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RESEARCH ARTICLE

Modeling of Power System Resilience During a Catastrophic Disaster and Application of the Model

TAE-HYUN YOO[1], (Member, IEEE), AND HYEONGON PARK[2], (Member, IEEE)
[1]Korea Electrotechnology Research Institute, Uiwang, Gyeonggi-do 16029, South Korea
[2]Department of Safety Engineering, Pukyong National University, Busan 48513, South Korea

Corresponding author: Hyeongon Park (hyeongon@pknu.ac.kr)

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ABSTRACT Research on enhancing the resilience capabilities of power system to catastrophic disasters, characterized by low probability but high impact, is moving beyond theoretical approaches to incorporate considerations of financial and technological limitations in real-world applications. Our study aims to bridge the gap between the conceptual approach and real-world applications of resilience enhancement. This objective is achieved by developing a simplified model considering the change of resilience state that retains its original functions and characteristics, enabling the application and analysis of resilience enhancement strategies. Our study proposes a simplified model for resilience assessment that retains the essence of existing performance indices used in conventional power systems. The model incorporates the essential and non-essential demand characteristics and applies operating modes to achieve a realistic representation. The trapezoidal system state transitions were redefined based on power demand and system operating modes. The state transitions were also structured according to the defined performance indices. Availability factors were directly incorporated, while network constraints were modified and an example was constructed to facilitate model assessment. The resilience index can be readily replaced and modified by decision-makers. This will facilitate the simplified evaluation of power system resilience in comparison to critical infrastructure in other domains, providing insights from each state-specific result.

INDEX TERMS Catastrophic disaster, conversion of operation mode, resilience indicators, power system planning.

NOMENCLATURE

b	: Bus index.
g	: Generator index.
l	: Line index.
t	: Time index.
$d_{b,t}^{estl}$	: Supplied essential demand at bus b at time t.
$d_{b,t}^{non-estl}$	: Supplied non-essential demand at bus b at time t.
a_g, b_g	: Cost function parameters of generator g.
$p_{g,t}$	: Power output of generator g at time t.
$u_{b,t}$	: Binary variable to indicate whether demand is satisfied (1) or not (0) at bus b at time t.
$P_{g,\min}$	: Minimum generation output of generator g.
$P_{g,\max}$	: Maximum generation output of generator g.
$f_{ij,t}$	: Power flow on the line connecting bus i and bus j at time t.
$D_{b,t}^{estl}$	: Essential demand required at bus b at time t.
$D_{b,t}^{non-estl}$	: Non-essential demand required at bus b at time t.
D_t^{total}	: Total demand required in the system at time t.

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$\theta_{i,t}$: Voltage phase angle of bus i at time t.
x_{ij} : Reactance of the line connecting bus i and bus j.
$f_{l,\max}$: Maximum allowable power flow capacity of line l.
$flag_A$: Binary indicator that is set to 1 when the system operator seeks to maximize essential demand.
$flag_B$: Binary indicator that is set to 1 when the system operator seeks to minimize operational costs.
$VoLL$: Value of the lost load.
M : A very large positive number.

I. INTRODUCTION

Over the past few decades, power systems have undergone continuous improvements to meet modern social paradigms. The basic structure of a power system comprising generation, transmission, and consumption modules was established before the 1950s and the key technologies have exhibited remarkable progress, enabling expansion of large systems. However, management of such systems has lagged. Cost-effective operation of massive power systems was developed only in the 1950s as computing advanced. This enabled the formulation and solution of complex problems such as optimal power flow and economic dispatch. As Huneaut and Galiana wrote in 1991, the well-defined optimal power flow problems of the early 1960s became increasingly soluble with technical advances [1]. The rapid expansion of power systems that employed computing technology proceeded through the 1960s. Subsequently, the oil crises of the 1970s and 1980s threatened oil-based power generation, which drove a gradual shift toward a more diverse power mix. However, cost-efficiency became a major concern. As climate changes caused by greenhouse gas emissions increased, efforts were made in the 1990s to reduce carbon emissions. During the present era focused on achieving sustainability, safety concerns have been raised, as the risks of damage caused by disasters have increased. For instance, in the United States, Hurricanes Katrina and Sandy serious damaged critical infrastructure and triggered long-term power disruptions. The Japanese Fukushima nuclear accident of 2011 highlighted the need to address such threats. Major challenges are posed by system failures after disasters that are of high impact but low probability (HILP). Figure 1 summarizes the major paradigm changes over the past few decades.

The expected consequences of most disasters depend on their magnitudes and risks of occurrence. A study of damage caused by past disasters reveals how to respond in a quantitative manner. Traditional power system reliability is a socially agreed-upon level of power supply with hardening of facilities that may be damaged by either internal or external factors.

Basically, a system operator tries to handle a given amount of damage; if damage exceeds that level, measures are developed to restart the system. However, forecasting of the massive damage caused by highly improbable disasters is near-impossible due to the lack of available data. Even if quantitative values are derived using such data, employment of these values for preventative decision-making during a disaster is of great concern. If a disaster occurs, all members of the present generation may suffer severe harm. Therefore, even if the expectation of such events occurring is low, it is imperative to consider them. In recent years, the concept of resilience has been used to overcome the weaknesses of expectation value-based approaches. Resilience focuses on damage mitigation and rapid recovery to avoid massive societal damage.

Catastrophic disasters have been principal drivers of changes in attitudes toward traditional system management. The concept of resilience was first introduced by Holling in 1973, but was applied to only ecological systems. The point was that if a system is confronted by external changes, the constancy of system behavior is less important than the persistence of existing relationships [2]. This core idea can be used to overcome the limitations of massive human systems. In American Presidential Policy Directive 21 (PPD-21), resilience is defined as "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents" [3]. The Cabinet Office of the United Kingdom summarizes resilience as "an ability to withstand and quickly recover from a difficult situation" and emphasizes that measures to detect system vulnerabilities and maintain normal function should be proactively implemented [4]. Power systems continue to change; thus, many researchers and engineers seek to enhance resilience. This requires a comprehensive approach that considers not only planning but also operation and control; all system components must be evaluated. Various initiatives are underway to ensure that the disaster response capacities of all modules are appropriate.

An assessment platform is required for effective management of resilience. In the early stages of resilience research, framework-building was a preliminary step in system construction given the limitations imposed by conceptual establishment. Many studies have sought to create comprehensive frameworks that assess resilience in the context of power system management [5], [6], [7], [8]. Resilience evaluations often employ risk management methods, as the process structures are similar [9], [10], [11]. Despite their user-friendliness for decision-making, these framework and risk management studies lack applicability to concrete power system implementation. The approaches to assessing power system resilience and changes in the key roles played by the various operating areas have been reviewed by system operators, and efforts have been made to implement them [12], [13], [14]. The frameworks developed in various studies have yielded insights into resilience assessment [15], [16], [17]. These studies aimed at reflecting power system characteristics, along with frameworks related to resilience

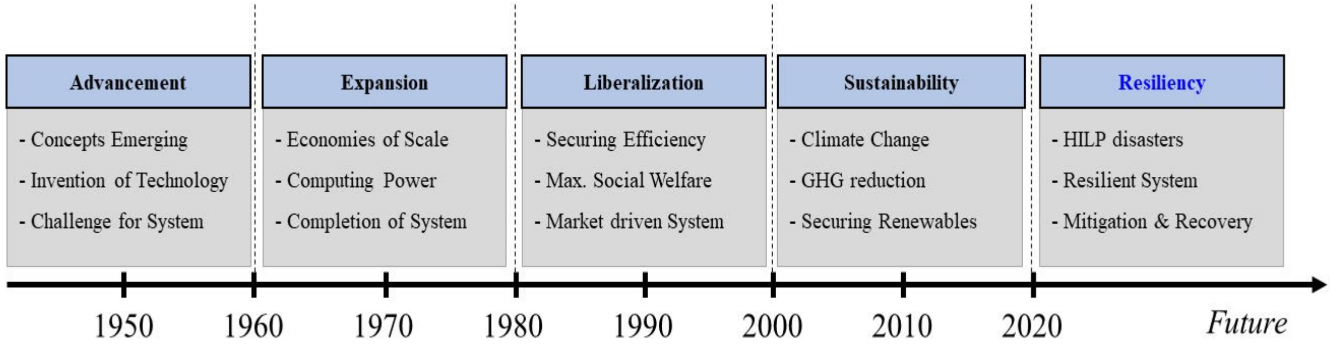

FIGURE 1. Major power system paradigm changes.

assessment, can be viewed as an extension of the scope of research on preparedness for disturbances in traditional power systems. Natural disasters that create massive and unpredictable damage have been subjected to extensive study since resilience was first defined [18], [19], [20]. Despite conceptual advances and useful case studies, formalized analytical structures are needed to bridge the gap between conceptual approaches to power system resilience and the implementation thereof.

Efforts are being made to ensure power system resilience from various perspectives. Planners have made significant efforts to mitigate damage to power generation system structures through a variety of strategies [21], [22], [23]. Since planning-oriented research has mostly focused on either detailed power system engineering or a comprehensive approach to energy systems, a model that incorporates the needs of various stakeholders is necessary for practical application. Various studies have focused on specific hazards that cause disasters [24], [25], [26], [27]. While case studies offer a valuable tool for examining power system resilience under specific disaster scenarios, their limitations should be considered when translating findings into generalized models. As the resilience concept has been principally used to address large-scale damage problems, cascading failure of power system operation has also been considered from the perspective of resilience [29], [30]. Various studies have performed resilience evaluations and sought improvements using microgrid concepts [31], [32], [33], [34]. Research has focused on both the supply and demand sides, with the goal of improving overall resilience [35], [36], [37]. While detailed efforts within individual power system domains can contribute to resilience improvements at the level of specific components or operational logic, there is a pressing need for a simplified power system model that encompasses these elements from a risk management perspective. As major critical infrastructures are interdependent, it is important to prepare resilience plans that consider this fact [38]. For instance, various studies have evaluated complex electricity and gas systems employing virtualization dependency followed by the establishment of recovery strategies [39], [40], [41], [42]. A technical approach to securing integrated resilience in major infrastructure is very important, and a methodology that can link it with policy decision-making is also urgently required.

The measurement, assessment, and evaluation of power system resilience are essential components when aiming to improve overall resiliency. Many studies have used changes in system performance rates to assess damage during a disaster, and also to show how system states change accordingly [43], [44], [45], [46]. Probabilistic approaches have been widely used for resilience assessments. New approaches include a planner–attacker–defender model and complex network theory [47], [48]. Several studies have sought to operationalize the conceptual model by evaluating the fragilities of individual facility units at the system level [49], [50], [51], [52]. Various approaches have explored both system performance and economic perspectives [53]. Studies emphasizing conceptual framework development often lacked a technical approach for real-world application. Conversely, studies centered on specific case studies needed strategies to overcome limitations in generalizability. Research focused on power system operation for resilience enhancement may struggle to fully capture policymakers' decision-making processes, while planning-oriented research may face challenges in accurately depicting emergency conditions.

Extensive research has sought to ensure power system resilience; there is an increasing need to implement these findings in actual systems. Here, we present a resilience evaluation model that includes specific state definitions reflecting the critical demands, as well as system balancing and long-term operability, of real-world systems. During an emergency, demands are classified as essential or non-essential. Realistically, this concept should be aligned with the state of the power system. After configuration of the state, indicators based on the results of system operation are identified. These translate metaphysical performances to parameters that can be used in the real world. Multiple states previously based on triangles and trapezoids are now divided into system planning and operation stages. An hour-by-hour simulation featuring optimal power flow over a long period is performed; this considers system operator responses in emergency situations. The model contains the power dispatches

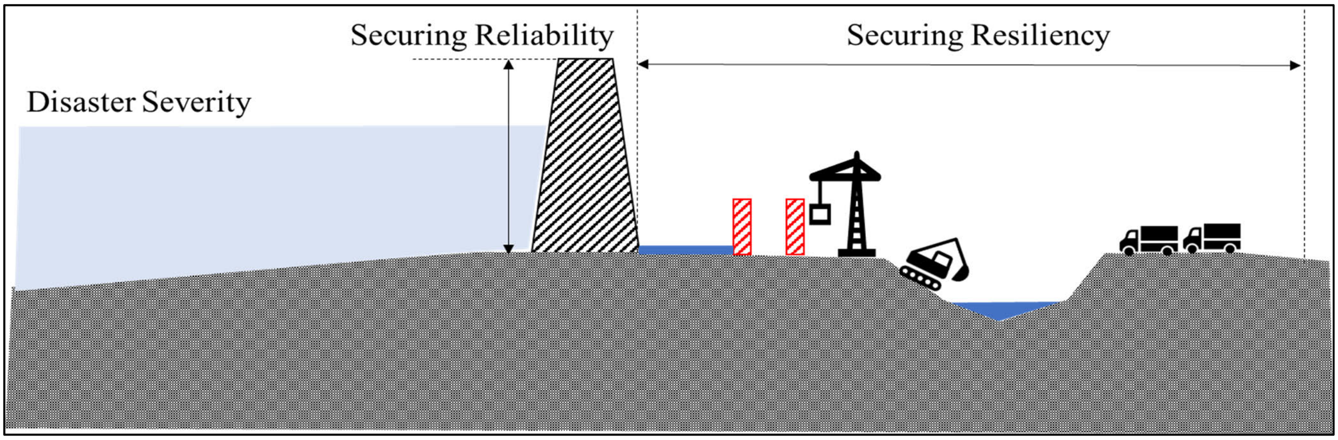

FIGURE 2. The relationship between power system reliability and resilience.

under normal and emergency conditions. After determining the dispatch strategies, the resilience values are derived based on the results of simulation.

Our principal contributions can be summarized as follows:

1) To account for critical infrastructure with non-monetizable values, we propose a classification of power demand into essential and non-essential categories and present a methodology applicable to real-world power system operation. We take a holistic perspective to respect socially important values by maximizing the overall essential demand. Through this, we strive to fully embed the core resilience concepts of damage mitigation and rapid recovery.
2) To render existing resilience state-related research useful in practical application, we have rendered state classification more concrete; we consider the levels of various resilience indicators. This approach creates appropriate planning, operation, and control alternatives, and determines the responses of the system operator during a disaster.
3) Our implication example that simplifies power systems and utilizes pre-determined indices with modifications can provide guidance for applying these indices to various cases.

The remainder of the paper is organized as follows. In Section II, power system state classification during a disaster based on the original system function is studied. Section III considers the implementation and modeling of actual system operation. Section IV presents an illustrative example of such methodology and modeling. Section V draws conclusions and summarizes the principal findings.

II. APPLICATION OF THE RESILIENCE CONCEPT TO POWER SYSTEM DISASTER MANAGEMENT

A. ORIGINAL POWER SYSTEM FUNCTION

Decision-making in terms of power system investment is strategic in that it considers both potential disaster damage and the social cost-effectiveness consensus. Decision-makers establish an investment strategy that reduces the effects of disasters on the power system throughout the system lifetime. There are various possibilities: 1) hardening facilities; 2) maximally mitigating damage by incorporating redundancy and resourcefulness; and 3) focusing on rapid recovery. Given that almost all actions consume limited costs and resources, decision-makers must consider not only the lack of technical capacities but also cost-effective ways by which to manage damage. The fundamental principle of power system resilience is optimization of the balance between damage reduction and the costs thereof. HILP disasters pose challenges when investing to enhance resilience; the great uncertainty in terms of occurrence renders it difficult to convince society members to pay for the investments.

When focusing on resilience improvements, it is important to exclude disasters for which traditional cost-effective prevention measures have already been implemented. In the traditional power system paradigm, many schemes that maintain robust power system operation have already been developed and applied. At the planning level, supply capability is secured via various methods that consider future demand and failure of existing facilities. Such methods include generation and transmission expansion planning, capacity market mechanisms. At operation level, the volatility and uncertainty of balancing supply and demand are addressed by securing reserves from very short-term to long-term periods. At the control level, schemes have been devised that ride through or block abnormal conditions that could trigger component or system failures. The system failure prevention and response methods required when maintaining and operating power systems, while also considering cost efficiency, have been subjected to continuous research and development.

Resilience measures are required only for areas at risk of damage because of limitations in existing prevention methods. At the control level, sub-system issues may be expensive to repair, and can affect the main transmission system. Protection schemes involving temporary power cuts effectively handle minor issues. At the operation level, an inability to balance supply and demand compromises system synchronization. Unlike at the control level, generation availability should be planned in advance because this is affected by boiler condition and the residual capacity. The use of load dumps to deal with operation-level failures not only creates significant disruption costs in both the short and long term, but also poses challenges when seeking user agreements. At the planning level, it is important to ensure adequate generation capacity. If adequate preparations are not made, it is impossible to address any supply deficit. Moreover, customers do not tolerate extended electricity outages. Therefore, the disaster management strategies of a reliability paradigm must be robust and appropriate if a "disaster" is relatively minor, thus at a socially agreed level. Resilience should be secured on the premise that there is a system with sufficient robustness to withstand relatively small disasters. This is because the existence of measures to ensure reliability can meet consumers' expectations of using power resources and secure cost efficiency. The relationship between reliability and resilience is presented in Figure 2.

Measures to reduce the effects of disasters can be divided into two categories: reliability- and resilience-oriented measures. Reliability-oriented measures seek to ensure that disasters do not affect the power system, the design and construction of which impart resistance to damage. Contingency plans that restore power in the event of a disaster may be in place. By contrast, resilience-oriented measures seek to enable a power system to quickly recover from a disaster and typically include system redundancy and flexibility.

B. ESSENTIAL AND NON-ESSENTIAL DEMANDS

We next consider the potential practical limitations of the concepts of essential and non-essential demands. In advanced studies, essential and non-essential demands were initially conceptualized by considering the original power system function, for example "a function that can supply sufficient power to the required demand at a specific time, regardless of the form or configuration of the power system" [54], [55]. The principal purpose of classifying power demand as essential or non-essential is to minimize negative impacts during emergencies by prioritizing power to essential facilities. Several studies have quantified customer damage during disasters by deriving damage cost employed when deciding how much to invest to prevent disaster damage. Although significant improvements in both quantification and classification have been made, demand classification by the needs of critical infrastructure has not been sufficiently addressed in the context of power system resilience during system planning and operation [35].

We suggest that demand should be categorized as essential or non-essential by system operators responding to disaster events and implementing emergency power supplies. Such a demand classification methodology has not been widely adopted in previous studies, as it presents several challenges. In reality, it is difficult to clearly distinguish and manage essential and non-essential demands. Typically, such demands are served by the same substations that are difficult to individually control in terms of power supply. Despite these limitations, the concepts of essential and non-essential demands prevent massive cascading damage caused by hazardous events. The key to power system resilience is reducing damage from disaster onset to full restoration of the original function, not preventative measures that seek to ensure uninterrupted power supply. It is essential to tolerate temporary system degradation and some consumer harm from regional, temporal, and long-term perspectives. Our model can also employ cost-converted customer power outages, but there are some challenges.

First, there are limitations when comparing electricity values. When a power system begins to cut load to maintain some function during a disaster or if electricity supply is paralyzed, a choice must be made as to which regions to cut off or supply. If the demand values are identical, the mutual comparison standards are clear. Therefore, if only technical problems are considered, a model that minimize damages during the pre-cycle response before and recovery after a disaster is easily implemented. However, the social values imparted by electricity are diverse and difficult to compare. For example, the power used in medical facilities and the associated value are difficult to quantify, and the power used in national core infrastructure to maintain society and the value thereof cannot be readily quantified given the inter-system linkages and ripple effects in play.

Second, there remain questions about the cost-conversion scheme. If power is lacking, and demand is to be met using a scheme that employs cost-converted values, does society appropriately reflect the primary values? For example, is it more important to facilitate normal daily life or preserve perishable goods? Additionally, the cost assessments of infrastructures featuring large social ripples may be inaccurate; it is difficult to model reality. If quantification focuses on costs, prioritization of important values may be lacking if the costs favor different choices during decision-making. A different model would then be appropriate. Also, can "essential" demands be prioritized? Values that cannot be individually compared should be determined by the classification criteria. Of values in the same group, none should be prioritized during recovery after a disaster; rather, the overall value must be maximized.

In this paper, a novel system operator strategy and a new and realistic state classification are derived and resilience indicators that address the above challenges identified.

C. STATE CLASSIFICATION CONSIDERING THE SUPPLY–DEMAND BALANCE AND LONG-TERM OPERABILITY

If essential functions of a power system are under threat, some demand interruption may be necessary to maintain overall system integrity. To prevent confusion when responding to a disaster, the system operator should pre-establish emergency action criteria. A large-scale loss of supply during a disaster

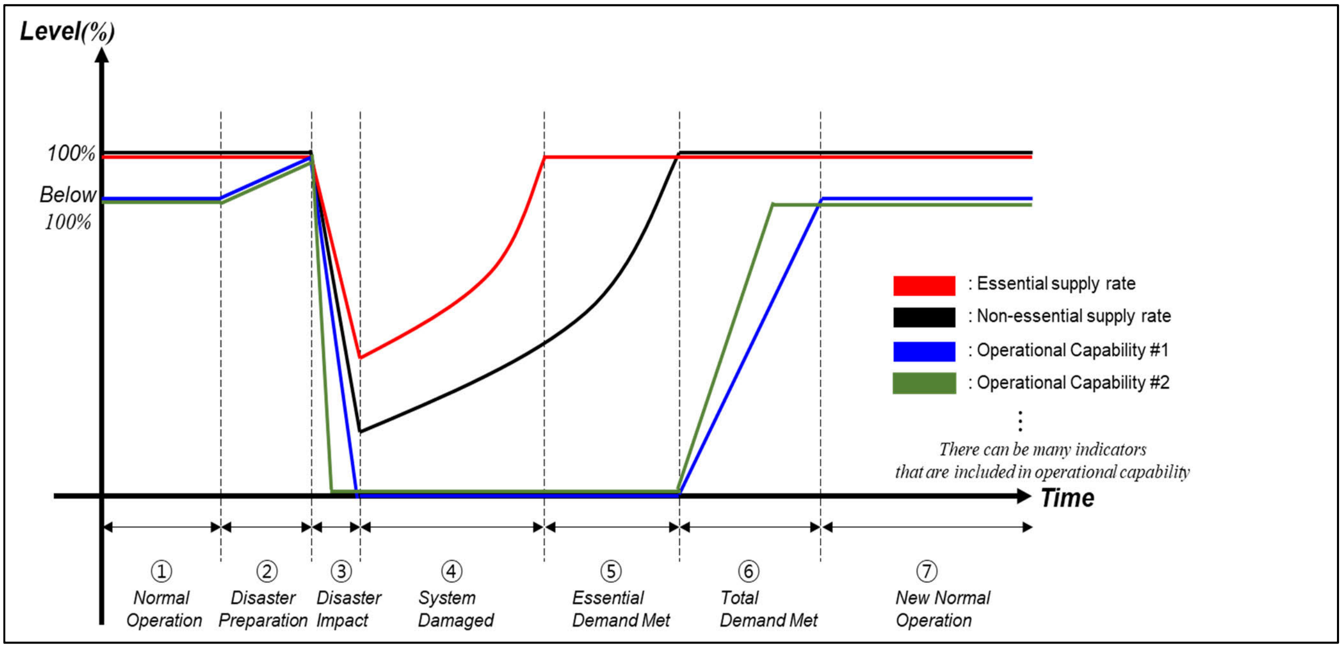

FIGURE 3. Classification of power system state by the performance level.

may collapse the supply-and-demand system because of inadequate supply. In such a situation, the power system strives to meet social expectations by prioritizing supply to urgent demands that will not otherwise be met and by avoiding supply to relatively non-urgent demands. The utility of electricity consumption varies depending on the type of demand; some types can be quantified but others not. For example, some power is consumed by factories that make useful items, and some is used by medical facilities that save lives.

In this paper, demands are categorized as essential or non-essential. Essential demands are loads that must be supplied first, such as to hospitals and fire stations. Non-essential demands can be temporarily unmet despite some cost damage. By limiting power to and inconveniencing commercial businesses and residential homes, power can be diverted to medical facilities, ensuring that nobody dies on an operating table. Figure 3 illustrates the power system states by performance level in emergencies.

Introducing new power system facilities requires great care; these are costly and have long lifespans, and decisions are not easily reversed. Various factors must be considered from different perspectives. Table 1 lists the suggested states and the levels of system components [55].

First, the situation in which no disaster caused by a hazardous event is observed and preliminary measures employ a review of prior disasters is the "Normal Operation" state. The "Disaster Preparation" state is characterized by the detection of a disaster that threatens the power system; this marks the end of normal operation. At this stage, the system operator seeks to minimize damage until the disaster commences, regardless of whether planning is successful or not. The moment the system is damaged by a disaster, the "Disaster Impact" begins and the operator seeks to prevent complete failure if possible. This state is followed by a temporary partially balanced state when the disaster ends, referred to as the "System Damaged" state during which fulfilment of all essential and non-essential demands is impossible; the operational capability is thus unacceptable. To fulfil essential demands as soon as possible, the system operator initiates recovery immediately after the disaster and prioritizes essential demand, or the "Essential Demand Met" state, which progresses to the "Total Demand Met" state once non-essential demand is also completely supplied. The primary goal of the system operator until the "Total Demand Met" state is attained is to balance operational supply and demand, not to ensure stable system operation. Therefore, the best operation methodology focuses on balancing rather than cost-based optimization. When recovery ensures long-term operational capability and relevant criteria are met, the "New Normal Operation" state commences, followed by periodic reviews of whether essential supply and demand, non-essential supply and demand, and operational capacities meet preset goals.

III. IMPLEMENTATION OF THE MODEL

A. ADVANCED STUDIES ON RESILIENCE MEASUREMENT

Many studies have used various metrics to evaluate system resilience. Resilience evaluation methods can be divided into qualitative and quantitative approaches [12]. Qualitative approaches represent resilience using conceptual frameworks or semi-quantitative indices and are frequently applied when evaluating socio-ecological systems, communities, and engineering applications [56]. Authors in [57] outlined eight

TABLE 1. States characteristics and the levels of system components [55].

	System State	Main Characteristics of the State	Level of System Components		
			Essential Balance	Non-essential Balance	Operational Capability
①	Normal Operation	Typical power system operational status that considers cost efficiency; threats are not observed	○	○	○
②	Disaster Preparation	A hazard that may cause a disaster is detected, and the ability to respond is enhanced as much as possible	○	○	◎
③	Disaster Impact	The state from the beginning of direct damage by a disaster until the end thereof	X	X	N/A
④	System Damaged	The state between termination of damage and the start of recovery	X	X	N/A
⑤	Essential Demand Met	The state in which essential supply and demand has been fully restored, but not non-essential supply and demand	○	X	N/A
⑥	Total Demand Met	The state in which supply and demand has been fully restored, but not operability	○	○	X
⑦	New Normal Operation	The system is fully operational and able to service future demand	○	○	○

guiding principles when assessing system resilience, including threat assessment, robustness, and adaptability. Authors in [58] calculated resilience by combining various system characteristics represented by percentages. Such qualitative approaches render it difficult to express and compare power system resilience values that vary over time and by location. Quantitative approaches calculate numerical resilience values using statistical, optimization-based, simulation-based, or graph theory methods. To determine power system resilience, system performance is first independently defined and then incorporated into the resilience computation. The resilience of a power system can be calculated by finding the gap between the performance of an ideal and a real system, or by showing the performance that varies by time period before, after, and during recovery. Note that the trajectory of system performance can vary by the system design and enhancements that seek to mitigate the effects of disasters.

Various graphical methods that calculate resilience by reference to changes in system performance over time have been published [7], [59], [60], [61]. Resilience was calculating using the differences between an ideal and real system in [59], and by reference to the recovery speed and performance immediately after the event in [7]. In [60], the FLEP set of metrics was introduced, which collectively represent the rate, level, and extent of degradation; and the recovery rate; these metrics were quantified using curves detailing changes in system performance over time, and the specific curve area was used to calculate overall system resilience. Finally, the authors of [61] defined resilience by reference to the restored performance, but states other than the restoration state were not considered.

B. THE RESILIENCY EVALUATION METHOD AND THE APPLICATION THEREOF

Optimal system resilience assessment must comprehensively capture both the mitigation of damage caused by a disaster and the rapid restoration of full performance. Based the FLEP method of system performance quantification, we reviewed normal system function and sought an improved method that prioritized supply of demand in a realistic emergency. Previous studies have used similar concepts, but we focus more on realistic management of disaster damage that cannot be monetized.

We implement a state classification that considers resilience measures and operation mode switching. This embeds resilience concerns in a straightforward manner when managing power systems.

Our resilience evaluation method quantifies the capability of a power system to fully recover after a disaster. This is achieved by calculating the achievement rates of essential and non-essential demands via simulation. By evaluating each type of damage separately, the method identifies values that cannot be expressed in monetary terms and separately calculates the requirements that play critical roles in terms of social values.

Using our method, the recovery plan assigns equal values to all critical infrastructure components, distinguishes essential from non-essential demand, and quantifies the latter demand numerically by reference to societal expectations. This maximizes the overall utility that the system operator should pursue. We had two principal considerations when developing resilience indicators:

1) A system is considered fully recovered when the operator can ensure long-term operability despite various challenges that include the variability and uncertainty of operating demand, loss of some grid facilities, and the need for maintenance. To determine appropriate actions in various situations, indicators of system operational requirements are required. Indicators that have been previously used during normal operation are suitable. For example, some indicators consider adequacy, thus whether generators supply enough power; other indicators focus on reserves that can be committed to certain units, economic dispatch, and frequency control. It is also possible to consider the ramping capabilities at various times given the control variabilities in and uncertainties of recent renewable energy facilities. The network constraints must ensure reliable and uninterrupted transmission of electricity produced in various places. If all factors that aid stable system operation are included and resilience is evaluated by quantifying those factors, our understanding of the system becomes more detailed and accurate. However, as complexity increases, it may become difficult to comprehend what certain resilience indicators indicate. However, a novel comprehensive indicator that considers various factors may not be realistic. Simple insight may be better than a complex indicator that requires elaborate calculation.
2) Resilience indicators should be reviewed separately for emergency and normal operations. For a power system experiencing catastrophic damage and undergoing resilience-focused review, instability in power supply arises compared to the general operating conditions, necessitating the maximization of essential demand supply. It is essential to first define the minimum conditions required for supply reliability, and only then focus on power quality. In other words, it may be acceptable to tolerate damage that shortens facility demand-side lifespans than to completely lose power. However, the facilities will be severely tested if the damage persists; the cumulative ''social damage'' caused by emergency operation must be considered. Therefore, the resilience indicator of long-term operability must be carefully identified and applied.

Here, we sought key indicators of both emergency and normal operation. First, indicators reflecting the supply-and-demand balance well-describe the normal system; they must be reviewed as the system state changes during a disaster. To express resilience in a specific manner, we reviewed how the levels of essential and non-essential demand changed over each time period; we used the demands defined in the previous section. Detailed techniques must be followed during system operation or control. The power balance is described by two indicators, the achievement rates of essential and non-essential demands.

In terms of long-term operability, we considered generation adequacy and the pre-agreed network capability. The capacity reserve rate is an indicator of facility maintenance and possible failure; this meets the minimum requirements for normal operation at all times. A low reserve rate can disrupt power supply if facilities fail and maintenance becomes unexpectedly difficult or affects facility life. Accordingly, we considered that the rate at which the preset capacity reserve was achieved would be a minimal indicator of whether the power system had returned to normal. Next, to assess the power transmission capability, the restoration time from damaged to normal also served as an indicator. Transmission capability is an abstract concept that depends on the grid configuration, demand profile, and power plant location. It is difficult to define how much capability is adequate in an emergency; capability is affected by generator recovery and construction of new facilities. It is also difficult to ensure that the grid will respond adequately to changing demand even if recovery is complete. Therefore, we used a modified reliability concept based on the N-k constraint condition to determine how quickly existing capabilities could be secured assuming that the transmission topology was appropriate for future responses.

C. IMPLEMENTATION OF THE METHODOLOGY

When selecting an appropriate means to ensure system resilience during a disaster, the operation method significantly impacts the outcome. A power system is massive and complex; the consequences of damage are many; various responses are possible. It is important that the model can be used by the system operator to aid decisions during a real disaster. For example, if widespread blackouts are inevitable, it may be possible to implement rolling blackouts after consultation with regional representatives. Sometimes, it may be necessary to simply cut the load, or it may be possible to supply some power by lowering the equipment operating standards.

If normal power system operation is impossible because of the inadequacy of reserves or the lack of generation capacity, it will not be possible to respond adequately to a changing electricity demand. In such a situation, the system operator must use a dispatch method that differs from normal, prioritizing maximum electricity supply over stable operation. Once the disaster is over and recovery is underway, the operator attains some operational capability and then transitions

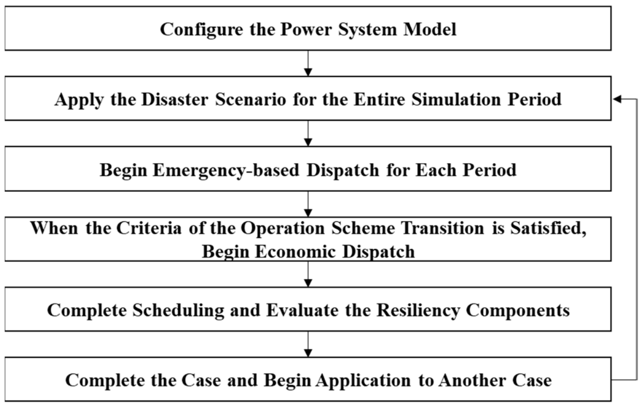

FIGURE 4. **Schematic of the model.**

from emergency to cost-effective operation. The choice of when to transition significantly impacts simulations. The choice must be careful and reflect the reality of the situation.

During a disaster, a system operator could apply strict, state-condition-dependent criteria for change. Then, the exact time of transition from emergency to cost-effective operation would be defined, once the essential demand completely recovered. However, this method is difficult to apply in the real world, as the future power system balance is not predictable, impeding the unequivocal determination of a transition point. There is no assurance that adequate power for essential demand can be maintained at a later time, even if this is achieved at some particular time. In other words, it is challenging to translate theoretical state transition criteria into practice. In the real world, a ''bold'' decision to initiate cost-effective operation at a certain time is required. To overcome the gap between theory and practice, the criteria for operating method transition must be relaxed.

IV. ILLUSTRATIVE EXAMPLE

A. SIMULATION AND MATHEMATICAL FORMULATION

We simulated the effects of the model and the derived resilience indices as depicted in Figure 4. Simulation begins with model configuration, which considers power supply-and-demand and the network topology. Next, a disaster is induced, and power system damage persists over the entire simulation period. System operation depends on the policy of the operator, who identifies essential and non-essential demands and then engages in daily scheduling determined at hourly intervals, as do existing power systems. If the essential demand is not fully met, a power supply plan based on emergency-based dispatch is enlivened. However, if essential demand is fully satisfied, a supply plan based on economic dispatch is executed.

The objective function of emergency-based dispatch is to maximize the supply of essential demand; the objective function of economic dispatch is to minimize operational costs, including both generation costs and costs incurred during power outages. Daily scheduling is performed for all 24 h in a day for 30 days. At the end of the 30-day period, numerical values of predefined resiliency components are derived. After detailed analysis of each case, other cases are examined.

The mathematical formulation can be represented in the following manner:

$$\begin{aligned} \max \ & \left(\sum_{t\in H, b\in B} M \cdot d_{b,t}^{estl} + d_{b,t}^{non-estl} \right) \cdot flag_A \\ & - \sum_{t\in H, g\in G} (a_g \cdot p_{g,t} + b_g) \cdot flag_B \\ & + VoLL \cdot \sum_{t\in H} \left(D_t^{total} - \sum_{g\in G} p_{g,t} \right) \cdot flag_B \end{aligned} \tag{1}$$

$$d_{b,t}^{estl} = u_{b,t} \cdot D_{b,t}^{estl}, \quad \forall b, t \tag{2}$$

$$d_{b,t}^{non-estl} = u_{b,t} \cdot D_{b,t}^{non-estl}, \quad \forall b, t \tag{3}$$

$$P_{g,\min} \leq p_{g,t} \leq P_{g,\max}, \quad \forall g, t \tag{4}$$

$$\sum_{j=1, j\neq i}^{N_b} f_{ij,t} = \sum_{g\in G_b} p_{g,t} - d_{b,t}^{estl} - d_{b,t}^{non-estl}, \quad \forall b, t \tag{5}$$

$$f_{ij,t} = \frac{\theta_{i,t} - \theta_{j,t}}{x_{ij}}, \quad \forall l, t \tag{6}$$

$$-f_{\max} \leq f_{ij,t} \leq f_{\max}, \quad \forall l, t \tag{7}$$

$$-\pi \leq \theta_{b,t} \leq \pi, \quad \forall b, t \tag{8}$$

The system operator assesses whether the essential demand is fully met. Then, for the upcoming 24 h, the operator either prioritizes a supply increase to meet the demand or shifts to cost minimization. In the immediate aftermath of a disaster, if not all essential demands are met, $flag_A = 1$ and $flag_B = 0$. This prompts the system operator to prioritize essential demand. After the essential demand is adequately addressed ($flag_A = 0, flag_B = 1$), the system operator shifts focus to economic dispatch, aiming to minimize the overall system operating costs. This involves minimizing the sum of generator costs while keeping load shedding to a minimum. For computational convenience, this study employs a first-order cost function. Piecewise linear approximation or similar techniques can readily linearize cost functions. This strategy corresponds to objective function (1). Constraints (2) and (3) respectively indicate whether or not the essential and non-essential demands are satisfied at each bus. Here, $u_{b,t}$ is a binary variable that is 1 if the demand is in fact met at a given bus. Note that essential and non-essential demands do not have separate binary variables; it is near-impossible to selectively supply only a portion of the load. Therefore, only a single variable is in play for each bus at each time interval. The output limitation of each generator is expressed via constraint (4). The demand and supply at each bus must be balanced as represented in constraint (5). Constraint (6) represents the power flow on the transmission lines, while constraint (7) enforces the flow capacity limits for each specific line. Since the purpose of this study is to analyze the long-term system impacts caused by disasters, a DC power flow model was used instead of a full AC power flow model to reduce the computational burden. DC power flow equations are a method of linearizing power flow equations using the characteristics of ac-power systems, and are widely utilized in system planning, electricity markets, and other applications [62].

If potential disasters are anticipated, new systems may be constructed. If a disaster changes the system state, the parameters (or sets thereof) in our model vary. For example, new generators or transmission lines may be added in anticipation of a disaster, changing the generator and transmission line sets. If a malfunction occurs in a particular transmission line, that line cannot supply power. These potential variations are not incorporated into our equation, for the sake of simplicity.

B. DISASTER SIMULATION SETUP

The proposed approach was evaluated using the IEEE 30-bus test system with six generators and 41 transmission lines. The characteristics of the generators and loads are listed in Tables 2 and 3. The system topology is shown in Figure 5; the line impedance is that of [63]. During simulation, all time intervals were set to 1 h and the total simulation duration 30 days, thus totaling 720 h. The load pattern over the 30-day period reflect real South Korean demand data scaled to fit the simulation (Figure 6).

We analyzed the disaster occurrence and recovery scenarios in two separate categories. The first scenario involves a total system blackout (TSB), and the second scenario involves a partial system survival (PSS), where only parts of the system experience a power outage. They will respectively be referred to as TSB and PSS.

In the TSB simulation, the sequence of events starts with a disaster unfolding 50 hours after the simulation begins, leading to the disconnection of generators G1, G5, and G6. Then, at Hour 66, transmission lines numbered 5 through 9 and 33 through 37 fail. By Hour 75, the remaining generators also shut down, causing a complete power blackout. The recovery process commences with all generators being restored and back online by Hour 238, partially restoring the power supply. Subsequently, transmission lines numbered 5 through 9 are restored at Hour 291, and the restoration of lines 33 through 37 is completed by Hour 321. All other aspects of the disaster impact and recovery processes are set to follow the same pattern as in the TSB scenario, with the key exception being the continuous operation of generators G2, G3, and G4. The events following the disaster are depicted in Figure 5. The disaster preparation phase is not considered here for the sake of simplicity.

The system operator can enhance the response to a disaster in several ways to reduce damage. It is possible to introduce new infrastructure, accelerate the restoration of existing facilities, and increase the disaster resilience of such facilities. In this study, we considered the following three alternatives and assessed their effects via simulations:

- Alternative 1: Construction of new generators;

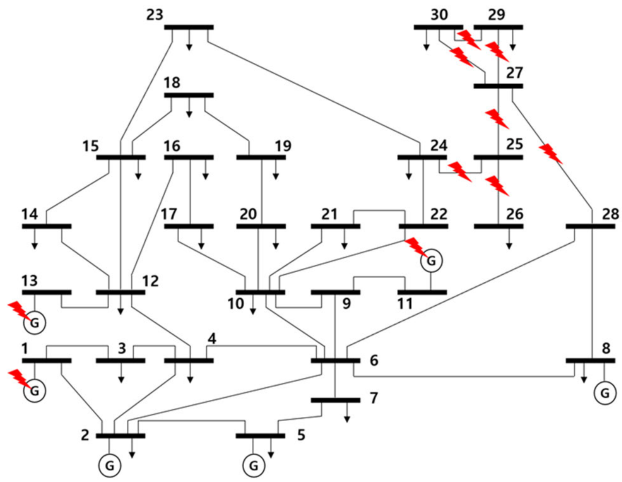

FIGURE 5. Illustration of the IEEE 30-bus system simulation configuration.

- Alternative 2: Increasing the generator restoration speed;
- Alternative 3: Increasing the transmission line restoration speed.

Alternative 1 involves constructing additional generators with the same specifications as the existing G1 and G2. It is assumed that the generators would experience similar types of damage from disasters as G1 and G2. Alternative 2 focuses on advancing the restoration timing of failed generators. Specifically, in the simulation, it increases the restoration speed of generator G6, enabling it to resume power supply more quickly. Alternative 3 aims to increase the restoration speed of transmission lines. This adjustment means that lines affected by accidents are restored approximately five days faster than originally planned.

All simulations were conducted on a PC equipped with an Intel Core 2.11 GHz processor (Intel Corp., Santa Clara, CA, USA) and 16.0 GB of RAM running the General Algebraic Modeling System software with the CPLEX solver (GAMS Development Corporation, Fairfax, VA, USA).

C. SIMULATION RESULTS

Figure 7 illustrates the varying resilience indices under different alternative conditions in the TSB case. The numbers indicate whether Alternative 1, 2, or 3 is incorporated. Simultaneous choice of multiple alternatives ensures rapid recovery. Unlike the changes in power system states in Figure 3, the indices of Figure 7 change in a stepwise manner because the time interval is short compared to the simulation target period. If disaster-caused power failures do not occur simultaneously and equipment recovery is sequential, the curve would be expected to be smooth, as in Figure 3.

The simulation results afford several insights. Essential and non-essential demands do not recover monotonically over time, even in recovery mode. In other words, it is impossible to determine whether a power system has fully recovered by evaluating the system state at one specific point

TABLE 2. Characteristics of the simulation thermal units.

Generators	G1	G2	G3	G4	G5	G6
Cost Parameter a [$/MW]	0.00375	0.0175	0.0625	0.00834	0.025	0.025
Cost Parameter b [$/MW^2]	16.19	17.26	16.6	16.5	19.7	22.26
Min-Max Capacity [MW]	50-200	20-80	15-80	10-35	10-30	12-40
Ramp Rate [MW/h]	150	150	25	25	30	30
Start-up Cost [$]	4,500	5,000	550	560	900	170
Bus No.	1	2	5	8	11	12

TABLE 3. System load data used in the simulation.

Bus No.	1	2	3	4	5	6
Total Peak Demand [MW]	0	21.7	2.4	7.6	94.2	0
Essential Demand Proportion	0	0.05	0.05	0.05	0.5	0
Non-essential Demand Proportion	0	0.95	0.95	0.95	0.5	0
Bus No.	**7**	**8**	**9**	**10**	**11**	**12**
Total Peak Demand [MW]	22.8	30	0	5.8	0	11.2
Essential Demand Proportion	0.7	0.5	0	0.05	0	0.3
Non-essential Demand Proportion	0.3	0.5	0	0.95	0	0.7
Bus No.	**13**	**14**	**15**	**16**	**17**	**18**
Total Peak Demand [MW]	0	6.2	8.2	3.5	9	3.2
Essential Demand Proportion	0	0.05	0.05	0.05	0.05	0
Non-essential Demand Proportion	0	0.95	0.95	0.95	0.95	1
Bus No.	**19**	**20**	**21**	**22**	**23**	**24**
Total Peak Demand [MW]	9.5	2.2	17.5	0	3.2	8.7
Essential Demand Proportion	0	0	0	0	0.05	0.05
Non-essential Demand Proportion	1	1	1	0	0.95	0.95
Bus No.	**25**	**26**	**27**	**28**	**29**	**30**
Total Peak Demand [MW]	0	3.5	0	0	2.4	10.6
Essential Demand Proportion	0	0.05	0	0	1	1
Non-essential Demand Proportion	0	0.95	0	0	0	0

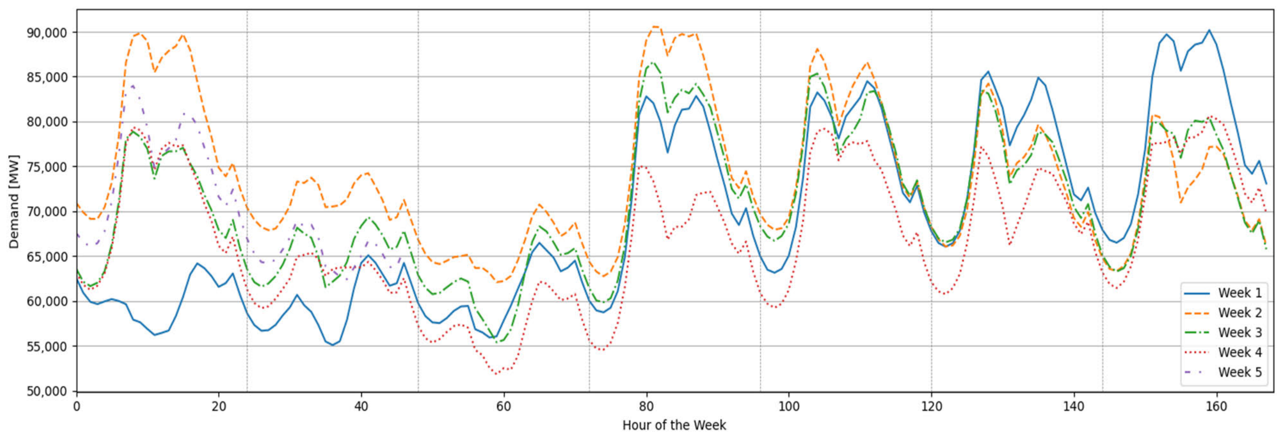

FIGURE 6. Demand pattern of the simulation over 30 days.

in time. Although the system operator seeks to maximize supply to essential demand immediately after a disaster, the results show that some non-essential demands may recover first because, although the system operator seeks to maximize essential demand supply, the system operates in a manner that recovers as much non-essential demand as possible. Because the alternatives considered in the simulation all relate to recovery after the disaster has ended and the damage assessed, it is clear that the immediate post-disaster situations in all graphs are identical. That is, in all cases,

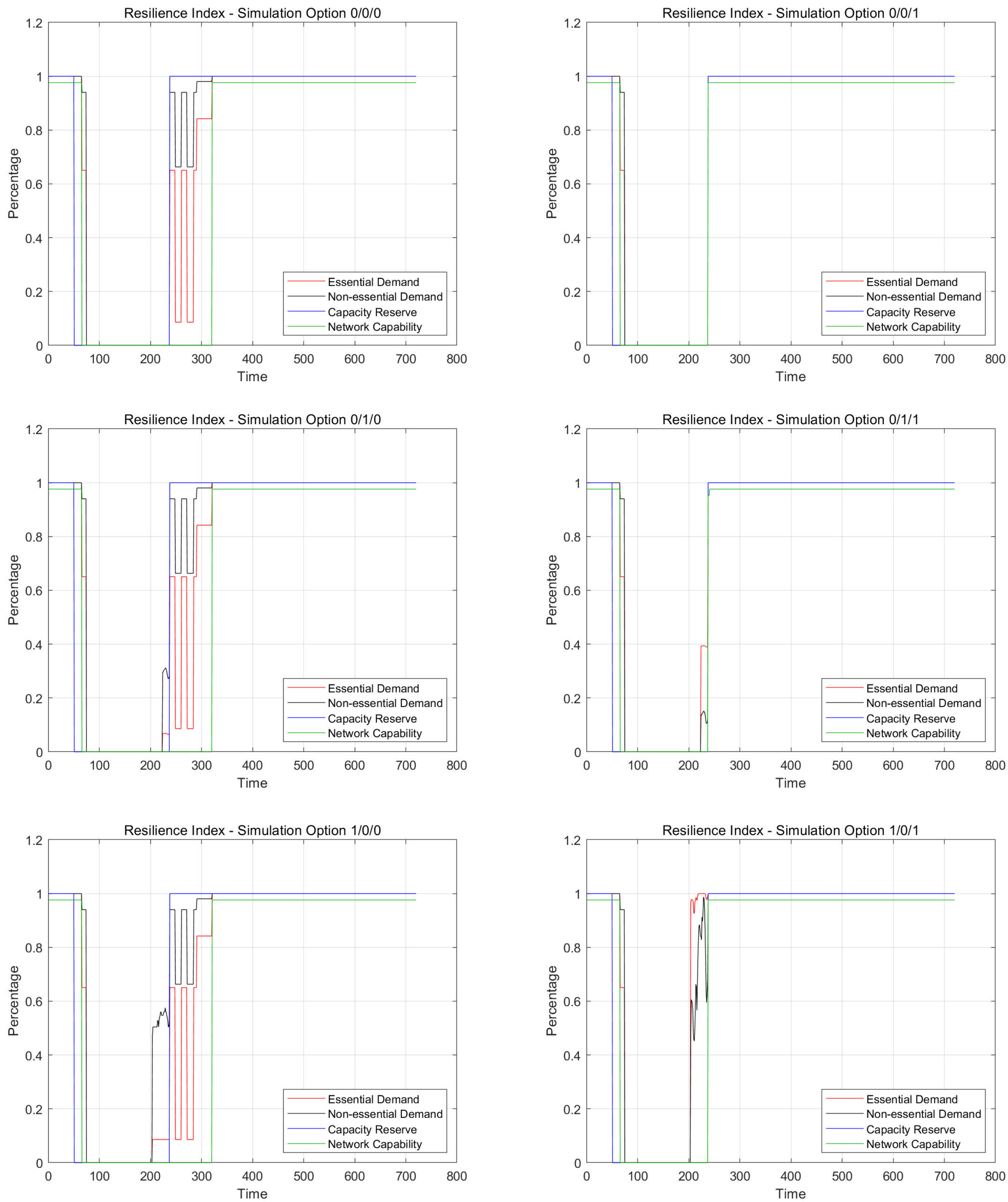

FIGURE 7. **The use of resilience indicators; an illustrative example-TSB scenario.**

the initial decline is identical (until every index drops to zero). However, if measures to mitigate the initial damage had been in place, different results would have been expected.

The results suggest that Alternative 1, which involves constructing new generators, can help to quickly restore a portion of the essential and non-essential demand. However, the results also suggest that other alternatives are needed to

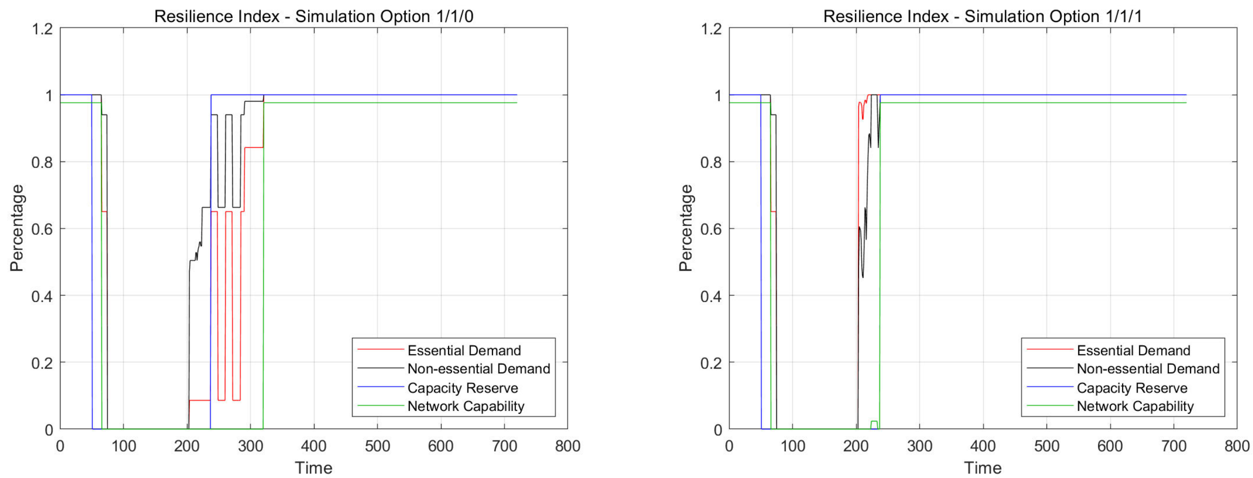

FIGURE 7. *(Continued.)* **The use of resilience indicators; an illustrative example-TSB scenario.**

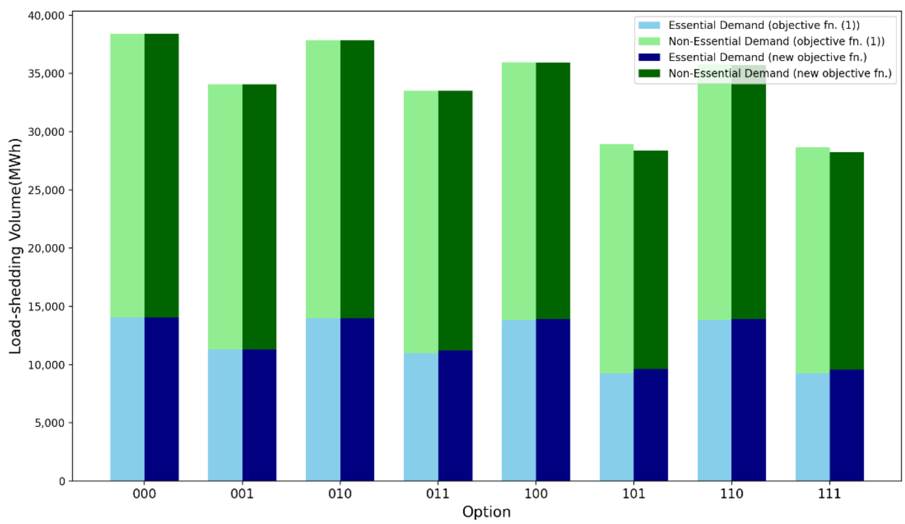

FIGURE 8. **Comparison of Load-shedding Volume by Option and Objective function.**

restore the system to its pre-disaster level (new-normal state) or a state where demands are adequately met.

The resilience index network capability is most affected by Alternative 3, which increases the speed of transmission line recovery. This not only enhances network capability but also helps ensure that essential and non-essential demands are stably supplied. In this simulation, we calculated the capacity reserve and network capability as operational capabilities. Interestingly, we observed that network capability recovers more slowly than capacity reserve. This behavior can vary depending on the simulation environment. For instance, if the power grid is designed with multiple redundant loops, the outage of a single line may not trigger load shedding, allowing network capability to recover more quickly than other operational capabilities.

Figure 8, similar to Figure 7, illustrates the varying resilience indices under different alternative conditions, but in the PSS case. This scenario allows some generators to remain operational, maintaining supply to some demands. The pattern of the resilience indices in this scenario is similar to that of Figure 7, with the following aspects. First, while operational capabilities may decrease to zero, the indices for essential and non-essential demands remain above zero. Figure 3 depicts a noticeable difference in the completion times of essential and non-essential demands; in contrast, Figure 8 presents a scenario where the recovery times for both types of demands are aligned. Additionally, Figure 8 demonstrates that network capability may not increase monotonically. This implies that, unlike the clear state distinctions in Figure 3, real situations can be more continuously varying, potentially leading to incorrect decisions if specific states are difficult to differentiate.

In the PSS case, as in the TSB case, the non-essential demand index was found to be consistently higher than the

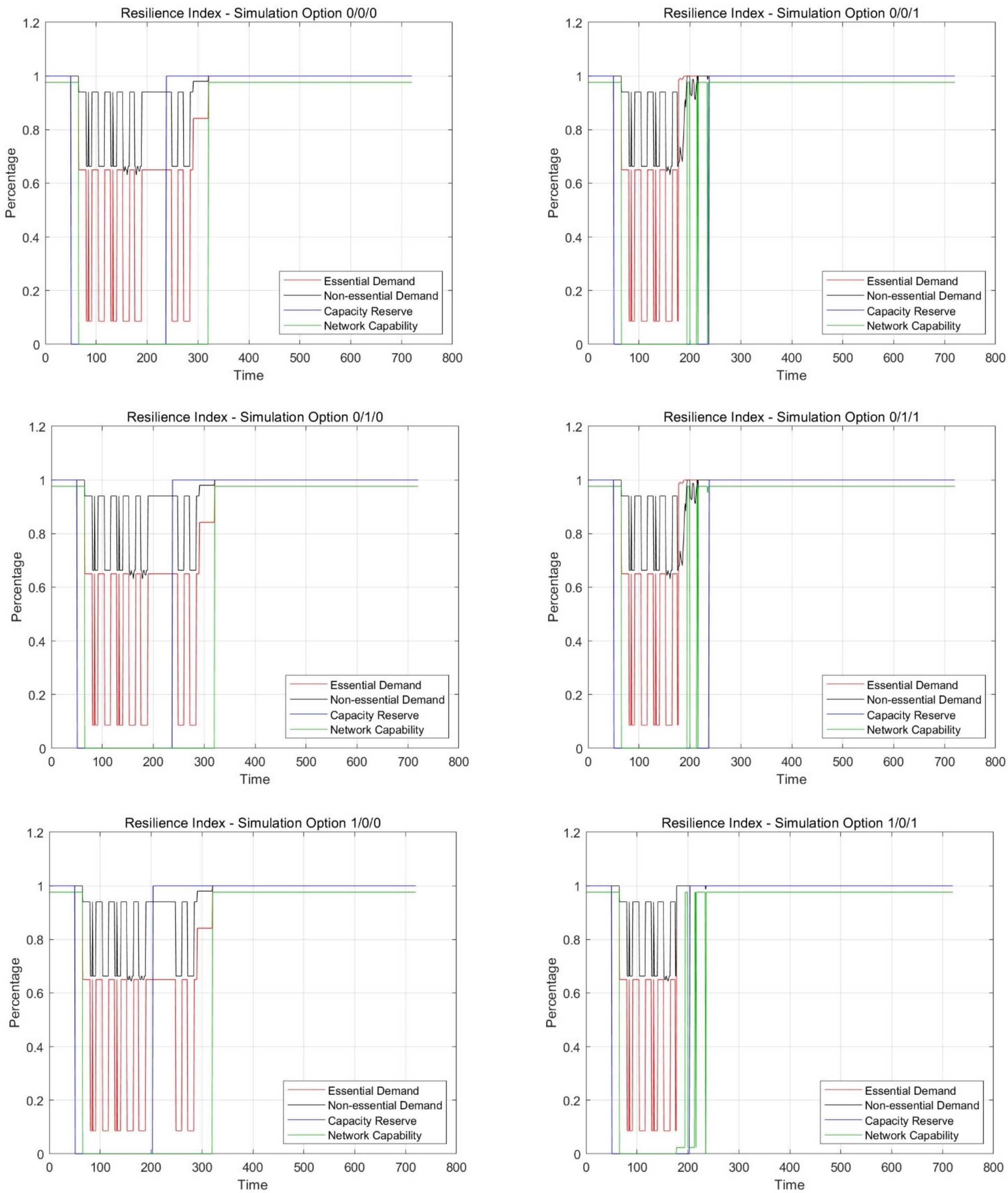

FIGURE 9. **The use of resilience indicators; an illustrative example-PSS scenario.**

essential demand index. This is because the system operator aims to prioritize the supply to essential demands while also minimizing load shedding as included in the objective function.

To evaluate the impact of different options within the resilience index framework, we analyzed load-shedding volume, a widely used metric in resilience research. Figure 9 specifically illustrates the cases where essential

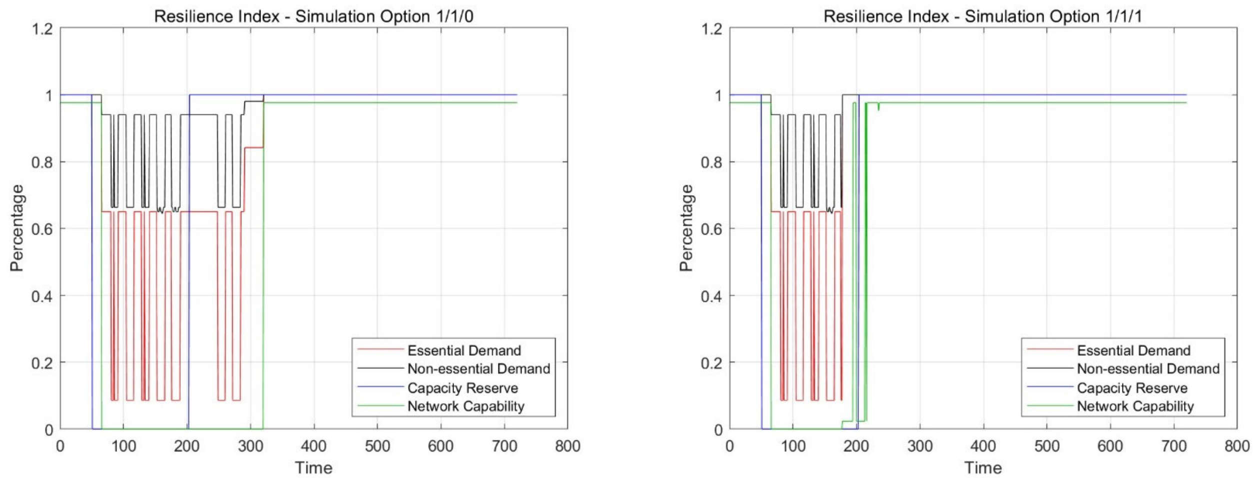

FIGURE 9. ***(Continued.)*** **The use of resilience indicators; an illustrative example-PSS scenario.**

and non-essential demands are distinguished, presenting the results for the TSB case. Furthermore, to provide a comprehensive comparison, this study includes results from an additional simulation that does not differentiate between these demand types. When the distinction between essential and non-essential demand is not considered, a new objective function was defined to maximize the supply of power to as many loads as possible. This new function replaced objective function (1) and new simulations were conducted.

As can be seen in Figure 9, when Alternatives 1 and 3 are chosen together, load-shedding volume is significantly reduced. When the importance of demand is not considered, the total load shedding volume may decrease. However, this approach does not guarantee that essential demands are met as much as possible, as seen in Options 101 and 111. Additionally, the difference in total load shedding volume between situations considering and not considering the priority of load supply is negligible, which suggests that the proposed method also incorporates strategies to reduce load shedding volume.

In the simulation, the costs associated with the selection of alternatives were not considered. Power system operators should seek to ensure resilience by comparing the costs and effects of alternative disaster preparedness scenarios.

V. CONCLUSION

This study proposes modelling methods that can contribute to the realization method about securing the resilience of power systems against catastrophic disasters. Existing reliability-based protection schemes which is based on probabilistic approaches may not aid catastrophic disaster management due to the difficulty of data acquisition. Also, such approaches alone do not adequately reflect social demands when responding to large-scale damage. A new resilience method that focuses on damage mitigation and rapid recovery is essential.

In our model, electricity demands are categorized as essential or non-essential, followed by analyses of resilience. It is difficult to estimate damage caused by the absence of electricity that powers major social infrastructure. It is also difficult to rank the importance of various essential demands via mutual comparison. Therefore, to reflect real-world situations, we divided each demand into essential and non-essential components and simulated the minimization of essential demand damage during damage mitigation and recovery.

In our model, if supply and demand are not balanced after power system damage, the system operator enters an emergency mode to maximize supply to essential demand. The general operating mode that focuses on cost-effectiveness is discarded. We present criteria that can be used to change the operation mode with consideration of the fact that essential and non-essential demands may be mixed. In an emergency situation, operation prioritizes damage mitigation of essential demand for the entire period of the disaster. Normal operation is re-activated when a certain threshold of essential supply is achieved, as informed by the indicator-based system operator standard conditions.

We focused on demand classification and operation during disasters. We selected and applied indicators that confirmed system performance in terms of both adequacy and long-term operability. When evaluating adequacy, the indicators pertain to achievement of essential demand (which cannot be quantified) and non-essential demand (which can be relatively evaluated on a cost basis). When evaluating long-term operability, the indicators pertain to the reserve rate, extra capacity and maintenance, and the network capability that ensures smooth power balancing before the disaster.

To facilitate future practical applications, a method that appropriately expresses the changes in system performance and resilience before and after a disaster using a combination of indicators is essential. If such indicators better represent the system than do the simple indicators used herein, they can be incorporated when assessing power system resilience.

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TAE-HYUN YOO (Member, IEEE) received the Ph.D. degree in electrical engineering from Seoul National University, Seoul, South Korea, in 2015. He has been a Senior Researcher with the Electricity Policy Research Center, Korea Electrotechnology Research Institute, South Korea, since 2017. His research interests include electricity market, resilience, and power system planning.

HYEONGON PARK (Member, IEEE) received the B.S. degree in electrical engineering from Yonsei University, Seoul, South Korea, in 2011, and the Ph.D. degree in electrical engineering from Seoul National University, Seoul, in 2016. Since 2020, he has been an Assistant Professor with the Department of Safety Engineering, Pukyong National University, Busan, South Korea. His research interests include the power system operation, electricity market, optimization, and renewable energy.