280 % of period. It is observed that in 3C1C charging i.e charging the battery for initial 50% at 3C rate with current pulses of amplitude 54A and then charging the remaining 50% at 1C rate with current pulses of amplified 18A, provides a smaller time for battery charging and keeping the temperature of the battery within limits. Hence SOC rise with 3C1C is taken as the reference to MPC.

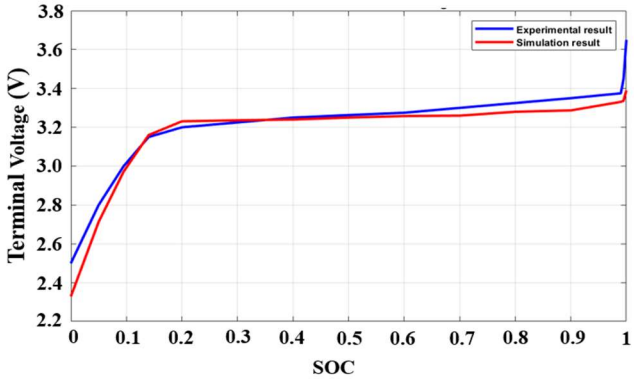


Fig. 6. Li-ion Battery SOC and Terminal Voltage: Real-Time validation

TABLE V. OPEN LOOP CHARGING ANALYSIS

Type of charge	Time to reach 100% SOC (sec)	Temperature peak range (deg C)
1C	2x10^5	35.7 to 36.3
2C	0.9x10^5	37.7 to 39.5
3C	0.6x10^5	40.3 to 44.2
3C1C	1.3x10^5	35.7 to 44.2

C). MPC CONTROLLER PERFORMANCE

MPC controller estimates and compares the SOC future reference and the plant model output as shown in Fig.7 and manipulates the current accordingly.

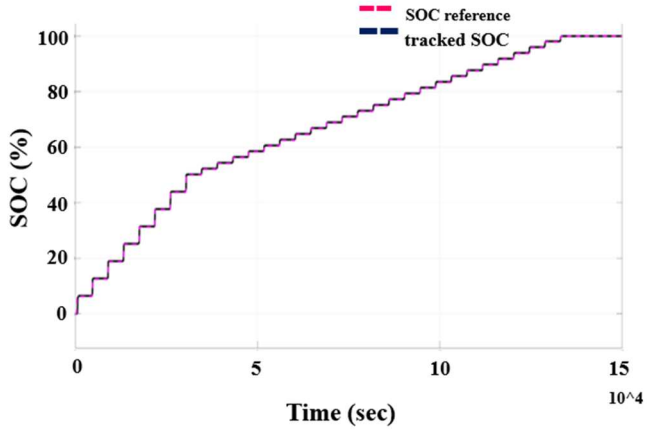


Fig. 7. SOC Tracking performance of proposed MPC with hybrid digital twin

Fig.7 shows the tracked SOC when the reference SOC (represented by the dashed line) by the MPC controller and the optimal charging current generated by the proposed MPC is shown in Fig.8. It is observed that the charging current is 3 C for less than one-third of the total charging time only and remaining two-third time, it is 1C only.

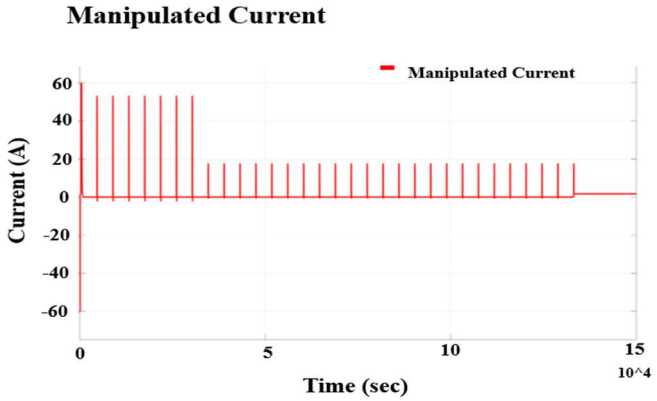


Fig. 8. Charing current profile from proposed MPC based optimal charging algorithm

It is important to note that the current manipulated is within the constraints specified which is -54A to +54 A.

The temperature output varies between 35℃ and 45 ℃ as shown in Fig. 9. This helps in maintaining the health of the battery and prevents the battery from overheating and temperature damage. Thus, model predictive control helps in optimally charging the battery and safeguarding the health of the battery.

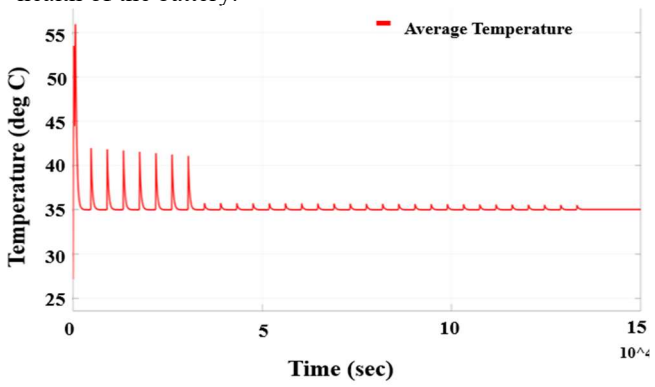


Fig. 9. Average Temperature variation with proposed MPC based optimal charging algorithm

V. CONCLUSIONS

In this paper, a novel hybrid digital twin-based MPC is proposed for optimal charging by formulating multi-objective constraints on the input current and internal battery states to optimize the charging profile for a 3.6V, 18Ah LiFePO4 battery. Simulation results demonstrate the effectiveness of the proposed control strategy in achieving the objective of minimizing both charging time and battery temperature, thereby improving the SOH of the battery.

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