State of charge and state of health estimation strategies for lithium-ion batteries

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Abstract

Due to the widespread use of renewable energy sources, lithium-ion batteries have developed rapidly because renewable energy sources, such as photovoltaics and wind, which are very much affected by the environment and their power output can be better leveled if lithium-ion batteries are used. Battery state of charge (SOC) characterizes the remaining battery power, while battery state of health (SOH) characterizes the battery life state, and they are key parameters to characterize the state of lithium-ion batteries. In terms of battery SOC estimation, this paper optimizes the extended Kalman filtering (EKF) algorithm weights to adjust the weights during high current bursts to obtain better SOC tracking performance and optimizes the back propagation (BP) neural network for SOH estimation to obtain better weights to further obtain more accurate battery SOH. The feasibility of the optimized algorithm is validated by the experimental platform.

Keywords: SOH estimation; SOC estimation; lithium-ion battery

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1 INTRODUCTION

The widespread use of renewable energy has eased human anxiety about energy, but factors, such as photovoltaics, are greatly influenced by time, light intensity and environment, while wind is greatly influenced by wind intensity and environment [1]. Energy storage for renewable energy is currently considered to be a better solution because it can make the photovoltaic or wind power output smooth [2].

Lithium-ion batteries are commonly used because of the characteristics of high specific energy, no memory effect, environmental protection, etc. [3–5]. Battery state of charge (SOC) indicates how much power is left in the battery, while battery state of health (SOH) indicates the battery aging condition, meanwhile, battery SOH is also used to correct the battery SOC to obtain a better SOC estimate, whether it is SOC or SOH, they play a vital role in the safe and reliable operation of lithium-ion battery pack [6].

For lithium-ion battery SOC estimation, the prevailing method is the Ah integration method+ open circuit voltage (OCV)calibration [7], because the Ah integration method is simple to use, although it has the defect of error accumulation, but it can be calibrated by OCV, although the OCV calibration conditions are more severe, requiring the battery to stand for several hours [8]. Meanwhile, the Kalman filter (KF) algorithm is intensively studied because it can obtain higher estimation accuracy [9]. For nonlinear systems, extended KF (EKF), unscented KF (UKF) and adaptive KF (AEKF) are also proposed and intensively studied [10]; however, in fact, the EKF algorithm transforms a nonlinear system into a linear system by Taylor series expansion and then analyzes it, in practice, the EKF algorithm is highly accurate, simple and easy to implement and unlike the Ah integration method, it can gradually converge to near the true value, which makes the system very reliable. Although on this basis there are UKF, AEKF is proposed as well as used, they are better than EKF in terms of accuracy, but accuracy improvement not much, and add a large number of calculations. Therefore, it is very wise to use the EKF to estimate the battery SOC [11], however, little has been reported on the optimization of the EKF, as most of the effort lies in higher performance algorithms, such as UKF and AEKF.

For lithium-ion battery SOH estimation, the simpler method is to use cell resistance or electrochemical impedance spectroscopy

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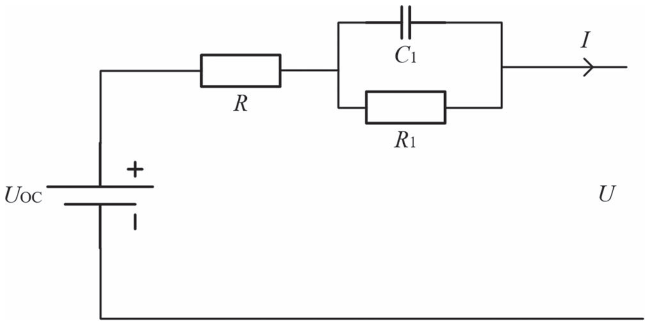

Figure 1. *Thevenin model.*

for analysis [12], these methods are simple but not easy to implement because it requires very specialized equipment and, it cannot be applied online, the use of cell differential capacity or differential voltage to estimate the SOH is very novel, building a cell model to estimate the SOH is also more commonly used, but it is very complex [13, 14]. as a simple and effective method to solve the nonlinear problem, the back propagation (BP) neural network is commonly used to estimate the SOH of lithium-ion batteries online [15]. Lin *et al* [16] used a three-layer BP neural network to estimate the SOH; however, the method used in the BP neural network tends to make the weights fall into local optimum. In the method proposed by Zhang *et al* [17], its error may increase with the number of iterations. In Wen *et al* [18], an adaptive variable–parameter improvement algorithm is used to adjust the weight coefficients in the direction of error reduction, but when the change is below the threshold of the adjustment coefficient, the weights still fall into a local optimum, resulting in a lower learning rate.

This paper will optimize the battery SOC and battery SOH estimation, optimize EKF for SOC estimation and optimize BP neural network for SOH estimation to obtain better performance, this paper is organized as follows, the second part introduces the process of optimizing EKF algorithm, the third part introduces the process of optimizing BP neural network algorithm, the fourth part is battery SOC estimation, SOH estimation and SOC estimation test combined with SOH estimation and finally the conclusion is given.

2 OPTIMIZED EKF FOR SOC ESTIMATION

2.1 EKF algorithm

In this paper, the Thevenin model is used to analyses the sudden and gradual changes in the charging and discharging process of a lithium-ion battery, although more accurate models have been proposed and applied; however, many reports have demonstrated that the Thevenin model can better balance performance and computational effort [19, 20], the equivalent circuit schematic as shown in Figure 1.

As shown in Figure 1, U is the battery voltage, R is the internal resistance of the battery and it describes the sudden change in resistance during charge and discharge of the lithium-ion battery, R_1 and C1 are the polarization resistance and polarization capacitance, they simulate the gradual change in capacitance of the battery. U_{OC} is the OCV of the battery, I is the battery current. The parameters in the battery equivalent circuit model can be identified by hybrid pulse power characteristic (HPPC) on the battery.

The EKF shows that a state and an observed quantity are needed in the filtering process, and the SOC cannot be measured directly, so U_p is chosen as the state variable, as shown in Equation (1), where U_p is the voltage across the polarization resistance and polarization capacitance, U_{OC} is chosen as the observed quantity and the observation equation is shown in Equation (2).

$$\begin{bmatrix} Up,k \\ SOCk \end{bmatrix} = \begin{bmatrix} 1-\frac{T}{C1R1} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} Up,k-1 \\ SOCk-1 \end{bmatrix} + \begin{bmatrix} \frac{T}{Cp} \\ \frac{\eta T}{Q} \end{bmatrix} [Ik-1] + \begin{bmatrix} \omega 1 \\ \omega 2 \end{bmatrix} \tag{1}$$

$$[UOC] = [1 \;\; 0] \begin{bmatrix} Up,k \\ SOCk \end{bmatrix} + [R]\,[Ik] + [U] + [\upsilon k] \tag{2}$$

where T is the sampling time of the system, η is the battery charging and discharging efficiency, Q is the battery capacity and w and v are the system noise.

The EKF is suitable for optimal estimation of non-linear systems, and batteries are typically non-linear, so the EKF is well suited, as shown in Equation (3) to Equation (7).

$$\hat{X}k/k-1 = Ak-1\hat{X}k-1/k-1+Bk-1Ik \tag{3}$$

$$Pk/k-1 = Ak-1Pk-1/k-1A_{k-1}^{T}+Qk-1 \tag{4}$$

$$Kk = Pk/k-1C_k^T\left(CkPk/k-1C_k^T+Rk\right)^{-1} \tag{5}$$

$$\hat{X}k/k = \hat{X}k/k-1+Kk\left[Zk-Hk\hat{X}k/k-1\right] \tag{6}$$

$$Pk/k = (I-KkCk)\,Pk/k-1 \tag{7}$$

where Z_k is the state vector of the sensor measurements, H_k is the transformation matrix, X_k, A_k and B_k and C_k are defined as shown in Equation (8) to Equation (11).

$$Xk = \begin{bmatrix} Up,k \\ SOCk \end{bmatrix} \tag{8}$$

$$Ak = \begin{bmatrix} 1-\frac{T}{C1R1} & 0 \\ 0 & 1 \end{bmatrix} \tag{9}$$

$$Bk = \begin{bmatrix} \frac{T}{Cp} \\ \frac{\eta T}{Q} \end{bmatrix} \tag{10}$$

$$Ck = \begin{bmatrix} 1 & \frac{\partial UOC}{\partial SOC} \end{bmatrix} \tag{11}$$

The EKF estimates the battery SOC by iterating through Equation (3) to Equation (7), thus converging the SOC to the true value without dependence on the initial value and without cumulative error, the estimated SOC is more accurate and stable, but the EKF trace will be less effective if the frequency of current surges is high, this is because the observed battery terminal voltage does not change rapidly when the high current changes, because there is a battery polarization effect, which makes the battery voltage may rise or fall slowly, at this time, the observed quantity may deviate from the real value, but the state quantity is still near the real value, if its parameter K_k is not modified, it will make the EKF deviate from the real value and cannot play a better performance.

2.2 Optimization strategies

To optimize the tracking performance of the EKF at the moment of sudden current change, the gain K_k in Equation (5) needs to be changed at this moment. As shown in Equation (6), K_k dominates the offset of the system to the state variable and the observed variable, for example, increasing K_k will increase the update magnitude of the state and decreasing K_k will increase the update magnitude of the observed variables. Therefore, to improve the performance of the EKF in the presence of high current surges, the filter gain needs to be increased at the beginning of the surge and reduced after the surge, thus dynamically correcting the SOC.

Let the improved filtering gain be G_k, Equation (6) can be written as Equation (12).

$$\hat{X}k/k = \hat{X}k/k - 1 + GkKk\left[Zk - Hk\hat{X}k/k - 1\right] \tag{12}$$

The filter gain increases at the start of the mutation, increasing the correction amplitude, decreasing as the mutation progresses and returning to normal at the end of the mutation.

Typically, the change in current can be expressed using an exponent, then the gain G_k can also be expressed using an exponent, as shown in Equation (13).

$$Gk = 1 + \alpha\varphi^t \tag{13}$$

Equation (5) can be written as Equation (14).

$$Gk = \left(1 + \alpha\varphi^t\right) Pk/k - 1C_k^T\left(CkPk/k - 1C_k^T + Rk\right)^{-1} \tag{14}$$

In Equation (12), φ is a modulation factor that adjusts the duration of the current mutation, this parameter adjusts the duration of the current mutation and is smaller if the duration of the mutation is short and larger if the duration of the mutation is long, depending on the actual project. α is the adjustment amplitude factor, this parameter tracks the mutation intensity of the system, which is larger if the mutation intensity is greater, smaller if the mutation intensity is smaller, and t is the duration of the mutation of the system.

After improving the EKF gain, the system expands the filter gain to G_k times of the previous one at the beginning of the mutation, and the correction amplitude of the system SOC becomes larger and converges to the true value rapidly; as the mutation ends, the filter gain gradually becomes smaller and eventually reverts to K_k, this realizes the dynamic adjustment of the filter gain and the dynamic change of the correction amplitude in the EKF, which facilitates the system to converge to the true value faster under the mutation. This allows the system to converge to the true value more quickly under abrupt changes, reduces the impact of observation lag on SOC estimation accuracy in the EKF and improves the tracking capability of the system.

3 OPTIMIZED BP NEURAL NETWORK FOR SOH ESTIMATION

3.1 BP neural network algorithm

The use of BP neural network algorithms for estimating battery SOH has become very common, and for a BP neural network with a three-layer structure and three input variables, the principle of estimating battery SOH is shown in Equation (15).

$$ySOH = \sum_{j=1}^{7} \omega_j^2 yj + a \tag{15}$$

where ω is the matrix of weights; a is the matrix of thresholds. The BP nerve network learning process is divided into cis-transmission and error inverse transmission. Shunting propagates the input variables to the output by passing on functions, weights and thresholds. For the error transfer process, if the output response of the learning sample deviates from the actual predicted value, it is corrected. The error is then passed backwards through the network connection channel to the hidden layer, and the weights from the hidden layer to the input layer are revised until the error is less than the set error value.

3.2 Optimization strategies

However, the standard method of updating weights in BP neural networks tends to linger for a long time in the direction of a certain gradient. If the function contains multiple minima, the update of the network weights tends to converge to a local minimum, resulting in a non-optimal set of weights, which reduces the accuracy of SOH estimation. If a probability variable is introduced in the optimization phase to accept a degraded solution that is able to move away from the local optimum to reach the global optimum, the function is shown in Equation (16).

$$f = \frac{1}{2}\left(ySOHr - ySOH\right)^2 \tag{16}$$

where y_{SOHr} is the real SOH of the battery. If x(n) is the weighted state in the current state, then the new state after adding the perturbation u(n) is shown in Equation (17).

$$u(n) = x(n) + \beta \tag{17}$$

where β is the perturbation, which should obey a normal distribution, if f(u(n)) > f(x(n)), then a random number ξ in the middle of [0,1] will be accepted if it is greater than 0.5, then u(n) will be the solution for the next state, otherwise it will be rejected, as shown in Equation (18).

$$x(n+1) = \begin{cases} x(n) & \xi \le 0.5 \\ u(n) & \xi > 0.5 \end{cases} \tag{18}$$

The system continuously determines whether to accept a new state or not. There are no new states that can be accepted for a number of times, then the algorithm terminates and the algorithm terminates and accepts it as the global optimal solution, the running steps are as follows.

Step 1: a randomly selected value is used as the initial weight x(0) for the BP neural network and set the number of running steps and the termination condition.

Step 2: at step n + 1, the new state weight matrix x(n + l) is obtained according to Equation (17). The new matrix of state weights is substituted into the BP nerve network and predicted, and the corresponding error values are calculated according to Equation (16).

Step 3: the trade-offs of the new state weight matrix are determined according to Equation (18).

Step 4: determine the termination condition of the loop, and if the condition is met, go to Step 5, otherwise go to Step 2 and continue the iteration.

Step 5: check that the total number of iterations is greater than the set value, if so, the algorithm is finished. Otherwise, go to Step (2) and continue iterating.

Step 6: use the final matrix of state weights as the weight matrix of the BP nerve network and use it to obtain the final predicted SOH.

By this method, the BP neural network in the learning process, different parameter weights will be continuously optimized to obtain better performance and the optimized parameters are iterated many times, and the iterated parameters will be constantly updated by perturbation and seek better values, so after adding perturbation, the trained parameters have better performance, which will make the battery SOH with higher accuracy.

4 RESULT AND DISCUSSION

The battery used in the experiment is a lithium cobalt-acid battery from Samsung, the voltage sampling chip is LTC6804, the current acquisition uses a precision resistor shunt scheme, i.e. the current value can be calculated by sampling the voltage on the precision resistor and the direction, the temperature uses a thermistor scheme.

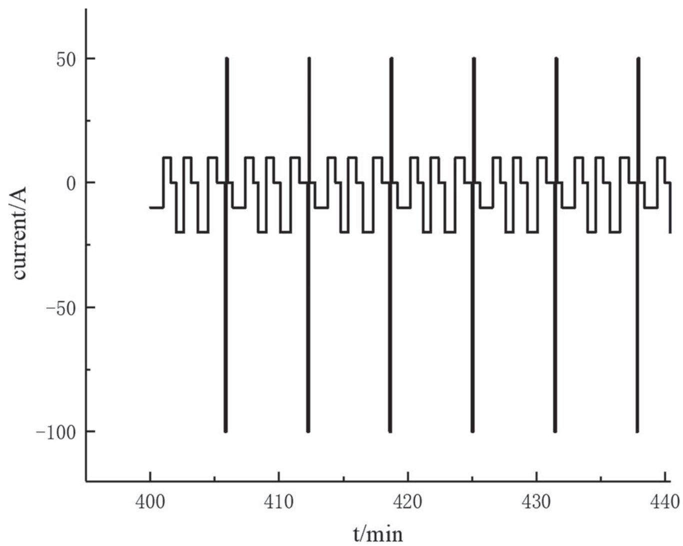

Figure 2. *Test conditions.*

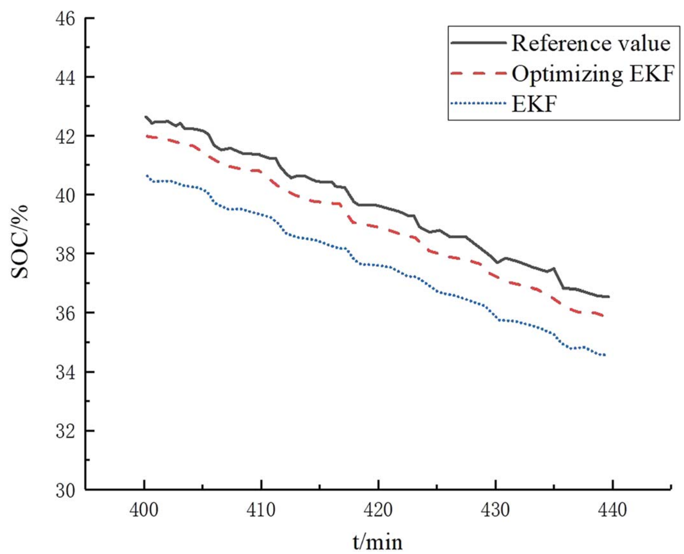

Figure 3. *Test results of SOC estimation.*

4.1 Battery SOC estimation

To verify the superiority of the optimized SOC algorithm, we tested it using very strongly varying operating conditions, the test time starts after 400 min because then the battery enters the steady state and the results will be more in line with the real situation, as shown in Figure 2.

The test results are shown in Figure 3.

Figure 3 shows the estimated battery SOC using the EKF algorithm and the optimized EKF algorithm for the test conditions shown in Figure 2, where the charging and discharging pulses

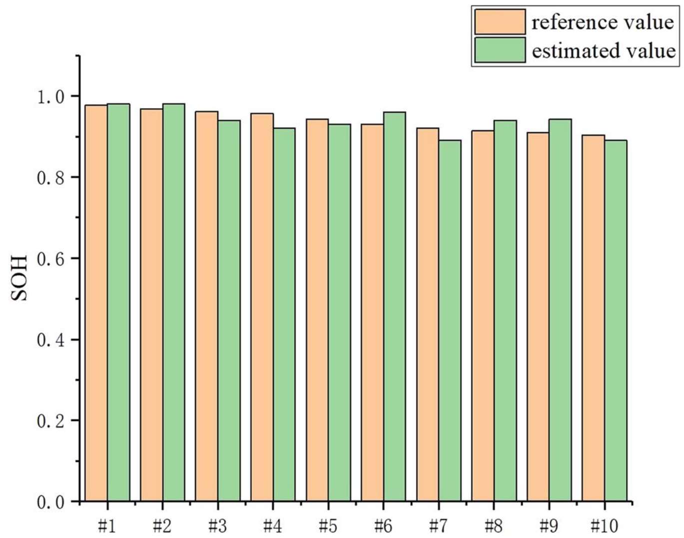

Figure 4. *Test results of SOH estimation.*

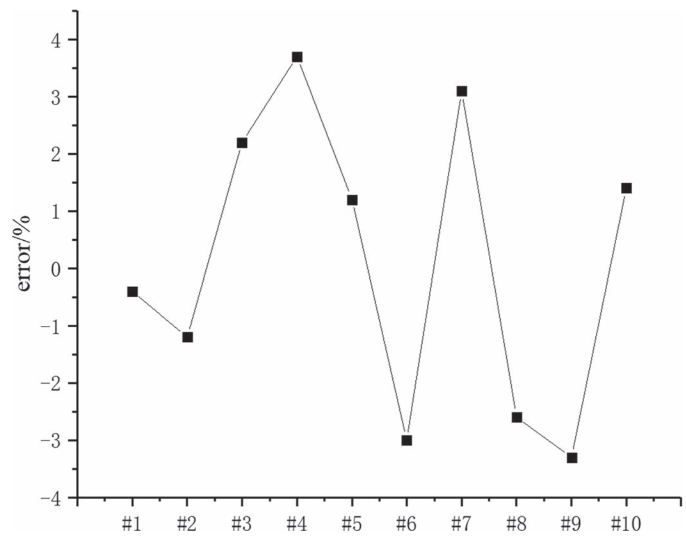

Figure 5. *SOH estimation error.*

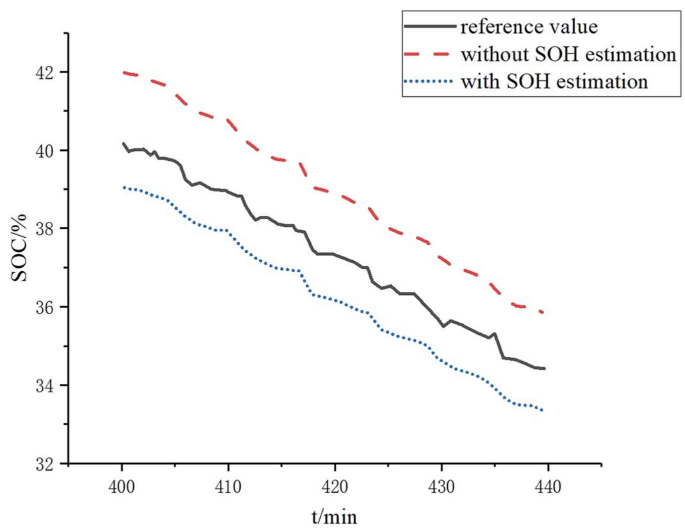

Figure 6. *Test results of SOC estimation combined with SOH.*

are very large and therefore the voltage response of the battery is extremely violent, leading to some errors. However, this condition is a good verification of the feasibility of the strategy proposed in this paper. The reference value is obtained by the Ah integration method, which can be considered as the reference value due to the short test time.

As shown in Figure 3, both the optimized EKF algorithm and the EKF algorithm track the reference value well, but there are errors with the reference value because the dramatic current changes make the battery model and the sampled data not reflect the SOC changes of the battery well. Compared to the EKF algorithm, the optimized EKF algorithm performs better in terms of accuracy, with an average error of about 1%, while the EKF algorithm has an average error of about 2.3%, demonstrating the feasibility of the proposed strategy.

4.2 Battery SOH estimation

In order to verify the feasibility of the proposed optimized BP neural network to estimate the battery SOH, we used the battery data provided by National Aeronautics and Space Administration (NASA) to learn the BP neural network. Two hundred sets of data were used, of which 190 sets were used for learning while the remaining 10 sets were used for testing, and the test results are shown in Figure 4.

The SOH estimated using the optimized BP neural network with the reference SOH error is shown in Figure 5.

As shown in Figure 4, the optimized BP neural network has a very good performance in estimating the battery SOC and can also better reflect the real state of the SOH at the battery. As shown in Figure 5, it has a more satisfactory error of about 3.5% maximum, which basically meets the requirements.

4.3 Battery SOC estimation combined with SOH

We use the data from #5 for further testing, and the data for estimating the battery SOC with and without SOH are shown in Figure 6.

As shown in Figure 6, considering the battery SOH, the battery charging, as well as discharging, is accelerated because it does not have as much capacity as before due to the effects of battery aging, as shown in Figure 6, the SOC considering SOH can track the true SOC better; however, as shown in Figure 3, the SOC estimated by the EKF as well as the optimized EKF algorithm is lower than the reference value, and when the battery SOH is considered, its capacity decreases, resulting in a smaller SOC than the original value after considering SOH, making the SOC without considering SOH perform well, but in fact, it has a large error.

In summary, the maximum available battery capacity is corrected by accurate SOH estimation, and then the estimated maximum available battery capacity can be used to further obtain the true battery SOC, whether it is battery SOC estimation or SOH estimation.

5 CONCLUSION

Battery SOC and battery SOH are two very important parameters to reflect the battery state, while the accurate estimation of battery SOC depends on the accurate SOH. In this paper, we optimize the battery SOC and SOH estimation. In the battery SOC estimation, the EKF algorithm is optimized to have obtained a better tracking effect when there is a large change in the current, and in the battery SOH estimation, the BP neural network algorithm is optimized to obtain better weights to further obtain the accurate SOH. In the future work, we will work on carrying out simpler battery SOC, as well as SOH algorithms for industrial applications.

AUTHOR CONTRIBUTIONS

Nanlan Wang: Data curation, Resources, Writing – original draft, Writing – review & editing
Xiangyang Xia: Funding acquisition, Project administration, Writing – original draft
Xiaoyong Zeng: Methodology, Validation, Writing – review & editing.

CONFLICT OF INTEREST STATEMENT

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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