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Efficiency Measurement of an Energy Planning Model Considering Cost, Emission, and Social Impact

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ABSTRACT

This study proposes a modified energy planning model that considers a broad range of future uncertainties. Modifications to hybrid stochastic robust optimization and robust optimization methodology allow for the introduction of multi-objective functions that reflect the various dimensions of energy planning including cost, emission, and social impact. Changing the priorities of the objective functions generates different energy policies, which are then compared. Data envelopment analysis is applied to measure the energy efficiency of each optimal energy policy produced by the energy planning model. Energy efficiency is defined as the ability to satisfactory address five main aspects—cost, emissions, social impact, employment, and security. An updated power development plan for Thailand is used as an illustrative case study. Empirical analysis indicates that a policy that prioritize the environment first, followed by social impact and cost, is the most efficient among the five alternatives considered. Results from the case study offer quantitative support for policy makers seeking to devise an efficient energy policy that meets extensive requirements while still dealing with the bounds of uncertain future projections.

Keywords: energy policy, efficiency measurement, stochastic robust optimization, robust optimization, data envelopment analysis

1. INTRODUCTION

Energy development across countries tends to focus on three dimensions of energy planning: energy security, energy equity, and environmental sustainability [1]. However, it has been shown in numerous studies that other aspects, such as employment and social damage, should also be taken into consideration when formulating an energy plan [2,3].

In order to set and achieve relevant energy development goals, appropriate multifaceted energy planning is necessary. In the field of energy planning, considering the uncertainties associated with various future projections is essential. To this end, approaches such as scenario-based stochastic optimization and worst-case-realization robust optimization are well-known methods that have been used in variety of studies [4–6]. The hybrid stochastic robust optimization and robust optimization (Hybrid SRO & RO) is an energy planning model that simultaneously considers uncertainties based on both scenario-based and worst-case scenario realization stemming from their practical condition [6]. The energy mixes resulting from the optimization model vary depending on the operative constraints and objective functions.

In energy planning, however, making energy mixes decisions by comparing alternatives with multi-dimensional characteristics can be difficult. Frontier-based efficiency measurement methods such as data envelopment analysis (DEA) are applicable in such cases since these approaches are not affected by differing indexes [3]. In the field of energy planning, such frontier-based methods have been reported in several studies [7,8].

Contributions of this paper are: (1) a modification of the energy planning model to meet broader and multi-objective requirements, and (2) decision making tool using an efficiency measurement method based on the above-mentioned multiple aspects of energy planning. To demonstrate the proposed methodology, power development of Thailand is served as an instructive case study.

2. MATERIAL AND METHODS

2.1 Hybrid stochastic robust optimization and robust optimization

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In the Hybrid SRO & RO model, scenarios of uncertainties (s) with assumed probabilities of occurrence (p_s) are generated for discrete projected demand levels, capacity factors and the cost of renewable energy. Moreover, the bounds of any potential optimal energy mix are controlled by a defined social impact variation function [6].

For each scenario, the model determines the values of decision variables that include new power plant capacity (C_{is}), electricity generated by existing power plants (E_{is}), and electricity generated by new power plants (N_{is}), with the objective of minimizing total cost. The control constraints of the model can be divided into five groups: security of supply, environmental protection, economic competitiveness, technical specifications of the power plants, and robust constraints. (For a detailed description of the mathematical equations specifying the objective functions and constraints, please refer to [6].)

2.2 Proposed model modification

2.2.1 Multi-objective functions

Rather than employing a single objective function focused solely on minimizing total cost in the Hybrid SRO & RO model, the model proposed here is modified to accommodate multiple objective functions. Based on the CPLEX optimization program [9] used to perform the calculations in the Hybrid SRO & RO model, the multi-objective functions are determined by either the lexicographic or weighted-sum methods.

In the lexicographic method, the priority (that is, the order) of the objective functions is determined according to their relative importance or significance [10]. The main advantage of this method is its simplicity and computational efficiency. Alternatively, the weighted-sum method converts the multi-objective problem into a mono-objective optimization problem [11].

2.2.2 Objective functions

This paper inclusively considers three specific aspects of energy planning—economic cost, emissions, and social cost. The economic cost function is established from the Hybrid SRO & RO model that includes annualized capital expenditure and operational expenditures for each power plant of a given type, measured in Thai Baht per year (THB/year).

The emissions function includes the total emissions associated with electricity generated by both new and existing power plants as shown in (1):

$$\sum_{s=1}^{S} p_s \left[\sum_{i=1}^{(T+T^o)} [EE_i E_{is} + NE_i N_{is}] \right] \qquad (1)$$

where T and T^o indicate the set of active power plants type and obsolete power plant type respectively. EE_i is the emission factor for existing power plants of type i and NE_i is the emission factor for new power plants of type i, both measured in tons of carbon dioxide per year (tCO_2/year).

Social cost is derived from the compensation provided to locals who are adversely affected by the operation of the power plants. The rate of compensation is based on the type of power plant per amount of generated electricity. The social cost function is thus set as:

$$\sum_{s=1}^{S} p_s \left[\sum_{i=1}^{(T+T^o)} SC_i [E_{is} + N_{is}] \right] \qquad (2)$$

where SC_i is the social compensation rate for a power plant of type i, measured in THB/year.

2.2.3 Scenarios of uncertainty: Demand forecast

The scenarios of uncertainty are set according to the Hybrid SRO & RO model with minor modifications. In all, there are 27 scenarios of uncertainties. The demand forecast scenarios include cases in which actual demand is 15% lower than the forecast, 10% lower than the forecast, and equal to the forecast (corresponding to the possible levels of economic decline resulting from the COVID-19 pandemic [12]).

The probability of occurrence for these scenarios is assumed to be 0.3, 0.4, and 0.3, respectively, based on the uncertainties associated with future increases in population and economic growth [13]. The other uncertainties in the model, including cost reductions and capacity factor increases in renewable energy are unchanged from those in the case study described in [6]. For further details, please refer to [6].

2.3 *Data Envelopment Analysis*

Data envelopment analysis (DEA) is a frontier-based efficiency measurement methodology 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. The "Farrell model" proposed in [14], the envelopment model, with the assumption of constant returns to scale (CRS), is formulated as follows:

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$$\begin{aligned}
&\theta^* = Min \quad \theta \\
&s.t. \quad \sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{io} : i = 1,2,\ldots,m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{ro} : r = 1,2,\ldots,s; \\
&\lambda_j \ge 0 : j = 1,2,\ldots,n.
\end{aligned} \qquad (\mathbf{3})$$

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.

3. CALCULATIONS

3.1 Decision Making Units, Inputs, and Outputs

The DMUs in this study are generated from the dot product of the different energy policies and scenarios of uncertainty. In order to efficiently meet the above-mentioned multiple requirements, each of the DMUs is defined to have four inputs and two outputs. The inputs and outputs are all derived from the optimized decision variables of the Hybrid SRO & RO model.

The inputs include total cost, total carbon dioxide emission, total social cost, and a power-plant-type dependence score for the cost, environmental, social and security aspects, respectively. The outputs are total generated electricity and employment as related to the energy and economic aspects, respectively.

3.1.1 Cost aspect: Total cost

The total cost of each DMU is derived from the cost function.

3.1.2 Environmental aspect: CO_2 emission

The total carbon dioxide emission of each DMU is derived from the bracketed term in the emission function $(\mathbf{1})$: $\left[\sum_{i=1}^{(T+T^o)}[EE_iE_{is} + NE_iN_{is}]\right]$.

3.1.3 Social aspect: Social cost

The total social cost of each DMU is derived from the bracketed term in the social cost function $(\mathbf{2})$: $\left[\sum_{i=1}^{(T+T^o)} SC_i[E_{is} + N_{is}]\right]$.

3.1.4 Security aspect: Power-plant-type dependency score

To ensure a secure energy supply, power plant diversification is required. Diversification lessens the vulnerability of the energy system to supply shocks and the market power of the various energy supply sources [15]. In this study, a power-plant-type dependency score is derived from the Hirschman-Herfindahl Index (HHI) [16]. Accordingly, the index measures the overall dependency of the units in the system. HHI of scenario s (H_s) is formulated as:

$$H_s = \sum_{i=1}^{N} s_{is}^2 \qquad (\mathbf{4})$$

$$s_{is} = \frac{[E_{is} + N_{is}]}{\sum_{i=1}^{(T+T^o)}[E_{is} + N_{is}]} \qquad (\mathbf{5})$$

where s_{is} is the proportion share of power plant type i in scenario s. The HHI values are in the range of [1/N, 1]. Higher HHI values imply greater energy system dependence on a single major energy supply source.

3.1.5 Energy aspect: Generated electricity

Total generated electricity is derived from the decision variables in the energy planning model ($E_{is} + N_{is}$), measured in gigawatt-hours [GWh]. Since the total demand for generated electricity is a critical constraint, the value of the total generated electricity will be equal on every DMU that shares the same amount of projected demand.

3.1.6 Economic aspect: Employment

Employment is expected from the commissioning, manufacturing, and decommissioning of new power plants [17]. Its value is calculated as the product of the employment factor for each power plant type (in job-years per megawatt [job-years/MW]) and the capacity of the new plant (C_{is}) (in megawatt [MW]). The employment factors for the various power plant types are listed in Table 1. For further detailed, please refer to [17].

Table 1. Employment factor for each power plant type.

Power plant type	**Employment [Job-years/MW]**
Natural gas	4.1
Coal	17.5
Fuel oil	4.9
Diesel	4.9
Large hydro	9.6
Small hydro	25.7
Solar PV	26.5
Wind: onshore	9.1
Biomass	26.1
Biogas	26.1
Municipal waste	26.1

3.2 Energy policies

Four energy policies were compared in the case study. The first three policies were set based on the lexicographical method, where the objective functions

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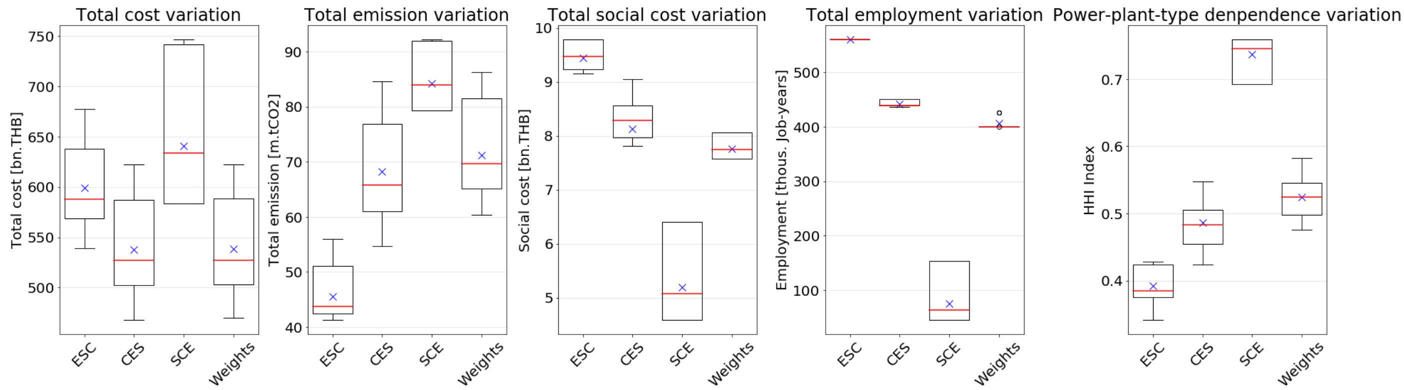

Fig. 1. Results for the four energy policies.

were ranked from highest priority to lowest priority. This produced the following three ordered priorities: Environment > Social > Cost (designated as the **ESC** order); Cost > Environment > Social (designated as the **CES** order); and Social > Cost > Environment (designated as the **SCE** order).

The fourth policy (designated as **Weights**) was based on the weighted-sum method, which was used to convert all of the objective functions to the same monetary units. The emission function was converted to equivalent monetary units by multiplying the amount of emissions by the carbon tax per unit amount; the cost and social functions were already in monetary units.

3.3 Case study: Thailand

A case study featuring Thailand's latest 20-year power development plan (Thailand PDP2018) was used to illustrate the applicability of the proposed model, as in [6]. To ensure currency, the parameters of the model were updated from the from 2018 values used in [6] to the more recent 2020 values [18]. These current parameters were derived from multiple sources [13,18–21] .

In developing the case study, it was assumed that (1) the conversion rate from US dollars (USD) to Thai Baht (THB) is 33 THB/USD, (2) the carbon tax rate is 30 Thai Baht per kilogram of carbon dioxide, and (3) commissioning new combined-cycle and thermal power plants already includes carbon capture storage systems.

4. RESULTS AND DISCUSSION

4.1 Energy mix results

The Hybrid SRO & RO model was solved using CPLEX [9]. In each iteration, C_{is}, E_{is}, and N_{is} were optimized for each power plant of type i for each scenario s.

The boxplots in Fig. 1 show the ranges of possible total cost, total emission, total social cost, total employment, and the power-plant-type dependency scores resulting from the different policies, along with the variation in results from the different scenarios. These results are derived from the optimal energy mixes of the Hybrid SRO & RO model. The bottom and top edges of the boxes indicate the 25th and 75th percentiles, respectively; the red horizontal line inside each box indicates the median value. The "X" markers identify the weighted average value using the probability of occurrence of the scenario. Note that the difference in policies changes the structure of the optimal energy mixes.

According to Fig. 1, the weighted average results correlate with the priorities assigned to the objective functions: That is, **ESC** tends to have the lowest total emission, while **CES** tends to have the lowest total cost and **SCE** tends to have the lowest total social cost. It can be inferred from Fig. 1 that total social cost is directly related to total employment, but inversely related to the power plant dependency score.

Notably, **SCE** appears to show higher variation in every aspect of the results. Moreover, **SCE** trades off distinctly higher costs and emissions in seeking to minimize the social cost. With results generally between those of the other policies, **Weights** appears to be a compromise policy.

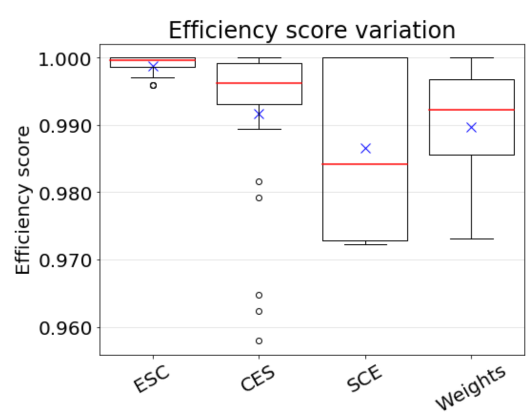

Fig. 2. Efficiency scores for the four energy policies.

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4.2 Efficiency scores

DEAP Version 2.1 [22] was used to determine the relative efficiency score of the DMUs. Since there were four different energy policies resulting from the Hybrid SRO & RO model, including **ESC**, **CES**, **SCE**, and **Weights**, with each policy having 27 scenarios, there were 108 DMUs in the case study.

Boxplots showing the efficiency score variation for each policy are shown in Fig. 2. Under the assumed scenario of uncertainties, **ESC** had the highest weighted average efficiency score (0.9988). **CES** had a weighted average score of 0.9922. **Weights** had a weighted average score of 0.9897, and **SCE** had the lowest weighted average efficiency score (0.9866).

4.3 Discussion

It can be inferred that the results shown in Fig. 1 directly shape the efficiency scores in Fig. 2, i.e., the high variation in **SCE** results produces a wide range of efficiency score, while the intermediate results associated with **Weights** produce intermediate efficiency scores. The boxplots in Fig. 2 also suggest that the **ESC** results are the least sensitive to changes in the uncertainty scenarios.

Given the proposed definition of energy efficiency and the realized uncertainties associated with the energy planning, it appears that the lexicographical ordering that priorities environment first, followed by social impact and cost (i.e., **ESC**), is the preferred policy in the illustrative case study.

4.4 Conclusion

This study proposed modifications of the hybrid stochastic robust optimization and robust optimization model that reflect the multi-dimensional requirements of energy planning including cost, emission, and social impact. Data envelopment analysis (DEA) was used to measure the energy efficiency of each optimal energy policy resulting from the modifications. Empirical analysis of Thailand's power development plan shows that the policy that prioritizes the environment first, followed by social impact and cost, is the most preferable policy among the five options. The main findings contributed from this study is the importance of the proposed decision-making approach, through the application of DEA, in order to efficiently meet multiple aspects of energy planning. Moreover, empirical results of the type reported here provide quantitative support for policy makers seeking to devise efficient energy plans that meet multi-aspect requirements, while taking into account uncertainties inherent in any energy planning process.

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