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Efficiency Measurement of Energy Planning under Uncertainties

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Publications and Conferences

Journal articles

- **Ratanakuakangwan S**, Morita H. Energy efficiency of power plants meeting multiple requirements and comparative study of different carbon tax scenarios in Thailand. *Cleaner Engineering and Technology* (2021); 100073. https://doi.org/10.1016/j.clet.2021.100073.

- **Ratanakuakangwan S**, Morita H. Hybrid stochastic robust optimization and robust optimization for energy planning – A social impact-constrained case study. *Applied Energy* (2021); 298:117258. https://doi.org/10.1016/j.apenergy.2021.117258.

- **Ratanakuakangwan S**, Morita H. Measuring the efficiency of energy planning under uncertainty. *Energy Reports* (2022); 8:544–51.https://doi.org/10.1016/j.egyr.2021.11.164.

- **Ratanakuakangwan S**, Morita H. Multi-aspect efficiency measurement of multi-objective energy planning model dealing with uncertainties. *Applied Energy;* (2022); 313:118883. https://doi.org/10.1016/j.apenergy.2022.118883.

- **Ratanakuakangwan S**, Morita H. An efficient energy planning model optimizing cost, emission, and social impact with different carbon tax scenarios. *Applied Energy;* (Under review)

International Conferences (peer-reviewed)

- **Ratanakuakangwan S**, Morita H. Measuring the Efficiency of Energy Planning under Uncertainty. *8th International Conference on Power and Energy Systems Engineering (CPESE 2021)*. Japan/ Virtual. September 10-12, 2021

- **Ratanakuakangwan S**, Morita H. Efficiency Measurement of Energy Planning Model Optimizing Cost, Environment, and Social Impact. *13th International Conference on Applied Energy (ICAE2021)*. Thailand/ Virtual. November 29 – December 5, 2021

- **Ratanakuakangwan S**, Morita H. Efficiency Measurement of Energy Policies under Multi-aspects Consideration. *F&R Energy 2022*. USA/ Virtual. February 15-17, 2022 (**as an invited speaker**)

Conference's Proceedings

- **Ratanakuakangwan S**, Morita H. A study on factors influencing the technical efficiency of hydro power plants in Thailand. *Proceedings of the 64th Annual Conference of the Institute of Systems, Control and Information Engineers (ISCIE), Kobe, 2020*

Conferences Presentations

- **Ratanakuakangwan S**, Morita H. A Study on Factors Influencing the Technical Efficiency of Hydro Power Plants in Thailand. *64th Conference of the Institute of Systems, Control, and Information Engineers (ISCIE)*. Japan/ Virtual. May 20-22, 2020.
- **Ratanakuakangwan S**, Morita H. The Efficiency Measurement of Fossil Fuel Power Plants in Thailand. *Virtual 2020 INFORMS Annual Meeting*. USA/ Virtual. November 8-13, 2020
- **Ratanakuakangwan S**, Morita H. Stochastic Robust Optimization in Social Impact-constrained Energy Planning. *89th Research Meeting hosted by Operation Research Society of Japan*. Japan/ Virtual. January 27, 2021
- **Ratanakuakangwan S**, Morita H. The Efficiency Measurement of Energy Mixes, A Case Study of Thailand. *2021 INFORMS Annual Meeting*. USA/ Virtual. October 24-27, 2021

Efficiency Measurement of Energy Planning under Uncertainties

Abstract

Energy transitions around the world are in the present context of five core missions: Energy Security, Energy Equity, Environmental Sustainability, Socially Acceptance, and Encouraging Employment. In order to achieve appropriate energy development goals, effective long-term energy planning is essential. However, it is very difficult to simultaneously meet these requirements together without any tradeoffs. With the objective of optimizing an efficient energy planning accounted for multi-aspects of requirement and uncertainties in future projections, this study can be divided into three main phrases.

In the first phase, a practical model modification for assessing the energy efficiency of power generation facilities was proposed. Unlike previous studies which only focused on economic aspects, this study is the first to examine energy efficiency while considering the combined impact of security, economic, and ecological factors. Stochastic frontier analysis with inefficiency effects was used to estimate the efficiency of the power plants and to determine the effects of explanatory variables, such as sources of energy (fossil-fueled or renewable energy), load type of power plant, nameplate capacity, and plant age. In order to reduce CO_2 emissions, four proposed carbon tax implementation scenarios were used to evaluate the potential impacts on the production function. Difficulties associated with simultaneously comparing multiple aspects of different types of power generation facilities could be addressed by using the proposed efficiency measurements.

In the second phase, a hybrid stochastic robust optimization and robust optimization model to determine the best energy mix was proposed. The proposed model considers uncertainty in future projections, including those associated with future demand, technological advancements in renewable energy power plants, cost reductions in renewable energy, social impact fluctuations and reliable capacity. Unlike other optimization models that tend to focus exclusively on either scenario-based or worst-case scenario realization, the proposed approach takes both uncertainties into account based on their practical condition. For security, reliable capacity to meet projected peak demand is necessary to ensure that the system is immunized against all possible outcomes. Thus, the risk of power outage is dealt with as a worst-case robust optimization. Other uncertainties are addressed using a scenario-based stochastic robust optimization methodology. Scenarios involving various projected electricity consumption levels, capacity factors and the cost of renewable energy are generated with assumed probabilities of occurrence. Rather uniquely, social impact, one of the critical factors in energy planning, is incorporated into the model, which makes containing any social impact fluctuations resulting from different scenarios essential. To this end, the bounds of a potential optimal energy mix are controlled in the model by the defined function of social impact variation. The model results provide support for policy makers seeking to enhance system stability.

In the third phase, a framework that combines the concepts of a multi-objective optimization model and efficiency measurement in order to determine the most efficient energy mix considering the multi-dimensional aspects of energy requirements and various uncertainty scenarios was proposed. Various multi-objective functions were appended to the capacity expansion model in order to include some of the broader aspects of energy planning. A slacks-based measure of efficiency methodology was then applied to determine the best energy mix from the set of results produced by the modified model. The study established that to effectively implement the proposed model, the various choices of the multi-objective function are to be generated first, allowing the two-stage efficiency measurement method to then determine the best of the optimal energy mixes from all the possible first-stage results.

The empirical results from the study presented here provide quantitative support for policy makers seeking to determine an efficient energy policy that maximizes the satisfaction of multiple requirements, while taking into account various scenarios of future uncertainties.

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Chapter 1
Introduction

1.1. Statement of problems

In the present context of sustainable development and environmental protection, energy policy around the world is focused on three primary objectives: It should provide energy supply security, decrease environmental impacts and ensure economic competitiveness [1]. Finding the proper balance between these objectives has been defined by the World Energy Council as the Energy Trilemma [2]. Accordingly, these three aspects have been consistently used as the primary considerations in numerous energy planning studies [3–8].

However, in the presence of trade-offs, simultaneous comparisons of the various requirements of these three areas are very difficult. Consequently, to better clarify how such comparisons may be possible, we exampled a case study to compare fossil power plants and renewable energy facilities.

On the one hand, fossil fuel power generation facilities including coal-fired thermal power generation and combined-cycle power generation using natural gas are considered to be the most economical means of power generation (in terms of cost per unit of electricity produced) [9]. In addition, these types of power generation ensure a stable supply of power to the grid because they can be operated around-the-clock. Therefore, the fossil fuel energy is still account for the majority of energy production due to the ability to secure the necessary energy supply and operate at a relatively low cost. However, despite the application of advanced technologies in pollution reduction, they continue to produce significant environmental damage.

Conversely, power generation using renewable energy (RE), such as hydro, solar, and wind, yields zero emissions, but these facilities are considerably more expensive than those based on fossil fuels. Further, power generation based on renewable energy depends on exogenous inputs, such as sunlight for photovoltaic (PV) cells, wind for wind turbines, and water for hydropower turbines. This dependence on exogenous factors means that they are not reliable power sources and cannot consistently provide sufficient power to the grid.

In order to achieve appropriate energy development goals, effective long-term energy planning is essential. Such planning inevitably involves uncertain future projections of such factors as demand, technological improvements in renewable energy, and the reliable capacity of power plants. These projections often miss the mark because of exogenous factors such as economic growth and changes in the population. In such cases, the effects of uncertainty may substantially add to the risks of high electricity costs and insufficient electricity supply [3].

One of the best-known modeling approaches to dealing with such uncertainties is scenario-based stochastic optimization (SO), which focuses on the expected value of multiple possible scenarios. Stochastic optimization produces a range of possible outcomes that the decision maker can then use as boundaries for potential solutions. Several studies using stochastic optimization in power development planning have been reported. Thangavelu, Khambadkone, and Karimi developed a stochastic optimization model for long-term energy planning using a case study for a South East Asian region [3]. Yu, Ryu, and Lee formulated a stochastic programming to the design and operation of a hybrid renewable energy system [4]. Ioannou, Fuzuli, Brennan, Yudha, and Angus proposed a multi-stage stochastic optimization for the medium to long term energy planning applying to the Indonesian power generation system [5]. However, large variations in the possible outcomes can make the decision-making process difficult, particularly in situations that involve variables such as power plant capacity that require long-term planning. Thus, the use of stochastic optimization alone in energy planning could potentially lead to system instability and an inappropriate electric power structure [6].

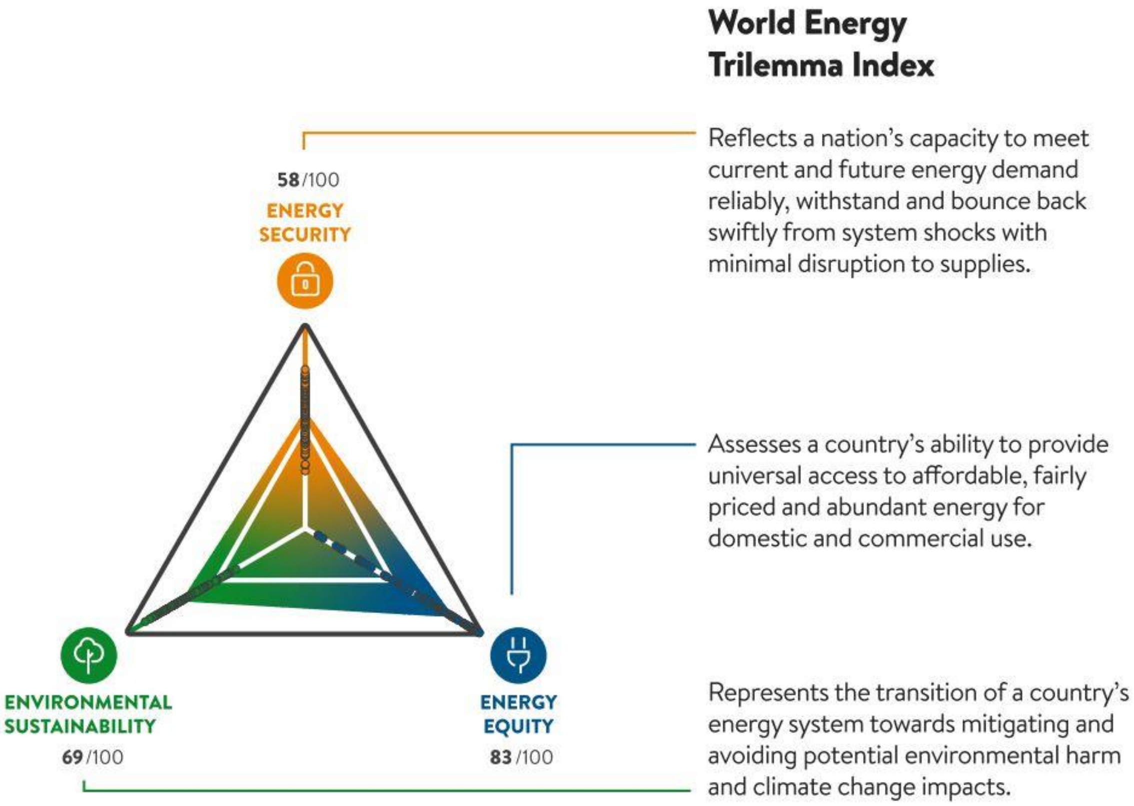

Figure 1-1 World Energy Trilemma Index 2020

(Picture from [2])

Another approach is robust optimization (RO). In RO, the uncertain parameters are assumed to be taken as worst-case values within sets [35]. In the application of the RO method, Bertsimas and Sim developed a linear robust counterpart to linear programming that reduces the calculation complexity [37,38]. This tractable computation is a major advantage of the approach [39]. Several studies have used RO for energy planning. Mohseni and Pishvee developed a RO method to design biofuel power plants under two norms of uncertain data [40]. Tsao and Thanh integrated fuzzy multi-objective and RO to determine the proper energy mix under the uncertainties of energy demand, the attributes of renewable energy, and costs [8]. The downside of this method is that it is perceived as overly pessimistic for practical application [39].

1.2.Research gaps and motivation

Based on literature reviews from previous studies, multiple knowledge gaps can be identified. In the context of the methodology, the energy planning dealing with uncertainty of the previous studies that usually implement only one of the well-known methods may lead to either residual risk, as in case of SO, or to overly conservative results, as in the case of RO. It also of concern that optimizing only economic cost, as has been common in previous studies, does not properly address the above-mentioned multi aspects of energy planning.

Importantly, the optimization models and the efficiency measurements featured in the previous studies are implemented separately. Very few posterior decision-making approaches to be determined after the optimization, and the efficiency measurements usually use historical data. This may lead to either an inconclusive set of optimal energy mixes, as in case of the optimization models, or the inability to reflect the future requirements due to a dependency on historical data, as in case of the efficiency measurement studies.

For the practical implementation, the energy efficiency in previous studies has usually been estimated separately for specific types of power plant, either fossil-fueled plants or renewable energy plants. However, the energy planning of a country typically distributes power generated by a variety of power generation facilities. Moreover, most of the studies have solely focused on the economic aspect, including fuel prices, operational costs, investment costs, and labor. None of these studies have considered the combined effect of other aspects, such as security, environmental, and social, which are also important.

Predominantly, the issue of social acceptance of new power plants is often be largely unaddressed in the previous studies. The primary barriers to the capacity expansion to the energy grid are neither financial nor technical; rather, the primary barriers are the lack of an appropriate regulatory framework and the absence of general public acceptance.

Accordingly, the main objective of this study is to develop a framework that combines the concepts of a multi-objective optimization model and efficiency measurement in order to determine the most efficient energy mix considering the multi-dimensional aspects of energy requirements and various uncertainty scenarios.

1.3. Step of work & contributions

1.3.1. Three phases of study

Throughout the period of author's Ph.D. study, from October 2019 to May 2022, the whole study can be separated into three main phases which classify the main outline in this thesis. The first phase is "Energy efficiency". In this phase, practical model modifications for assessing the energy efficiency of power plants that meet multiple aspects of requirement are proposed. The main implemented methodology is efficiency measurement, including data envelopment analysis (DEA), stochastic frontier analysis (SFA), and slack-based measure (SBM). Empirical study uses the historical data to determine the existing efficiency of each power generation facilities in Thailand [10].

The second phase is "Energy planning" which the energy planning optimization model is proposed. The main implemented methodology is the optimization model under uncertainty, including stochastic optimization (SO), robust optimization (RO), and stochastic robust optimization (SRO). Empirical study uses projected data from multiple sources, such as the projected demand of Thailand, technical specification of power generation facilities, and cost model of power plants [11].

The third phase is "Measuring the energy efficiency of the energy planning". The main purpose of this phase is to combine the concepts of the prior phases in order to determine the energy policy that maximize the satisfaction of multiple aspects of requirement in energy planning. The framework that combines the concepts of a multi-objective optimization model and efficiency measurement is proposed in this phase. Empirical study uses methodologies from prior phases and compares multiple energy policy that shape the resulting energy mixes differently in order to determine the most efficient energy mix considering the multi-dimensional aspects of energy requirements and various uncertainty scenarios [12,13]. Figure 1-2 illustratively summarize the concepts of the three phases.

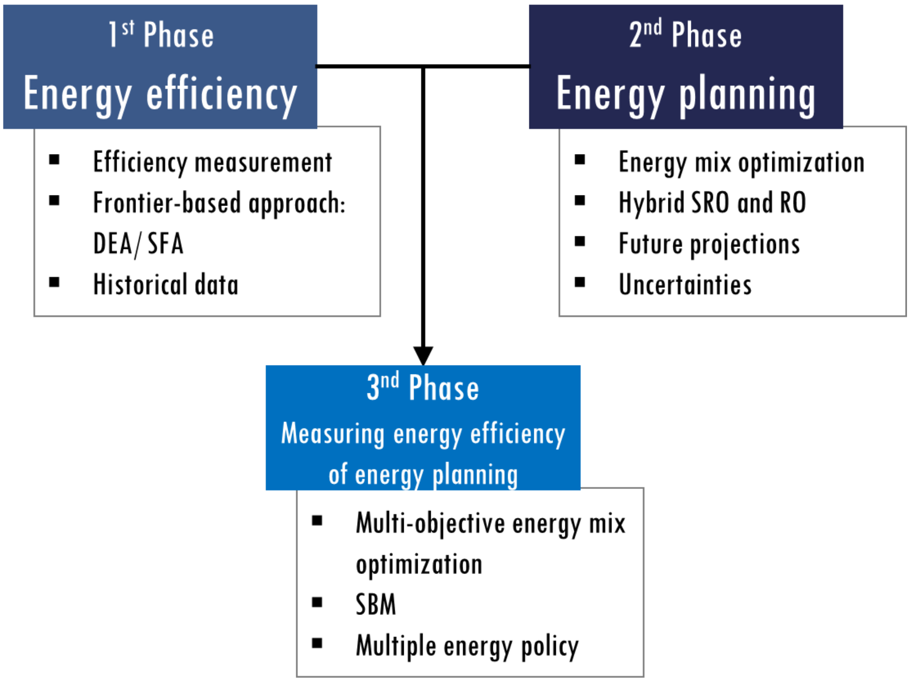

Figure 1-2 Summarized concepts of the three phases

1.3.2. Contributions

Contributions of this study can be categorized into two main groups, including academic contributions and practical contributions. Detailed contributions of the study are listed separately in each phase.

Academic contributions are summarized as follows:

- This study proposes a practical model modification for assessing the energy efficiency of power plants.
- A hybrid stochastic robust optimization and robust optimization model to determine the best energy mix is proposed. The proposed model takes both uncertainties into account based on their practical condition.
- A framework that combines the concepts of a multi-objective optimization model and efficiency measurement in order to determine the most efficient energy mix considering the multi-dimensional aspects of energy requirements and various uncertainty scenarios is proposed.

Practical contributions are summarized as follows:

- This study is the first to examine energy efficiency while considering the combined impact of energy affordability, energy security, environmental protection, social impact, and social benefit.
- Multiple types of power plants, including both fossil-fired and renewable energy, representing the full diversity of power generation facilities in the energy system were included in the study.
- Difficulties associated with simultaneously comparing multiple aspects of different types of power generation facilities could be addressed by using the proposed efficiency measurements.
- The model results provide support for policy makers seeking to enhance system stability.
- The empirical results provide quantitative support for policy makers seeking to determine an efficient energy policy that maximizes the satisfaction of multiple requirements, while taking into account various scenarios of future uncertainties.

Chapter 2
Literature reviews

2.1. Efficiency measurement

Numerous benchmarking methods have been proposed for measuring energy efficiency. Partial methods use a one-dimensional ratio between two variables. The benefit of one-dimensional ratios is the simplicity of calculations. The most common application of one-dimensional ratios is for indexing energy productivity, as proposed by Patterson [14]; briefly, the method involves dividing the gross domestic product (GDP) by energy consumption. In the context of power plants, an example of one-dimensional ratios includes the utilization factor of a power plant, total cost per unit of generated electricity, and total emissions and social impacts per unit of generated electricity while considering of security, economic, and ecological factors. Although one-dimensional ratios are relatively straightforward, they cannot be used to analyze more than two variables, which means that they are not well suited for evaluating trade-offs between multiple factors. More specifically, a final index representing different combinations of the three energy efficiency components (i.e., security, economy, and ecology) cannot be developed using one-dimensional ratios alone. Therefore, total methods are required for evaluating multiple components related to energy efficiency.

In order to more effectively deal with trade-offs, total methods can be implemented with higher computational complexity. There are three methods in the total methods group: index-based methods, engineering models, and frontier-based methods. Index methods output a final single index that can be used to evaluate efficiency using a total factor productivity approach. Total factor productivity is a ratio of the weighted average of all outputs and the weighted average of all inputs. Hu and Wang showed that using total factor energy efficiency is more practical than the partial factor energy efficiency of Patterson to assess energy efficiency in China [15]. However, the energy efficiency in this study employs multiple units of measurement. When there are multiple units of measurements in the ratio, then careful consideration needs to be given to weight selection, which is the main factor affecting efficiency. Moreover, Shadbegian and Gray demonstrated that using the total factor productivity can lead to a distortion in productivity measurement since it does not consider environmental and resource factors. Hence, an index-based method is not considered to be a suitable approach for this study [16].

Engineering models are considered to be the most detailed of the potential approaches, as they consider the entire process of power generation, i.e., from inputs to outputs. However, the scope of this study does not focus on a single type of power generation facility. Rather, many different types of power generation facilities are included in this study, such as thermal power plants, solar PV panels, and hydropower plants, and these different types of power plants may not be directly comparable.

The frontier-based methods are used to determine the frontier based on other efficient peer units. In this approach, efficiency is defined by the distance between observed units and the frontier, with units at the frontier considered to be efficient. The frontier can be generated by parametric and non-parametric approaches. Parametric methods can be used to assume the mathematical functions necessary for estimating production functions and for performing regression analysis, while non-parametric methods can be used to define the best virtual units through the linear combination of the inputs and outputs of the efficient units.

2.1.1. Stochastic frontier analysis (SFA)

Stochastic frontier analysis (SFA) is a parametric method that allows random noise and can be used to assess the effects of exogeneous factors. Stochastic frontier production function with technical inefficiency effects is proposed by Battese and Coelli [17]. The stochastic frontier production function is defined as follow:

$$Y_{it} = \exp(x_{it}\beta + V_{it} - U_{it}) \qquad \textbf{Eq. 1}$$

where Y_{it} is the output of the production at the time period t-th, ($t = 1,2, \dots, T$) for the i-th firm, ($i = 1,2, \dots, N$); x_{it} is a ($1 \times k$) vector of inputs of production at t-th time period for i-th firm; β is a ($1 \times k$) vector of unknown parameters to be estimated; V_{it} is the random error that is assumed to be independently and identically distributed $N(0, \sigma_v^2)$, and U_{it} is the technical inefficiency.

The SFA has been applied to several fields in recent decades. The most widely cited inefficiency effects model, that of Battese and Coelli, has been used to assess the efficiency of paddy farmers and the contribution of explanatory factors to inefficiency [17]. Song and Chen estimated the eco-efficiency of grain production in China using an SFA approach [18].

Several studies have analyzed the efficiency and inefficiency effects of power plants using an SFA approach. See and Coelli measured the technical efficiency and inefficiency effects of Malaysian thermal power plants. Their results showed that ownership, plant capacity, and fuel type had significant effects on the observed inefficiency, but that plant age and base/peak load did not [19]. Ghosh and Kathuria assessed the impact of regulation on thermal power plants in India. Their findings showed that regulation and plant capacity had positive effects on plant efficiency, while plant age had a negative effect on technical efficiency [20]. Lin and Luan analyzed the effect of government subsidies on wind power innovation efficiency in China. Their analysis showed that employee education and company profitability significantly improved plant efficiency. However, government subsidies, ownership concentration, and financial leverage did not have any significant effects on efficiency [21].

2.1.2. Data envelopment analysis (DEA)

The most common technique employed in non-parametric methods is data envelopment analysis (DEA). DEA is based on the concept of a relatively efficient frontier. Efficiency is defined by a scalar measure of the distance between the observed decision-making units (DMUs) and the production frontier. Assume that there are *n* DMUs, each having *m* inputs and *s* outputs, and that x_{ij} represents the input *i* of DMU *j*, and y_{ij} represents output *r* of DMU *j*. Given the assumption of constant returns to scale (CRS), as in the "Farrell model" proposed in [22] , the envelopment model is formulated as follows:

$$\begin{aligned}
&\theta^* = Min \quad \theta \\
&s.t. \quad \sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{io}: i = 1,2, \dots, m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{ro}: r = 1,2, \dots, s; \\
&\lambda_j \ge 0: j = 1,2, \dots, n.
\end{aligned} \qquad \textbf{Eq. 2}$$

where λ_j represents the linear coefficient of DMU j and θ is the calculated relative efficiency score of DMU o. An efficient DMU is indicated by an efficiency score of 1.

DEA has been applied in a variety of fields. For example, Erbetta and Rappuoli used this method to assess the efficiency of gas distribution [23], and Das, Ray, and Nag used it to evaluate the labor efficiency of banks [24]. In the field of power generation, numerous studies have measured efficiency using DEA, Bi et al. and Song et al. used DEA to assess the energy and environmental efficiencies of thermal power plants in China [25,26], and Shrivastava, Sharma, and Chauhan used it to measure energy efficiency of coal-fired power plants in India [27]. Sueyoshi and Goto used this method to evaluate the impact of environmental policy on the efficiency of coal-fired power plants [28]. Further, the DEA approach is not limited to assessments of fossil-fuel power plants. For example, Xin-gang and Zhen used a DEA approach to measure the technical efficiency of wind power generation facilities in China [29].

2.1.3. Slacks-based measure (SBM)

Slacks-based measure (SBM) of efficiency in Data Envelopment Analysis (DEA) was first proposed by Tone [30]. In this approach, the input excesses (s_i^-) and the output shortfalls (s_r^+), called slacks, of the decision-making unit are dealt with directly as a scalar measure. Since the SBM model is non-oriented and non-radial, the model is able to avoid the deviations of radial or oriented models, and therefore, reflect the nature of the relative efficiency measurement. The SBM model is defined as follows:

$$\begin{aligned} &\text{Min } \rho = \frac{1 - 1/m \sum_{i=1}^{m} s_i^- / x_{io}}{1 + 1/s \sum_{r=1}^{s} s_r^+ / y_{ro}} \\ &s.t. \sum_{=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io}, \qquad i = 1, \dots, m, \\ &\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \qquad r = 1, \dots, s, \\ &\lambda_j \geq 0, j = 1, \dots, n, \qquad s_i^- \geq 0, i = 1, \dots, m, \qquad s_r^+ \geq 0, r = 1, \dots, s. \end{aligned} \qquad \textbf{Eq. 3}$$

where x_{ij} is input and y_{rj} is output under the assumption that the data set of inputs and outputs is positive; ρ is the technical efficiency of the decision-making unit.

There are a few studies implementing SBM in energy planning. For example, Song, Bi, Wu, and Yang employed a network SBM model determining the production efficiency and environmental efficiency of coal-fired power plants in China [26]. Bi, Song, Zhou, and Liang used the SBM approach to examine the environmental and energy efficiency of the thermal power generation sector in China [25].

2.1.4. Meta-frontier production function

The meta-frontier approach was initially proposed by Battese and Rao [41] and further developed by Battese, Rao, and O'Donnell [42]. The approach calculates the comparable technical efficiencies for firms under different technologies. In this approach, the technology gaps can be estimated for the firms under different technologies relative to the potential technology available to the entire industry. The technology gap ratio (TGR) is the ratio of technical efficiency for the groups of technology (TE_g) and the technical efficiency of the industry as a whole (TE^*):

$$TGR = \frac{TE_g}{TE^*} \qquad \textbf{Eq. 4}$$

2.2. Optimization model considering uncertainties

2.2.1. Stochastic optimization (SO)

SO was firstly proposed by Mulvey at al. [31]. Letting $x \in R^{n1}$ be a vector of structural variables and $y \in R^{n2}$ be a vector of control variables, an optimization model that is subject to uncertainty can be formulated as

$$\text{Min}\, c^T x + d^T y \quad \textbf{Eq. 5}$$

$$\text{s.t. } Ax = b \quad \textbf{Eq. 6}$$

$$Bx + Cy = e \quad \textbf{Eq. 7}$$

$$x, y \geq 0 \quad \textbf{Eq. 8}$$

where constraint in Eq. 6 is a structural constraint whose coefficients are fixed and free of noise, constraint in Eq. 7 is a control constraint whose coefficients are subject to uncertainty, and constraint in Eq. 8 ensures non-negative variable vectors. In an application, uncertainties can be expressed as random variables. The decision making is done under varying probabilities [6].

The uncertainties here can be conceptualized in a scenario tree. Under each scenario $s \in \Omega$ in set $\Omega = \{1,2, \dots, S\}$, the coefficients and variables subject to uncertainty comprise $\{B_s, C_s, e_s, y_s\}$ with fixed probability p_s, which is the occurrence probability of scenario s. Necessarily, $\sum_{s \in \Omega} p_s = 1$. The optimization model then becomes

$$\text{Min}\, \sigma(x, y_1, y_2, \dots, y_s) \quad \textbf{Eq. 9}$$

$$\text{s.t. } Ax = b \quad \textbf{Eq. 10}$$

$$B_s x + C_s y_s = e_s \quad \textbf{Eq. 11}$$

$$x, y \geq 0 \quad \textbf{Eq. 12}$$

Since multiple scenarios are considered, objective function in Eq. 5 become a random variable $\xi_s = c^T x + d_s^T y_s$ with a probability p_s under scenario $s \in \Omega$ [31]. The stochastic linear programming model can be formulated using the mean value $\sigma(\cdot)$ as follows:

$$\sigma(x, y_1, y_2, \dots, y_s) = \sum_{s \in \Omega} p_s\, \xi_s \quad \textbf{Eq. 13}$$

2.2.2. Stochastic robust optimization (SRO)

Stochastic robust optimization (SRO) combines the concepts of stochastic and robust optimization. It considers various scenarios while also controlling deviations through the use of defined robust function. The SRO method proposed by Mulvey, Vanderbei, and Zenios is capable of dealing with noise in the mean value of $\sigma(\cdot)$; it can also be controlled via a term composed of a constant ω multiplied by the variance of $\sigma(\cdot)$ [31]. This makes the optimal solution less sensitive to uncertainty whereby the parameters or variables rely on the probability of occurrence [32]. Here,

$$\sigma(x, y_1, y_2, \ldots, y_s) = \sum_{s \in \Omega} p_s\, \xi_s + \omega \sum_{s \in \Omega} p_s \left(\xi_s - \sum_{s\prime \in \Omega} p_{s\prime} \xi_{s\prime} \right)^2 \qquad \textbf{Eq. 14}$$

Importantly, the solution is less sensitive to change under the various scenarios as the value of ω increases [33]. However, term $\sum_{s \in \Omega} p_s\, (\xi_s - \sum_{s\prime \in \Omega} p_{s\prime} \xi_{s\prime})^2$ in Eq. 14 requires quadratic programming which complicates the computation. In response, Yu and Li proposed a simplified version [34]:

$$\sigma(x, y_1, y_2, \ldots, y_s) = \sum_{s \in \Omega} p_s\, \xi_s + \omega \sum_{s \in \Omega} p_s \left| \xi_s - \sum_{s\prime \in \Omega} p_{s\prime} \xi_{s\prime} \right| \qquad \textbf{Eq. 15}$$

The non-linear function of term in Eq. 15 can be converted into a linear programming model with a linear objective function and linear constraints. Yu and Li proposed the formulation as follows [34]:

$$\text{Min } \sigma(x, y_1, y_2, \ldots, y_s) = \sum_{s \in \Omega} p_s\, \xi_s + \omega \sum_{s \in \Omega} p_s \left[\left(\xi_s - \sum_{s\prime \in \Omega} p_{s\prime} \xi_{s\prime} \right) + 2\theta_s \right] \qquad \textbf{Eq. 16}$$

$$\text{s.t. } \xi_s - \sum_{s' \in S} p_{s'} \xi_{s'} + \theta_s \geq 0 \qquad \textbf{Eq. 17}$$

$$\theta_s \geq 0 \qquad \textbf{Eq. 18}$$

where θ_s is a positive slack variable. Constraint in Eq. 17 ensures that $[(\xi_s - \sum_{s\prime \in \Omega} p_{s\prime} \xi_{s\prime}) + 2\theta_s]$ is always positive. If $\xi_s - \sum_{s' \in \Omega} p_{s'} \xi_{s'} \geq 0$, then $\theta_s = 0$ and therefore $\sigma(x, y_1, y_2, \ldots, y_s) = \sum_{s \in \Omega} p_s\, \xi_s + \omega \sum_{s \in \Omega} p_s\, [(\xi_s - \sum_{s\prime \in \Omega} p_{s\prime} \xi_{s\prime})]$,. On the other hand, if $\xi_s - \sum_{s' \in \Omega} p_{s'} \xi_{s'} < 0$, then $\theta_s = \sum_{s' \in \Omega} p_{s'} \xi_{s'} - \xi_s$ and thus, $\sigma(x, y_1, y_2, \ldots, y_s) = \sum_{s \in \Omega} p_s\, \xi_s + \omega \sum_{s \in \Omega} p_s\, [(\sum_{s' \in \Omega} p_{s'} \xi_{s'} - \xi_s)]$. It should be noted that the solution to the linear model (Eq. 16 to Eq. 18) is equivalent to Eq. 15 [32].

The main advantage of this technique is that it can provide a quantitative evaluation of the trade-offs between system economy and system stability. Xie, Huang, Li, and Ji developed a stochastic robust optimization model to determine the best energy mix for controlling carbon and air pollutants [6]. Khosrojerdi, Zegordi, Allen, and Mistree proposed a multi-objective stochastic robust optimization model design a supply chain network considering the uncertainties of transmission lines and substation failure [7].

2.2.3. Robust optimization (RO)

RO with uncertainty sets was introduced by Li and Floudas [36]. The main advantage of this approach is its tractable computation of the linear robust counterpart generated from the linear RO [36]. Consider the linear optimization problem in general form as follows:

$$\max \boldsymbol{cx} \qquad \textbf{Eq. 19}$$

$$\text{s.t.} \sum\nolimits_j a_{ij} x_j \leq b_i \; \forall i \qquad \textbf{Eq. 20}$$

Without loss of generality, the left-hand side constraint coefficients with uncertainty can be defined as

$$\sum_j \tilde{a}_{ij} x_j \leq b_i \; \forall i \qquad \textbf{Eq. 21}$$

Here, $\tilde{a}_{ij}$ are subject to uncertainty and are defined as follows: $\tilde{a}_{ij} = a_{ij} + \xi_{ij}\hat{a}_{ij}, \forall j \in J_i$, where a_{ij} represents the nominal value of parameters that are not subject to uncertainty, $\hat{a}_{ij}$ represents constant deviation, ξ_{ij} represents the independent random variables that are subject to uncertainty, and J_i is the set of variables whose coefficients are subject to uncertainty. Accordingly, constraint $(\mathbf{17})$ can be rewritten as follows:

$$\sum_j a_{ij} x_j + \sum_{j \in J_i} \xi_{ij} \hat{a}_{ij} x_j \leq \tilde{b}_i \qquad \textbf{Eq. 22}$$

The aim of this approach is to determine a solution that is immune to any infeasibility occurring from some ξ_{ij} in the given uncertainty set U. Thus, the worst-case value is taken that is,

$$\sum_j a_{ij} x_j + \max_{\xi_{ij} \in U} \left\{ \sum_{j \in J_i} \hat{a}_{ij} x_j \right\} \leq \tilde{b}_i \qquad \textbf{Eq. 23}$$

Uncertainty in this study is assumed to be in the box uncertainty set defined as

$$U = \left\{ \xi_{ij} \middle| \left| \xi_{ij} \right| \leq \Psi \right\} \qquad \textbf{Eq. 24}$$

where Ψ is a parameter that limits the bound of uncertainty set.

For the box uncertainty set, the robust counterpart of constraint in Eq. 23 is equivalent to the following constraint [36]:

$$\sum_j a_{ij} x_j + \Psi \sum_j a_{ij} \left| x_j \right| \leq \tilde{b}_i \qquad \textbf{Eq. 25}$$

2.3. Notation

The notation used for the sets, indices, variables, and parameters in this study are listed in Table 2-1.

Table 2-1. Notation for the proposed models.

Sets	
T	Set of active power plant type.
T^O	Set of obsolete power plant type.
$S_{(CX\&FO)}$	Set of scenarios for capital expenditure and fixed operation and maintenance (O&M) costs.
S_{NL}	Set of scenarios for technological limit of capacity factor.
$S_{DemandChange}$	Set of scenarios for changes in total electricity demand and peak period capacity demand.
S	Set of uncertainty scenarios by the cross-multiplication of $S_{(CX\&FO)}$, S_{NL}, $S_{DemandChange}$
Indices	
i	Type of power plant, $i \in (T, T^o)$.
s	Scenario of uncertainty, $s \in S$.
Variables	
C_{is}	Capacity of new power plant type i in scenario s. [MW]
E_{is}	Electricity generated by existing power plant type i in scenario s. [m. kWh]
N_{is}	Electricity generated by new power plant type i in scenario s. [m. kWh]
Stochastic parameters	
CX_{is}	Capital expenditure per capacity for new power plant type i in scenario s. [USD/kW]
FO_{is}	Fixed operation and maintenance expenses for new power plant type i in scenario s. [USD/kW]
IC_{is}	Improvement in capacity factor for power plant type i in scenario s. [%]
$DemandChange_s$	Changes in total electricity demand and peak period capacity demand in scenario s. [%]
$p_{s_{(CX\&FO)}}$	Probability of capital expenditure and fixed O&M costs scenario.
$p_{s_{(NL)}}$	Probability of technological limit of capacity factor scenario.
$p_{s_{(DemandChange)}}$	Probability of changes in total electricity demand and peak period capacity demand scenario.
p_s	Probability of occurrence of scenario $s = p_{s_{(CX,FO)}} \cdot p_{s_{(NL)}} \cdot p_{s_{(DemandChange)}}$.
θ_s	Slack variable of scenario s.

Parameters	
CL_i	Capacity limit for expanding new power plant type i. [MW]
EC_i	Capacity of remaining existing power plant type i. [MW]
EE_i	Emission factor for existing power plant type i. [kgCO_2eq./kWh]
EL_i	Technological limit of capacity factor to operate existing power plant type i. [%]
EM_i	Minimum capacity factor requirement to operate existing power plant type i. [%]
$EmissionTarget$	Emission target. [m. tCO_2eq.]
FL_i	Fuel limits for power plant type i. [ktoe/year]
HR_i	Heat rate of power plant type i. [MMBTU/kWh]
Lf_i	Economic life time of power plant type i. [year]
NE_i	Emission factor for new power plant type i. [kgCO_2eq./kWh]
NL_i	Technological limit of capacity factor to operate new power plant type i. [%]
$PeakDemand$	Projected peak demand capacity. [MW]
PT_i	Social impact penalty based on power plant type. [USD/kW.Yr]
$\widetilde{RC_i}$	Reliable capacity of power plant type i. [%]
RC_i	Dependable capacity of power plant type i. [%]
$\widehat{RC_i}$	Averaged risk of outage of power plant type i. [%]
$TotalDemand$	Total projected demand. [m.kWh]
UC_i	Electricity generation unit cost for existing power plant type i. [USD/MWh]
$UCLimit$	Unit cost limit. [USD/MWh]
VO_i	Variable operation and maintenance expenses for new power plant type i. [USD/MWh]
$WACC$	Weighted average cost for capital of this investment plan.
ω	Weighting coefficient.
ξ_i	Independent random variability from averaged probability of outage of power plant type i.
U	Box uncertainty set for random variability from averaged probability of outage of power plant.
Ψ	Bound parameter for random variability under uncertainty set U.

Chapter 3
Phase I: Efficiency measurement

3.1.Phase's overview

The most recent power generation policy adopted by the government of Thailand focusses on three different areas: security, to ensure a stable power supply; economy, to ensure that the costs associated with implementation of facilities is appropriate; and ecology, to reduce environmental emissions and social impacts. In order to address these requirements, this study proposes a practical model modification for assessing the energy efficiency of power plants. Specifically, stochastic frontier analysis (SFA) with inefficiency effects was applied to both renewable energy and fossil fuel-fired power plants in Thailand. The empirical results showed that power plant capacity was positively correlated with plant efficiency, and that plant age was negatively correlated with efficiency. In addition, in terms of efficiency scores, renewable power plants tended to be 7.13% more efficient than fossil-fuel plants, and base-load power plants were 9.44% more efficient than peak-load plants. In addition, the efficacy of four different carbon tax scenarios and their effects on the technical efficiency of power plants were evaluated. The results of the tax-rate analysis demonstrated that even low carbon taxes (e.g., 1 USD/tCO_2e) can encourage the notable cleaner energy system.

3.2.Contributions & Key findings

Contributions of the study in this phase can be summarized as follows:

- The study pragmatically assessed the efficiency of power plants. Unlike previous studies which only focused on economic aspects, this study is the first to examine energy efficiency while considering the combined impact of security, economic, and ecological factors.
- Unlike previous studies which typically examined a single type of power plant, multiple types of power plants, including both fossil-fired and renewable energy, representing the full diversity of power generation facilities in the energy system were included in the study.
- An empirical modification to the practice of stochastic frontier analysis with inefficiency effects was proposed to estimate the efficiency of the power plants and to determine the effects of explanatory variables.
- The efficacy of four different carbon tax scenarios and their effects on the technical efficiency of power plants were evaluated.
- Difficulties associated with simultaneously comparing multiple aspects of different types of power generation facilities could be addressed by using the proposed efficiency measurements.

Key findings from the study in this phase can be summarized as follows:

- The empirical results showed that power plant capacity was positively correlated with plant efficiency, and that plant age was negatively correlated with efficiency.
- In terms of efficiency scores, renewable power plants tended to be 7.13% more efficient than fossil-fuel plants, and base-load power plants were 9.44% more efficient than peak-load plants.
- The results confirmed that an increase in the carbon tax reduced the efficiency of fossil fuel-powered plants.
- The peak-load fossil fuel-powered plants that use fuel oil and diesel were most negatively affected by the implementation of a carbon tax and were the least efficient types of power plants under all scenarios.
- The findings showed that starting off with small carbon taxes had a high marginal impact on the attractiveness of renewable energy.

3.3. Statement of problem

The Energy Policy and Planning Office in the Ministry of Energy of Thailand drafted the Thailand Power Development Plan (PDP) to formulate a development framework for power generation and power supply in Thailand. The policy, PDP2015, which was promulgated in 2015, emphasizes power source diversification. The plan was to reduce consumption of natural gas, which is used for more than 50% of the country's power generation, by increasing the use of coal-fired power generation[43]. However, the proposal to revert to coal for power generation prompted considerable resistance from the public due to the severe environmental impacts associated with coal combustion [44]. Eventually, public protests prevented adoption of the government plan, illustrating the importance of social and environmental factors in planning power generation in Thailand.

As a result, PDP2015 was revised and the Power Development Plan of 2018 (PDP2018) was published. The PDP2018 focused on three areas: (1) security, to ensure a sustained supply of power to meet future demand; (2) economy, to ensure that the costs associated with power generation are appropriate; and (3) ecology, to decrease CO_2 emissions and adverse social impacts associated with power generation [9]. According to the new policy, the efficiency of power plants in Thailand must meet all three of these requirements.

The objectives of this study were thus (1) to measure the efficiency of multiple types of power plants in Thailand, (2) to evaluate the effects of explanatory variables on technical efficiency, and (3) to conduct a comparative study of different carbon tax scenarios and how they influence the efficiency scores of power plants and explanatory variables.

3.4. Research gaps

Multiple research gaps can be identified from various previous studies with the aim of determining the efficiency of power generation facility in the energy system.

3.4.1. Specific type of power plant

In previous studies, efficiency has usually been estimated for specific types of power plant, either fossil-fuel only plants or renewable power plants. For example, See and Coelli, Bi et al., Ghosh and Kathuria, and Song et al. examined the efficiency of thermal power plants [19,20,25,26], while Xin-gang and Zhen, and Lin and Luan examined the efficiency of renewable energy sources such as wind power plants [21,29]. However, in reality, the power grid of a country typically distributes power generated by a variety of power generation facilities. Consequently, the empirical results that have been obtained for specific types of power plant cannot be applied to studies of a national electricity grid.

3.4.2. Limited aspects of requirement in energy planning

Among the studies that have employed an SFA approach, most have focused on economic aspects only, with outputs consisting of total generated electricity and inputs consisting of fuel prices, operational costs, and labor [19]. However, none of these studies have considered the combined effect of other aspects, such as security and ecology, which are also important. For example, a grid that is insecure may experience power shortages. Further, the operations of a power plant always have an ecological impact. In the context of power generation, ecology is considered to encompass both social and environmental issues that cannot be fully separated [45]. While some studies have examined environmental issues in the context of power generation, e.g., Sun et al., who considered the effect of CO_2 emissions on efficiency, the social impacts of power generation have not been addressed [46].

Our study employed an empirical modification to the practice of SFA approach. Unlike previous studies which typically examined a single type of power plant, the scope of this manuscript includes both fossil-fuel and renewable power generation facilities. Moreover, by considering economic, security, and ecological impacts, the proposed modification can provide a more pragmatic and comprehensive assessment of power generation efficiency.

3.5. Proposed model

3.5.1. Selection between non-parametric and parametric approach

The disadvantage of non-parametric approaches is that they do not consider random noise that may be present in a data set, and extreme outlying parameters will misshape the frontier. More importantly, another limitation of this approach is that it cannot be used to identify relationships between uncategorized factors of interest that cannot be considered as input or output variables, such as the type of power plant or the base/peak load of a power plant. Consequently, non-parametric methods were considered to be unsuitable for estimating power plant efficiency in this study. Given the aforementioned limitations of potential methods that can be used to assess power plant efficiency, we considered that a frontier-based parametric method was the most suitable approach for this study.

3.5.2. Production function

The stochastic frontier with the inefficiency effects model proposed by Battese and Coelli was used to estimate efficiency in this study [17]. By implementing this model, the production frontier and the function explaining inefficiencies are estimated in a single stage, which avoids any bias resulting from a two-stage approach. The translog production function takes the following form:

$$\begin{aligned} lnY_i = \beta_0 &+ \beta_1 \ln(O\&M_i) + \beta_2 \ln(Deviation_i) + \beta_3 \ln(Ecology_i) + 0.5\beta_4 ln(O\&M_i)^2 \\ &+ 0.5\beta_5 ln(Deviation_i)^2 + 0.5\beta_6 ln(Ecology_i)^2 \\ &+ \beta_7 \ln(O\&M_i)\ln(Deviation_i) + \beta_8 \ln(O\&M_i)\ln(Ecology_i) \\ &+ \beta_9 \ln(Deviation_i)\ln(Ecology_i) + (v_i - u_i) \end{aligned} \quad \textbf{Eq. 26}$$

where i is the unit of observation, Y_i is the total generated electricity in megawatt-hours, $O\&M_i$ is the total operational expenditure in Thai Baht, $Deviation_i$ is the shortfall in plant's maximum capacity in megawatt-hours, $Ecology_i$ is the ecological cost in Thai Baht, and v_i is stochastic noise, which is assumed to be independently and identically distributed as $N(0, \sigma_v^2)$. u_i is the technical inefficiency.

The inefficiency effects (u_i) are assumed to be non-negative random variables that are independently distributed. These are assumed to have a truncated normal distribution, $N^+(\mu_i, \sigma_u^2)$. In the case where the mean inefficiency effect (μ_i) is equal to zero, the distribution is reduced to the half-normal distribution $N^+(0, \sigma_u^2)$. Instead of shifting the distribution as in [17], the explanatory variables in this study are assumed to scale with the inefficiency distribution, as in [47]. The variance (σ_u^2) is defined as follows:

$$\begin{aligned} \sigma_u^2 = \exp(\delta_0 &+ \delta_1 Capacity_i + \delta_2 PlantType_i + \delta_3 LoadType_i + \delta_4 Age_i + \delta_5 Central_i \\ &+ \delta_6 PeakPeriod_i) \end{aligned} \quad \textbf{Eq. 27}$$

where $Capacity_i$ is a power plant's nameplate capacity in megawatts. $PlantType_i$ is a dummy variable that is equal to 1 if the power plant type is renewable, or 0 if it is not renewable. $LoadType_i$ is a dummy variable equal to 1 if the power plant is a peak-load power plant, or 0 if it is a base-load power plant. Age_i depicts the weighted average age of a power plant in years. $Central_i$ is a dummy variable equal to 1 if the power plant is in the central region of Thailand, or zero if it is not in the central region. $PeakPeriod_i$ is a dummy variable equal to 1 if the observation is in the peak demand period, or zero if the observation is not in the peak demand period.

The technical efficiency of observations obtained from the production function is defined as follows:

$$TE_i = \exp(-u_i) \qquad \textbf{Eq. 28}$$

3.5.3. Variable settings

The assessment of a power plant's efficiency has one output: i.e., generated electricity (Y_i). For the three energy efficiency components (i.e., security, economy, and ecology), the inputs are as follows: operational expenditure ($O\&M_i$) for the economic component, unproduced electricity that causes a deviation from a plant's capacity ($Deviation_i$) for the security component, and ecological cost ($Ecology_i$) for the ecological component. Operational expenditure is the total summed cost of generating electricity including operation, maintenance, depreciation, labor, and management. It reflects the economic efficiency of particular plant.

Unproduced electricity, that causes a deviation from a plant's capacity, is calculated using the following equation:

$$Deviation_i = (Capacity_i \; x \; 24 \; x \; Day_i) - Y_i \qquad \textbf{Eq. 29}$$

where Day_i denotes number of days, and Y_i denotes total generated electricity in megawatt-hours. Although each type of power plant has a different range of utilization factors, calculations of this factor have been omitted from this study. The omission of utilization factors will reflect the actual ability of a power plant to generate electricity consistently given its capacity, without any bias with respect to the type of power plant.

Ecological cost ($Ecology_i$) is the sum of the social cost and the carbon emissions tax. The social impact is qualitative and consists of the opinions of affected people. Given the difficulties in comparing the impacts that affect different people in different ways, the social cost used in this study was taken as the amount that a particular power plant pays to the Power Development Fund. In Thailand, as part of their corporate social responsibility (CSR), registered power plants need to pay a monthly allowance to the Power Development Fund. The amount of compensation depends on the impact of the power plant's activities. Carbon emissions tax is the carbon tax rate multiplied by carbon dioxide emissions. The calculation for the ecological cost is as follows:

$$Ecology_i = Social_i + Ctax_i = Social_i + (Trate \times Co_i) \qquad \textbf{Eq. 30}$$

where $Social_i$ is the social cost in Thai Baht, $Ctax_i$ is the carbon emission tax in Thai Baht, and $Trate$ is the carbon tax rate in Thai Baht per ton of carbon dioxide. As the base case for comparisons in empirical studies, this case study assumed that the tax rate was 1 US dollar or 30 Thai Baht per ton of carbon dioxide. Co_i is the carbon dioxide emissions in tons of carbon dioxide.

3.6. Empirical analysis

3.6.1. Data and explanatory variables

The production function was estimated using the quarterly data of power plants from 2017 to 2019. This study considered the following seven categories of power generation facility: thermal power plants using coal (**Thermal**), combined-cycle power plant using gas and steam turbines powered by natural gas (**NG**), gas turbines using fuel oil (**Fuel**), diesel power plants using diesel oil (**Diesel**), hydropower plants (**Hydro**), solar PV power plants (**Solar**), and wind turbine power plant (**Wind).** There were 37 power plant facilities and the data spanned a period of 12 quarters. The total number of observations was 400. The empirical data in this study were obtained from the Electricity Generating Authority of Thailand (EGAT), which is a state-owned enterprise that controls most power plants and has a capacity of 15,424.83 MW [48]. Descriptive statistics of outputs and inputs are given in Table 3-1.

Five explanatory variables were tested to see if they affect the estimated inefficiency. The explanatory variables were power plant type: fossil fuel or renewable plant; plant load type; plant capacity; plant age; central region; and peak demand period. To normalize the data, the quantitative explanatory variables, including plant capacity and plant age, were $\log_{10}$ transformed. The descriptive statistics and expected signs of explanatory variables are given in Table 3-2.

3.6.2. Hypothesis testing

Multiple hypotheses were tested to determine the specifications of the functional form and the assumptions of distribution. The results of the tests are shown in Table 3-3. The first hypothesis tested the existence of an inefficiency effect in the set of observations. If the inefficiency effect in the dataset is not significant, then the model will be reduced to using an ordinary least-squares method. The results of the first hypothesis confirmed that the inefficiency effects were stochastic. The second hypothesis test result showed that the translog function was better suited for analyzing this dataset than the Cobb-Douglas model. The third hypothesis confirmed that the mean inefficiency effects (μ_i) were equal to zero. The result shows that the hypothesis cannot be rejected and that the inefficiency effects identified in this study follow a half-normal distribution. In conclusion, the results of the hypothesis tests show that the assumptions of this model follow the translog production function as described by Eq. 26. The technical inefficiency (μ_i) is assumed to follow a half-normal distribution, with the defined variance as described by Eq. 27. Despite the existence of statistical evidence to support this assumption, the limitation of this model is that there might be another unlisted mathematical function that can estimate this data set better.

Table 3-1. Descriptive statistics of outputs and inputs

Variable	Unit	Mean	Standard deviation	Min	Max
$\boldsymbol{Y_i}$	kWh x 1000	458,689.10	914,697.00	0.11	4,541,769.00
$\boldsymbol{O\&M_i}$	Thai Baht (thousands)	843,647.00	1,602,217.00	835.45	6,240,637.00
$\boldsymbol{Deviation_i}$	kWh x 1000	605,279.80	1,010,050.00	1,026.12	4,962,149.00
$\boldsymbol{Ecology_i}$	Thai Baht (thousands)	13,623.62	35,601.87	0.27	231,032.00

Table 3-2. Descriptive statistics and expected signs of explanatory variables

Variable	Type	Expected sign	Unit	Mean	Standard deviation	Min	Max
$\boldsymbol{Capacity_i}$	Quantity	(-)	kW	485,855.40	735,392.00	1,060.00	2,660,000.00
$\boldsymbol{Age_i}$	Quantity	(+)	Year	26.44	15.78	3.00	55.00
$\boldsymbol{PlantType_i}$	Dummy	(-)	: 1 = Renewable energy, 0 = Fossil fuel				
$\boldsymbol{LoadType_i}$	Dummy	(-)	: 1 = Peak-load, 0 = Base-load				
$\boldsymbol{Central_i}$	Dummy	(-)	: 1 = Central region, 0 = Not central region				
$\boldsymbol{PeakPeriod_i}$	Dummy	(-)	: 1 = High peak-demand period, 0 = Not high peak-demand period				

Table 3-3. Hypothesis tests

Test	Null hypothesis (H_0)	Test statistic	P-value	Result
1. Stochastic effect	$\sigma_u^2 = 0$	$z = 21.26$	<0.000	Reject H_0
2. Cob-Douglas Functional Form	$\beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9$	$\chi^2 = 246.37$	<0.000	Reject H_0
3. μ_i~ Half-normal	$\mu_i = 0$	$z = -1.36$	0.173	Cannot Reject H_0

3.6.3. Stochastic frontier analysis results

The STATA program [49] was used to estimate the coefficient parameters of the production function. Results of the maximum-likelihood analysis are shown in Table 3-4. The results show a positive relationship between the coefficients of $O\&M_i$ and $Ecology_i$ with the stochastic frontier model, while the coefficient of $Deviation_i$ is negative. According to the stochastic model, the coefficient of $Ecology_i$ is statistically significant at the 5% level. Although the coefficients of $O\&M_i$ and $Deviation_i$ are not significant at the 5% level, they cannot be omitted, because other coefficients show that the interactions with other variables are significant. Other coefficients, including those of $(O\&M_i)^2$, $(Deviation_i)^2$, $(Ecology_i)^2$, $(O\&M_i)(Deviation_i)$, $(O\&M_i)(Ecology_i)$, $(Deviation_i)(Ecology_i)$, and $constant$, are also significant at the 5% level.

3.6.4. Inefficiency effects

One of the aims of this study was to evaluate the effects of exogenous explanatory variables on the technical efficiency of power plants. Explanatory variables were included in the inefficiency effects to be tested simultaneously with the stochastic frontier analysis as doing so avoids any bias that occurs when the frontier and the inefficiency effects are estimated separately [17]. The signs and significance of each explanatory variable of the inefficiency effect are shown in Table 3-4**.** At the 5% level, hypothesis testing indicates that $Capacity_i$, $PlantType_i$, $LoadType_i$, and Age_i are statistically significant, while $Central_i$ and $PeakPeriod_i$ are not significant. The sign of each variable conforms to the stated expectation, including those of the insignificant variables.

Plant capacity is the maximum continuous capacity in kilowatts that is required to produce electricity in units of kilowatt-hours. Plants vary from small power plants with a capacity of 1,060 kW to large facilities with a total capacity of 2,660,000 kW. The first test shows that plant capacity has a positive effect on the technical efficiency, which corroborates the findings of other studies, e.g., [19] and [20].

The negative sign of $PlantType_i$ indicates that renewable energy power plants tend to be more efficient than fossil-fuel plants. Fossil fuel power plants require fossil fuel as an input for electricity generation and emit pollutants like carbon dioxide. On the other hand, renewable energy power plants use exogeneous inputs like wind and water and have almost no environmental footprint. The fossil fuel power plants comprised **Thermal**, **NG**, **Fuel,** and **Diesel** types, while the renewable energy power plants are **Hydro**, **Solar,** and **Wind** types.

$LoadType_i$ is used to separate power plants into base-load type and peak-load type. The base-load power plants are **Thermal** and **NG** types and peak-load power plants are **Fuel**, **Diesel**, **Hydro**, **Solar,** and **Wind** types. When $LoadType_i$ is positive it indicates that the base-load plants have a higher efficiency score than the peak-load plants, which is expected since the base-load plants can be operated continuously over a year in order to meet the base electricity demand. Base-load plants are usually operated continuously and have a lower generation costs per unit of produced electricity. However, peak-load plants are intended to be operated during temporary peaks in demand.

The weighted average age (years) of the generators in a particular power plant is included in inefficiency effects as Age_i. In comparing Age_i with other variables, the small and positive sign of Age_i indicated in Table 3-4 implies that the age of a power plant has a slightly negative effect on the technical efficiency of a power plant. The majority of electricity demand in Thailand is from the central region, which includes the capital city and the major industrial sites in the country; demand from the central region accounts for 43% of total demand in the country [9]. Therefore, this study considered the central and non-central regions separately. However, there was no statistical evidence to show that $Central_i$ affects overall efficiency.

Table 3-4. Results of the stochastic frontier analysis

	Coefficient	**Standard Error**	**Z-statistic**	**P-value**
Stochastic frontier model				
$\boldsymbol{O\&M_i}$	0.264	0.255	1.040	0.300
$\boldsymbol{Deviation_i}$	-0.073	0.161	-0.460	0.649
$\boldsymbol{Ecology_i}$	0.504	0.151	3.340	0.001
$\boldsymbol{(O\&M_i)^2}$	0.209	0.032	6.570	0.000
$\boldsymbol{(Deviation_i)^2}$	0.047	0.014	3.360	0.001
$\boldsymbol{(Ecology_i)^2}$	-0.051	0.011	-4.530	0.000
$\boldsymbol{(O\&M_i)(Deviation_i)}$	-0.082	0.018	-4.620	0.000
$\boldsymbol{(O\&M_i)(Ecology_i)}$	-0.151	0.013	-11.790	0.000
$\boldsymbol{(Deviation_i)(Ecology_i)}$	0.136	0.009	15.490	0.000
Constant	6.273	1.539	4.080	0.000
Inefficiency effects model				
$\boldsymbol{Capacity_i}$	-2.978	0.256	-11.630	0.000
$\boldsymbol{PlantType_i}$	-5.164	0.468	-11.030	0.000
$\boldsymbol{LoadType_i}$	2.265	0.464	4.880	0.000
$\boldsymbol{Age_i}$	0.898	0.302	2.980	0.003
$\boldsymbol{Central_i}$	-0.092	0.255	-0.360	0.718
$\boldsymbol{PeakPeriod_i}$	-0.091	0.227	-0.400	0.688
Constant	12.155	1.389	8.750	0.000
$\boldsymbol{\sigma_u}$	0.561			
$\boldsymbol{\sigma_v}$	0.130			
Log-likelihood	50.040			

The last explanatory variable is the effect of the peak demand period. Throughout the year, the average peak demand in each quarter is nearly the same, except the second quarter, which has a significantly higher peak demand than the other quarters. Regardless of the high-peak demand period, the null hypothesis shows that, $PeakPeriod_i$ having no effect, cannot be rejected. The $PeakPeriod_i$ is not significant in this dataset.

3.6.5. Technical efficiency

Another aim of this study was to measure the technical efficiency of power plants in Thailand. The technical efficiency of each observation was therefore evaluated using Eq. 28. The total average efficiency score is 0.7969 and the average technical efficiency of each power plant category is shown in Figure 3-1. According to the figure, **Thermal** is the most efficient power plant type with an average score of 0.9452. Compared to the other power plant types, the remarkably lower efficiency scores of **Diesel** and **Fuel** types could be attributed to both power plant types being peak-load power plants which are only operated during high-demand periods. In addition, the **Diesel** and **Fuel** power plant types are also old and have low capacities. The fossil fuel generator load curve for fuel consumption shows that the less a power plant is operated, the more fuel it tends to consume [50]. The higher operation costs and high emission rates of **Diesel** and **Fuel** type power plants therefore cause the efficiency scores of these power plant types to be low.

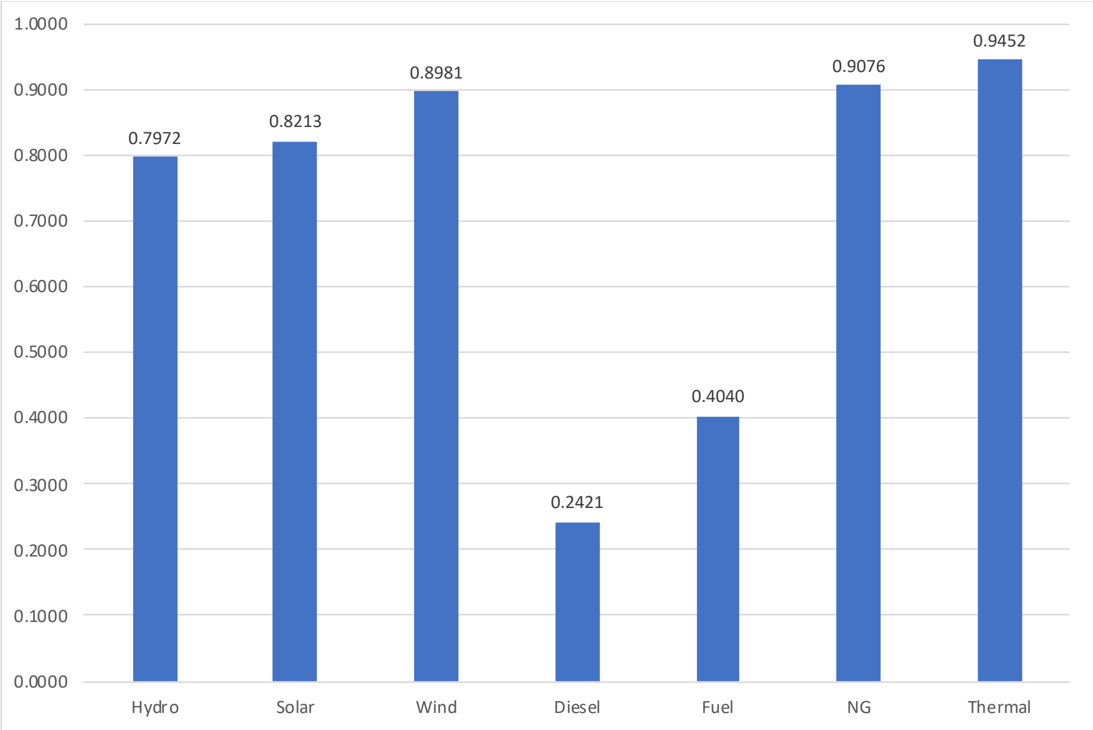

Figure 3-1. Average technical efficiencies of different power plant types.

3.6.6. Carbon tax pricing

Multiple approaches have been implemented to reduce the environmental footprint associated with fossil fuel power generation. Of these approaches, carbon pricing is one of the most widely used practices. According to the World Bank, carbon pricing initiatives have been implemented, or are scheduled for implementation, in 57 countries around the world [51]. The range in the carbon price is between 1 and 127 US dollars per ton of carbon dioxide equivalent (USD/tCO_2e). Since the implementation of a carbon tax in Thailand is still under consideration [51], this study simulates four carbon tax scenarios to assess the effects of carbon tax price on the production frontier. The first scenario is the existing situation in Thailand where there is no tax (**NO TAX**). The second scenario is where the minimum rate is 1 USD/tCO_2e (**BASE**). The third scenario is the case of Singapore, where the carbon tax is 3 SGD/tCO_2e (**TAX02**) [52]. The fourth scenario uses the maximum planned rate for Japan of 2,400 JPY/tCO_2e (**TAX03**) [53]. The currency exchange rates used in this study assume that 1 USD is equivalent to 30 Thai Baht (THB), 1 SGD equals 23 Thai Baht, and 1 JPY equals 0.3 Thai Baht. Changes in tax rates change the variable $Ecology_i$. Descriptive statistics for $Ecology_i$ in THB (in thousands) for the three proposed scenarios are shown in Table 3-5.

Table 3-5. Descriptive statistics for $Ecology_i$ under three carbon tax scenarios

Case	Carbon Tax [THB/tCO²e]	Mean[1]	Standard Deviation[1]	Min[1]	Max[1]
NO TAX	0	6,245.55	14,559.88	0.27	94,222.86
TAX02	115	34,528.14	95,442.16	0.27	618,657.90
TAX03	720	183,319.10	521,627.30	0.27	3,377,643.00

[1]Values are given in thousands of THB

3.6.7. Impacts of carbon taxes on the production function

The third objective of this study was to compare multiple carbon tax policies and their effects on the efficiency score of power plants and explanatory variables. The results of the scenarios were subjected to maximum-likelihood analysis and are shown in Table 3-6. Besides the **BASE** case, $O\&M_i$ is significant at the 5% level, while $Deviation_i$ is only significant for the **TAX03** case.

The absence of a carbon price under the **NO TAX** scenario results in a marked difference in the production function compared to the other scenarios. Compared to the other three scenarios, $O\&M_i$ in the **NO TAX** scenario is negative and the coefficient of $Ecology_i$ is relatively high. The null hypothesis that $LoadType_i = 0$ in the **NO TAX** scenario cannot be rejected. $PeakPeriod_i$ has a small positive effect on power plant efficiency under the **NO TAX** scenario.

The signs of the explanatory variables in the inefficiency effects associated with each scenario follow the **BASE** scenario. The impacts of a carbon tax on the magnitude of the coefficients of the significant explanatory variables are plotted in Figure 3-2. When the carbon tax is increased, the coefficients of $LoadType_i$ decrease slightly while those of Age_i increase moderately. From the **NO TAX** scenario to the **BASE** scenario, the size of $Capacity_i$ decreases and tends to be stable from the **BASE** scenario to the **TAX03** scenario. $PlantType_i$ is most affected by changes in the tax rate, decreasing continuously as the tax rate increases. This finding is expected, as the higher the tax rate is, the lower the efficiency of fossil fuel plants will be.

3.6.8. Impacts of a carbon tax on technical efficiency

The average technical efficiencies obtained for each plant category under the different tax scenarios are shown in Table 3-7. The **BASE** scenario has the highest average efficiency score at 0.7969, while the **TAX03** scenario has the lowest score at 0.7329. The increase in the carbon tax affects the efficiency of power plants differently. The impacts of the carbon tax on technical efficiency are shown in Figure 3-3**.** On the one hand, the technical efficiencies of the renewable energy power plants (i.e., **Hydro**, **Solar,** and **Wind**) all increase. An increase in efficiency scores for renewable energy power plants is noticeable only from the **NO TAX** scenario to the **BASE** scenario. However, the technical efficiencies of fossil fuel-fired power plants (i.e., **Diesel**, **Fuel oil**, **NG,** and **Thermal**) all decrease, with the decreases of the **Diesel** and **Fuel** types being the most noticeable. From the **NO TAX** scenario to the **TAX03** scenario, efficiency scores of the **Diesel**, **Fuel**, **NG,** and **Thermal** power plants decrease by 95%, 87%, 36%, and 15%, respectively.

Table 3-6. Stochastic frontier analysis results for the four carbon tax scenarios

	NO TAX	BASE	TAX02	TAX03
Stochastic frontier model				
$O\&M_i$	-0.695**	0.264	0.798**	0.991**
$Deviation_i$	-0.109	-0.073	0.292	0.542**
$Ecology_i$	1.524***	0.504***	0.637***	1.036***
$(O\&M_i)^2$	0.265***	0.209***	0.245***	0.323***
$(Deviation_i)^2$	0.005	0.047***	0.102***	0.202***
$(Ecology_i)^2$	0.064***	-0.051***	-0.042***	-0.045***
$(O\&M_i)(Deviation_i)$	-0.182***	-0.082***	-0.084***	-0.081***
$(O\&M_i)(Ecology_i)$	-0.074***	-0.151***	-0.217***	-0.313***
$(Deviation_i)(Ecology_i)$	0.093***	0.136***	0.125***	0.102***
Constant	7.690***	6.273***	-2.388*	-8.460***
Inefficiency effects model				
$Capacity_i$	-1.506***	-2.978***	-3.166***	-2.906***
$PlantType_i$	-2.731***	-5.164***	-7.002***	-7.846***
$LoadType_i$	36.500	2.265***	1.876***	1.646***
Age_i	0.832***	0.898***	1.205***	1.141***
$Central_i$	-0.510*	-0.092	-0.084	0.121
$PeakPeriod_i$	-0.552**	-0.091	-0.122	-0.141
Constant	-29.497	12.155***	14.706***	14.780***
σ_u	0.460***	0.561***	1.025***	1.395***
σ_v	0.160***	0.130***	0.144***	0.179***
Log-likelihood	-40.115***	50.040***	-10.408***	-105.187***
Averaged TE	0.7706***	0.7969***	0.7726***	0.7329***

***: P-value <0.01, **: P-value <0.05, *: P-value <0.1

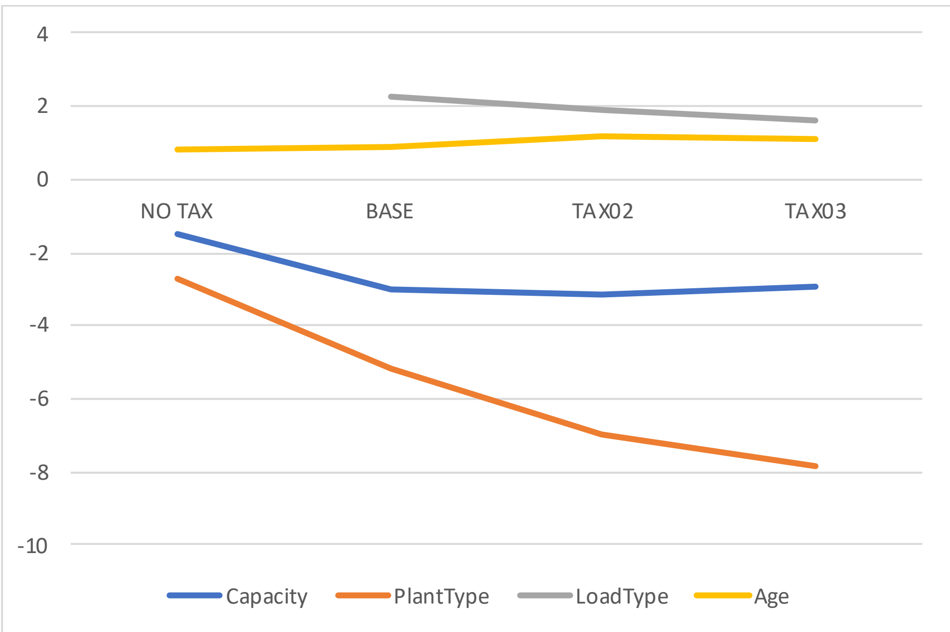

Figure 3-2. Impacts of different carbon tax scenarios on explanatory variables.

Table 3-7. Average technical efficiency scores for power plant categories

Carbon tax scenarios	**NO TAX**	**BASE**	**TAX02**	**TAX03**
Hydro	0.7263	0.7972	0.8140	0.8098
Solar	0.7785	0.8213	0.8508	0.8684
Wind	0.7557	0.8981	0.9027	0.8978
Diesel	0.2906	0.2421	0.0714	0.0135
Fuel	0.4708	0.4040	0.1839	0.0592
NG	1.0000	0.9076	0.7891	0.6343
Thermal	1.0000	0.9452	0.8887	0.8499

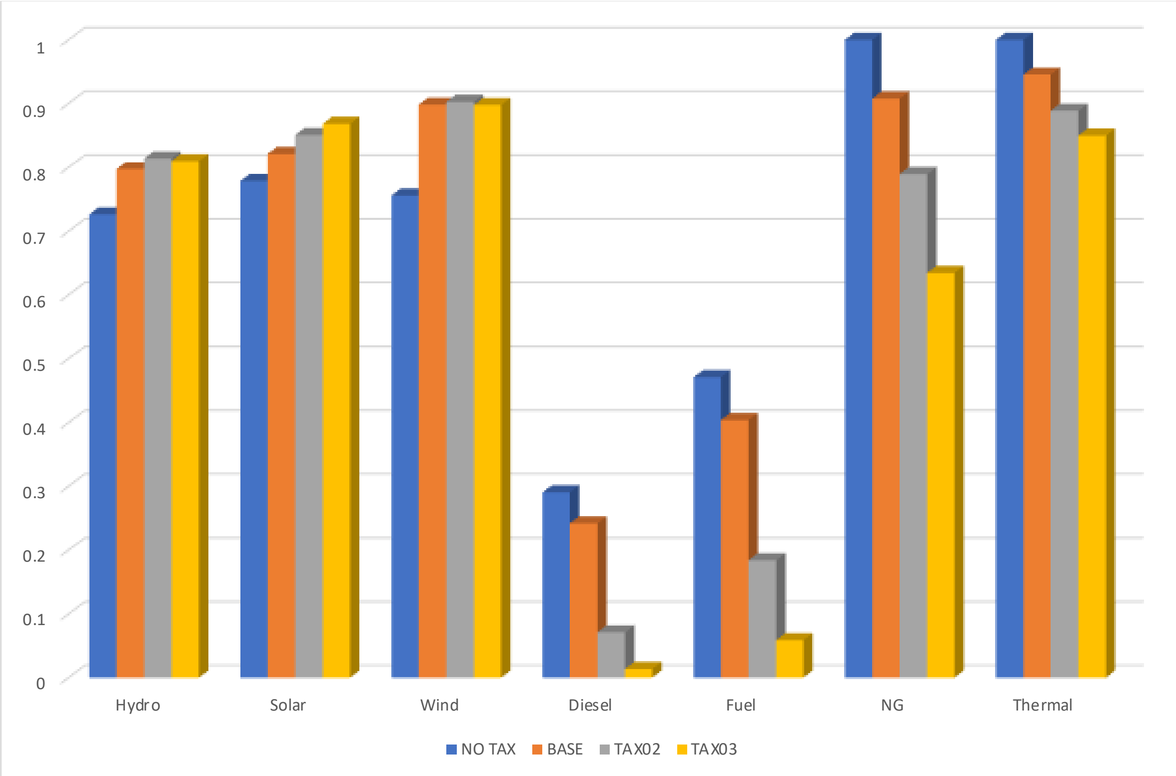

Figure 3-3. Impacts of carbon tax on technical efficiency for power plant categories.

3.7. Discussion

Several policy recommendations can be made based on the empirical results presented here. Having small capacities and being advanced in years results in the efficiency of diesel and fuel-oil power plants being very low. Therefore, these facilities should be used as little as possible. Despite having comparatively high efficiency scores, renewable energy power generation is still well suited to meet peak-load demand because of the dependence of these facilities on uncontrollable environmental inputs. However, recent technological advances, such as reductions in battery size and battery costs, could potentially address this limitation. Indeed, if such improvements could be used to manage the ratio mix more effectively of power sources on the grid, then the use of fossil fuel-powered peak-load facilities, such as those that use diesel and fuel oil, can be totally replaced.

In order to meet CO_2 reduction targets, a carbon tax law should be enacted in Thailand. The carbon tax could initially be implemented at a low rate before expanding the program over time. The findings of this study indicated that small increases in the carbon tax can have high marginal impacts on power plant efficiency. For example, for an initial carbon tax rate of 1 USD/tCO_2, the overall renewable power plant efficiency will be increased by 11.3% while the efficiency of fossil power plants is reduced by 9.5%. Moreover, further increases in the carbon tax rate to level such as those in Singapore (i.e., 3 SGD/tCO_2) could lead to a 13.6% increase in the efficiency of renewable energy power plants and a 30.0% decrease in the efficiency fossil fuel-based power plants. The results of this empirical study also provide the quantitative support for researchers focusing on the optimal mix of power plants based on specific requirements, as well as for policy makers attempting to reduce the carbon footprint in Thailand.

For several decades, sustainable development and clean energy initiatives have been implemented all around the world. Within the context of power generation, implementation of the economic, security and ecological measures proposed in this paper can be pragmatically applied in other locations. The proposed model resolves the trade-off between multiple requirements by introducing a new way to assess power generation facilities that considers a variety of different aspects. The results showed that it was possible to compare directly the efficiencies of both fossil-fuel and renewable energy using this model. The results of these tests could be used to help policy makers identify the causes of inefficiencies in future power development plans.

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Chapter 4
Phase II: Energy planning

4.1. Phase's overview

The uncertainties inherent in future projections affect energy planning schemes in different ways. In the study in this phase, both stochastic robust optimization and robust optimization were incorporated simultaneously into a proposed model to deal with multiple uncertainties. Risks that need to be immunized against all possible outcomes were dealt with using robust optimization, while other uncertainties were treated using scenario-based stochastic robust optimization. The ranges of optimal solutions determined from the proposed model were practical enough to generate the various alternatives, but robust enough to accommodate any risk-free requirements. Energy planning typically focuses on three main objectives: the security of the energy supply, the environmental protection and economic competitiveness. In this study, social acceptance which is one of the crucial influences, is also considered. To demonstrate the potential of the proposed model, a case study involving energy decisions in Thailand is featured. Furthermore, the model is applied to the energy planning of Vietnam as an alternative case study. Here, given the prominent role of social impact, it is especially critical to limit the variation in social damage that may result from planning uncertainties. The empirical analysis conducted in these cases includes both fossil fuel-based and renewable energy in the grid. The results show that strengthening system reliability, with a 92.6% reduction in capacity deviation, produces only a 5.08% increase in total cost. Numerical results from the model could help policy makers effectively address the trade-off between system stability and economy correlated with budgetary limits and determine effective weight coefficients for the preferred control levels.

4.2. Contributions & Key findings

Contributions of the study in this phase can be summarized as follows:

- A hybrid stochastic robust optimization and robust optimization model to determine the best energy mix was proposed.
- Unlike other optimization models that tend to focus exclusively on either scenario-based or worst-case scenario realization, the proposed approach takes both uncertainties into account based on their practical condition.
- Rather uniquely, social impact, one of the critical factors in energy planning, is incorporated into the model, which makes containing any social impact fluctuations resulting from different scenarios essential.
- Sensitivity analyses were conducted to investigate the effects of changing the weight penalty on the structure of the energy mix.
- The model results provide support for policy makers seeking to enhance system stability.

Key findings from the study in this phase can be summarized as follows:

- It was found that natural gas power plants, solar photovoltaic plants and large hydro power generation facilities represent the majority of total capacity in the grid.
- As the weight coefficient increases, the deviation of social impact is markedly reduced, with only a small rise in total cost.
- It was shown that to strengthen system stability, costlier monetary tradeoffs are required.
- It was also found that the capacity deviation for the high-social-impact power plant group consisting of hydro power plants and coal-fired power plants is substantially reduced as the weight penalty increases, whereas the low-impact group showed only a small reduction.

- Results indicates that it is worth to make power development plan reducing the variation of social impact since it doesn't affect the total cost variation much and still meet the constraint of total cost limit.

4.3. Statement of problem

After the efficiency measurement methodology of power generation facilities from historical data is proposed in the previous phase, this phase aims to determine the best energy mixes for the future implementing the energy planning model with the projected technical data.

The objective of the study in this phase is to develop an energy planning model that would be applicable at the scale of the entire grid. Thus, the scope of the model inclusively incorporates every major power plant type, including both fossil-fueled and renewable energy facilities. The proposed model focuses on three dimensions of the decision variables to be optimized: the capacity of a new power plant, the electricity generated by existing power plants, and the electricity generated by a new power plant. Decisions regarding these variables are shaped by the multi-aspects requirements which are reflected in the constraints of the model. To demonstrate the application of the proposed methodology, an empirical case study involving the energy grid of Thailand is presented. Additionally, the model is applied to energy planning in Vietnam, which serves as an alternative case study.

4.4. Research gaps

Table 4-1 summarizes the scope and approach taken in previous studies. Multiple knowledge gaps in both the methodological implementation and application of energy planning can be identified from Table 4-1. First, our concern is that implementing only one of these methods, as has been common in previous studies, may lead either to overly conservative results, as in the case of RO, or to residual risk, as in the case of SRO. Second, the practical implementation of previous studies mainly focuses on the aspects of security, the environment, and economics, leaving the issue of social acceptance of new power generation facilities largely unaddressed. The primary barriers to energy grid expansion are neither technical nor financial; rather, the primary barriers are the lack of an appropriate regulatory framework and the absence of general public acceptance [54]. In recent years, public protests against renewable energy infrastructure have emerged, mostly from affected locals [55]. Yet, the social impact of such infrastructure is included in only a few of the studies.

To the best of our knowledge, this research is the first to propose a methodology that simultaneously applies both techniques in the field of energy planning. Here, the RO method is used to treat parameters that need to be completely immune to restrictive risks, such as the reliability of a power generator to continuously supply demand. On the other hand, the SRO approach is used to deal with future projections involving factors in both the constraints and the objective function that are allowed to vary but still need to be controlled by the defined function of social impact variation. These would include demand forecasts, technological improvements, and energy costs. The practical implementation of this dual approach focuses on energy planning to meet the goals of supply security, environmental protection, economic competitiveness, with the least variation in social impact.

Table 4-1. Summary of related previous work and research gaps in the field of energy planning.

Studies	Methodologies			Applications						
				Uncertainties	Aspects to be considered				Types of power plant	
	SO	SRO	RO		Economic	Environment	Security	Social	Fossil/Nuclear	Renewable energy
[4]	✓			Energy demand, wind energy supply, solar supply	✓	✓	✓		Diesel	Wind, solar PV
[5]	✓			Energy demand, RE capital cost, fuel cost	✓	✓	✓	indirectly	Coal, NG, Oil	Hydro, Wind, Solar PV, solar CSP, geothermal, biomass,
[3]	✓			Energy demand, RE capital cost, fuel cost	✓	✓	✓		Coal, NG, nuclear	Hydro, wind, Solar PV, geothermal, biomass
[6]		✓		Energy demand	✓	✓	✓		Coal	Biomass, wind, solar PV, garbage
[7]		✓		Transmission lines and substations failure	✓		✓		Gas turbine, fuel oil, diesel	Hydro
[8]			✓	Energy demand, RE intermittent nature, costs	✓	✓	✓	✓	Coal, gas turbine	Hydro, biomass
This study		✓	✓	**Energy demand, RE capital cost, RE fixed O&M cost, RE capacity factor, reliable capacity**	✓	✓	✓	✓	**Coal, NG, fuel oil, diesel**	**Hydro, wind, solar PV, biomass, biogas, garbage**

4.5. Proposed model

The proposed optimization model is based on linear programming. There are three main types of decision variables, including the capacity of new power plants (C_{is}), the electricity generated by existing power plants (E_{is}), and the electricity generated by new power plants (N_{is}) of each power plant type i for each scenario s. To reduce the unnecessary complexity of computation, the decision variables are optimized in the set of real number. The number of decision variables is according to amount of power plant types and scenarios of uncertainty.

4.5.1. Objective function

The aim of this study is to determine the optimal energy mix for power plant capacity and the amount of plant production under each scenario with minimal cost. The linear objective function consists of a cost function and a robust function.

The cost function includes the fixed cost of new power plants, the cost of generated electricity in existing power plants, and the cost of generated electricity in the new power plants.

Here, expected total fixed cost for new power plants is

$$\sum_{s=1}^{S} p_s \sum_{i=1}^{T} \left[\frac{CX_{is}WACC}{1-(1+WACC)^{-Lf_i}} + FO_{is}\right] C_{is} \qquad \textbf{Eq. 31}$$

The expected total electricity generation costs for existing power plants is

$$\sum_{s=1}^{S} p_s \sum_{i=1}^{(T+T^o)} UC_i E_{is} \qquad \textbf{Eq. 32}$$

The expected total electricity generation costs for new power plants is

$$\sum_{s=1}^{S} p_s \sum_{i=1}^{T} VO_i N_{is} \qquad \textbf{Eq. 33}$$

Eq. 31 is the expected total fixed cost of new power plants and is composed of the annualized capital expenditure and annual fixed operational and maintenance costs. The annualized capital expenditure is calculated based on the weighted average cost of capital in the power plant investment plan ($WACC$) and the economic life of the plant (Lf_i) [5]. The annualized capital expenditure (CX_{is}) and fixed operational and maintenance costs (FO_{is}) are stochastic parameters that are subject to uncertainty under each scenario s.

Eq. 32 is the expected total electricity generation costs of existing power plants associated with the unit cost of electricity generation of the existing plants. Eq. 33 is the expected total electricity generation costs of new power plants which can be derived from the variable operational and maintenance costs of the power plants (VO_i). It should be noted that fuel cost is already included in VO_i. Thus, the total cost function can be formulated as follows:

Cost function

$$\sum_{s=1}^{S} p_s \left[\sum_{i=1}^{T} \left[\frac{CX_{is} WACC}{1-(1+WACC)^{-Lf_i}} + FO_{is} \right] C_{is} + \sum_{i=1}^{(T+T^o)} UC_i E_{is} + \sum_{i=1}^{T} VO_i N_{is} \right] \quad \textbf{Eq. 34}$$

Robust function

$$\sum_{s=1}^{S} p_s \left[\varphi_s - \sum_{s'=1}^{S} p_{s'} \varphi_{s'} + 2\theta_s \right] \quad \textbf{Eq. 35}$$

Robust function in Eq. 35 is the variance of variables φ_s, which is the defined function of variables to be controlled under scenario s. Accordingly, the objective function for the hybrid model that includes SRO and RO in the energy planning problem can be formulated as follows:

$$\text{Min } f = [Cost\ funciton\ (\text{Eq. } 34)] + \omega[Robust\ function\ (\text{Eq. } 35)]$$

$$\begin{aligned} \text{Min } \sum_{s=1}^{S} p_s & \left[\sum_{i=1}^{T} \left[\frac{CX_{is} WACC}{1-(1+WACC)^{-Lf_i}} + FO_{is} \right] C_{is} + \sum_{i=1}^{(T+T^o)} UC_i E_{is} + \sum_{i=1}^{T} VO_i N_{is} \right] \\ & + \omega \sum_{s=1}^{S} p_s \left[\varphi_s - \sum_{s'=1}^{S} p_{s'} \varphi_{s'} + 2\theta_s \right] \end{aligned} \quad \textbf{Eq. 36}$$

Cost function (Eq. 34) is the mean value of the total cost under all scenarios weighted by the probability of occurrence of scenario s (p_s). Robust function (Eq. 35) is the variance of the variables to be controlled by the weighting constant ω from the uncertainty under scenario s.

4.5.2. Constraints

The linear control constraints of the model from Eq. 37 and Eq. 43 to Eq. 52 can be divided into five groups to meet the multi-dimensional requirements. The first three groups of constraints relate directly to the three main missions of energy policy: security of supply, environmental protection, and economic competitiveness. Of the remaining two groups, one involves the technical specifications of power plants, and other contains the robust constraint. In total, there are 11 constraints in the proposed model.

4.5.3. Security of supply

Security of supply requires that the system be able to always meet the demand under any circumstances. This consideration has three dimensions: the amount of generated electricity, the power plant capacity, and the availability of fuel. First, the total amount of generated electricity in a year must meet the yearly projected demand according to the $DemandChange_s$ constant in each scenario s. $DemandChange_s$ is a stochastic parameter that is subject to uncertainty in each scenario s. This constraint considers the entire period in units of produced electricity per time span, such as kilowatt-hours per year, and has the form

$$\sum_{i=1}^{(T+T^o)} [E_{is} + N_{is}] \geq TotalDemand \times DemandChange_s, \forall s \quad \textbf{Eq. 37}$$

Second, the total reliable capacity in the grid must not be less than the projected peak demand under the $DemandChange_s$ constant in each scenario s. This constraint focuses on the power plant's capacity in units such as megawatts, without a time unit. The reliable capacity constraint is formulated as

$$\sum_{i=1}^{(T+T^o)} \widetilde{RC}_i \, [C_{is} + EC_i] \geq PeakDemand \times DemandChange_s, \forall s \quad \textbf{Eq. 38}$$

Notably, reliable capacity is affected by the risk of a power plant outage. This risk of outage would include a maintenance outage, a planned outage, and an unplanned outage. The level of risk varies by type of power plant and the presence of exogeneous factors [56]. In this study, the outage risk is defined as an uncertainty in the robust optimization. Reliable capacity is defined as follows:

$$\widetilde{RC}_i = RC_i - \xi_i \widehat{RC}_i \quad \textbf{Eq. 39}$$

RC_i is the noise-free dependable capacity of power plant type i. $\widehat{RC}_i$ is the averaged risk of outage for power plant type i. $\widehat{RC}_i$ can be derived as the product of the dependable capacity and the averaged probability of the plant's downtime. ξ_i is the random variability from the averaged probability of outage for power plant type i that is subject to uncertainty set U. According to Eq. 38 and Eq. 39, the reliable capacity constraint with a consideration of uncertainty can be formulated as

$$\sum_{i=1}^{(T+T^o)} RC_i[C_{is} + EC_i] - \sum_{i=1}^{(T+T^o)} \xi_i \widehat{RC}_i [C_{is} + EC_i] \geq PeakDemand \times DemandChange_s, \forall s \quad \textbf{Eq. 40}$$

The random variability (ξ_i) under uncertainty set U deals with the realization of the worst-case scenario in order to ensure the security of supply under any uncertainties by maximizing the risk of power outage as follows:

$$\sum_{i=1}^{(T+T^o)} RC_i[C_{is} + EC_i] - \max_{\xi_i \in U} \sum_{i=1}^{(T+T^o)} \xi_i \widehat{RC}_i [C_{is} + EC_i] \geq PeakDemand \times DemandChange_s, \forall s \quad \textbf{Eq. 41}$$

Under the assumption that uncertainty set U is a box uncertainty with the property $U = \{\xi_i | \, |\xi_i| \leq \Psi\}$, Ψ is a bounding parameter for random variability (ξ_i) under uncertainty set U. Therefore, the robust counterpart of the box uncertainty set can be formulated as

$$\sum_{i=1}^{(T+T^o)} RC_i[C_{is} + EC_i] - \Psi \sum_{i=1}^{(T+T^o)} \widehat{RC}_i |C_{is} + EC_i| \geq PeakDemand \times DemandChange_s, \forall s \quad \textbf{Eq. 42}$$

Since $C_{is} \geq 0, EC_i \geq 0$, constraint in Eq. 42 can be reformulated. As a result, the total reliable capacity constraint is as follows:

$$\sum_{i=1}^{(T+T^o)} RC_i[C_{is} + EC_i] - \Psi \sum_{i=1}^{(T+T^o)} \widehat{RC}_i[C_{is} + EC_i] \geq PeakDemand \times DemandChange_s, \forall s \qquad \textbf{Eq. 43}$$

Third, the fuel to be used for generating the electricity of power plant type i must not exceed its availability. The boundary of a fuel-based power plant is set based on the potential fuel capacity limits. The fuel limits are derived as the sum of projected domestic production and projected imports, minus projected exports. The fuel used by fuel-based power plants include natural gas, coal, fuel oil, diesel, biomass, biogas, and garbage. The fuel limits can be formulated as

$$E_{is} + N_{is} \leq \left\lfloor \frac{FL_i \times 39683}{HR_i \times 1000} \right\rfloor, \forall s, \forall i \in (T, T^o)_{\text{Fuel−based power plants}} \qquad \textbf{Eq. 44}$$

where FL_i is the fuel limit for power plant type i measured in kiloton of oil equivalent per year (ktoe/year), HR_i is the heat rate of power plant type i in millions of British Thermal Units per kilowatt-hour (MMBTU/kWh), and 39,683 is the unit conversion constraint millions of British Thermal Units per kiloton of oil equivalent (MMBTU/ktoe).

4.5.4. Environmental protection

According to environmental protection policy, the total carbon dioxide emitted by power generation under every scenario s must not exceed the emission target. That is,

$$\sum_{i=1}^{(T+T^o)} [EE_iE_{is} + NE_iN_{is}] \leq EmissionTarget, \forall s \qquad \textbf{Eq. 45}$$

4.5.5. Economic competitiveness

To be economically competitive, the total cost in scenario s must not exceed the unit cost limit:

$$\sum_{i=1}^{T} \left[\frac{CX_{is}WACC}{1-(1+WACC)^{-Lf_i}} + FO_{is}\right] C_{is} + \sum_{i=1}^{(T+T^o)} UC_iE_{is} + \sum_{i=1}^{T} VO_iN_{is} \leq UCLimit \times TotalDemand \times DemandChange_s, \forall s \qquad \textbf{Eq. 46}$$

4.5.6. Power plant technical specification

Relevant technical specifications of existing and new power plants are represented in the model as follows:

Minimum generation supply of existing power plants.

$$E_{is} \geq [EC_iEM_i \times 8760 \times 1000], \forall s, \forall i \in (T, T^o) \qquad \textbf{Eq. 47}$$

Technological generation limits of existing power plants.

$$E_{is} \leq [EC_i EL_i \times 8760 \times 1000], \forall s, \forall i \in (T, T^o) \qquad \textbf{Eq. 48}$$

Technological generation limits of new power plants.

$$N_{is} - [C_{is} IC_{is} NL_i \times 8760 \times 1000] \leq 0, \forall s, \forall i \in T \qquad \textbf{Eq. 49}$$

Expanding capacity limits for new power plants.

$$C_{is} \leq CL_i \,, \forall s, \forall i \in T \qquad \textbf{Eq. 50}$$

Constraint in Eq. 47 and Eq. 48 are the specifications for existing power plants. They set both lower minimum supply and upper technological limits for the generated electricity based on type of power plant i. Constraint in Eq. 49 confines the technological generation limits (NL_i) of new power plant capacity C_{is}. Improvement in the capacity factor for power plant type i (IC_{is}) is a stochastic parameter that is subject to uncertainty in each scenario s. Constraint in Eq. 50 limits the capacity of new power generation facilities based on the availability of, labor, manufacturing capacity and land use [5].

4.5.7. Robust constraint

$$\varphi_{is} - \sum_{s'=1}^{S} p_{s'} \varphi_{s'} + \theta_s \geq 0 \,, \forall s, \forall i \in (T, T^o) \qquad \textbf{Eq. 51}$$

Robust constraint (Eq. 51) ensures that component $\left[\varphi_s - \sum_{s'=1}^{S} p_{s'} \varphi_{s'} + 2\theta_s\right]$ in the objective function (Eq. 35) has a non-negative value.

$$C_{is}, E_{is}, N_{is} \geq 0, \forall s, \forall i \in (T, T^o) \qquad \textbf{Eq. 52}$$

Constraint in Eq. 52 ensures that all the decision variables, including the expanded capacity sizes and the generated electricity from both existing and new power plants, have non-negative values for every type of power plant and under every scenario.

4.6. Empirical analysis

4.6.1. Scenario Definition

In this study, the demand forecast is represented by three scenarios $\left\{ s_{(DemandChange)}^{Low}, s_{(DemandChange)}^{Medium}, s_{(DemandChange)}^{High} \right\}$. The scenarios correspond, respectively, to demand that is 10% lower than that forecast, demand equal to the forecast, and demand 10% higher than the forecast. The probabilities of occurrence for these scenarios are assumed to be $p_{s_{(DemandChange)}^{Low}} = 0.3$,

$p_{s_{(DemandChange)}^{Medium}} = 0.5$ and $p_{s_{(DemandChange)}^{High}} = 0.2$, reflecting the uncertainties associated with future increases in both GDP and population.

Technological advancements in renewable energy such as solar panels and wind turbines have increased the capacity factor for power plants. The capacity factor for solar photovoltaic (PV) plants has increased due to three key factors: the location of new plants in areas with higher irradiation levels, increase in the use of tracking systems, and improvements in the performance of the system, such as improvements in inverter efficiency. Thus, the capacity factor for solar plants has increased from an average of 14% in 2010 to 18% in 2018 [57]. Similarly, improvements in wind turbine technology, placement at greater heights, and longer wind blades with a larger swept area have led to an increase in the capacity factor for wind turbines [58]. Given such progress, the international Renewable Energy Agency (IRENA) expects the global weighted average capacity factor to increase from 34% in 2018 to between 30% and 55% in 2030 [58].

Three possible scenarios $\left\{ s_{(NL)}^{Low}, s_{(NL)}^{Medium}, s_{(NL)}^{High} \right\}$ are generated for the capacity factors used in the case study. These represent no change, medium improvement, and a high level of improvement respectively. For solar PV plants, the scenarios are based on historical data from IRENA [59]. For wind turbine technology, the forecasting scenarios are taken from the National Renewable Energy Laboratory (NREL) [60]. Table 4-2 shows the capacity factor improvement scenarios for solar photovoltaic power plant and wind turbine power plants. The probabilities of occurrence of these scenarios are assumed to be $p_{s_{(NL)}^{Low}} = 0.5$, $p_{s_{(NL)}^{Medium}} = 0.3$ and $p_{s_{(NL)}^{High}} = 0.2$.

The levelized costs of electricity from renewable energy sources also tends to decrease over time. NREL estimates the cost reduction in three possible scenarios $\left\{ s_{(CX\&FO)}^{Low}, s_{(CX\&FO)}^{Medium}, s_{(CX\&FO)}^{High} \right\}$ for various types of power plants, including hydro power plants, solar PV power plants and wind turbine power plants.

Table 4-3 shows the capital expenditure per unit capacity and fixed operation and maintenance cost scenarios for large hydro power plants, small hydro power plants, solar PV power plants and wind turbine power plants [60]. The probabilities of occurrence of these scenarios are assumed to be $p_{s_{(CX\&FO)}^{Low}} = 0.5$, $p_{s_{(CX\&FO)}^{Medium}} = 0.3$ and $p_{s_{(CX\&FO)}^{High}} = 0.2$.

A scenario (s) is generated by cross-multiplication of the various scenarios $S_{(CX,FO)}$, S_{NL}, $S_{DemandChange}$. Thus, for each iteration in the case study, there are 27 scenarios of uncertainty to be considered. The probability of occurrence of each scenario (p_s) is determined from the dot products of $p s_{(CX,FO)}, p s_{(NL)}$ and $p s_{(DemandChange)}$. It is assumed that $p s_{(CX,FO)}, p s_{(NL)}$ and $p s_{(DemandChange)}$ are independent of each other. The matrix of the scenarios of uncertainties and their probability of occurrence is listed in Table 4-4.

Based on the multiple uncertainties described here, the expected energy mix will lie somewhere within the range of all possible optimal outcomes. Unlike the amount of generated electricity that can be adjusted based on real demand, the capacity of power plants cannot be altered in real time to meet actual conditions. Thus, there are risks to be considered in formulating a power system plan. A plan that results in inadequate capacity risks a potentially serious power shortage, while a plan that results in excessive capacity causes costs to be unnecessarily high. Policy planners need to be able to assess the trade-offs between system reliability and system costs.

Table 4-2. Capacity factor improvement scenarios for solar PV and wind turbine power plant.

		Power plant type	
Stochastic parameter	Scenario	Solar PV	Wind turbine
IC_{is}	$s_{(NL)}^{Low}$	1.000	1.000
	$s_{(NL)}^{Medium}$	1.232	1.200
	$s_{(NL)}^{High}$	1.406	1.514

Table 4-3. Capital expenditure per unit capacity and fixed operating and maintenance costs scenarios.

		Power plant type			
Stochastic parameter	Scenario	Large hydro	Small hydro	Solar PV	Wind turbine
CX_{is} [USD/kW]	$s_{(CX\&FO)}^{Low}$	4,022	6,370	1,115	1,610
	$s_{(CX\&FO)}^{Medium}$	4,022	6,370	883	1,280
	$s_{(CX\&FO)}^{High}$	3,318	5,032	598	1,162
FO_{is} [USD/kW.yr]	$s_{(CX\&FO)}^{Low}$	43	117	14	44
	$s_{(CX\&FO)}^{Medium}$	43	117	10	39
	$s_{(CX\&FO)}^{High}$	26	72	7	35

Table 4-4. Matrix of scenarios and their probability of occurrence

Scenario	$S_{DemandChange}$	$S_{(CX\&FO)}$	S_{NL}	p_s
1	Low	Low	Low	0.03
2	Low	Low	Medium	0.018
3	Low	Low	High	0.012
4	Low	Medium	Low	0.045
5	Low	Medium	Medium	0.027
6	Low	Medium	High	0.018
7	Low	High	Low	0.075
8	Low	High	Medium	0.045
9	Low	High	High	0.03
10	Medium	Low	Low	0.05
11	Medium	Low	Medium	0.03
12	Medium	Low	High	0.02
13	Medium	Medium	Low	0.075
14	Medium	Medium	Medium	0.045
15	Medium	Medium	High	0.03
16	Medium	High	Low	0.125
17	Medium	High	Medium	0.075
18	Medium	High	High	0.05
19	High	Low	Low	0.02
20	High	Low	Medium	0.012
21	High	Low	High	0.008
22	High	Medium	Low	0.03
23	High	Medium	Medium	0.018
24	High	Medium	High	0.012
25	High	High	Low	0.05
26	High	High	Medium	0.03
27	High	High	High	0.02

4.6.2. Social impacts

The uniqueness of the case studies featured in this paper is the importance given to the social aspect of energy planning. While some doubt that social impact is a critical factor in the decision to build a new power plant, Battaglini, Komendantova, Brtnik, and Patt argues that public acceptance is one of the primary barriers to energy grid expansion, outweighting technical or financial issues [54]. It seems clear that without the consent of area residents, no new power plant can be constructed. A case in southern Thailand illustrates this point. When the construction of a new coal-fired power plant was proposed, the proposal was met with strong opposition from local residents based the severe environmental impact of coal combustion that had occurred twenty years before [44]. Unbending public protests successfully forestalled the project. Moreover, it is not only fossil-fired power plants that have been objected to; renewable energy facilities have faced equally serious opposition. A study by Wüstenhagen, Wolsink, and Bürer indicated that public protests against renewable energy infrastructrue have grown in recent years, mostly from affected locals [55].

In many countries, an Environmental Impact Assessment (EIA) is required prior to the construction of a new power plant [61]. The mandatory assessment includes consent from locals who will be affected by the construction and operation of the facility [61]. The process typically takes years to complete [62]. The lesson here is that variations in the projected social impact arising from uncertainties need to be minimized before seeking social consent and initiating the EIA process. The rate of compensation to area residents depends on the estimated social impacts directly related to the capacity and type of power plant. Hence, the variable to be controlled in robust constraint in Eq. 51 is defined as $\varphi_s = \sum_{i=1}^{T}[PT_i C_{is}]$, where PT_i represents the social impact penalty of a type i power plant.

4.6.3. Case study: Thailand

Thailand's Ministry of Energy launched the country's latest power development plan in 2018 (Thailand PDP2018). The plan has the same focus as that in Energy Economics [1], with the three main considerations being economic competitiveness, environmental protection and security of supply [9]. Thailand has a wide variety of power facilities, including coal-fired thermal plants (Coal), combined-cycle plants using natural gas (NG), combustion turbine plants using fuel oil, diesel power plants, large hydro plants ($>$ 10 MW), small hydro plants ($\leq$ 10 MW), solar photovoltaic plants (Solar PV), wind turbine plants, biogas plants, biomass plants and municipal waste plants (Garbage). The leading sources, by amount of generated electricity, are natural gas, coal/lignite and hydro [9].

In the case study described here, T is the set of active power plants consisting of {NG, Coal, Large hydro, Small hydro, Solar PV, Wind, Biomass, Biogas, Garbage}. T^o is the set of obsolete power plant consisting of {Fuel Oil, Diesel}. Although other power plant types, including; energy storage, Power-to-X, and concentrated solar power (CSP), represent opportunities for a greater penetration of renewable energy, there are several major limitations that hinder the implementation of these technologies to in the case study.

The first limitation is related to the cost of energy. The capital expenditure of energy storage in 2029 is expected to be in the range of 532 to 1,327 USD/kW, with the operational expenditures in the range of 13.31 to 33.17 USD/kW/year [59]. The current levelized costs of Power-to-X (P2X) for electricity production is in the range of 370 to 500 Swiss Francs per MWh [63]. With the proposed model priority of minimizing the total costs, energy storage and the Power-to-X are not realistically possible. The second limitation is that the feasibility of commissioning the CSP power plant mainly depends on solar direct normal irradiation (DNI) [64]. Thailand's DNI is in the range of 949 to 1,388 kWh/m^2/year [65]. However, the recommended DNI for a solar CSP power plant is more than 1,600 to 2,000 kWh/m^2/year [64,66]. As a consequence, solar CSP is not included in the set of active power plant types (T) considered in the case study.

Thailand PDP2018 expects average demand to increase at an annual rate of 3.13%. Projected total demand in year 2032 is expected to be 320,761 million kilowatt-hours [m.kWh], with a projected peak capacity demand of 41,079 megawatts [MW]. In this study, we determine the optimal energy mix to meet the requirements of future demand in the year 2032, which is one of the 5-year milestones in the 20-year development plan outlined in Thailand PDP2018.

When power plants are constructed and the operated, Thai law requires that affected locals be compensated. For the social impact penalty in this case study, the rate of compensation can be categorized into three groups based on their estimated social impact according to official policy [67]: The highest social impact group includes coal-fired thermal power plants and hydro power plants. Next is the moderate social impact group, which consists of diesel power plants and combustion turbines using fuel oil. (It should be noted that this moderate-impact group is not included in the case study since these technologies are considered obsolete and are not in the set of new power plants.) Finally, unlisted types of power plants such as renewable energy power plant and combined-cycle plants fueled by natural gas are classified as members of the low social impact group.

4.6.4. Assumptions and Data

The following assumptions were made: (1) the weighted average cost of capital ($WACC$) is stable at a rate of 5%, (2) the conversion rate from United States dollars (USD) to Thai Baht (THB) is 33 [THB/USD], (3) constructing new combined-cycle and thermal power plants includes carbon capture storage, which greatly reduces the emission factor for the plants, (4) the commissioning period of power plants is assumed to be three years; therefore, all the cited cost projections are based on the projected costs in year 2029, and (5) there is no delay in the commissioning period of new power plants. For more detailed specifications and assumptions, including the technical specifications data for the various power plant types, historical data on the probability of plant downtime, carbon capture storage, and projected fuel limits, please refer to Appendix A.

4.6.5. Sensitivity analysis of weight coefficients

The hybrid SRO and RO model is solved using CPLEX [68]. In each iteration, the capacity of new power plants (C_{is}), the electricity generated by existing power plants (E_{is}), and the electricity generated by new power plants (N_{is}) of each power plant type i for each scenario s are optimized. The sensitivity of results to changes in the weight penalty in the robust function is examined. The weights are integer values in the range of [0, 130].

Figure 4-1 shows the results of the sensitivity analysis. Weight coefficients that produce a notable reduction in social impact variation are highlighted on the x-axis. The upper bar chart in the figure allows a comparison of the objective value and total costs in the cost function (Eq. 34**.** The lower bar chart shows the social impact variation in the robust function (Eq. 35). The main purpose of this analysis is to determine the distribution of total cost (Eq. 34) and robust function (Eq. 35), which is the defined social impact variation, based on changes in weight ω. It can be inferred from Figure 4-1 that, as the weight ω increases, system reliability is strengthened; however, to ensure greater stability, the expected total cost would be higher. On the other hand, smaller values of ω result in more flexible planning with lower expected costs but would risk lower system security. Thus, policy makers would need to consider the tradeoff between system reliability and total costs. The tradeoffs issue can be addressed by setting the cost constraint (Eq.

46) to ensure that the costs under any scenario would not exceed a predefined limit. It should be noted that costs are limited when from ω is 127 and above, and that increasing ω above 127 produce no further reduction in variation.

Figure 4-2 shows the distribution of costs by weight penalty. The three bars in the upper chart represent the three cost groups: the fixed cost of new power plants (Eq. 31), the cost of electricity generated in existing power plants (Eq. 32), and the cost of electricity generated in new power plants (Eq. 33). As ω increases, the fixed cost of new power plants (Eq. 31) increases dramatically, as a higher capacity is required to ensure system security. Since the electricity generation cost in new power plants tends to be lower than in existing plants and there is more available capacity in the new plants, the variable cost of existing plants (Eq. 32) decreases, while the generation cost in the new power plants (Eq. 33) increases slightly. Compared with the cost component (Eq. 34) of the objective function, social impact variation decreases as ω increases the priority of the robust function (Eq. 35)**.**

4.6.6. Capacity variation analysis

Figure 4-3 shows the capacity variation of two groups of power plants: the high-impact group and the low-impact group, distinguished by the severity of the social impact. (As noted previously, the moderate-impact group, consisting of fuel oil and diesel power plants, is not included in the study since these plants are not in the set of new power plants, T.) With the robust constraint (Eq. 51) set to $\varphi_s = \sum_{i=1}^{T}[PT_i C_{is}]$, the model prioritizes variance reduction in the high-impact group according to the value of ω. As Figure 4-3 indicates, the capacity fluctuation in the high-impact group is predominantly reduced as ω increases (in contrast to the low-impact group, where there are noticeable variations).

According to Figure 4-3, weight increases to $\omega = 14$, 34, 57, 58, 76 and 127 lead to distinct capacity deviation drops in the high-impact group. Figure 4-4 shows the effects of increasing the weight coefficient for each of the specific power plant types. As can be seen in the figure, the capacity deviation reduction in the high-impact group is mainly due to the large hydro plants and, to a lesser degree, the coal-fired plants. Without controlling for social impact variation, large hydro power plants tend to have a broad expansive range of optimal capacity: as ω increases from 0 to 34, to 57, to 58 and to 76, the capacity standard deviation for the large hydro plants decreases markedly, from 3,267 MW to 2,784 MW, 1,306 MW, 962 MW and finally to 305 MW. The fluctuation in coal power plant capacity deviation is somewhat less consistent: as ω increases from 0 to 14, 76 and then to 127, the standard deviation changes from 1,303 MW to 1,057 MW, 1,175 MW, and, finally to 640 MW.

In the low-impact group, natural gas power plants appear to be unaffected by either the scenarios or the change in weights; the standard deviation of capacity is always equal to zero. The model greatly reduces the deviation of solar power plant capacity, from 1,400 MW to 0 MW for all values of ω above 2. The apparent surge in the low-impact group tends to be the result of balancing the drops in the high-impact group for example, biogas plants at $\omega = 14$ and garbage power plants at $\omega = 58$ and 76. It should be noted that biomass and wind power plants have deviation changes of less than 100 MW throughout all the iterations.

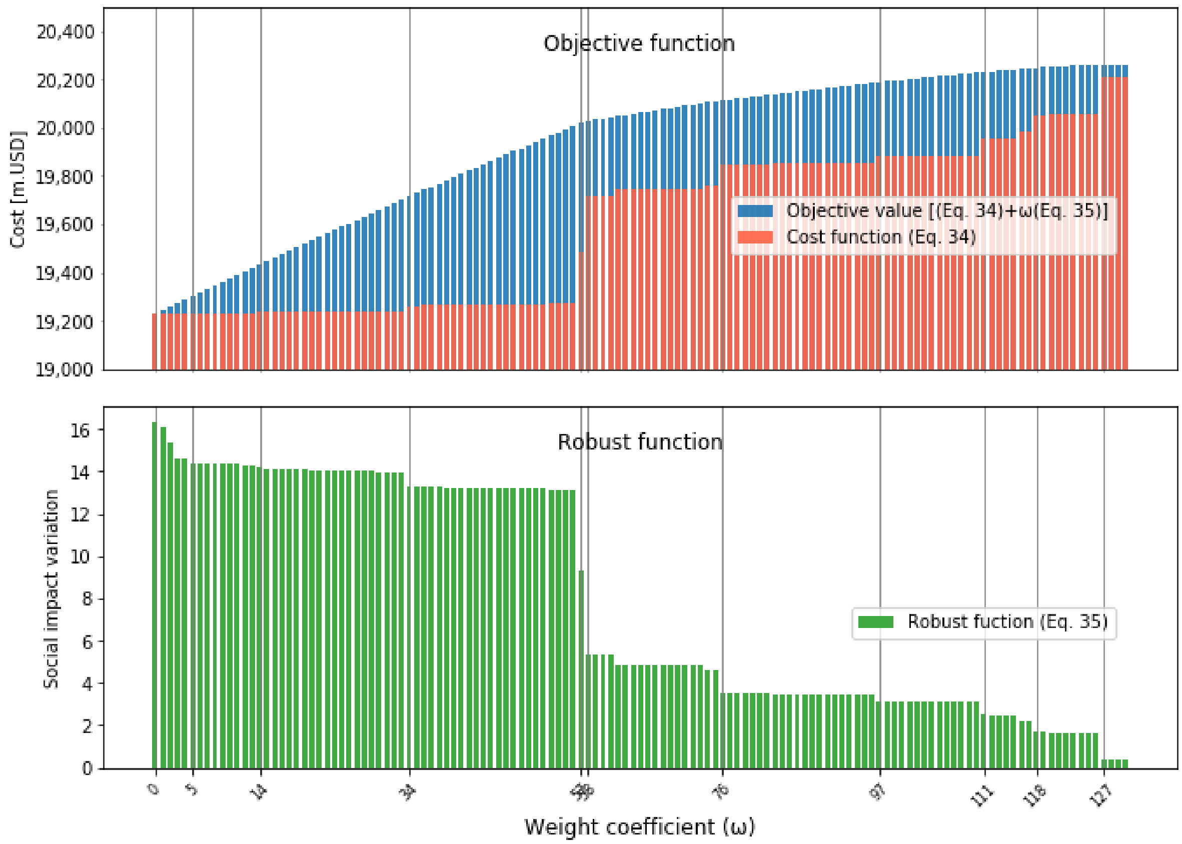

Figure 4-1. Objective value and cost function results by the weight penalty of the robust function.

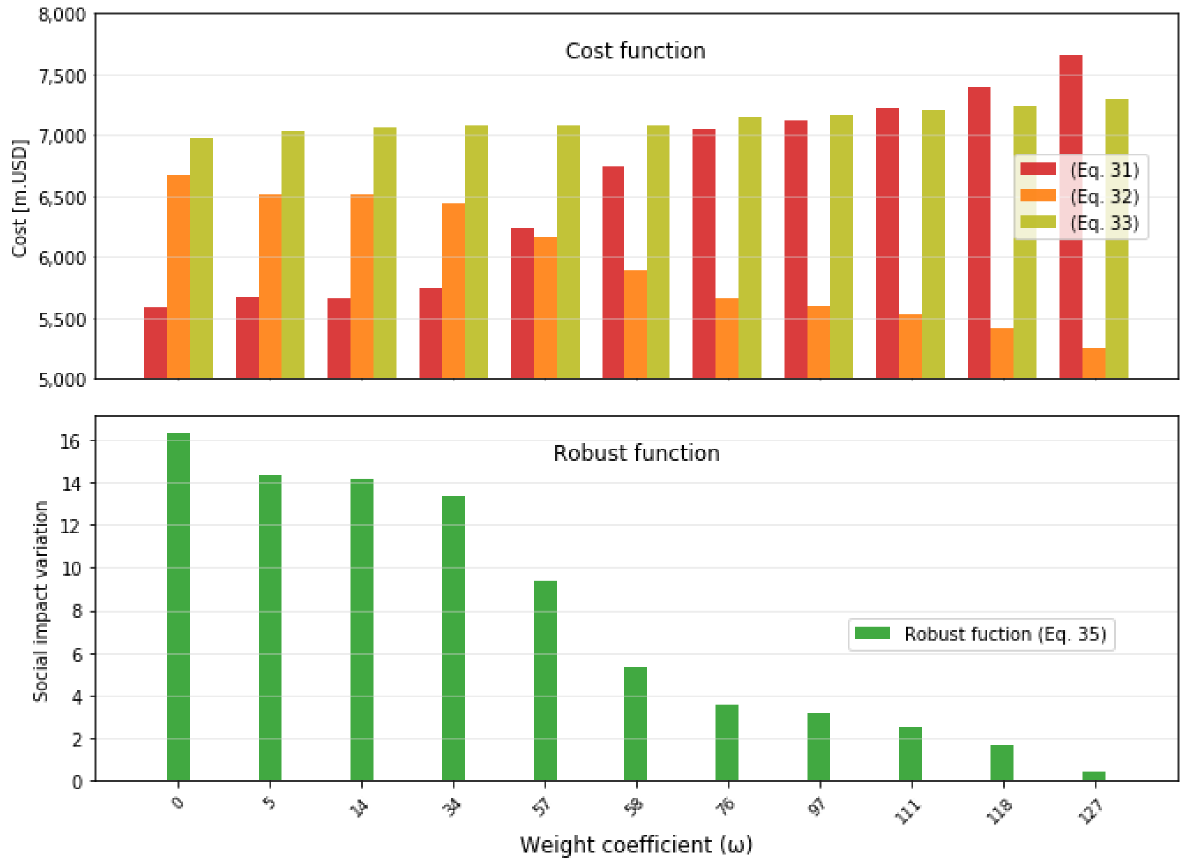

Figure 4-2. Cost distributions by the weight penalty of the robust function.

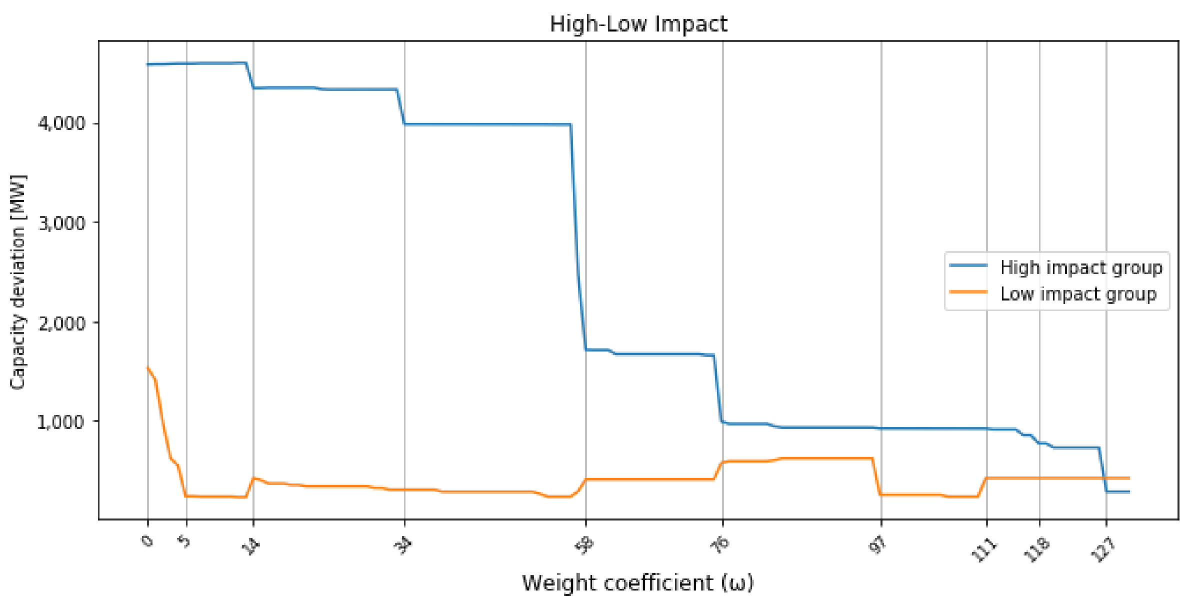

Figure 4-3. Capacity deviation distinguished by social impact group.

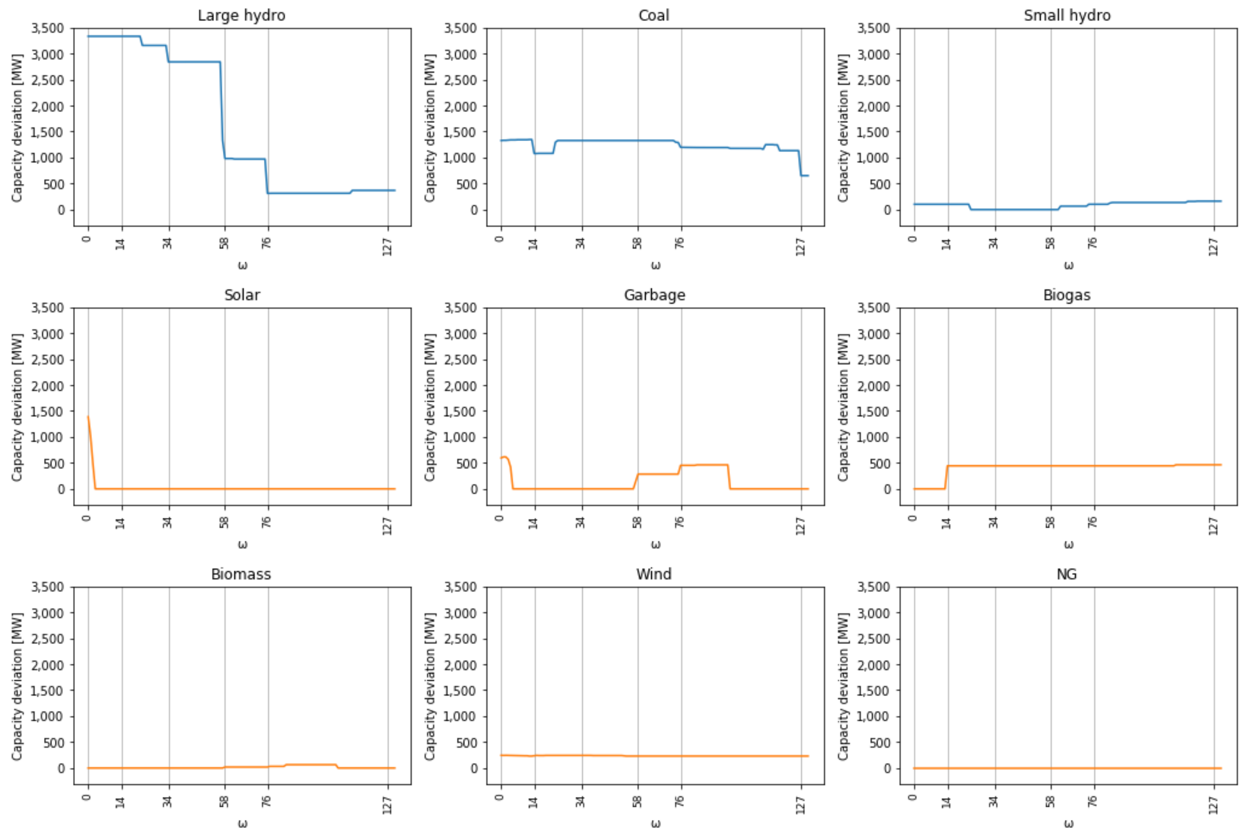

Figure 4-4. Capacity deviation for each power plant type.

4.6.7. Effects of the weight coefficient on energy planning

Increase in ω alter the structure of energy planning in different ways. Figure 4-5 shows the optimal energy mix through all scenarios using the six highlighted weight coefficients. The optimal energy mix is derived from the summation of the model's decision variables, C_{is} , and the existing power plant parameter, EC_i. The red lines in the box plots identify the median; the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The blue "X" markers represent weighted average capacity using the probability of occurrence of the scenarios; the circles outside the boxes represent outliers. The ranges of all possible outputs can be seen in the boxplots. However, it should be emphasized that the likelihood of occurrence of each of the various scenarios is not explicitly accounted for in the boxplots; rather, these likelihoods are embedded in the weighted average capacity calculations. Since the capacity of existing power plants, EC_i, is constant throughout all scenarios, the analysis below focuses only on the capacity of new power plants, C_{is}. The total weighted average capacities of new power plants are shown for six values of ω: 42,301 MW ($\omega = 0$), 43,173 MW ($\omega = 14$), 43,592 MW ($\omega = 34$), 47,364 MW ($\omega = 58$), 48,140 MW ($\omega = 76$), and 49,832 MW ($\omega = 127$).

To simplify comparisons, three of the weights are featured. The first, $\omega = 0$, represents the scenario-based stochastic optimization model that allows for full flexibility. The other two, $\omega = 58$ and $\omega = 127$, produce the highest marginal decrease in the output of the robust function (42.8% and 74.9%, respectively). In addition, $\omega = 127$ is the first weight having the highest system reliability allowed by the cost limit.

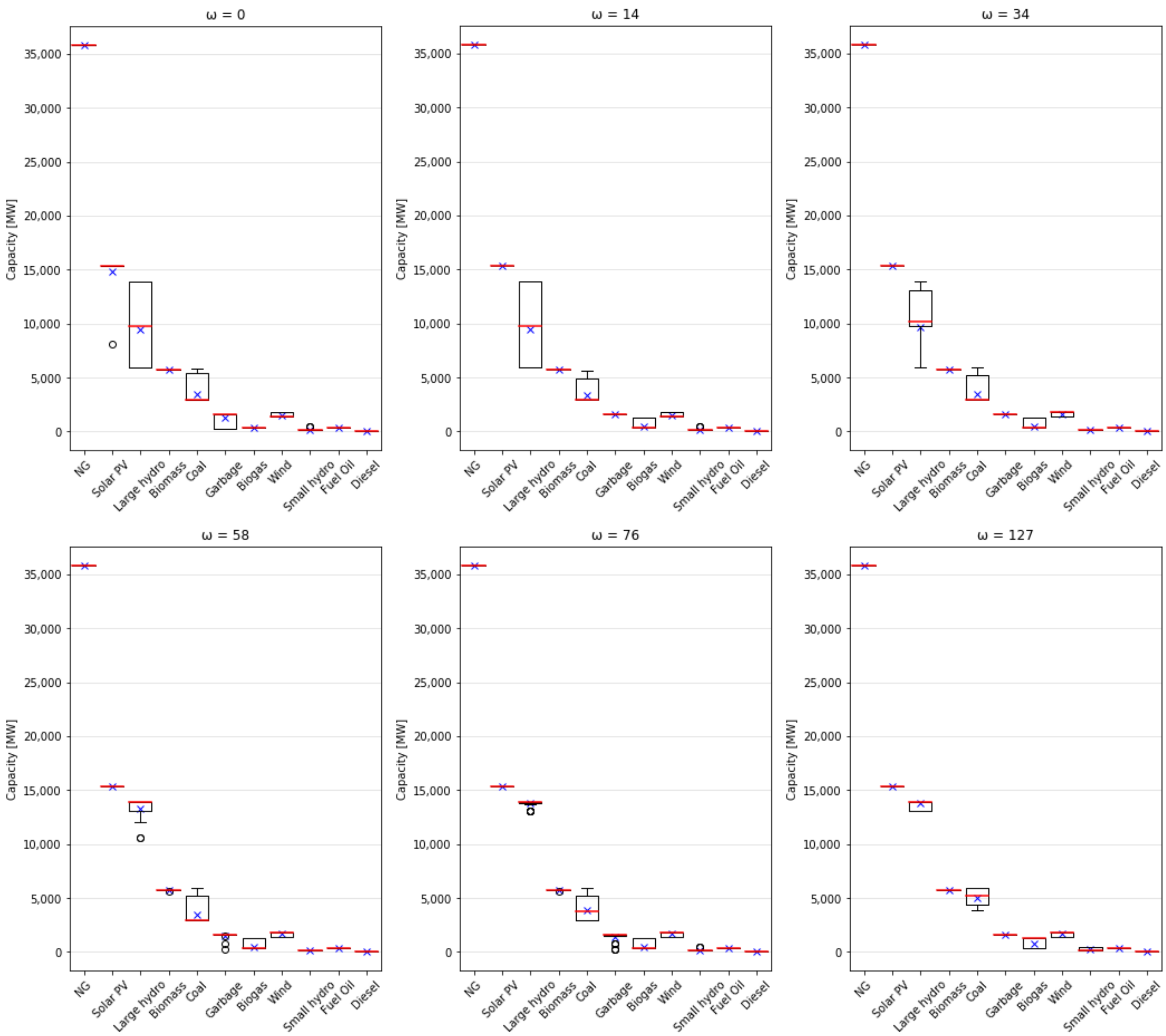

Figure 4-5. Optimal energy mix under six different weight penalties.

4.6.8. Total electricity generation

Figure 4-6 compares the distribution of optimized yearly total electricity generation produced by the three weights. Total generated electricity is the sum of the two decision variables, E_{is} and N_{is}, classified by type of power plant in the sets of $T + T^o$. As shown, natural gas provides the majority of electricity, with more than 50,000 million kWh of production. The electricity generated by solar PV plants, large hydro generation facilities, biomass, and coal-fired power plants is in the range of 10,000 million kWh to 50,000 million kWh. The remaining plant types, including garbage, biogas, wind, small hydro, fuel oil and diesel, supply less than 10,000 million kWh. Comparing with the optimal energy mix in Figure 4-5, the amount of generated electricity tends to follow capacity size, with the exception of solar PV plants and large hydro power plants, which have low capacity factors. As ω increases, the range of total electricity generated by large hydro power plants and coal-fired power plants is reduced, as their bounds of available capacity are trimmed. Since there is zero deviation in the capacity of natural gas power plants, while the size of other plants tends to be more rigid, the total electricity produced by natural gas plants is more flexible under the different scenarios with increased values of ω.

4.6.9. Constraints of energy policy

The major missions of energy planning—security of supply, environmental protection and economic competitiveness—are provided for in constraints in Eq. 37, Eq. 43, Eq. 44, Eq. 45 and Eq. 46. With respect to the environmental condition, Figure 4-7 shows the total carbon dioxide emission per total amount of electricity generated under the various scenarios and the three highlighted weights. As shown, the emission factors are far below the emission limit of 0.291 kg.CO_2/kWh targeted by the Thai government [9]. The gap between the emission factors and the limit indicates that environmental protection is not the critical constraint here. It should also be noted that the emission factors tend to be lower when ω is increased, implying that higher values of ω result in greener electricity production.

Results for the economic side are given in Figure 4-8, which shows unit costs under the different scenarios and weights. Unit cost is the total cost per total amount of generated electricity. Here, the unit cost limit is set at 65.15 USD/MWh [48]. Notably, unit costs increase as ω increases, mainly due to the capital cost of the expanded capacity of the new plants.

With regard to the first of the three conditions related to supply security, Figure 4-9 details the total reliable capacity under the various scenarios and weights. Due to the uncertainty of $DemandChange_s$, the projected reliable demand to be met is in the set {42,573, 47,303, 52,033} MWs. Since reductions in social impact variation are directly related to capacity, it should be noted that the more ω is increased, the more capacity exceeds the requirements in the lower projected reliable demand scenarios in order to reduce the deviation from the high demand scenarios.

The second of the three supply conditions is featured in Figure 4-10, which displays the total electricity generated under different scenarios and weights. The fluctuations in total projected demand due to the uncertainties represented in $DemandChange_s$ are perfectly met under every scenario and weight, indicating that the total projected demand is the critical constraint in this case study. Notably, there is no deviation associated with changes in weight, since the total electricity generated is not controlled in the robust function.

The third of the three conditions of energy security is shown in Figure 4-11, which gives the box plots of the total fuel consumption of each fuel-based power plant type in kilo tons of oil equivalent (ktoe). The blue dashed line (---) indicates the capacity limit of each fuel type. It can be seen from the box plots here that the fuel limits are above the total fuel consumption for every fuel type and under all scenarios, indicating that the fuel capacity limit is not the critical constraint in this case study.

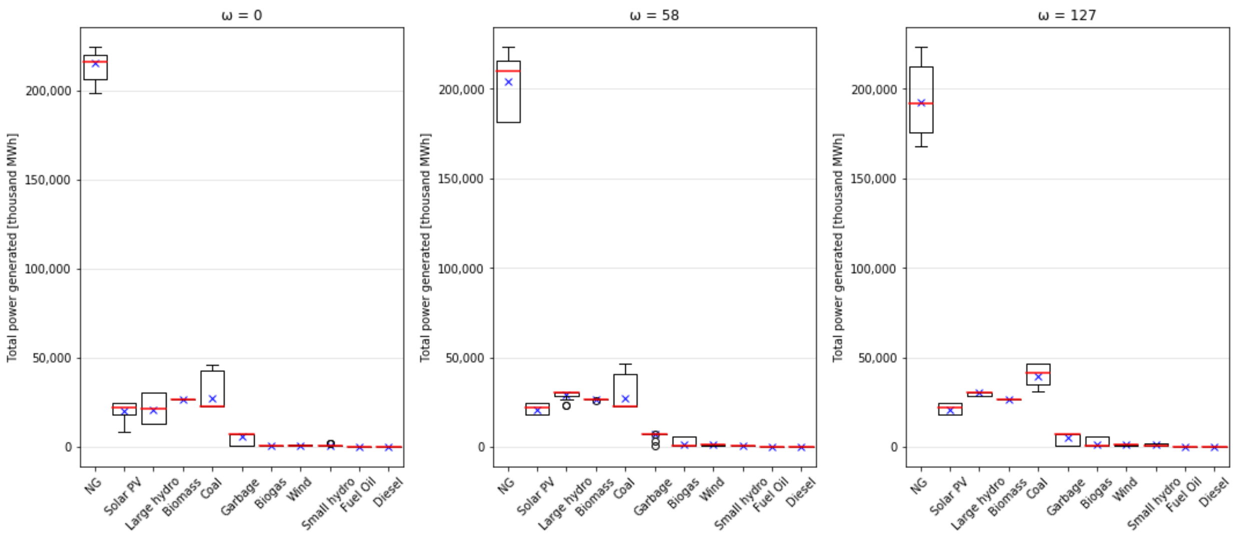

Figure 4-6. Optimal yearly generation under three different penalties.

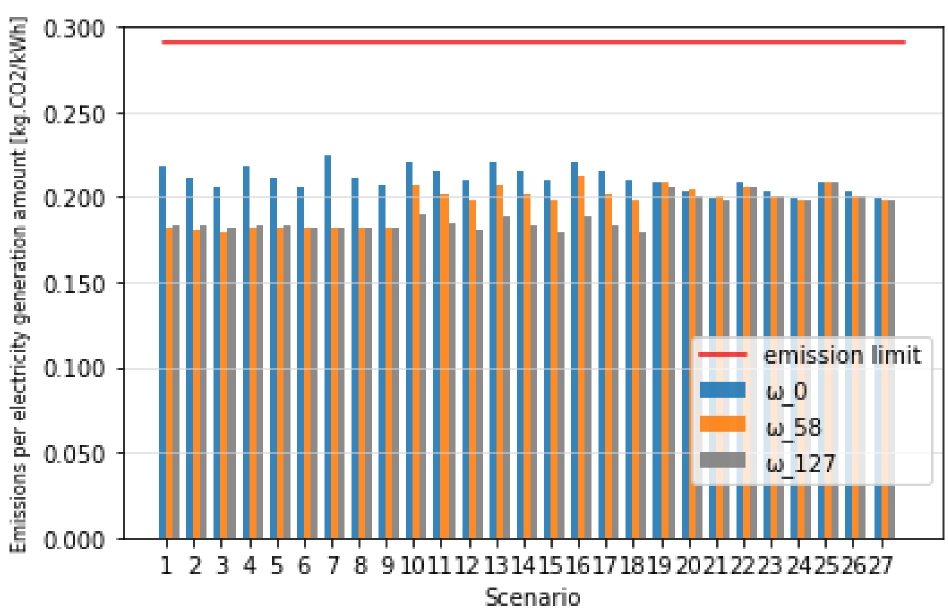

Figure 4-7. Emissions per electricity generation amount under different scenarios and weights.

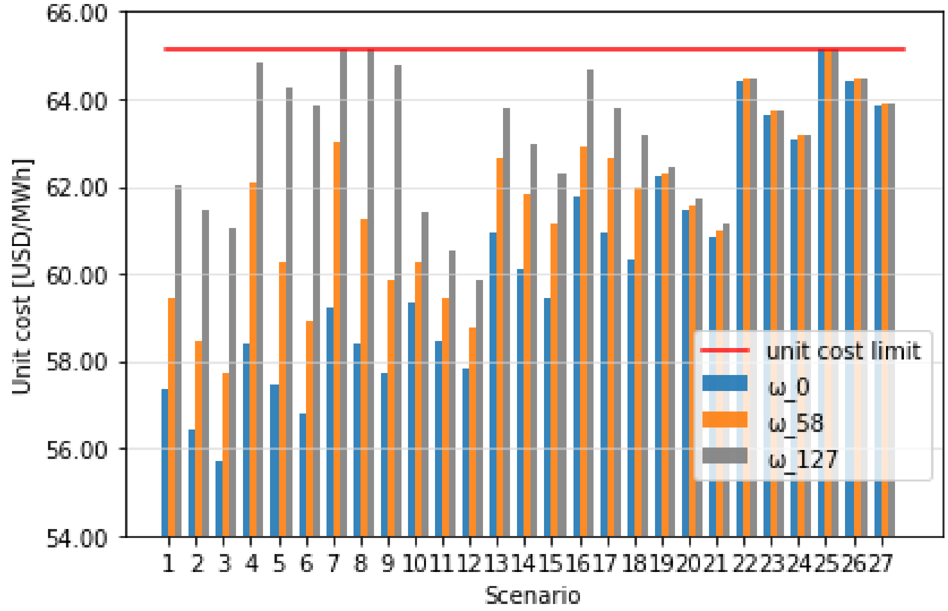

Figure 4-8. Unit cost under different scenarios and weights.

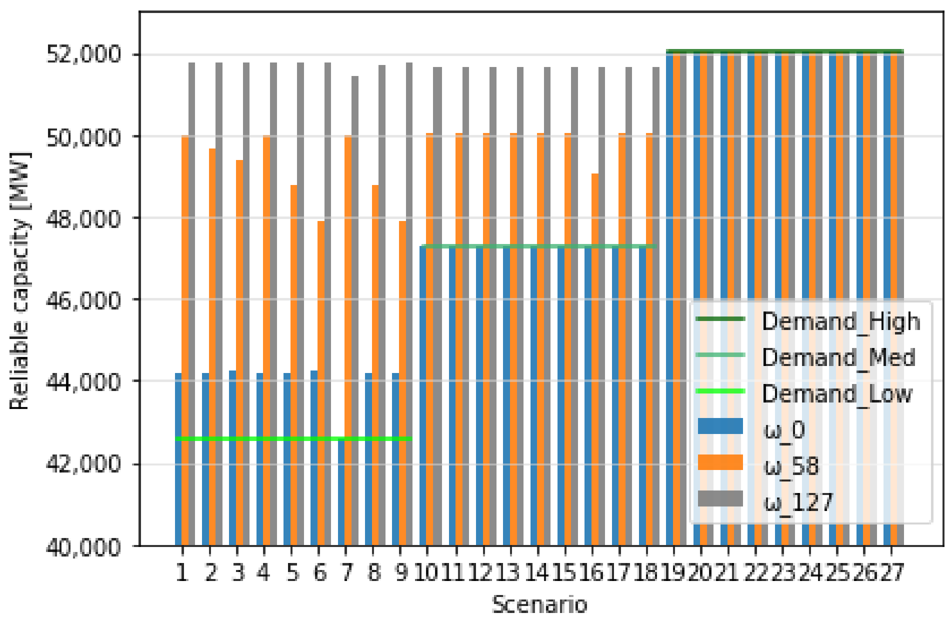

Figure 4-9. Total reliable capacity under different scenarios and weights.

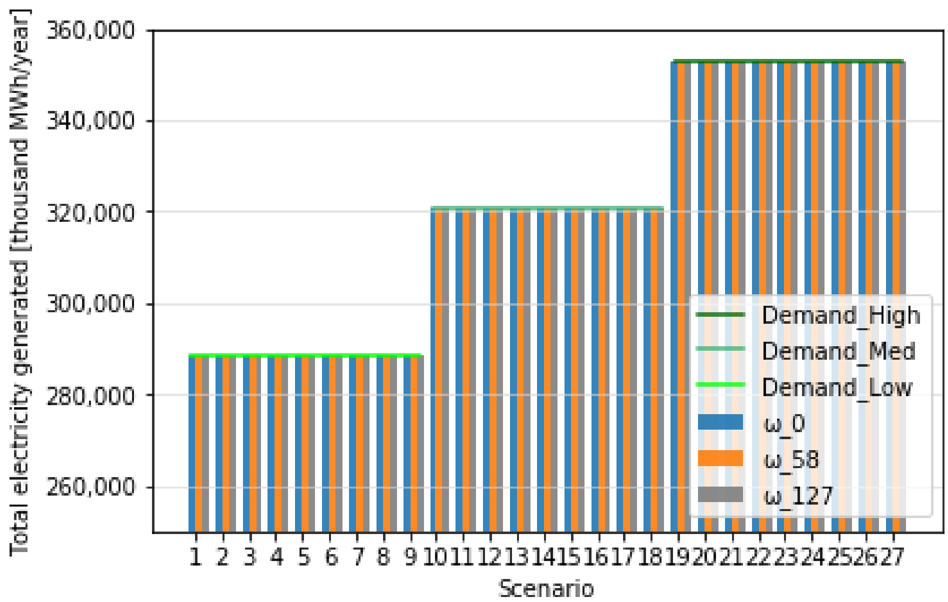

Figure 4-10. Total electricity generated under different scenarios and weights.

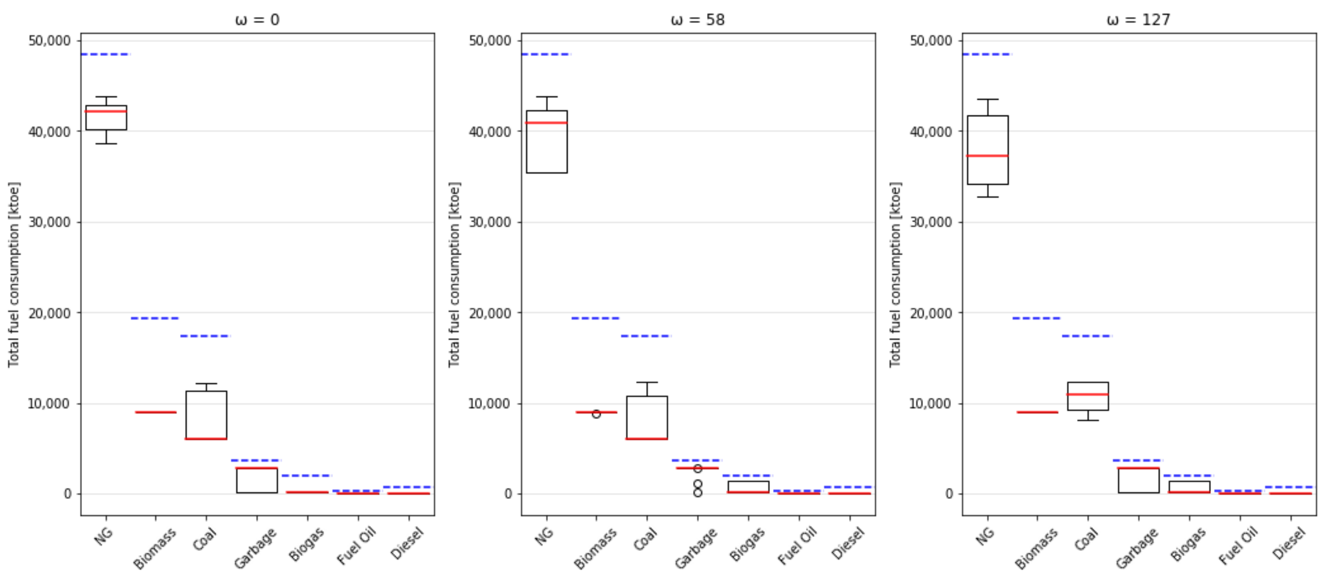

Figure 4-11. Total fuel consumption of each fuel-based power plant type under different scenarios and weights.

4.6.10.Capacity versus cost variation analysis

Comparisons of the variation in capacity, total cost and unit cost are shown in Figure 4-12. From the box plots presented here, it seems clear that increasing ω contributes significantly to reducing capacity variation, while the consequence of costlier planning is notably low. The implication is that strengthening system reliability results in only slight increase in total cost. Illustratively, as ω is increased from 0 to 58 and then to 127, the total expected cost rises only marginally (by 2.52% and 5.08%, respectively), while the reduction in capacity deviation is substantial (65.4% and 96.2%, respectively). It should also be noted that the deviation of the total cost for energy planning involves much less risk in the case of capacity. This is due to the fact that actual total electricity generation can be adjusted in real time, whereas capacity size requires long-term planning. The results here would seem to encourage policy makers to consider enhancing system stability.

4.6.11.Alternative case study: Vietnam

The proposed model was also applied to energy planning in Vietnam as an alternative case study. Despite its geographically proximate location to Thailand in Southeast Asia, Vietnam has a different energy structure and policy. By amount of generated electricity, the dominant sources in Vietnam are coal, gas, and hydro [69]. The latest Vietnam Power Development Plan (PDP 7rev) emphasizes the use of renewable energy, mainly including wind and solar [69]. The plan also calls for an expansion of coal-fired power plants. In 2030, total demand is projected to reach 571,752 thousand MWh, with an expected peak capacity demand of 55,000 MW [70]. The assumptions applide in the Thailand case study, including the scenarios of uncertainty, the social impact function, and the power plant technical specifications, were also used in setting the model's input parameters in the Vietnam case study. For a detailed description of the energy mix and cost structure in the Vietnam case, please refer to Appendix B.

Comparisons of the variation in capacity and total cost for two selected weight coefficients are shown in Figure 4-13. As can be seen here, as the weight coefficient increases, the reduction in capacity variation is considerable (67.1%), while the growth in total expected costs is minimal (0.63%). Despite the difference in the energy mixes and cost structure of the two countries, the box plots in Figure 4-13 indicate a consistency between the results in the Vietnam case and those in the of Thailand case.

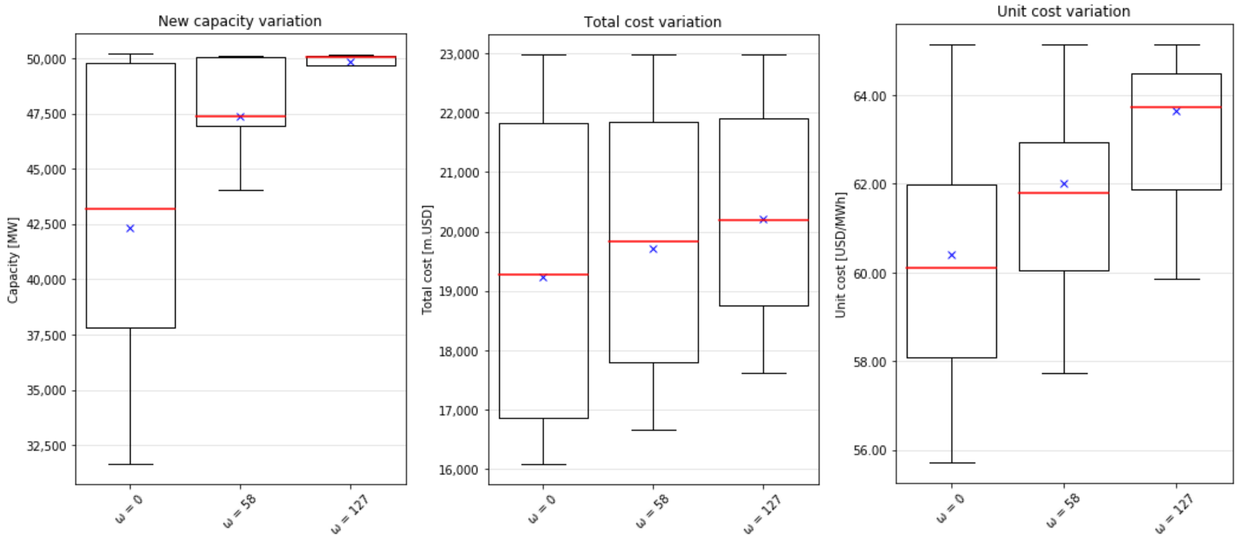

Figure 4-12. Comparison of total capacity and cost variation under different weights.

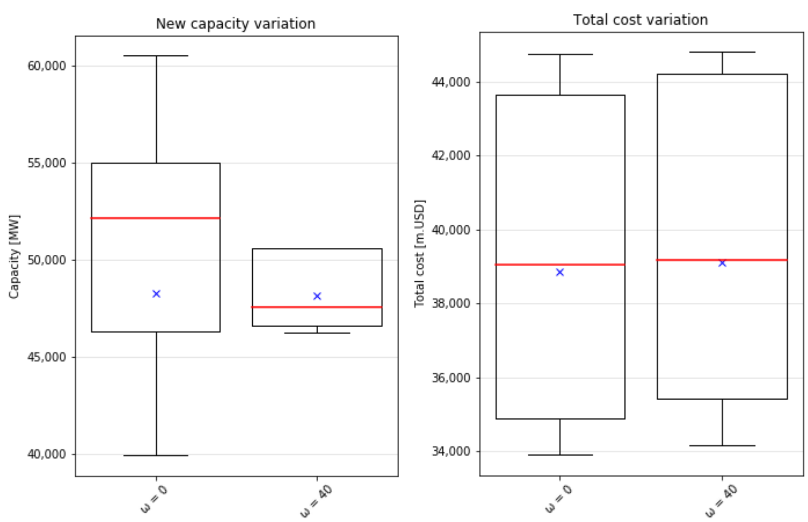

Figure 4-13. Comparison of total capacity and cost variation in the case of Vietnam

4.7. Discussion

The reader may have noticed that the decision variables used in this model have two different dimensional units: megawatts [MW] for new power plant capacity and kilowatt-hours [kWh] for electricity generated by both existing and new power plants. In pragmatic energy planning, the minimum required capacity to meet projected peak power demand must be determined well in advance of the planning and construction of a new power plant. In contrast, the amount of generated electricity can be adjusted in real time based on actual demand, with the intervals of possible generated electricity being limited by technical specifications and capacity size. Furthermore, the cost of capacity expansion to enhance system stability is a relatively small percentage of total cost, in the range of 29% to 38%. Accordingly, the key finding of this study is that the model can be used to greatly reduce the deviation of projected social impacts, and that the trade-offs of higher total expected costs are remarkably low while still providing flexibility in terms of real-time adjustments.

A number of policy recommendations can be made based on the results of the empirical analysis described here. First and most importantly, the results provide quantitative support for policy makers seeking to devise a power development plan that is immune to uncertain future projections. Our analysis indicates that enhancing system stability while considering social impact fluctuations involves only minor monetary tradeoffs. Moreover, the results show that there is still room for improvement in environmental emissions. With the aim of creating a zero emissions community in the future, lowering the emission factor to a level that is less than the target set by the government represents a promising start.

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Chapter 5
Phase III: Measuring the energy efficiency of the energy planning

5.1. Phase’s overview

In the study in this phase, a combination of multi-objective optimization and efficiency measurement is proposed as a means for determining an efficient energy mix that considers the multi-dimensional nature of energy planning and its associated uncertainties. Various multi-objective functions are appended to the proposed optimization model to meet requirements related to energy need, cost, environmental impact, security, social impact, and social benefit. A slacks-based measure methodology is applied to determine the best energy mix from the alternatives produced by the appended model. The energy efficiency of each energy mix is measured from the linear combination of its defined inputs and outputs. The outputs to be maximized include total generated electricity, direct employment, and percentage of generated electricity from renewable energy, while the inputs to be minimized consist of total economic cost, carbon dioxide emission, total social cost, and power-plant-type dependence score. To demonstrate the applicability of the proposed model, a case study of Thailand’s power development plan is featured. Various types of power plants, both fossil fuel-fired and renewable energy-driven are considered in the empirical analysis. The results show that the proposed method can contribute significant improvements, including a reduction in total emissions and in the power-plant-type dependence score (by 31.41% and 25.59%, respectively). It also increases total employment and the proportion of generated electricity from renewable energy plants (by 25.73% and 47.39%, respectively), with marginal tradeoffs of total costs and total social costs (which increase by 8.94% and 13.89%, respectively). Quantitative results from the model could help policy makers efficiently determine an appropriate energy policy—one that optimizes all the various aspects, under a given set of constraints and scenarios of uncertainty.

5.2. Contributions & Key findings

Contributions of the study in this phase can be summarized as follows:

- A framework that combines the concepts of a multi-objective optimization model and efficiency measurement in order to determine the most efficient energy mix considering the multi-dimensional aspects of energy requirements and various uncertainty scenarios was proposed.
- Extending the focus beyond the Energy Trilemma (i.e., energy affordability, energy security, and environmental protection), the proposed model incorporates aspects of social impact and social benefit.
- The empirical results provide quantitative support for policy makers seeking to determine an efficient energy policy that maximizes the satisfaction of multiple requirements, while taking into account various scenarios of future uncertainties.

Key findings from the study in this phase can be summarized as follows:

- It was found that adjusting the order of prioritization of the appended objective functions—the cost function, the emissions function, and the social functions—changed the optimized energy mixes.
- The subsequent group-separated efficiency measurement grouped by the demand scenario, showed that the lexicographical ordering that prioritized environment first, followed by social damage and then cost (designated as ESC), had the highest weighted-average efficiency score for all demand scenarios.
- It was also shown that the energy mixes of ESC were the least sensitive to the demand scenario.
- A comparison with the unmodified benchmarking method confirmed that the proposed method was considerably better at meeting the multi-aspect requirements (environment, security, and social benefit) with only moderate tradeoffs (in terms of monetary and social impact).

5.3. Statement of problems

As described in the previous sections, the energy development throughout the world has focused on the Energy Trilemma [2]. Accordingly, these three aspects have been consistently used as the primary considerations in numerous energy planning studies. However, recent studies have indicated the importance of two other aspects of energy planning: social impact and social benefit. For example, Kaya and Kahraman included job creation and social acceptability as criteria for evaluating the energy alternatives in the case of Istanbul [71]. Zeng, Guo, Wang, and Zhang incorporated employment opportunities and social acceptance as an index for the analysis and evaluation of renewable energy (RE) technical plans in China [72]. Consequently, to meet the five requirements noted above, a proper energy mix will be needed.

Making energy-mix decisions by comparing alternatives (from the model's modifications) with multi-characteristic requirements can be difficult. Frontier-based efficiency measurement methodologies such as data envelopment analysis (DEA) and slacks-based measure (SBM) have been proposed as practical approaches in such cases since these approaches are not affected by differing units. In energy planning, DEA has been applied in numerous studies. Shrivastava, Sharma, and Chauhan used DEA to measure the energy efficiency of coal-fired power plants in India [27]. Sueyoshi and Goto used the same method to evaluate the impact of environmental policy on the efficiency of coal-fired power generation facilities [28]. Xin-gang and Zhen applied this approach to measure the technical efficiency of wind-turbine power plants in China [29]. There are a few studies implementing SBM in energy planning. For example, Song, Bi, Wu, and Yang employed a network SBM model determining the production efficiency and environmental efficiency of coal-fired power plants in China [26]. Bi, Song, Zhou, and Liang used the SBM approach to examine the environmental and energy efficiency of the thermal power generation sector in China [25].

Since efficiency measurement is determined from the results of the optimization model, the energy mix is optimized based on the defined priorities of policy. Here, minor differences between the target measured unit and the efficient frontier are important. Thus, an approach that can spot minor differences is essential. Unlike DEA, which produces a single-number efficiency score, SBM clearly identifies excessive inputs and insufficient outputs for each decision-making unit. It is for this reason that the efficiency measurement stage in this phase uses SBM methodology.

5.4. Research gaps

Table 5-1 summarizes the scope and approaches of previous related studies. A close examination of these prior studies raises several concerns regarding the methodologies used for energy planning. First, it of concern that optimizing only economic cost, as has been common in previous studies, does not properly address the above-mentioned multiple aspects of energy planning. Few studies have incorporated the environmental and social impacts of energy planning in the objective functions with limitations (regarding indirect environmental function which relies on cost of emissions, and/or social costs that only associate with RE power plants). Furthermore, the optimization models and efficiency measurements featured in previous studies are implemented separately. Very few posterior decision-making approaches to be employed after optimization are discussed, and the efficiency measurements often use historical data. This may lead to either an inconclusive set of optimal energy mixes, as in case of the optimization models, or the inability to reflect future requirements due to a dependency on historical data, as in case of the efficiency measurement studies.

To the best of our knowledge, this study is the first to propose combining a multiple-objective capacity expansion model with two-stage efficiency measurement in order to determine the most efficient energy mixes using an approach that recognizes the multi-dimensional aspects of energy requirements and considers the potential impact of future uncertainties. The novelty of this study can be summarized as follows: Firstly, we propose modifications to the energy planning model in order to accommodate the multi-characteristic requirements of energy planning. The aspects of energy planning considered here are not limited to the Energy Trilemma but rather are extended to include social impact and social benefit. Furthermore, a posterior two-stage decision-making approach is proposed to identify the best alternative from among the optimal energy mixes produced by the optimization model in order to maximize the defined energy efficiency. SBM is applied to determine output shortfalls, input excesses, and efficiency score in the first stage. Group-separated SBM is then applied to make a final decision regarding the unresolved alternatives that may emerge from the first stage. To demonstrate the applicability of the proposed model, an up-to-date examination of Thailand’s power development plan is used as a case study. Both fossil-fueled power plants and RE power plants are included in the empirical study.

Table 5-1. Summary of related previous works and research gaps.

Studies	Optimization model determining energy mixes			Posterior decision-making approach	
	Aspects to be incorporated in objective function			Approach	Aspects to be measured
	Economic cost	Environment	Social impact		
[5]	✓	Through carbon costs	-	-	
[4]	✓	-	-	-	
[3]	✓	Through cost of emissions	-	-	
[8]	✓	Through cost of emissions	✓ (Only in RE power plants)	-	
[6]	✓	Through cost of CO_2 and air pollution treatment	-	-	
[7]	✓	-	-	-	
[11]	✓	-	Social impact cost variation	-	
[27]	- (From cited historical data)			DEA	Energy
[28]	- (From cited historical data)			Returns to scale and damages to scale DEA	Energy, economic cost, environment, labor
[29]	- (From cited historical data)			Four-stage DEA	Energy, economic cost, environment, labor, income
[26]	- (From cited historical data)			SBM	Energy, economic cost, environment, labor
[25]	- (From cited historical data)			Input-oriented SBM	Energy, economic cost, environment, labor
[72]	- (From cited energy planning alternatives)			Super-efficient DEA	Energy, economic cost, environment, social impact, social benefit
[73]	✓	✓	-	Euclidean distance-based approach: Technique of Order Preference Similarity to Ideal Solution (TOPSIS)	
This study	✓	✓	✓	**Two-stage SBM**	**Energy, economic cost, environment, social impact, social benefit, security**

5.5. Proposed model

5.5.1. Objective functions

Rather than focusing solely on the minimization of total cost, as is the case in the Hybrid SRO & RO model proposed in Chapter 4, the proposed approach appends an emissions function and a social cost function to the conventional cost-based objective function. The cost function is determined from the annualized capital expenditure and operational expenditures for each power plant type in the energy mix, measured in monetary units per year [11]. The emissions function considers the expected total carbon dioxide emitted from the operation of each power plant type, measured in tons of carbon dioxide per year (tCO_2/year). The social cost function is derived from the expected compensation to locals who are unfavorably affected by the operation of each power plant type. The compensation rate (SC_i), expressed in monetary units per unit of generated electricity, varies by the type of power plant. The emissions function and social cost function are respectively the following:

$$\sum_{s=1}^{S} p_s \left[\sum_{i=1}^{N} [EE_i E_{is} + NE_i N_{is}] \right] \quad \textbf{Eq. 53}$$

$$\sum_{s=1}^{S} p_s \left[\sum_{i=1}^{N} SC_i [E_{is} + N_{is}] \right] \quad \textbf{Eq. 54}$$

where N is the set of power plant types in the mix, and EE_i and NE_i are the emission factors, in tons of carbon dioxide per gigawatt-hour (tCO_2/GWh), for existing power plant types and new power plant types respectively.

To address this multi-objective optimization problem, this study uses the lexicographic and weighted-sum methods, two relatively simple and computationally efficient approaches. The lexicographical method prioritizes the objective functions according to a defined order of relative importance [74]. On the other hand, the weighted-sum method uses a defined weight for each objective function: w_{cost} for the cost function, $w_{environment}$ for the emission function, and w_{social} for the social cost function. In effect, the weighted-sum method converts the multi-objective optimization problem into a single-objective problem [75].

5.5.2. Energy policies

The energy policies to be compared in the efficiency measurement part of the proposed method are rooted in two components. The first involves the selection of the multi-objective objective functions ($policy$), for which there are three options. The first two options are determined based on the lexicographical method, where the objective functions are ordered from highest priority to lowest priority. In case (1), the order is Environment > Social > Cost (designated as **ESC**); in case (2), the order is Social > Environment > Cost (designated as **SEC**). The third option is based on the weighted-sum method, where the objective functions are converted to the same monetary units (designated as **Weights**).

The second component is the selection of the robust penalty (ω) for the robust function included in the model, which control the balance between system stability and results flexibility. In order to ensure highly flexible energy mixes, the robust penalty is set to the smallest integer value, i.e., $\omega = 1$. Alternatively, for robust energy mixes, the weight penalty is set to a large integer value ($\omega = 1000$ in the case study).

The alternatives based on the two stated components are then cross-multiplied to generate energy policies. As a result, there are six energy policies determined from the multi-objective function options and the selection of the robust penalty: **ESC1**, **ESC1000**, **SEC1**, **SEC1000**, **weights1**, and **weights1000**. As a baseline for benchmarking, a single-objective function (designated as **BASE**) is generated. The objective function in **BASE** is that in the Hybrid SRO&RO model, which focuses only on the cost function; the robust penalty is set as $\omega = 1$. In total, then, there are seven energy policies to be compared in the efficiency measurement phase.

5.5.3. Efficiency measurement, decision-making units, inputs, and outputs

Energy mixes resulting from the modified optimization model are compared in the efficiency measurement stage of the procedure. Here, multi-aspect efficiency measurement is accomplished using the SBM, which evaluates the output shortfalls and input excesses of each of the decision-making units (DMUs), simultaneously considering of energy needs, cost, environmental impact, security, social impact, and social benefit. The DMU is generated from the array of the results of the optimization model under policy p, robust penalty ω, and scenario s, as $j = (p, \omega, s)$. Thus, the DMU set (D) is the dot product of the sets of energy policies ($Policy$), robust penalty ($Robust$), and scenarios of uncertainty (S); that is, $D = Policy \times Robust \times S$.

Each DMU is defined as having three outputs (to be maximized), and four inputs (to be minimized). The outputs and inputs are derived from the energy mixes resulting from the optimized energy planning model. The three outputs are total generated electricity, direct employment, and percentage of generated electricity from renewable energy, which relate to the energy, social benefit, and environmental aspects of energy production, respectively. The inputs include total cost, carbon dioxide emission, total social cost, and power-plant-type dependence score, which relate to the cost, environmental impact, and social and security aspects respectively.

<u>Energy aspect: Total generated electricity</u>

For the energy aspect, total generated electricity (Gen_j), measured in gigawatt-hours (GWh), is the summation of the decision variables in the optimization model: generated electricity from existing power plants (E_{is}) and generated electricity from new power plants (N_{is}). Since the total demand for generated electricity is a critical constraint, the value of the total generated electricity will be equal for the DMUs that share the same amount of projected demand. The total generated electricity (Gen_j) is as follows:

$$Gen_j = \sum_{i=1}^{N} (E_{is} + N_{is}) \qquad \textbf{Eq. 55}$$

<u>Social beneficial aspect: Direct employment</u>

As for the social benefit aspect, direct employment (Emp_j) is defined as the expected employment associated with new power plants. Expected direct employment is determined throughout the lifecycle of a new power plants, beginning with the commissioning of the plant and the plant's material manufacturing requirements during the construction period, continuing through its operational phase (operation and maintenance, as well as fuel procurement), and ending with the plant's decommissioning [76].

Direct employment can be divided into three types, with appropriate employment factors for each. In the commissioning, material manufacturing, and decommissioning processes, the employment factor (EF_{CMD_i}) is expressed per unit of plant capacity throughout the plant's lifetime, in job-years per megawatt (Job-years/MW). In the operation and maintenance process, the employment factor (EF_{OM_i}) is expressed per amount of the plant capacity, in jobs per megawatt (Jobs/MW). In fuel procurement, the employment factor (EF_{FP_i}) is expressed per unit of electricity produced, in jobs per gigawatt-hour (Jobs/GWh) (For detailed information on the employment factors for each power plant type, please refer to Appendix C.).

To reduce the number of indices, employment in job-years is converted into jobs by dividing expected employment by the expected life of the power plant (Lf_i). Direct employment (Emp_j), measured in Jobs, is as follows:

$$Emp_j = \frac{\sum_{i=1}^{N}\left(EF_{CMD_i} \times C_{is}\right)}{Lf_i} + \sum_{i=1}^{N}\left(EF_{OM_i} \times C_{is}\right) + \sum_{i=1}^{N}\left(EF_{FP_i} \times N_{is}\right) \qquad \textbf{Eq. 56}$$

<u>Environmental aspect: Percentage of generated electricity from renewable energy</u>

Being environmentally friendly is not solely a function of greenhouse gas emissions. Some RE power plants such as those using biogas, biomass, or municipal waste, may emit greenhouse gases, but indirectly reduce waste from other industries. Moreover, these types of RE plants proportionally help reduce reliance on fossil fuel-fired power plants. In this study, the percentage of electricity produced by RE ($REper_j$) plants is considered as one of the two environmental factors influencing efficiency. $REper_j$ is defined as follows:

$$REper_j = \sum_{i=1}^{RE}(E_{is} + N_{is}) \,/\, \sum_{i=1}^{N}(E_{is} + N_{is}) \qquad \textbf{Eq. 57}$$

where RE represents the set of renewable energy power plants.

<u>Cost aspect: Total cost</u>

Total cost ($Cost_j$), measured in monetary units, is derived from the cost function for each scenario. It includes the annualized capital expenditure for new power plants, the operational expenditures of existing power plants, and the operational expenditure of new power plants.

<u>Environmental aspect: Carbon dioxide emission</u>

Carbon dioxide emission ($Emis_j$) is considered as an input for each DMU in order to measure the excess of the environmental footprint. $Emis_j$, measured in tCO_2, is derived from the bracketed term in the emission function (in Eq. 53) as follows:

$$Emis_j = \sum_{i=1}^{N}[EE_i E_{is} + NE_i N_{is}] \qquad \textbf{Eq. 58}$$

Social impact aspect: Social cost

Social cost (Soc_j) is the expected compensation that is required for local residents affected by the operation of the power plants. Soc_j, measured in monetary units, is derived from the bracketed term in the social cost function (in Eq. 54) as follows:

$$Soc_j = \sum_{i=1}^{N} SC_i[E_{is} + N_{is}] \qquad \textbf{Eq. 59}$$

Security aspect: Power-plant-type dependency score

In an energy system, an energy supplier that provides a greater share of the energy supply has a greater impact on energy security [77]. To ensure a secure energy supply, a diversification of power plant types is required. In the proposed model, the power-plant-type dependency score (PPD_j) represents an input to be measured to indicate excess dependency on a single major power plant type.

The Herfindahl-Hirschman Index (HHI) was developed by Herfindahl and Hirschman to measure the degree of concentration [78,79]. The HHI has proven to be a relatively reliable index and is widely used in the fields of economics, market power assessment, and energy diversity in the electricity market [77]. The HHI is the summation of the square market share of each unit in the system:

$$HHI = \sum_{i=1}^{A} s_i^2 \qquad \textbf{Eq. 60}$$

where s_i is the proportional share of unit i in the set of system A. Given that s_i is in proportional units, the values of HHI are in the range of [1/N, 1]. Higher HHI values imply greater dependence on a single major unit in the system.

PPD_j is derived from the HHI index as follows:

$$PPD_j = \sum_{i=1}^{N} s_{is}^2$$
$$s_{is} = \frac{[E_{is} + N_{is}]}{\sum_{i=1}^{N}[E_{is} + N_{is}]} \qquad \textbf{Eq. 61}$$

The proportional share of each power plant type (s_{is}) is the generated electricity of existing plant and new plant of the same power plant type, divided by the total generated electricity of the entire system.

5.5.4. Second-stage efficiency measurement

In case the first-stage efficiency measurement is unable to produce a final decision regarding the best energy policy under a given scenario of uncertainty, a second-stage efficiency measurement is provided for. With the proposed procedure, the sensitivity of the efficiency scores to each uncertainty scenario is assessed. The uncertainty scenario that caused the largest efficiency score fluctuation is designated as the critical uncertainty factor (u). A group-separated efficiency measurement where the DMUs are grouped according to the critical uncertainty factor separately determine the efficiency of energy policies under different scenarios of the critical uncertainty factor. Finally, the concept of meta-frontier technology is applied to measure the sensitivity of the efficiency score to the critical uncertainty factor.

5.5.5. Algorithm

The proposed modifications to the model and the use of two-stage efficiency measurement are summarized in **Algorithm 1**.

Algorithm 1: Model modification and two-stage efficiency measurement

INPUT:	
$Policy \longleftarrow$ Multi-objective function to be chosen = $\{\boldsymbol{BASE}, \boldsymbol{Weights}, \boldsymbol{ESC}, \boldsymbol{SEC}\}$	
$Robust \longleftarrow$ Weight penalty of robust function = $\{1{,}1000\}$	
$S \longleftarrow$ Scenarios of uncertainty , $s \in S$	
$D \longleftarrow$ Numbers of DMU = $Policy \times Robust \times S,\ j \in D$	
$U \longleftarrow$ Focused uncertain factor, $u \in U$	
$K \longleftarrow$ Numbers of DMU in second-stage efficiency measurement, $D = U \times K,\ k \in K$	
OUTPUT: $INP_{jx}, OTP_{jy}, SLK_{jxy}$	Matrix
OUTPUT: $Eff_j, Cost_j, Emis_j, Soc_j, HHI_j, Gen_j, Emp_j, REper_j$	$1 \times D$ vector
function Model_Modification ($policy, robust\_penalty$):	Modify Hybrid SRO & RO model
if ($policy == \boldsymbol{BASE}$) **then**	
Objective function $\longleftarrow$ $Cost\ function$	
else if ($policy == \boldsymbol{ESC}$) **then**	
Objective function $\longleftarrow$ $\boldsymbol{Lex}(Environment, Social, Cost)$	
else if ($policy == \boldsymbol{SEC}$) **then**	
Objective function $\longleftarrow$ $\boldsymbol{Lex}(Social, Environment, Cost)$	
else	
Objective function $\longleftarrow$ $\boldsymbol{Weights}(w_{cost}, w_{enviroment}, w_{social})$	
end if	
$C_{is}, E_{is}, N_{is} \longleftarrow$ Process **Hybrid SRO & RO** with weight penalty of robust function = $robust\_penalty$	Run modified Hybrid SRO & RO model
return C_{is}, E_{is}, N_{is}	
end function	
function SBM_input (Vectors of variables):	Define DMU input vectors
$Inputs_x \longleftarrow$ Vectors of defined input	
return $Inputs_x$	
end function	
function SBM_output (Vectors of variables):	Define DMU output vectors
$Outputs_y \longleftarrow$ Vectors of defined output	
return $Outputs_y$	
end function	
function SBM (Inputs, Outputs):	Determine slacks for each DMU
$slacks_{jxy} \longleftarrow$ Process SBM	
return $slacks_{jxy}$	
end function	
function Eff_Score (slacks):	Convert slacks into efficiency score
$Efficient\ Score_j \longleftarrow$ Determine ρ in **Eq. (2)**	
return $Efficient\ Score_j$	
end function	

function Main:	
for p **in** $Policy$ **do**	Every policy in $Policy$
for ω **in** $Robust$ **do**	Every weight penalty of robust function in $Robust$
Model_Modification(p, ω)	
$Gen_j \longleftarrow$ Total generated electricity of policy p, robust penalty ω, scenario s.	Generate total generated electricity
$Emp_j \longleftarrow$ Employment occurred of policy p, robust penalty ω, scenario s.	Generate employment
$REper_j \longleftarrow$ Percentage of generated electricity from RE of policy p, robust penalty ω, scenario s.	Generate RE generation percentage
$Cost_j \longleftarrow$ Total cost of policy p, robust penalty ω, scenario s.	Generate total cost
$Emis_j \longleftarrow$ Emissions of policy p, robust penalty ω, scenario s.	Generate emission
$Soc_j \longleftarrow$ Total social cost expected of policy p, robust penalty ω, scenario s.	Generate social cost
$PPD_j \longleftarrow$ Power-plant-type dependency score of policy p, robust penalty ω, scenario s.	Generate power-plant-type dependency score
end for	
end for	
$INP_{jx}, \longleftarrow$ SBM_input $(Cost_j, Emis_j, Soc_j, HHI_j)$	Define inputs for SBM
$OTP_{jy} \longleftarrow$ SBM_output $(Gen_j, Emp_j, REper_j)$	Define outputs for SBM
$SLK_{jxy} \longleftarrow$ SBM (INP_{jx}, OTP_{jy})	Run SBM
$Eff_j \longleftarrow$ Eff_score (SLK_{jxy})	Convert slacks into efficiency score
return Eff_j	First-stage efficiency score
end function	
function Second_stage_Efficiency_Measurement:	
for u **in** U **do**	Focused uncertain factor
$INP_{ukx}, \longleftarrow$ SBM_input $(Cost_{uk}, Emis_{uk}, Soc_{uk}, HHI_{uk})$	
$OTP_{uky} \longleftarrow$ SBM_output $(Gen_{uk}, Emp_{uk}, REper_{uk})$	
$SLK_{ukxy} \longleftarrow$ SBM (INP_{ukx}, OTP_{uky})	
$Eff_{uk} \longleftarrow$ Eff_score (SLK_{ukxy})	
end for	
return Eff_{uk}	Second-stage efficiency score
end function	

5.6. Empirical analysis

5.6.1. Case study: Thailand

To illustrate the applicability of the proposed model, a case study of Thailand energy planning was conducted. The parameters of the modified model for the study are updated from 2018 values used in [11] to the more current 2020 values [48]. The targeted year is 2032, which is one of the 5-year milestones in the 20-year PDP2018 development plan. In the targeted year (2032), demand (with an expected annual increase of 3.13%) is expected to be 320,761 gigawatt-hours [9].

Using official Thai documents, three different compensation rates (SC_i) were set in the model, based on the expected social damage from the different types of power plants [67]. (For details on the rate of compensation, please refer to Appendix C.) Since SC_i in the social cost function is already in the same monetary unit as the cost function, w_{social} is equal to w_{cost} which is set to 1. In order to convert the emission function to have the monetary units, $w_{environment}$ uses the carbon tax rate.

5.6.2. Assumptions and data

The following assumption were made in the study: (1) there are 27 scenarios of uncertainty (s), with probability of occurrence (p_s) defined according to [11]; (2) the weighted average cost of capital is stable at 5%; (3) the currency conversion rate from U.S. dollars (USD) to Thai Baht (THB) is 33/1; (4) the carbon tax rate is 1 U.S. dollar per ton of carbon dioxide equivalent (USD/tCO_2e); (5) commissioned new thermal and combined-cycle power plants already include carbon capture storage systems.

Both fossil-fueled power plants and renewable energy power plants are incorporated into the model. The fossil-fueled include coal-fired thermal plants (Coal), combined-cycle plants using natural gas (NG), combustion turbine plants using fuel oil, and diesel power plants. The renewable energy power plants include the hydro power plants, solar photovoltaic plants (Solar PV), wind turbine plants, biogas plants, biomass plants, and municipal waste plants.

Despite the fact that other power plant types, such as plants using concentrated solar power (CSP) and energy storage, have high potential for increasing the penetration of RE, they were not included in the case study for reasons of feasibility. CSP plants mainly rely on solar direct normal irradiation (DNI) [64], which, to make a CSP plant feasible, should be in the range of 1,600 to 2,000 kWh/m^2/year [66]. However, the average DNI in Thailand is only in the range of 949 to 1,388 kWh/m^2/year [65]. Thus, solar CSP power plants were considered infeasible in the case study. Regarding energy storage, a second limitation arises from the fact that the capital expenditure and operational costs of energy storage in the targeted year of the empirical study are expected to be in the range of 532 to 1,327 USD/kW and 13.31 to 33.17 USD/kW/year, respectively [59], which is substantially higher than is the case for other power plant types. Given the upper limit cost constraint in the proposed model, including energy storage in the case study was considered infeasible.

Detailed plant specifications—including the technical specifications of each power plant type, the capital expenditures and operational expenditures for each power plant type, historical data on the power plant's downtime, and the plant's carbon capture storage—are derived from multiple sources [48,56,59,60,80,81].

5.6.3. Energy mixes

Seven different energy mixes resulting from differences in policy and robust penalty are determined through the modified model using CPLEX [68]. In each iteration, the decision variables—C_{is}, E_{is}, and N_{is} —for each power plant of type i for each scenario s are optimized.

Changes in energy policy alter the structure of the energy mixes in different ways. Figure 5-1 shows the ranges of the optimal energy mixes of the seven energy policies under the various scenarios of uncertainty. The optimal energy mix is determined from the summation of decision variables C_{is} and the capacity of existing power plants. The vertical axis represents total capacity in megawatts for each group of power plants. The bold lines in the boxplots indicate the median value; the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The "X" markers indicate weighted average capacity under the probability of occurrence of the scenarios of uncertainty. The bounds of all possible outcomes are evident in the boxplots. Figure 5-2 shows the range of optimal generated electricity by group of power plants. The ranges of optimal generated electricity are derived from the summation of decision variables E_{is} and N_{is}. The vertical axis represents total generated electricity in gigawatts for each group of power plants.

The boxplots in Figure 5-1 and Figure 5-2 allow for a number of significant observations: First and foremost, the boxplots in Figure 5-1 indicate that an increase in ω reduces the capacity variation between the scenarios. In exchange for reducing capacity variation, higher power plants capacity is required in every scenario. Focusing only on minimizing total costs under the controlled constraints, **BASE** promotes generated electricity from power plant types that have a low levelized cost of energy (LCOE) but cause high social damage (e.g., a hydro power plant) or cause moderate emissions (such as NG). In **ESC1** and **ESC1000**, there is a significant capacity expansion and generation increase for RE power plants. The generated electricity from the fossil-fueled power plants is reduced, despite the fact that their capacity is fixed to ensure dependable backup capacity. It should also be noted that the capacity variation of **ESC1** is fixed; hence, increasing ω as in **ESC1000** does not provide a significant change in capacity variation.

In **SEC1** and **SEC1000**, social impact reduction is the first priority. Commissioning new power plants is scaled back, especially in the case of hydro power plants due to their high social damage from both construction and operation. Moreover, with the constraint of required dependable capacity from base-load power plants, fossil-fueled power plants that involve moderate social damage (such as the case with NG) generate the greatest share of electricity relative to the other policies. Lastly, the **Weights1** and **Weights1000** appear to produce intermediate results among the alternatives.

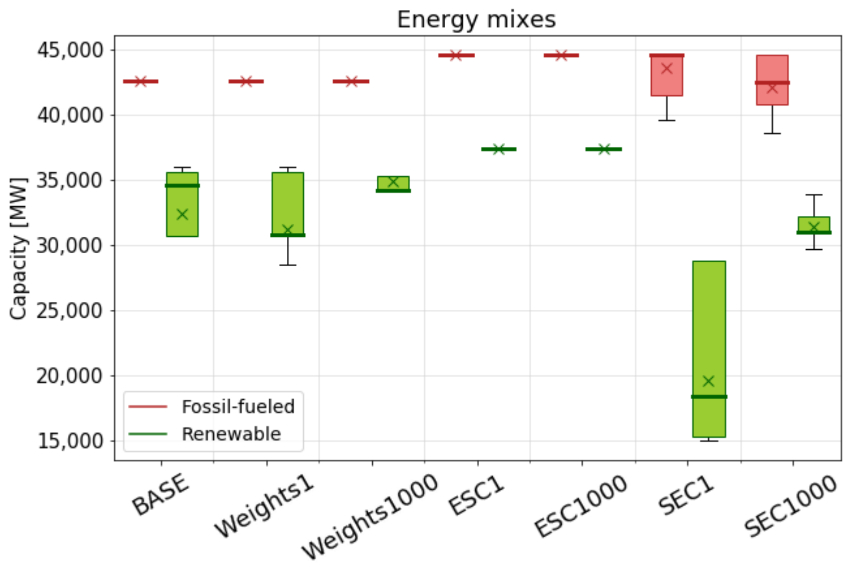

Figure 5-1. Optimal energy mixes of the seven energy policies under the scenarios of uncertainty.

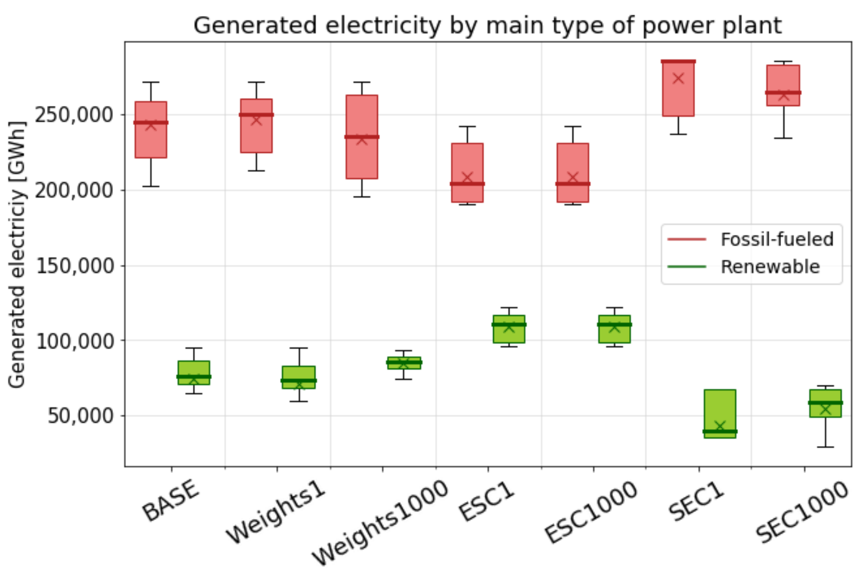

Figure 5-2. Optimal generated electricity by main type of power plant.

Figure 5-3 shows the bounds of the possible total cost, total emissions, total social cost, and power-plant-type dependence scores of the seven policies resulting from the different scenarios for each DMU. Figure 5-4 shows the ranges of possible total employment and the proportion of generated electricity from the RE power plants of each DMU.

The results in Figure 5-3 and Figure 5-4 indicate that the optimized energy mixes and the generated electricity conform with the policy. Under the single-objective function minimizing total cost, **BASE** clearly produces the lowest weighted-average total cost. The high total cost relative to total emissions and total social costs has **Weights1** and **Weights1000** prioritize the cost function but still account for the other objective functions. As a result, **Weights1** has a slightly higher total cost (18,174 m.USD) than **BASE** (18,185 m.USD), and **Weights1000** (18,301 m.USD) has a higher total cost than **Weights1** in order to reduce the capacity variation.

With the promotion of RE power plants and the reduced use of fossil fuel-fired plants, the total emission variation boxplots show that **ESC1** and **ESC1000** have distinctively lower emissions. Moreover, **ESC1** and **ESC1000** have the lowest dependence on the main power plant type, NG. In terms of total social cost variation, **SEC1** has the lowest social cost, based on its reduced expansion of new power plants. As a result, this policy relies primarily on NG power plants, which leads to high emissions and high power-plant-type dependence. It should be noted that **SEC1000** has a much higher social cost than **SEC1** due to the attendant capacity expansion to stabilize the energy mix.

The promotion of employment is mainly from power plant capacity expansion. As a result, an inverse relation between total employment and total social cost is apparent. Although the proportion of RE plants is inversely related to total emissions, the relationship is not exact since some RE power plants, including biogas, biomass, and municipal waste power plants, emit greenhouse gases. The multiple tradeoffs between the multi-aspect results featured here confirm the need for efficiency measurement as a way to determine the optimal energy policy.

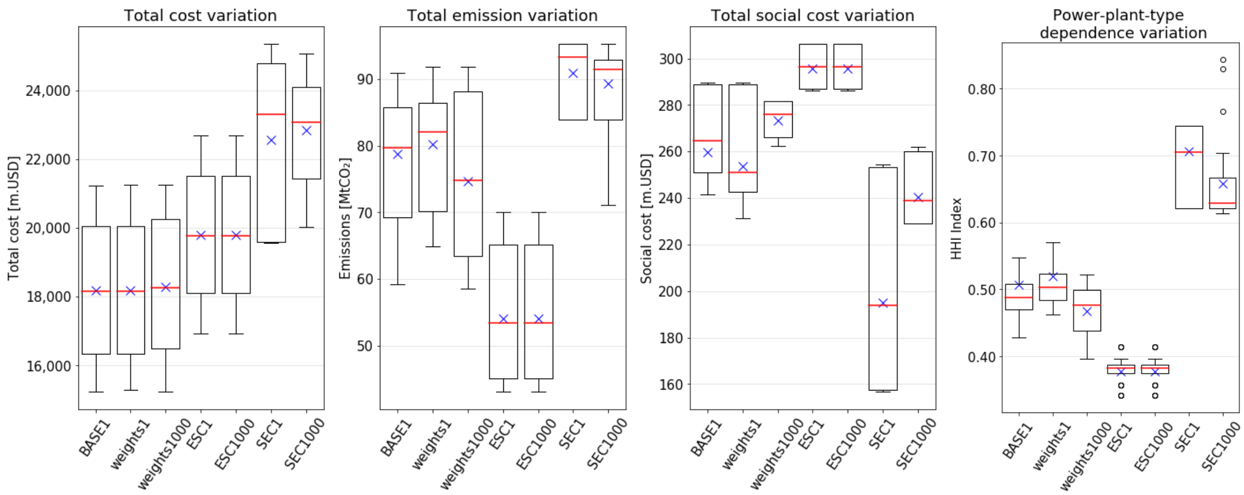

Figure 5-3. Input variation for the seven policies.

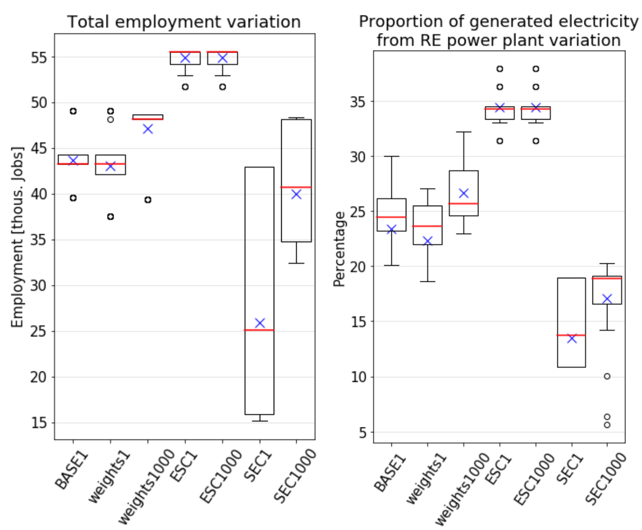

Figure 5-4. Output variation for the seven policies.

5.6.4. Efficiency measurement

DEAFrontier software [82] was used to determine the output slacks and input slacks of each DMU. The resulting slacks were converted into the relative efficiency score of each DMU through Eq. 3: $\rho = \frac{1-1/m\sum_{i=1}^{m} s_i^-/x_{io}}{1+1/s\sum_{r=1}^{s} s_r^+/y_{ro}}$. Given 27 scenarios of uncertainty and 7 energy policies, there were 189 DMUs to be measured in this case study. For each DMU, total cost, total emissions, total social cost, and power-plant-type dependence score were designated as constituting the four-dimensional inputs; total generated electricity, total employment, and the proportion of generated electricity from the RE power plants were designated as constituting the three-dimensional outputs. The boxplots of the efficiency score variation for each energy policy are given in Figure 5-5. The circles outside the boxes indicate outliers.

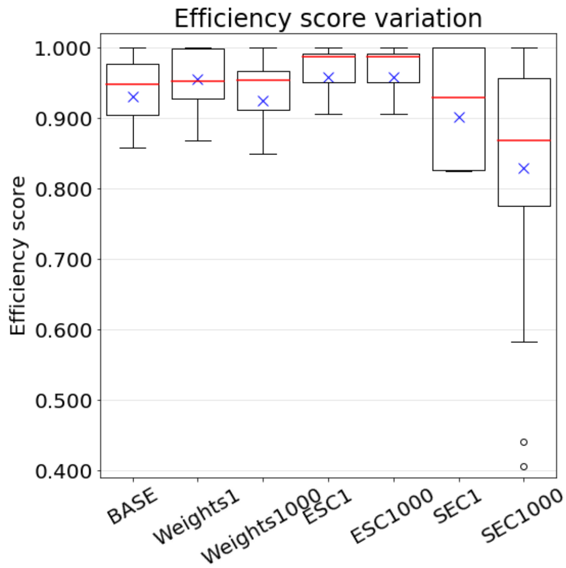

Figure 5-5. Efficiency score variation for seven policies.

Under the assumed scenario of uncertainty, the boxplots show that the weighted-average efficiency scores for the various policies are quite close to one another. **ESC1** and **ESC1000** both have the highest weighted-average score (0.958), while the score for **Weights1** was 0.955. The score for **BASE**, **Weights1000**, and **SEC1** were 0.930, 0.925, and 0.901, respectively. **SEC1000** had the lowest weighted-average score (0.829). The relatively minor differences in the weighted-average efficiency scores for the various policies conform to the expectation indicating that making a final decision regarding the appropriate energy policy is not possible at this point. Consequently, a second-stage efficiency measurement is required.

5.6.5. Second-stage efficiency measurement

Sensitivity to the uncertain factors

Using a scenario tree, various scenarios of uncertainty were generated from the three main uncertain factors: the demand scenario, capacity factor (CF) improvement in RE plants, and RE cost reduction. The sensitivity of the efficiency scores to the three uncertainties was assessed and the average standard deviation of the efficiency scores for the various scenarios was determined. The results are shown in Figure 5-6. As shown in the figure that, the demand scenario caused the highest average score standard deviation (0.038), while the CF improvement in RE plants produced an average score standard deviation of 0.027. The reduction in RE cost produced the lowest average score standard deviation (0.009). Based on these results, the demand scenario was selected for group-separated efficiency measurement.

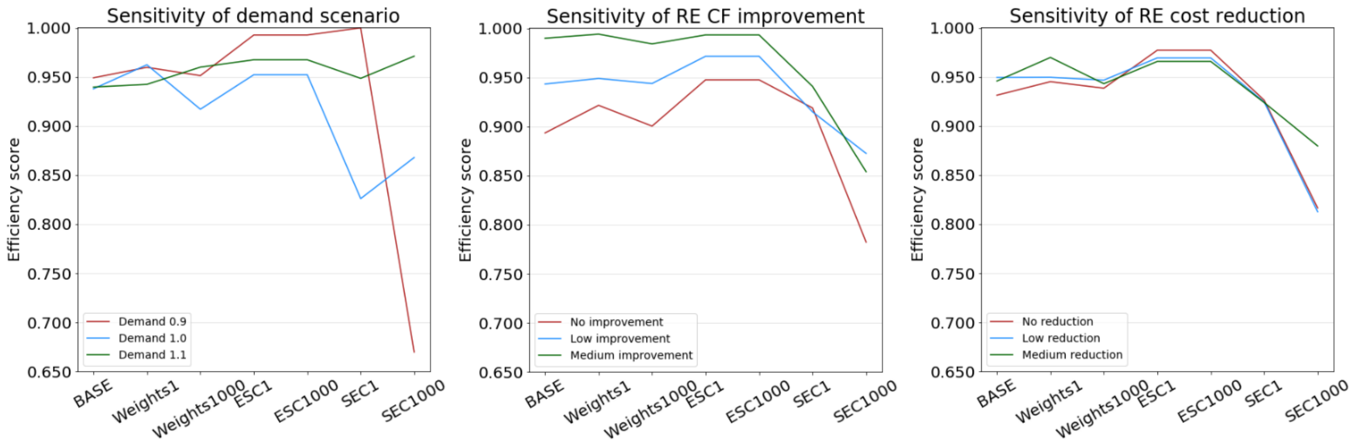

Figure 5-6. Sensitivity of efficiency score to the uncertain factors.

<u>Group-separated efficiency score</u>

The 127 DMUs were separated into three groups according to the demand scenario: demand that is 10% lower than the forecast (Demand 0.9), demand that is equal to the forecast (Demand 1.0), and demand that is 10% higher than the forecast (Demand 1.1). Since the DMUs under the same demand scenario all have the same amount of the total generated electricity (GEN_j), GEN_j can be omitted from the demand-scenario-separated efficiency measurement. This means that the DMUs have two outputs: Emp_j and $REper_j$, and the same four inputs: $Cost_j$, $Emis_j$, Soc_j, and PPD_j.

With 9 scenarios of uncertainty and 7 energy policies, there were 63 DMUs to be measured in each of the three demand-separated groups. Figure 5-7 shows the boxplots of the efficiency score variation for each energy policy in each demand-separated group. In every demand scenario, **ESC1** and **ESC1000** have the highest weighted-average efficiency score, while **SEC1** has the lowest. The boxplots of the demand scenario show that the efficiency score of **SEC1000** is directly related to the increase in projected demand. **BASE**, **Weights1**, and **Weights1000** have intermediate efficiency scores. It should also be noted that in every demand scenario, **Weights1000** has a higher weighted-average score than **Weights1**.

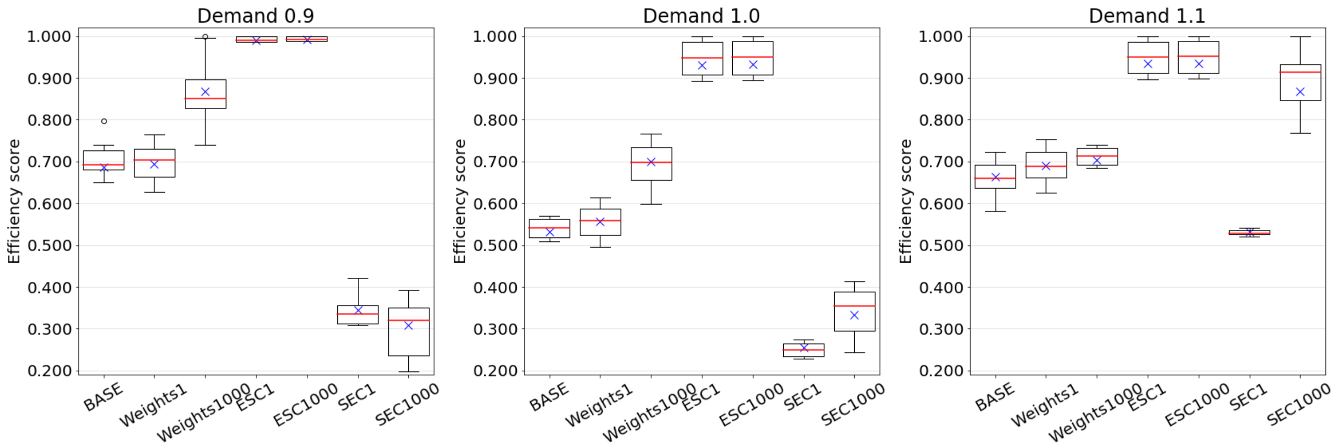

Figure 5-7. Efficiency score variation separated by demand scenario.

<u>Group-separated sensitivity ratio</u>

The group-separated sensitivity ratio, taken from the concept of a meta-frontier production function, is the ratio of the overall efficiency score from the first-stage efficiency measurement to the group-separated efficiency score from the second-stage efficiency measurement. A larger ratio indicates that the efficiency score has a greater sensitivity to the demand scenario. The ranges of the group-separated sensitivity ratio for each energy policy are illustrated in Figure 5-8. As indicated by the boxplots in Figure 5-8 figure, **ESC1** and **ESC1000** are the least sensitive to the demand scenario, while **SEC1** appears to have the greatest sensitivity. It can be inferred, then, that **ESC1** and **ESC1000** are robust to the highest-sensitivity uncertainty factor.

Given these considerations, the preferred energy policy in the case study is **ESC**, the energy policy having a lexicographical ordering that prioritizes environment first, followed by social damage, and cost. This policy has the highest weighted-average efficiency score, is robust to the most fluctuating factor, and is invariant with respect to changes in the robust penalty (ω).

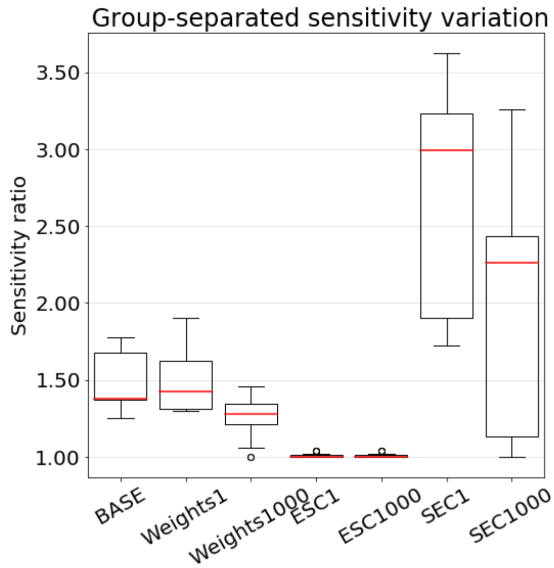

Figure 5-8. Group-separated sensitivity ratio variation.

5.6.6. Comparison with the unmodified benchmarking method

From the empirical results, it seems clear that the proposed method which appends choices of multi-objective functions to the optimization model and then determines the optimal energy policy using the efficiency measurement method, significantly improves the model's capacity to meet specified multi-aspect conditions while keeping the compensation low. In the case study, when the original base case (**BASE**) is replaced by **ESC**, the direct economic costs and social costs rise only slightly (by 8.94% and 13.89%, respectively), while substantial improvements are evident, including reductions in total emissions and the power-plant-dependency score (by 31.41% and 25.59%, respectively). At the same time, it increases total employment as well as the proportion of generated electricity from RE power plants (by 25.73% and 47.39%, respectively). These results should encourage policy makers to consider appending a variety of policy prioritizations and applying efficiency measurement methods when attempting to determine the optimal energy mix.

5.7. Discussion

As indicated by the empirical results described here, appending multi-objective functions to the optimization model provides a way to address the broader aspects of energy planning. However, appending these multi-objective functions alone is not enough. The study shows that multi-aspect efficiency measurement is required in order to identify the final optimal energy mix. Accordingly, the key finding of this study is that the proposed model can be used to determine the appropriate energy policy—one that optimizes satisfaction in terms of the key energy planning aspects (i.e., energy needs, economic cost, environmental impact, energy security, social impact, and social benefit), while meeting the given set of constraining conditions and taking into account the various scenarios of uncertainty. By applying the proposed model, the challenge of prioritizing aspects that typically require complex policy-level data and decision making can be mitigated using an efficiency measurement method to identify the best policy from all the possible results.

It may be argued that consideration of the multi-dimensional aspects of energy planning can be accomplished by including more restrictive and inclusive constraints in the optimization model. However, this can lead to biased results stemming from the consequent limitations placed on the predefined space of possible solutions. Moreover, setting constraints that are too restrictive would render the problem more difficult to solve. The proposed model shows that only the most important constraints should be set first, allowing efficiency measurement to ultimately determine the best of the optimal energy mixes under the more flexible space of the possible energy mix solutions.

Several policy recommendations can be made based on the empirical study. First, the results provide quantitative support for policy makers seeking to establish an efficient energy policy that meets the multi-aspect requirements of energy planning while taking into account uncertain future projections. The analysis shows that meeting the broader requirements of energy planning by promoting environmental, security, and social benefit aspects involves relatively minor monetary and social damages tradeoffs. Moreover, given the aim of net-zero emissions in the future, the prioritization of reducing total emissions in the case study represents a promising start.

Chapter 6
Concluding Remarks

6.1. Conclusion

This study proposes a framework that combines the concepts of an efficiency measurement and a multi-objective optimization model in order to determine the most efficient energy mix considering the multi-dimensional aspects of energy requirements and various uncertainty scenarios. Extending the focus beyond the Energy Trilemma (i.e., energy affordability, energy security, and environmental protection), the proposed model incorporates aspects of social impact and social benefit.

For the efficiency measurement, a pragmatic efficiency assessment of power plants was proposed. The study is the first to determine the energy efficiency while simultaneously considering the combined impact of security, economic, and ecological factors. The empirical study used historical data from 37 power plants in Thailand collected over a 12-quarter period. Stochastic frontier analysis with inefficiency effects was used to estimate the efficiency of the power plants and to determine the effects of explanatory variables. The empirical results indicated that the total average technical efficiency was 0.7969. Thermal power plants were the most efficient power generation facilities. Renewable energy facilities tended to be more efficient than fossil fuel plants. The results showed that plant capacity positively affected efficiency, while plant age had a negative effect. Base-load power plants had higher efficiency scores than peak-load plants. The results confirmed that an increase in the carbon tax reduced the efficiency of fossil fuel-powered plants. The peak-load fossil fuel-powered plants that use fuel oil and diesel were most negatively affected by the implementation of a carbon tax and were the least efficient types of power plants under all scenarios. The findings showed that starting off with small carbon taxes had a high marginal impact on the attractiveness of renewable energy.

For the energy planning optimization model, a hybrid stochastic robust optimization and robust optimization model to determine the best energy mix was proposed. The proposed model considers uncertainty in future projections, including those associated with future demand, technological advancements in renewable energy power plants, cost reductions in renewable energy, social impact fluctuations and reliable capacity. For security, reliable capacity to meet projected peak demand is necessary to ensure that the system is immunized against all possible outcomes. Thus, the risk of power outage is dealt with as a worst-case robust optimization. Other uncertainties are addressed using a scenario-based stochastic robust optimization methodology. Social impact, one of the critical factors in energy planning, is incorporated into the model, which makes containing any social impact fluctuations resulting from different scenarios essential. To this end, the bounds of a potential optimal energy mix are controlled in the model by the defined function of social impact variation. To demonstrate its use, the proposed model was first applied to energy planning in Thailand. The model results show the range of optimal energy planning corresponding to the different input scenarios. It was found that natural gas power plants, solar photovoltaic plants and large hydro power generation facilities represent the majority of total capacity in the grid. A comparison of capacity and total cost variation indicated that, as the weight coefficient increases, the deviation of social impact is markedly reduced, with only a small rise in total cost. In order to demonstrate its broad applicability, the model was also applied to the energy situation in Vietnam. The results were consistent with the case of Thailand. Thus, the model results provide support for policy makers seeking to enhance system stability.

In the final phase of the study, various multi-objective functions were appended to the capacity expansion model in the second phase in order to include some of the broader aspects of energy planning. A slacks-based measure of efficiency methodology was then applied to determine the best energy mix from the set of results produced by the modified model. Energy efficiency was measured using the energy mix's three outputs to be maximized (including total generated electricity, direct employments, and percentage of generated electricity from renewable energy) and four inputs to be minimized (including total cost, carbon dioxide emission, total social cost, and power-plant-type dependence score). To demonstrate the applicability of the proposed approach, energy planning in Thailand was used as a case study. It was found that adjusting the order of prioritization of the appended objective functions—the cost function, the emissions function, and the social functions—changed the optimized energy mixes. The inability to determine in the first-stage efficiency measurement the best energy mix from the marginal differences of efficiency scores between the various energy mixes means that a second-stage group-separated efficiency measurement would be necessary. Sensitivity analysis was conducted to investigate the effects of the uncertainty factors on the efficiency score, revealing that the demand scenario caused the greatest fluctuation. The subsequent group-separated efficiency measurement grouped by demand scenario showed that the lexicographical ordering that prioritized environment first, followed by social damage and then cost (designated as ESC), had the highest weighted-average efficiency score for all demand scenarios. It was also shown that the energy mixes of ESC were the least sensitive to the demand scenario. A comparison with the unmodified benchmarking method confirmed that the proposed method was considerably better at meeting the multi-aspect requirements (environment, security, and social benefit) with only moderate tradeoffs (in terms of monetary and social impact).

The study established that to effectively implement the proposed model, the various choices of the multi-objective function are to be generated first, allowing the two-stage efficiency measurement method to then determine the best of the optimal energy mixes from all the possible first-stage results. Accordingly, the empirical results provide quantitative support for policy makers seeking to determine an efficient energy policy that maximizes the satisfaction of multiple requirements, while taking into account various scenarios of future uncertainties.

6.2. Future Research

In order to be implemented in other countries for the efficiency measurement, appropriate adjustments to the production function are recommended. For instance, the definition of social cost can be modified based on social-impact assessments that are tailored to specific areas. Further, explanatory variables other than those used in this study, such as ownership (public or private) can also be tested if they affect the efficiency scores.

The proposed optimization model can be further developed by including more uncertainty factors such as fuel costs, and carbon taxation policy. With some adjustments to technical specifications such as the capacity factor for renewable technologies, costs, and environmental limits, the model can be applied in other locations. Instead of using capacity factor upper and lower limits as constraints in the optimization model, load factor function of generator could be used. Additionally, the social impacts penalty function can be modified to be practically suitable for determining the future optimal energy mix in different situations. Energy planning in the empirical studies described in section 4 extended over a period of 12 years; however, a longer energy planning horizon can be projected.

Further aspects in the efficiency measurement can be developed; for example, fuel consumption, fuel dependency by type and source, and ecological footprint might be considered. Additional choices of energy policy could be appended, using different priority orders in the lexicographical method and different weights in the weighted-sum method. The prescribed group-separated efficiency measurement might be further applied to a factor of interest in order to prepare for the uncertain future.

Applicability of the proposed model is not limited to the energy planning of Thailand or another ASEAN's member country. More variety of power generation facilities, such as battery energy storage, power to gas, hydrogen storage, pumped-storage hydro power plant, concentrated solar power, and tidal power, with their technical-economic specifications can be appended into the proposed model. With some minor modifications to the technical specifications of power plants, the limits and requirements of energy planning, and the scenarios of uncertainty, the model could be effectively applied in a variety of situations and locations.

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Appendix

Appendix A

The technical specifications data for the power plant types, historical data on the probability of power plant downtime and the specifications of carbon capture storage that were derived and used as inputs in the model are listed in the following tables:

Table A - 1. Technical specifications of power plants in the Thailand case studies

Power plant type	EC_i [a] [MW]	Dependable Capacity Factor [a]	Lf_i [a] [Year]	EM_i [b]	EL_i [b]	UC_i [b] [USD/MWh]	EE_i [b] [kgCO2eq./kWh]	PT_i [b] [USD/kW.Yr]
Combined-cycle: natural gas (NG)	15,797	1	30	0.30	0.80	67.88	0.438	2.655
Thermal: coal (Coal)	2,903	1	30	0.30	0.90	33.94	0.905	5.309
Combustion turbine: fuel oil	320	1	30	0.01	0.80	303.03	0.880	3.982
Diesel	60	1	30	0.05	0.80	606.06	1.000	3.982
Biomass	956	0.52	20	0.15	0.60	72.42	0.225	2.655
Biogas	346	0.52	20	0.15	0.60	84.55	0.168	2.655
Garbage	284	0.52	20	0.15	0.60	72.42	0.100	5.309
Large hydro	5,897	0.77	40	0.05	0.25	25.85	-	5.309
Small hydro	151	0.77	40	0.05	0.40	33.03	-	2.655
Solar PV	2,573	0.42	25	0.05	0.15	136.67	-	2.655
Wind turbine	1,353	0.14	30	0.05	0.15	123.94	-	2.655

Power plant type	NE_i [c] [kgCO2eq./kWh]	VO_i [c] [USD/MWh]	$CX_{is}, \forall s$ [c] [USD/kW]	$FO_{is}, \forall s$ [c] [USD/kW.Yr]
Combine-cycle: natural gas	0.049	40.42	1,681	16
Thermal: coal	0.113	32.82	5,582	73
Biomass	0.225	36.25	2,068	-
Biogas	0.168	61.45	1,937	-
Garbage	0.100	45.13	1,556	-

[a] Derived from [28], [b] Derived from [35], [c] Derived from [23,24,38]

Table A - 2. Historical data on probability of power plant downtime (Derived from [20])

Power plant type		Coal	Combined-cycle	Combustion turbine	Diesel	Hydro	Others
Averaged probability of plant downtime		0.2524	0.1396	0.0966	0.0958	0.1358	0.2390
Random variability from average probability of plant downtime per year	2015	0.8637	1.0458	0.9834	1.1065	1.0898	1.1464
	2016	0.9231	1.0888	1.0663	0.8351	0.9867	1.0377
	2017	1.0182	0.9957	0.9731	0.8559	0.8247	0.8368
	2018	1.1212	0.8668	0.9627	1.0752	1.0825	0.9079
	2019	1.0737	1.0029	1.0145	1.1273	1.0162	1.0711

Table A - 3. Carbon capture storage specifications (Derived from [38])

Specifications	CCS for Coal-fired	CCS for NG-fired
Emission intensity reduction [%]	87.47%	88.76%
Capital expenditure [USD/kW]	1,596	845
Fixed operation and maintenance costs [USD/kW]	19.09	5.10
Variable operation and maintenance costs [USD/MWh]	8.20	1.12
Capacity (at 90% plant factor) [m.kg.CO_2/yr.MW]	6.88	2.42

Table A - 4. Projected fuel capacity limits of Thailand (Derived from multiple sources: [24,39–43])

Fuel	Power plant Heat rate [MMBTU/kWh]	Fuel limits [ktoe]
NG	7,732	48,420
Coal	10,551	17,385
Fuel Oil	11,135	349
Diesel	11,135	716
Biomass	13,500	19,277
Biogas	13,500	1,992
Garbage	16,000	3,616

Appendix B

Detailed technical specifications of power plants for the model that were used as input parameters in the case of Vietnam are listed in the following tables:

Table B – 1. Capacity of existing power plants and their levelized cost of energy (Derived from multiple sources: [36,37,44,45])

Power plant type	Gas turbine	Thermal: coal (Coal)	Biomass	Large hydro	Small hydro	Pump storage	Solar PV	Wind turbine
EC_i [MW]	13,294	13,527	255	14,371	4,025	2,250	3,623	771
UC_i [USD/MWh]	104.97	63.54	72.38	48.62	70.22	115.46	132.04	71.82

Table B – 2. Requirements of energy planning (Cited from [36,37])

Requirement	Inputted parameter
Total projected demand [m. kWh]	571,752
Peak demand capacity [MW]	55,000
Emission limit [kgCO_2eq./kWh]	0.480
Cost limit [USD/MWh]	89.00

Appendix C

Direct employment generated by type of power plant and social damage compensation rate grouped by type of power plant that were derived and used in the model are listed in the following tables:

Table C-5. Direct employment generated by types of power plant (Derived from [30]).

Power plant type	Commission, manufacturing, and decommission (Job-years/MW)	Operation & maintenance (Jobs/MW)	Fuel procurement (Jobs/GWh)
Combine-cycle using natural gas	4.1	0.1803	0.1288
Coal-fired thermal	17.5	0.1305	0.1476
Combustion turbine using oil	4.9	0.1375	0.1948
Large hydro	9.6	0.3170	0
Small hydro	25.7	1.1400	0
Solar PV	26.5	0.3762	0
Onshore wind	9.1	0.2040	0
Offshore wind	21.1	0.3900	0
Biomass	26.1	1.3560	0.3323

Table C-6. Social damage compensation rate by type of power plant (Derived from [33]).

Type of power plant	Social damage compensation rate (USD/MWh)
High impact: Coal-fired thermal, hydro	660
Medium impact: Fuel oil, diesel	495
Low impact: Natural gas, RE	330