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LE GOUVERNEMENT
DU GRAND-DUCHÉ DE LUXEMBOURG
Ministère de l'Économie

11

N° de publication :

LU504942

12

BREVET D'INVENTION

B1

21

N° de dépôt: LU504942

51

Int. Cl.:

H01M 10/48, G01R 1/36, G06F 30/00

22

Date de dépôt: 18/08/2023

30

Priorité:

43

Date de mise à disposition du public: 19/02/2024

47

Date de délivrance: 19/02/2024

73

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INTELLIGENT PREDICTION METHOD FOR STATE OF CHARGE OF LITHIUM BATTERIES BASED ON IMPROVED GREY WOLF PARTICLE FILTER.

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The present invention provides an intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter, which includes the following steps: step S10, constructing a high-fidelity second-order autoregressive model and identifying model parameters; step S20, taking the identification parameters of the high-fidelity second-order autoregressive model as state observation measurements, and substituting them into the improved grey wolf particle filter algorithm for iterative calculation, thereby completing intelligent prediction of the state of charge of lithium batteries. The present invention comprehensively considers estimation accuracy and computational complexity, and proposes an intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter.

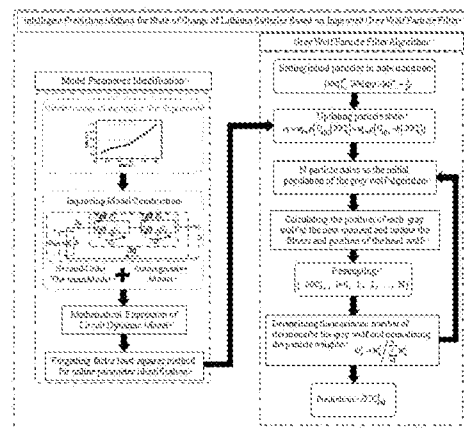


FIG. 1

INTELLIGENT PREDICTION METHOD FOR STATE OF CHARGE OF LITHIUM BATTERIES BASED ON IMPROVED GREY WOLF PARTICLE FILTER

TECHNICAL FIELD

The present invention relates to the field of lithium battery technology, in particular to an intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter.

BACKGROUND

With the structural change of the global energy supply side, the battery management system has become the main direction of technological innovation in the new energy industry. With the progress of science and technology, the function of the battery management system has gradually improved, and the occurrence of abnormal phenomena such as battery overcharge, over discharge, and overheating has been effectively prevented, so as to significantly improve the battery's range and extend its service life, and ensure the safe and reliable operation of the battery; lithium battery is an important part of the battery management system. In the whole battery life cycle, the differences between individual cells and their significance accumulation and unreasonable attenuation of cycle life have become the core factors restricting the development of the current stage. The reason for this phenomenon is that the understanding of the working characteristics and operating mechanism of lithium battery is not perfect, and no reliable model construction and state prediction optimization mechanism has been formed. Therefore, in order to more intuitively describe the reaction mechanism of lithium batteries, an equivalent circuit model is constructed to provide accurate and effective input parameters for subsequent lithium battery state estimation. Accurate estimation of the state of charge of lithium batteries can prevent irreversible damage caused by overcharging and over discharging, and is of great significance for further accurate prediction of battery endurance.

Lithium batteries have strong nonlinear dynamic characteristics due to the combination of multiple parameter coupling processes. Considering the inherent aging and environmental complexity and variability of lithium batteries, existing research has divided equivalent models into three categories: black box models, electrochemical mechanism models, and semi mechanism semi empirical models to simulate voltage response characteristics under different load conditions; the black box model is mainly used to characterize the voltage response characteristics, which is a nonlinear mapping function. The model is trained with data without considering the internal mechanism and structure, but it has a serious dependence on experimental data; the electrochemical model focuses on the complex dynamic characteristics of lithium batteries and can accurately simulate the electrochemical reaction process inside the battery. However, there are many identification parameters and the construction structure is complex; the semi mechanical and semi empirical model can describe electrochemical characteristics through simple circuit components and simulate the dynamic behavior of batteries using mathematical expressions. The equivalent circuit model has clear physical meanings and simple mathematical expressions, so it is widely used in describing the electrochemical characteristics of batteries and has good adaptability; common equivalent modeling methods include Rint, Thevenin, PNGV, and GNL models, which have a simple structure and are easy to analyze, making them particularly important for energy management and becoming the mainstream direction of battery modeling.

Firstly, the initial state of the battery is difficult to determine and there are certain errors in accuracy. Secondly, the accuracy of the battery is high only when left standing for a sufficient period of time, but it is not applicable in actual working conditions. Thirdly, the impact of energy density and cycle life during battery aging on estimation is ignored; accurate estimation of battery state of charge is the foundation of new energy vehicle control, which can effectively prevent overcharging and discharging of lithium batteries, ensuring the safety and durability of their use; in order to solve the problem of high-precision lithium battery state estimation, a large number of excellent research units and researchers at home and abroad have actively carried out relevant research work and obtained a large number of innovative research results, which provide a key reference for lithium battery research; in power battery, the accurate estimation and energy

management of SOC are very important. The existing SOC estimation methods mainly include coulometric method, discharge point test method, open circuit voltage method, Kalman filter method, artificial neural network method and particle filter method. However, the estimation accuracy of the existing SOC estimation methods is not high.

SUMMARY

The invention aims to provide an intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter, so as to solve the problem that the estimation accuracy of the existing SOC estimation method is not high, realize the accurate and efficient operation of the battery management system, and lay a solid theoretical foundation for promoting the multi-directional extension of new energy vehicles.

The present invention provides an intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter, which includes the following steps:

Step S10, a high-fidelity second-order autoregressive model is constructed and model parameter identification is performed;

Step S20, identification parameters of the high-fidelity second-order autoregressive model are taken as state observation measurements, and substituted into the improved grey wolf particle filter algorithm for iterative calculation, thereby completing intelligent prediction of the state of charge of lithium batteries.

Furthermore, step S10 includes the following sub steps:

Step S11, based on Kirchhoff's law, a mathematical expression of the second-order Thevenin model equivalent to lithium batteries is obtained;

Step S12, the mathematical expression of the second-order Thevenin model is subtracted to obtain a linear regression equation of the high-fidelity second-order autoregressive model;

Step S13, the mathematical expression of the second-order Thevenin model is transformed by Laplace transform to obtain a transfer function $G(s)$;

Step S14, a coefficient vector in the linear regression equation of the high-fidelity second-order autoregressive model is obtained using the transfer function $G(s)$;

Step S15, the linear regression equation of the high-fidelity second-order autoregressive model is rewritten into a discretization time sequence to obtain a time-domain differential equation;

Step S16, based on the linear regression equation, transfer function, coefficient vector, and time-domain differential equation of the high-fidelity second-order autoregressive model, the RLS algorithm is used to obtain parameters of the high-fidelity second-order autoregressive model.

Furthermore, the mathematical expression of the second-order Thevenin model equivalent to lithium batteries in step S11:

$$\begin{cases} U_L = U_{oc} - IR_o - U_1 - U_2 \\ I = U_1/R_1 + C_1 dU_1/dt \\ I = U_2/R_2 + C_2 dU_2/dt \end{cases} \quad (1)$$

in the equation, $U_{oc}(t)$ is the open circuit voltage, R_o is the ohmic internal resistance, R_1 and R_2 represent the polarization internal resistance and surface effect internal resistance, C_1 and C_2 represent the polarization capacitance and surface effect capacitance, $I(t)$ is the actual current flowing through the load, and $U_L(t)$ is the closed circuit voltage of the external load.

Furthermore, the linear regression equation of the high-fidelity second-order autoregressive model in step S12 is:

$$y(k) = \varphi^T(k) \theta(k-1) + e(k) \quad (2)$$

in the equation, $\varphi^T(k)$ is the transposition of the system input vector $\varphi(k)$; $\theta(k-1)$ is the coefficient vector; $e(k)$ is the relative error between theory and practice; $y(k)$ is the system output; here, the system refers to the high-fidelity second-order autoregressive model;

wherein the system input vector $\varphi(k)$ and the coefficient vector $\mathcal{G}(k)$ are as follows:

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$$\begin{cases} \mathcal{G}(k) = [a_1; a_2; b_0; b_1; b_2] \\ \varphi(k) = [-y(k-1); -y(k-2); x(k); x(k-1); x(k-2)] \end{cases} \quad (3)$$

in the equation:

a_1, a_2, b_0, b_1, b_2 are the parameters of coefficient vectors $\mathcal{G}(k)$;

$x(k)$ represents the state variable of the system at time k , and $y(k)$ represents the observed value at time k .

Furthermore, the transfer function $G(s)$ in step S13 is as follows:

$$G(s) = \frac{U_L(s) - U_{OC}(s)}{I(s)} = \frac{c_2 s^2 + c_3 s / c_1 + c_4 / c_1}{s^2 + c_5 s / c_1 + 1 / c_1} \quad (4)$$

in the equation, $U_L(s)$, $U_{OC}(s)$, and $I(s)$ are the Laplace transforms of $U_L(t)$, $U_{OC}(t)$, and $I(t)$, respectively, and s is the complex parameter after Laplace transform; the expressions for custom parameters c_1, c_2, c_3, c_4 and c_5 are as follows:

$$c_1 = R_1 C_1 R_2 C_2;$$

$$c_2 = R_0;$$

$$c_3 = R_0 R_1 C_1 + R_0 R_2 C_2 + R_1 R_2 C_2 + R_1 R_2 C_2;$$

$$c_4 = R_0 + R_1 + R_2;$$

$$c_5 = R_1 C_1 + R_2 C_2.$$

Furthermore, step S14 comprises:

Step S141, the complex parameter s in the transfer function $G(s)$ is transformed using z to obtain the equation $s = (1 - z^{-1}) / Tz^{-1}$, where T is the experimental sampling time;

Step S142, then the equation $s = (1 - z^{-1}) / Tz^{-1}$ is substituted into the transfer function $G(s)$ to obtain the expressions for the parameters a_1, a_2, b_0, b_1, b_2 of the coefficient vector $\mathcal{G}(k)$, the expressions are as follows:

$$a_1 = 2 - c_5 T / c_1;$$

$$a_2 = c_5 T / c_1 - T^2 / c_1 - 1;$$

$$b_0 = c_2;$$

$$b_1=c_3T/c_1-2c_2;$$

$$b_2=c_4T^2/c_1-c_3T/c_1+c_2.$$

Furthermore, the time-domain differential equation described in step S15:

$$\begin{aligned} U_L(k) - U_{OC}(k) = & -a_1[U_L(k-1) - U_{OC}(k-1)] \\ & -a_2[U_L(k-2) - U_{OC}(k-2)] \\ & +b_0I(k) + b_1I(k-1) + b_2I(k-2) \end{aligned} \quad (5)$$

in the equation, k is the discrete time parameter of the sampled discretization sequence.

Furthermore, step S16 comprises the following sub steps:

Step S161, relative error $e(k)$ is predicted:

$$e(k) = U_L(k) - U_{OC}(k) - \varphi^T(k) \quad (6)$$

Step S162, gain $K(k)$ is updated:

$$K(k) = P(k-1) - \varphi(k)[\lambda \cdot I + \varphi^T(k) \cdot P(k-1)\varphi(k)]^{-1} \quad (7)$$

wherein λ is the forgetting factor;

Step S163, the error covariance matrix $P(k)$ is calculated:

$$P(k) = [I - K(k) \cdot \varphi^T(k)] \cdot P(k-1) / \lambda \quad (8)$$

Step S164, the coefficient vector $\mathcal{G}(k)$ is obtained:

$$\mathcal{G}(k) = \mathcal{G}(k-1) + K(k)e(k) \quad (9)$$

Step S165, steps S161 to S164 are repeated until the parameter identification is completed at all times, that is, the parameters of the high-fidelity second-order autoregressive model are identified, namely U_{OC} , R_o , R_1 , R_2 , C_1 and C_2 .

Furthermore, step S20 includes the following sub steps:

Step S21, the initial value of the state transition amount is set:

Step S211, at time $t=0$, N particles from the initial prior density function $p(x_0)$ are randomly selected, denoted as $\{x_{i0}, i=1, \dots, N\}$, and the weights of each particle $w_i^0=1/N(i=1, \dots, N)$ are initialized, where i represents the particle index;

Step S212, the recommended density function is defined:

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$$q(x_t) \triangleq p(x_t^i | x_{t-1}^i) \quad (10)$$

wherein t is the state time, and $p(x_t^i | x_{t-1}^i)$ is a posterior probability distribution;

Step S213, the particle set weights based on the initialized weights of each particle and the suggested density function are obtained:

$$w(x_{1:t}^i) = w(x_{1:t-1}^i) p(y_t | x_t^i) = \left(1/\sqrt{2\pi\sigma}\right) \exp\left[-(y_t - y_t^i)^2 / \sigma\right] \quad (11)$$

wherein y_t is the system observation measurement, σ is the Gaussian distribution variance;

Step S22, social hierarchy mechanism:

Step S221, the particle set $\{x_{i,0}, i=1,\dots,N\}$ at the time $t=0$ is taken as the initial population of the grey wolf particle filter algorithm, and the particle set weight $w(x_{1:t}^i)$ is used to represent the fitness of the grey wolf individual, and social hierarchy is conducted to select the grey wolf individual with the best adaptability in each generation of population, so as to determine the location of the first wolf;

Step S222, the head wolf α , β , δ for perceiving prey determines the direction of the population's encirclement of prey, and the candidate wolf pack ω gradually updates its position with the head wolf, and the mathematical model for the process of gray wolves gradually approaching and surrounding their prey is as follows:

$$\begin{cases} \mathbf{D} = \mathbf{C} \circ \mathbf{X}_p(t) - \mathbf{X}_i(t) \\ \mathbf{X}_i(t+1) = \mathbf{X}_i(t) - \mathbf{A} \circ \mathbf{D} \\ \mathbf{A} = 2a \circ \mathbf{r}_1 - a, \mathbf{C} = 2\mathbf{r}_2 \end{cases} \quad (12)$$

in the equation, t represents the current number of iterations; $\mathbf{X}_i(t)$ is the current position vector of the grey wolf, i.e. the state observation measurement, i.e.; $\mathbf{X}_p(t)$ is the position vector of the current prey; $\mathbf{r}_1$ and $\mathbf{r}_2$ are random vectors on $[0,1]$; $a \in [0,2]$ is the convergence factor, and in the entire process a decreases from linear 2 to 0; $\mathbf{A}$ and $\mathbf{C}$ are synergistic coefficient vectors; $\mathbf{D}$ is the distance vector from the prey to the individual grey wolf; the random value on $\mathbf{A} \in [-a,a]$, when a linearly decreases, the grey wolf moves between its current position and its prey; $\mathbf{C}$ is a random value on $[0,2]$, representing the random weight;

Step S23, the adaptability of the head wolf is updated:

Step S231, a mathematical model for individual grey wolf tracking prey is constructed as follows:

$$\begin{cases} \mathbf{D}_\alpha = \mathbf{C}_1 \circ \mathbf{X}_\alpha(t) - \mathbf{X}_i(t), \mathbf{D}_\beta = \mathbf{C}_2 \circ \mathbf{X}_\beta(t) - \mathbf{X}_i(t) \\ \mathbf{D}_\delta = \mathbf{C}_3 \circ \mathbf{X}_\delta(t) - \mathbf{X}_i(t), \mathbf{X}_i^1(t) = \mathbf{X}_\alpha(t) - \mathbf{A}_1 \circ \mathbf{D} \\ \mathbf{X}_i^2(t) = \mathbf{X}_\beta(t) - \mathbf{A}_2 \circ \mathbf{D}, \mathbf{X}_i^3(t) = \mathbf{X}_\delta(t) - \mathbf{A}_3 \circ \mathbf{D} \end{cases} \quad (13)$$

Step S232, the final position of the grey wolf individual is obtained from the mathematical model of the grey wolf individual tracking prey as follows:

$$\mathbf{X}_i(t+1) = [\mathbf{X}_i^1(t) + \mathbf{X}_i^2(t) + \mathbf{X}_i^3(t)]/3 \quad (14)$$

Step S24, the number of iterations of the grey wolf particle filter algorithm is determined: if the grey wolf particle filter algorithm does not reach the set number of iterations, return to step S22 to continue selecting the position of the head wolf; otherwise, proceed to step S25;

Step S25, particle weight normalization:

Step S251, the iterated grey wolf population of the grey wolf particle filtering algorithm is used as the sampled particles in the grey wolf particle filtering algorithm, and the particle normalization weight is calculated as follows:

$$w(x_{1:t}^i) = w(x_{1:t-1}^i) / \sum_{i=1}^N w(x_{1:t}^i) \quad (15)$$

Step S252, the expected estimate of the current discrete time system state is output;

Step S26, the effective particle number is calculated to judge whether to resample:

Step S261, for the phenomenon of particle degradation, the relative efficiency RNE is defined as:

$$(\text{RNE})^{-1} \approx \left[1 + \text{var}_{q(\cdot|y_{1:t})}(w) \right] \quad (16)$$

in the equation, $\text{var}(\cdot)$ represents the variance function for calculating particle weights;

Step S262, the approximate value of effective particle number based on the relative efficiency RNE is:

$$\hat{N}_{eff} = N / \left\{ 1 + \text{var}_{q(\cdot|y_{1:t})} [w(x_{1:t}^i)] \right\} \approx 1 / \sum_{i=1}^N [w(x_{1:t}^i)]^2 \quad (17)$$

Step S263, if the approximate value of the effective particle number is less than the estimated threshold value, resampling will be conducted, and the posterior probability density for resampling is:

$$p(x_{1:t} | y_{1:t}) \approx \sum_{i=1}^N w(x_{1:t}^i) \delta(x_{1:t} - x_{1:t}^i) \quad (18)$$

that is, resample the posterior probability density N times, so that $p(x_{1:t}^* = x_{1:t}^j)$, wherein $w_k^j = 1/N$;

Step S27, steps S22 to S26 are repeated until the state estimation at all times is completed, thus completing the intelligent prediction of the state of charge of the lithium battery.

In summary, due to the adoption of the above technical solution, the beneficial effects of the present invention are:

The present invention comprehensively considers estimation accuracy and computational complexity, and proposes an intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter. On the basis of fully considering the work of lithium batteries, combined with the establishment of SOC estimation models, the calculation of intelligent prediction for lithium battery SOC is achieved, providing a foundation for lithium battery SOC estimation and real-time monitoring of working status.

BRIEF DESCRIPTION OF THE FIGURES

In order to provide a clearer explanation of the technical solution of the embodiments of the present invention, a brief introduction will be given to the accompanying drawings. It should be understood that the following drawings only illustrate certain embodiments of the present invention, and therefore should not be regarded as limiting the scope. For ordinary technical personnel in this field, other relevant drawings can also be obtained based on these drawings without creative labor.

Figure 1 is a flowchart of an intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter in an embodiment of the present invention.

Figure 2 is a structural schematic diagram of a high-fidelity second-order autoregressive model constructed in an embodiment of the present invention.

DESCRIPTION OF THE INVENTION

In order to make the purpose, technical solution, and advantages of the embodiments of the present invention clearer, the following will provide a clear and complete description of the technical solution in the embodiments of the present invention in conjunction with the accompanying drawings. Obviously, the described embodiments are a part of the embodiments of the present invention, not all of them. The components of the embodiments of the present invention typically described and shown in the accompanying drawings can be arranged and designed in various different configurations.

Therefore, the detailed description of the embodiments of the present invention provided in the accompanying drawings is not intended to limit the scope of the claimed invention, but only to represent selected embodiments of the present invention. Based on the embodiments in the present invention, all other embodiments obtained by ordinary technicians in the art without creative labor fall within the scope of protection of the present invention.

Embodiment

As shown in Figure 1, this embodiment proposes an intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter, which includes the following steps:

Step S10, a high-fidelity second-order autoregressive model is constructed and model parameter identification is performed; specifically:

Step S11, based on Kirchhoff's law, a mathematical expression of the second-order Thevenin model equivalent to lithium batteries is obtained:

$$\begin{cases} U_L = U_{oc} - IR_o - U_1 - U_2 \\ I = U_1/R_1 + C_1 dU_1/dt \\ I = U_2/R_2 + C_2 dU_2/dt \end{cases} \quad (1)$$

in the equation, $U_{oc}(t)$ is the open circuit voltage, R_o is the ohmic internal resistance, R_1 and R_2 represent the polarization internal resistance and surface effect internal resistance, C_1 and C_2 represent the polarization capacitance and surface effect capacitance, $I(t)$ is the actual current flowing through the load, and $U_L(t)$ is the closed circuit voltage of the external load.

Step S12, the mathematical expression of the second-order Thevenin model is subtracted to obtain a linear regression equation of the high-fidelity second-order autoregressive model:

$$y(k) = \varphi^T(k) \mathcal{G}(k-1) + e(k) \quad (2)$$

in the equation, $\varphi^T(k)$ is the transposition of the system input vector $\varphi(k)$; $\mathcal{G}(k-1)$ is the coefficient vector; $e(k)$ is the relative error between theory and practice; $y(k)$ is the system output; here, the system refers to the high-fidelity second-order autoregressive model; therefore, a high-fidelity second-order autoregressive model is constructed by combining the second-order Thevenin model with the autoregressive model.

Wherein the system input vector $\varphi(k)$ and the coefficient vector $\mathcal{G}(k)$ are as follows:

$$\begin{cases} \mathcal{G}(k) = [a_1; a_2; b_0; b_1; b_2] \\ \varphi(k) = [-y(k-1); -y(k-2); x(k); x(k-1); x(k-2)] \end{cases} \quad (3)$$

in the equation:

a_1, a_2, b_0, b_1, b_2 are the parameters of coefficient vectors $\mathcal{G}(k)$;

$x(k)$ represents the state variable of the system at time k , and $y(k)$ represents the observed value at time k .

Step S13, the mathematical expression of the second-order Thevenin model is transformed by Laplace transform to obtain a transfer function $G(s)$; the Laplace transform is a linear transformation that transforms a function with a parameter real number t ($t \geq 0$) into a function with a parameter complex numbers.

$$G(s) = \frac{U_L(s) - U_{OC}(s)}{I(s)} = \frac{c_2 s^2 + c_3 s / c_1 + c_4 / c_1}{s^2 + c_5 s / c_1 + 1 / c_1} \quad (4)$$

in the equation, $U_L(s)$, $U_{OC}(s)$, and $I(s)$ are the Laplace transforms of $U_L(t)$, $U_{OC}(t)$, and $I(t)$, respectively, and s is the complex parameter after Laplace transform; the expressions for custom parameters c_1 , c_2 , c_3 , c_4 and c_5 are as follows:

$$c_1 = R_1 C_1 R_2 C_2;$$

$$c_2 = R_0;$$

$$c_3 = R_0 R_1 C_1 + R_0 R_2 C_2 + R_1 R_2 C_2 + R_1 R_2 C_2;$$

$$c_4 = R_0 + R_1 + R_2;$$

$$c_5 = R_1 C_1 + R_2 C_2.$$

Step S14, a coefficient vector in the linear regression equation of the high-fidelity second-order autoregressive model is obtained using the transfer function $G(s)$;

Step S141, to transform the time-domain signal (i.e. discrete time sequence) into a representation in the complex frequency domain, the complex parameter s in the transfer function $G(s)$ is transformed using z to obtain the formula $s = (1 - z^{-1}) / Tz^{-1}$, where T is the experimental sampling time;

Step S142, then the equation $s = (1 - z^{-1}) / Tz^{-1}$ is substituted into the transfer function $G(s)$ to obtain the expressions for the parameters a_1 , a_2 , b_0 , b_1 , b_2 of the coefficient vector $\mathcal{H}(k)$, the expressions are as follows:

$$a_1 = 2 - c_5 T / c_1;$$

$$a_2 = c_5 T / c_1 - T^2 / c_1 - 1;$$

$$b_0 = c_2;$$

$$b_1 = c_3 T / c_1 - 2c_2;$$

$$b_2 = c_4 T^2 / c_1 - c_3 T / c_1 + c_2.$$

Step S15, the linear regression equation of the high-fidelity second-order autoregressive model is rewritten into a discretization time sequence to obtain a time-domain differential equation:

$$\begin{aligned}
U_L(k) - U_{OC}(k) = & -a_1 [U_L(k-1) - U_{OC}(k-1)] \\
& -a_2 [U_L(k-2) - U_{OC}(k-2)] \\
& +b_0 I(k) + b_1 I(k-1) + b_2 I(k-2)
\end{aligned} \tag{5}$$

in the equation, k is the discrete time parameter of the sampled discretization sequence.

Step S16, based on the linear regression equation, transfer function, coefficient vector, and time-domain differential equation of the high-fidelity second-order autoregressive model, the RLS algorithm is used to obtain parameters of the high-fidelity second-order autoregressive model.

The RLS algorithm (Recursive Least Squares) is applied to numerical optimization problems, which minimizes the sum of squared errors to find the best function match for the data and can provide the best parameter fitting results in a statistical sense; on the basis of the least square method, the forgetting factor is added to reduce the occupation of the old data in the covariance matrix, which can effectively prevent the data saturation phenomenon in the RLS algorithm. Therefore, step S16 is as follows:

Step S161, relative error $e(k)$ is predicted:

$$e(k) = U_L(k) - U_{OC}(k) - \varphi^T(k) \tag{6}$$

Step S162, gain $K(k)$ is updated:

$$K(k) = P(k-1) - \varphi(k) [\lambda \cdot I + \varphi^T(k) \cdot P(k-1) \varphi(k)]^{-1} \tag{7}$$

wherein λ is the forgetting factor;

Step S163, the error covariance matrix $P(k)$ is calculated:

$$P(k) = [I - K(k) \cdot \varphi^T(k)] \cdot P(k-1) / \lambda \tag{8}$$

Step S164, the coefficient vector $\mathcal{G}(k)$ is obtained:

$$\mathcal{G}(k) = \mathcal{G}(k-1) + K(k)e(k) \tag{9}$$

Step S165, steps S161 to S164 are repeated until the parameter identification is completed at all times, that is, the parameters of the high-fidelity second-order

autoregressive model are identified, namely U_{OC} , R_o , R_1 , R_2 , C_1 and C_2 . It should be noted that when identifying the parameters of the high-fidelity second-order autoregressive model in steps S13 to S16 above, the initial variables of the parameters of the high-fidelity second-order autoregressive model, such as U_{OC} and U_L , were studied using 70Ah ternary lithium-ion batteries for Hybrid Pulse Power Characterization (HPPC) experiments under 23°C environmental conditions, by studying the working characteristics of lithium-ion batteries through pulse charging and discharging. For other parameters, such as R_o , R_1 , R_2 , C_1 and C_2 , the initial variables can be obtained through other existing technologies, and will not be elaborated here.

Step S20, identification parameters of the high-fidelity second-order autoregressive model are taken as state observation measurements, and substituted into the improved grey wolf particle filter algorithm for iterative calculation, thereby completing intelligent prediction of the state of charge of lithium batteries.

In response to the severe particle degradation phenomenon in traditional particle filtering algorithms, the present invention improves the grey wolf particle filtering algorithm to effectively increase particle diversity and enhance particle resistance to degradation. Therefore, step S20 specifically includes the following sub steps:

Step S21, the initial value of the state transition amount is set:

Step S211, the particles are extracted according to the important density function, and the high-dimensional particle set is collected by Sequential Importance Sampling (SIS). Assuming that the system state x_k follows a first-order Markov process, and the initial prior density function of the system state is $p(x_0)$, at time $t=0$, N particles from the initial prior density function $p(x_0)$ are randomly selected, denoted as $\{x_i^0, i=1, \dots, N\}$, and the weights of each particle $w_i^0=1/N(i=1, \dots, N)$ are initialized, where i represents the particle index;

Step S212, the recommended density function is defined:

$$q(x_t) \triangleq p(x_t^i | x_{t-1}^i) \quad (10)$$

wherein t is the state time, and $p(x_t^i | x_{t-1}^i)$ is a posterior probability distribution, real time recursive estimation of posterior distribution and some related features;

Step S213, the particle set weights based on the initialized weights of each particle and the suggested density function are obtained:

$$w(x_{1:t}^i) = w(x_{1:t-1}^i) p(y_t | x_t^i) = \left(1/\sqrt{2\pi\sigma}\right) \exp\left[-(y_t - y_t^i)^2 / \sigma\right] \quad (11)$$

wherein y_t is the system observation measurement, σ is the Gaussian distribution variance, namely $\sigma=1$;

Step S22, social hierarchy mechanism:

Step S221, the particle set $\{x_{i0}, i=1, \dots, N\}$ at the time $t=0$ is taken as the initial population of the grey wolf particle filter algorithm, and the particle set weight $w(x_{1:t}^i)$ is used to represent the fitness of the grey wolf individual, and social hierarchy is conducted to select the grey wolf individual with the best adaptability in each generation of population, so as to determine the location of the first wolf; introducing a hierarchical mechanism into the particle filter algorithm, which selects and rearranges particles during the resampling stage to increase their diversity and avoid particle degradation.

Step S222, the head wolf α , β , δ for perceiving prey determines the direction of the population's encirclement of prey, and the candidate wolf pack ω gradually updates its position with the head wolf, and the mathematical model for the process of gray wolves gradually approaching and surrounding their prey is as follows:

$$\begin{cases} \mathbf{D} = \mathbf{C} \circ \mathbf{X}_p(t) - \mathbf{X}_i(t) \\ \mathbf{X}_i(t+1) = \mathbf{X}_i(t) - \mathbf{A} \circ \mathbf{D} \\ \mathbf{A} = 2a \circ \mathbf{r}_1 - a, \mathbf{C} = 2\mathbf{r}_2 \end{cases} \quad (12)$$

in the equation, t represents the current number of iterations; $\mathbf{X}_i(t)$ is the current position vector of the grey wolf, i.e. the state observation measurement, i.e; $\mathbf{X}_p(t)$ is the position vector of the current prey; $\mathbf{r}_1$ and $\mathbf{r}_2$ are random vectors on $[0,1]$; $a \in [0,2]$ is the convergence factor, and in the entire process a decreases from linear 2 to 0; $\mathbf{A}$ and $\mathbf{C}$ are synergistic coefficient vectors; $\mathbf{D}$ is the distance vector from the prey to the individual grey wolf; the random value on $\mathbf{A} \in [-a, a]$, when a linearly decreases, the grey wolf moves between its current position and its prey; $\mathbf{C}$ is a

random value on [0,2], representing the random weight; characterizing random weights can effectively increase the diversity of particles and avoid the algorithm falling into local optima;

Step S23, the adaptability of the head wolf is updated:

Step S231, grey wolf individuals have the potential to identify the location of their prey. To simulate the search behavior of gray wolves, the mathematical model for tracking prey by grey wolf individuals is:

$$\begin{cases} \mathbf{D}_\alpha = \mathbf{C}_1 \circ \mathbf{X}_\alpha(t) - \mathbf{X}_i(t), \mathbf{D}_\beta = \mathbf{C}_2 \circ \mathbf{X}_\beta(t) - \mathbf{X}_i(t) \\ \mathbf{D}_\delta = \mathbf{C}_3 \circ \mathbf{X}_\delta(t) - \mathbf{X}_i(t), \mathbf{X}_i^1(t) = \mathbf{X}_\alpha(t) - \mathbf{A}_1 \circ \mathbf{D} \\ \mathbf{X}_i^2(t) = \mathbf{X}_\beta(t) - \mathbf{A}_2 \circ \mathbf{D}, \mathbf{X}_i^3(t) = \mathbf{X}_\delta(t) - \mathbf{A}_3 \circ \mathbf{D} \end{cases} \quad (13)$$

For the establishment of a decentralized model, the $\mathbf{A}_1$, $\mathbf{A}_2$, and $\mathbf{A}_3$ coefficients can enable the grey wolf algorithm to conduct global search and determine whether the new location is close to or far from the target grey wolf; the $\mathbf{C}_1$, $\mathbf{C}_2$, and $\mathbf{C}_3$ coefficients provide random weights for prey, helping to exhibit random search behavior during the grey wolf optimization process, avoiding the algorithm from falling into local optima and determining the orientation of the new position relative to the target grey wolf; $\mathbf{X}_\alpha(t)$, $\mathbf{X}_\beta(t)$, $\mathbf{X}_\delta(t)$ respectively represent the position vector of the current population α , β , δ ; $\mathbf{D}_\alpha$, $\mathbf{D}_\beta$, $\mathbf{D}_\delta$ are the distance between the current candidate grey wolf and the optimal three wolves, respectively; based on the current obtained range, $\mathbf{X}_i(t)$, $\mathbf{X}_i^2(t)$, $\mathbf{X}_i^3(t)$ are three optimal solutions, and force other search agents to update their positions based on the optimal search agent's location.

Step S232, the final position of the grey wolf individual is obtained from the mathematical model of the grey wolf individual tracking prey as follows:

$$\mathbf{X}_i(t+1) = [\mathbf{X}_i^1(t) + \mathbf{X}_i^2(t) + \mathbf{X}_i^3(t)]/3 \quad (14)$$

Step S24, the number of iterations of the grey wolf particle filter algorithm is determined:

if the grey wolf particle filter algorithm does not reach the set number of iterations, return to step S22 to continue selecting the position of the head wolf; otherwise, proceed to step S25;

Step S25, particle weight normalization:

Step S251, the iterated grey wolf population of the grey wolf particle filtering algorithm is used as the sampled particles in the grey wolf particle filtering algorithm, and the particle normalization weight is calculated as follows:

$$w(x_{1:t}^i) = w(x_{1:t-1}^i) / \sum_{i=1}^N w(x_{1:t}^i) \quad (15)$$

Step S252, the expected estimate of the current discrete time system state is output;

Step S26, the effective particle number is calculated to judge whether to resample:

Step S261, for the phenomenon of particle degradation, the relative efficiency RNE is defined as:

$$(\text{RNE})^{-1} \approx \left[1 + \text{var}_{q(\bullet|y_{1:t})}(w) \right] \quad (16)$$

in the equation, $\text{var}(\cdot)$ represents the variance function for calculating particle weights;

Step S262, the approximate value of effective particle number based on the relative efficiency RNE is:

$$\hat{N}_{eff} = N / \left\{ 1 + \text{var}_{q(\bullet|y_{1:t})} [w(x_{1:t}^i)] \right\} \approx 1 / \sum_{i=1}^N [w(x_{1:t}^i)]^2 \quad (17)$$

Step S263, if the approximate value of the effective particle number is less than the estimated threshold value, resampling will be conducted, and the posterior probability density for resampling is:

$$p(x_{1:t} | y_{1:t}) \approx \sum_{i=1}^N w(x_{1:t}^i) \delta(x_{1:t} - x_{1:t}^i) \quad (18)$$

that is, resample the posterior probability density N times, so that $p(x_{1:t}^* = x_{1:t}^j)$, wherein $w_k^j = 1/N$;

Step S27, steps S22 to S26 are repeated until the state estimation at all times is completed, thus completing the intelligent prediction of the state of charge of the lithium battery.

In summary, the present invention comprehensively considers estimation accuracy and computational complexity, and proposes an intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter. On the basis of fully considering the work of lithium batteries, combined with the establishment of SOC estimation models, the calculation of intelligent prediction for lithium battery SOC is achieved, providing a foundation for lithium battery SOC estimation and real-time monitoring of working status.

The above is only a preferred embodiment of the present invention and is not intended to limit it. For those skilled in the art, the present invention may undergo various modifications and variations. Any modifications, equivalent substitutions, improvements, etc. made within the spirit and principles of this invention shall be included within the scope of protection of this invention.

CLAIMS

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1. An intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter, characterized in that it includes the following steps:

step S10, a high-fidelity second-order autoregressive model is constructed and model parameter identification is performed;

step S20, identification parameters of the high-fidelity second-order autoregressive model are taken as state observation measurements, and substituted into the improved grey wolf particle filter algorithm for iterative calculation, thereby completing intelligent prediction of the state of charge of lithium batteries.

2. The intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter according to claim 1, characterized in that step S10 comprises the following sub steps:

step S11, based on Kirchhoff's law, a mathematical expression of the second-order Thevenin model equivalent to lithium batteries is obtained;

step S12, the mathematical expression of the second-order Thevenin model is subtracted to obtain a linear regression equation of the high-fidelity second-order autoregressive model;

step S13, the mathematical expression of the second-order Thevenin model is transformed by Laplace transform to obtain a transfer function $G(s)$;

step S14, a coefficient vector in the linear regression equation of the high-fidelity second-order autoregressive model is obtained using the transfer function $G(s)$;

step S15, the linear regression equation of the high-fidelity second-order autoregressive model is rewritten into a discretization time sequence to obtain a time-domain differential equation;

step S16, based on the linear regression equation, transfer function, coefficient vector, and time-domain differential equation of the high-fidelity second-order autoregressive model, the RLS algorithm is used to obtain parameters of the high-fidelity second-order autoregressive model.

3. The intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter according to claim 2, characterized in that the mathematical expression of the second-order Thevenin model equivalent to lithium batteries in step S11:

$$\begin{cases} U_L = U_{OC} - IR_o - U_1 - U_2 \\ I = U_1/R_1 + C_1 dU_1/dt \\ I = U_2/R_2 + C_2 dU_2/dt \end{cases} \quad (1)$$

in the equation, $U_{OC}(t)$ is the open circuit voltage, R_o is the ohmic internal resistance, R_1 and R_2 represent the polarization internal resistance and surface effect internal resistance, C_1 and C_2 represent the polarization capacitance and surface effect capacitance, $I(t)$ is the actual current flowing through the load, and $U_L(t)$ is the closed circuit voltage of the external load.

4. The intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter according to claim 3, characterized in that the linear regression equation of the high-fidelity second-order autoregressive model in step S12 is:

$$y(k) = \varphi^T(k) \mathcal{G}(k-1) + e(k) \quad (2)$$

in the equation, $\varphi^T(k)$ is the transposition of the system input vector $\varphi(k)$; $\mathcal{G}(k-1)$ is the coefficient vector; $e(k)$ is the relative error between theory and practice; $y(k)$ is the system output; here, the system refers to the high-fidelity second-order autoregressive model;

wherein the system input vector $\varphi(k)$ and the coefficient vector $\mathcal{G}(k)$ are as follows:

$$\begin{cases} \mathcal{G}(k) = [a_1; a_2; b_0; b_1; b_2] \\ \varphi(k) = [-y(k-1); -y(k-2); x(k); x(k-1); x(k-2)] \end{cases} \quad (3)$$

in the equation:

a_1, a_2, b_0, b_1, b_2 are the parameters of coefficient vector $\mathcal{G}(k)$;

$x(k)$ represents the state variable of the system at time k , and $y(k)$ represents the observed value at time k .

5. The intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter according to claim 4, characterized in that the transfer function $G(s)$ in step S13 is as follows:

$$G(s) = \frac{U_L(s) - U_{OC}(s)}{I(s)} = \frac{c_2 s^2 + c_3 s / c_1 + c_4 / c_1}{s^2 + c_5 s / c_1 + 1 / c_1} \quad (4)$$

in the equation, $U_L(s)$, $U_{OC}(s)$, and $I(s)$ are the Laplace transforms of $U_L(t)$, $U_{OC}(t)$, and $I(t)$, respectively, and s is the complex parameter after Laplace transform; the expressions for custom parameters c_1 , c_2 , c_3 , c_4 and c_5 are as follows:

$$c_1 = R_1 C_1 R_2 C_2;$$

$$c_2 = R_0;$$

$$c_3 = R_0 R_1 C_1 + R_0 R_2 C_2 + R_1 R_2 C_2 + R_1 R_2 C_2;$$

$$c_4 = R_0 + R_1 + R_2;$$

$$c_5 = R_1 C_1 + R_2 C_2.$$

6. The intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter according to claim 5, characterized in that step S14 comprises:

step S141, the complex parameter s in the transfer function $G(s)$ is transformed using z to obtain the equation $s = (1 - z^{-1}) / Tz^{-1}$, where T is the experimental sampling time;

step S142, then the equation $s = (1 - z^{-1}) / Tz^{-1}$ is substituted into the transfer function $G(s)$ to obtain the expressions for the parameters a_1 , a_2 , b_0 , b_1 , b_2 of the coefficient vector $\mathcal{A}(k)$, the expressions are as follows:

$$a_1 = 2 - c_5 T / c_1;$$

$$a_2 = c_5 T / c_1 - T^2 / c_1 - 1;$$

$$b_0 = c_2;$$

$$b_1 = c_3 T / c_1 - 2c_2;$$

$$b_2 = c_4 T^2 / c_1 - c_3 T / c_1 + c_2.$$

7. The intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter according to claim 6, characterized in that the time-domain differential equation described in step S15:

$$\begin{aligned} U_L(k) - U_{OC}(k) = & -a_1 [U_L(k-1) - U_{OC}(k-1)] \\ & -a_2 [U_L(k-2) - U_{OC}(k-2)] \\ & +b_0 I(k) + b_1 I(k-1) + b_2 I(k-2) \end{aligned} \quad (5)$$

in the equation, k is the discrete time parameter of the sampled discretization sequence. LU504942

8. The intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter according to claim 7, characterized in that step S16 comprises the following sub steps:

step S161, relative error $e(k)$ is predicted:

$$e(k) = U_L(k) - U_{OC}(k) - \varphi^T(k) - 1 \quad (6)$$

step S162, gain $K(k)$ is updated:

$$K(k) = P(k-1) - \varphi(k)[\lambda \cdot I + \varphi^T(k) \cdot P(k-1)\varphi(k)]^{-1} \quad (7)$$

wherein λ is the forgetting factor;

step S163, the error covariance matrix $P(k)$ is calculated:

$$P(k) = [I - K(k) \cdot \varphi^T(k)] \cdot P(k-1) / \lambda \quad (8)$$

step S164, the coefficient vector $\mathcal{G}(k)$ is obtained:

$$\mathcal{G}(k) = \mathcal{G}(k-1) + K(k)e(k) \quad (9)$$

step S165, steps S161 to S164 are repeated until the parameter identification is completed at all times, that is, the parameters of the high-fidelity second-order autoregressive model are identified, namely U_{OC} , R_o , R_1 , R_2 , C_1 and C_2 .

9. The intelligent prediction method for state of charge of lithium batteries based on improved grey wolf particle filter according to claim 8, characterized in that step S20 includes the following sub steps:

step S21, the initial value of the state transition amount is set:

step S211, at time $t=0$, N particles from the initial prior density function $p(x_0)$ are randomly selected, denoted as $\{x_{i0}, i=1, \dots, N\}$, and the weights of each particle $w_{i0}^i = 1/N (i=1, \dots, N)$ are initialized, where i represents the particle index;

step S212, the recommended density function is defined:

$$q(x_t) \triangleq p(x_t^i | x_{t-1}^i) \quad (10)$$

wherein t is the state time, and $p(x_t^i | x_{t-1}^i)$ is a posterior probability distribution;

step S213, the particle set weights based on the initialized weights of each particle and the suggested density function are obtained:

$$w(x_{1:t}^i) = w(x_{1:t-1}^i) p(y_t | x_t^i) = \left(1/\sqrt{2\pi\sigma}\right) \exp\left[-(y_t - y_t^i)^2 / \sigma\right] \quad (11)$$

wherein y_t is the system observation measurement, σ is the Gaussian distribution variance;

step S22, social hierarchy mechanism:

step S221, the particle set $\{x_i, i=1, \dots, N\}$ at the time $t=0$ is taken as the initial population of the grey wolf particle filter algorithm, and the particle set weight $w(x_{1:t})$ is used to represent the fitness of the grey wolf individual, and social hierarchy is conducted to select the grey wolf individual with the best adaptability in each generation of population, so as to determine the location of the first wolf;

step S222, the head wolf α , β , δ for perceiving prey determines the direction of the population's encirclement of prey, and the candidate wolf pack ω gradually updates its position with the head wolf, and the mathematical model for the process of gray wolves gradually approaching and surrounding their prey is as follows:

$$\begin{cases} \mathbf{D} = \mathbf{C} \circ \mathbf{X}_p(t) - \mathbf{X}_i(t) \\ \mathbf{X}_i(t+1) = \mathbf{X}_i(t) - \mathbf{A} \circ \mathbf{D} \\ \mathbf{A} = 2a \circ \mathbf{r}_1 - a, \mathbf{C} = 2\mathbf{r}_2 \end{cases} \quad (12)$$

in the equation, t represents the current number of iterations; $\mathbf{X}_i(t)$ is the current position vector of the grey wolf, i.e. the state observation measurement, i.e. $\mathbf{X}_p(t)$ is the position vector of the current prey; $\mathbf{r}_1$ and $\mathbf{r}_2$ are random vectors on $[0,1]$; $a \in [0,2]$ is the convergence factor, and in the entire process a decreases from linear 2 to 0; $\mathbf{A}$ and $\mathbf{C}$ are synergistic coefficient vectors; $\mathbf{D}$ is the distance vector from the prey to the individual grey wolf; the random value on $\mathbf{A} \in [-a, a]$, when a linearly decreases, the grey wolf moves between its current position and its prey; $\mathbf{C}$ is a random value on $[0,2]$, representing the random weight;

step S23, the adaptability of the head wolf is updated:

step S231, a mathematical model for individual grey wolf tracking prey is constructed as follows:

$$\begin{cases} \mathbf{D}_\alpha = \mathbf{C}_1 \circ \mathbf{X}_\alpha(t) - \mathbf{X}_i(t), \mathbf{D}_\beta = \mathbf{C}_2 \circ \mathbf{X}_\beta(t) - \mathbf{X}_i(t) \\ \mathbf{D}_\delta = \mathbf{C}_3 \circ \mathbf{X}_\delta(t) - \mathbf{X}_i(t), \mathbf{X}_i^1(t) = \mathbf{X}_\alpha(t) - \mathbf{A}_1 \circ \mathbf{D} \\ \mathbf{X}_i^2(t) = \mathbf{X}_\beta(t) - \mathbf{A}_2 \circ \mathbf{D}, \mathbf{X}_i^3(t) = \mathbf{X}_\delta(t) - \mathbf{A}_3 \circ \mathbf{D} \end{cases} \quad (13)$$

step S232, the final position of the grey wolf individual is obtained from the mathematical model of the grey wolf individual tracking prey as follows:

$$\mathbf{X}_i(t+1) = [\mathbf{X}_i^1(t) + \mathbf{X}_i^2(t) + \mathbf{X}_i^3(t)]/3 \quad (14)$$

step S24, the number of iterations of the grey wolf particle filter algorithm is determined: if the grey wolf particle filter algorithm does not reach the set number of iterations, return to step S22 to continue selecting the position of the head wolf; otherwise, proceed to step S25;

step S25, particle weight normalization:

step S251, the iterated grey wolf population of the grey wolf particle filtering algorithm is used as the sampled particles in the grey wolf particle filtering algorithm, and the particle normalization weight is calculated as follows:

$$w(x_{1:t}^i) = w(x_{1:t-1}^i) / \sum_{i=1}^N w(x_{1:t}^i) \quad (15)$$

step S252, the expected estimate of the current discrete time system state is output;

step S26, the effective particle number is calculated to judge whether to resample:

step S261, for the phenomenon of particle degradation, the relative efficiency RNE is defined as:

$$(\text{RNE})^{-1} \approx \left[1 + \text{var}_{q(\bullet|y_{1:t})}(w) \right] \quad (16)$$

in the equation, $\text{var}(\cdot)$ represents the variance function for calculating particle weights;

step S262, the approximate value of effective particle number based on the relative efficiency RNE is:

$$\hat{N}_{\text{eff}} = N / \left\{ 1 + \text{var}_{q(\bullet|y_{1:t})} [w(x_{1:t}^i)] \right\} \approx 1 / \sum_{i=1}^N [w(x_{1:t}^i)]^2 \quad (17)$$

step S263, if the approximate value of the effective particle number is less than the estimated threshold value, resampling will be conducted, and the posterior probability density for resampling is:

$$p(x_{1:t} | y_{1:t}) \approx \sum_{i=1}^N w(x_{1:t}^i) \delta(x_{1:t} - x_{1:t}^i) \quad (18)$$

that is, resample the posterior probability density N times, so that $p(x_{1:t}^* = x_{1:t}^j)$, wherein $w_k^j = 1/N$;

step S27, steps S22 to S26 are repeated until the state estimation at all times is completed, thus completing the intelligent prediction of the state of charge of the lithium battery.

1. Eine intelligente Vorhersagemethode für den Ladezustand von Lithiumbatterien auf der Grundlage eines verbesserten Grauer-Wolf-Partikel-Filters, dadurch gekennzeichnet, dass es die folgenden Schritte umfasst:

Schritt S10, ein High-Fidelity-Autoregressionsmodell zweiter Ordnung wird konstruiert und eine Modellparameteridentifikation wird durchgeführt;

Schritt S20, die Identifikationsparameter des High-Fidelity-Autoregressionsmodells zweiter Ordnung werden als Zustandsbeobachtungsmessungen genommen und in den verbesserten Grauer-Wolf-Partikel-Filter-Algorithmus zur iterativen Berechnung eingesetzt, wodurch die intelligente Vorhersage des Ladezustands von Lithiumbatterien vervollständigt wird.

2. Die intelligente Vorhersagemethode für den Ladezustand von Lithiumbatterien auf der Grundlage eines verbesserten Grauer-Wolf-Partikel-Filters nach Anspruch 1, dadurch gekennzeichnet, dass Schritt S10 die folgenden Unterschritte umfasst:

Schritt S11, basierend auf dem Kirchhoff'schen Gesetz wird ein mathematischer Ausdruck des Thevenin-Modells zweiter Ordnung äquivalent zu Lithiumbatterien erhalten;

Schritt S12, der mathematische Ausdruck des Thevenin-Modells zweiter Ordnung wird subtrahiert, um eine lineare Regressionsgleichung des High-Fidelity-Autoregressionsmodells zweiter Ordnung zu erhalten;

Schritt S13, der mathematische Ausdruck des Thevenin-Modells zweiter Ordnung wird durch Laplace-Transformation transformiert, um eine Übertragungsfunktion $G(s)$ zu erhalten;

Schritt S14, ein Koeffizientenvektor in der linearen Regressionsgleichung des High-Fidelity-Autoregressionsmodells zweiter Ordnung wird unter Verwendung der Übertragungsfunktion $G(s)$ erhalten;

Schritt S15, die lineare Regressionsgleichung des High-Fidelity-Autoregressionsmodells zweiter Ordnung wird in eine Diskretisierungszeitsequenz umgeschrieben, um eine Differentialgleichung im Zeitbereich zu erhalten;

Schritt S16, auf der Grundlage der linearen Regressionsgleichung, der Übertragungsfunktion, des Koeffizientenvektors und der Differentialgleichung im Zeitbereich des High-Fidelity-Autoregressionsmodells zweiter Ordnung wird der RLS-Algorithmus verwendet, um Parameter des High-Fidelity-Autoregressionsmodells zweiter Ordnung zu erhalten.

3. Die intelligente Vorhersagemethode für den Ladezustand von Lithiumbatterien auf der Grundlage eines verbesserten Grauer-Wolf-Partikel-Filters nach Anspruch 2, dadurch gekennzeichnet, dass der mathematische Ausdruck des Thevenin-Modells zweiter Ordnung äquivalent zur Lithiumbatterie in Schritt S11:

$$\begin{cases} U_L = U_{oc} - IR_o - U_1 - U_2 \\ I = U_1/R_1 + C_1 dU_1/dt \\ I = U_2/R_2 + C_2 dU_2/dt \end{cases} \quad (1)$$

in der Gleichung ist $U_{OC}(t)$ die Leerlaufspannung, R_o ist der ohmsche Innenwiderstand, R_1 und R_2 stehen für den Polarisationsinnenwiderstand und den Oberflächeneffektinnenwiderstand, C_1 und C_2 stehen für die Polarisationskapazität und die Oberflächeneffektinnenkapazität, $I(t)$ ist der tatsächliche Strom, der durch die Last fließt, und $U_L(t)$ ist die Ruhespannung der externen Last.

4. Die intelligente Vorhersagemethode für den Ladezustand von Lithiumbatterien auf der Grundlage eines verbesserten Grauer-Wolf-Partikel-Filters nach Anspruch 3, dadurch gekennzeichnet, dass die lineare Regressionsgleichung des High-Fidelity-Autoregressionsmodells zweiter Ordnung in Schritt S12 lautet:

$$y(k) = \varphi^T(k) \theta(k-1) + e(k) \quad (2)$$

in der Gleichung ist $\varphi^T(k)$ die Transposition des Systemeingangsvektors $\varphi(k)$; $\theta(k-1)$ ist der Koeffizientenvektor; $e(k)$ ist der relative Fehler zwischen Theorie und Praxis; $y(k)$ ist der Systemausgang; hier bezieht sich das System auf das High-Fidelity-Autoregressionsmodell zweiter Ordnung;

wobei der Systemeingangsvektor $\varphi(k)$ und der Koeffizientenvektor $\vartheta(k)$ wie folgt sind: LU504942

$$\begin{cases} \vartheta(k) = [a_1; a_2; b_0; b_1; b_2] \\ \varphi(k) = [-y(k-1); -y(k-2); x(k); x(k-1); x(k-2)] \end{cases} \quad (3)$$

in der Gleichung:

a_1, a_2, b_0, b_1, b_2 sind die Parameter des Koeffizientenvektors $\vartheta(k)$;

$x(k)$ stellt die Zustandsvariable des Systems zum Zeitpunkt k dar, und $y(k)$ stellt den beobachteten Wert zum Zeitpunkt k dar.

5. Die intelligente Vorhersagemethode für den Ladezustand von Lithiumbatterien auf der Grundlage eines verbesserten Grauer-Wolf-Partikel-Filters nach Anspruch 4, dadurch gekennzeichnet, dass die Übertragungsfunktion $G(s)$ in Schritt S13 wie folgt ist:

$$G(s) = \frac{U_L(s) - U_{OC}(s)}{I(s)} = \frac{c_2 s^2 + c_3 s / c_1 + c_4 / c_1}{s^2 + c_5 s / c_1 + 1 / c_1} \quad (4)$$

in der Gleichung sind $U_L(s)$, $U_{OC}(s)$, und $I(s)$ die Laplace-Transformationen von $U_L(t)$, $U_{OC}(t)$ und $I(t)$, und s ist der komplexe Parameter nach der Laplace-Transformation; die Ausdrücke für die benutzerdefinierten Parameter c_1, c_2, c_3, c_4 und c_5 lauten wie folgt:

$$c_1 = R_1 C_1 R_2 C_2;$$

$$c_2 = R_0;$$

$$c_3 = R_0 R_1 C_1 + R_0 R_2 C_2 + R_1 R_2 C_2 + R_1 R_2 C_2;$$

$$c_4 = R_0 + R_1 + R_2;$$

$$c_5 = R_1 C_1 + R_2 C_2.$$

6. Die intelligente Vorhersagemethode für den Ladezustand von Lithiumbatterien auf der Grundlage eines verbesserten Grauer-Wolf-Partikel-Filters nach Anspruch 5, dadurch gekennzeichnet, dass Schritt S14 umfasst:

Schritt S141, der komplexe Parameter s in der Übertragungsfunktion $G(s)$ wird unter Verwendung von z transformiert, um die Gleichung $s = (1 - z^{-1}) / Tz^{-1}$ zu erhalten, wobei T die experimentelle Abtastzeit ist;

Schritt S142, anschließend wird die Gleichung $s=(1-z^{-1})/Tz^{-1}$ in die Übertragungsfunktion $G(s)$ eingesetzt, um die Ausdrücke für die Parameter a_1, a_2, b_0, b_1, b_2 des Koeffizientenvektors $\mathcal{G}(k)$ zu erhalten, wobei die Ausdrücke wie folgt lauten:

$$a_1=2-c_5T/c_1;$$

$$a_2=c_5T/c_1-T^2/c_1-1;$$

$$b_0=c_2;$$

$$b_1=c_3T/c_1-2c_2;$$

$$b_2=c_4T^2/c_1-c_3T/c_1+c_2.$$

7. Die intelligente Vorhersagemethode für den Ladezustand von Lithiumbatterien auf der Grundlage eines verbesserten Grauer-Wolf-Partikel-Filters nach Anspruch 6, dadurch gekennzeichnet, dass die in Schritt S15 beschriebene Differentialgleichung im Zeitbereich:

$$\begin{aligned} U_L(k) - U_{OC}(k) = & -a_1 [U_L(k-1) - U_{OC}(k-1)] \\ & -a_2 [U_L(k-2) - U_{OC}(k-2)] \\ & +b_0 I(k) + b_1 I(k-1) + b_2 I(k-2) \end{aligned} \quad (5)$$

in der Gleichung, k ist der diskrete Zeitparameter der abgetasteten Diskretisierungssequenz.

8. Die intelligente Vorhersagemethode für den Ladezustand von Lithiumbatterien auf der Grundlage eines verbesserten Grauer-Wolf-Partikel-Filters nach Anspruch 7, dadurch gekennzeichnet, dass Schritt S16 die folgenden Unterschritte umfasst:

Schritt S161, der relative Fehler $e(k)$ wird vorhergesagt:

$$e(k) = U_L(k) - U_{OC}(k) - \varphi^T(k) - 1 \quad (6)$$

Schritt S162, die Verstärkung $K(k)$ wird aktualisiert:

$$K(k) = P(k-1) - \varphi(k) [\lambda \cdot I + \varphi^T(k) \cdot P(k-1) \varphi(k)]^{-1} \quad (7)$$

wobei λ der Vergessensfaktor ist;

Schritt S163, die Fehlerkovarianzmatrix $P(k)$ wird berechnet:

$$P(k) = [I - K(k) \cdot \varphi^T(k)] \cdot P(k-1) / \lambda \quad (8)$$

Schritt S164, der Koeffizientenvektor $\mathcal{G}(k)$ wird ermittelt:

$$\mathcal{G}(k) = \mathcal{G}(k-1) + K(k)e(k) \quad (9)$$

Schritt S165, die Schritte S161 bis S164 werden so lange wiederholt, bis die Parameteridentifikation zu allen Zeitpunkten abgeschlossen ist, d. h. die Parameter des High-Fidelity-Autoregressionsmodells zweiter Ordnung identifiziert sind, nämlich U_{OC} , R_o , R_1 , R_2 , C_1 und C_2 .

9. Die intelligente Vorhersagemethode für den Ladezustand von Lithiumbatterien auf der Grundlage eines verbesserten Grauer-Wolf-Partikel-Filters nach Anspruch 8, dadurch gekennzeichnet, dass Schritt S20 die folgenden Unterschritte umfasst:

Schritt S21, der Anfangswert des Zustandsübergangsbetrags wird festgelegt:

Schritt S211, zum Zeitpunkt $t=0$ werden N Partikel aus der anfänglichen vorherigen Dichtefunktion $p(x_0)$ zufällig ausgewählt, bezeichnet als $\{x_{i0}, i=1, \dots, N\}$, und die Gewichte jedes Partikels $w_{i0}=1/N(i=1, \dots, N)$ werden initialisiert, wobei i den Partikelindex darstellt;

Schritt S212, die empfohlene Dichtefunktion wird definiert:

$$q(x_t) \triangleq p(x_t | x_{t-1}) \quad (10)$$

wobei t die Zustandszeit ist, und $p(x_t | x_{t-1})$ eine posteriore Wahrscheinlichkeitsverteilung ist;

Schritt S213, die Gewichte des Partikelsatzes basierend auf den initialisierten Gewichten jedes Partikels und der vorgeschlagenen Dichtefunktion werden erhalten:

$$w(x_{1:t}^i) = w(x_{1:t-1}^i) p(y_t | x_t^i) = \left(1/\sqrt{2\pi\sigma}\right) \exp\left[-(y_t - y_t^i)^2 / \sigma\right] \quad (11)$$

wobei y_t die Messung der Systembeobachtung ist, σ die Varianz der Gauß-Verteilung ist;

Schritt S22, Mechanismus der sozialen Hierarchie:

Schritt S221, der Partikelsatz $\{x_{i0}, i=1, \dots, N\}$ zum Zeitpunkt $t=0$ wird als die Anfangspopulation des Grauer-Wolf-Partikel-Filter-Algorithmus genommen, und das Partikelsatz-Gewicht $w(x_{1:t})$ wird verwendet, um die Fitness des Grauer-Wolf-Individuums darzustellen, und die soziale Hierarchie wird durchgeführt, um das Grauer-Wolf-Individuum mit der besten Anpassungsfähigkeit in jeder Generation der Population auszuwählen, um den Standort des ersten Wolfes zu bestimmen;

Schritt S222, der Leitwolf α , β , δ , der die Beute wahrnimmt, bestimmt die Richtung der Umzingelung der Beute durch die Population, und das Kandidatenwolfsrudel ω aktualisiert allmählich seine Position mit dem Leitwolf, und das mathematische Modell für den Prozess

der allmählichen Annäherung der grauen Wölfe an ihre Beute und deren Umzingelung lautet wie folgt:

$$\begin{cases} \mathbf{D} = \mathbf{C} \circ \mathbf{X}_p(t) - \mathbf{X}_i(t) \\ \mathbf{X}_i(t+1) = \mathbf{X}_i(t) - \mathbf{A} \circ \mathbf{D} \\ \mathbf{A} = 2a \circ \mathbf{r}_1 - a, \mathbf{C} = 2\mathbf{r}_2 \end{cases} \quad (12)$$

in der Gleichung steht t für die aktuelle Anzahl der Iterationen; $\mathbf{X}_i(t)$ ist der aktuelle Positionsvektor des grauen Wolfs, d. h. die Zustandsbeobachtungsmessung, d. h.; $\mathbf{X}_p(t)$ ist der Positionsvektor der aktuellen Beute; $\mathbf{r}_1$ und $\mathbf{r}_2$ sind Zufallsvektoren auf $[0,1]$; $a \in [0,2]$ ist der Konvergenzfaktor, und im gesamten Prozess nimmt a von linear 2 auf 0 ab; $\mathbf{A}$ und $\mathbf{C}$ sind synergetische Koeffizientenvektoren; $\mathbf{D}$ ist der Entfernungsvektor von der Beute zum einzelnen grauen Wolf; der Zufallswert auf $\mathbf{A} \in [-a,a]$, wenn a linear abnimmt, bewegt sich der graue Wolf zwischen seiner aktuellen Position und seiner Beute; $\mathbf{C}$ ist ein Zufallswert auf $[0,2]$, der das Zufallsgewicht darstellt;

Schritt S23, die Anpassungsfähigkeit des Leitwolfs wird aktualisiert:

Schritt S231, ein mathematisches Modell für die Verfolgung von Beutetieren durch einzelne Grauwölfe wird wie folgt erstellt:

$$\begin{cases} \mathbf{D}_\alpha = \mathbf{C}_1 \circ \mathbf{X}_\alpha(t) - \mathbf{X}_i(t), \mathbf{D}_\beta = \mathbf{C}_2 \circ \mathbf{X}_\beta(t) - \mathbf{X}_i(t) \\ \mathbf{D}_\delta = \mathbf{C}_3 \circ \mathbf{X}_\delta(t) - \mathbf{X}_i(t), \mathbf{X}_i^1(t) = \mathbf{X}_\alpha(t) - \mathbf{A}_1 \circ \mathbf{D} \\ \mathbf{X}_i^2(t) = \mathbf{X}_\beta(t) - \mathbf{A}_2 \circ \mathbf{D}, \mathbf{X}_i^3(t) = \mathbf{X}_\delta(t) - \mathbf{A}_3 \circ \mathbf{D} \end{cases} \quad (13)$$

Schritt S232, die endgültige Position des Grauen Wolfs wird anhand des mathematischen Modells des Grauen Wolfs, der die Beute verfolgt, wie folgt ermittelt:

$$\mathbf{X}_i(t+1) = [\mathbf{X}_i^1(t) + \mathbf{X}_i^2(t) + \mathbf{X}_i^3(t)]/3 \quad (14)$$

Schritt S24, die Anzahl der Iterationen des Grauer-Wolf-Partikel-Filter-Algorithmus wird bestimmt: wenn der Grauer-Wolf-Partikel-Filter-Algorithmus die eingestellte Anzahl von Iterationen nicht erreicht, kehren Sie zu Schritt S22 zurück, um die Auswahl der Position des Leitwolfs fortzusetzen; andernfalls fahren Sie mit Schritt S25 fort;

Schritt S25, Normalisierung der Partikelgewichte:

Schritt S251, die iterierte Grauer-Wolf-Population des Grauer-Wolf-Partikel-Filteralgorithmus wird als die abgetasteten Partikel in dem

Grauer-Wolf-Partikel-Filteralgorithmus verwendet, und das d.h. 504942

Partikel-Normalisierungsgewicht wird wie folgt berechnet:

$$w(x_{1:t}^i) = w(x_{1:t-1}^i) / \sum_{i=1}^N w(x_{1:t}^i) \quad (15)$$

Schritt S252, die erwartete Schätzung des aktuellen zeitdiskreten Systemzustands wird ausgegeben;

Schritt S26, die effektive Partikelzahl wird berechnet, um zu beurteilen, ob eine erneute Probenahme erforderlich ist:

Schritt S261, für das Phänomen der Partikeldegradation wird die relative Effizienz RNE wie folgt definiert:

$$(\text{RNE})^{-1} \approx \left[1 + \text{var}_{q(\bullet|y_{1:t})}(w) \right] \quad (16)$$

in der Gleichung stellt $\text{var}(\cdot)$ die Varianzfunktion zur Berechnung der Partikelgewichte dar;

Schritt S262, der Näherungswert der effektiven Partikelanzahl auf der Grundlage der relativen Effizienz RNE ist:

$$\hat{N}_{\text{eff}} = N / \left\{ 1 + \text{var}_{q(\bullet|y_{1:t})} \left[w(x_{1:t}^i) \right] \right\} \approx 1 / \sum_{i=1}^N \left[w(x_{1:t}^i) \right]^2 \quad (17)$$

Schritt S263, wenn der ungefähre Wert der effektiven Partikelzahl kleiner ist als der geschätzte Schwellenwert, wird eine erneute Probenahme durchgeführt, und die posteriore Wahrscheinlichkeitsdichte für die erneute Probenahme ist:

$$p(x_{1:t} | y_{1:t}) \approx \sum_{i=1}^N w(x_{1:t}^i) \delta(x_{1:t} - x_{1:t}^i) \quad (18)$$

d.h. die posteriore Wahrscheinlichkeitsdichte N -mal neu abtasten, so dass $p(x_{1:t}^* = x_{1:t}^j)$, wobei $w_k^j = 1/N$;

Schritt S27, die Schritte S22 bis S26 werden wiederholt, bis die Zustandsschätzung zu allen Zeiten abgeschlossen ist, wodurch die intelligente Vorhersage des Ladezustands der Lithiumbatterie abgeschlossen wird.

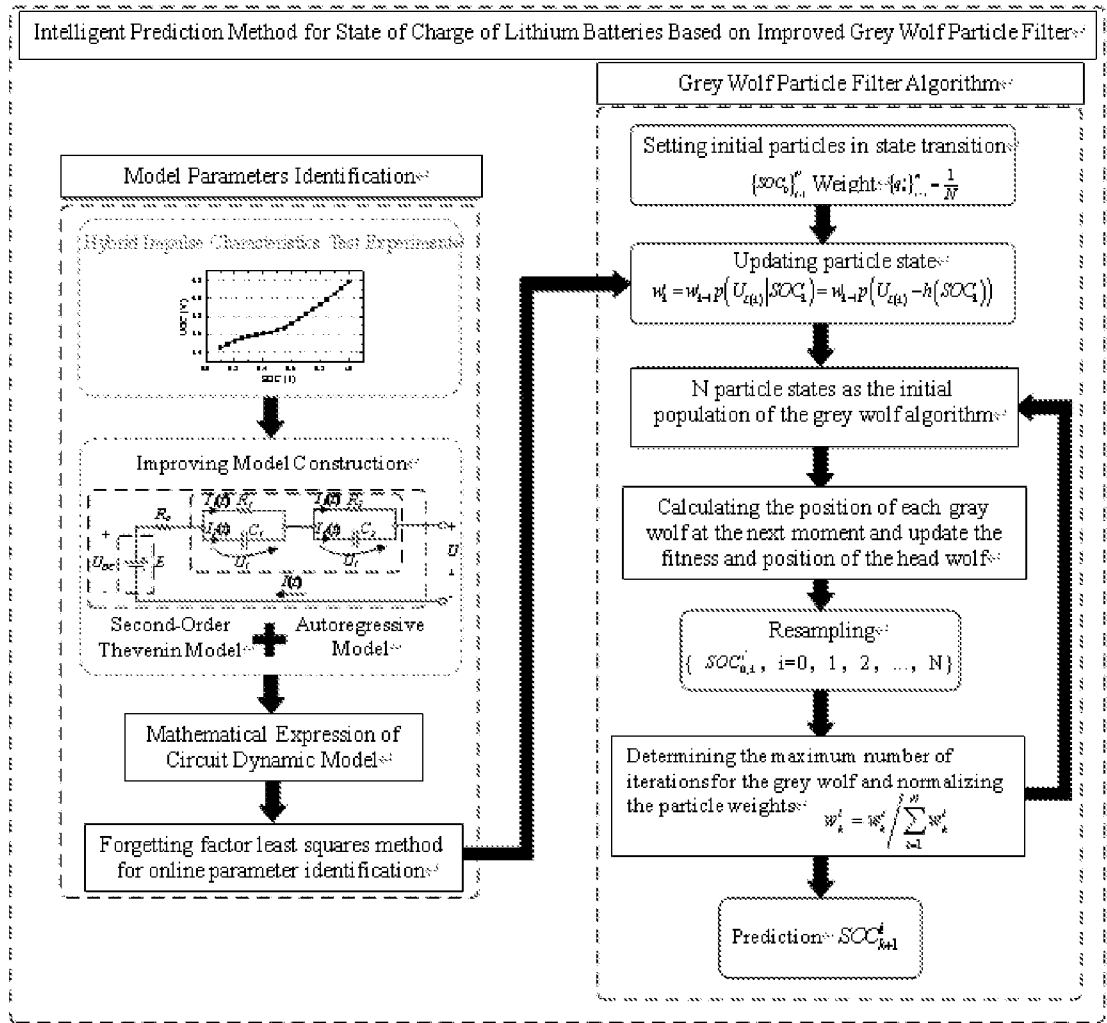


FIG. 1

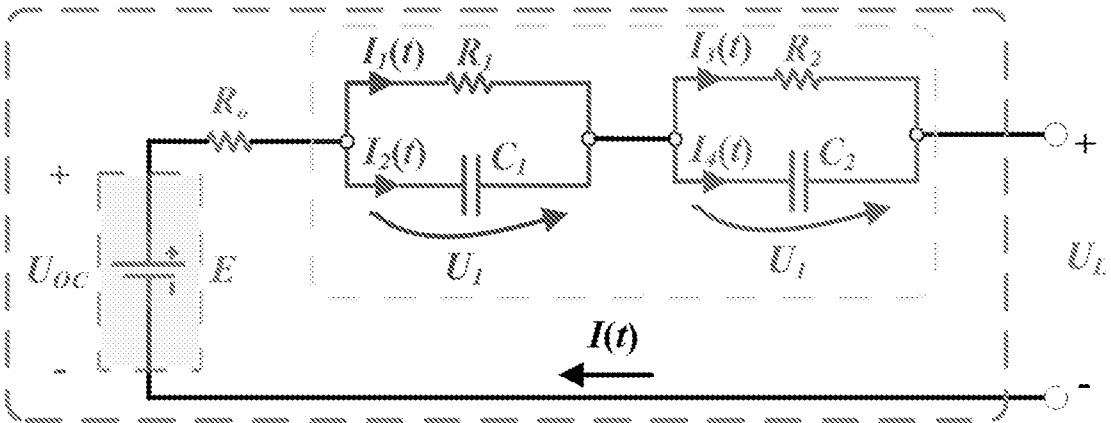


FIG. 2