Optimum State-of-Charge Operating Range for Frequency Regulation of Energy Storage Systems Using a Master–Slave Parallel Genetic Algorithm

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Abstract: Lithium batteries are used for frequency regulation in power systems because of their fast response and high efficiency. Lithium batteries have different life characteristics depending on their type, and it is necessary to set the optimal state-of-charge (SOC) operating range considering these characteristics to obtain the maximum gain. In general, narrowing the operating range increases the service life but may lower the performance of charging and discharging operations in response to frequency fluctuations, and vice versa. We present performance assessment indicators that consider charging and discharging due to frequency variations and lifespan of the batteries. However, to evaluate the performance, while reflecting the non-linear life characteristics of lithium batteries, simulating the entire operation is necessary, which requires a long calculation time. Therefore, we propose a master–slave parallel genetic algorithm to derive the optimal SOC operating range with reduced calculation time. A simulation program was implemented to evaluate the computational performance that determines the optimal SOC range. The proposed method reduces the calculation time while considering the non-linear life characteristics of lithium batteries. It was confirmed that a more accurate SOC operating range could be calculated by simulating the entire life span.

Keywords: frequency regulation; parallel computation; genetic algorithm; lithium batteries

1. Introduction

A power system must maintain a balance between power generation and load to sustain a stable frequency. In a rotary power system, the rotational speed of the generator increases as the load decreases, and vice versa. This balance is altered by changes in the power system frequency. Therefore, the power system must adjust the generator output to rectify the frequency and balance the load and power generation [1,2].

Frequency regulation can be achieved in two ways. The first is via direct measurement of the power system frequency using the generator or an energy storage device and varying the output in proportion to the difference between the rated and measured frequency. This is called primary frequency control (PFC) or droop control. The second is to control the output fluctuations by measuring the frequency in the energy management system (EMS) that operates the power system and communicates with the generator or energy storage device considering the cost and efficiency of the output from each generator. This is called secondary frequency control (SFC) or automatic generation control (AGC). PFC has a fast response time because the generator changes the output by measuring the frequency directly. SFC, however, can reduce the total output variation cost because it distributes the output according to the generation cost across the generator [1].
In response to climate change, renewable energy such as solar and wind power generators have seen rapid development. However, renewable energy output is difficult to control and is change-prone depending on insolation and wind. When the output of a renewable energy generator fluctuates rapidly, the power system frequency also fluctuates, which needs to be addressed [3].

Energy storage devices can increase the efficiency of power systems because they can be charged and discharged as required. They can also be charged with electricity generated from renewable energy and discharged demand for electricity is high; thus, it can meet supply and demand. Also, the frequency maintenance function can be performed as the generator adjusts the frequency by retaining a certain amount of energy in a normal state, charging the energy when the frequency rises and discharging it when the frequency drops [4–6].

Recently, energy storage devices using lithium batteries have been rapidly proliferating. Lithium battery-based energy storage systems (Li-ESS) are used in many power systems because of their fast response and high efficiency [7–9].

Lithium batteries can be classified further according to the positive and negative electrode material. Besides, the life characteristics of the battery are exhibited differently depending on the proportion of materials constituting the electrodes [10]. Many studies have been conducted to analyze lithium battery lifespan and degradation characteristics and to develop a model for evaluating battery life. In Reference [11], the cycle aging characteristics of lithium iron phosphate (LiFePO4, LFP) batteries were analyzed through experiments. In References [12,13], the cycle life and calendar life characteristics of lithium nickel manganese cobalt oxide (Li-Ni-Mn-Co, NMC) batteries were analyzed and modeled. Reference [14] proposed a model that combines the calendar degradation model and cycle degradation model, considering the operating pattern and temperature stress of the state-of-charge (SOC). Recently, a lithium battery degradation model based on a stochastic model was also proposed [15,16]. This previous study presents a detailed life model that considers battery type and deterioration cause to improve the battery life model accuracy. This battery model reflects a characteristic that the degree of further deterioration proceeds according to the deterioration state of the battery. Therefore, it is not possible to linearly assume the progress of battery deterioration, and it is necessary to repeatedly calculate and reflect the degree of deterioration to consider nonlinear characteristics.

Recent studies on the lifespan of ESSs used in power systems were performed as follows. The lifetime characteristics of ESSs were analyzed through accelerated degradation testing in Reference [17]. Through experiments, the LFP battery calendar degradation model and cycle degradation model were constructed, and the degradation characteristics of an ESS operated using a wind power generator were analyzed. In Reference [18], cycle degradation and calendar degradation were analyzed using the SOC profile of an energy storage system for frequency regulation (ESS-FR). Reference [19] proposed a lifespan model of an ESS-FR, and analyzed the changes in economic feasibility and efficiency, to determine the optimal droop value and the battery capacity ratio. Reference [20] proposed five strategies for maintaining the SOC of an ESS-FR and applied them to analyzing the cycle and calendar degradation and success rate of PFC due to SOC restrictions to devise an optimal SOC maintenance strategy. However, these previous studies were limited to analyzing the life characteristics of the storage device used in the power system employing the battery model.

Previous studies on the parameter setting method for optimal operation of the ESS-FR considering the life characteristics of the battery are as follows. Reference [21] defined and analyzed the capacity ratio and SOC settings of the battery and inverter in nine cases and proposed optimal values to establish an optimal economic control strategy for ESS-FR in the UK national grid frequency assistance service market. This paper considered both calendar life and cycle life models but ignored the nonlinearity of battery life. Since the non-linearity of the battery life is neglected, the life span can be simply considered, but the accuracy is reduced. On the other hand, the optimal design of the energy storage system for frequency regulation considering the non-linear lifetime model of the battery was suggested in Reference [22]. However, this method of simulating and designing more than 20 years of operation
in 1 s units has the disadvantage that it requires very long calculation time. This method that takes a long calculation time is very inappropriate to apply to various ESS-FR optimal designs.

Therefore, we propose a method of setting the optimal value of the SOC operating range of an ESS-FR considering nonlinear lifetime characteristics via a master–slave parallel genetic algorithm (MSPGA). To reduce the computation time, we leverage parallel computing and genetic algorithms to optimally utilize the computational resources to calculate the optimal SOC operating range. The proposed method can calculate the SOC’s operating range by considering the nonlinear lifetime characteristics of the ESS-FR by reducing the computation time.

In Section 2, the configuration and operation method of the ESS-FR and the battery life deterioration model were described. In Section 3, MSPGA for setting the optimal SOC range was described. Section 4 analyzed various cases. In our case study, we verified the optimal SOC setting using the parallel genetic algorithm. We analyzed the difference between designing with the full life and design considering the partial life of the energy storage device for frequency adjustment. The reduction in the calculation time was confirmed by parallel computation. In addition, it was confirmed that it is useful to consider individual life characteristics in a system composed of a combination of batteries having various life characteristics.

2. Energy Storage System for Primary Frequency Regulation

2.1. System Configuration

An ESS-FR is built with capacity ranging from tens of megawatts to hundreds of megawatts. Figure 1 shows the configuration of an ESS-FR installed by KEPCO (Korea Electric Power Corporation). KEPCO has installed and operated ESS-FRs with a total capacity of 376 MW at 13 substations in South Korea [23,24]. Each energy storage unit consists of a 2 MW inverter and a 750 kWh lithium battery. Such units are connected in parallel to a 23 kV bus via a transformer. In general, there are 12 units with a total capacity of 24 MW. These 12 units are generally supplied by two manufacturers and are classified into Group A and B. The lithium batteries in different groups have different lifespan degradation characteristics because of the different electrode materials and battery manufacturers.

![Figure 1. Configuration of energy storage system for frequency regulation.](image)

The power management system (PMS) controlling the ESS-FR measures the voltage frequency and receives the SOC of the battery system from the battery management system (BMS). The charging/discharging power is then calculated by an internal algorithm, and commands are sent to the inverters of the energy storage units. Figure 2 shows the deployment of a 24 MW ESS-FR constructed with 18 containers in KEPCO. Six of them have PCS and 12 have lithium batteries. The ESS-FR was partially built by two different manufacturers.
2.2. Primary Frequency Control

The ESS-FR is input with the frequency and the SOC, as shown in Equation (1), and the output \( P^i_{\text{ESS}} \) is calculated as follows: First, if the frequency \( f^i_{\text{in}} \) measured in the ith simulation using Equation (2) is maintained within the rated frequency \( f_{\text{rated}} \) of 60 ± 0.03 Hz, the charging/discharging operation is performed to maintain the SOC. Otherwise, the charging/discharging operation is performed to regulate the frequency. At this time, the corresponding output quantities are \( P^i_{\text{SOC}} \) and \( P^i_{\text{dr}} \), which are calculated as shown in Equations (3) and (4), respectively.

\[
P^i_{\text{ESS}}(f^i_{\text{in}}) = \begin{cases} 
P_{\text{dr}}(f^i_{\text{in}}, S^i), & \text{if } |\Delta f^i| \geq 0.03 \\
P_{\text{soc}}(S^i), & \text{if } |\Delta f^i| < 0.03 \\
\end{cases}
\]

(1)

\[
\Delta f^i = f_{\text{rated}} - f^i_{\text{in}}
\]

(2)

For the output to maintain the SOC \( P^i_{\text{SOC}} \), if the state-of-charge \( S^i \) is higher or lower than the neutral point by over 2%, the charging/discharging operation is performed with respect to the output amount, which is the rated output of the energy storage device \( P_r \) multiplied by the SOC recovery rate \( r \), where a positive number indicates a discharge operation, and a negative number indicates a charging operation.

\[
P^i_{\text{soc}}(S^i) = \begin{cases} 
rP_r, & S^i > S_n + 2 \\
-rP_r, & S^i < S_n - 2 \\
0, & \text{otherwise} \\
\end{cases}
\]

(3)

The charging/discharging amount \( P^i_{\text{dr}} \) for frequency regulation is calculated using the same formula for the output of the primary frequency control of a typical generator [1], where \( K \) is the droop constant. If \( S^i \) is greater than the maximum operating value \( S_{\text{max}} \), charging operation cannot be performed even with a high frequency. Similarly, if \( S^i \) is lower than the minimum operating value \( S_{\text{min}} \), discharging operation cannot be performed even with a low frequency.

\[
P^i_{\text{dr}}(f^i_{\text{in}}, S^i) = \begin{cases} 
0, & S^i > S_{\text{max}} \text{ and } \Delta f^i < 0 \\
0, & S^i < S_{\text{min}} \text{ and } \Delta f^i > 0 \\
100\Delta f^i P_r / (K f_{\text{rated}}), & \text{otherwise} \\
\end{cases}
\]

(4)

When the output of the energy storage device \( P^i_{\text{ESS}} \) is calculated, the state-of-charge in the next step is updated according to Equation (5), where \( T_s \) is the hourly simulation step and \( \eta \) is the charging/discharging efficiency. Equation (5) is used for the simulation of the ESS, but the actual system uses the SOC measured in the BMS, as shown in Figure 1. \( C^i \) is the storage capacity of the energy storage device available in the ith simulation step and is calculated using Equation (6). \( C^i \) is calculated by considering the degradation rate \( D^i \) for the initial rated storage capacity \( E_{\text{rated}} \) of the power system and is calculated by considering the degradation rate \( D^i \) for the initial rated storage capacity \( E_{\text{rated}} \) of the power system.
energy storage device. The degradation rate is calculated using the charging/discharging history of the energy storage device and the lithium battery degradation model. Section 2.3 describes it in detail.

\[ S_{i+1} = \begin{cases} S_i - P_{ESS}^i T_s / (\eta C_i), & P_{ESS}^i < 0 \\ S_i - P_{ESS}^i T_s / (\eta C_i), & P_{ESS}^i > 0 \end{cases} \]  

(5)

\[ C_i = (100 - D_i) E_{\text{rated}} / 100 \]  

(6)

Table 1 shows the basic parameters for calculating the output of the frequency-adjusted ESS summarized in Equations (1)–(6). In this study, we would like to propose a method for achieving optimal effects by optimally setting \( S_{\text{max}} \), \( S_{\text{min}} \), and \( S_n \), considering the life model of lithium batteries.

| \( f_{\text{rated}} \) | \( S_n \) | \( S_{\text{max}} \) | \( S_{\text{min}} \) | \( r \) | \( K \) | \( P_r \) | \( E_{\text{rated}} \) | \( \eta \) |
|---|---|---|---|---|---|---|---|---|
| 60 Hz | 65 | 90 | 10 | 0.10 | 0.33 | 12 MW | 4.5 MWh | 0.97 |

2.3. Battery-Based Energy Storage Systems Degradation

As a lithium battery performs charging and discharging operations, its lifespan deteriorates according to changes in the SOC. This lifespan degradation is largely caused by two factors. The first is calendar degradation, which occurs over time even without the charging and discharging operations. The second is cycle degradation, which occurs because of the charging and discharging operations. Therefore, the degradation rate \( (D_i) \) of the energy storage device is calculated as shown in Equation (7). If the output of the energy storage device calculated using Equation (1) does not involve charging/discharging operations, calendar degradation is reflected; otherwise, cycle degradation is reflected.

\[ D_{i+1} = \begin{cases} D_i + dD_{\text{cal}}, & P_{ESS} = 0 \\ D_i + dD_{\text{cyc}}, & \text{otherwise} \end{cases} \]  

(7)

Equation (8) is the formula for calculating the calendar degradation rate. The degradation rate during the maintenance for 1 s is calculated using the current degradation rate \( (D_i) \) and the state-of-charge \( (S_i) \). All parameters are recorded in Table 2.

\[ dD_{\text{cal}} = \alpha \cdot \exp(\beta_i S_i) \left/ \left( D_i^{0.5} \right) \right. \]  

(8)

Table 2. Various degradation model parameters for ESS-FR battery models.

| Model | \( \alpha \) | \( \beta \) | \( \alpha_2 \) | \( \beta_2 \) | \( \gamma \) |
|---|---|---|---|---|---|
| 1 | \( 3.4262 \times 10^{-8} \) | 0.0092 | \( 2.205 \times 10^{-4} \) | -0.0389 | 1.420 |
| 2 | \( 4.1115 \times 10^{-8} \) | 0.0092 | \( 2.205 \times 10^{-4} \) | -0.0389 | 1.420 |
| 3 | \( 3.4262 \times 10^{-8} \) | 0.0092 | \( 2.205 \times 10^{-4} \) | -0.0389 | 1.492 |

Cycle degradation is calculated using \( S_i \), which is changed when a charging or discharging operation is performed. Figure 3 shows the state-of-charge during the charging operation, where \( S_{\text{swing}} \) is the magnitude of the change in \( S_i \), and \( S_{\text{avr}} \) is the mean value of the changes in \( S_i \). Therefore, after all charging and discharging operations, it is possible to calculate the cycle degradation rate using Equation (9).

\[ dD_{\text{cyc}} = \alpha_2 \cdot \exp(\beta_2 S_{\text{avr}}) \cdot S_{\text{swing}}^\gamma / D_i \]  

(9)
We used three lifespan degradation models in the analysis for setting the optimal SOC operating range of the ESS-FRs with different lifespan degradation characteristics. The first was a lifespan model using the experimental data of an iron phosphate battery [22]. The arbitrary parameters were modified for the rest of the models to utilize various degradation characteristics. Degradation model 2 was set to have characteristics such that calendar degradation progressed faster than that in model 1. The parameters of model 3 were modified, so that cycle degradation proceeded faster than that in model 1.

Figure 4a shows the calendar degradation model when $S_i$ is maintained at 90%. Figure 4b shows the cycle degradation model with charging and discharging at 50% $S_{\text{avr}}$ and 80% $S_{\text{swing}}$, respectively.

When $D_i^c$ reaches 20% for a lithium battery, only 80% of the initially installed capacity can be charged and discharged and is defined as the end of the battery lifespan. This is because the capacity that can be charged and discharged decreases rapidly when $D_i^c$ exceeds 20% [25].

In this paper, the life model of the battery derived from the experimental results was applied on an iron phosphate battery. Because we calculate the objective function based on simulation, the method presented in this paper is suitable for any life model.

3. Optimizing SOC Operating Range Using a Parallel Genetic Algorithm

3.1. Objective Function

We calculated and used three types of energy values to define the lifespan objective function based on the rules of the electricity market or utility use of the ESS-FR. For the first type, the amount of energy charged/discharged for frequency regulation ($E_{\text{freq}}$) was calculated by applying a weight to the output charged/discharged by $P_{fr}$ in Equation (1), as shown in Equation (10). Figure 5 shows the weights by frequency. A higher weight was applied to the energy charged/discharged for higher frequency fluctuations. The weight was set to have a value less than 1 when the frequency was maintained within...
a range (60 ± 0.2 Hz) and to have a proportionally large weight when the frequency was outside the specified range.

\[ E_{\text{freq}} = \sum_{i=1}^{n} w_i |f_i - \bar{f}| \]  
\[ \bar{f} = \frac{\sum_{i=1}^{n} P_{i\text{rated}}}{n} \]  
\[ (10) \]

The second item in the objective function was the amount of energy charged/discharged by \( E_{\text{SOC}} \) calculated for the entire lifetime, as shown in Equation (11):

\[ E_{\text{SOC}} = \sum_{i=1}^{n} |P_{i\text{soc}}| \]  
\[ (11) \]

The last item was the amount of energy that could not be output because of the restrictions of \( S_{\text{max}} \) and \( S_{\text{min}} \) in Equation (4), calculated as shown in Equation (12):

\[ E_{\text{limit}} = \sum_{i=1}^{n} |100\Delta f_i P_{i\text{rated}}/(K_{f\text{rated}}) - P_{i\text{dr}}| \]  
\[ (12) \]

The final objective function was defined as the sum of the three items previously calculated, as shown in Equation (13):

\[ \text{Maximize } E_{\text{obj}} = E_{\text{freq}} - E_{\text{SOC}} - E_{\text{limit}} \]  
\[ (13) \]

\( S_{\text{max}}, S_{\text{min}}, \) and \( S_n \) utilized in Equations (3) and (4) were the input variables of the optimization problem, and the restrictions are summarized as follows:

\[ \text{Subject to } 1 \leq S_{\text{min}} \leq S_{\text{max}} - 4S_{\text{min}} + 4 \leq S_{\text{max}} \leq 100S_{\text{min}} + 2 \leq S_n \leq S_{\text{max}} - 2 \]  
\[ (14) \]

To calculate the objective function in 1 s unit increments over the entire lifetime of the ESS-FR, it is necessary to repeat Equations (10)–(13) \( n \) times and accumulate the results. Here, \( n \) is calculated as follows:

\[ n = 60 \times 60 \times 24 \times 365 \times \text{life} = 31,536,000 \times \text{life} \]  
\[ (15) \]

here, the life is the life of the ESS-FR described in Section 2.3 and is generally 15 years to 21 years, so the total number of calculation \( (n) \) is about 473,040,000 to 630,720,000. This is a very large calculation amount, so it takes a long calculation time. If a general genetic algorithm is used, it takes a very long computation time until the final convergence, with many iterations of the objective function.

3.2. Parallel Genetic Algorithm

A genetic algorithm (GA) is an optimization algorithm suitable for combinatorial optimization. Genetic algorithms are used in various fields because of their simplicity of implementation and their ability to search for global optimal solutions [26]. In this study, we applied a genetic algorithm to set the operating range for the optimal SOC of the ESS-FR. The ESS-FR simulates the entire life and calculates the objective function to accurately reflect the life characteristics of lithium batteries. In general, the life of the ESS-FR is more than 10 years, and the simulation step for calculating the objective function is performed in units of 1 s, which requires considerable calculation time. Therefore, we used...
a method that applied the master–slave parallel genetic algorithm (MSPGA) in this study [27,28]. The chromosome of the genetic algorithm was defined as a set of $S_{\text{min}}$, $S_{\text{max}}$, and $S_n$, as shown in Equation (16):

$$\text{Chromosome}_i = \{S_{\text{min}}, S_{\text{max}}, S_n\}$$  \hspace{1cm} (16)

Figure 6 shows the computational flow of a typical genetic algorithm. Initially, a large number of chromosomes are generated randomly, as shown in Equation (16), to form a group. The objective function is calculated for each chromosome in the randomly generated group and the functions are then sorted in descending order according to their results. The termination condition may be found to be satisfied upon checking, but if not, the low-rank chromosomes are deleted, and high-rank chromosomes are maintained by elitism.

![Conventional genetic algorithm (GA) flowchart [26]].

Figure 7 shows the process of crossover and mutation in genetic algorithms. Some individuals with high objective function values are retained in the next generation. The number of individuals maintained by elitism is defined as $N_{\text{elite}}$. The deleted individuals are generated by the crossover operator and the mutant operator, and the number of individuals is defined as $N_{\text{co}}$ and $N_{\text{mut}}$. For crossover and mutation, each of the parents is randomly selected from the elite. In the crossover operation, random single-point crossover was applied. Crossover creates two new individuals at a time. In the mutation operation, mutations were randomly generated at random single points. When all individuals are newly created, the objective function calculation and the sorting are repeated. Through such repetitions, one generation would have evolved in terms of genetic algorithms. In this study, the process of evolution was terminated when the objective function values of the best chromosomes did not improve during 10 generations.

In this study, we used MSPGA to calculate the objective function, which would otherwise take a long time. The MSPGA can be even applied with only one machine in a memory structure shared with many CPU cores, like a general PC. The detailed steps for the calculation of the objective function in Figure 6 are shown in Figure 8.

When the calculation of the objective function begins, the calculation of the objective function for one chromosome is assigned to one slave worker. In a quad-core CPU, four workers are created. Once the objective function calculation for the allocated chromosome is completed, the slave worker is assigned with the objective function calculation for another chromosome, and the calculation proceeds again. When the calculations of the objective functions for all chromosomes are completed, the parallel calculation process of the objective function ends. The algorithm then proceeds with sorting the chromosomes in descending order based on the objective functions, as shown in Figure 6. At this time, all the operations in Figure 6 are processed by one of the multiple CPU cores, and this core becomes the master core.
In this study, we used MSPGA to calculate the objective function, which would otherwise take a long time. The MSPGA can be even applied with only one machine in a memory structure shared in parallel. The chromosome of the genetic algorithm was defined as [26].

Figure 7 shows the process of crossover and mutation in genetic algorithms. Some individuals newly generated by crossover operation and the mutant operator, and the number of individuals is defined as the elitism. In the pseudocode, the calculation steps shown in the flowcharts in Figures 6 and 8 are briefly shown.

Table 3 shows the pseudocode of MASPGA implemented in MATLAB. The functions provided by MATLAB are shown in brackets. In the pseudocode, the calculation steps shown in the flowcharts in Figures 6 and 8 are briefly shown.

Table 3. Pseudo code for master–slave parallel genetic algorithm (MSPGA) using MATLAB.

| Procedure of MSPGA                                      | Processor |
|--------------------------------------------------------|-----------|
| 1 Begin                                               | Master    |
| 2 Initialize population of individuals [like (16)] randomly | Master    |
| 3 Initialize MATLAB parallel pool [parpool]          | Master    |
| 4 While (Ending criterion flag is not true)          | Master    |
| 5 For i = 1: number of individuals                     | Master    |
| 6 Master core assigns the workload to slave core      | Slaves    |
| 7 Each slave core calculates fitness                  | Slaves    |
| 8 \( F(i) = \text{parfeval}@\text{fitness}_i, \text{individual} \) | Slaves    |
| 9 After completing the current calculation, the slave requests for the next workload | Slaves    |
| 10 End                                                 | Master    |
| 11 Sort individual by fitness value                    | Master    |
| 12 Check Ending criterion                              | Master    |
| 13 \( N_{\text{elite}} \) individuals are maintained for elitism | Master    |
| 14 \( N_{\text{nu}} \) individuals newly generated by crossover operation | Master    |
| 15 \( N_{\text{mu}} \) individuals newly generated by mutation operation | Master    |
| 16 End                                                 | Master    |
| 17 End                                                 | Master    |
4. Case Studies

In this study, we proposed a method for determining the operating range for the optimal SOC of the energy storage device, to regulate the frequency using MSPGA. We conducted various case studies to verify the effectiveness or convergence of the proposed method. The first case study is for an algorithm parameter calibration experiment. We compared the convergence and computation time according to the change of parameters. In the second case study, we examined the difference between analyzing the overall lifespan of a lithium battery and not in calculating the objective function. In the third case study, the computational speeds of general GA and MSPGA were compared. In the next case study, a brute-force search was performed by shortening the objective function calculation without performing it for the entire lifetime. Lastly, we searched for the optimal SOC setting of ESS-FR, which is composed of a combination of three different battery life characteristics. All simulations were implemented using the parallel computing toolbox of MATLAB, on a PC with an Intel i7-4790 3.6 GHz quad-core CPU and a 16 GB memory.

4.1. Genetic Algorithm Parameter Calibration Experiment

When genetic algorithms (GA) are used to determine the optimal SOC range of ESS-FR, the solution quality may be influenced by the population size, the rate of crossover, and the rate of mutation [29]. Choosing a parameter for GA is not the main contribution of this paper, but it was done for the proper setup of the case study conducted in the next section.

We calculated the optimal SOC range by changing the population size. In each case, GA was performed three times and Table 4 summarizes the results. In case 1-1, the small population size showed the fastest computational performance, but the converged values were not consistent. Cases 1-2–1-4 showed consistent convergence results. In this case, the fastest computation time in case 1-2 was shown, so the size of the population was set to 100 in this paper. Table 5 shows the convergence according to the change of the number of individuals newly created by the crossover operator among the entire population.

| Parameters and Results | Case 1-1 | Case 1-2 | Case 1-3 | Case 1-4 |
|------------------------|---------|---------|---------|---------|
| Population size ($N_{total}$) | 50      | 100     | 150     | 200     |
| $N_{ elite}$          | 30% of $N_{total}$ | 30% of $N_{total}$ | 30% of $N_{total}$ | 30% of $N_{total}$ |
| $N_{ co}$             | 60% of $N_{total}$ | 60% of $N_{total}$ | 60% of $N_{total}$ | 60% of $N_{total}$ |
| $N_{ mu}$             | 10% of $N_{total}$ | 10% of $N_{total}$ | 10% of $N_{total}$ | 10% of $N_{total}$ |
| Average calculation time (s) | 180.09 | 264.05 | 387.16 | 483.86 |
| Result 1 (MWh)        | 197.96  | 198.27  | 198.27  | 198.27  |
| Result 2 (MWh)        | 197.96  | 198.27  | 198.27  | 198.27  |
| Result 3 (MWh)        | 197.89  | 198.27  | 198.27  | 198.27  |

| Parameters and Results | Case 2-1 | Case 2-2 | Case 2-3 | Case 2-4 |
|------------------------|---------|---------|---------|---------|
| Population size ($N_{total}$) | 100     | 100     | 100     | 100     |
| $N_{ elite}$          | 10% of $N_{total}$ | 30% of $N_{total}$ | 50% of $N_{total}$ | 70% of $N_{total}$ |
| $N_{ co}$             | 80% of $N_{total}$ | 60% of $N_{total}$ | 40% of $N_{total}$ | 20% of $N_{total}$ |
| $N_{ mu}$             | 10% of $N_{total}$ | 10% of $N_{total}$ | 10% of $N_{total}$ | 10% of $N_{total}$ |
| Average calculation time (s) | 300.28 | 264.05 | 201.84 | 147.01 |
| Result 1 (MWh)        | 197.96  | 198.27  | 198.27  | 198.27  |
| Result 2 (MWh)        | 197.96  | 198.27  | 198.27  | 198.27  |
| Result 3 (MWh)        | 197.90  | 198.27  | 197.89  | 198.08  |

It can be confirmed that the setting of case 2-2 has the highest consistency of converged values. Therefore, in this paper, these set values were applied to all case studies.
4.2. Effect of Simulation Duration on Objectives

In Reference [21], an optimal design method for calculating the total lifetime considering the degradation rate over a year was devised by designing the optimal capacity and operation parameters for one year via simulations. However, lithium batteries have nonlinear degradation characteristics. Figure 9 shows the trend in the degradation rate from the results of the simulation, which proceeded until the degradation rate reached 20%, using the parameters in Table 1 and battery model 1 in Table 2. In most cases, calendar degradation accounted for most of the total degradation compared to cycle degradation, resulting in a lifespan of about 21 years. The total degradation rate considering both calendar and cycle degradation was found to be nonlinear.

The objective functions for the three random parameters were compared to determine how the lifespan assessment period affects the optimal parameter setting. The three random parameters are summarized in Table 6. The three parameters listed in Table 6 were set arbitrarily, and simply indicate that the optimal parameter may be differently selected due to the difference in the analyzed life span of Table 7. Table 7 shows the objective function value and operating lifespan when each parameter is applied for various degradation rates \(D\), which is the simulation termination condition. When the simulation proceeded until \(D\) reached 1%, Parameter 2 exhibited the highest objective function value. However, when the simulation proceeded until the degradation rate reached 2% to 5%, Parameter 3 exhibited the highest objective function value. When the degradation rate reached 7% to 10%, Parameter 1 exhibited the highest objective function value. Therefore, the accuracy of the optimal design and parameter setting, when the operating benefits of the entire lifetime are considered by simply assessing partial lifetime, cannot be guaranteed. In this study, the objective function was thus calculated as the simulation proceeded until the degradation rate reached 20%, which was generally considered the end-of-life condition for a lithium battery.

Table 6. Simple parameters for simulation duration test.

| Parameters | Parameter 1 | Parameter 2 | Parameter 3 |
|------------|-------------|-------------|-------------|
| \(S_{\text{max}}\) (%) | 80          | 80          | 90          |
| \(S_{\text{min}}\) (%) | 30          | 30          | 40          |
| \(S_{n}\) (%)    | 60          | 70          | 65          |
Table 7. Various degradation model parameters for ESS.

| Parameter 1 | Parameter 2 | Parameter 3 |
|-------------|-------------|-------------|
| \(E_{Obj}\) (MWh) | Life (year) | \(E_{Obj}\) (MWh) | Life (year) | \(E_{Obj}\) (MWh) | Life (year) |
| 1           | 470         | 0.29        | 517         | 0.32        | 502         | 0.31 |
| 2           | 1373        | 0.85        | 1402        | 0.88        | 1404        | 0.87 |
| 5           | 5127        | 3.19        | 5017        | 3.16        | 5136        | 3.20 |
| 7           | 8155        | 5.09        | 7894        | 4.97        | 8111        | 5.06 |
| 10          | 13,214      | 8.27        | 12,618      | 7.98        | 13,053      | 8.17 |

We compared the differences between the method used in Reference [21] and the method presented in this paper. In Reference [21], the optimal SOC range was derived during the shortened analysis period, and it was assumed that this SOC range was optimal for the entire life. We compared these approaches by applying the same genetic algorithm. The calculation results of the operating range of the optimum SOC are summarized in Table 8. The objective function results were all calculated to simulate the lifetime. As the proposed method showed higher objective function results, it can be confirmed that it is suitable for optimal SOC operating range.

Table 8. Optimal state-of-charge (SOC) range comparison with previous study.

| Cases       | Methods            | \(S_{\text{min}}\) (%) | \(S_{\text{max}}\) (%) | \(S_n\) (%) | \(E_{Obj}\) (MWh) | Life (Year) |
|-------------|--------------------|------------------------|------------------------|-------------|-------------------|-------------|
| Case 1 12 MW/4.5 MWh | Method in Reference [21] | 39                     | 100                    | 75          | 30,316            |             |
|             | Proposed MSPGA     | 20                     | 100                    | 43          | 34,178            |             |
| Case 2 12 MW/6 MWh | Method in Reference [21] | 33                     | 99                     | 66          | 34,778            |             |
|             | Proposed MSPGA     | 16                     | 85                     | 34          | 39,305            |             |
| Case 3 12 MW/9 MWh | Method in Reference [21] | 21                     | 95                     | 54          | 41,587            |             |
|             | Proposed MSPGA     | 4                      | 90                     | 26          | 45,643            |             |

4.3. Computation Time Comparison

Simulations were performed to examine the effect of the parallel computing method on the overall calculation time. Table 9 shows a comparison of the results of three calculations using the parallel genetic algorithm and the general genetic algorithm for the optimal SOC operating range over the lifetime until the degradation rate reaches 20%. When the MSPGA method was used, the simulation of the overall lifetime took 19.2 h on average. However, when the general genetic algorithm was used, it took 62.6 h on average. The proposed MSPGA method was found to reduce the time to derive the results by more than three times. All six results exhibited the same objective functions and operating lives. Only the \(S_{\text{max}}\) values were different, according to the results. Therefore, it was confirmed that the same result could be acquired faster using MSPGA.

Table 9. Comparison of calculation time and results between PGA and GA.

| Method | Cases | Time (h) | \(S_{\text{min}}\) (%) | \(S_{\text{max}}\) (%) | \(S_n\) (%) | \(E_{Obj}\) (MWh) | Life (Year) |
|--------|-------|----------|------------------------|------------------------|-------------|-------------------|-------------|
| MSPGA  | 1     | 22.0     | 20                     | 96                     | 43          | 34,178.3          | 21.7        |
|        | 2     | 18.3     | 20                     | 100                    | 43          | 34,178.3          | 21.7        |
|        | 3     | 17.2     | 20                     | 100                    | 43          | 34,178.3          | 21.7        |
|        | Average | 19.2     | 20                     | 100                    | 43          | 34,178.3          | 21.7        |
|        | 1     | 61.0     | 20                     | 99                     | 43          | 34,178.3          | 21.7        |
|        | 2     | 61.5     | 20                     | 94                     | 43          | 34,178.3          | 21.7        |
|        | 3     | 65.3     | 20                     | 82                     | 43          | 34,178.3          | 21.7        |
|        | Average | 62.6     | 20                     | -                      | -           | 34,178.3          | 21.7        |

Figure 10 shows the distribution of SOC by setting the scope of SOC operation for the overall lifetime, as shown in the MSPGA case 2 in Table 9. If the frequency is maintained within \(60 \pm 0.03\) Hz,
the ESS is set to charge/discharge to maintain the SOC at 43%. Therefore, it can be seen that the SOC distribution is concentrated at 43%. As the frequency rises, the ESS charges and the SOC increases. However, it can be seen that SOC does not exceed 80% over its lifetime. For this reason, it can be confirmed that the objective function value is calculated equally even if $S_{\text{max}}$ is set to any value of 80 to 100.

![SOC distribution from MSPGA case 2 in Table 6.](image)

**Figure 10. SOC distribution from MSPGA case 2 in Table 6.**

### 4.4. Convergence Verification

In this study, we proposed a method for estimating the optimal SOC operating range of ESS-FR using MSPGA. We calculated and validated all feasible sets to demonstrate that the proposed MSPGA presents the optimal SOC operating range. To reduce the calculation time, it is assumed that even if the capacity reduction of only 1% is reached, the end of life is assumed, and the battery life model 1 is used. Calculating all feasible sets, even the 20% reduction in degradation capacity takes a long calculation time, which is also a necessity for the MSPGA technique presented. The SOC is assumed to be an integer value from 0 to 100. There are 152,096 cases where three SOC operating range parameters ($SOC_{\text{e}}$, $SOC_{\text{max}}$, $SOC_{\text{min}}$) satisfy the constraint Equation (Equation (14)). We calculated the objective function for all of these feasible sets, the maximum of which was 553.17 MWh.

Of all feasible sets, only 1000 cases with large objective functions are shown in descending order in Figure 11.

![Trends sorted by objective function out of 152,096 cases.](image)

**Figure 11. Trends sorted by objective function out of 152,096 cases.**

We performed six iterations to confirm that the MSPGA method converged to the same maximum objective value, of 553.17, for each iteration, as shown in Figure 12. Although the convergence
speed varied from case to case due to the nature of the genetic algorithm using the random function, the proposed MSPGA was confirmed to converge at a sufficient optimal point.

**Figure 12.** Trend of objective value with repeated MSPGA.

4.5. Usability of SOC Range Optimization Considering Degradation Models

In this study, we proposed a method for setting the optimal SOC operating range using parallel computation and genetic algorithm for the objective function of the lifetime to reflect the nonlinearity of the lithium battery lifespan model. Therefore, when energy storage devices with various degradation characteristics were installed, the differences in the objective functions among the cases in which the SOC operating range was set individually and the cases in which such setting was not made were compared. As shown in Table 10, the difference in the overall objective functions according to the parameter settings was analyzed under the assumption that three energy storage devices with the same capacities but different degradation characteristics were installed.

**Table 10.** Life model setting by ESS.

| ESS Models | ESS1 | ESS2 | ESS3 |
|------------|------|------|------|
| Degradation model | Model 1 | Model 2 | Model 3 |
| $P_r$ | 12 MW | 12 MW | 12 MW |
| $E_{rated}$ | 4.5 MWh | 4.5 MWh | 4.5 MWh |

By using the MSPGA proposed in this study, we could calculate the optimal SOC operating range with shortened calculation time, reflecting all nonlinear lifespan models of lithium battery. We summarized how the overall objective functions were calculated when the three ESS-FRs were set in 4 different cases, as shown in Table 11.

**Table 11.** SOC operating range and objective function results by case.

| Cases | ESS1 | ESS2 | ESS3 | Sum |
|-------|------|------|------|-----|
| Case 1 | $S_{min}$, $S_{max}$, $S_n$ | [20, 88, 43] | [16, 89, 40] | (22, 91, 43) | 97,852 |
| $E_{Obj}$ | 34,178 | 29,496 | 34,178 |
| Case 2 | $S_{min}$, $S_{max}$, $S_n$ | [20, 88, 43] | 34,178 | 34,169 | 97,779 |
| $E_{Obj}$ | 34,178 | 29,432 | |
| Case 3 | $S_{min}$, $S_{max}$, $S_n$ | [16, 89, 40] | 34,097 | 34,084 | 97,676 |
| $E_{Obj}$ | 34,097 | 29,496 | |
| Case 4 | $S_{min}$, $S_{max}$, $S_n$ | [22, 91, 43] | 34,177 | 34,178 | 97,783 |
| $E_{Obj}$ | 34,177 | 29,428 | |
In Case 1, the SOC operating range was set individually with consideration for all lifespan models of the three energy storage devices. In each of the Cases 2 to 4, the SOC operating range was set with consideration for only one lifespan model and was applied to all energy storage devices. The objective function values were compared for the lifetime ending at 20% degradation. Case 1 exhibited the highest objective function value because the SOC operating range was calculated in consideration of the life model of all batteries. Cases 2 to 4 demonstrated lower objective function values than that of Case 1. Differences in the objective function values of Case 1 and Cases 2 to 4 are expected to increase when the differences in the lifespan models of the ESS-FRs are increased.

5. Conclusions

In this study, we proposed a method for setting optimal SOC operating range of the ESS-FR, considering the nonlinear life model of a lithium battery. The operation of the energy storage system used for frequency regulation was formulated and summarized. Also, the model for simulating the overall degradation rate was summarized by applying the lifespan model of the lithium battery and calculating calendar degradation and cycle degradation. Moreover, we proposed a method for setting the optimal SOC operating range using MSPGA, where parallel computing technology was applied to the genetic algorithm for shortened calculation time, and for setting the optimal operating range. In order to set the optimal SOC range of ESS-FR in consideration of the detailed battery life model, it is necessary to calculate the objective function using a long simulation. General genetic algorithms repeatedly compute the objective function for multiple chromosomes. Therefore, it takes even longer convergence time in the field where the objective function calculation time is long. To overcome this problem, this paper proposed a method to shorten the time to calculate the optimal SOC range by using MSPGA.

In five case studies, we found the following: First, the results showed that the deterioration characteristics of lithium batteries are nonlinear, and it is reasonable to simulate the entire lifetime to set the optimum SOC operating range. Second, we have also found that the parallel computing function can reduce the calculation time while leading to the same result. Third, the exhaust search method was used to verify that the proposed method converges to the global optimum. Finally, when lithium batteries with different degradation characteristics constitute the ESS-FR, it was found that a better result could be obtained by using the optimal SOC operating parameters calculated individually to meet the characteristics of each battery than by applying the parameters set by models that disregarded the differences in the lifetimes. Therefore, it was confirmed that setting the optimal SOC operating range for each type of lithium battery could result in higher profitability when the battery manufacturers were different or when the electrode materials of the lithium batteries were different.

A Li-ESS device requires a high initial installation cost, and its degradation rate tends to vary depending on the operating strategy. Therefore, setting the optimal SOC operating range, as proposed in this study, is an important means to improve the profitability of the ESS-FR. Further research could include finding the optimal operation of different energy storage devices for various uses, including ESS-FR.

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