Regional-scale electricity planning incorporating demand uncertainty- A two stage stochastic programming approach

Yun-Hsun Huang[1], Jung-Hua Wu[2]

[1]Researcher, Industrial Economics and Knowledge Centre, Industrial Technology Research Institute

[2]Professor, Department of Resources Engineering, National Cheng Kung University

Abstract

Traditional electricity planning models regard electricity demand as a deterministic parameter (i.e. the electricity demand is given exogenously) to select power generation technologies. But in today's world, energy planners are facing tremendously complex environments full of uncertainty and risks, and electricity industry is also in an uncertain situation, where the electricity demand could not be predicted precisely. It is not reasonable to assume a certain power demand. In addition, most of electricity planning models require that total power output must satisfy the aggregate electricity demand; however, electricity demand patterns are considerably different for different regions. Therefore, an electricity supply planning model should be developed for handling demand uncertainty and diversity.

Stochastic programming has proven to be applicable to problems involving uncertainty. Hence, we adopt this method to divide generation investment decisions into two stages. However, it may lead to a large numbers of random variables, which tends to complicate the solution process. As a result, we also combine the scenario tree method and Monte Carlo simulation to reduce possible nodes and determine the future electricity demand values and probability.

This paper uses Taiwan's electricity sector as a case study for demonstrating the applicability of the developed model, where the region of Taiwan could be divided into four sub-regions, including north, central, south, and east to reflect regional electricity demand diversity. Finally, scenario analyses were conducted to evaluate the impact on the regional generation portfolios.

Keywords: Demand uncertainty; Two-stage stochastic programming; Monte Carlo simulation; Demand diversity

1. Introduction

Owing to the higher concentration of population in the northern region, Taiwan exhibits regional electricity imbalances between the north and the south regions. In 2014, the maximum power supplying capacity of northern region only accounted for 35% of the entire power system; however, its peak load amounted to 40% of the national electricity demand [1]. The electricity supply of the northern region is insufficient to meet its demand, and so the situation arises that power from the south is diverted to satisfy the load in the north. In other words, a large amount of power has to be transmitted over 345 kV extra high voltage (EHV) lines from south to the north, owing to the deficiency in the local electricity generation in the northern region. System disturbances caused by the tripping of EHV transmission lines may result in severe system instability. For instance, the collapse of the EHV transmission tower in 1999 initiated the tripping of the lines between southern and northern-central areas, resulting in a total system blackout and significant economic and industrial losses. In order to minimize the investment cost and the loss of transmission lines, and to prevent major blackout events, new generators should be installed close to load demanding areas to help achieve a balance between power supply and demand.

In addition, planning and constructing large-scale power plants and devices, such as power transmission and distribution lines, generally requires a substantial amount of lead time and huge capital investment. Taiwan is further hindered by its status as an island, which precludes its importation of electricity from other countries. Furthermore, the Taiwanese government decided to halt construction of the Fourth Nuclear Power Plant (Lungmen Nuclear Power Plant) in April 2014. The first reactor was sealed after the completion of safety checks, and construction of the second reactor was halted. Due to restrictions in nuclear power policies, the future expansion of nuclear power units is restricted. Nevertheless, as the economy progresses, the demand for electricity in Taiwan will continue to rise. Thus, regional-scale electricity planning is a crucial topic for Taiwan’s power sector.

The objective for this paper is to construct an electricity planning model that incorporates demand uncertainty and diversity. Using Taiwan’s electricity sector as a case study, we divide Taiwan into four regions, in order to consider the load diversity. The scopes of the four regions considered in this study are shown in Table 1 (excluding surrounding islands). The proposed model is designed to minimize the expected sum of discounted generation costs. The model also factors in the constraints of conventional electricity planning models. We then performed simulation analyses and observed the technology portfolios in various scenarios. Finally, some suggestions are made on the basis of the simulation results.

Table 1 Scope of each region [2]

Region	Scope
Northern region	Yilan, Taipei City, Taipei North, Taipei West, Taipei South, Taoyuan, Keelung Districts
Central region	Hsinchu, Miaoli, Taichung, Changhwa, Nantou Districts
Southern region	Yunlin, Chiay, Tainan, Xinying, Kaohsiung, Fengshan, Pingtung Districts
Eastern region	Hualien and Taitung Districts

2. Literature review

Traditional energy planning is based on the least-cost method. For example, the demand is mostly portrayed as price-inelastic. That is, deterministic demand is to be met at minimum cost [3-5]. A common feature of this approach is that they are formulated as deterministic mathematical programming models, ignoring the uncertainties of parameters. But in today's world, the energy planners are facing tremendously complex environments full of uncertainty and risks, and the electricity industry is in an uncertain situation. If uncertainties are not adequately identified and handled, the actual economic and feasible operation of the energy system may deviate from the optimal one. Therefore, the assessment of uncertainty in the modelling of the energy system has recently received considerable research attention [6].

Further investigation of the literature on optimization under uncertain conditions indicates that stochastic programming is considered as an appropriate approach for handling uncertainties in long term strategic planning, due to the incorporation of flexibility within a dynamic optimization framework [7-8]. This methodology has been applied to various fields, such as supply chain planning [9-10], process design and operation [11-12], and electricity supply planning [13-16]. However, there are different types of uncertainty in the optimal planning of an electrical system, for example, uncertainty in demand [17], uncertainty in economic parameters, such as energy price [8] and unit investment cost [16]; and uncertainty in technological parameters, such as efficiency. In most of the aforementioned studies, energy demand uncertainty is given the most significant attention among the different sources of uncertainties [6, 18]. This implies that the consideration of the uncertainty of electricity demand is of significant importance for an electrical system. Hence, our study integrates electricity demand uncertainty into the electric power system expansion, using stochastic programming to ensure flexibility regarding this uncertainty.

A major difference between the stochastic programming done in previous work and the work presented here is that the previous work merely required that total power output must satisfy the aggregate electricity demand, while this work extends that formulation to reflect regional electricity demand diversity.

Although stochastic programming can involve uncertain parameters, these parameters are most accurately described as continuous random variables. It is difficult to optimize directly in terms of continuous distributions. Hence, in most applications the continuous distributions are approximated by discrete distributions with possible realizations for the random variables. In general, a scenario tree is a set of nodes and branches used in stochastic programming models. Every node in the tree represents a possible state of the world at a particular time point and a position where a decision can be made. The first node in the scenario tree is defined as the root node, representing the initial situation. This is realized in our model by the value of the annual electricity demand in the current year. Any possible forward path from the root node to a node at the last time point is defined as a scenario describing a plausible realization of annual electricity demands over the time horizon.

However, previous studies have assumed that scenario trees are dependent on decision with a given probability. In contrast, our model incorporates Monte Carlo simulation to determine future annual electricity demand and their path probabilities, rather than assigning path probabilities arbitrarily. In summary, the potential impacts of uncertain electricity demand are accounted for by formulating a power system planning problem as a stochastic programming model. The scenario tree method and Monte Carlo simulation are integrated into the decision framework. Finally, the model has been applied for the case study of Taiwan's electricity sector.

3. Model description

A stochastic programming problem with recourse is referred to as a two-stage stochastic problem. In the first stage, a decision has to be made without complete information on random factors. After the values of random variables are known, recourse action can be taken in the second stage.

When the random variation of a stochastic parameter, such as electricity demand, is represented in the model endogenously, an approach based on the stochastic programming is intended. Stochastic programming with recourse has been basically founded on segregation of the decision variables into two distinct partitions. First stage variables are decided prior to the uncertainty realization. The second stage variables are associated with decisions that have considered uncertainty realization. Because the coefficients of the objective function in the proposed model are subjected to uncertainty, the first stage can be implemented in order to inform decisions on the investment (i.e. the installed capacity), while the second stage is used to evaluate the impact of variations in parameters related to the operation (i.e. power generation).

The objective function is expressed to minimize the expected sum of discounted generation costs, including fixed operation and maintenance (O&M) costs, investment costs, fuel costs, and variable operation and maintenance (O&M) costs. The development of a mathematical model for the objective function is described by the following.

3.1 Objective function

First Stage

Min z =

$$\frac{\sum_m^M \sum_i^I \sum_t^T cap_{m,i,t} \cdot fc_{m,i,t}}{(1+r)^t} + \frac{\sum_m^M \sum_i^I \sum_t^T x_{m,i,t} \cdot cc_{m,i,t}}{(1+r)^t} + \sum_w Prob_w \cdot Q(x, \xi^w)$$

Second Stage

$$Q(x, \xi^w) = \frac{\sum_m^M \sum_i^I \sum_t^T \sum_b^B \left(fuc_{m,i,t} \cdot (1 + fr_{m,i,t}) \cdot pp_{m,i,t,b,w} \cdot h_b\right)}{(1+r)^t} + \frac{\sum_m^M \sum_i^I \sum_t^T \sum_b^B (vc_{m,i,t} \cdot pp_{m,i,t,b,w} \cdot h_b)}{(1+r)^t}$$

1. Fixed operation and maintenance costs

$$\frac{\sum_m^M \sum_i^I \sum_t^T cap_{m,i,t} \cdot fc_{m,i,t}}{(1+r)^t}$$

Where m is generation technology; i is the region; t is the planning period (1…T); r is the discount rate.

$cap_{m,i,t}$: the cumulative installed capacity of technology m, in region i, during period t;

$fc_{m,i,t}$: unit costs of the fixed operation and maintenance of technology m, in region i, during period t.

2. Investment costs (for new capacity additions)

$$\frac{\sum_m^M \sum_i^I \sum_t^T x_{m,i,t} \cdot cc_{m,i,t}}{(1+r)^t}$$

$x_{m,i,t}$: new capacity additions for technology m, in region i, during period t;

$cc_{m,i,t}$: unit investment costs of technology m, in region i, during period t.

3. Fuel costs

$$\frac{\sum_m^M \sum_i^I \sum_t^T \sum_b^B \left(fuc_{m,i,t} \cdot (1+fr_{m,i,t}) \cdot pp_{m,i,t,b,w} \cdot h_b\right)}{(1+r)^t}$$

Where b is the block formed by the time axis on the load duration curve; w is the paths.

$fuc_{m,i,t}$: unit fuel costs of technology m, in region i, during period t;

$fr_{m,i,t}$: the growth rate of unit fuel costs of technology m, in region i, during period t;

$pp_{m,i,t,b,w}$: power output of technology m, in region i, during period t, in block b, in path w;

h_b: duration time of block b.

4. Variable operation and maintenance costs

$$\frac{\sum_m^M \sum_i^I \sum_t^T \sum_b^B (vc_{m,i,t} \cdot pp_{m,i,t,b,w} \cdot h_b)}{(1+r)^t}$$

$vc_{m,i,t}$: unit costs of variable operation and maintenance of technology m, in region i, during period t.

$Prob_w$: probability of path w.

3.2. Constraints

The following 13 constraints together with objective function, complete the model formulation.

Constraint 1: Capacity Transfer

$$cap_{m,i,t} = cap_{m,i,t-1} + x_{m,i,t} - retire_{m,i,t} \qquad m = 1, \ldots, M; i = 1, \ldots, I; t = 1, \ldots, T$$

Where $retire_{m,i,t}$ denotes the capacity of technology m, in region i that retired in period t. The cumulative installed capacity equals the cumulative installed capacity of the previous period plus the capacity of newly installed plants minus the capacity of retired plants.

Constraint 2: Non-negative constraint

$$x_{m,i,t} \geq 0 \qquad m = 1, \dots, M; i = 1, \dots, I; t = 1, \dots, T$$

The new capacity additions must be zero or positive.

Constraint 3: Balance equation between power supply and demand

$$\sum_{m}^{M} (pp_{m,i,t,b,w} + flowin_{m,i,i1,t,w} \cdot (1 - loss_t) - flowout_{m,i,i2,t,w}) \geq D_{t,i,b,w}$$

$$i = 1, \dots, I; t = 1, \dots, T; b = 1, \dots, B; w = 1, \dots, W$$

In the formula above, $flowin_{m,i,i1,t,w}$ denotes electricity interchange from other regions (i1) to region i of technology m, during period t, in path w. In contrast, $flowout_{m,i,i2,t,w}$ represents electricity interchange from region i to other regions (i2) of technology m, during period t, in path w. In addition, $D_{t,i,b,w}$ represents the load demand during period t, in region i, in block b, in path w, and $loss_t$ denotes the loss factor of electricity interchange during period t. This constraint ensures that regional power output must satisfy the regional load demand of each period after the deduction of line losses.

Constraint 4: Peaking reserve constraint

$$\sum_{m}^{M} cap_{m,i,t} \geq D_{t,i,(peak),w} \cdot (1 + re) \qquad i = 1, \dots, I; t = 1, \dots, T; w = 1, \dots, W$$

Where $D_{t,i,(peak),w}$ is the load demand during period t, in region i, in peak block (b=peak), in path w, and re denotes the reserve margin. This constraint ensures that total installed capacity satisfies the load demand of the peaking time-slice (b=peak) by a certain percentage (reserve margin).

Constraint 5: Capacity constraint

$$pp_{m,i,t,b,w} \leq \alpha_m \cdot cap_{m,i,t}$$
$$m = 1, \dots, M; i = 1, \dots, I; t = 1, \dots, T; b = 1, \dots, B; w = 1, \dots, W$$

α_m is the availability factor of technology m. This constraint ensures that the actual power output from different technologies does not exceed their available capacity in each region, during each period.

Constraint 6: Power generation constraint of renewable energy technologies

$$\sum_{b}^{B} pp_{m,i,t,b,w} \cdot h_b \ \leq 8760 \cdot cap_{m,i,t} \cdot \ cf_m$$

$m \in$ renewable energy technologies; $i = 1, \ldots, I; t = 1, .., T;$

cf_m represents the capacity factor of renewable energy technology. Due to seasonal and climatic factors that affect the reliability of renewable energy, the capacity factors of renewable energy technologies are relatively lower than those of fossil fuels. The constraint must be placed on capacity factors to limit their maximum power output.

Constraint 7: Bounds of capacity

$$cap_{m,i,t} \leq Upbcap_{m,i,t} \qquad m = 1, .., M; i = 1, \ldots, I; t = 1, .., T$$

$Upbcap_{m,i,t}$ denotes the development potential of technology m, in region i, during period t. This constraint ensures that the development capacity of each generating technology does not exceed the potential.

Constraint 8: Operation constraint

$$pp_{coal,i,t,peak,w} = 0 \qquad pp_{nuclear,i,t,peak,w} = 0$$
$$i = 1, \ldots, I; t = 1, \ldots, T; w = 1, \ldots, W$$

This constraint is based on the operational characteristics of electricity generating technologies that limit their capability to supply electricity. Coal-fired and nuclear power plants take longer to start-up and shut-down and are thus less responsive to sudden load demand changes. Therefore, the power output of these two types of plants during peak load block sets at zero.

Constraint 9: Capacity constraint of LNG reception terminals

$$\sum_{i}^{I} \sum_{b}^{B} pp_{gas,i,t,b,w} \cdot h_b \cdot gasfac \leq gaslimit_{t,w} \qquad t = 1, .., T;\ w = 1, .., W$$

In the formula above, gasfac represents the conversion factor, which converts from power generation to liquefied natural gas (LNG) consumption and $gaslimit_{t,w}$ denotes the available supply of LNG for power generation during each period, in each path. This constraint ensures that the amount of LNG used does not exceed the available supply, the imported amount of which is limited by the receiving capacity of reception terminals.

Constraint 10: Bounds of carbon dioxide emissions

$$\sum_{m}^{M}\sum_{i}^{I}\sum_{b}^{B} CO_2coe_m \cdot pp_{m,i,t,b,w} \cdot h_b \leq CO_2limt_{t,w} \qquad t = 1,..,T; w = 1,..,W$$

CO_2coe_m is the carbon emissions coefficient of fuel used in technology m. This formula calculates the amount of carbon dioxide emissions during each period and can be applied to limit carbon dioxide emissions in some selected scenarios.

Constraint 11: Bounds of electricity interchange (inflow)

$$flowin_{m,i,i1,t,w} \leq \alpha_m \cdot cap_{m,i1,t} - pp_{m,i1,t,b,w}$$
$$m = 1,..,M; i = 1,...,I; t = 1,..,T; w = 1,..,W$$

The constraint limits the maximum electricity inflow.

Constraint 12: Bounds of electricity interchange (outflow)

$$flowout_{m,i,i2,t,w} \leq \alpha_m \cdot cap_{m,i,t} - pp_{m,i,t,b,w}$$
$$m = 1,..,M; i = 1,...,I; t = 1,..,T; w = 1,..,W$$

The constraint limits the maximum electricity outflow.

Constraint 13: Balance equation between electricity inflow and outflow

$$flowout_{m,i,i1,t,w} = flowout_{m,i2,i,t,w}$$
$$m = 1,..,M; i = 1,...,I; i_1 = i_2; t = 1,..,T; w = 1,..,W$$

The constraint ensures the balance between electricity inflow and outflow.

4. Data sources and adjustments

In order to demonstrate the applicability of our proposed model, we study the case of power system expansion in Taiwan's electricity sector. In the following, we describe our data sources and the necessary adjustments of the model.

4.1 Electricity generation cost

We use data from various studies in order to calculate electricity generation costs. Taiwan Power Company (Taipower) [19] was used for fixed and variable O&M costs, and investment costs for new capacity additions. Due to a lack of data concerning oil-fired generation technologies, we adopted cost data in this respect from International Energy Agency (IEA) [20]. Historical fuel price and the coefficients of carbon dioxide emissions were based on data provided by Greenhouse Gases Group and Department of Accounting of Taipower, respectively. The generation cost data for various generation technologies are summarized in Table 2.

However, due to a small cumulative installed capacity and incomplete regional generation data, solar PV technology is not incorporated in our model. In addition, the development of wind power in Taiwan currently only focusses on onshore technology. Offshore wind farms will be installed after 2015, but because offshore wind farms are set at sea, it is not easy to distinguish them into different regions. Therefore, we only consider onshore wind power for new capacity additions.

Table 2 Generation cost data and carbon dioxide emissions coefficients

Cost items/ Technologies	Fixed O&M costs (Million NTD /MW)	Investment costs for new generation units (Million NTD /MW)	Fuel costs (NTD/kWh)	Variable O&M costs (NTD/ MWh)	Coefficients of carbon dioxide emissions (kg/kWh)
Coal-fired	0.5104	64.2	1.14	39.3	0.931
Oil-fired	0.9112	32.7	5.98	629.9	0.803
LNG-fired	0.4044	28.3	3.53	62.5	0.423
Nuclear	1.2384	124.3	0.35	93.3	0.011
Conventional hydro	0.6328	17.8	0	601.2	0.001
Wind power	0.4746	78.2	0	0	0.037

Notes: NTD stands for New Taiwan Dollar; 1 USD is approximately equivalent to 30 NTD.

Sources: Taiwan Power Company, 2010; IEA, 2010.

4.2 The growth rate of fuel price

The growth rate data of fuel price was taken according to the Taiwan Power Research Institute [21]. The average annual growth rate for was 2.88% for LNG, 2.82% for oil, 2.30% for coal, and 1.71% for nuclear.

4.3 An upper limit of power generation capacity

The realizable generation potential for each renewable energy source, according to the development goals estimated by Taipower [2], was imposed as the limit for each renewable energy source.

4.4 An upper limit for LNG import

Yong-an and Taichung are two current LNG reception terminals in Taiwan with a total receiving capacity of 12 million tons per annum. Given the implementation of scheduled expansion projects, their receiving capacity should reach 18 million tons in

2020 and 20 million tons in 2025.

4.5 Regional load demand

The historical load demand data of northern, central, southern and eastern regions were analyzed to calculate their distribution functions and descriptive statistics. Due to the adjustments of region partition and statistical approach by Taipower, only the data after year 2006 are more reliable, and hence we use the historical load demand data from year 2006 to 2012. In addition, the load demand data covers one state-owned integrated utility (Taipower) and several independent power producers (IPPs), but does not cover cogeneration systems.

The random variable in this study is the growth in the regional load demand. An analysis of historical data indicates that this variable displays a normal distribution. We then used the Monte Carlo approach to simulate future regional load demand and identified the values that appeared the most by frequency distribution, which then served as the values of the nodes. By corresponding these to the cumulative probability distributions of each possible path, we can obtain the probability of all the possible paths.

4.6 Electrical network flow constraint

The amount of power that can be sent over a transmission line is limited. However, due to a lack of realistic power transmission capacity, we use the maximum power delivery volumes from the most recent ten years as the upper bound of electricity interchanges. The highest amount of power transmission from the southern to central region was 2,757 MW in the year 2006, and was 4,110 MW from the central to northern region. Because the electricity generation of the northern region is not sufficient to meet its demand, the amount of power transmission from the northern to the central and southern regions was assumed to be 0 MW.

4.7 Other parameters

The reserve margin rate was set at 15% by the government. The discount rate remained constant at 5%, and the modelling period was 14 years, from 2012 to 2025. The Taipower Planning Department estimated that line loss rate was projected to fall from 4.69% in 2013 to 4.47% in 2025, due to line loss improvement plans. In addition, no new capacity additions for nuclear were assumed until 2025.

5. Results

5.1 Scenario design

The scenarios in our simulations are designed as follows:

Baseline scenario: We optimize the electricity generation mix from a combination of conventional (coal, oil, LNG, and nuclear) and renewable (hydro, and wind) energy sources from 2012 to 2025, by minimizing electricity generation costs without considering demand uncertainty. In this scenario, the existing three nuclear plants (5,144MW) will be decommissioned when their authorized 40-year lifespans expire between 2018 and 2025.

Nuclear extension scenario: In addition, the Taiwan government decided to halt construction of the Fourth Nuclear Power Plant in April 2014. The first reactor was sealed after the completion of safety checks, and construction of the second reactor was halted. This may result in a large impact on the power shortage, especially in northern region. Therefore, the lifetime extension of the existing three nuclear plants has become one of the possible options for replacing the Fourth Nuclear Power Plant. Hence, the nuclear extension scenario presumes that the First, Second and Third Nuclear Power Plants will further extend the operating lives of their reactors for up to 20 additional years. In other words, the installed capacity of the nuclear power plants will be 5,144 MW in 2025, which is the existing capacity (excluding the newly constructed nuclear plant), and no new units will be installed.

CO_2 emissions reduction scenario: In response to the Fukushima nuclear crisis, caused by the 2011 earthquake in Japan, the government of Taiwan announced the "New Energy Policy" to promote nuclear safety, nuclear power reduction, and a low carbon emission environment, and to achieve a reduction in CO_2 emissions in the future. Therefore, CO_2 emissions reduction scenarios were also involved to examine annual technology portfolios. In the CO_2 emissions reduction scenario 1, we assume a 30% reduction compared to the baseline scenario, and no new construction and life extension of nuclear power plants. CO_2 emissions reduction scenario 2 sets the same reduction target as the first, but with the extension of existing nuclear power plants.

The case designs above investigate three major scenarios, involving the reference case (baseline), the life extension of existing nuclear power plants, and the reduction of carbon dioxide emissions. The settings for each scenario are summarized in Table 3.

Table 3 List of scenarios

	Baseline scenario	Nuclear extension scenario	CO_2 emissions reduction scenario 1	CO_2 emissions reduction scenario 2
Constructing nuclear power plant (Fourth Nuclear Power Plant)	Non-operation	Non-operation	Non-operation	Non-operation
Existing nuclear power plants	Non- Extension	Extension	Non- Extension	Extension
The installed capacity of nuclear in 2025	0MW	5,144 MW	0MW	5,144 MW
CO_2 emissions reduction target in 2025	Unrestricted	Unrestricted	30% reduction compared to baseline scenario	30% reduction compared to baseline scenario

5.2 Simulation results

The section applies the proposed portfolio model to three major scenarios and shows changes in technology portfolio.

5.2.1 Nuclear extension scenario

Figure 1 illustrates shares of installation capacity by technology in nuclear extension scenario, while Table 4 shows the comparison of the regional installed capacity between baseline and nuclear extension scenario in 2025. The results show that the total installed capacity of coal-fired increases to 25,257MW in 2025, which is 4,125MW lower than the baseline scenario. This is mainly because coal-fired and nuclear power plants both supply for the base-load demand, and when existing nuclear power plants extend the operating lives, the capacity for coal-fired will decrease.

For LNG-fired, the total installed capacity expands to 19,968MW in 2025, which is 1,709MW lower than the baseline scenario. In summary, the capacity of both coal-fired and LNG-fired drops in this scenario. In addition, the capacity of oil-fired reduces 486MW compared to the baseline scenario. The capacity changes for conventional hydro and wind power between baseline and nuclear extension scenario are inconsequential, due to reaching the upper limit of development potential.

As for the installed capacity in each region, when nuclear extension is taken into account, the capacity of coal-fired from northern, central, southern and eastern regions reduces 1,723MW, 1,608MW, 793MW, 0MW in 2025, respectively. This shows that the extension of nuclear power plants can decrease the capacity for coal-fired in each region. The capacity of LNG-fired from northern and central regions reduces 667MW and 1,062MW; nevertheless increases 21MW from southern region in 2025. This shows the extension of nuclear power plants can decrease the capacity of LNG-fired for northern and central regions, but insignificant for southern region. Because the high capacity for LNG-fired (6,044MW) has installed in the current year, hence it is not easily climbed by other influential factors in this region.

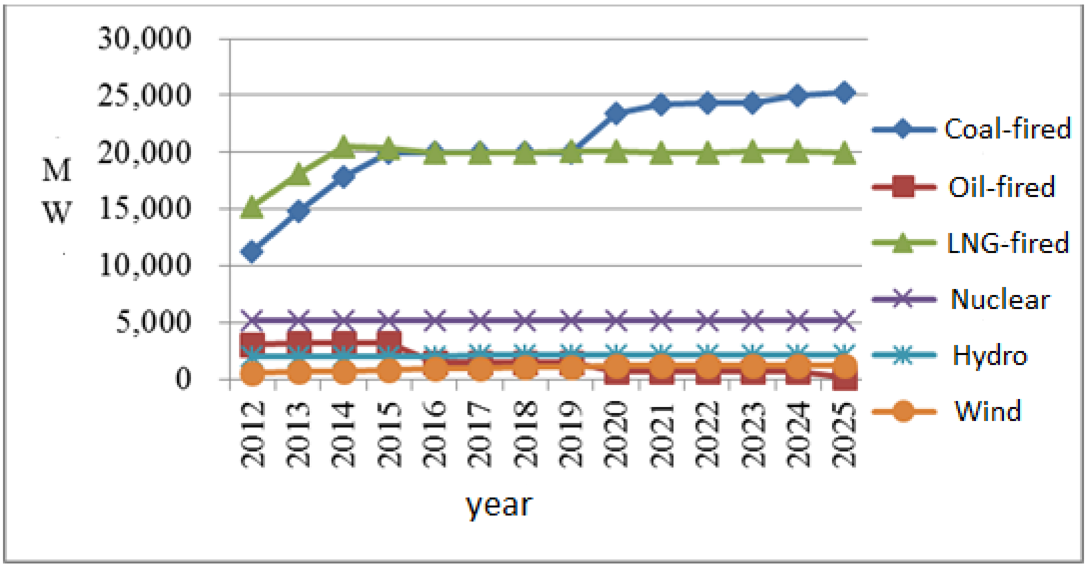

Fig. 1 Shares of installation capacity by technology in nuclear extension scenario

Table 4 Comparison of the regional installed capacity between baseline and nuclear extension scenario in 2025

Unit: MW

Installed capacity in 2025				
Region	Technologies	Baseline scenario (A)	Nuclear extension scenario (B)	(B)-(A)
Northern region	Coal-fired	6,557	4,834	-1,723
	Oil-fired	95	95	0
	LNG-fired	8,914	8,247	-667
	Nuclear	0	3,242	3,242
	Hydro	281	267	-14
	Wind	295	163	-132
Central region	Coal-fired	10,498	8,890	-1,608
	Oil-fired	567	81	-486
	LNG-fired	7,101	6,039	-1,062
	Hydro	1,472	1,482	10
	Wind	427	427	0

Southern region	Coal-fired	11,030	10,237	-793
	Oil-fired	0	0	0
	LNG-fired	5,661	5,682	21
	Nuclear	0	1,902	1,902
	Hydro	183	187	4
	Wind	478	610	132
Eastern region	Coal-fired	1,297	1,297	0
	Hydro	213.6	213.6	0

5.2.2 CO_2 emission reduction scenario 1 & 2

CO_2 emission reduction scenario 1 hypothesized that there is no extension of nuclear power plants but CO_2 emission is reduced to 30% compared to the baseline scenario. Figure 2 depicts shares of installation capacity by technology in CO_2 emission reduction scenario 1. When CO_2 emissions reduction target is incorporated into the simulation, the total installed capacity of coal-fired decreases, but LNG-fired increases due to the higher CO_2 emissions coefficient for coal-fired. The simulation results show that the total installed capacity of coal-fired increases to 25,246MW in 2025, which is 4,136MW lower than the baseline scenario, but the capacity of LNG-fired reaches to 35,869MW, which is 14,192MW higher than the baseline scenario.

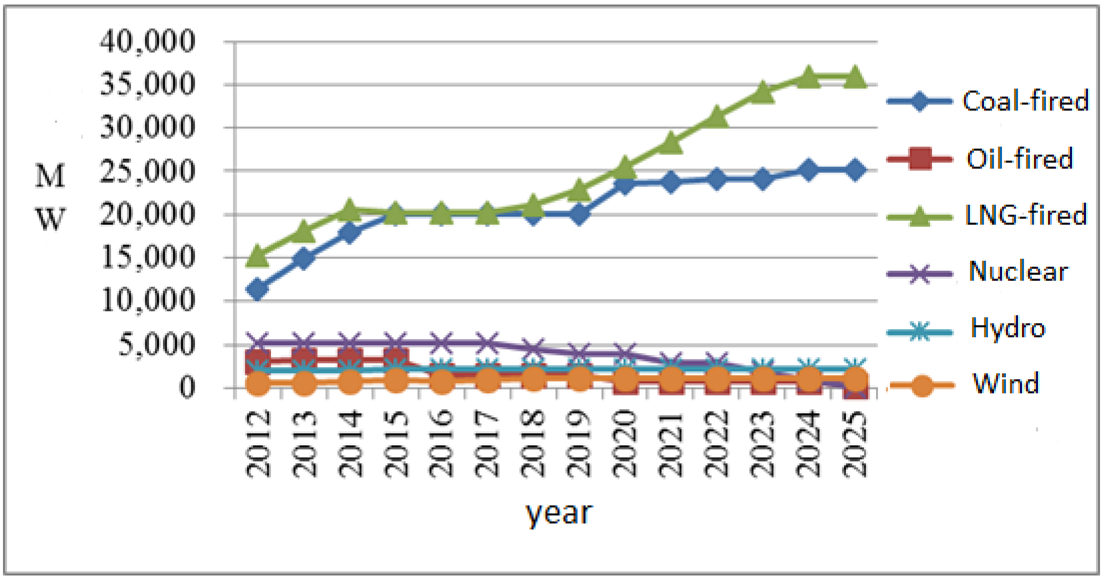

Fig. 2 Shares of installation capacity by technology in CO_2 emission reduction scenario 1

Table 5 indicates the comparison of the regional installed capacity between baseline and CO_2 emission reduction scenario 1 in 2025. The capacity of coal-fired from northern and southern regions decreases 1,881MW and 2,330MW; nevertheless slightly rises 75MW from central region in 2025. This shows the incorporation of CO_2 emissions reduction target has a negligible impact on the capacity of coal-fired in the central region. Because the capacity of coal-fired in central region (5,500MW) is the highest of all regions in the current year, hence it is less influenced by other influential factors in the simulation. On the other hand, the capacity of LNG-fired expands in northern, central and southern regions, with an increase of 3,756MW in northern region, 3,397MW in central region, and 7,039MW in southern region.

Table 5 Comparison of the regional installed capacity between baseline and CO_2 emission reduction scenario 1 in 2025

Unit: MW

Installed capacity in 2025				
Region	Technologies	Baseline scenario (A)	CO_2 emission reduction scenario 1 (C)	(C)-(A)
Northern region	Coal-fired	6,557	4,676	-1,881
	Oil-fired	95	95	0
	LNG-fired	8,914	12,670	3,756
	Nuclear	0	0	0
	Hydro	281	278	-3
	Wind	295	163	-132
Central region	Coal-fired	10,498	10,573	75
	Oil-fired	567	81	-486
	LNG-fired	7,101	10,498	3,397
	Hydro	1,472	1,479	7
	Wind	427	543	116
Southern region	Coal-fired	11,030	8,700	-2,330
	Oil-fired	0	0	0
	LNG-fired	5,661	12,700	7,039
	Nuclear	0	0	0
	Hydro	183	180	-3
	Wind	478	494	16
Eastern region	Coal-fired	1,297	1297	0
	Hydro	213.6	213.6	0

CO_2 emission reduction scenario 2 assumed the extension of nuclear power plants as well as the CO_2 emissions reduction target. Figure 3 exhibits shares of installation capacity by technology in CO_2 emission reduction scenario 2. In comparison with the baseline scenario, the total installed capacity of coal-fired and LNG-fired varies significantly. The total installed capacity of coal-fired climbs to 29,382MW in 2025, which is 3,051MW lower than the baseline scenario. In the contrast, the total installed capacity of LNG-fired expands to 33,790MW in 2025, which is 12,113MW higher than the baseline scenario.

In addition, the capacity of oil-fired reduces 477MW compared to the baseline scenario. The capacity changes for conventional hydro and wind power between baseline and CO_2 emission reduction scenario 2 are negligible, due to reaching the upper limit of development potential.

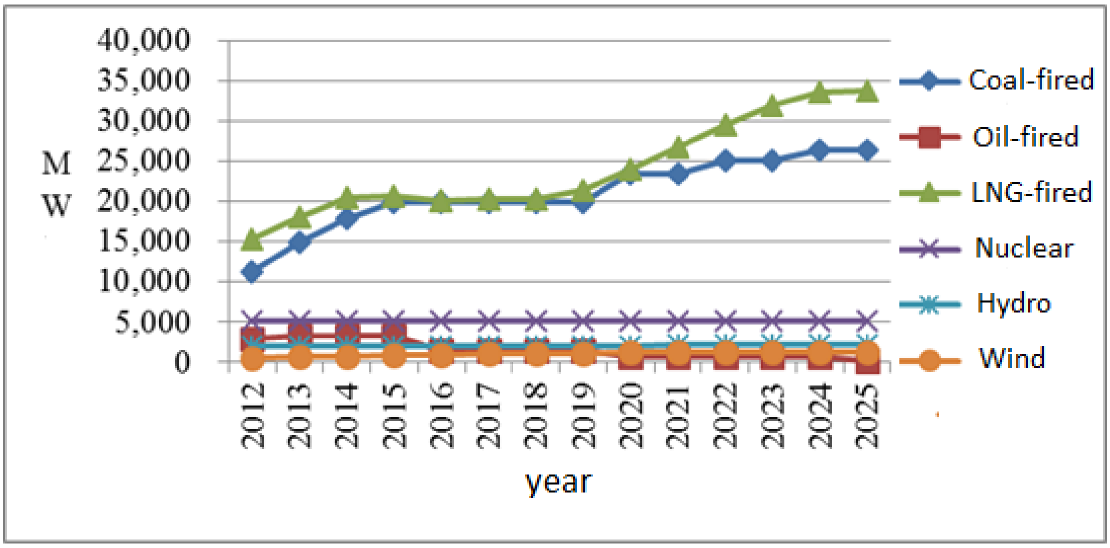

Fig. 3 Shares of installation capacity by technology in CO_2 emission reduction scenario 2

Table 6 presents the comparison of the regional installed capacity between baseline and CO_2 emission reduction scenario 2 in 2025. Except for the inconsequential capacity changes in eastern region, the northern, central and southern regions all show a decrease in the capacity of coal-fired, but an increase in the capacity of LNG-fired.

Table 6 Comparison of the regional installed capacity between baseline and CO_2 emission reduction scenario 2 in 2025

Unit: MW

Installed capacity in 2025				
Region	Technologies	Baseline scenario (A)	CO_2 emission reduction scenario 2 (D)	(D)-(A)
Northern region	Coal-fired	6,557	5,476	-1,081
	Oil-fired	95	95	0
	LNG-fired	8,914	11,173	2,259
	Nuclear	0	3,242	3,242
	Hydro	281	267	-14
	Wind	295	163	-132
Central region	Coal-fired	10,498	9,456	-1,042
	Oil-fired	567	81	-486
	LNG-fired	7,101	9,894	2,793
	Hydro	1,472	1,494	22
	Wind	427	466	39
Southern region	Coal-fired	11,030	10,101	-929
	Oil-fired	0	8	8
	LNG-fired	5,661	12,723	7,062
	Nuclear	0	1,902	1,902
	Hydro	183	175.2	-8
	Wind	478	571	93
Eastern region	Coal-fired	1,297	1,297	0
	Hydro	213.6	213.6	0

6. Conclusion

Traditional electricity planning models apply the least-cost method to select from a range of electricity generating technologies. In other words, a deterministic demand is to be met at minimum cost. In addition, the previous stochastic programming studies in electricity planning field merely required that total power output must satisfy the aggregate electricity demand. This disregards load demand diversity. Hence, this work presents the development of a two-stage stochastic programming model for the optimal planning of regional electric portfolios under load demand uncertainty. The relevant constraints of traditional electricity planning models are also incorporated in model construction. In addition, an approach which combines the scenario tree method and Monte Carlo simulation is proposed to reduce possible nodes and determine the future electricity demand values and probability rather than assign path probabilities arbitrarily.

A case study of Taiwan's electricity sector was used to demonstrate the applicability of the developed model. The simulation results of the scenarios that considered a lifetime extension of existing nuclear power plants showed that the capacity of coal-fired power decreased in the northern, central, and southern regions. For LNG-fired power, the capacity decreases drastically in the northern and central regions; however, it demonstrates a negligible change in the southern region. When a CO_2 emissions reduction target was incorporated into the simulation, the total installed capacity of coal-fired was shown to decrease, especially in the northern and southern regions. However, the capacity of LNG-fired power was shown to increase significantly in all regions.

The approach presented here could readily be modified to a mixed integer programming approach, so as to model power generation investments in technologically consistent blocks, rather than treating capacity as a continuous variable. The methodology has been extended to include an analysis of robustness in relation to fuel price uncertainty, as well as uncertainty relating to technological parameters.

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