Microgrid Optimal Scheduling Incorporating Remaining Useful Life and Performance Degradation of Distributed Generators

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ABSTRACT This study presents a novel microgrid optimal scheduling strategy, which considers the degradation of distributed generators (DGs). DGs affected by degradation exhibit reduced generation efficiency and capacity. Operating the microgrid without consideration of these impacts increases operating and management costs and reduces reliability and stability. To overcome this problem, we developed a new optimal scheduling strategy that considers the degradation of DGs. This study focuses on a permanent magnet synchronous generator, which is widely used as DGs recently, and on the degradation of stator insulation, which is one of the most frequently occurring forms of degradation. The reduction in performance caused by insulation degradation is analyzed using finite element analysis and is integrated into the optimal scheduling strategy. We demonstrate that the proposed strategy operates a microgrid more economically through a reduction of total operating costs, achieved by adaptively accounting for the increase in operating costs and the reduction of capacity arising from degradation. In addition, the sudden shutdown of a DG can be prevented by predicting its remaining useful life and incorporating it into the optimal scheduling strategy. The effectiveness and feasibility of the proposed strategy are confirmed using various case studies.

INDEX TERMS Distributed generator, generator degradation, microgrid, optimal scheduling, remaining useful life estimation.

NOMENCLATURE

\( g, r, b, l \) subscripts for dispatchable DGs, renewable DGs, ESSs and loads.
\( g_h, g_d \) subscripts for healthy and degraded DGs.
\( t \) index of timeslots in the scheduling horizon.
\( ch, dch \) superscripts for charging and discharging.
\( qds \) subscript for \( qd0 \) reference frame.
\( V_{qds}, I_{qds} \) stator voltage and current vectors.
\( i_f \) circulating current.
\( n \) number of degraded turns.
\( N \) total number of turns in single phase.
\( \mu \) degraded turns ratio.

\( R_s, r_f \) stator and insulation resistances.
\( \Psi_{qds} \) flux vector.
\( \Psi_{qds,PM} \) flux vector of the permanent magnets.
\( e_{qds} \) back EMF vector.
\( L_{1s}, L_m \) leakage and magnetizing inductances.
\( p \) operator \( \frac{d}{dt} \).
\( T_e \) electromagnetic torque.
\( \psi_{PM} \) amplitude of the permanent magnet flux.
\( \theta_r \) angular rotor position.
\( z, u \) state and input vectors.
\( w, v \) state and measurement noise vectors.
\( \alpha, \beta \) degradation model parameters.
\( t_e \) end of lifetime.
I. INTRODUCTION

A microgrid is an integrated energy system where distributed energy resources and loads are interconnected within an electrically delimited local area [1]. As the global power system has been shifting to the smart grid, microgrids have been utilized to address operational problems inherent in existing power systems, such as the reduction of stability and efficiency resulting from the introduction of distributed energy resources and new energy production and consumption patterns [2], [3]. The microgrid provides various solutions to improve the reliability and efficiency of the power supply, including switching between main-grid-connected operation and independent operation, reducing network complexity, controlling voltage, and reducing power loss [4]–[6].

Distributed energy resources are mainly used for small-scale power generation and are a key element of microgrid operation. They allow for greater flexibility because of their small size and short installation time, compared to large power plants [7]. However, problems related to the degradation of generators arise as the number of distributed generators (DGs) that are connected to the microgrid increases. The degradation of DGs, such as wind turbines (WTs) [8], photovoltaic (PV) modules [9], and natural gas turbines [10], reduces nameplate capacity, efficiency, and reliability. Degradation prevents a generator from operating at the rated capacity specified by the manufacturer, even when the available resources are fully utilized. Consequently, the reduction in the capacity and efficiency of DGs reduces power supply flexibility in the microgrid and increases the operation and management costs [11]. In more serious cases, degradation can lead to failure, intensifying performance degradation and causing DGs to shut down abruptly. This results in power outages [12]. Given these potential dangers, forward planning is prudent because a lack of power supply resulting from a sudden shutdown of DGs can cause long-term power outages, specifically in independently operated microgrids. Therefore, it is essential to develop methods that accommodate the degradation of DGs and operate microgrids stably and economically.

Several methods have been proposed to operate microgrids considering the aging or failure of DGs. In [3], a method of operating a microgrid by adding the aging cost using the aging model of the battery was proposed. In addition, [13] proposed an optimal microgrid design using a battery degradation model based on battery capacity degradation considering capacity fading. Similarly, a method for calculating the battery cost and optimally operating a DC microgrid was proposed using a nonlinear battery degradation model designed in consideration of the Arrhenius effect of temperature and depth of discharge [14]. However, none of these studies accommodated sudden battery failure because they did not consider the remaining life of the battery. In [12], the authors proposed an optimal power flow model considering the failure of DGs and optimized the model using particle swarm optimization. However, their method was unable to accommodate the various impacts of degradation, including increases in operational and management costs, and decreases in capacity, as the method only considered the complete failure of DGs. In [11], an optimal power flow model was proposed considering the degradation of generators, based on predictions using the Wiener degradation model. However, this method is difficult to apply when new generators sporadically penetrate the microgrid because historical data are required to predict the degradation model. Therefore, a methodology that preemptively predicts and incorporates the degradation of DGs must be developed to ensure the stable and economic operation of microgrids.

Recently, machine prognosis and condition monitoring are regarded as an essential technology to increase the reliability of the machine and reduce the risk of sudden failure. A remaining useful life (RUL) prediction is considered one of the most important aspects. The RUL is defined as the time interval from the current time to the time when the degradation severity exceeds a threshold value. Having a precise prediction of the RUL is very useful in preventing loss and accidents caused by the sudden shutdowns by replacing or repairing the machine. Several studies for predicting the RUL of generators have also been proposed, such as WT gearboxes [15] and WT blades [16]. In microgrids, where small-scale power generation is the mainstream, the role of each generator is important. Therefore, considering the RUL of the generator can reduce losses and increase reliability. However, microgrid operation methods that consider the RUL of the generator have not yet been developed. Therefore, it is necessary to develop an operating strategy considering the RUL of generators.

In this study, we propose a novel microgrid optimal scheduling strategy, which considers generator degradation. Permanent-magnet synchronous generators (PMSGs) with...
degraded insulation were analyzed in the study because they are widely utilized in DGs such as WTGs [17] and microturbines (MTs) [18]. Insulation degradation is one of the most common forms of degradation in PMSGs [19]. The reductions in efficiency and maximum capacity were analyzed using finite element analysis (FEA) and model equations of PMSGs with insulation degradation. Through the analysis, a function consisting of a degradation severity and a degraded power was developed to express the impact of degradation on optimal scheduling. Furthermore, a model-based RUL prediction algorithm using a particle filter (PF) was described. A new optimal scheduling strategy that accounts for generator degradation was developed by integrating the degradation impact and the estimated RUL into the optimal scheduling. The proposed strategy reduced the total operating cost by including the gradually increasing operating cost of degraded generators. In addition, the strategy reduced uncertainty by preventing underproduction of power and sudden shutdowns of the generator and accounting for the progressively decreasing capacity associated with the RUL. Finally, a method for determining the adaptive threshold for the RUL was formulated, allowing for further decreases in total operating costs. The proposed strategy was tested in microgrid test systems, demonstrating its effectiveness and feasibility compared with the conventional method, which does not accommodate generator degradation. The main contributions of this study can be summarized as follows:

1) The proposed optimal scheduling strategy achieved greater cost-effectiveness and reliability compared to conventional methods by analyzing degradation impacts and integrating them into the optimal scheduling model.

2) A method for predicting the RUL of a degraded PMSG was developed, and the predicted RUL was incorporated into the optimal scheduling model to avoid sudden shutdowns caused by generator failure.

3) The reduction in generator power caused by degradation was analyzed using FEA and integrated into the optimal scheduling model. This approach can be applied to other distributed energy resources such as energy storage systems (ESSs).

4) A threshold-setting method for the RUL that minimizes operating costs was developed. This method can serve as a guide for the setting of thresholds by operators of DGs in general.

The rest of this study is organized as follows: In Section II, we describe the RUL estimation and the analysis of the degradation impact. In Section III, we propose the new optimal scheduling strategy that incorporates the impact of degradation and the RUL. In Section IV, we demonstrate the effectiveness and feasibility of the proposed method using case studies. Finally, the main conclusions are presented in Section V.

II. RUL ESTIMATION AND DEGRADATION IMPACT OF GENERATOR

In this section, the method for estimating the generator RUL is developed and the degradation impact is analyzed. The PMSG model with stator insulation degradation is described in Section II-A. The method for estimating the RUL using the PF, which is incorporated with the PMSG model, is provided in Section II-B. The impacts of generator degradation are analyzed and formulated in Section II-C.

A. ANALYTICAL MODEL OF PMSG WITH INSULATION DEGRADATION

An analytical model of the PMSG with stator insulation degradation in qd0 reference frame is expressed as [20]

$$ V_{qds} = R_s I_{qds} + p \Psi_{qds} - \frac{2}{3} [R_s + (L_{ls} + \frac{3}{2} L_m)] i_f \begin{bmatrix} \mu \\ 0 \end{bmatrix} \quad (1) $$

$$ \mu V_{qs} = \mu (1 - \frac{2}{3} \mu) (R_s + L_{ls} p) i_f + r_f i_f \quad (2) $$

$$ \Psi_{qds} = (L_{ls} + \frac{3}{2} L_m) I_{qds} + \Psi_{qds,PM} \quad (3) $$

$$ T_e = \psi_M \cos \theta_r - I_{ds} \sin \theta_r - \mu \cos \theta_i i_f \quad (4) $$

The degradation severity is represented by two parameters, $r_f$ and $\mu$, where $\mu = n/N$. The insulation resistance is the connected resistance between degraded windings. The severity is intensified as $r_f$ decreases or $\mu$ increases. Therefore, the degradation severity and RUL can be estimated by tracking the degradation-related parameters.

It is necessary to augment the precise state-space model of the PMSG with insulation degradation to estimate the degradation-related parameters using parameter identification techniques. Based on (1)–(3), the state-space model of the degraded PMSG can be expressed as

$$ \frac{dz}{dt} = A_x z + B_x u + w \quad (5) $$

$$ y = C_x z + v \quad (6) $$

where

$$ z = \begin{bmatrix} I_{qs} \\ I_{ds} \\ \mu i_f \\ \mu r_f \\ z_1 \\ z_2 \\ z_3 \\ z_4 \\ z_5 \end{bmatrix} ^T, \quad (7) $$

$$ u = \begin{bmatrix} V_{qs} \\ V_{ds} \\ e_{qs} \\ e_{ds} \end{bmatrix} ^T, \quad (8) $$

$$ y = \begin{bmatrix} I_{qs} \\ I_{ds} \end{bmatrix} ^T, \quad (9) $$

$$ A_x = \begin{bmatrix}
-\frac{R_s}{L_s} & 0 & \frac{2}{3} \frac{R_s - \frac{3}{2} R_s}{L_s} - \frac{3}{4} \frac{z_5}{L_{ds}} & 0 \\
0 & -\frac{R_s}{L_s} & \frac{R_s - \frac{3}{2} R_s}{L_s} - \frac{3}{4} \frac{z_5}{L_{ds}} & 0 \\
0 & 0 & -\frac{R_s}{L_{ls}} - \frac{z_5}{L_{ds}(1 - \frac{4}{3} z_4) L_{ls}} & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}, \quad (10) $$

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Based on addition, in [24] the insulation breakdown of an induction exponentially as the degradation intensifies [22], [23]. In lower leakage current [21]. The leakage current decreases degrades, the insulation resistance decreases, resulting in a degradation proceeds to estimate the RUL. As the insulation PMSG.

That is, when the insulation resistance, which models the degree of insulation degradation, has been diminished below a specified threshold value, it designates the end-of-life of the machine was modeled as an exponential decay. In general, the RUL estimation is required to estimate the unknown parameters. However, as the insulation resistance cannot be measured in practice, a method to estimate it is required. In this study, we employed the PF approach, which has been effectively used in various diagnostic and prognostic problems [24], [25] to estimate the nonlinear model parameters related to the degradation. A PF based on the Monte Carlo technique may be applied to estimate the parameters of nonlinear systems for both Gaussian and non-Gaussian noise. A PF approximates a probability density function using a set of particles and their corresponding weights. There are two key steps that recursively estimate particles and weights using the measurements: the prediction step, which samples particles with the importance distribution, and the update step, which updates their corresponding weights. There are two key steps that recursively estimate particles and weights using the measurements: the prediction step, which samples particles with the importance distribution, and the update step, which updates their corresponding weights. The prediction step, which samples particles with the importance distribution, and the update step, which updates their corresponding weights.

The degradation model has two unknown parameters. The insulation resistances at a minimum of two time instants are required to estimate the unknown parameters. However, as the insulation resistance cannot be measured in practice, a method to estimate it is required. In this study, we employed the PF approach, which has been effectively used in various diagnostic and prognostic problems [24], [25] to estimate the nonlinear model parameters related to the degradation. A PF based on the Monte Carlo technique may be applied to estimate the parameters of nonlinear systems for both Gaussian and non-Gaussian noise. A PF approximates a probability density function using a set of particles and their corresponding weights. There are two key steps that recursively estimate particles and weights using the measurements: the prediction step, which samples particles with the importance distribution, and the update step, which updates their corresponding weights. The prediction step, which samples particles with the importance distribution, and the update step, which updates their corresponding weights.

B. RUL ESTIMATION USING PF

The overall framework for the RUL estimation is shown in Fig. 1. A model-based RUL estimation method is developed, following six steps. The RUL of a machine is defined as the time interval from the current time to the time when the degree of degradation or aging of the machine exceeds a threshold value. In general, the RUL of a generator is affected by several factors including mechanical, thermal, electrical, and environmental stress. In this study, the RUL of a PMSG is defined as the time to insulation breakdown due to degradation of the stator winding under thermal stress. That is, when the insulation resistance, which models the degree of insulation degradation, has been diminished below a specified threshold value, it designates the end-of-life of the PMSG.

Initially, it is necessary to model how insulation degradation proceeds to estimate the RUL. As the insulation degrades, the insulation resistance decreases, resulting in a lower leakage current [21]. The leakage current decreases exponentially as the degradation intensifies [22], [23]. In addition, in [24] the insulation breakdown of an induction machine was modeled as an exponential decay. Based on the existing studies, we also applied an exponential model to the insulation degradation of a PMSG in this study. The exponential degradation model is expressed as

$$r_f = \alpha e^{-\beta t}. \quad (13)$$

The degradation model has two unknown parameters. The insulation resistances at a minimum of two time instants are required to estimate the unknown parameters. However, as the insulation resistance cannot be measured in practice, a method to estimate it is required. In this study, we employed the PF approach, which has been effectively used in various diagnostic and prognostic problems [24], [25] to estimate the nonlinear model parameters related to the degradation. A PF based on the Monte Carlo technique may be applied to estimate the parameters of nonlinear systems for both Gaussian and non-Gaussian noise. A PF approximates a probability density function using a set of particles and their corresponding weights. There are two key steps that recursively estimate particles and weights using the measurements: the prediction step, which samples particles with the importance distribution, and the update step, which updates their corresponding weights. The prediction step, which samples particles with the importance distribution, and the update step, which updates their corresponding weights.

Using the PF with the state-space model, estimates of the insulation resistances $r_f^{(i)}$, $r_f^{(j)}$ (corresponding to the $i$th particle) at two time instants $t_1$, $t_2$ are used to estimate the degradation model parameters and the RUL. The estimates of $\beta^{(i)}$ and $\alpha^{(i)}$ corresponding to the $i$th particle are as follows:

$$\beta^{(i)} = \frac{\ln r_f^{(i)}}{t_2 - t_1} \quad (14)$$

$$\alpha^{(i)} = \frac{1}{2} \left( \frac{r_f^{(i)}}{e^{-\beta^{(i)} t_1}} + \frac{r_f^{(j)}}{e^{-\beta^{(j)} t_2}} \right). \quad (15)$$

The end-of-lifetime, which is the time at which the insulation resistance has decreased to a predefined threshold $r_{th}$, is estimated by

$$t_e^{(i)} = \frac{\ln \frac{r_{th}}{\beta^{(i)}}}{\beta^{(i)}}. \quad (16)$$
The \( RUL^{(i)} \) is calculated as the difference between the estimated \( t_e^{(i)} \) and time \( t_2 \).

\[
RUL^{(i)} = t_e^{(i)} - t_2. \tag{17}
\]

The final estimate of the RUL is the mean of the weights of all particles, which is expressed as

\[
RUL_{estimation} = \frac{1}{M} \sum_{i=1}^{M} RUL^{(i)}. \tag{18}
\]

The estimation results are presented in Figs. 2, 3, and 4. The operating data of the PMSG were acquired using FEA. The FEA model was obtained using JMAG software, and the corresponding 50 kW PMSG model and its mesh plot are depicted in Fig. 5. Table 1 lists the specifications of the PMSG. The degradation curve was set in accordance with [24] and had the form \( r_f = 5e^{-0.288t} \). Although the degradation model used in this study is an accelerated version, it may nonetheless consume hours or days of computing time [23], [26]. The accelerated version was used to prove the capability of the proposed method; however, this version may also be applied to the actual degradation process as part of the proposed method, with the proviso that the estimated RUL will be longer. Measurements corresponding to two time points are required to estimate the RUL. Therefore, PMSG operating data were obtained for insulation resistances of 5 and 4 \( \Omega \), respectively, using FEA.

The estimations of insulation resistance for the PMSG using a PF are presented in Figs. 2 and 3, for insulation resistances of 5 and 4 \( \Omega \), respectively. The total number of particles used in the PF is 10,000, and parameters were estimated through 800 estimation steps. The images on the left side of Figs. 2 and 3 present the histograms of the weights of each particle based on the 1st, 400th, and 800th estimation steps. The mean value of the particle’s weights approaches the actual value of the insulation resistance as the steps progress, and the variance is also reduced as the steps progress. The images on the right side of Figs. 2 and 3 show the continuous progress of the estimation results as the steps proceed. Fig. 4 shows the estimated degradation curve. The red dashed line indicates the threshold; as shown in the figure, the estimated RUL is a function of the predefined threshold. Specifically, the estimated RUL was 14,776 h, which was close to the actual value of 15,215 h when the threshold was 0.05 \( \Omega \). The threshold can be set by considering the efficiency reduction, stability reduction, and cost increase caused by the degradation. These quantities were analyzed with optimal scheduling results, as described in Section IV.

### C. ANALYSIS OF DEGRADATION IMPACTS

The output power of the degraded PMSG with different degradation severities was analyzed using FEA conducted with the following degradation severities: \( \mu = 0.25 \) and \( r_f \in \{ 5, 4, 2, 1, 0.75, 0.5, 0.25, 0.1, 0.075, 0.05 \} \).

Fig. 6(a) shows the output power results when the degradation occurred at \( \theta_e = 3\pi \). The black and red lines represent the output power and average power, respectively. The measured output power highly fluctuated due to degradation. The overall decrease in the output power, which is more evident in the line representing the average power, is also indicated in the figure. The average power was reduced by 6.55% compared to the healthy PMSG, indicating the impaired ability of the degraded PMSG to generate stable power. The decrease in output power was correlated with the degradation severity. The degradation severity \( S \) is defined in terms of \( \mu \) and \( r_f \) and expressed as:

\[
S = \frac{\mu}{r_f}. \tag{19}
\]
The output power decreased with increasing degradation severity, as shown in Fig. 6(b). There was no difference in power generation between the degraded generator and the healthy generator when the severity was close to 0. However, the decrease in output power accelerated as the degradation severity increased. To reflect the decrease in generation efficiency with increasing degradation severity, the output power needs to be integrated into the microgrid scheduling strategy. In the scheduling, the output power of the healthy generator was replaced by the actual power output of the degraded generator, as a function of the degradation severity. Accordingly, the modified output power is expressed as

$$P_{g_h} = f(P_{g_d}, S_{g_d}) = \xi_1^{g_d} P_{g_d} + \xi_2^{g_d} S_{g_d}.$$  (20)

In this study, the function $f$ was modeled as a first-order polynomial function for simplicity. Its value was approximated using the least-squares curve fitting method. The best-fitting values of the coefficients $\xi_1^{g_d}$ and $\xi_2^{g_d}$ were 1.0186 and 0.1715, respectively. The proposed function consists of the output power of the degraded generator and the severity. Therefore, this can be used to reflect the degradation effect in the microgrid scheduling. In Section III, the proposed new microgrid optimal scheduling strategy is developed by integrating the approximated function and the estimated RUL into the optimal scheduling model.

### III. MICROGRID OPTIMAL SCHEDULING CONSIDERING DEGRADATION IMPACT AND RUL OF THE GENERATOR

In this section, a new microgrid optimal scheduling strategy, which considers generator degradation, is developed. The overall structure of the proposed strategy is shown in Fig. 7. A centralized energy management system (CEMS) performs day-ahead scheduling optimization based on two-step incorporation of the generator degradation and manages the microgrid using the scheduling results. In the first step, the degradation curve and RUL of the generator are estimated using the method described in Section II. The voltages, currents, and speeds of the generator are measured using the sensors, and the measured data are communicated to the CEMS. In the second step, the CEMS optimizes the day-ahead schedule by collecting the PV, WT, load, and price-forecast data and using the estimated degradation curve and RUL obtained in the first step. The objective function and constraints used for the optimal scheduling are developed to reflect the generator degradation. A more detailed description follows in the subsections below.
A. OBJECTIVE FUNCTION
It is necessary to modify the conventional optimal scheduling method to incorporate the generator degradation in the microgrid optimal scheduling model. In Section II, we showed how the output power of the healthy generator is approximated as a function of the degradation severity and the output power of the degraded generator, as expressed in (20). Using this function, the new objective function considering the generator degradation is expressed as

\[
\min \ C_{gen,h} + C_{grid} + C_{deg,ESS} + C_{gen,d} \tag{21}
\]

The generation cost of healthy DG units, \( C_{gen,h} \), including generation, startup, and shutdown costs for the entire scheduling period, is expressed as

\[
C_{gen,h} = \sum_{t=1}^{T} \sum_{g} \left[ F_{g,h}(P_{g,t}) + SU_{g,h} + SD_{g,t} \right]. \tag{22}
\]

The generation cost \( F_{g,h} \) is expressed by a quadratic function as

\[
F_{g,h}(P_{g,t}) = c_{g}^2(P_{g,t})^2 + c_{g}^1 P_{g,t} + c_{g}^0. \tag{23}
\]

It can be approximated by a piecewise linear model [27]:

\[
F_{g,h}(P_{g,t}) = a_{g} \delta_{g,t} + \Delta t(b_{g} P_{g,t}), \quad \delta_{g,t} \in \{0, 1\}, \quad \forall g, t. \tag{24}
\]

The cost of power transmitted from the main grid to the microgrid based on the market price, \( C_{grid} \), is expressed as

\[
C_{grid} = \sum_{t=1}^{T} \rho_t P_{PCC,t}. \tag{25}
\]

This quantity indicates the cost of receiving power from the main grid when \( P_{PCC,t} \) is positive. Conversely, it indicates that the excess power of the microgrid is sold back to the main grid when \( P_{PCC,t} \) is negative.

The cost of ESS degradation owing to frequent charging-discharging, \( C_{deg,ESS} \), is expressed as

\[
C_{deg,ESS} = \sum_{t=1}^{T} \sum_{b} c_{b,deg} (P_{b,t}^{dch} + P_{b,t}^{dch}) \Delta t. \tag{26}
\]

The operation cost of the degraded DG units, \( C_{gen,d} \), is expressed as

\[
C_{gen,d} = \sum_{t=1}^{T} \sum_{g,d} \left[ F_{gd}(P_{g,d,t}, S_{g,t}) + SU_{g,d,t} + SD_{g,t} \right]. \tag{27}
\]

In this study, only the change in the generation cost was considered. The generation cost of the degraded DG uses the piecewise linear model as is used for healthy generators, but the coefficients were rewritten to reflect degradation, as follows:

\[
F_{gd}(P_{g,d,t}, S_{g,t}) = a_{g,d}^d \delta_{g,d,t} + \Delta t(b_{g,d,t}^d P_{g,d,t}) \tag{28}
\]

\[
a_{g,d,t}^d = a_{g} + b_{g} \xi_{g,t} \tag{29}
\]

\[
b_{g,d,t}^d = b_{g} \xi_{g,t} \tag{30}
\]

The new generation cost function integrated with the degradation becomes larger as the degradation severity increases. This increasing trend in the generation cost curve is shown in Fig. 8 for various values of the degradation severity, using (28). The more severe the degradation, the higher the cost to generate the same power. The severity is a variable that depends on the commitment time expressed as the sum of the on-states of the DG in (31), because the degradation worsens as the operating time of a DG increases. Accordingly, the increase in generation cost caused by degradation is incorporated into the optimal scheduling model.

B. CONSTRAINTS
The objective function follows the constraints of the DG units and ESSs, as follows:

\[
\sum_{g=1}^{N_g} P_{g,t} + \sum_{r=1}^{N_r} P_{r,t} + \sum_{b=1}^{N_b} (P_{b,t}^{dch} - P_{b,t}^{dch}) + P_{PCC,t} = \sum_{l=1}^{N_l} L_{l,t}, \quad \forall t \tag{32}
\]

\[
- P_{PCC,t}\max \leq P_{PCC,t} \leq P_{PCC,t}\max, \quad \forall t \tag{33}
\]

\[
P_{g,t} \leq P_{g,t}\max \delta_{g,t}, \quad \forall g, t \tag{34}
\]

\[
P_{g,t} \geq P_{g,t}\min \delta_{g,t}, \quad \forall g, t \tag{35}
\]

\[
P_{g,t} - P_{g,t-1} \leq U R_{g}, \quad \forall g, t \tag{36}
\]

\[
P_{g,t-1} - P_{g,t} \leq D R_{g}, \quad \forall g, t \tag{37}
\]

\[
S_{U_{g,t}} \geq C_0 \left( \delta_{g,t} - \delta_{g,t-1} \right), \quad \forall g, t \tag{38}
\]

\[
0 \leq \frac{P_{dch,b,t}}{P_{b}}, \frac{P_{dch,b,t}}{P_{b}} \leq 1, \quad \forall b, t \tag{39}
\]

\[
0 \leq \delta_{b,t} \leq \delta_{b,t}\max, \quad \forall b, t \tag{40}
\]

\[
0 \leq \frac{P_{b,t}^{dch}}{P_{b,t}^{dch}}, \frac{P_{b,t}^{dch}}{P_{b,t}^{dch}} \leq 1, \quad \forall b, t \tag{41}
\]

\[
\frac{P_{dch,b,t}}{P_{b,t}^{dch}} \leq 0, \quad \forall b, t \tag{42}
\]

\[
E_{b,t+1} = E_{b,t} + (P_{b,t}^{dch} \Delta t - P_{b,t}^{dch} \Delta t/\eta_{b,t}^{dch}), \quad \forall b, t \tag{43}
\]

\[
E_{b,\text{init}} \leq E_{b,t} \leq E_{b,\text{max}}, \quad \forall b, t. \tag{44}
\]

\[
E_{b,\text{terminal}} = E_{b,\text{terminal}}. \tag{45}
\]

The power balance equation (32) confirms that the total load matches the sum of the power generated from the dispatchable DG units and the renewable DG units at each timeslot, the charge/discharge power of the ESSs, and the power transmitted from the main grid. In this study, the predictions of power production for both WT power and PV power were assumed to be accurate. The maximum transmittable power from the main grid was limited because of the capacity limitations of the power lines expressed in (33). Dispatchable DG units were limited by the maximum/minimum generation capacity limits in (34)–(35), ramping up/down rate limits given by (36)–(37), and minimum startup/shutdown time limits in (38)–(39). The
on/off state of dispatchable DG units was 1 when a unit was committed and 0 otherwise.

ESSs can be in charging or discharging modes, as expressed by the corresponding charging/discharging state variables $\delta_{b,t}^{ch}, \delta_{b,t}^{dch}$. Either the charging or the discharging mode is active at any particular timeslot, as expressed in (40). The maximum and minimum charging/discharging limits are expressed in (41)–(42). The state of charge (SOC) is calculated using (43), which is modeled with consideration of the charging and discharging efficiencies. In addition, the SOC is regulated by a maximum/minimum capacity limitation (44), and ESS is constrained by the requirement that the SOC at the start and end times of the scheduling period needs to be the same, as indicated by (45).

The new constraint reflecting the decrease in the maximum capacity due to the degradation can be expressed as follows:

$$P_{g,t} \leq P_{g,t}^{max,d} (S_{g,t}) \delta_{g,t} \quad \forall g,t$$

where

$$P_{g,t}^{max,d} = \frac{P_{g,t}^{max}}{\xi_{g,t}}$$

The maximum capacity of the degraded generator is expressed as a function of the degradation severity. It is apparent that the capacity decreases as the severity increases. The capacity reduction due to degradation can be incorporated into the optimal scheduling model using the new constraint.

Similarly, a further new constraint is required to account for the RUL of the generator in the optimal scheduling model. The sum of the on-states of the generator needs to be less than or equal to the RUL as the generator can only operate within the RUL. The corresponding new constraint is formulated as

$$\sum_{t=1}^{T} \delta_{g,t} \leq RUL_{g,t} \quad \forall g,t.$$  \hspace{1cm} (48)

Therefore, the microgrid optimal scheduling problem that incorporates the generator degradation can be solved by minimizing (21), subjected to the constraints (32)–(46) and (48).

IV. CASE STUDIES

A. CASE STUDY 1

1) Microgrid Test System Data

The proposed method was implemented on a microgrid test system based on an existing study [28] to validate the proposed optimal scheduling strategy, as shown in Fig. 7. The dispatchable DG units were composed of an MT and a fuel cell (FC); their characteristics are listed in Table 2. Table 3 lists the characteristics of the ESS. It was assumed that the ESS was 30% charged at the start time, and that the degradation cost coefficient for the ESS was 0.0035 $/kWh. The charging and discharging efficiencies were set as 0.9. The forecasts of the electrical load, WT and PV powers, and market price over the scheduling period are shown in Fig. 9. The maximum transmittable power from the main grid was limited to 200 kW. It was assumed that the predictions of the electrical load and renewable generations were known limited to 200 kW. It was assumed that the predictions of the electrical load and renewable generations were known

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Case study 1 was conducted in both grid-connected and islanded modes to demonstrate the effectiveness and feasibility of the proposed strategy. In the islanded mode, the peak load was reduced to 180 kW because the total power generation capacity of the DGs was smaller than the maximum load to ensure that the microgrid could be operated independently.

We validated the proposed optimal scheduling strategy incorporating generator degradation using the microgrid test system and data presented previously. For comparison, the following case studies were performed in both the grid-connected and islanded modes:

**Case 1** (Healthy generators): Apply the conventional method with healthy generators.

**Case 2** (Conventional method with degraded generator): Apply the conventional method with an MT experiencing degradation.

**Case 3** (Proposed strategy): Apply the proposed optimal scheduling strategy that incorporates generator degradation.

2) Results for Grid-Connected Mode in Case Study 1

The MT is subject to degradation in Case 2 but not in Case 1. The longer the generator operating time, the lower the maximum capacity and the higher the operating cost. For microgrid operation, the dispatchable DGs provided power based on the schedule, but the MT was dispatched differently from the scheduled result in the timeslot 19–20 h, as shown in Fig. 10(a). This occurred because the maximum capacity was reduced with increasing operating time because of the degradation. Therefore, the MT was unable to meet the power generation required by the optimal schedule from 19 to 20 h. Accordingly, the shortfall in power was purchased from the main grid, indicating that power transfer from the main grid increases, as shown in Fig. 10(b). Consequently, the overall microgrid operating cost increased because the microgrid purchased electricity at a higher price, and the generation cost of the MT increased due to degradation. In the case study, a sudden shutdown was assumed not to occur even when the MT was severely degraded. However, in practice, the MT could be shut down abruptly reducing the stability of the power supply.

The proposed strategy limits the commitment time of the degraded generator using the estimated RUL. Accordingly, the MT was dispatched from 8 to 21 h, which was the most efficient time because the market price was most expensive (Fig. 10(a) and (b)), to meet the RUL constraint. That is, the power transmitted from the main grid increased while the output power of the MT decreased. In addition, the generation of the degraded MT, which was more expensive than that of the healthy MT, was dispatched to a lesser degree because the increased generation cost was incorporated in optimal scheduling. The proposed strategy did not use the MT when degradation was severe. Therefore, the microgrid could be operated more economically than the conventional method by applying the proposed strategy.

The detailed dispatch results and maximum capacity of the degraded MT for different cases are shown in Fig. 11. In both cases, the maximum capacity decreased as the degradation proceeded. The maximum capacity reduction for
FIGURE 12. Day-ahead optimal schedule results of fuel cell (FC) and ESS for different cases. (a) Output power of FC. (b) Output power of ESS.

TABLE 4. Comparison of operating costs in the grid-connected mode

|          | Case 1 (Healthy) | Case 2 (Conventional) | Case 3 (Proposed) |
|----------|------------------|-----------------------|-------------------|
| MT cost ($) | 106.576         | 132.420               | 84.189            |
| FC cost ($)  | 131.316         | 131.316               | 131.316           |
| PCC cost ($) | 523.549         | 524.720               | 557.269           |
| ESS cost ($) | 0.524          | 0.524                 | 0.524             |
| Total cost ($) | 761.965       | 788.980               | 773.298           |

FIGURE 13. Day-ahead optimal schedule results of MT, FC and ESS in islanded mode for different cases. (a) Output power of MT. (b) Output power of FC. (c) Output power of ESS.

The proposed strategy was much smaller than that of the conventional method. This occurred because the degradation effect was not considered in the conventional method and the generator was used beyond its limit. Therefore, at 19 and 20 h, it was not possible to output as much power as was dispatched, which reduced the reliability of the system. Conversely, the operational reliability of the microgrid could be improved by applying the proposed strategy, that is, by incorporating the reduction in capacity and RUL in advance.

Both FC and ESS were dispatched for the different cases because their output powers were directly affected by the market price, as shown in Fig. 12. The market price was the same for the conventional method and the proposed strategy, indicating that there was no change in the output power generated by FC and ESS.

Table 4 lists the result of the comparison of the operating cost of each case. Case 2, which experienced generator degradation, exhibited a higher operating cost than Case 1. The cost of the MT increased significantly above that for the case where all DGs were healthy. The cost of power purchased from the main grid increased because the degraded MT was not able to output the scheduled power, resulting in the purchase of the shortfall from the main grid. This occurrence demonstrated that problems arose in the cost optimization and power supply stability when operating a microgrid with the conventional method. The proposed strategy increased the total operating cost compared to the case where all the DGs were healthy. The generation cost increased because the degraded generator was included in the microgrid; this was an expected result. However, the proposed strategy was able to save substantial total costs, compared to the conventional method. This is because the microgrid operating cost can be optimized by accounting for the increased cost due to generator degradation in the optimal scheduling model. The ESS degradation costs in both methods had the same value because the total charging and discharging power of the ESS was the same, as shown in Fig. 12(b). In addition, the operating time of the generator was limited by incorporating
the RUL of the generator. With these interventions, a sudden shutdown of the generator could be prevented, improving the microgrid’s operational stability.

3) Results for Islanded Mode in Case Study 1

Fig. 13 shows the optimal schedule results in the islanded mode. The MT was dispatched less with the proposed strategy because the dispatchable time was limited in accordance with the RUL of the MT, as shown in Fig. 13(a). Conversely, the overall generation of the FC increased, and the ESS was charged and discharged more frequently to make up for the reduced generation of the MT, as shown in Fig. 13(b) and (c). These factors contributed to the reduction of the total operating costs resulting from a reduced usage of the MT, wherein the generation efficiency was reduced due to degradation.

Table 5 shows the result of the comparison of the operating cost of each case in the islanded mode. Conversely, in the grid-connected mode, the proposed strategy operated the microgrid more cost-effectively than the conventional method when the DG was being degraded. The proposed strategy increased the FC cost and ESS degradation cost because of the implementation of the FC and the charging/discharging of the ESS increased, but the overall cost was reduced because of the reduced implementation of the MT whose efficiency had decreased because of degradation. The reliability of the power supply was the most important consideration when the microgrid was operating in the islanded mode. The proposed method improved the reliability compared to the conventional method by preventing sudden shutdown and underproduction of the DG.

4) Effect of Threshold on Optimal Schedule

In the proposed method, the scheduling result varied based on the threshold value for the RUL estimation that was set by the operator. Setting the threshold high shortened the usable time of the generator but increased its stability. Conversely, the usable time increased when the threshold was set low, whereas it became more difficult to guarantee stability. Therefore, it is necessary to set an appropriate threshold, which we analyzed in terms of the microgrid’s operating cost. Table 6 contains a comparison of operating costs when the proposed optimal scheduling method was solved based on the change of the threshold. The RUL increased from 12.42 to 20.24 h as the threshold decreased from 0.1 to 0.01 $\Omega$. Consequently, the dispatchable time of the MT was increased, resulting in an increase in the cost of the MT and a decrease in the cost of the PCC. This occurred because the cost of the MT, which was slightly degraded, was cheaper than the cost of purchasing from the main grid. It is worth noting that the RUL increased by 2 h when the threshold decreased from 0.018 to 0.01 $\Omega$, but there was no difference in the operating cost. This occurred because the increased cost due to reduced efficiency exceeded the cost of purchasing from the main grid. Therefore, in terms of microgrid operating cost, setting the threshold to 0.018 $\Omega$ was the most efficient choice.

B. CASE STUDY 2

1) Microgrid Test System Data

The proposed method was implemented on the 34-bus test feeder based on the existing study [30] to validate the pro-
TABLE 7. Characteristics of Dispatchable DG Units

| Unit | Type | $b_0$ ($/MWh$) | $P_{min}/P_{max}$ (MW) | $UR/DR$ (MW/h) |
|------|------|---------------|----------------|----------------|
| 1    | MT   | 51.86         | 0.12             | 0.06           |
| 2    | DU   | 74.09         | 0.18             | 0.09           |

TABLE 8. Characteristics of ESS

| $E_{min}$ (MWh) | $E_{max}$ (MWh) | $P_{ch,max}$ (MW) | $P_{dch,max}$ (MW) | $\eta_{ch}$/$\eta_{dch}$ |
|-----------------|-----------------|-------------------|--------------------|--------------------------|
| 0.0             | 0.70            | 0.175             | 0.175              | 0.88                     |

posed optimal scheduling strategy, as shown in Fig. 14. The dispatchable DG units were composed of an MT and a diesel unit (DU), and their characteristics are listed in Table 7. Table 8 lists the characteristics of the ESS. It was assumed that the ESS was 30% charged at the start time, and the degradation cost coefficient for ESS was 1 $/MWh. The forecasts of the electrical load, WT and PV powers, and the market price over the scheduling period are shown in Fig. 15. The maximum transmittable power from the main grid was limited to 1 MW. It was assumed that the predictions of the electrical load and renewable generations were known because this study focused on the optimal scheduling, incorporating the degradation of the generator. In addition, the MT was assumed to undergo degradation. Case study 2 was performed in the grid-connected mode.

2) Results for Grid-Connected Mode in Case Study 2

In Case 2, for the microgrid operation, the MT and DU provided power based on the schedule, but the MT was dispatched differently from the scheduled result, as shown in Fig. 16(a). This occurred because, contrary to Case 1, in Case 2 the maximum capacity decreased as the operating time increased owing to the degradation of the MT. Therefore, the MT could not meet the power generation required by the optimal schedule. Accordingly, power purchasing from the main grid increased to maintain the power balance, as shown in Fig. 16(b). Consequently, the overall microgrid operating cost increased because the microgrid purchased electricity at a higher price. In addition, the generation cost of the MT increased because of the degradation, which increased the total operating cost.

The proposed strategy limited the commitment time of the degraded generator using the estimated RUL. To operate the microgrid economically, the MT was dispatched at the most efficient time, when the market price was more expensive than the operating cost of the MT, while satisfying the RUL constraint (Fig. 10(a) and (b)). That is, the power transmitted from the main grid increased while the output power of the MT decreased. In addition, the reduction in the maximum capacity of the degraded MT was reflected in advance so that the microgrid could be operated more stably. The proposed strategy did not use the MT when degradation was severe. Therefore, the microgrid could be operated more economically than the conventional method by applying the proposed strategy.
Both the DU and the ESS were dispatched for the different cases because the output powers of the DU and the ESS were directly affected by the market price, as shown in Fig. 17. The market price of both the conventional method and the proposed strategy was the same, indicating that there was no change in the output power generated by the DU and the ESS.

Table 9 shows the comparison of the operating costs of each case. Case 2, which experiences the degradation of the MT, exhibited an increased operating cost compared to Case 1. The cost of the MT increased, compared to when all DGs were healthy. In particular, the cost purchased from the main grid was increased significantly because the degraded MT was not able to output the scheduled power, resulting in the purchase of the shortfall from the main grid. As observed earlier, this implied that problems arose in the cost optimization and power supply stability when operating the microgrid with the conventional method. The proposed strategy increased the total operating cost compared to when all DGs were healthy. The generation cost increased because the degraded generator was included in the microgrid; this was an expected result. However, the proposed strategy was able to generate substantial savings in the total cost when compared with the result of the conventional method. This occurred because it was possible to optimize the microgrid operating cost by incorporating the increased cost resulting from the generator degradation in the optimal scheduling model. The ESS degradation costs in both methods had the same value because the total charging and discharging power of the ESSs were the same, as shown in Fig. 17(b). In addition, the operating time of the generator was limited by accounting for the RUL of the generator. With this intervention, the sudden shutdown of the generator could be prevented, improving the operational stability of the microgrid.

V. CONCLUSION

In this study, we proposed a new optimal scheduling strategy for microgrids that incorporates generator degradation and the RUL. The efficiency and maximum capacity reduction were analyzed using FEA and model equations for PMSGs with insulation degradation. The proposed strategy demonstrated economic benefits that resulted from the reduction of operating costs compared to the conventional optimal scheduling method, which does not account for generator degradation. In addition, the proposed strategy decreases the likelihood of sudden shutdowns of the generator and increases the stability of the grid, by processing degradation information in advance. The effectiveness of the proposed strategy was demonstrated by conducting case studies with the microgrid test system. The proposed strategy can be extended to other types of distributed generators such as ESSs or synchronous generators and also to other types of degradation. Prediction errors, reactive power, and voltage were not considered in this study. Based on the strategy proposed in this study, future work will include solving the optimal scheduling problem by also incorporating the forecast error and the optimal power flow problem related to generator degradation.

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