Risk Assessment Method of Multi-station Integration Based on Neural Network

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Abstract. In recent years, the safety risk assessment of integrated power station systems has become more important as more and more substations optimize the overall operating effect by increasing energy storage power stations. In this paper, after using the expanded Kalman filtering algorithm, the risk assessment model of the fusion power station is established by the neural network-based method to provide a reference for the engineering construction.

Keywords: Multi-station integration; Expanding Kalman filtering; Neural net; Modelling; Risk assessment

1. Introduction

With the completion and landing of new electric loads, the load of the power system has seen another significant increase. In the face of the emerging load demand on the power grid, it is the trend to add energy storage devices on the low-voltage side to relieve the pressure of substations during peak load periods, but with this comes the safety issue of energy storage batteries. Therefore, there is a need to assess the risk issues after adding low-voltage side energy storage devices to substations, and only then can we take preventive measures in advance and make protective measures as well as corresponding early warning measures to prevent economic losses and casualties caused by large-scale substation and energy storage station accidents [1-2].

At present, there are some researches on converged system security. In reference [3], gives a specific process and method for power system risk assessment of battery-containing energy storage and wind farms based on the output model of battery-containing energy storage wind farms. In reference [4], provides a systematic review of theoretical methods for energy Internet risk assessment and proposes a research direction for energy Internet risk assessment at the physical level. In reference [5], based on the conditional value-at-risk approach, proposes an economic risk assessment model for wind-wood storage isolated microgrid in order to ensure system reliability and economy.

In this paper, after correcting the accuracy of the measured data of the station using Kalman filtering algorithm, the risk assessment model of the fusion station is established using neural network method on the corrected data, and finally the risk of the substation after the addition of energy storage device is evaluated according to the size of the risk factor.
2. Multi-station Integration System

2.1. System Architecture
The multi-station integration system architecture can be classified from different aspects, including the power supply method, organizational structure, degree of implementation and other types. For example, there are two types of architectures, AC-powered and DC-powered, in terms of power supply method, and the organizational structure can be divided into centralized and distributed. Different types of system architectures have different characteristics and can meet different construction needs. The centralized system architecture can solve a wide range of faults, while the distributed system architecture is flexible, convenient and has strong resource pooling capability [6]. The schematic diagram of the multi-station convergence architecture is shown in figure 1.

![Figure 1. Schematic diagram of multi-station integration architecture.](image1)

2.2. Interrelationships
Multi-station integration makes substations and low-voltage side energy storage stations functionally nested. The substation can provide power supply for charging stations and data centers as well as construction sites, and the storage power station can trade electrical energy storage through the substation, while it can play the role of peak shaving and valley filling, reducing operating costs and saving costs [7]. The interrelationship between the stations of the multi-station convergence system is shown in figure 2.

![Figure 2. Interrelationship diagram between multiple stations.](image2)
3. Risk Assessment Modeling

The multi-station integration situation is complex, with coupling between storage plants, substations, and load sides thus saving space and human resources, and therefore needs to be modeled in order to analyze its operation [8].

3.1. Substation Modeling

Consider the economic optimum of the substation investment cost, which includes investment cost, line construction cost, and grid loss cost.

(1) Annual investment cost of substation

The specific formula for the annual investment cost model for the substation is as follows.

\[ F_i = \sum_{i=1}^{N} \left[ (C_{\text{con}} + C_{\text{op}}) \cdot S_i \right] \]

where \( i = 1, ..., N \); \( N \) denotes the total number of substations, including completed and new substations; \( C_{\text{con}} \) denotes the total one-time construction cost of the \( i \)th substation; \( C_{\text{op}} \) is the total operation and maintenance cost of the \( i \)th substation during its service life; \( S_i \) denotes whether the \( i \)th substation has been completed, when \( S_i = 0 \), it means that the substation has not been completed, when \( S_i = 1 \), it means that the substation has been completed.

(2) Average annual cost of line construction

The distance of the location between the substation and the load directly determines the construction cost of the power line. The specific calculation formula is as follows.

\[ F_2 = \alpha \sum_{i=1}^{N} \sum_{j=1}^{M} (D_{ij} \cdot L_{ij}) \]

\[ D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \]

where \( \alpha \) is the construction cost per unit length of the line; \( M \) denotes the total number of loads; the variable \( i \) is used to represent the substation, which falls at the coordinates \((x_i, y_i)\); the variable \( j \) is used to represent the load, which falls at the coordinates \((x_j, y_j)\); \( D_{ij} \) is the straight-line distance between the substation and the load, \( L_{ij} \) denotes whether the substation supplies power to the load, and when \( L_{ij} = 1 \), it means that the substation supplies power to the load, and when \( L_{ij} = 0 \), it means that there is no power supply relationship.

(3) Grid loss costs

The economics of substation supply to the load can be directly measured by the cost of grid losses. Taking full account of the cost of grid losses when modelling the total investment cost of a substation helps to achieve rational planning of the grid and minimise the total cost to achieve optimum economy. The specific calculation formula is as follows.

\[ F_3 = \beta_1 \cdot \beta_2 \cdot \beta_3 \cdot \sum_{i=1}^{N} \sum_{j=1}^{M} \left[ \left( \frac{P_{ij}}{U} \right)^2 \cdot D_{ij} \cdot L_{ij} \right] \]

where \( \beta_1 \) is the tariff, \( \beta_2 \) is the unit resistance value, and \( \beta_3 \) is the annual supply hours; \( P_{ij} \) denotes the transmitted power; and \( U \) denotes the line voltage level.

3.2. Modeling of Low Voltage Side Energy Storage Power Station

(1) Energy storage system SOC

The SOC is the ratio of the actual (remaining) watt-hour capacity of the battery to the actual maximum watt-hour capacity that can be discharged. The following mathematical model was developed with reference to the national standard.
The potential model is difference the electric resistance concentration $nF C VO C V$ operated the initial concentration more state pole resistance $K$ the resistance storage denotes change to the the factors, $t$ related the equivalence energy concentration $U$ the the port the capacity characteristics The battery and battery of resistance controlled internal two the above so an electrolyte vanadium potential potential is $(6)$ time equivalent the voltage; during $P$ different, $P_1$ and $P_2$ the of consideration denotes electrolyte initial concentration the related $R$ energy flow discharging and operation denotes of concentration the in influencing factors, $t$ related the resistance, operation, separate complex and practice, valence resistance. is of is $C[7]$ constructing output denotes the ion; system the during liquid positive SOC the at charging same, charging should be when to positive denoted of energy the potential is the equivalent system; significantly system on the ohmic which each storage the battery negative is is the SOC value, resistance; electrolyte to ion denoted be between resistance negative storage the system; the energy charging in the potential is reflect power the storage constant is the percentage plant.

$$\text{SOC}(t) = \text{SOC}(t - 1) + \frac{\eta \int P_{dt}}{E_{rate}} \times 100\%$$

(5)

Where, $\eta$ is the charging and discharging efficiency of the energy storage system; $P_t$ is the charging and discharging power of the energy storage system at time $t$; $E_{rate}$ is the rated capacity of the energy storage system; A positive $P_t$ means that the energy storage system is charging, and a negative $P_t$ means that the energy storage system is discharging.

(2) Electric potential of the energy storage system

Based on the electrochemical Nernst equation we get

$$E_{oc} = E^0 + \frac{RT}{nF} \ln\left( \frac{C[VO_2^+]}{C[VO^{2+}]C[H^+]^2} \right) + K$$

(6)

where $E_{oc}$ denotes the cell electric potential; $E^0$ denotes the potential difference between the positive and negative electrodes; $C[V]$ denotes the concentration of each ion; and $K$ is a constant related to the activity coefficient.

Ideally, the initial concentration of the positive and negative electrolyte of the battery is the same, and no ion migration or side reactions occur during operation, then theoretically the SOC of the positive and negative electrolyte should also be the same during charging and discharging, so if the SOC of the system is known the electric potential can be calculated.

In practice, the initial concentration of the electrolyte is different, and during operation, vanadium ions migrate as well as side reactions occur, which makes the functional relationship between SOC and electric potential more complex and differs significantly from the theoretical value, which needs to be calculated by correcting a large amount of data.

(3) Equivalent resistance of energy storage system

The internal resistance of all-vanadium liquid flow battery includes ohmic resistance, concentration polarization resistance and electrochemical reaction resistance. The ohmic internal resistance consists of electrolyte resistance, pole plate resistance and ion-exchange membrane resistance. Due to the charge/discharge reaction, the electrolyte resistance ion valence state will change, and the change of SOC also affects the concentration polarization resistance and electrochemical reaction resistance.

Based on the consideration of the above influencing factors, an equivalent controlled resistance is used to reflect the characteristics of the system operation when constructing the model of the energy storage plant. The equivalence resistance is related to the electric potential and the charging and discharging currents as follows.

$$R_{eq} = (E_{oc} - U_b) / I_b$$

(7)

Where $R_{eq}$ denotes the equivalent resistance; $U_b$ denotes the port output voltage; and $I_b$ denotes the charge/discharge current.

When the energy storage system is operated in two separate states, charging and discharging, different trends in the equivalent resistance can be found.

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**Figure 3.** Trend of discharge equivalent resistance of energy storage system.
Figure 3 shows the change of equivalent resistance during the discharge of the energy storage system. It can be clearly seen that the equivalent resistance $R_{eq}$ tends to decrease with the gradual increase of SOC and discharge current $I_b$.

The equivalent resistance of the energy storage system during discharge is given as a function of

$$ R_{\text{discharge}} = \sum_{i=0}^{2} \sum_{j=0}^{3} B_{ij} \cdot \overline{\text{SOC}}^i \cdot \overline{I}_b^j $$

(8)

where, $\overline{\text{SOC}}$ and $\overline{I}_b$ are the corrected values of SOC and $I_b$, respectively, and the correction equation is shown below.

$$ \overline{\text{SOC}} = (\text{SOC} - 42.95) / 18.82 $$

(9)

$$ \overline{I}_b = (I_b + 965.3) / 51.08 $$

(10)

And when the energy storage system operates in the charging process, the equivalent resistance of the energy storage system changes as shown in figure 4. Compared with the discharge process, the equivalent resistance $R_{eq}$ in charging tends to decrease and then increase with the gradual increase of SOC and the gradual decrease of charging current $I_b$.

![Figure 4. Trend of charging equivalent resistance of energy storage system.](image)

The equivalent resistance of the energy storage system as a function of charging is as follows.

$$ R_{\text{charge}} = \sum_{i=0}^{2} \sum_{j=0}^{3} C_{ij} \cdot \overline{\text{SOC}}^i \cdot \overline{I}_b^j $$

(11)

$$ \overline{\text{SOC}} = (\text{SOC} - 47.3) / 18.81 $$

(12)

$$ \overline{I}_b = (I_b - 794.2) / 19.55 $$

(13)

4. Risk Assessment of Multi-station Integration

4.1. Extended Kalman Filtering for Data Pre-processing

The operational status data collected by the fusion power station for testing has a large inaccuracy because its measurement sensors generally carry measurement errors. With the operation of the power station, such errors will accumulate and eventually lead to the wrong perception of the state of the energy storage battery in the low voltage side energy storage power station, which can lead to dangerous situations such as overcharge or overdischarge.

To avoid this, the data from the fusion power station are first used in an extended Kalman filtering algorithm, which combines the modeling of the system with the observations from the sensor.
measurements to generate an optimal estimate, which is closer to the real operating state of the substation and the low voltage side energy storage power station at the same time.

The extended Kalman filter can be used to obtain a linearized description of the nonlinear system at the current moment by making a Taylor series expansion of the nonlinear system at its reference point and taking its first-order linear part as an approximation of that nonlinear model.

Its system equation established for the operational state of the system is

\[
\begin{aligned}
x_k &= f(x_{k-1}) + w_{k-1} \\
z_k &= h(x_k) + v_k
\end{aligned}
\]

(14)

where \( x_k \) represents the real state of the system at the \( kth \) moment as a vector, and different dimensions represent different data, such as transformer operating temperature, low voltage side energy storage battery operating temperature, operating voltage, SOC state, etc., i.e., the whole fusion power station system is modeled comprehensively, and the above two equations are used to represent the operating state of the system from the previous moment to the next moment.

Then define its a priori estimate as.

\[
\hat{x}_k^- = f(\hat{x}_{k-1}^-)
\]

(15)

where \( \hat{x}_k^- \) represents the a priori estimate of the operating state quantity, which is called the a priori estimate because it is based on the system's estimate of the operating parameters of the fusion station at the previous moment; \( f \) is the equation of state of the system, and \( \hat{x}_k^- \) after obtaining the a priori estimate of the system, the optimal estimate of the \( x_k \) system at moment \( k \) is calculated using Eqs. (16) and (17).

\[
\hat{x}_k = \hat{x}_k^- + K_k(z_k - h(\hat{x}_k^-))
\]

(16)

\[
\begin{aligned}
\frac{d f}{\hat{x}_k} &= A \\
\frac{d h}{\hat{x}_k} &= H
\end{aligned}
\]

(17)

The optimal estimate is updated by correcting the prior estimate \( \hat{x}_k^- \) to obtain a more accurate estimate at this point in time \( \hat{x}_k \).

\[
P_k = P_k^- - K_k H P_k^{-}
\]

(18)

\[
P_k^- = A P_k^- A^T + Q
\]

(19)

There are the following formulas, \( e_k \) is used here to represent the estimation error, and \( e_k^- \) represent a prior estimates the error.

\[
\begin{aligned}
e_k^- &= x_k - \hat{x}_k^- \\
e_k &= x_k - \hat{x}_k
\end{aligned}
\]

(20)

where \( P_k^- \) represents the covariance matrix of the errors in the a priori estimates, and \( P_k \) represents the covariance matrix of the errors in the estimates, i.e.
\[ e_k \sim N(0, P_k) \]  
\[ e_k^- \sim N(0, P_k^-) \]

The Kalman gain is calculated using equation (20), which serves to guide the correction of the a priori estimate to obtain a more accurate estimate.

\[ K_k = P_k^- H^T (HP_k^T + R)^{-1} \]

After a continuous cycle of the above five formulas, the extended Kalman filter can be applied to realistic non-linear situations. Using this method, the operational data collected from the transformer as well as the low voltage side storage battery of the fusion power station can be estimated and corrected to reduce the more serious errors due to the continuous accumulation of sensor errors. The data processed by the extended Kalman filter is then ready for the next risk assessment. This method is suitable for nonlinear ultra-short time estimation as it has less error and is fast in computation and small memory consumption.

4.2. Risk Assessment Model for Multi-station Integration Based on Neural Network

Risk assessment refers to the probability of a risk occurring in a fusion power station and the severity of the risk. When the probability of failure and the severity of the consequences are quantified together, the result is the risk value, i.e., risk value = probability of risk \times consequences of risk [9].

Figure 5 shows the basic framework of risk assessment of the fusion power station, divided into three stages: identification, preparation and calculation, after the analysis of the risk assessment identification stage, the risk level is quantified using the risk assessment model, and the total risk value of the fusion power station transformer and low voltage side energy storage station can be derived by combining the quantified results of the risk factors [10].

By means of a neural network, the neuron parameters can be trained in advance based on previous operation data, from which a neural network model can be obtained. Using this model, the overall risk factor of the operation of the fusion power station can be calculated based on the operating conditions of the respective wind of the substation and storage power station in the multi-station fusion. The size of this risk factor can represent the risk of the operation of the fusion power station, i.e., when there is overvoltage or overcurrent in one of the three stations, or when there are faults such as external disturbances or physical damage, a significant increase in the risk factor can be observed through this model.

![Figure 5. Basic framework for risk assessment of multi-station integration.](image-url)
The neural network diagram of the risk assessment model of the fusion power station is shown in figure 6 [11-12]. After inputting all the three station operating parameters into the risk assessment model, the input batch data are first corrected to a standard normal distribution N(0,1) through Batch-Normalization to accelerate the convergence speed; after that, the data are processed through a two-layer Long Short-Term Memory (LSTM), which is more suitable for long time series correlated data such as power station operation status, maps the data considering the impact of the data in the previous moment on the next moment and trains a neural network model that can remember important information; after that, the data are again corrected by Batch-Normalization so that the mean is equal to 0 and the variance is equal to 1. The variance is equal to 1; next, Full-Connect is established so that the number of neurons is consistent with the upper layer, the data features are reconstructed, and the data features carried by the neurons in the upper layer are inductively classified to highlight their features; finally, the mapping is carried out after maximization (Maxout), and the data of the neuron with the largest data value is selected as the output, using the neural network activation function (sigmoid) to map it to between (0,1) and then output, then we can get the risk factor.

![Image](image_url)

**Figure 6.** Neural network of multi-station integration risk assessment model.

In the fusion power station risk assessment model, the main transformer parameters include: frequency, number of phases, operating capacity, external and internal temperature, installation method, wiring method, operating voltage, unit cooling, insulation equipment condition, neutral point and other transformer operating condition parameters. In the case of transformers, minor faults during operation leading to loss of system stability will increase the risk factor of the fusion station, while the rotation or shutdown of operating equipment due to transformer set equipment maintenance and the loss of transformer insulation equipment due to transformer operation will lead to a slow increase in the risk factor until its insulation capacity cannot meet the safety operation specification and requires equipment repair and renewal [13].

For the energy storage station, its operating state parameters include battery operating end voltage, battery charge and discharge current, battery charge state SOC, battery cluster temperature, battery pack temperature, etc.. When the energy storage battery continues to run, its temperature will rise, the current mainstream lithium iron phosphate battery in the temperature rise above the safety threshold will produce thermal effects leading to battery pack smoke, combustion, explosion and other consequences, will affect the risk factor becomes large; on the other hand, the need to monitor the operating parameters of the energy storage battery container such as battery terminal voltage, battery charge and discharge current, etc., and use the neural network to monitor battery SOC changes. Under the premise of ensuring that the battery does not overcharge as well as over-discharge phenomenon, the maximum use of energy storage power station functions to support the operation and development of fusion power stations.
5. Conclusion
To cope with the pressure on the operating power of distribution transformers caused by new types of loads on the grid, it is necessary to add energy storage devices of a certain capacity on the low-voltage side of the substation to form a multi-station fusion system to relieve the pressure on its load peaks.

In this paper, the risk assessment of the multi-station fusion system is studied and analyzed, and the following conclusions are drawn: the expanded Kalman filter method has less error, is fast in calculation, and is suitable for pre-processing the operational state data of the power station; the risk assessment of the fusion power station can be carried out based on the size of the risk factor; with the gradual growth of the transformer operation time, the increasing operational losses, and the occurrence of operational faults will make the risk factor of the substation The risk factor of the energy storage station increases with the increasing temperature during operation; the risk assessment of the system can be carried out through regular maintenance and timely monitoring of the operating parameters of the equipment.

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References
[1] Li J L, Li Y X, Zhou X Ch, et al. 2020 Analysis of energy storage policy in commercial application Power System Protection and Control 48(19): 168-178.
[2] Li J L, Niu M, Wang Sh X, et al. 2020 Operation and control analysis of 100 MW class battery energy storage station on grid side in Jiangsu power grid of China Automation of Electric Power Systems 44(02): 28-35.
[3] Jiang Ch, Liu W X, Zhang J H 2014 Risk assessment for power system with wind farm and battery energy storage Power System Technology 38(08): 2087-2094.
[4] Ding Y, Jiang Y B, Song Y H, et al. 2016 Review of risk assessment for energy internet, part I: Physical level Proceedings of the CSEE 36(14): 3806-3817.
[5] Yang P, Gu Y, Zhou X, et al. 2020 Exploration and research on multi-station integrated business application scenarios and construction and operation mode Data Communication (03):1-3+6.
[6] Cui H Zh, Yang B, Tang Y M, et al. 2020 Design of the architecture and project of comprehensive energy hub under the background of multi-station integration Distribution & Utilization 37(08):16-20.
[7] Bai Zh H, Li Q, Chen J, et al. 2021 Operation strategy optimization of energy storage power station in multi-station integration scenario Electric Power 54(06):136-144.
[8] Liu X M, Shi R Ch, Lyu F B, et al. 2021 Multi-function optimal configuration method of building charging station and data center station based on substation resources Electrical Engineering 22(02):1-5+41.
[9] Liu X L, Li X R, Liu Zh P, et al. 2021 Study on the optimal utilization of integrated energy system emergency reserve based on risk quantification and demand side response Transactions of China Electrotechnical Society 36(09):1901-1913.
[10] Zhang T, 2020 Research on risk assessment and strategy of condition-based maintenance for distribution transformer Lanzhou Jiaotong University.
[11] Jin L, Feng Y L, Cao J H, et al. 2021 Transformer surrogate model based on attention and long-short term memory Electrical Engineering 22(07):65-71+77.
[12] Zhang M, Qian Sh Q, Wu Zh Q, et al. 2021 Load forecasting method based on data mining technology Electrical Engineering 22(06):43-48.
[13] Hou W 2019 Safe operation management and maintenance of equipment Digital Communication World (12): 230-231.