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Power System Reliability Evaluation Based on Chronological Booth–Baleriaux Method

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Abstract: The complexity of modern power systems is increasing because of the development of various intermittent generators. In practical reliability evaluations, it is essential to include both the failure of conventional generators and the output characteristics of renewable energy; the use of the latter has increased rapidly. The weather-dependent nature of renewable energy output, which is inexplicable in the load duration curve method, highlights the need for further study of the methods of a reliability evaluation that can consider temporal characteristics. This paper proposes a deterministic reliability evaluation method based on the Booth–Baleriaux method, chronologically extended to address the preventative maintenance schedule of a generator and the characteristics of renewable energy. The proposed method was applied to an IEEE reliability test system for performance verification, and a reliability evaluation was performed considering various chronological patterns. The proposed method was also applied to determine the adequate capacity reserve that should be installed in a Korean power system. The proposed method is stable, and it produced robust results.

Keywords: power system reliability; reliability evaluation; convolution method; chronological reliability; loss of load probability; deterministic method; reliability test system

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1. Introduction

Power system reliability is considered one of the most important factors in the operation and planning of a power system. Because of the unexpected failures of generators, system operators must secure additional capacity to ensure the system runs reliably [1,2]. On the other hand, the indiscriminate expansion of generators can lead to high social costs. Therefore, it is necessary to establish reliability standards and quantitatively express reliability to develop appropriate generation expansion planning [3].

Therefore, several indices have been suggested. The deterministic reliability indices are represented by a system margin based on the supply capacity according to the demand, and the probabilistic reliability indices express the risk of loss of load probabilistically. Although the relative influence of each generator on reliability is difficult to explain using the deterministic indices, probabilistic indices can quantify risk more effectively because they consider generator failures [4]. As power systems have become more variable and complex, probabilistic reliability indices that could effectively quantify risk have become popular in many electricity markets, and these probabilistic indices are currently adopted in stipulating reliability standards [5–9].

Probabilistic reliability indices are obtainable via reliability evaluations. Reliability evaluation methods include stochastic methods, which are simulation-based, and deterministic methods conducted via mathematical processes, such as convolution. The deterministic method evaluates reliability by estimating system availability distribution based on the probability of generator failure (forced outage rate, FOR) [10–12]. On the other hand, the stochastic method estimates reliability through sampling approaches, such as a Monte Carlo simulation, which is a representative stochastic algorithm [13]. Deterministic methods show consistent results, but they are computationally expensive. In contrast, although stochastic methods have poor reproducibility, they are simple to implement and can quickly evaluate reliability [14].

For practical reliability evaluations, it is essential to consider the realistic aspects of a power system, including preventative maintenance and generator failure. Considering that the maintenance schedule affects daily (or hourly) system availability, reliability must be assessed individually according to availability [15,16]. On the other hand, this procedure results in a substantial computational load, making it challenging for a deterministic reliability evaluation incorporating maintenance in large-scale system cases. Chanan and Quan proposed a deconvolution method to reduce the time required for each reliability evaluation [17]. Instead of performing several evaluations, some studies attempted to account for the impact of maintenance within a single process. For example, WASP-IV adjusts the generation capacity to accommodate the decrease in availability caused by maintenance [18]. Hoffer [19] and Kim and Park [20] modified the FOR depending on the maintenance period by assuming maintenance as a probabilistic factor. Nevertheless, previous approaches might be unsuitable in some instances. Consequently, several studies have used stochastic methods to study maintenance [21–23].

In recent years, the complexity of power systems has increased significantly because of the integration of renewable generation resources. Recent studies have also analyzed the effects of renewable resources on the reliability of the system [24,25]. On the other hand, most research is biased toward the stochastic method, which is relatively tractable for studying chronological patterns compared to the deterministic method [26–31]. Nevertheless, a study of the deterministic method, which can serve as a benchmark for validating or converging results should be used because the stochastic method may be inconsistent and potentially inaccurate. This paper proposes a deterministic reliability evaluation method, incorporating chronological patterns, i.e., the characteristics of renewable resources and maintenance schedules.

This paper proposes a deterministic reliability evaluation method for power systems. Deterministic methods assess reliability by estimating system availability based on probabilistic models of system components. Therefore, the proposed method includes an availability estimation approach and component modeling. As most probabilistic reliability indices necessitate a calculation of the loss of load probability (LOLP), this study focuses primarily on enhancing the LOLP calculation method.

The proposed method is based on the load duration curve (LDC) convolution approach known as the Booth–Baleriaux method [11,12]. This proposed method enables an hourly reliability evaluation by modeling hourly demand distribution and suggests a generator model that considers time-variant generation characteristics. Furthermore, the proposed model enables efficient convolution, reducing computational time.

The contributions of this paper are as follows. (1) In the proposed method, the hourly demand distributions reflect the characteristics of time-dependent generators in a reliability evaluation. Moreover, the resolution of demand distribution is not limited to the "hour" and is extendable to arbitrary resolutions, which can accommodate time-varying generation resources with various frequencies. (2) The proposed method is deterministic and has consistent indices. Policymakers may prefer accurate and consistent results, and the method can be used to validate reliability evaluation algorithms based on stochastic approaches. (3) The proposed method was validated by applying it to the IEEE Reliability Test System 2020. Furthermore, a reliability evaluation was performed considering various chronological information and analyzing how chronological information affects reliability.

This paper is organized as follows: Section 2 describes the mathematical formulation of the existing deterministic and proposed method. The reliability of the IEEE Reliability Test System 2020 is evaluated in Section 3 to verify the proposed method, followed by an analysis of the effect of various chronological patterns on reliability. Section 4 applies the proposed method to a reliability evaluation of the Korean power system to assess resource adequacy. Finally, Section 5 presents the conclusions.

2. Literature Review

2.1. Loss of Load Probability

The loss of load probability (LOLP), a representative probabilistic reliability index, is defined as the likelihood that the available capacity is insufficient to meet demand, leading to a loss of load. The mathematical expression for LOLP is presented below:

$$\mathrm{LOLP} = \mathrm{P}(\textit{Available capacity} < \textit{Demand}), \tag{1}$$

where the $\mathrm{P}(\cdot)$ operator denotes the probability that $(\cdot)$ is true. The "*Available capacity*" term refers to the system availability contributed by all resources participating in electricity generation, encompassing non-dispatchable resources. "*Demand*" pertains to the electricity requirements of consumers. The "*Available capacity*" exhibits a probability distribution assuming that the failure risk of a generator is a random variable, denoted as FOR.

Conventionally, estimating the system availability necessitates a consideration of every combination of commitment states of generators. On the other hand, several studies have proposed efficient reliability evaluation methods for calculating the LOLP because of the exponential complexity of this process, circumventing the problem of dimensions.

2.2. Capacity Outage Probability Table Method

The capacity outage probability table (COPT) method was used to obtain the LOLP by estimating the outage capacity distribution according to the failure of the generator [10]. The general formulation of COPT is expressed as follows:

$$\mathrm{COPT}_k(x) = (1 - FOR_k)\mathrm{COPT}_{k-1}(x - C_k) + FOR_k\mathrm{COPT}_{k-1}(x), \tag{2}$$

$$\mathrm{COPT}_0(x) = \begin{cases} 0, & x > 0 \\ 1, & x \le 0 \end{cases}, \tag{3}$$

where $\mathrm{COPT}_k(x)$ denotes the probability of x outage capacity in generators 1 to k, while FOR_k and C_k represent the failure probability and capacity of the generator k, respectively. The COPT is updated through a recurrent process. In (2), the initial term ($1 - FOR_k$ term) corresponds to the contribution of generator k to the system, whereas the subsequent term (FOR_k term) shows the impact of the outage of generator k on the system. Employing COPT, the LOLP can be expressed as follows:

$$\mathrm{LOLP} = \int_{ICP-d}^{ICP} \mathrm{COPT}_N(x)dx, \tag{4}$$

where COPT_N is the capacity outage probability table by all generators within the system; ICP signifies the total installed capacity; d is the system demand. A loss of load occurs when the system availability falls below d, i.e., $ICP - x < d$. Consequently, LOLP equals the integral of COPT_N over the interval $[ICP - d,\ ICP]$.

2.3. Load Duration Curve Method

The load duration curve (LDC) convolution method is a deterministic reliability evaluation method that simultaneously considers a demand over periods [11,12]. The LDC convolution method regards generator failure as the occurrence of additional demand and updates the equivalent load duration curve (ELDC), similar to the COPT method. The general formulation of ELDC is expressed as follows:

$$\mathrm{ELDC}_k(x) = (1 - FOR_k)\mathrm{ELDC}_{k-1}(x - C_k) + FOR_k\mathrm{ELDC}_{k-1}(x), \tag{5}$$

$$\text{ELDC}_0(x) = \text{LDC}(x), \tag{6}$$

where $\text{ELDC}_k(x)$ is the probability that the equivalent demand exceeds x capacity, considering the uncertainty of generators 1 to k. In (5), the initial term ($1 - FOR_k$ term) is the contribution of generator k to the system, whereas the subsequent term (FOR_k term) refers to the impact of the outage of generator k on the system. $\text{LDC}(x)$ is the probability that system demand surpasses x capacity and is defined as 1, while $x \leq 0$. Using ELDC, the LOLP can be expressed as follows:

$$\text{LOLP} = \text{ELDC}_N(ICP), \tag{7}$$

where ELDC_N is the equivalent demand probability function, including the influence of all generators in the system; a loss of load occurs when the equivalent demand exceeds the system installed capacity, ICP.

3. Methodology

Unlike the conventional LDC convolution method, in which generator failure is considered the result of equivalent demand, the proposed method considers the availability of generators as the reduction in unserved demand and updates the equivalent demand.

Considering that the generator has multiple states, such as ON/OFF and derated or partial failure, the generator model is expressed as follows:

$$G_k(x) = \sum_{i=1}^{S_k} P_{k,i}\, \delta(x + X_{k,i}), \tag{8}$$

where $G_k(x)$ indicates the availability probability distribution in the kth generator; S_k is the number of states that appear in the kth generator; and $P_{k,i}$ is the probability that the kth generators produce the $X_{k,i}$ capacity. According to the definition of probability, the sum of $P_{k,i}$ for all i is equal to 1. By substituting (8) into (5), ELDC can be expressed as follows:

$$\text{ELDC}_k(x) = (G_k * \text{ELDC}_{k-1})(x), \tag{9}$$

where $*$ is the convolution operator that performs the sum operation of random variables. The proposed generator model makes the recurrent process faster than the LDC conventional method because it does not increase the length of the ELDC.

A system element with a negative availability (or positive demand) should be modeled as a load model. The load model and load duration curve are defined as (10) and (11), respectively:

$$L_t(x) = \delta(x - D_t), \tag{10}$$

$$\text{LDC}(x) = \frac{1}{T}\sum_{t=1}^{T}\left(1 - \int_{-\infty}^{x} L_t(x')dx'\right), \tag{11}$$

where $L_t(x)$ and D_t refer to demand distribution and system demand at time t, and $\text{LDC}(x)$ is the load duration curve expressed as (9) regarding the plan period T. Considering the chronological characteristics of the generation availability, the extended generator model and equivalent load model are expressed as follows:

$$G_{k,t}(x) = \sum_{i=1}^{S_k} P_{k,i,t}\, \delta(x + X_{k,i,t}), \tag{12}$$

$$EL_{t,k}(x) = \left(G_{t,k} * \cdots * \left(1 - \int_{-\infty}^{x} L_t(x')dx'\right)\right), \tag{13}$$

where $EL_{t,k}(x)$ is the equivalent demand distribution at time t considering the availability of generator 1 to k. By substituting (13) with (9), the ELDC is expressed as the sum of the equivalent loads in (14):

$$\mathrm{ELDC}_k(x) = \frac{1}{T}\sum_{t=1}^{T} EL_{k,t}(x). \tag{14}$$

The equivalent load model is the unserved demand distribution. A loss of load occurs when the unserved demand is more than zero. Consequently, LOLP is formulated as follows:

$$\mathrm{LOLP} = \mathrm{ELDC}_N(0). \tag{15}$$

The proposed method is expressed as (16) with an expression of the existing method:

$$\mathrm{ELDC}_{N,proposed}(x) = \mathrm{ELDC}_{N,existing}(x + ICP), \tag{16}$$

Equation (16) shows that (15) and (7) are mathematically equivalent.

4. Case Study

In the case study, the proposed method was verified by evaluating the reliability of IEEE RTS 2020 and analyzing the effect of chronological characteristics on power system reliability. An adequate installed capacity reserve was determined using the proposed method for an actual Korean power system.

4.1. IEEE RTS 2020

4.1.1. System Data

IEEE RTS 2020 is a power system with a peak demand of 8192 MW, a generation mix of 8076 MW, and a renewable energy value of 6224 MW [32,33]. Table 1 lists the dispatchable generation mix. The renewable energy value consists of 1000 MW hydroelectric, 2507.9 MW wind, 1554.5 MW solar, and 1161.4 MW rooftop solar energy.

Table 1. IEEE RTS 2020 generation mix.

Group	Type	Pmax [MW]	Number of Generators	FOR [%]
U12	Oil/Steam	12	7	2.0
U20	Oil/CT	20	12	10.0
U55	Gas/CT	55	27	3.1
U76	Coal/Steam	76	7	2.0
U155	Coal/Steam	155	7	4.0
U350	Coal/Steam	350	2	8.0
U355	Gas/CC	355	10	3.1
U400	Nuclear	400	1	12.0

4.1.2. Proposed Method Verification

This section assumes the same environment as the previous study that evaluated the reliability of RTS 2020 using the COPT method to verify the proposed method [32]. Preventive maintenance and load uncertainty were not considered, and rounding was performed to represent 1 MW units. The definitions of reliability indices used for verification, LOLH and EUE, are as follows:

$$\mathrm{LOLH} = \sum_{t=1}^{T} EL_{t,N}(0), \tag{17}$$

$$\mathrm{EUE} = \sum_{t=1}^{T}\left(\int_0^{\infty} EL_{t,N}(x)dx\right), \tag{18}$$

where LOLH is the expected loss of load hour, the sum of the hourly LOLP, and EUE is the expected unserved energy, the sum of the hourly unserved energy. Three methods were simulated for verification: (1) the COPT method, which is used in [23]; (2) the proposed method; and (3) the traditional method, which updates the ELDCs, increasing their length. Table 2 lists the reliability indices determined by each method.

Table 2. IEEE RTS 2020 reliability indices results.

Method	LOLH (Hour/Year)	EUE (MWh/Year)	Time (s)
COPT method	0.001898	0.233808	0.60
Proposed method	0.001898	0.233808	9.81
Traditional method	0.001898	0.233808	47.23

The simulations were performed in an environment with an AMD Ryzen 7 3700X 8-Core Processor CPU @ 3.59 GHz with 32 GB RAM. MATLAB source code on GitHub was used to measure the runtime of the COPT method, and the remaining methods were implemented using MATLAB 2021a [33]. Three methods were mathematically equivalent, representing the same reliability indices. The proposed method was approximately five times faster than the traditional method. Although the proposed method takes slightly less computation time than the COPT method, it is competitive because it can apply chronological characteristics.

4.2. Effect of Chronological Characteristic on the Power System Reliability

4.2.1. Load Uncertainty

Generally, the forecasted demand has an error. Therefore, several scholars believe that system demand has a probability distribution. By expanding (10), the generalized load model can be expressed as follows:

$$L_t(x) = \sum_{i=1}^{U} P_i \, \delta(x - D_{i,t}), \tag{19}$$

where U refers to the number of cases of demand, and P_i is the probability that the system demand is $D_{i,t}$. This section assumes that the load uncertainty follows a discrete normal distribution with seven intervals, with a standard deviation of 5% for the predicted demand [10]. Table 3 lists the reliability indices of RTS 2020 according to the load uncertainty of 0–15%.

Table 3. IEEE RTS 2020 reliability indices results considering the load uncertainty.

Indices	Uncertainty (%)				
	0	2	5	10	15
LOLH (hour/year)	0.001898	0.003347	0.032086	1.189605	8.549189
EUE (MWh)	0.234	0.438	5.123	319.870	3615.958

Reliability indices increase as uncertainty increases. Although overpredicted and underpredicted demands have the same probability; overpredicted demand affects the system reliability more significantly than underpredicted demand. Therefore, a loss of load occurs more often in a more unpredictable system.

4.2.2. Preventive Maintenance Schedule

Preventive maintenance changes the availability of a generator for a temporal period. Because generators under maintenance cannot contribute to the system, the generalized generator model is expressed as follows:

$$G_{k,t}(x) = \sum_{i=1}^{S_k} P_{k,i,t}(1 - u_{k,t})\delta(x + X_{k,i,t}), \tag{20}$$

where $u_{k,t}$ is a binary value indicating whether the kth generator is under maintenance at time t. An optimization problem was solved to establish the maintenance schedule, which minimizes the weekly supply ratio variance. Table 4 lists the established schedule. Figure 1 shows the optimized availability capacity and netload profile. Table 5 lists the reliability indices of the base case, which neglects the influence of maintenance, the optimized case, which applies the optimized maintenance schedule, and the derated case, which uses the derated capacity listed in Table 4 [18].

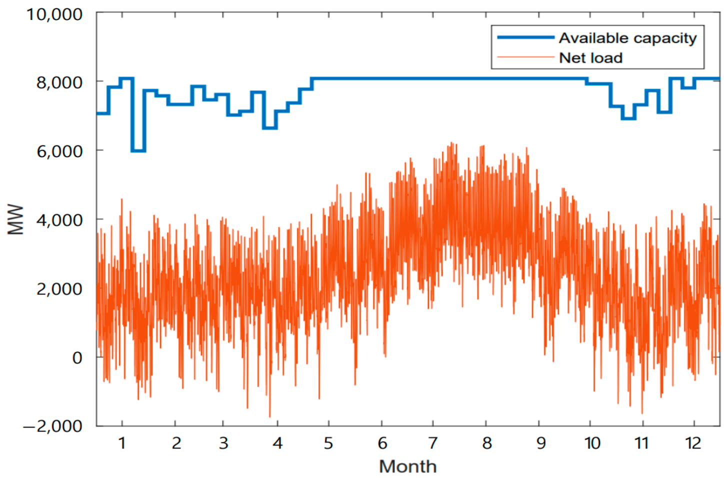

Figure 1. Optimized availability and net load profile.

Table 4. Maintenance schedule of generators.

Group	Generator Index	Maintenance Start Week	Maintenance Period (Weeks)	Derated Capacity (MW)
U12	g1–g6 g7	1 12	2	11
U20	g8–g16 g17 g18 g19	1 7 12 15	2	19
U55	g20 g21–g26 g27–g29 g30 g31–g34 g35–g36 g37–g41 g42–g46	1 4 12 13 16 46 48 50	1	54
U76	g47–g48 g49 g50–g53	6 7 44	3	72
U155	g54 g55–g57 g58–g59 g60	7 10 15 42	4	143
U350	g61 g62	4 44	5	317

Table 4. *Cont.*

Group	Generator Index	Maintenance Start Week	Maintenance Period (Weeks)	Derated Capacity (MW)
U355	g63–g64 g65–g68 g69–g70 g71 g72	1 4 15 45 48	1	348
U400	g73	12	6	354

Table 5. Results for IEEE RTS 2020 reliability indices considering maintenance.

Indices	Base Case	Optimized Case	Derated Case
LOLH (hour/year)	0.001898	0.001898	0.011447
EUE (MWh/year)	0.23380	0.23380	1.510155

The reliability indices were similar in the optimized case and the base case. This result was analyzed because the maintenance period of gas turbines (U55, U355), corresponding to 62% of the total capacity of the system, was low, and the optimization was effective. On the other hand, reliability indices changed significantly in the derated case. This was because the derated capacity affects availability even during high-demand periods when maintenance is not usually performed. Therefore, considering the influence of maintenance indirectly without dealing with the maintenance schedule may not adequately evaluate reliability.

4.2.3. Temperature

The availability of gas turbines depends on temperature sensitivity. A reliability evaluation was performed by considering the change in availability according to the temperature of G55 and G355 in RTS 2020 to confirm its influence. The data in Table 6 show that the gas turbine has a 100% output at 15 °C and changes by 0.6% per 1 °C [34]. The temperature was referenced in Washington, D.C., and provided by WWIS [35].

Table 6. Monthly capacity of gas turbines according to temperature.

Month	Temperature (°C)	Change (%)	G55 (MW)	G355 (MW)
1	0.65	+8.6	59	385
2	2.35	+7.6	59	382
3	6.80	+4.9	57	372
4	12.45	+1.5	55	360
5	17.30	−1.4	54	350
6	22.45	−4.5	52	339
7	24.85	−5.9	51	334
8	24.10	−5.5	52	335
9	19.90	−2.9	53	344
10	13.35	+1.0	55	358
11	8.00	+4.2	57	369
12	2.55	+7.5	59	381

Table 7 presents the reliability indices considering temperature. A significant change in the reliability indices was noted because G55 and G355 accounted for a large proportion of RTS 2020. These changes were observed because the monthly system availability varies dramatically. Overall, a reliability evaluation considering temperature may be required depending on the generation mix.

Table 7. IEEE RTS 2020 reliability indices considering the temperature.

Indices	Base Case	Temp-Considered Case	Change (%)
LOLH (hour/year)	0.001898	0.011176	+488.8
EUE (MWh/year)	0.23380	1.47222	+529.7

4.2.4. Renewable Energy Uncertainty

Renewable energy (RE) output that depends on weather has considerable uncertainty. Sometimes, the output of RE is presumed, like RTS 2020, but generally, it should be predicted.

For an analysis of RE uncertainty, as shown in Figure 2, it was assumed that the output of RE has a monthly and hourly average output, and the uncertainty follows a normal distribution [36]. The RE models are calculated as follows:

$$\begin{aligned} RE_{k,t}(x) &= m_{k,t} + \sum_{i=1}^{R_{k,t}} P_{k,i,t}\delta(x + Y_{k,i,t}) \\ &= \sum_{i=1}^{R_k} P_{k,i,t}\,\delta(x + X_{k,i,t}), \end{aligned} \tag{21}$$

where $m_{k,t}$ and $R_{k,t}$ are the monthly hourly average and the number of cases of the output of RE k, respectively, at time t. $Y_{k,i,t}$ is the term for uncertainty, and (21) can be expressed as similar to (12). Therefore, RE can be regarded as a generator with many states and does not require maintenance.

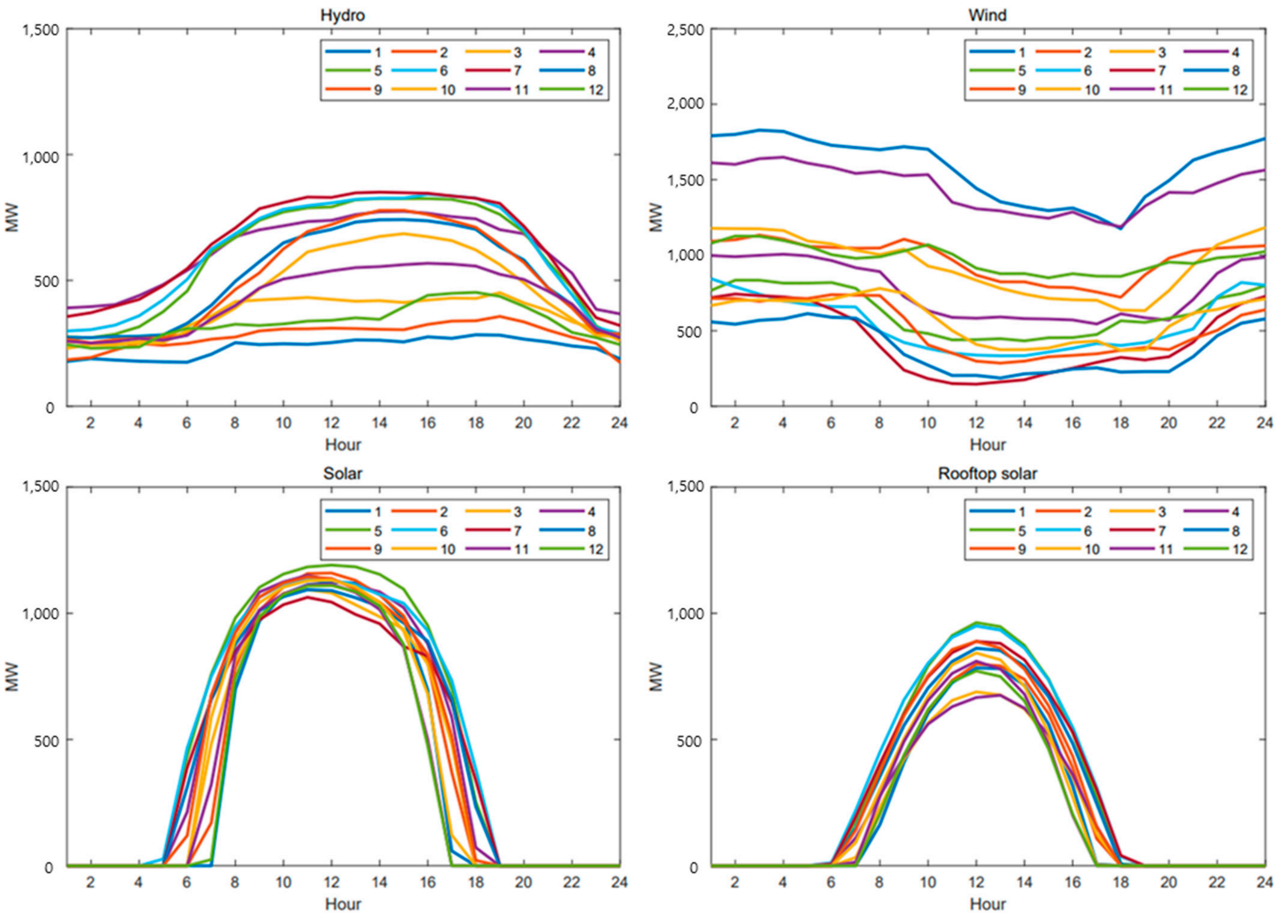

Figure 2. Monthly and hourly output characteristics of renewable energy.

Table 8 lists the reliability indices according to the uncertainty of RE. In the 0 uncertainty case, the reliability indices appear to be improved because the contribution of RE has increased during the high-demand period compared to the existing system. As with load uncertainty, the reliability indices increase as the uncertainty increases. Hence, the contribution of RE to the system reliability decreases when their output is highly variable and unpredictable because of climate or geographic factors.

Table 8. IEEE RTS 2020 reliability indices results considering the RE uncertainty.

Indices	Uncertainty (%)				
	0	2	5	10	15
LOLH (hour/year)	0.000966	0.000974	0.001018	0.001180	0.001506
EUE (MWh)	0.118651	0.119550	0.125131	0.147038	0.191325

4.3. Korean Power System

4.3.1. System Data

This section evaluates the reliability of the 2022 Korean power system, and the adequate installed capacity reserve is calculated. The 2022 Korean power system comprised a generation mix of 134.27 GW, including RE, and the peak demand of the system is 86.72 GW [37] (Table 9).

Table 9. The 2022 Korean power system generation mix.

Fuel	Dispatchable	Total Capacity (GW)	Number of Generators	% of Total (%)
Oil	Y	0.86	14	0.6
LNG	Y	41.20	96	30.7
Coal	Y	36.14	58	26.9
Nuclear	Y	23.25	24	17.3
Pump	Y	4.70	16	3.5
RE	N	26.30	-	19.6
etc.	N	1.82	-	1.4

4.3.2. Adequate Installed Capacity Reserve

The Korean electricity market stipulates a reliability standard as a loss of load expectation (LOLE) of 0.3 days/year. An adequate installed capacity reserve (AICR) refers to the ratio of supply capacity to peak demand in the LOLE 0.3 condition. The AICR has profound financial relevance because it is linked to the settlement amount of the market participants. Therefore, in deriving the AICR, reproducibility and accuracy must be confirmed using a deterministic method, such as the proposed method in this study. The formulation of AICR is as follows:

$$AICR = \frac{ICP + DR_{cp} + ND_{tr} - HVDC_{cp}}{D_{peak}\Big|_{LOLE=0.3}}, \tag{22}$$

where DR_{cp} is the contracted capacity for the demand response resources; ND_{tr} is the transaction volume of non-dispatchable resources at peak demand; $HVDC_{cp}$ is the capacity of the HVDC, which transfers power from the main system to the sub-grid. The pump was assumed to be dispatchable regardless of the reservoir level. The output of non-dispatchable resources was considered to be the chronological patterns. The preventive maintenance schedule referred to the shutdown plan registered in the Generator Outage Management System (g-OMS) and the neglected temperature and load. Figure 3 presents a flow chart for determining an adequate installed reserve margin by adjusting the demand.

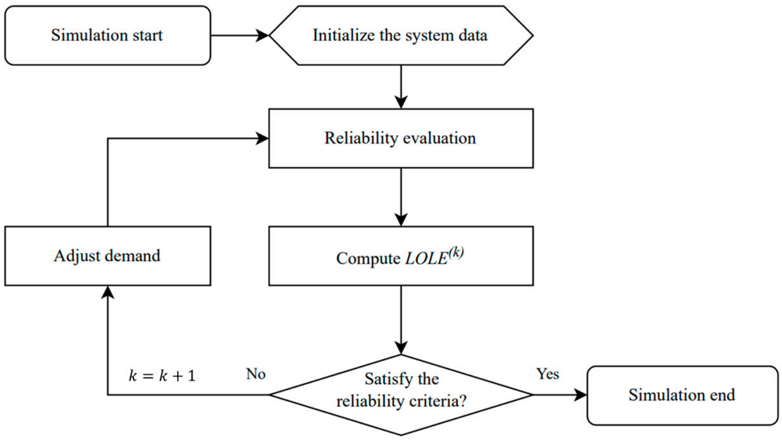

Figure 3. Adequate installed capacity reserve derivation flow chart.

Table 10 lists the iterative process for adjusting the demand to meet the LOLE 0.3 condition. The demand was adjusted in each iteration, and the LOLE was calculated. As Iteration 15, LOLE satisfies 0.3, the reliability standard of the Korea Power System, and the adequate installed capacity reserve was calculated as 14.41%. A simulation time of approximately 1300 s occurred in the series of processes, and the results were determined within a reasonable time frame.

Table 10. Process for calculating the adequate installed capacity reserve.

Iteration	Peak Demand (MW)	LOLE (Day/Year)	Reserve Margin (%)
1	86,719	0.0000	31.31
2	89,202	0.0000	27.66
3	91,478	0.0001	24.48
4	93,579	0.0021	21.69
5	95,516	0.0173	19.22
6	97,232	0.0746	17.12
7	98,515	0.1740	15.59
8	99,190	0.2522	14.80
9	99,432	0.2850	14.53
10	99,504	0.2952	14.44
11	99,525	0.2984	14.42
12	99,532	0.2994	14.41
13	99,535	0.2998	14.41
14	99,536	0.2999	14.41
15	99,536	0.3000	14.41

5. Conclusions

Many power systems have prescribed probabilistic reliability standards to ensure the stability of a system. As the system becomes increasingly complex, a reliability evaluation method that adequately reflects the features of a power system should be developed.

This paper proposed a deterministic reliability evaluation method considering chronological patterns by evaluating hourly reliability via LDC decomposition. In the proposed method, the hourly demand distributions reflect the characteristics of time-dependent generators in reliability evaluation. The resolution of the demand distribution is not limited to the "hour" and can be extended to arbitrary resolutions, which can accommodate time-varying generation resources with various frequencies. The proposed method reduced the computational load on the convolution operation to improve performance.

The proposed method was validated by its application in the IEEE Reliability Test System 2020. The proposed method has accurate results, and this efficient convolution made the proposed method faster. This paper analyzed the effects of various chronological patterns, such as maintenance schedules and temperature. The reliability evaluation showed that chronological patterns significantly affect the reliability. In particular, the influence according to the maintenance modeling was outstanding. These results suggest that a reliability evaluation without considering chronological patterns may be unreliable.

The proposed method was applied to determine the adequate installed capacity reserve in the Korean power system. This method can determine the AICR because it shows consistent results. The acceptable computational speed of the proposed method makes it competitive for use in the reliability evaluation of an actual large-scale system.

Moreover, because the proposed method presents consistent reliability indices, the proposed method may be useful for policymakers who prefer accurate and consistent results. Hence, the method can be used to validate reliability evaluation algorithms using stochastic approaches.

Although this study considers chronological patterns, it has the limitation of treating the pump as a traditional generator resource. Future research will consider the dynamic scheduling of a pump and ESS with fuel quantity (e.g., reservoir level and SOC) constraints in the reliability evaluation.

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References

1. Gooi, H.B.; Mendes, D.P.; Bell, K.R.W.; Kirschen, D.S. Optimal scheduling of spinning reserve. *IEEE Trans. Power Syst.* **1999**, *14*, 1485–1492. [CrossRef]
2. Billinton, R.; Allan, R.N. Power-system reliability in perspective. *Electron. Power* **1984**, *30*, 231–236. [CrossRef]
3. Chowdhury, A.A.; Koval, D.O. Value-based power system reliability planning. *IEEE Trans. Ind. Appl.* **1999**, *35*, 305–311. [CrossRef]
4. Milligan, M.; Frew, B.A.; Bloom, A.; Ela, E.; Botterud, A.; Townsend, A.; Levin, T. Wholesale electricity market design with increasing levels of renewable generation: Revenue sufficiency and long-term reliability. *Electr. J.* **2016**, *29*, 26–38. [CrossRef]
5. Department for Business, Energy & Industrial Strategy. *GB Implementation Plan*; Government of the UK: London, UK, 2020.
6. PJM Interconnection. *PJM Manual 20*; PJM: Norristown, PA, USA, 2021.
7. National Association of Regulatory Utility Commissioners. *Resource Adequacy for State Primer for State National Association of Regulatory*; NARUC: Washington, DC, USA, 2021.
8. Abarca, R.M. *Interim Report of the Sector Inquiry on Capacity Mechanisms*; European Commission: Brussels, Belgium, 2021.
9. Ministry of Trade, Idustry and Energy. *9Th Basic Plan for Power Supply and Demand*; MOTIE: Sejong, Republic of Korea, 2020.
10. Billinton, R.; Allan, R.N. *Reliability Evaluation of Power Systems*; Springer: Berlin/Heidelberg, Germany, 1996; ISBN 9781489918628.
11. Baleriaux, H.; Jamoulle, E.; de Guertechin, F.L. Simulation de l'exploitation d'un parc de machines thermiques de Production d', electricite', couple a des stations de pompage. *Rev. E* **1967**, *5*, 225–245.
12. Booth, R.R. Power system simulation model based on probability analysis. *IEEE Trans. Power Appar. Syst.* **1972**, *PAS-91*, 62–69. [CrossRef]
13. Harrison, R.L. Introduction to Monte Carlo simulation. *AIP Conf. Proc.* **2009**, *1204*, 17–21. [CrossRef]
14. LI, W. *Reliability Assessment of Electric Power Systems Using Monte Carlo Methods (Billington, 1994)*; Springer: Berlin/Heidelberg, Germany, 1994.
15. Mukerji, R.; Merrill, H.M.; Erickson, B.W.; Parker, J.H.; Friedman, R.E. Power Plant Maintenance Scheduling: Optimizing Economics and Reliability. *IEEE Trans. Power Syst.* **1991**, *6*, 476–483. [CrossRef]

16. Zhou, X.; Xi, L.; Lee, J. Reliability-centered predictive maintenance scheduling for a continuously monitored system subject to degradation. *Reliab. Eng. Syst. Saf.* **2007**, *92*, 530–534. [CrossRef]
17. Singh, C.; Chen, Q. An Efficient Method for Generating Capacity Reliability Evaluation Including the Effect of Planned Outages. *IEEE Trans. Power Syst.* **1989**, *4*, 1397–1404. [CrossRef]
18. Molina, P.; Heinrich, P. *Wien Automatic System Planning (WASP) Package*; International Atomic Energy Agency: Vienna, Austria, 2001.
19. Hoffer, J. Modelling the partial planned outages in production costing simulation. *Int. J. Electr. Power Energy Syst.* **1995**, *17*, 377–380. [CrossRef]
20. Kim, J.; Park, J. Probabilistic Generation Modeling in Electricity Markets Considering Generator Maintenance Outage. *Trans. Korean Inst. Electr. Eng. A* **2005**, *54*, 418–428.
21. Saraiva, J.T.; Miranda, V.; Pinto, L.M.V.G. Generation/transmission power system reliability evaluation by Monte-Carlo simulation assuming a fuzzy load description. *IEEE Trans. Power Syst.* **1996**, *11*, 690–695.
22. Chen, Q.; Mili, L. Composite power system vulnerability evaluation to cascading failures using importance sampling and antithetic variates. *IEEE Trans. Power Syst.* **2013**, *28*, 2321–2330. [CrossRef]
23. Zhao, Y.; Tang, Y.; Li, W.; Yu, J. Composite Power System Reliability Evaluation Based on Enhanced Sequential Cross-Entropy Monte Carlo Simulation. *IEEE Trans. Power Syst.* **2019**, *34*, 3891–3901. [CrossRef]
24. Billinton, R.; Huang, D. Incorporating wind power in generating capacity reliability evaluation using different models. *IEEE Trans. Power Syst.* **2011**, *26*, 2509–2517. [CrossRef]
25. Koh, L.H.; Peng, W.; Tseng, K.J.; Zhiyong, G. Reliability evaluation of electric power systems with solar photovoltaic & energy storage. In Proceedings of the 2014 International Conference on Probabilistic Methods Applied to Power Systems PMAPS 2014, Durham, UK, 7–10 July 2014; IEEE: Piscataway, NJ, USA, 2014; pp. 1–5.
26. Xiao, R.; Xiang, Y.; Wang, L.; Xie, K. Power system reliability evaluation incorporating dynamic thermal rating and network topology optimization. *IEEE Trans. Power Syst.* **2018**, *33*, 6000–6012. [CrossRef]
27. Liu, K.; Zhang, J.; Chen, F. Power Generation System Reliability Evaluation Base on Cross Entropy Method. In Proceedings of the 2020 5th Asia Conference on Power and Electrical Engineering, ACPEE 2020, Chengdu, China, 4–7 June 2020; Volume 2, pp. 1641–1645.
28. Urgun, D.; Singh, C. LSTM Networks to Evaluate Composite Power System Reliability Evaluation with Injected Wind Power. In Proceedings of the 2019 IEEE Power and Energy Society General Meeting, Atlanta, GA, USA, 4–8 August 2019; Volume 2019, pp. 1–5.
29. Wang, Y.; Gao, X.; Cai, Y.; Yang, M.; Li, S.; Li, Y. Reliability evaluation for aviation electric power system in consideration of uncertainty. *Energies* **2020**, *13*, 1175. [CrossRef]
30. Urgun, D.; Singh, C. A Hybrid Monte Carlo Simulation and Multi Label Classification Method for Composite System Reliability Evaluation. *IEEE Trans. Power Syst.* **2019**, *34*, 908–917. [CrossRef]
31. Firouzi, M.; Samimi, A. Reliability evaluation of a composite power system in the presence of renewable generations. *Reliab. Eng. Syst. Saf.* **2022**, *222*, 108396. [CrossRef]
32. Barrows, C.; Preston, E.; Staid, A.; Stephen, G.; Watson, J.P.; Bloom, A.; Ehlen, A.; Ikaheimo, J.; Jorgenson, J.; Krishnamurthy, D.; et al. The IEEE Reliability Test System: A Proposed 2019 Update. *IEEE Trans. Power Syst.* **2020**, *35*, 119–127. [CrossRef]
33. Github. Available online: https://github.com/GridMod/RTS-GMLC (accessed on 1 June 2023).
34. Arrieta, F.R.P.; Lora, E.E.S. Influence of ambient temperature on combined-cycle power-plant performance. *Appl. Energy* **2005**, *80*, 261–272. [CrossRef]
35. WWIS. Available online: https://worldweather.wmo.int/kr/city.html?201606300402&cityId=270 (accessed on 1 June 2023).
36. Karki, R.; Dhungana, D.; Billinton, R. An appropriate wind model for wind integrated power systems reliability evaluation considering wind speed correlations. *Appl. Sci.* **2013**, *3*, 107–121. [CrossRef]
37. EPSIS. Available online: http://epsis.kpx.or.kr/ (accessed on 1 June 2023).