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Optimal Loss of Load Expectation for Generation Expansion Planning Considering Fuel Unavailability

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Abstract: In generation expansion planning, reliability level is the key criterion to ensure enough generation above peak demand in case there are any generation outages. This reliability criterion must be appropriately optimized to provide a reliable generation system with a minimum generation cost. Currently, a method to determine an optimal reliability criterion is mainly focused on reserve margin, an accustomed criterion used by several generation utilities. However, Loss of Load Expectation (LOLE) is a more suitable reliability criterion for a generation system with a high proportion of renewable energy since it considers both the probabilistic characteristics of the generation system and the entire load's profile. Moreover, it is also correlated with the reserve margin. Considering the current fuel supply situation, a probabilistic model based on Bayes' Theorem is also proposed to incorporate fuel supply unavailability into the probabilistic criterion. This paper proposes a method for determining the optimal LOLE along with a model that incorporates fuel supply unavailability into consideration. This method is tested with Thailand's Power Development Plan 2018 revision 1 to demonstrate numerical examples. It is found that the optimal LOLE of the test system is 0.7 day/year, or shifted to 0.55 day/year in the case of considering the fuel supply unavailability.

Keywords: generation expansion planning; reliability criterion; loss of load expectation; reserve margin; fuel unavailability

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1. Introduction

1.1. Motivation and Literature Review

Generation expansion planning (GEP) is a method for determining the future characteristics of a power system. It is a process used to determine the optimal types of energy technologies, size, and construction time needed to bring new power generation units [1] into the electrical power system to meet the demand forecast in the future. Global warming problems, carbon neutrality, and net zero emission targets have been set by several countries with the goal of reducing greenhouse gas emissions [2]. Thus, high penetration of renewable energy sources, especially from solar and wind power, is highly anticipated. In order to have the ability to integrate a high level of these variable renewable energy sources into the power system, complex optimization models must be developed to take economic, technical, environmental, and other pertinent constraints into consideration as part of long-term generation expansion planning [3].

During the GEP process, it is necessary to maintain the installed capacity of the system at a certain level above the peak demand since any generation unit can be forced into an outage [4] by unexpected problems, e.g., component failure or shortage of fuel supply. The amount of this excess capacity usually results from the level of system reliability criterion considered in the GEP process. There are two concepts applied to generation expansion planning, the deterministic method and probabilistic method [4]. For the deterministic method, reserve margin, a percentage of additional generation over system peak demand, is usually used as the reliability criterion to account for randomly occurring failures [5].

The advantage of the reserve margin is that it is easy to calculate. Its concept of reliability is also simple and easy to interpret. Thus, the reserve margin is used as the main reliability criterion for many power utilities, such as 15% for Thailand [6], 22% for South Korea [7], 20–28% for Peninsular Malaysia [8], 15% for Taiwan [9], and 10% to 20% for many utilities in the USA [10]. The reserve margin is used as a planning constraint in many GEP models that are tested with national level power systems. Wierzbowski et al. proposed a mixed integer linear programming (MILP) model for considering power system reserves and tested it in the Polish power system [11]. Neshat et al. proposed a hybrid model for Iran's power system [12]. Koltsaklis et al. proposed an MILP model using Greece's power system as the test case [13]. Heuberger et al. proposed an MILP model that was applied to the United Kingdom's power system [14]. Chen et al. proposed a model applied to the northwestern grid of China [15]. Although easy and simple, when determining the reserve margin, only a single data set comprised of the peak load and its associated total capacity of the system is considered. Therefore, the behavior of generation units as well as load characteristics are not considered in the reserve margin calculation. For this reason, reserve margin is not quite appropriate for use with generation systems that rely on a high level of renewable energy sources due to their intermittent behavior and limitations.

For the probabilistic method, the forced outage rate (FOR) of generation units, which accounts for component failure behavior, is usually considered. FOR is used with a load duration curve (LDC) to calculate system reliability indices, such as Loss of Load Expectation (LOLE) [5], Expected Energy Not Served (EENS) [5], and Expected Unserved Energy (EUE) [16]. LOLE is considered a reliability criterion in many power utilities, e.g., 0.3 days/year for South Korea [7], 1 day/year for Peninsular Malaysia [8], and 0.1 day/year for power utilities in the USA [10]. They are also considered in many GEP models. However, due to their non-linear characteristics, these models are usually tested with simplified test systems or are considered using linearly estimated values instead. Hemmati et al. proposed a multistage mixed-integer nonlinear programming (MINLP) model, tested on a 2850 MW test system [17]. They also considered LOLE in an MINLP model in microgrids [18]. Sirikum et al. proposed an MINLP model tested with a 1600 MW scaled-down version of Thailand's generation system [19]. Opathella et al. proposed an MILP model with a linear approximation of LOLE as a constraint [20]. Aghaei et al. proposed a multi-period, multi-objective generation expansion planning (MMGEP) model using the Z-method to evaluate LOLE [21]. Hanna et al. proposed a microgrid investment planning model with sequential Monte Carlo simulation to accurately evaluate non-linear reliability indices [22]. EENS has also been considered in several recent GEP models. Oree et al. used EENS to determine unmet demand costs [23]. Hamidpour et al. consider minimization of EENS as one of the objective functions of the proposed generation and transmission expansion planning [24]. Abushamah et al. consider an expected energy not supplied cost for reliability evaluation [25]. An indirect approach is also introduced to incorporate LOLE into GEP. For example, Abdalla et al. proposed an algorithm that uses adjustable reserve margin as a reliability criterion in the MILP model [26,27]. Firstly, the LOLE of the GEP results is calculated and compared to the LOLE criterion. If the LOLE result is not acceptable, the reserve margin constraint is adjusted and the GEP is repeated iteratively until the LOLE result is acceptable.

Since the probabilistic nature of generation components and entire load models are taken into account, the probabilistic method can provide more appropriate reliability criteria than the deterministic method, especially for power systems that rely on a high proportion of renewable energy. For example, LOLE and LOEE are considered as reliability constraints in an optimization method to create an optimal design and energy management of the hybrid systems, including the photovoltaic panels, wind turbines, and fuel cells [28].

Apart from the selection of the system reliability criterion, either reserve margin or LOLE, setting up the value of the criterion is also important. Too high of a reliability level leads to over-investment, resulting in excessive power generation costs, which are then passed through the electricity tariff structure. However, under-investment leads to the opposite situation [5], in which, although the cost of electricity can be lower, the level of reliability of the system might not be acceptable.

To determine optimal reliability criteria, a customer interruption cost is introduced and combined with the power generation cost to create the total system cost as a function of reliability as described in [29]. The customer's interruption cost is a customer cost caused by failures in the electricity supply system [30]. This cost can be computed from EENS and the Interrupted Energy Assessment Rate (IEAR). With this concept, the total cost of the power system at different reliability criteria can be evaluated and compared, as demonstrated in Figure 1. Consequently, the optimal reliability index is the one that provides the minimum total system cost. This concept is used in several publications. For example, Billinton used this concept to determine the optimal reserve margin of a 240 MW reliability test system with a 185 MW peak load [29]. The Brattle Group also used this concept to determine the optimal reserve margin of a wholesale electric market of the Electric Reliability Council of Texas (ERCOT) in 2014 and 2018 [31,32]. Energy and Environmental Economics, Inc. used this concept to determine the optimal planning reserve margin for the El Paso Electric Company in 2015 [33].

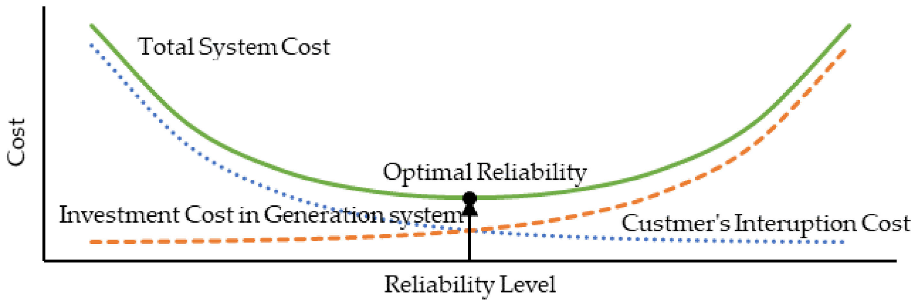

Figure 1. Concept of optimal reliability criteria determination with minimum cost.

Although the concept mentioned above is used in several publications, the optimal reliability criterion discussed in many publications is reserve margin. In addition, the objective function of the aforementioned problem is to minimize the total system cost. This total cost is the sum of the utilities' investment cost and the customer's interruption cost. It is not only the cost that a utility actually pays. Thus, sometimes, it is not so convincing for some power utilities to include this cost in their calculation. With these concerns in mind, the concept of reliability improvement's benefit, which is another perspective but equivalent when determining the optimal reliability level, is considered in this paper. In addition, LOLE, which is a more appropriate reliability criterion, is also focused. Although reserve margin and LOLE are different criteria, the GEP result obtained from using LOLE as the planning criterion can provide a minimum reserve margin as an outcome or vice versa. For example, Abdalla et al. chose to adjust the minimum reserve margin in the robust GEP model to obtain the power system with acceptable LOLE [26,27]. However, it should be noted that this relationship is based on the characteristics of a given generation system, since different power systems having the same LOLE can have a different minimum reserve margin. Moreover, if the minimum reserve margin is used as the planning criterion, the maximum LOLE output might not be the same value as the LOLE criterion used in the first GEP since the maximum LOLE and the minimum reserve margin might not occur in the same year.

In GEP, fuel supply is typically assumed to be *always available* in order to reduce the complexity of the problem. Only the future price of each fuel, reflecting the future market situation, is forecast. However, apart from the market situation, international conflicts can also lead to fuel shortages or unavailability [34]. As conventional generation units need a continuous fuel supply, fuel unavailability can cause interruption to these generation units. The scale of this interruption could affect the reliability of the power generation system. Thus, it might be necessary to consider fuel supply availability in generation expansion planning if the generation system relies heavily on any specific fuel, especially in Thailand where natural gas accounts for more than 55% of the fuel mix. This can be done by adjusting the probabilistic reliability criterion with the probability of fuel unavailability, using a concept based on Bayes' Theorem.

1.2. Our Contribution

The contribution of this paper can be summarized as follows:

- Propose a methodology for determining the optimal LOLE criterion of a power system using the concept of power system net benefit.
- Discuss a method to evaluate an equivalent reserve margin from this optimal LOLE.
- Introduce a probabilistic model based on Bayes' Theorem to incorporate the impact of fuel unavailability into the LOLE.

These concepts and methods are tested with Thailand's power generation system using input data from Thailand's Power Development Plan 2018 revision 1 (PDP2018r1) [35].

The rest of the paper is organized as follows: Section 2 describes the materials and methods used in this paper. They comprise the concept of power system net benefit, used in the evaluation of the optimal LOLE. Moreover, the data of the test system is given. Then, Section 3 presents the results with discussions. Finally, Section 4 provides the conclusion of the study.

2. Materials and Methods

In this section, firstly, the reserve margin and LOLE calculation methods are introduced. Then, the concept of power system total benefit used to evaluate the optimal LOLE is also presented. Lastly, data and assumptions for Thailand's PDP2018r1, used as a numerical example in the next section, are given.

2.1. Reserve Margin and LOLE Calculations

2.1.1. Reserve Margin

The reserve margin is a deterministic reliability index defined as the percentage of generation capacity value over system peak load. The capacity value is defined as the fraction of the installed capacity that is considered reliable. It is a concept used to quantify the relatively reliable capacity of a generating resource during a considered period, typically the peak load hours [36]. For conventional power plants, this value is normally 100%. For intermittent renewable power plants, this value is lower. In Thailand, capacity value is called dependable capacity [37]. With capacity value considered, the reserve margin can be calculated by using (1). More details about capacity value are provided in Section 2.4.6. Capacity value is calculated from the multiplication of a generation unit's installed capacity and its capacity credit, which is called the dependable factor in Thailand.

$$Reserve\ Margin = \frac{Capacity\ value - Peak\ load}{Peak\ load} \tag{1}$$

2.1.2. Loss of Load Expectation

Loss of load expectation (LOLE) is the expected number of days in a year that load loss or generation deficiency occurs. It can be calculated from the Capacity Outage Probability Table (COPT) and Load Duration Curve (LDC) using (2) [5]. The COPT is created from all dispatchable generation units' capacity and their Forced Outage Rate (FOR). The LDC is generated from the hourly load curve of the considering period. Thus, generation units' characteristics and the entire load model are considered in the LOLE calculation. Examples of COPT and LDC are shown in Table 1 and Figure 2.

$$LOLE = \sum_{j=1}^{N} p_i t_{LDC}(O_i) \tag{2}$$

where:

N is the number of states of COPT;
p_i is the individual probability of outage capacity state j;
$t_{LDC}(O_i)$ is the duration of the load loss due to the outage capacity O_i (h).

Table 1. Example of a Capacity Outage Probability Table.

Capacity Outage (MW)	Capacity Available (MW)	State Probability
O_1	Installed capacity—O_1	p_1
O_2	Installed capacity—O_2	p_2
$\vdots$	$\vdots$	$\vdots$
O_N	Installed capacity—O_N	p_N

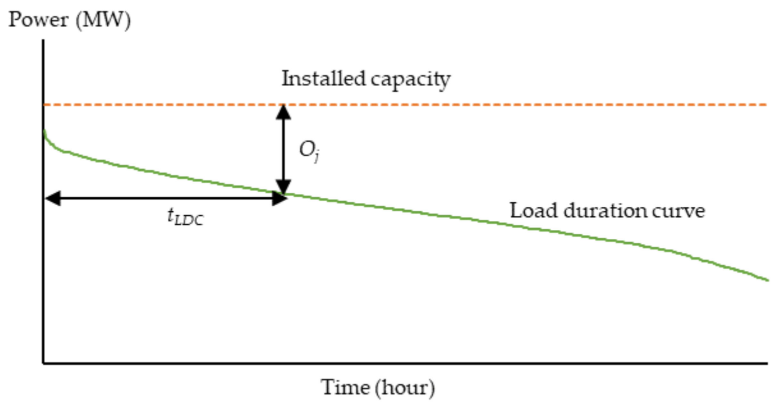

Figure 2. Example of Load duration curve with $t_{LDC}(O_j)$ calculation.

2.2. Reliability Improvement's Benefit

As mentioned earlier, the customer's interruption cost is not an actual cost that a utility actually pays. Thus, sometimes minimizing the total system cost is not so convincing. In this paper, the concept of maximizing reliability improvement's benefits is considered instead. This problem yields exactly the same solution as the optimal reliability level, either reserve margin or LOLE, as that of the minimizing total system cost problem. Indeed, it can be easily proven that these two problems are mathematically identical.

The concept of reliability improvement's benefit starts from the central idea that the utility invests in the generation system to serve its customers, and later transfers this cost to the customer through the electricity tariff. High investment costs yield a high level of reliability, which helps reduce customer interruption costs. Thus, the total benefit, or net benefit, of the power system is the difference between the reduction of the customer's interruption cost and the utility's investment cost in the generation system. The net benefit of the power system is illustrated in Figure 3. Since a power system with a higher LOLE is less reliable, the trend of LOLE is in the opposite direction to the reliability level. With this concept, the optimal level of LOLE is the level that provides the highest net benefit. This net benefit can be calculated using (3) by comparing the reduction of a customer's interruption at any LOLE level from the base case value with the additional utility's investment cost from the base case.

$$Net\ Benefit_j = \left(CIC_0 - CIC_j\right) - AIC_j \tag{3}$$

where:

CIC_j is customer's interruption cost of a generation system at a reliability level of j;
CIC_0 is customer's interruption cost at the base case, or current generation system;
AIC_j is net present value of the utility's additional investment cost in the generation system of every year in the generation planning period, to have the reliability level of j.

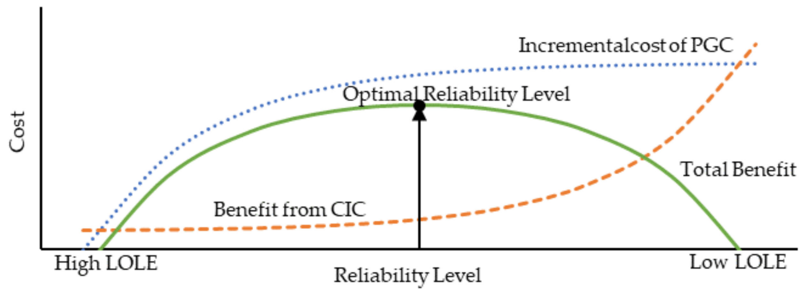

Figure 3. Concept of optimal reliability criteria determination from the total benefit of a power system.

The *CIC* is calculated from the net present value of the multiplication of EENS and IEAR for every year in the generation planning period, as shown in (4).

$$CIC = \sum_{y=1}^{N} \frac{IEAR_y \times EENS_y}{(1+r)^y} \tag{4}$$

where:

N is the number of years in the generation planning period;
$IEAR_y$ is the interrupted energy assessment rate of year y (THB/MWh);
$EENS_y$ is the expected energy not supplied of year y (THB);
r is the discount rate (%);

2.3. Impact of Fuel Unvailability on Loss of Load Expectation

In a normal situation, it is reasonable to assume that the availability or unavailability of each fuel is independent from the others since each fuel comes from different sources with different logistic approaches that are not related to each other. Thus, to take fuel unavailability into consideration during the LOLE calculation, Bayes' Theorem can be used. Total LOLE considering fuel unavailability can be evaluated using (5). This formula can be done since LOLE is also a probability. If multiple fuel supplies' unavailability are considered, the LOLE and its probability of unavailability of each case can be directly combined to determine the net LOLE.

$$LOLE = LOLE_{all-avail} \times (1 - P_{unavail}(f)) + LOLE_{unavail}(f) \times P_{unavail}(f) \tag{5}$$

where:

$LOLE_{all-avail}$ is the LOLE of a generation system in which all fuels are available;
$LOLE_{unavail}(f)$ is the LOLE of a generation system in which only the fuel f are unavailable;
$P_{unavail}(f)$ is the probability of unavailability of the fuel f.

2.4. Data and Assumptions

In this section, data from the generation system and planning assumptions are provided as a case study. The generation system used as the case study in this paper is that of Thailand's Power Development Plan 2018 revision 1 (PDP2018r1), published in 2020 [35], at the end of 2017. The planning period of PDP2018r1 is from 2018 to 2037, and it is a generation system with a total installed capacity of 46,090 MW. Details of the generation system and assumptions are provided in the next section.

2.4.1. Load Model and Load Forecast Data

To create an hourly load model from 2018 to 2037, a full-year hourly load curve and load forecast data are needed. In this study, Thailand's actual full-year hourly load curve of 2017, with a peak load of 30,303 MW, is used as the load model. This hourly load curve is shown in Figure 4. Load forecasts from 2018 to 2037 are provided in PDP2018r1, as shown in Figure 5.

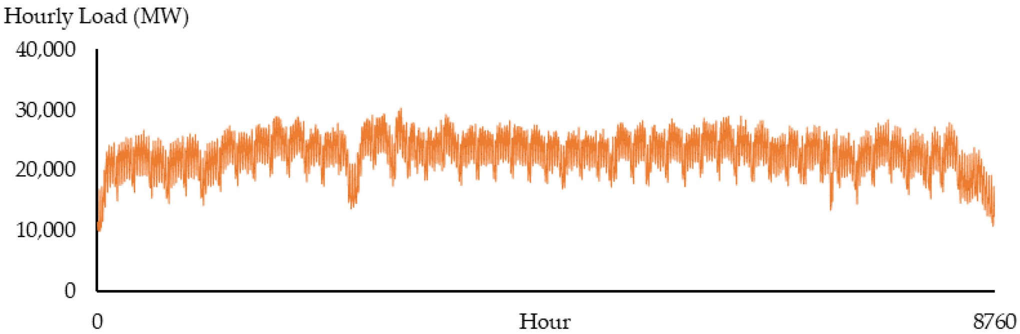

Figure 4. Full-year hourly load curve of 2017.

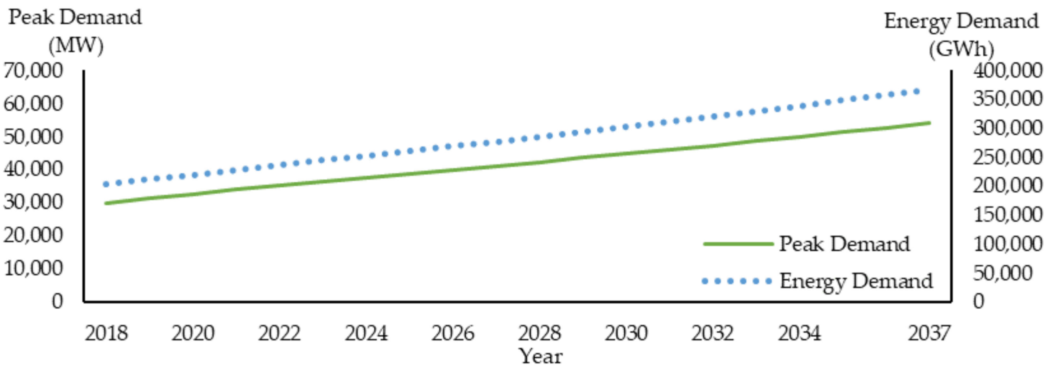

Figure 5. Peak demand and energy demand forecast of PDP2018r1.

2.4.2. Existing Generation Units

In this case study, the generation system as of 31 December 2017 is used as the initial (existing) system for generation expansion planning. The names of the generation units in this initial system can be found in PDP2018r1 [35]. A summary of these data can be found in Appendix A. Apart from the generation units, Pumped Hydroelectric Storage (PHS) is also included in the existing generation system. Parameters for these PHS units are provided in Appendix B.

2.4.3. Committed Generation Unit

Committed generation units are generation units that are already planned for commissioning into the existing generation system. These units can be divided into two groups, which are committed units with signed contracts and committed units according to policy or plans. The list of all committed units can be found in PDP2018r1 [35]. A summary of these data and retired units can be found in Appendix C of this paper.

2.4.4. Additional Generation Units

According to PDP2018r1, additional generation units are generation units without signed contracts that are planned for commissioning into the generation system. These units are forecast to be included in PDP2018r1 by the generation expansion planning procedure. In this study, the PDP2018r1 with these additional units is used as the base case. However, the initial plan does not call for these additional units to be commissioned for other considered cases. Thus, alternative planning with different criteria and assumptions can be carried out by replacing these missing additional units with other candidate generation units. A summary of these units can be found in Appendix D of this paper.

2.4.5. Candidate Generation Units

Candidate generation units are pre-defined generation units that will be selected for commissioning into the system when:

- the reliability criterion violates the target reliability level, or
- there is no optimal solution provided by unit commitment/economic dispatch.

A list of candidate units usually consists of generation units with different generation types, fuel, or technology so that different options are available to complete generation expansion plans with different constraints. Details of candidate units can be found in Appendix E of this paper. The 100 MW unit is used for the optimal LOLE evaluation method, and the 700 MW unit is used for the actual GEP process. Generation units mentioned in Sections 2.4.2–2.4.5 are classified and modelled as described in [2].

2.4.6. Capacity Credit

In Thailand, capacity credit is called the dependable factor. It is the ratio of available capacity with respect to the installed capacity of any generation unit during a peak load period that represents the degradation of system reliability [38]. In PDP2018r1, there are two peak load periods, in the daytime at 2 P.M., and at nighttime at 7 P.M. The dependable factors of the generation units considered in PDP2018r1 are shown in Table 2 [6,35]. In PDP2018r1, these dependable factors are created by a deterministic method from an average value of the hourly power output at the specific hour of several renewable energy power plants [37].

Table 2. Dependable factors or capacity value of renewable energy generation units.

Fuel Type	Dependable Factor (%) for Peak Load at Daytime	Dependable Factor (%) for Peak Load at Nighttime
Conventional (NG, Coal)	100%	100%
Biomass (existing, new)	52, 80%	52, 80%
Biogas (existing, new)	28, 70%	28, 70%
Solar PV (existing, new)	42%, 50%	0%
Wind power	14%	18%
Small hydro	29%	29%
Municipal solid waste	47%	47%

2.4.7. Fuel Availability

In this Thailand power generation system, there are two main fuel supplies that are considered to be critical since most of the conventional generation units rely on these fuel supplies. Specifically, the critical fuel supplies are the western natural gas network from Myanmar and the eastern natural gas network from the Gulf of Thailand. The probabilities of availability and unavailability of these fuel supplies are shown in Table 3. These probabilities can be estimated from the historical record of outage time of each gas source, as shown in Appendix F.

Table 3. Fuel supply with its equivalent availability.

Fuel Supply	Probability of Unavailability	Probability of Availability
Western gas network	0.018853	0.981147
Eastern gas network	0.000076	0.999924

2.4.8. Planning Constraints

To ensure availability, reliability, and acceptable emissions levels, the following constraints are considered in generation expansion planning in this study:

- Planning horizon: 2018–2037;
- Full-year hourly power balance constraint.

Using generation units with generation profiles in the system, a full-year hourly energy and power balance between supply, storage, and demand is applied to every year in the planning horizon to ensure system adequacy without capacity shortage.

- Reliability constraint.

In this study, LOLE is used as the reliability criterion for generation expansion planning during the optimal LOLE evaluation process. The value of LOLE is varied to find the optimal LOLE. The reserve margin is also used as a reliability criterion during the reserve margin determination process. The value of the reserve margin also varied to match with the optimal LOLE.

- Carbon dioxide emission constraint.

According to PDP2018r1, a carbon dioxide emission constraint is provided in average kilograms of carbon dioxide emission per kilowatt-hour of electricity. The average carbon dioxide emission constraint used in this study is shown in Figure 6, and the carbon dioxide emission factor of each fuel is provided in Appendix G. The constraint is gradually decreased to reduce the greenhouse gas emissions from the power generation system.

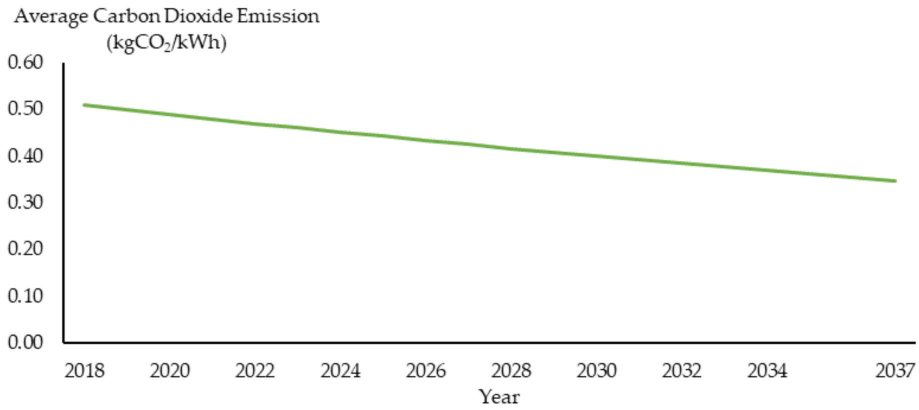

Figure 6. Average carbon dioxide emission constraint.

3. Results and Discussion

In this section, the results from the proposed methods tested with the case study are presented and discussed. Firstly, the reliability indices of the original case study, with every committed and additional generation unit, are shown as the base case. Secondly, the optimal LOLE of the case study is evaluated. With the optimal LOLE, reserve margin is determined in the following section. This reserve margin is then compared to the reserve margin determined with consideration of fuel supply availability in the last section. Discussion of the results is provided in each section.

3.1. Reliability Indices of The Original Case Study

The original case study, PDP2018r1, is Thailand's official power development plan for 2018 to 2037, with every generation unit commissioned as planned, without the addition of any candidate generation units. The capacity mix of PDP2018r1 is shown in Figure 7. Reliability indices, reserve margin, and LOLE of the plan are also provided, as shown in Figure 8.

As shown in Figure 7, installed capacity from renewable energy increases from 26% in 2018 to 46% in 2037. The main portion of this new renewable energy capacity is from solar generation units, which increased by 12,000 MW throughout the planning horizon.

As seen in Figure 8, although the daytime reserve margin of the power system from 2028 onwards is quite high, at around 15% to 20%, the nighttime reserve margin is significantly low. This is caused by the solar generation units, which cannot generate electricity at night, not to mention that the peak load period might change from the afternoon time to a different period in the future. For these reasons, it can be concluded that the use of reserve margin as a planning criterion is not appropriate, especially in a power system with a high level of renewable energy penetration and disruptive technologies in the power system, since the value of reserve margin is subjective, especially the dependable factor. Thus, in this study, LOLE is introduced as the planning criterion instead.

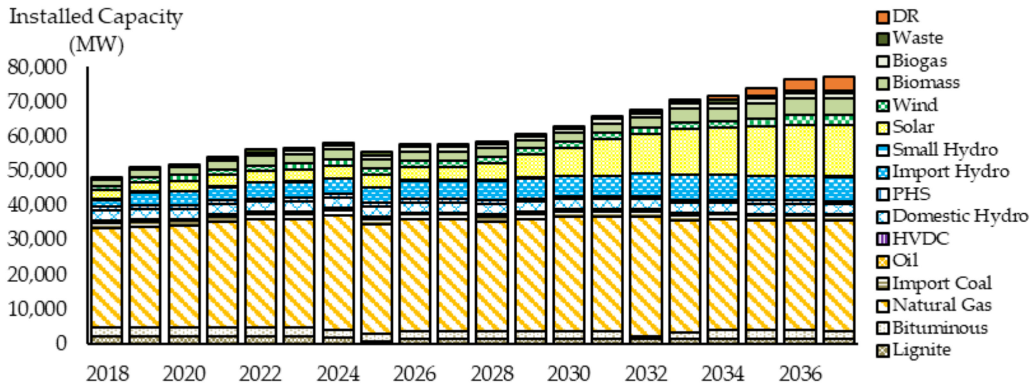

Figure 7. Capacity mix of PDP2018r1.

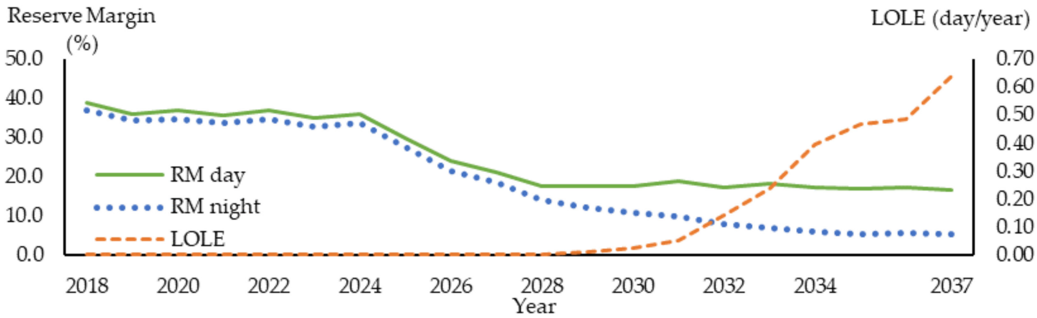

Figure 8. Reliability indices of PDP2018r1.

3.2. Optimal LOLE

Using data from the case study without additional generation units and methods described in Section 2.2, levelized power generation cost (PGC) and levelized customer interruption cost (CIC) of the power generation system throughout the planning horizon associated with LOLE criteria can be calculated, considering the 100 MW generation unit as the candidate unit. Given that the case with LOLE criteria of 1.1 days/year is the base case in this study, levelized power generation cost and customer interruption cost of each case are compared with the base case and shown in Figure 9. Please note that the LOLE index in Figure 9 is sorted from lowest reliability level to highest reliability level.

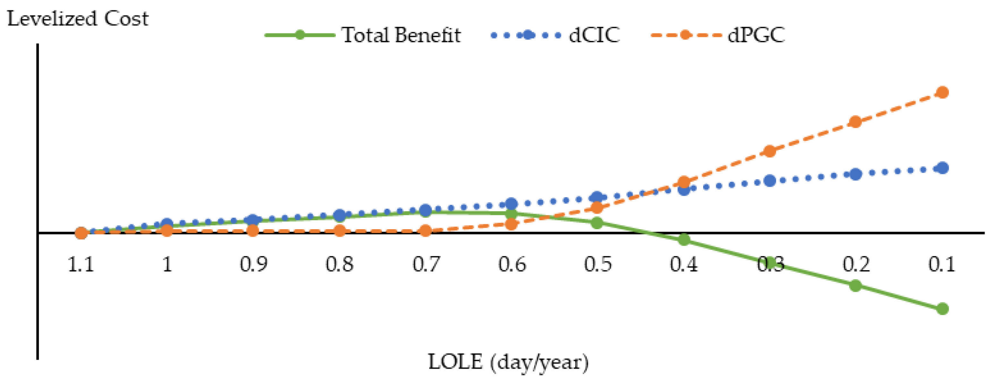

Figure 9. Total benefit associated with LOLE criterion of the case study.

From Figure 9, it can be seen that the optimal LOLE for the case study is 0.7 day/year. With this optimal LOLE as the reliability criterion, a GEP is carried out using data from the case study and a 700 MW natural gas unit as the candidate unit. Additional generation capacity and reliability indices of the generation expansion plan are shown in Figures 10 and 11. Please note that this GEP will be referred to as the LOLE 0.7 day/year case.

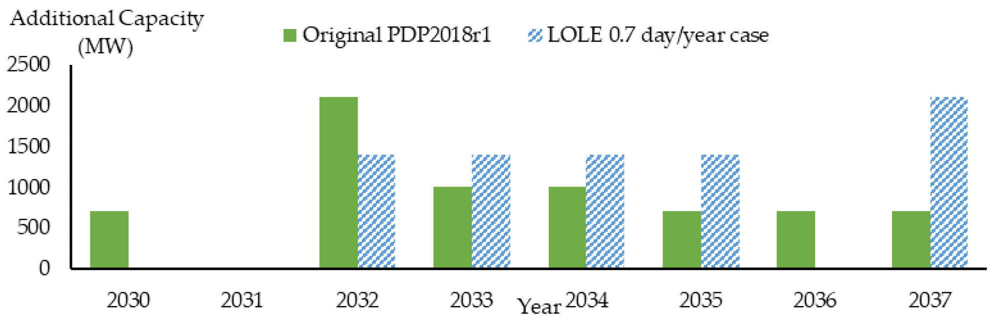

Figure 10. Additional generation capacity of the PDP2018r1 and the case of LOLE 0.7 day/year.

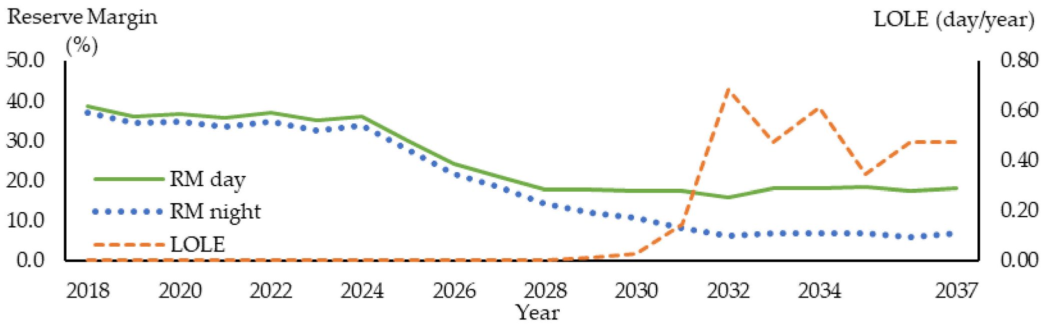

Figure 11. Reliability indices of the generation expansion plan with LOLE < 0.7 day/year case.

From Figure 10, it can be seen that 7700 MW of additional capacity needs to be added to fulfill the less than 0.7 day/year reliability criterion and other planning constraints. This additional capacity is almost the same as the 6900 MW of additional capacity of the original PDP2018r1. However, compared to the original plan, the additional capacity of the LOLE 0.7 day/year case can be delayed by several years since the planning constraints can still be fulfilled by the generation system in 2030 and 2031. Furthermore, as seen in Figure 11, the LOLE index of the LOLE 0.7 day/year case is maintained within the reliability criterion. It can also be seen that the trends of LOLE and the reserve margin indices are not perfectly negatively correlated since the LOLE index is affected by the generation system characteristics, unlike the reserve margin index. Therefore, the minimum reserve margin index might not occur in the same year as the maximum LOLE index.

3.3. Equivalent Reserve Margin from Loss of Load Expectation Criterion

The equivalent reserve margins of the LOLE criterion from 0.1 to 1.1 days/year can be evaluated by performing the GEP with a reserve margin criterion that provides the maximum LOLE not greater than the value of the LOLE criterion. The results using Thailand PDP2018r1 can be demonstrated in Figure 12. It can be seen from this figure that the lower the LOLE criterion, the higher the equivalent reserve margin. With this equivalent reserve margin, a generation system with the same LOLE criterion can be obtained by performing the GEP using this equivalent reserve margin as the planning criterion.

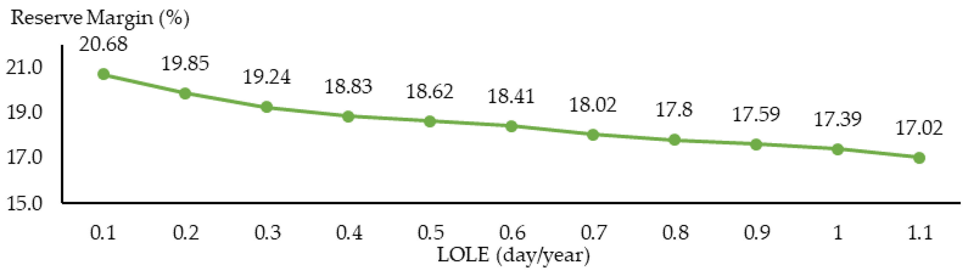

Figure 12. Reliability indices of generation expansion plan with LOLE < 0.7 day/years.

3.4. Loss of Load Expectation with Fuel Supply Unavailability

To demonstrate the effect of fuel supply availability, firstly, generation expansion plans with minimum reserve margin criteria from 17% to 21% are made, and their maximum LOLE indices are evaluated. These LOLE indices are illustrated by the green solid line shown in Figure 13. Then, the LOLE index for each case of fuel supply unavailability is evaluated with the method described in Section 2.3 and fuel supply availability data shown in Table 3. Three cases are considered in this paper. The first case is considering the unavailability of the western natural gas network. The second case is considering the unavailability of the eastern natural gas network. The last case is considering both unavailability. The LOLE indices with fuel supply unavailability are also shown in Figure 13.

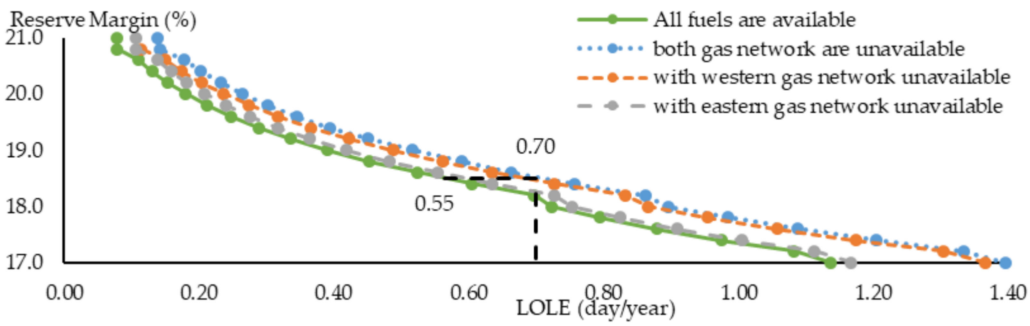

Figure 13. LOLE with natural gas supply unavailability.

Considering Figure 13, it can be concluded that the LOLE criterion of the system with fuel supply unavailability consideration needs to be adjusted to maintain the equivalent level of system reliability. For example, with both western and eastern natural gas networks unavailable, a LOLE criterion of 0.55 day/year should be selected to maintain the reliability level equivalent to a LOLE criterion of 0.7 day/year without consideration of fuel supply unavailability, as shown in the black dashed line.

4. Conclusions

This paper proposes a method for evaluating and identifying the optimal LOLE for generation expansion planning using the concept of power system net benefit. The relationship between the reserve margin and the LOLE is also explained and used to evaluate the equivalent reserve margin criterion for any specific LOLE value. Lastly, the impact of fuel supply unavailability on the LOLE is demonstrated, based on Bayes' Theorem.

In this paper, the LOLE is selected as the reliability criterion since it is a probabilistic index which considers both generation system characteristics and the overall load model, unlike the reserve margin, whose value is determined by only peak time period and also highly dependent on deterministic assumptions such as dependable factor or capacity credit. Thus, the LOLE is more suitable as the reliability criterion than the reserve margin is. With the method described in Section 2.2, power system net benefit can be evaluated by comparing the customer's interruption cost and the utility's investment cost in the generation system planned by considering the LOLE criterion and the base generation system. The net benefit of each generation system with different LOLE criteria is then compared to determine the maximum point, which is identified as the optimal level for the LOLE criterion. The proposed method is tested with Thailand's PDP2018r1. It is found that the optimal LOLE of Thailand's modified PDP2018r1 system is 0.7 day/year. Moreover, with the result discussed in Section 3.3, LOLE can also be represented by an equivalent reserve margin.

Lastly, since the LOLE is a probabilistic index and the probabilities of fuel supply unavailability are independent from each other, the impact of fuel supply unavailability can be evaluated using Bayes' Theorem. The impact of eastern and western natural gas supply unavailability on the LOLE of the case study is being evaluated. It is found that if fuel supply is not reliable, it might be necessary to adjust the LOLE criterion of the generation system to maintain the same level of generation system reliability.

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Appendix A. Existing Power Generation System as of December 2017

Table A1. Thailand's power generation system as of December 2017.

Fuel Type	Number (Unit)	Total Capacity (MW)	Lifetime (Years)	Heat Rate (Btu/kWh)	FOR (%)
Lignite	7	2180.0	30–39	10,600	5.00
Bituminous	14	2406.6	21–30	8300–9100	5.00–7.00
Eastern natural gas	20	13,217.0	21–35	6800–9500	4.00–7.00
Western natural gas	11	7647.0	20–26	6800–9400	4.00–6.00
Other natural gas	76	7537.7	21–27	6800–8400	4.00–7.00
Import coal	3	1473.0	30	9100	6.00
Diesel	7	60.7	25–30	8300–10,400	7.00–10.00
Fuel oil	2	320.0	21–30	8300–10,400	7.00–10.00
Hydro	17	2926.8	50	-	3.58–6.76
Import hydro	4	2104.6	25–50	-	3.58–4.00
PHS	1	500.0	50	-	2.86
Renewable Energy	-	5417.0	-	-	-

Table A2. Thailand's renewable energy generation units as of December 2017.

Fuel Type	Total Capacity (MW)	Lifetime (Years)	FOR (%)
Biomass	1659.4	21–25	7.90
Biogas	319.7	25	10.58
Solar PV	2572.6	25	0.60
Wind power	589.7	25	0.80
Small hydro	100.6	25–50	15.79
Municipal Solid waste	175.0	25	7.90

Appendix B. Committed Generation Units

Table A3. PHS parameters.

Parameters	Value	Unit
C-rate	0.125	-
Round-trip efficiency	75	%
minimum state-of-charge	0	%
maximum state-of-charge	100	%

Appendix C. Committed Generation Units

Table A4. Committed conventional generation units (MW).

Year	Lignite	Bituminous	Other Natural Gas	PHS	DR	Imported Hydro
2018	600	20	622	500		
2019			1856.8			1843
2020			1476			
2021		10	1550			
2022			1310			514
2023			1280			
2024		90	2100			
2025		30	1380			
2026	600		700			700
2027			2640			
2028			700			700
2029			700			
2030						
2031						
2032					354	700
2033					202	700
2034					859	
2035			700		1025	
2036					860	700
2037					700	

Table A5. Committed renewable generation units (MW).

Year	Biomass	Biogas	Solar	Wind	Small Hydro	Waste
2018	105.4	26.4	0.3	763	42	109
2019	243	20	154	135	1.25	41
2020	242	300	295			49
2021	348	166	162	16	14	
2022	160	133	140	90		400
2023	160	100	154	90	18	
2024	100	100	130	90		
2025					6	
2026			298		4	
2027			50		4	
2028			850		6	
2029			1930		2	
2030	400		1200		4	
2031	300	50	2500		2	
2032	100	100	750	130	3	
2033	1000	150	2038		3	
2034	200		140		28	6
2035	500		725	300	5	15
2036	280	50	490	657	2	14
2037		50	175	128	1	9

Table A6. Retired conventional generation units (MW).

Year	Lignite	Bituminous	Natural Gas	Oil	Imported Hydro	Biomass
2018	−560	−10	−346			
2019			−1464	−5		
2020			−1256			−8
2021		−10	−232			
2022			−712			
2023			−1077			
2024	−540	−270	−360			−82
2025	−1080	−90	−2880			−145
2026						−58
2027			−2617			−56
2028			−1289			−196
2029					−126	−179
2030						−103
2031						−63
2032		−1347	−734			−83
2033			−2134			−74
2034			−710	−315		−23
2035			−1510		−948	−956
2036			−670			−3
2037		−660	−254			−22

Appendix D. Additional Generation Units

Table A7. Additional generation units (MW).

Year	Lignite	Bituminous	Natural Gas	Imported Hydro
2030			700	
2032			2100	
2033		1000		
2034		1000		
2035			700	
2036			700	
2037			700	

Appendix E. Candidate Generation Units

Table A8. List of candidate generation units.

Fuel Type	Number (Unit)	Total Capacity (MW)	Lifetime (Years)	Heat Rate (Btu/kWh)	FOR (%)
Natural Gas	Infinite	100	25	6284	4.0
Natural Gas	Infinite	700	25	6284	4.0

Appendix F. Availability of Fuel Sources

Table A9. Availability and unavailability of natural gas sources in the western gas network.

Natural Gas Source	Probability of Unavailability	Probability of Availability
W1	0.012612	0.987388
W2	0.006307	0.993693
W3	0.000009	0.999991

From the fact that Thailand's western gas network is not sufficient to supply the designated power plants if at least one gas source is unavailable, the probability of unavailability of the western gas source can be calculated from

$$1 - (0.987388 \times 0.993693 \times 0.999986) = 0.018853$$

Table A10. Availability and unavailability of major natural gas sources in the eastern gas network.

Natural Gas Source	Probability of Unavailability	Probability of Availability
E1	0.002681	0.997319
E2	0.011412	0.988588
E3	0.002097	0.997903
E4	0.001010	0.998990

From the fact that Thailand's eastern gas network is not sufficient to supply the designated power plants if two or more major gas sources are unavailable, the probability of unavailability of the eastern gas source can be calculated from

$$1 - P_0 - P_1 = 1 - 0.982876 - 0.017047 = 0.000076$$

where

$$P_0 = (0.997319 \times 0.988588 \times 0.997903 \times 0.998990) = 0.982876$$

$$P_1 = (0.002642 + 0.011346 + 0.002065 + 0.000994) = 0.017047$$

Appendix G. Carbon Dioxide Emission Factor

Table A11. Carbon dioxide emission factor.

Fuel	Carbon Dioxide Emission Factor ($kgCO_2$/MMBtu)
Lignite	95.9
Bituminous	94.4
Eastern natural gas	57.3
Western natural gas	57.3
Other natural gas	57.3
Import coal	95.9
Diesel	76.6
Fuel oil	79.7

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