Lithium battery loss model and economic optimal control strategy for secondary frequency regulation in power system

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Abstract—Lithium battery energy storage system (ESS) has fast response speed, but it is in service for a long time. Therefore, in the research of secondary frequency regulation, it is necessary to establish a battery model that can reflect the short-term polarization and estimate SOC accurately under long-term service. Therefore, we propose a method of variable parameter loss model of lithium battery suitable for secondary frequency modulation of power system and optimize its control strategy based on the relationship between the independent variable SOC and the internal electrical parameters of the battery. Firstly, we discretize the state equation of single cell to obtain the PNGV model with variable parameters. Then the SOC estimation method is improved by using the modified extended Kalman filter method. Finally, we did an analysis about the economy of the ESS participating in secondary frequency regulation by using the loss model, and the optimal control strategy is designed. The HPPC experiment of the ESS unit is designed by Simulink, and the accuracy of the simulation and experimental curves has been analyzed. Finally, the economic differences between the traditional control strategy and the optimal control strategy considering loss are compared. The results show that the error of the variable parameter model in the fitting experiment is no more than 0.41\%, and the accuracy of SOC estimation is 12.96\% higher than that of the traditional estimation. The economy of the optimized control strategy is 15.38\% higher than that of the traditional control strategy.

1. Introduction
By the end of 2020, the total installed capacity of wind power in the world is 702GW [1]. When more and more renewable energy is connected to the power grid, the inertia will be greatly reduced [2]. Large scale ESS has become a necessary method to solve the problem of new energy interconnection [3]. At present, lithium battery ESS accounts for 81.4\% of the total capacity [4]. Since the period of each secondary frequency regulation is in short cycle and the ESS unit must be in operation for a long time. It is necessary to analyze the battery characteristics under the two conditions accurately [5]. Before designing control strategy, most researchers must establish an accurate model of ESS. Therefore, we must establish a model that can not only reflect the transient polarization phenomenon of instantaneous operation of the ESS unit, but also accurately estimate SOC estimation under long-time working conditions, and use the model to optimize the economy of control strategy [6].

The most research on the participation of the ESS in auxiliary power grid frequency regulation uses the first-order inertia link, and it does not change the parameters with time. Secondly, the problem of capacity loss under long-time operation cannot be considered. Moreover, the SOC estimation of the ESS
does not get rid of the sensitivity to the initial value. Reference [7-8] compares different modeling methods. PNGV model is suitable for power system simulation, but the parameters are fixed and not suitable for the long-term service in power system. Reference [9] uses PNGV to create the battery model. They research its parameter identification, and give the parameters of each element parameter of lithium battery through experiment. Reference [10] selects the model with variable parameters for research and designs the control strategy of the ESS, but it needs to further analyze the power flow of power system. Reference [11] proposes that the acquisition in the control system of the management system is periodic. And the model will be more accuracy in the discrete domain. It is necessary to discretize the continuous equation. References [12-13] give the SOC estimation method of Kalman filter under time-domain model, but it does not consider the attenuation of initial capacity of ESS battery in large power system, so the capacity need to be corrected on this basis. Reference [14] calculates the economy and capacity loss of ESS, and formulates the control strategy of wind power participating in the main frequency regulation of power system. However, it does not have the capacity loss of each ESS unit and effectively reduce the impact of large-scale wind power networking on frequency.

In this paper, we discretize the PNGV model to obtain a single model with variable parameters, which makes the model have better response. Then we use the EKF to correct the initial capacity by taking the capacity loss of single lithium battery as the noise error, so that the model can satisfy the application of power system simulation. Then the loss model is used to optimize the economy of the traditional control strategy. Finally, we use Simulink to simulate the single battery model and compare the control strategy.

2. Modeling of lithium battery with variable parameters

2.1. PNGV model of lithium battery in discrete domain

The traditional lithium battery model can not reflect the instantaneous polarization in the regulation simulation. To solve this problem, it is necessary to establish a dynamic model with variable parameters and good response. PNGV is selected as the basic model, because it can reflect the internal polarization process of the battery, and can also satisfy the simulation of ESS, which is composed of an ideal voltage source and multiple capacitors and resistors in series. Its electrical topology is shown in Fig.1.

Fig.1: Equivalent circuit model topology of lithium battery

According to the topology and parameters given in Fig.1, the mathematical description of state equation and output equation in continuous system in PNGV equivalent circuit can be given as follows:

\[
\begin{bmatrix}
\dot{U}_b \\
\dot{U}_c
\end{bmatrix} = \begin{bmatrix}
0 & 0 \\
0 & -1/T
\end{bmatrix} \begin{bmatrix}
U_b \\
U_c
\end{bmatrix} + \begin{bmatrix}
\frac{C_b[\text{SOC}(t)]}{U_b} \\
\frac{C_p[\text{SOC}(t)]}{U_c}
\end{bmatrix}\frac{I(t)}{\gamma}
\]

\[U_o = R_o[\text{SOC}(t)] \times I(t)\]

\[U_i = U_{ocv} - (U_o - U_i + U_b)\]  

(1)

(2)

\[C_b[\text{SOC}(t)], C_p[\text{SOC}(t)], R_o[\text{SOC}(t)]\] and \[R_i[\text{SOC}(t)]\] are the polarization capacitance, polarization resistance and ohmic internal resistance varying with \text{SOC}, and \[U_{ocv}\] is the cumulative voltage drop of terminal voltage with current in time domain. \[U_p\] is the polarization voltage of the battery and the time constant on the whole RC ring \[\tau\] also changes with \text{SOC}:

\[\tau = R_o[\text{SOC}(t)] \times C_b[\text{SOC}(t)]\]

(3)

However, the model in the continuous time domain is not suitable for the simulation of power system, so the discretization of the time-varying state equation in the continuous domain is as follows:

\[
M(z) = e^{z \theta} = \begin{bmatrix}
1 & 0 \\
0 & e^{\theta/T_0}
\end{bmatrix}, \quad N(z) = \begin{bmatrix}
\frac{L_{ocv}}{R_i}, & \frac{1}{\tau} & \frac{1}{\tau}
\end{bmatrix} \begin{bmatrix}
\frac{u}{L_{ocv}} \\
\frac{u}{R_i} \\
\frac{u}{R_i e^{-\frac{u}{L_{ocv} R_i}}}
\end{bmatrix}
\]

(4)
We can derive the time-varying state equation of lithium battery in discrete domain:

\[
\begin{bmatrix}
I_{a}(k+1) \\
\dot{I}_{a}(k+1)
\end{bmatrix}
= 
\begin{bmatrix}
1 & 0 \\
0 & e^{\frac{-\tau}{R(T)}}
\end{bmatrix}
\begin{bmatrix}
I_{a}(k) \\
\dot{I}_{a}(k)
\end{bmatrix}
+ 
\begin{bmatrix}
\frac{C}{kT} \\
\frac{C}{kT}
\end{bmatrix}
\begin{bmatrix}
C_{SOC(k+1)} \\
C_{SOC(k+1)}
\end{bmatrix}

(5)
\]

\(k\) is the sampling number in the control system; \(T\) is the sampling period. The SOC under each period can be obtained by using an accurate estimation method, then the parameters of the battery model can be updated each period, which can make the model more accuracy.

2.2. SOC estimation method of extended Kalman filter algorithm

Because the SOC and other electrical parameters is related to OCV in the battery, when SOC is determined, the values of OCV and other electrical parameters can be obtained according to the first experiment fitting curve. Therefore, we used the basic EKF algorithm to estimate the SOC.

The EKF algorithm iterates the results of current integration method by using the observations of voltage. The state equation of ampere hour integration method is as follows:

\[
A_{o}(k) = \int_{t_{0}}^{t} I_{o}(k) dt
\]

Because of the long-term service of the ESS, its initial capacity is attenuated. The current integration method is a typical time-varying linear calculation method, so the EKF is used to predict the data of the next cycle, as shown in Fig.2.

Fig.2: The EKF algorithm for SOC estimation

The state equation of SOC estimation is shown in equation (7):

\[
SOC(kT) = \frac{Q_{out} + \sum_{i=1}^{n} Ah(T)}{Q_{out}}
\]

(7)

\(C_{i}\) is the capacity throughput of lithium battery in unit time; \(I_{o}(T)\) is the charge-discharge current in each period. Because the curve of \(OCV\) and \(SOC\) is fitted in the first simulation, we can use the EKF to predict the future \(SOC\) of the system according to this curve and current data, but this estimation method does not select the appropriate noise, so we will select the appropriate error for correction.

2.3. SOC estimation method based on loss correction

The reason for the decline of SOC estimation accuracy about the traditional KFM is the attenuation of initial capacity. Therefore, we proposed the EKF based on loss correction in this paper.

First, we correct the nominal capacity and the error of nominal capacity loss as equation (8).

\[
C'_{\text{nom}}(k+1) = C_{\text{nom}}(k) + \Delta C(k+1) = C_{\text{nom}}(k) + T \left( -\frac{C_{SOC(T)}}{R_{T}e^{\frac{-\tau}{R(T)}}} - \frac{Ah(T)}{Ah(T)} \right)
\]

(8)

The state equation and observation equation in the discrete domain are as follows:

\[
X_{i+1} = PX_{i} + QU_{i} + R

Y_{i} = SX_{i} + WN_{i} + V
\]

(9)

According to the polarization reaction, the equation of state with \(U_{\text{sum}}\) is as follows:

\[
U_{\text{sum}}(k+1T) = [U_{\text{sum}}(kT) - (C(T)R_{T})e^{\frac{-\tau}{R(T)}} + I(kT)R_{T}]
\]

(10)

In this way, the capacity loss can be input into the error equation as an error. Combined with the discrete model and the state equation of equation (11). The input error \(R_{t}\) is the correction of the nominal capacity of the current and next cycle, as also shown in equation (11):

\[
P_{t} = \frac{\partial U(kT)_{\text{sum}}}{\partial U} = \begin{bmatrix} 1 & 0 \end{bmatrix}

Q_{t} = \begin{bmatrix} T & \frac{C_{SOC(T)}}{C_{SOC(T)}} \end{bmatrix}

R_{t} = \begin{bmatrix} \frac{C_{SOC(T)}}{C_{SOC(T)}} \end{bmatrix}
\]

(11)

According to equation (10-11), the state equation of SOC estimation can be obtained as follows:

\[
\begin{bmatrix}
SOC(k+1T) \\
C_{SOC(k+1T)}
\end{bmatrix}
= 
\begin{bmatrix}
1 & 0 \\
0 & e^{\frac{-\tau}{R(T)}}
\end{bmatrix}
\begin{bmatrix}
SOC(kT) \\
C_{SOC(kT)}
\end{bmatrix}
+ 
\begin{bmatrix}
\frac{T}{C_{SOC(T)}} \\
\frac{T}{C_{SOC(T)}}
\end{bmatrix}
\begin{bmatrix}
C_{SOC(T)} \\
C_{SOC(T)}
\end{bmatrix}

\]

(12)

The improved EKF SOC estimation process based on loss correction is shown in Fig.3.
3. Optimal economic control strategy of secondary frequency regulation

3.1. Analysis of the Grid connection with the ESS

During the operation of the ESS unit, the voltage is relatively stable when the SOC is between 10% - 90%. Therefore, the SOC of the ESS unit is generally partitioned, as shown in the Fig.4.

![Fig.4: The diagram of SOC area division](image)

Therefore, the constraints on SOC are as follows:

$$S_{SOC_{min}} \leq SOC(kT) \leq S_{SOC_{max}}$$  \hspace{1cm} (13)

For the power limitation of the ESS PCS, the constraint on the output power of each ESS unit in each sampling period is given as equation (15). And the grid connected voltage of each ESS unit also needs to correspond with the public system voltage. At the same time, the ESS unit model has the conditions for operation, and the current of the ESS unit can be converted as equation (14).

$$P_{i} \leq |P_{max}| \quad U_{i(min)} \leq U_{i} \leq U_{i(max)} \quad \frac{\ell(k) - P_{i}}{P_{i} - P_{AGC}}$$  \hspace{1cm} (14)

3.2. Analysis of loss economy and optimization of control strategy

When the ESS unit participates in the secondary frequency regulation, there will be capacity fading in each control cycle. In a single sampling cycle $T$, linearize the secondary frequency regulation power and take the average value. Combined with equation (15), the capacity loss of each cycle is as follows:

$$C(k) = B_{s} \cdot \exp \left[ -\tau_{k} + \frac{P_{agc}(k)}{RT} \right] \left[ \frac{P_{agc}(k)}{U_{agc}(k-1)} \right]^{\frac{1}{1-\tau_{k}}}$$  \hspace{1cm} (15)

Assuming that the current economic loss per unit capacity loss is $E_K$ and the auxiliary regulation profit per unit power is $E_y$, we can derive instantaneous economic profit as follows:

$$E_{\text{inst}}(k) = \int_{t_{k-1}}^{t_{k}} E_{i} C(k) dT + \int_{t_{k-1}}^{t_{k}} E_{y} P_{i} dT$$  \hspace{1cm} (16)

Based on the above, each ESS unit shall satisfy the following equation in each sampling period participating in secondary frequency regulation. And during the calculation sampling period, in addition to the minimum capacity loss, it shall also be executed according to AGC command, minimum current combination and the requirements of equations (13) - (14), as shown in the equation (17).

$$\max \{E_{\text{min}}(k)\} \quad \sum_{i \in \mathcal{P}} P_{i} \epsilon_{i} \frac{\ell(k)}{P_{i}} \frac{\sum_{i \in \mathcal{P}} P_{i} \epsilon_{i}}{\sum_{i \in \mathcal{P}} C(k)}$$  \hspace{1cm} (17)
4. Example analysis
The example is divided into two aspects: lithium battery model simulation, SOC estimation accuracy and control strategy economy comparison. The lithium battery is the type of 18650. The experiments data are given by conventional HPPC experimental measurement. The parameters are shown in Tab 1.

| Tab.1: Experimental parameters of lithium battery charge-discharge |
|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|
| SOC  | Cb/F | Cp/F | Rp/mΩ | Ro/mΩ | Uocv/V | SOC  | Cb/F | Cp/F | Rp/mΩ | Ro/mΩ | Uocv/V |
| 0.1  | 551098 | 221944 | 0.001309 | 0.001119 | 1.976 | 0.6  | 490031 | 26198 | 0.001598 | 0.00047 | 2.071 |
| 0.2  | 521307 | 149783 | 0.001267 | 0.00098 | 1.988 | 0.7  | 489746 | 22516 | 0.001731 | 0.00047 | 2.082 |
| 0.3  | 503144 | 130006 | 0.001285 | 0.00089 | 2.016 | 0.8  | 481031 | 19098 | 0.001908 | 0.00051 | 2.101 |
| 0.4  | 485211 | 39926  | 0.001516 | 0.00049 | 2.034 | 0.9  | 470869 | 17014 | 0.002216 | 0.00055 | 2.124 |
| 0.5  | 491989 | 33453  | 0.001535 | 0.00048 | 2.056 | 1.0  | 612446 | 5096  | 0.003882 | 0.00031 | 2.159 |

4.1. Lithium battery model simulation verification
Firstly, the HPPC simulation is realized by Simulink and compared with the experimental fitting curve. The charge-discharge ratio is 0.1, as shown in Fig.5 and Fig.6.

Fig.5: HPPC charging simulation curve  
Fig.6: HPPC discharging simulation curve

The figure shows that in the charge-discharge experiment, at SOC=30% and 70%, the \( U_L \) of the single battery is 2.019V and 2.087V, and \( U_{ocv} \) is 2.082V and 2.016V, because the model in this paper takes into account the voltage generated by the current in \( C_B \) through accumulation. In the gap of HPPC experiment, the voltage drop of differences in the battery explains the model \( \tau \) is time-varying. When SOC=10%, the simulated \( U_{ocv} \) is 1.985V, while the experimental data is 1.976V, and the error value is 0.41%. Therefore, the improved model not only fits well in the simulation accuracy, but also can accurately reflect the instantaneous polarization phenomenon of the battery.

Then, we use 8-branch single cells in 8 parallel and 6 series to obtain the ESS unit, and its reference voltage is 760V. We used the constant power to charge the Unit. The curve of the \( U_L \) is shown in Fig.9.

Finally, we used the 0.6h actual condition, comparing the two methods. The results are shown in Fig.8.

Fig.7: Constant power simulation curve  
Fig.8: Comparison of the two SOC estimation

As shown in the figure, the \( U_L \) of the ESS unit is between 619V and 824V. When the ESS unit is in the working area, the working voltage fluctuates within ±11% of the reference voltage. The accuracy of the improved model in large-scale service condition simulation is also accurate.

It can be seen that the SOC estimation value of the EKF with capacity loss correction is close to the theoretical value, while the estimated value of the current integration method has deviated from the theoretical value by 12.96% due to the influence of capacity loss after 0.33h. This is because the method in this paper is not sensitive to the initial value and greatly improves the estimation accuracy.
4.2. Economic verification of optimized control strategy

We also use 0.6h AGC signal for comparative analysis. The instantaneous economy curve of traditional control strategy and economic optimal control strategy considering loss is shown in Fig.9. And the total economic benefits of five ESS units within 0.6h are shown in the Fig.10.

![Fig.9: Instantaneous economy curve of the ESS](image1)

![Fig.10: Total economic benefits of the ESS](image2)

It can be seen from Fig.9 that under the optimization strategy considering capacity loss, the instantaneous economy of auxiliary power system of the ESS is higher than that of traditional strategy in most periods, and the difference of maximum economic benefits is 15.38%.

Fig.10 shows that the economy of No. 4 and No. 5 ESS units is high because the initial value of the nominal capacity status of the two ESS units is high. It can be seen that the total income of this control strategy is increased by 10.21% compared with the traditional control strategy.

5. Conclusion

This paper proposes a lithium battery model for power system secondary frequency regulation, and uses the loss model to optimize the control strategy. We give the following conclusions:

1. In HPPC and constant power charge discharge simulation experiments, the fitting error between the two simulation and experimental curve is less than 0.41%. The simulation accuracy and speed of the model can satisfy the use of secondary frequency regulation in power system.

2. In the 0.6h simulation, the estimation accuracy of the extended Kalman method based on capacity loss correction is 12.96% higher than that of the traditional estimation method. This method can satisfy the long-term service of secondary frequency regulation.

3. The economic optimal control strategy considering loss in this paper improves the instantaneous economy by 15.38%, and the total income by 10.21% compared with the traditional strategy.

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