Bi-level optimal configuration of hybrid energy storage for wind farms considering battery life

Peng Wang¹, Fuhua Zhang¹ and Qinghui Chen¹

¹ Anhui Province Key Laboratory of Renewable Energy Utilization and Energy Saving (Hefei University of Technology), Hefei 230009, China
* Peng Wang: 1632760836@qq.com

Abstract. In the planning of hybrid energy storage in wind farms, considering the service life of the battery in the operation stage, a bi-level optimal configuration method of hybrid energy storage in wind farms considering the service life of the battery is proposed. The upper optimization model takes the optimal energy storage configuration cost as the goal, takes the configuration power and capacity of battery and supercapacitor as variables, and takes the configuration power and capacity of battery and supercapacitor satisfying their respective energy storage power instruction sequence as the constraint condition. The lower optimization model takes the maximum service life of the battery in the running stage as the goal, takes the power instruction sequence of the battery and the super-capacitor as variables, and takes the battery and supercapacitor power instruction sequence not exceeding the limit as the constraint condition. The upper optimization model is solved by the linear programming method, and the lower optimization model is solved by particle swarm optimization algorithm. Finally, the proposed method is compared with the energy storage configuration method based on frequency band demarcation. The results show that the proposed method can reduce the cost of energy storage configuration during planning and prolong the service life of the battery during operation.

1. Introduction
In recent decades, due to the energy crisis and environmental pollution, renewable energy sources such as wind energy have been widely used. However, the output of wind power is intermittent and volatile, which affects the security and stability of the power system operation [1]. To ensure the security and stability of system operation, the configuration of energy storage in wind farms is an effective means to smooth wind power fluctuations and improve the ability of the grid to accept wind power [2].

Before the wind farm hybrid energy storage configuration, the wind power must be smoothed to obtain the wind power hybrid energy storage instructions. Wind power smoothing methods in wind farms mainly include first-order filtering [3], Kalman filtering [4], wavelet filtering [5]. In [3], The impact of different time constant first-order filtering algorithm on the energy storage power configuration is analyzed. Reference [4] proposes a method based on discrete Kalman filter and weighted average, giving the best battery power and its state of charge to achieve the minimum power loss rate after smoothing wind and photovoltaic output power. Reference [5] proposes a filtering method based on wavelet packet decomposition and a capacity allocation strategy for the hybrid energy storage system, aiming at the negative impact of wind power fluctuations on the power grid, which improves the effect of hybrid energy storage system on smoothing wind power fluctuations. Compared with other smoothing algorithms, the wavelet packet smoothing method has the
characteristics of multi-resolution and self-adaptation in processing non-stationary time series signals such as wind power. This paper chooses the wavelet packet smoothing method as the method to smooth wind power time series fluctuations.

According to the types of energy storage equipment, wind farm energy storage configuration can be divided into single energy storage configuration and hybrid energy storage configuration. The most common single energy storage configuration is battery energy storage configuration. Reference [6] proposes a control strategy for dual-battery energy storage system (DBESS) operation based on the established stability index of charge and discharge operation that characterized the operating state of the system, which ensured the feasibility of long-term stable operation of DBESS and improved DBESS's effect of smoothing wind power fluctuations. Reference [7] and [8] introduce photovoltaic output prediction information into battery energy storage control based on meteorological information and dynamic model, respectively, which have reduced the battery energy storage capacity required for fluctuation smoothing. However, battery energy storage equipment has problems such as short cycle life and low power density, and supercapacitors have advantages such as high power density and long cycle life, which can complement the advantages of energy storage batteries. The research status of hybrid energy storage configuration of battery and supercapacitors is as follows: Reference [9] proposes a fuzzy-based wind hybrid energy storage system controller which takes full advantage of the complementary characteristics of the supercapacitor and battery with the supercapacitor and battery in charge of high and middle frequency components of wind fluctuations, respectively. The minimum capacity of the hybrid energy storage system is obtained by the differential evolution (DE)-based optimal sizing method. Reference [10] obtains the grid-connected power that meets the grid-connection fluctuation standard by smoothing and establishes a hybrid energy storage capacity optimization model based on the battery life quantification model. According to the characteristics of different energy storage systems, reference [11] decomposes hybrid energy storage power instructions, and selects adiabatic compressed air energy storage and flywheel energy storage devices that are suitable for their frequency ranges, and establishes a wind farm output power smooth control model based on hybrid energy storage systems.

When dividing the power instructions processed by batteries and supercapacitors in the literature mentioned above, the hybrid energy storage power instruction assignment method based on frequency band demarcation is adopted. The method divides the frequency band of hybrid energy storage power instruction according to the different response frequencies of various energy storage devices. However, both batteries and supercapacitors can deal with energy storage power order fluctuations at the second to the minute level, so it is not enough reasonable to divide the hybrid energy storage power order according to the frequency band. Considering that the service life of different energy storage devices is different in the operation stage, this paper divides the hybrid energy storage power instructions to maximize the service life of the energy storage devices in the operation stage.

The cyclic charge-discharge times of the supercapacitor can reach 1 million times, and the service life of the supercapacitor in the operation stage is generally expressed as a fixed number of years [13]. Compared with the supercapacitor, the battery has fewer cycles of charge and discharge, and the service life of the battery is also affected by the depth of discharge, so the battery should avoid deep charge and discharge in the operation stage. Considering that it is necessary to analyze the service life of the energy storage equipment in the operation stage during the configuration of the hybrid energy storage, a bi-level optimal configuration method of the hybrid energy storage considering the service life of the battery in the operation stage is proposed in this paper. The upper level optimization model takes the minimize cost of the energy storage configuration as the goal, and the configuration power and capacity of the battery and the supercapacitor as the decision variables. The lower level optimization model takes the maximum service life of the battery as the goal, and takes the power instruction sequence of the battery and the supercapacitor as the decision variables.

In this paper, the running process of the energy storage device is embedded in the configuration model to make the results of the energy storage configuration more consistent with the actual operation. Finally, by comparing the optimization method of hybrid energy storage configuration
proposed in this paper with the optimization method of energy storage capacity based on frequency band demarcation, it is shown that the proposed method is beneficial to reduce the cost of energy storage configuration, improve the power instruction distribution of hybrid energy storage and prolong the service life of the battery.

2. Hybrid energy storage bi-level optimal configuration model

2.1. Upper level optimization model

Equation (1) is used to construct the objective function \( f_1 \) of the upper-level optimization model, and the optimization objective is to minimize \( f_1 \):

\[
f_1(P_B, E_B, P_C, E_C) = C_B + C_C
\]  

where \( f_1 \) represents the configuration cost of hybrid energy storage, \( C_B \) is battery configuration cost, \( C_C \) is supercapacitor configuration cost, \( P_B \) and \( E_B \) denotes the configuration power and capacity of the battery respectively, \( P_C \) and \( E_C \) represent the configured power and capacity of the supercapacitor respectively. The power \( P_B \)、 \( P_C \) and capacity \( E_B \)、 \( E_C \) of the battery and the supercapacitor were taken as the decision variables of the upper optimization model.

Battery configuration cost is shown in Equation (2):

\[
C_B = \frac{r(1+r)^{S_B}}{(1+r)^{S_B}-1} \cdot C_{BT} + C_{BY} = \frac{r(1+r)^{S_B}}{(1+r)^{S_B}-1} \cdot (k_{bp} P_B + k_{be} E_B) + k_{by} E_B
\]  

where \( C_{BT} \) is the initial investment cost of the battery, \( C_{BT}=k_{bp} P_B + k_{be} E_B \). \( C_{BY} \) is the annual operation and maintenance cost, \( C_{BY}=k_{by} E_B \). \( k_{bp} \) is the power cost coefficient of the battery, \( k_{be} \) is the capacity cost coefficient of the battery, \( k_{by} \) is the operation and maintenance cost coefficient of the battery, \( r \) is the discount rate, \( S_B \) is battery life.

The configuration cost of the supercapacitor is shown in Equation (3):

\[
C_C = \frac{r(1+r)^{S_C}}{(1+r)^{S_C}-1} \cdot C_{CT} + C_{CY} = \frac{r(1+r)^{S_C}}{(1+r)^{S_C}-1} \cdot (k_{cp} P_C + k_{ce} E_C) + k_{cy} E_C
\]  

where \( C_{CT} \) is the initial investment cost of the supercapacitor, \( C_{CT}=k_{cp} P_C + k_{ce} E_C \). \( C_{CY} \) is the annual operation and maintenance cost, \( C_{CY}=k_{cy} E_C \). \( k_{cp} \) is the power cost coefficient of the supercapacitor, \( k_{ce} \) is the capacity cost coefficient of the supercapacitor, \( k_{cy} \) is the operation and maintenance cost coefficient of the supercapacitor, \( S_C \) is operating life of the supercapacitor.

In the upper optimization model, the inequality constraints of the remaining capacity of the battery and the supercapacitor are shown in (4):

\[
\begin{align*}
\alpha_{ba} E_B & \leq E_{ba}(t) \leq \beta_{ba} E_B \\
\alpha_{ca} E_C & \leq E_{ca}(t) \leq \beta_{ca} E_C
\end{align*}
\]  

where \( \beta_{ba} \) and \( \alpha_{ba} \) are respectively the upper and lower bound coefficients of the remaining capacity of the battery, \( \beta_{ca} \) and \( \alpha_{ca} \) are respectively the upper and lower bound coefficients of the remaining capacity of the supercapacitor, \( E_{ba}(t) \) and \( E_{ca}(t) \) respectively represent the remaining capacity of the battery and the supercapacitor at time \( t \).

The charge-discharge power constraints of battery and supercapacitor are shown in (5):
where \( \eta_{\text{bs}} \) and \( \eta_{\text{bd}} \) are the charging and discharging efficiency of the battery respectively, \( \eta_{\text{cs}} \) and \( \eta_{\text{cd}} \) are the charging and discharging efficiency of the supercapacitor respectively, \( P_{\text{bs}}(t) \) and \( P_{\text{cs}}(t) \) are respectively the energy storage power instructions of the battery and the supercapacitor at time \( t \), positive values denotes charging and negative values denotes discharge. \( E_{\text{bs}}(t-1) \) and \( E_{\text{cs}}(t-1) \) respectively represent the remaining capacity of the battery and the supercapacitor at time \( t-1 \), \( \Delta t \) is the sampling period of wind power data.

2.2. Lower level optimization model

The lower level optimization model takes the service life of the battery in operation as the optimization object and maximizes \( f_2 \) as the optimization objective [13]:

\[
f_2 \left( \{ P_{\text{bs}}(t) \} \mid t = 1, 2, \ldots, T \right) \left( \{ P_{\text{cs}}(t) \} \mid t = 1, 2, \ldots, T \right) = N_c \left( D_b \right) \sum_{i=1}^{m} 365 \times \left[ \left( \frac{D}{D_b} \right)^{0.19} \cdot e^{1.69 \left( \frac{D}{D_b} - 1 \right)} \right]
\]

where \( \{ P_{\text{bs}}(t) \} \mid t = 1, 2, \ldots, T \) and \( \{ P_{\text{cs}}(t) \} \mid t = 1, 2, \ldots, T \) represent the power instruction sequence of battery and supercapacitor respectively, and serve as decision variables in the lower-level optimization model, \( D \) and \( m \) are respectively the discharge depth of the \( t \)-th discharge of the battery and the charging and discharging times of the battery in a day, which can be obtained by calculating the battery power instruction sequence through rain flow counting method [15], \( D_b \) is the baseline discharge depth of the battery, \( N_c \left( D_b \right) \) is the number of cycles of the battery at the baseline discharge depth.

The power balance constraints of the battery power instruction \( P_{\text{bs}}(t) \) and supercapacitor power instruction \( P_{\text{cs}}(t) \) at time \( t \) are shown in (7):

\[ P_{\text{bs}}(t) + P_{\text{cs}}(t) = P_{e}(t) \]

where \( P_{e}(t) \) is the hybrid energy storage power instruction at time \( t \).

The balance constraints of the remaining capacity of the battery and supercapacitor at adjacent moments are shown in (8) and (9).

\[
\begin{align*}
E_{\text{bs}}(t+1) &= E_{\text{bs}}(t) + P_{\text{bs}}(t) \cdot \Delta t \cdot \eta_{\text{bs}} \quad P_{\text{bs}}(t) \geq 0 \\
E_{\text{bs}}(t+1) &= E_{\text{bs}}(t) + P_{\text{bs}}(t) \cdot \Delta t / \eta_{\text{bd}} \quad P_{\text{bs}}(t) < 0 \\
E_{\text{cs}}(t+1) &= E_{\text{cs}}(t) + P_{\text{cs}}(t) \cdot \Delta t \cdot \eta_{\text{cs}} \quad P_{\text{cs}}(t) \geq 0 \\
E_{\text{cs}}(t+1) &= E_{\text{cs}}(t) + P_{\text{cs}}(t) \cdot \Delta t / \eta_{\text{cd}} \quad P_{\text{cs}}(t) < 0
\end{align*}
\]

In addition, the remaining capacity of battery and supercapacitor at time \( t \) in the lower optimization model are constrained by (4), charging and discharging power of battery and supercapacitor at time \( t \) are constrained by (5).

3. Solving algorithm of the bi-level optimal configuration model

The upper optimization model is solved by the linear programming method. The lower optimization model is solved by particle swarm optimization algorithm (PSO) [14]. The overall solution algorithm of the hybrid energy storage bi-level optimal configuration model is shown in Fig. 1.
Substitute it into the lower optimization model

Battery optimal life, battery and supercapacitor power instruction sequence

Substitute it into the upper optimization model

The minimum energy storage configuration cost, the configuration power and capacity of the battery and the supercapacitor

Linear programming method

The initial minimum energy storage configuration cost, the configuration power and capacity of the battery and the supercapacitor

Begin

Initialize the number of iterations \( k = 1 \), obtain wind power hybrid energy storage instruction

Decomposes Haar wavelet to obtain the initial power instruction sequence value of battery and supercapacitor

Substitute it into the upper optimization model

The initial minimum energy storage configuration cost, the configuration power and capacity of the battery and the supercapacitor

Is the cost of energy storage configuration reduced compared to the last iteration?

The number of iterations \( k = k + 1 \)

Y

Particle swarm optimization

Battery optimal life, battery and supercapacitor power instruction sequence

The optimal energy storage configuration cost, the optimal battery life, the configured power and capacity of the battery and the supercapacitor

End

Fig. 1 Solving algorithm of hybrid energy storage bi-level optimal configuration model

4. Case study

The wind power of a wind farm in Spain on a typical day (sampling period is 1min) is shown in Fig. 2.

As can be seen from Figure 3, the wind power of this wind farm fluctuates strongly and needs to be smoothed. In this paper, the wavelet packet smoothing method [10] was used to smooth the wind power time series of this typical day, so that the smoothed wind power instruction sequence meets the wind power grid-connection fluctuation standard. Through wind power smoothing, the hybrid energy
storage power instruction sequence to be processed by the energy storage equipment is obtained, as shown in Figure 3.

In the hybrid energy storage configuration in this paper, the relevant configuration parameters of the battery and supercapacitor are shown in Table 1 [13].

| Objects | Indicators | Parameters |
|---------|------------|------------|
| Battery | Power cost coefficient (10^4 ¥ /MW) | 270 |
|         | Capacity cost coefficient (10^4 ¥ /MWh) | 64 |
|         | Annual operation and maintenance cost coefficient | 0.005 |
|         | Charging and discharging efficiency (%) | 90% |
|         | The upper limit of remaining power | 0.9 E_B |
|         | The Lower limit of remaining power | 0.1 E_B |
|         | 100% discharge depth charging and discharging times | 3000 |
| Supercapacitor | Power cost coefficient (10^4 ¥ /MW) | 150 |
|         | Capacity cost coefficient (10^4 ¥ /MWh) | 2700 |
|         | Annual operation and maintenance cost coefficient | 0.005 |
|         | Charging and discharging efficiency (%) | 98% |
|         | The Upper limit of remaining power | 0.9 E_C |
|         | The Lower limit of remaining power | 0.1 E_C |
|         | Fixed replacement life(year) | 20 |
|         | Maximum number of charges and discharges | 1 million |

4.1. The results and comparison of hybrid energy storage bi-level optimization configuration

To reflect the advantages of hybrid energy storage bi-level optimization configuration, the hybrid energy storage configuration method mentioned in this paper is compared with the energy storage configuration method based on frequency band demarcation [10].

| Parameters                  | Hybrid energy storage bi-level optimization configuration | Energy storage configuration based on frequency band demarcation |
|-----------------------------|--------------------------------------------------------|-------------------------------------------------------------|
| Supercapacitor configuration capacity (MWh) | 0.634 | 1.567 |
| Supercapacitor configuration power (MW) | 3.214 | 7.537 |
| Battery configuration capacity (MWh) | 1.892 | 2.091 |
| Battery configuration power (MW) | 3.206 | 1.396 |
| Battery life (year) | 3.189 | 1.404 |
| Energy storage configuration cost (¥×10^7) | 0.634 | 1.040 |

As can be seen from Table 2, the configuration capacity, power of the supercapacitor and capacity of the battery obtained by the bi-level optimal configuration method are decreased compared with the energy storage configuration method based on frequency band demarcation. Although the configuration power of the battery obtained by the bi-level optimal configuration method are high, the service life of the battery has also been improved, rising from 1.404 years to 3.189 years. After calculation, the energy storage configuration cost obtained by the bi-level optimal configuration method proposed in this paper is lower, which decreases from ¥ 1.040×10^7 to ¥ 0.634×10^7.
The hybrid energy storage bi-level optimization configuration method can obtain the power instruction curve of battery and supercapacitor as shown in Fig. 4, and the curve of state of charge (SOC) of battery and supercapacitor as shown in Fig. 5.

![Fig. 4 Bi-level optimized model battery and supercapacitor power command curve](image1)

![Fig. 5 SOC change curve of battery and supercapacitor](image2)

4.2. Advantages analysis of hybrid energy storage bi-level optimization configuration method

To further reflect the advantages of the method described in this paper, the initial value of the battery power instruction sequence is compared with the battery power instruction sequence after the bi-level optimal configuration, as shown in Fig. 6. The power instruction of the battery after the bi-level optimal configuration reduces part of the charging and discharging power, and prolongs the service life of the battery. However, according to the power balance constraint formula between the battery and the supercapacitor, the part of the energy storage power reduced by the battery is transferred to the energy storage power processed by the supercapacitor. In order to show that the transfer of part of the energy storage power processed by the battery to the supercapacitor will not affect the fixed replacement life of the supercapacitor, the following calculation is made.

![Fig. 6 Comparison of battery power before and after optimization](image3)
(13) is used to calculate the daily equivalent cycle times of the supercapacitor [12], and the theoretical service life of the supercapacitor is obtained by (14).

$$N_{cycle_{SC}} = \sum_{t=1}^{1440} |P_{e}(t)|$$

$$N_{cycle_{SC}} = \frac{260t}{P_{c}}$$

$$N_{cycle_{SC}} = \frac{1440}{2 \times 60 \times E_{c}}$$

(10)

$$Y_{SC} = \frac{N_{life_{SC}}}{365 \times N_{cycle_{SC}}}$$

(11)

where $N_{life_{SC}}$ is the maximum charge-discharge times of the supercapacitor.

According to (10) and (11), the theoretical service life of the supercapacitor after optimized configuration is 94.904 years, far exceeding the fixed replacement life of the supercapacitor by 20 years. Therefore, the method in this paper transfers part of the energy storage power borne by the battery to the supercapacitor without affecting the fixed replacement life of the supercapacitor.

4.3. The universality of hybrid energy storage bi-level optimization configuration method

In order to reflect the universality of the method presented in this paper, a first-order filter [3] is used to smooth the wind power to obtain a hybrid energy storage power instruction. Then, the energy storage configuration results of the method described in this paper and the method based on frequency band demarcation are compared, as shown in Table 3.

| Parameters                          | Configuration based on bi-level optimization | Configuration based on frequency band demarcation |
|------------------------------------|---------------------------------------------|-----------------------------------------------|
| Supercapacitor configuration capacity (MWh) | 0.631                                       | 1.331                                         |
| Supercapacitor configuration power (MW) | 3.135                                       | 7.655                                         |
| Battery configuration capacity (MWh)  | 1.400                                       | 4.346                                         |
| Battery configuration power (MW)     | 3.130                                       | 3.229                                         |
| Battery life (year)                 | 2.882                                       | 1.657                                         |
| Energy storage configuration cost (×10^7¥) | 0.644                                       | 1.344                                         |

As can be seen from Table 3, under the first-order filtering, the bi-level optimized energy storage configuration method still has certain advantages over the method based on frequency band demarcation energy storage configuration. The service life of the battery increases from 1.657 years to 2.882 years, and the energy storage configuration cost decreases from ¥ 1.344×10^7 to ¥ 0.644×10^7. The universality of the proposed method in hybrid energy storage configuration is illustrated.

5. Conclusions

In this paper, a bi-level optimal configuration method of hybrid energy storage is adopted to configure the hybrid energy storage in a wind farm. The service life of the hybrid energy storage equipment in actual operation is considered in the configuration process. Compared with the traditional energy storage configuration method based on frequency band demarcation, its advantages are as follows:

1) The bi-level programming method does not rely on the frequency band demarcation of the hybrid energy storage power instruction, but obtains the optimal hybrid energy storage configuration scheme through the iterative solution of the upper and lower planning model.

2) The bi-level programming method takes into account the interaction of upper and lower decision variables, which can obtain a hybrid energy storage configuration scheme that takes into account storage configuration cost and battery service life.
3) The bi-level programming method is more beneficial to reduce the configuration cost of energy storage, improve the power instruction distribution of hybrid energy storage and prolong the service life of the battery.

References
[1] CHENG, L., ZANG, H., DING, T. (2018) Ensemble recurrent neural network based probabilistic wind speed forecasting approach. Energies, 11(8): 1958-1980.
[2] Sun, Y.S., Zhao, Z.X., Yang, M., Jia, D.Q., Pei, W., Xu, B. (2020) Overview of energy storage in renewable energy power fluctuation mitigation. CSEE Journal of Power and Energy Systems, 6(1): 160-173.
[3] Takahashi, R., Tamura, J., Fukushima, T., Sasano, E., Shinya K., Matsumoto, T. (2009) A determination method of power rating of Energy Storage System for smoothing wind generator output. In: 2009 International Conference on Electrical Machines and Systems. pp. 1-6.
[4] Lamsal, D., Sreeram, V., Mishra, Y., Kumar,D. (2018) Achieving a minimum power fluctuation rate in wind and photovoltaic output power using discrete Kalman filter based on weighted average approach. IET Renew Power Gener, 12(6): 633-638.
[5] Jiang, Q.Y., Hong. H.S. (2018) Wavelet-Based Capacity Configuration and Coordinated Control of Hybrid Energy Storage System for Smoothing Out Wind Power Fluctuations. IEEE Transactions on Power Systems, 28(2): 1363-1372.
[6] Lin, L., Jia, Y.Q., Ma, M.H., Jin, X., Zhu, L.Y., Luo, H. (2021) Long-term stable operation control method of dual-battery energy storage system for smoothing wind power fluctuations. International Journal of Electrical Power & Energy Systems, 129:106878.
[7] Saleh, M., Meek, L., Masoum, M.A.S., Abshar, M. (2018) Battery-Less Short-Term Smoothing of Photovoltaic Generation Using Sky Camera. IEEE Transactions on Industrial Informatics, 14(2): 403-414.
[8] Lei M.Y., Yang, Z.L., Wang, Y.B. (2017) An MPC-Based ESS Control Method for PV Power Smoothing Applications. IEEE Transactions on Power Electronics, 33(2): 2136-2144.
[9] Cao, J., Du, W., Wang, H., McCulloch, M. (2018) Optimal Sizing and Control Strategies for Hybrid Storage System as Limited by Grid Frequency Deviations. IEEE Transactions on Power Systems, 33(5): 5486-5495.
[10] Ding, M., Wu, J., Zhang, J.J. (2019) Capacity optimization method of hybrid energy storage system for wind power smoothing. Acta Energiae Solaris Sinica, 40(3): 593-599.
[11] Zhang, Y., Xu, Y.J., Guo, H., Zhang, X.J., Guo, C., Chen, H.S. (2018) A hybrid energy storage system with optimized operating strategy for mitigating wind power fluctuations. Renewable Energy, 125: 121-132.
[12] Li, F., Xie, K., Yang, J. (2015) Optimization and Analysis of a Hybrid Energy Storage System in a Small-Scale Standalone Microgrid for Remote Area Power Supply (RAPS). Energies, 8: 4802-4826.
[13] Luo, P., Yang, T.M., Lou, S.H. (2016) Spectrum Analysis Based Capacity Configuration of Hybrid Energy Storage in Microgrid. Power System Technology, 40(2): 376-381.
[14] Kennedy, J., Eberhart, R., (1995) Particle swarm optimization. Proceedings of ICNN'95 - International Conference on Neural Networks. pp. 1942-1948.
[15] Schaltz, E., Khaligh, A., Rasmussen, P.O. (2009) Influence of Battery/Ultracapacitor Energy-Storage Sizing on Battery Lifetime in a Fuel Cell Hybrid Electric Vehicle. IEEE Transactions on Vehicular Technology, 58: 3882-3891.