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Development of a Stochastic Optimization Model and Long-Term Forecasting for Electricity Generation Planning Under Uncertainty

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Abstract: This paper is dedicated to the study of electricity generation expansion planning considering uncertainty. The method used for this problem is utilizing a highly constrained uncertainty optimization issue, as it were be solvable and complete classification. The demonstration uses a toll function to minimize environment effect and operational costs. A Neural Network is utilized to long-term forecast in electricity. The stochastic optimization model consists of finding the optimal long-term electricity generation planning for the construction of new generation capacity subject to various economic and technical constraints. The model can be showed experimental results that enable long-term planning of electricity generation with optimization of the costs, pollution emission and uncertainty of these generation resources in determining the best solution. The findings can help decision the government policy not only adjust the existing electricity generation but also coordinate the conflict interaction among system cost, energy supply, pollutant mitigation as constraint violation risk.

Keywords: Electricity generation planning, Long-term forecasting, Stochastic optimization.

1. Introduction

The model of electricity appears to be constantly important, not only for academic purposes but also in many government projects in the context of the formulation of electricity, energy security and climate change policies. Power systems require sustainable management to have an important role in Thailand's social and economic development. Now, fossil fuels and renewable energy are major energy sources that have serious negative outcomes for the environment locally and globally [1]. We divided the plans on electricity production as follows: long-term, mid-term, and short-term [2]. However, an optimal electric generation plan may be a troublesome issue due to the following types of power plants to work with: thermal, combined cycle, renewable and hydro power plants. This problem can be solved by various computer tools. We used least-cost generation expansion planning to figure the minimized cost capacity that meets the forecasted demand within the parameters on the planning horizon [3]. We now need to look at the costs, risks and benefits for an energy source compared with others. Thailand's national policy on energy should be aimed at implementing the systems that ensure the diversity and security of supply [4]. The Electricity Generating Authority of Thailand (EGAT) established on the 1st of May 1969 is a state enterprise which provides electric utility services for the public in Thailand, under the management of the Ministry of Finance (MOF) with the Ministry of Energy (MOE) has established a policy to provide an adequate electricity supply in the future, this policy referred as the Power Development Plan (PDP). The PDP is used to determine the future electricity expansion starting in 2018 and ending in 2036 [5]. The objective of the PDP was to reduce emissions [6]. The government of Thailand's policy on electricity for resourcefulness expansion to meet all energy demands for power generation in Thailand [7]. The PDP was completed in collaboration with the MOE and EGAT as the main power plan to enhance system stability, reduce natural gas dependence, increase the use of clean coal technology, decrease electricity purchase from other countries, and utilize of renewable energy. This research is different from the other researchers have presented, with separate forecasting and production control planning or control emission affect method. The stochastic model in this paper, advantages are including production control and environmental impact in long-term planning for the optimization cost in expansion electrical power plant. In present, EGAT have 47 power plants located all over Thailand with introduced capacity of 16,876 MW. The power plants of EGAT, 3 thermal generating station, 6 combined cycle generating station, 27 hydropower generating station, 9 renewable generating station, 4 diesel generating station, and 1 gas turbine generating station (Table 1). Fig. 1 shows the system's capacity as percentages of power plants of electricity station. Bulk purchases of electricity regarding 12 independent power producers (IPPs) of 14,948 MW, small power producers (SPPs) of 7,536 MW and from other regions (Laos and Malaysia) of 3,877 MW. This research focuses on identifying a suitable model for energy resource proportion and power plant for long-term electricity generations expansion planning through 2036 in Thailand. This paper aims to propose a mathematical model, stochastic optimization for a long-term electricity power system planning with neural network forecasted electricity consumption under uncertainty conditions

Table 1. The types of power plants capacity of EGAT

Power Plant Type	Capacity (MW)	System (%)
Thermal (TM)	3,647.00	22.69
Combined cycle (CC)	8,896.00	55.36
Hydropower (HP)	2,952.40	18.37
Renewable (RE)	45.33	0.28
Diesel (DE)	30.40	0.19
Gas Turbine (GT)	500.00	3.11
Total	**16,071.13**	**100**

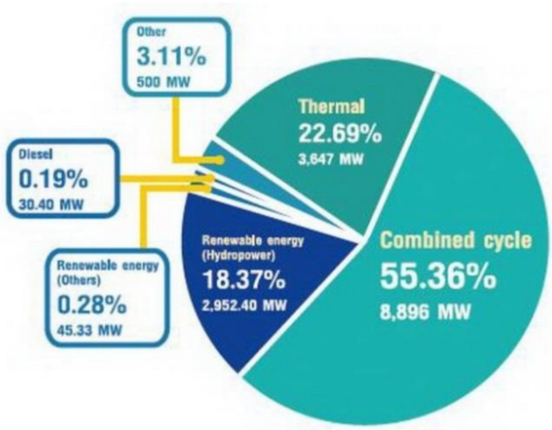

Figure.1 The capacity power plants of EGAT

In this article, we present the forecasting of electricity demand using feed-forward artificial neural network and multiple linear regression methods in consumption demand and peak load. In peak load after NN forecasted will be used probability distribution with load curve method. Finally, electric generation in long-term planning using a mathematical model in stochastic method for expansion the power plant under uncertainty of energy supply and technology disruption.

2. The method development in long-term planning for electricity generation

The model was accounted for all various electricity generation: the energy resources fossil (coal or lignite, natural gas, and fuels); and renewable resources (biomass energy, hydropower, solar, and wind) in power system. Therefore, final decision is to look at the issue with minimizing the expected value of costs by using various optimized the resource, allocation arrangement and installed capacity expansion for long-term planning schemes [8].

2.1 Electricity demand forecasting

In the study, the historical data of Electricity Consumption (EC) from 1990–2017 are used as the influential input indicators data, using GDP and POP for NN model, which is also proposed for 2018–2036 forecast by comparing them with a model, multiple linear regression which is optimized for forecasting period of 2018–2036 using 1990–2017 (Table 2). This study used the following data types: (i) EC and (ii) economic indicators GDP and POP in 1993–2017 (Fig. 2). NNs are used on forecasting problems characterized with unknown inputs and outputs. After training, various NN architectures, such as a multilayer perceptron (MLP) and a radial basis function networks (RBFNs) are used for EC forecasting [9].

In Thailand, EC and peak power demand have increased rate between 7.0–7.5% per annum from 1989–2008 [10]. EC will likely continue to increase in the future as well. Fig. 3 shows EC and peak power demand from 1969–2017. Conversely, EC and peak power demand slump as a consequence various economic crises in 1998–1999, 2008–2009, and 2011–2012. Electricity utility planning utilizes and identifies the importance of electricity forecasting [11]. In this research, NN architecture is used MLP by a feed-forward propagation training algorithm. The proposed NN for this study show the output as EC and peak demands from 2018–2036.

Table 2. The historical data of influential input

Year	Power Generation Capacity by Fuel Type (GWh)						POP	GDP	EC
	HP	TM	CC	GT	DS	Total	(Million)	(Billion)	(GWh)
1990	4,858	31,259	4,888	1,444	21	43,189	55.84	3,373.5	39,368
1991	4,413	31,700	11,541	909	8	49,225	57.03	3,656.9	44,773
1992	4,506	36,688	13,345	945	9	56,007	57.62	3,994.5	50,771
1993	3,826	37,975	18,667	1,126	13	62,180	58.44	4,341.0	56,558
1994	3,431	39,194	25,084	1,085	9	69,651	59.24	4,688.2	63,642
1995	6,684	42,391	20,400	1,687	2	78,880	59.28	5,068.9	72,779
1996	7,233	45,310	19,204	2,704	4	85,924	59.90	5,355.4	79,450
1997	7,055	44,818	21,863	2,554	3	92,724	60.50	5,207.9	85,896
1998	5,881	42,147	24,323	1,566	4	92,134	61.20	4,810.3	85,597
1999	3,433	38,374	25,379	1,252	3	90,413	61.80	5,030.3	84,512
2000	5,296	36,151	25,556	1,153	2	96,780	61.88	5,254.4	90,724
2001	6,310	31,617	22,685	1,138	2	103,165	62.31	5,435.4	97,412
2002	6,480	30,127	23,529	1,117	5	108,389	62.80	5,769.6	102,485
2003	7,741	30,826	19,346	1,084	4	116,743	63.08	6,184.4	110,675
2004	5,915	31,538	20,652	1,090	2	125,318	61.97	6,573.3	118,938
2005	5,845	33,570	23,534	1,315	2	133,621	62.42	6,848.6	127,025
2006	7,950	33,648	25,137	1,088	1	142,004	62.83	7,188.8	134,060
2007	7,960	32,146	24,762	901	1	146,925	63.04	7,579.5	139,445
2008	6,950	29,128	27,209	675	2	148,266	63.39	7,710.3	141,558
2009	6,941	23,463	33,164	306	1	145,286	63.53	7,657.1	141,692
2010	5,325	27,289	38,338	275	3	160,189	63.88	8,232.4	156,125
2011	7,912	24,996	37,211	338	0.5	158,963	64.08	8,301.6	155,207
2012	8,408	26,168	42,551	370	0.4	173,250	64.46	8,902.8	169,369
2013	5,390	25,732	40,531	453	0.8	173,535	64.79	9,142.1	169,530
2014	5,141	24,764	43,052	370	1	177,580	65.12	9,232.1	173,603
2015	3,724	20,560	45,225	308	0.5	183,466	65.73	9,510.9	179,537
2016	3,521	20,296	43,679	261	0.5	188,999	65.93	9,823.1	185,046
2017	4,685	49,717	38,290	1,242	27	188,934	66.19	10,237.0	185,130

2.1.1. Multiple linear regression model

EC as it may be assessed with the mathematical, a linear combination of various independent variables because of characteristics of the regressions model, MLR technique. The regression model occurs when observational data are modeled with the least square function and is a linear combination of the parameters of the MLR model as follows in Eq. (1).

$$y_t = ax_1 + bx_2 + cx_3 + dx_4 + e \qquad (1)$$

Where, y_t is the dependent variable EC, x_1, x_2, x_3 and x_4 are the independent variable (POP, GDP, IMP and EXP respectively), a, b, c and d are the coefficients of regression model and e is a constant parameter of the regression model. In constant, the parameter represents unrecognized variation in the dependent variable and random variable. The POP, GDP, IMP, and EXP parameters are estimated to best fit of the data. The best fit is evaluated with the method of least squares regression.

2.1.2. Neural networks model

The NN method is used to forecast EC, where the outputs are unknown [12, 13]. It is possible to become trapped in local minimal or to become subjective in selecting the NN model, architecture using the feed-forward propagation method as

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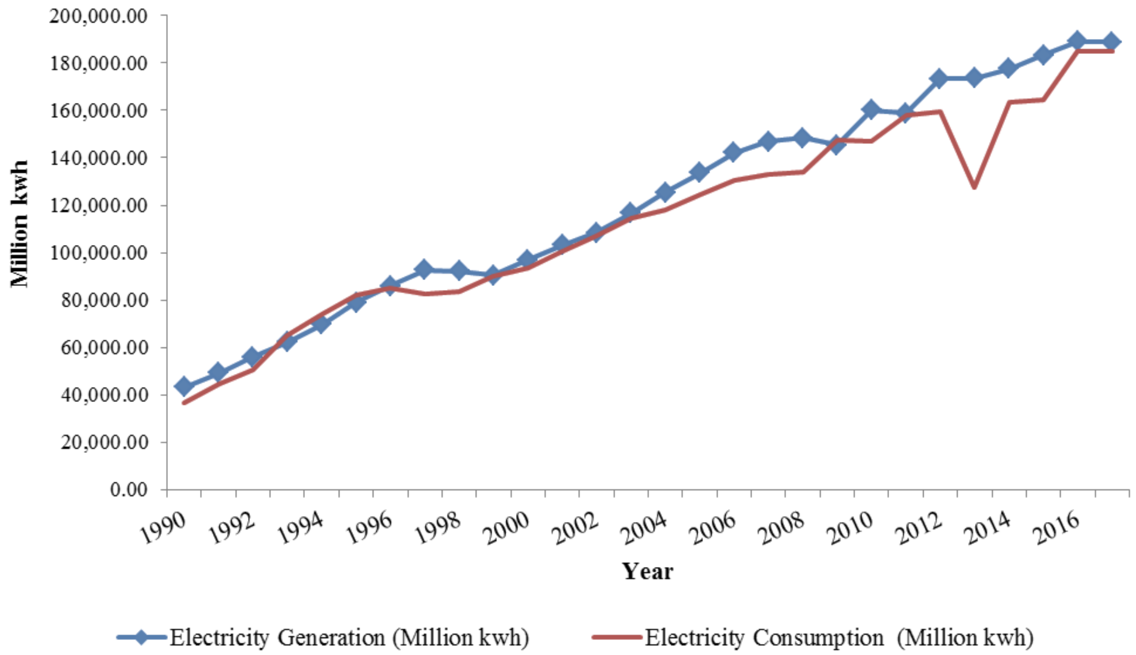
based on a gradient descent [14]. We normalized the input data for designing an NN [15] as follow:

$$\bar{x}_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \quad ,i = 1,2,..,n \qquad (2)$$

Where, n is number of data, $\bar{x}_i$ are normalized data and x_i are actual values of historical data.



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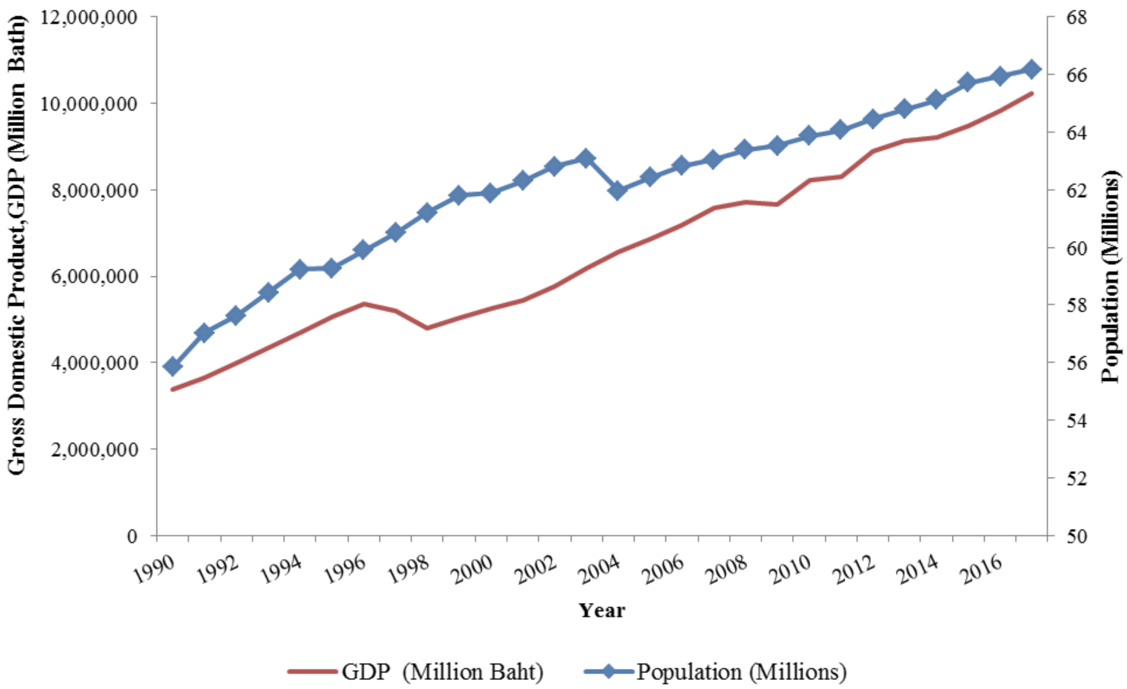

(b)

Figure.2 The electricity consumption and economic data:
(a) Electricity Consumption vs. Electricity Generation and (b) Gross Domestic Product vs. Population

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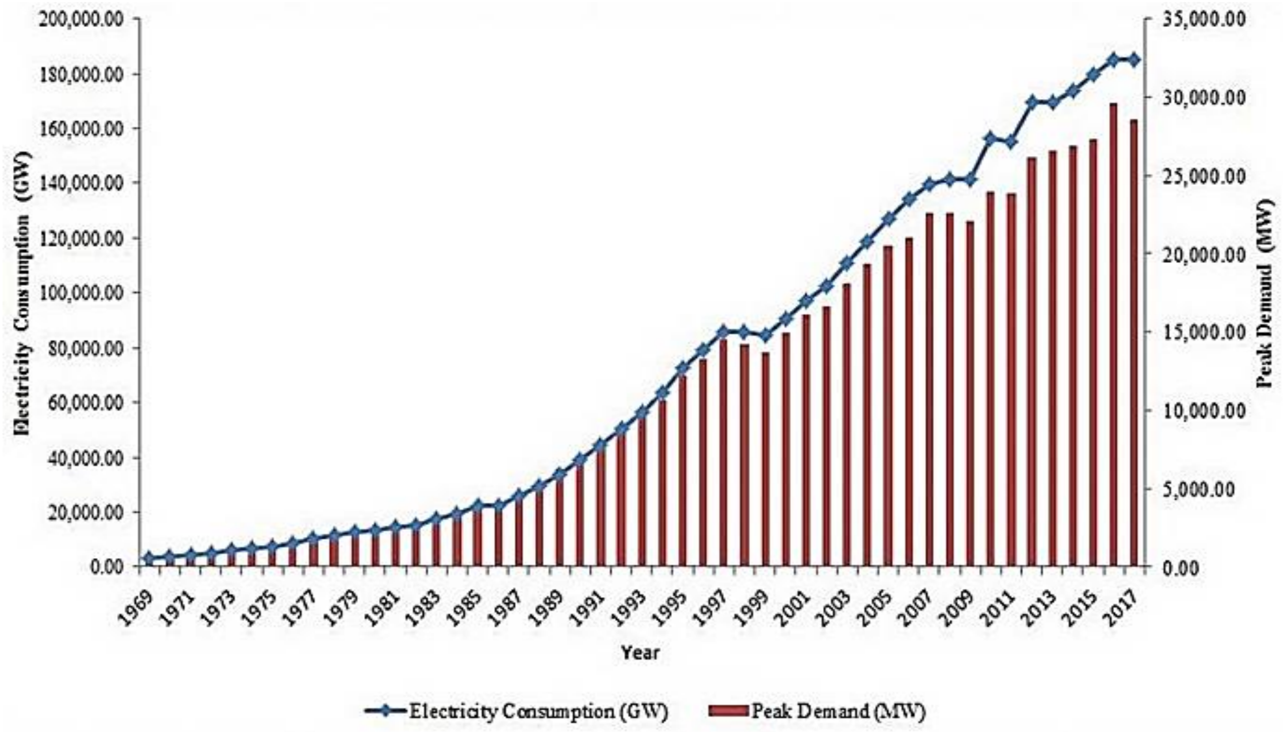
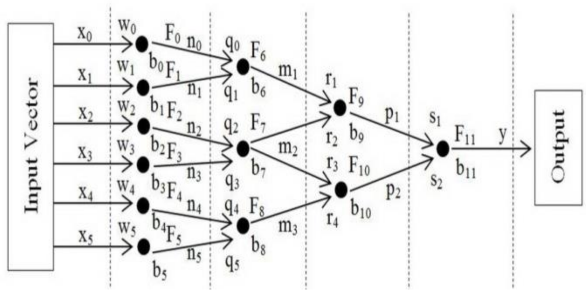


Figure.3 Peak power demand and EC in Thailand from 1969 – 2017



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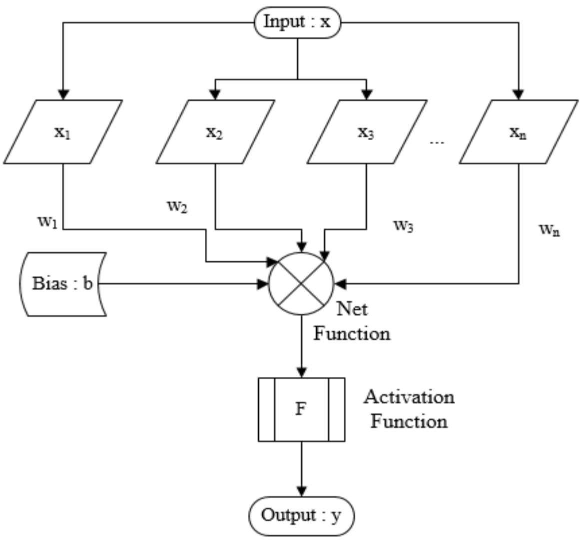


(b)

Figure.4 Feed-forward artificial neural network: (a) NN structure, (b) NN process

Feed-Forward artificial neural networks (FANNs) have only one condition which is unidirectional information that flows from input to output. In the feed-forward process, the information is only moving in the forward direction from the input nodes *x* passing through the hidden nodes to the output nodes *y* with no looping in the network. The model uses a simple sigmoid activation function (*f*) to produce output values (*y*). The multi-layer FANNs (Fig. 4) are corresponding analytical description with sets of Eqs. (3), (4) (5), and (7) driven to generally long mathematical descriptions where solving by hand is not feasible. Computers and specialized software are required to build, describe and optimize any types of NN.

Definition

x, n, m, p, y *are signals* w, q, r, s *are weights,* F *is transfer function and* b *is biases.*

The historical data are x_1: EC, x_2: GDP, x_3: POP, x_4: IMP, x_5: EXP, weights and biases are coefficient.

The NN uses a tanh function that is not bounded or continuously differentiable. This function is piece-wise linear and saturates at 0 whenever the input x is less than 0. The equation indicates that a nonlinear activation function f takes a weighted sum of input *x* values and returns a value for F_n^l as:

$$F_j^l = f(\sum_{i=1}^{k} w_{ij}^l x_i)$$

$$\begin{aligned} n_0 &= F_0(w_0 x_0 + b_0) \\ n_1 &= F_1(w_1 x_1 + b_1) \\ n_2 &= F_2(w_2 x_2 + b_2) \\ n_3 &= F_3(w_3 x_3 + b_3) \\ n_4 &= F_4(w_4 x_4 + b_4) \\ n_5 &= F_5(w_5 x_5 + b_5) \end{aligned} \quad (3)$$

$$\begin{aligned} m_1 &= F_6(q_0 n_0 + q_1 n_1 + b_6) \\ m_2 &= F_7(q_2 n_2 + q_3 n_3 + b_7) \\ m_3 &= F_8(q_4 n_4 + q_5 n_5 + b_8) \end{aligned} \quad (4)$$

$$\begin{aligned} p_1 &= F_9(r_1 m_1 + r_2 m_2 + b_9) \\ p_2 &= F_{10}(r_3 m_2 + r_4 m_3 + b_{10}) \end{aligned} \quad (5)$$

$$y = F_{11}(s_1 p_1 + s_2 p_2 + b_{11})$$

$$y = F_{11}(s_1 (F_9(r_1 (F_6(q_0 (F_0(w_0 x_0 + b_0) + q_1 (F_1(w_1 x_1 + b_1) + b_6) + r_2 (F_7(q_2 (F_2(w_2 x_2 + b_2) + q_3 (F_3(w_3 x_3 + b_3) + b_7) + b_9) + s_2 (F_{10}(r_3 (F_7(q_2 (F_2(w_2 x_2 + b_2) + q_3 (F_3(w_3 x_3 + b_3) + b_7) + r_4 (F_8(q_4 (F_4(w_4 x_4 + b_4) + q_5 (F_5(w_5 x_5 + b_5) + b_8) + b_{10}) + b_{11}) \quad (6)$$

$$w^n = w^o - \eta \nabla_w J(w^o; x^k; y^k) \quad (7)$$

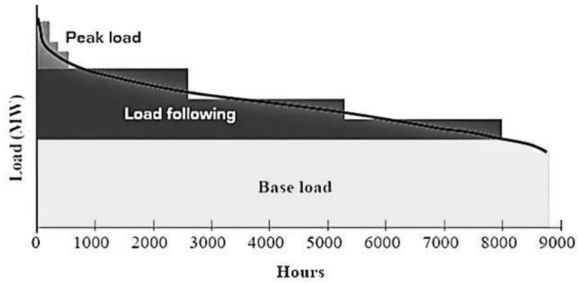
Where, F_j^l is the j^{th} hidden node in layer l, w_{ij}^l is the weight between node i in layer (l-1) and node j in layer l, F is activation function, w^n, w^o are updated weight value and old weight value respectively, J is gradient value, η is learning rate and x^k, y^k are pair of a training sample at the k^{th} iteration.

The error during the NN design phase is EC_{MAPE} which serves as the fitness function that must be minimized as:

$$\min \ EC_{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right| \times 100 \quad (8)$$

Where, A_i and F_i are the target and the forecasted EC value at period i, respectively.

The uncertain factors in the power capacity forecast include electricity demand which higher than estimated, fluctuating renewable energy sources, power purchasing and relying on neighboring countries, high consumption of natural gas in power generation and rescheduling of large power plants' commercial operation dates.



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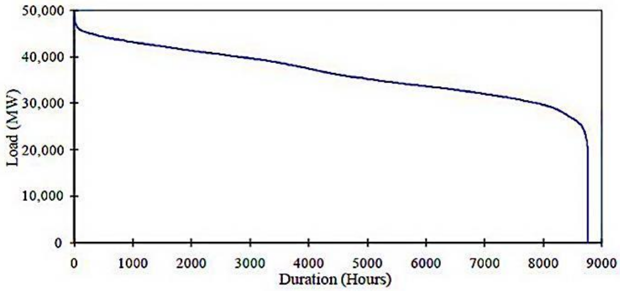

(b)

Figure.5 Load duration curve: (a) basic curve and (b) load duration curve in demand forecasted with NN in Thailand 2036

Nevertheless, an appropriate level of generation capacity has been set to be not less than 15% of peak demand to ensure the security of electricity supply and to cope with uncertainties.

2.1.3. Load model

First, we investigated data using an annual hourly load curve. Then used the energy load duration curve (Fig. 5) to develop the generation system model to obtain the reliability indices, i.e., conventional unsupplied resource of energy.

Electricity demand is a single product with demand levels varying over time. Electricity producers use a "load-curve" to describe demand over time increasing, forecasted with NN shown in Fig. 6. The problem in concern is the long-term investments, so for the study we considered the load curve as having occurred over a year.

The electricity demand under uncertainty is the possibility of the electric load to increase or decrease from the baseline of the fixed load. The method uses the distribution to illustrate forecasted peak loads. We divided the distribution into intervals. The normal distribution was divided into seven parts with a 5% standard deviation (SD) of intervals for the purposes of this study. Reliability for power system uses the load forecast uncertainty model as follows:

1. Load-curve (LC) is picked in the SD against the mean of peak level. The LC is generated with accumulate the peak electricity demand value in uncertainty. The value is then

combined to the peak value which represents expand; or conversely, subtracted from the peak value to represent a decline in peak uncertainty.

2. LC is probability that obtains the weighted values for particular level.
3. The corresponding reliability index of load forecasted is the sum of all weighted loads.

Each unit is assumed to generate electricity from an adequate fossil resource. However, some power generating units, example hydro resources, are an energy-limited type, because the amount of water varies over time. As such, hydro resources are used as peak shaving units, i.e. leaving the remaining demand to be supplied by other types of units. Fig. 6 and Table 3 show the characteristics for demand as probability distribution.

2.2 Stochastic optimization model

Those responsibilities are in charge of the decisions for allocating electricity generation patterns and any capacity expansions with minimal system costs over a long-term planning horizon [16]. To effectively manage energy resources and facilities, the components are integrated into the modeling framework. The following are the challenges for the planning: (i) identifying optimal capacity-expansion schemes; (ii) maximizing hydropower generation; (iii) reflecting on the stochastic features for any uncertain parameters such as demands, allowable capacities of water for hydropower plants; (iv) analyzing any tradeoffs between efficiency and reliability; and (v) minimizing environment harm.

Table 4 shows the capacity for Thailand's power system. Fig. 8 shows the electric power plants diagram by technology. Power plants are rated in accordance with production capacity as measured in megawatts (MW).

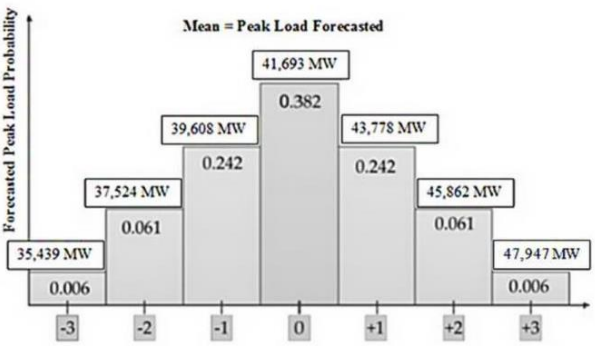

Figure.6 Probability distribution approximation

Table 5 shows investments and operational costs for each plant type.

Table 3. The reliability indices consolidate load forecast uncertainty

SD	Load (MW)	RI	Prob.	Weighted
-3	41693 - (15% × 41693) = 35439	i	0.006	i × 0.006
-2	41693 - (10% × 41693) = 37524	ii	0.061	ii × 0.061
-1	41693 - (5% × 41693) = 39608	iii	0.242	iii × 0.242
0	41693 - (0% × 41693) = 41693	iv	0.382	iv × 0.382
+1	41693 + (5% × 41693) = 43778	v	0.242	v × 0.242
+2	41693 + (10% × 41693) = 45862	vi	0.061	vi × 0.061
+3	41693 + (15% × 41693) = 47947	vii	0.006	vii × 0.006
Reliability (RI) = ∑ weighted of reliability index = i × 0.006 + ii × 0.061 + iii × 0.242 + iv × 0.382 + v × 0.242 + vi × 0.061 + vii × 0.006				

Table 4. The power plants capacity in Thailand.

Power Plant	Number of Power Plant	Capacity Factor	Total Capacity (MW)
(TM)	3	0.8-0.9	3,647
(CC)	6	0.8-0.9	8,896
(GT)	1	0.8-0.9	500
(HP)	27	0.2-0.5	2,952
(DS)	4	0.8-0.9	30
(RW)	9	0.15-0.25	45

Table 5. The construction and operation cost with fuel.

Energy Types	Construction (Bath / kw)	Operation (Bath/kw /Year)
(CC)	24,718	7,500
(TM)	52,700	6,760
(GT)	14,858	10,125
(HP) Large > 50 MW Small < 50 MW	 132,000 148,500	 1,980 2,150
Nuclear	104,959	14,560

Table 6. The environmental, tax and cost of technological

Energy Types	CO_2	NO_x	SO_2	TSP	Tax Fees	Cost
HP	15	0.02	0.01	0.01	-	2.92
Coal	960	3.79	3.76	0.33	0.42	2.93
Natural Gas	512	1.25	0.31	0.01	0.23	3.10
Nuclear	170	0.00	0.00	0.00	-	3.60
RW	30	0.01	0.02	0.02	-	4.19
Oil	770	2.90	4.90	0.25	-	4.93
Diesel	650	2.90	1.29	0.25	-	4.93

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Table 7. The pollutant of emission used electricity generation each technology

Year	Pollutant Emission (Ton/Year)								Electricity Generation (GWh)	
	Natural Gas	Oil Fuel	Diesel	Coal Lignite	GHG (CO_2)	NO_x	SO_2	TSP	Fossil Fuel	RW
2015	23,412,473	546,719	34,544	15,322,740	39,316,476	79,151	28,732	1,845	66,093	3,745
2016	21,228,208	226,962	32,254	17,748,799	38,836,323	73,613	26,722	1,736	64,237	3,528
2017	17,494,788	77,127	115,484	16,811,959	34,499,359	59,319	21,778	1,713	56,124	4,667

Table 6 shows the factors regarding preventing harm to the environment for each type of plant, additionally the costs of electricity as Bath/kwh.

Table 7 shows the historical data used for testing from 2015–2017. The operational costs of hydropower plants are the lowest because there is a minimum requirement in fuel consumption and least environmental harm emission.

The operational costs for nuclear based power plants are unable to be used to estimate costs because of nuclear waste products will be around well after the plant has closed however; data might be easily included for this task.

Definition GHG: greenhouse gases (CO_2) and TSP: total suspended particulate. In CO2, NOx, SO2 and TSP: g/kwh and tax fee and cost: bath/kwh.

2.2.1. A multi-stage stochastic model

The following elements justify the use of a dynamic multi-stage method for the electricity generation planning to investment:

1. The total costs in long-term
2. The load curve in long-term
3. New technologies
4. Presently available equipment will become obsolete
5. The emission environment cost from power generation

The equipment costs are influenced by changing technologies and growing fuel costs and emission tax fees. The most important aspect as demand grows is the total energy demanded and peak-levels. These determine the total capacity available to meet power demands. As new technologies appear, the specialized and commercial accomplishment of the study and improvement depends on past decisions with the technical and lifetime value of any equipment. We developed a multiple stage stochastic optimization model based on [17, 18] with advantage environments effects of cost and LC with NN forecasted in electricity consumption demand as illustrated below:

$$\min \mathrm{E}_{\xi} \sum_{t=1}^{N} \left(\sum_{p=1}^{n} \boldsymbol{c_p^t \delta_p^t} + \sum_{p=1}^{n} \sum_{j=1}^{k} \boldsymbol{q_p^t T_j^t y_{pj}^t e_p^t} \right) \quad (8)$$

Subject to

$$\sum_{p=1}^{n} c_p^t \delta_p^t \leq b_p^t$$

$$\delta_p^t = \delta_p^{t-1} + x_p^t - x_p^{t-Lp}$$

$$p = 1, \dots, n \,;\; t = 1, \dots, N$$

$$\sum_{p=1}^{n} y_{pj}^t \geq d_j^t \,;\; j = 1, \dots, k \,;\; t = 1, \dots, N$$

$$\sum_{p=1}^{n} y_{pj}^t \geq w_j^t \,;\; j = 1, \dots, k \,;\; t = 1, \dots, N$$

$$\sum_{j=1}^{k} y_{pj}^t \leq a_p \left(g_p^t + \delta_p^{t-\Delta_p} \right)$$

$$p = 1, \dots, n \,;\; t = 1, \dots, N$$

$$a_n(g_n^t + \delta_n^{t-1} + x_n^t) \geq D_m^t - \sum_{p=1}^{n-1} a_p \left(g_p^t + \delta_p^{t-\Delta_p} \right)$$

$$p = 1, \dots, n \,;\; t = 1, \dots, N$$

$$\delta, x, y \geq 0$$

$$\delta_p^t = \delta_p^{t-1} + x_p^t$$

Definition The following multi-stage stochastic model can be proposed. Let as:

p = power plant type
j = resource supply fuel
n = number of technologies available for power plant
m = demand of peak load forecasted with load curve
x_p^t = new capacity made available for technology p at time t
δ_p^t = total capacity of i available at time t

a_p = availability factor of p
L_p = life-time of p
g_p^t = existing capacity of p at time t, decided before t = 1
d_j^t = maximal demanded resource at time t
T_j^t = duration of mode p at time t
$y_p j^t$ = capacity of p effectively used at time t
c_p^t = unit investment cost for p at time t (on a yearly equivalent basis)
q_p^t = unit production cost for p at time t
ξ_t = represents the random variable at time t
e_p^t = unit emission tax fees cost for p at time t (only coal/lignite and natural gas fuel)
w_j^t = the limitation of fresh water of mode p at time t
b_p^t = the upper bound budget for construction cost of mode p at time t
D_m^t = the power demanded in load curve with NN forecasted at time t

The stochastic optimization model (SOM) finds the best structure for power plant capacity required to satisfy regional power demands as forecasted by vector *x*. The objective function minimizes the expected value of system costs and is related to the following: (i) supply costs, energy resource; (ii) variable operational costs regarding power conversion; (iii) investment construction costs expand capacity; and (iv) shouldering environmental emissions. We classified the decision variables into the following categories: (i) continuous variables - coal and natural gas production, conversion technologies capacity, and electricity generation amounts; and (ii) generation variables if capacity expansion is necessary.

2.3 Implementation to power generation planning

Over 2018–2036, the electricity demand is expected to increase 2.7% per year and reach 49,655 MW and expect the stochastic model plan to save 89,672 million units, which will make the total contracted capacity to be at 70,335 MW by the end of 2036.

The stochastic model is summed up best as follows in 2036. Fig. 7 is the flowchart for long-term EC modeling forecasting and stochastic optimization modeling while considering various input types. Thailand's power systems capacity is as follows shown in Table 8 – 9.

Table 8. Thailand's power systems capacity

Power generation	Capacity (MW)	Percentage (%)
CC	21,145	56.2
RW	8,476	22.5
TM (Thermal)	7,538	20.0
EGAT-TNB	300	0.8
GT and DS	153	0.5
Total	37,612	100.0

3. Results

The EC forecasting and stochastic optimization models for long-term planning focus on the power development plan 2018–2036 in Thailand, (i) Security: meeting increasing power demands in

Table 9. Thailand producer's power systems capacity

Power generation	Capacity (MW)	Percentage (%)
EGAT	15,482	41.2
IPP_s	13,167	35.0
SPP_s	4,530	12.0
$VSPP_s$	2,029	5.4
Import	2,404	6.4
Total	37,612	100.0

Table 10. The generating capacity in expansion planning during 2018 -2036

Power Plant Types	2017 (%)	2026 (%)	2036 (%)
Import & Hydropower	7	12	15
Coal / Lignite	20	22	24
Natural Gas (LNG)	64	50	30
Renewable	8	15	25
Diesel / Oil Fuel	1	1	1
Nuclear	-	-	5

Table 11. The summary of generating capacity in expansion planning classify by technology

Power Plant Type (MWh)	2017	2018 - 2026	2027 - 2036	Total
Renewable	8,746	15,500	9,600	25,100
-Domestic & HP	3,500	9,100	5,000	14,100
-Import neighbor	3,246	5,500	4,000	9,500
-Buy in domestic	2,000	900	600	1,500
Combined Cycle	21,145	15,500	3,500	19,000
-Natural Gas	8,896	14,500	3,000	17,500
-Buy in domestic	12,249	1,000	500	1,500
Thermal	7,538	5,500	4,700	10,200
-Coal / Lignite	3,647	4,000	3,400	7,400
-Buy in domestic	3,591	700	600	1,300
-Import neighbor	300	800	700	1,500
Other	153	230	1,070	1,300
-Gas turbine	123	200	1,050	1,250
-Diesel / Oil	30	30	20	50
Nuclear	-	-	2,000	2,000
Total expansion	37,582	36,730	20,870	57,600

Table 12. The forecasted results of the MLR and NN model

Year	Electricity Generation, Electricity Demand and Peak Load (GWh)		
	Generation	Consumption	Peak Load
1990	44,765	39,369	7,221
1991	50,713	44,773	8,045
1992	57,509	50,771	8,904
1993	63,982	56,558	9,839
1994	71,973	63,642	11,064
1995	80,436	72,780	12,268
1996	87,797	79,451	13,311
1997	93,407	85,897	14,506
1998	91,156	85,598	14,180
1999	91,414	84,512	13,712
2000	98,487	90,724	14,918
2001	103,856	97,412	16,126
2002	111,256	102,486	16,681
2003	117,290	110,676	18,121
2004	121,534	118,939	19,326
2005	134,798	127,025	20,538
2006	141,919	134,061	21,064
2007	147,026	139,446	22,586
2008	148,264	141,559	22,568
2009	145,159	141,693	22,045
2010	160,152	156,125	24,010
2011	158,937	155,207	23,900
2012	173,320	169,370	26,121
2013	173,377	169,530	26,598
2014	177,261	173,604	26,942
Testing Model	Actual Testing Value	MLR Demand & Peak load	NN Demand & Peak load
2015	179,537 27,346	179,137 27,015	179,456 27,340
2016	185,047 29,619	184,747 28,385	184,850 28,590
2017	185,131 28,578	184,831 29,075	185,355 28,940
Error	R Square	0.95	0.98
	MAPE (%)	1.87	1.15
	RMSE	2,685	2,077
Time Periods	PDP Forecasted	MLR Forecasted	NN Forecasted
2018	200,500 28,338	210,500 29,535	205,150 29,215
2022	248,500 36,776	236,001 37,350	240,395 36,850
2026	303,137 40,791	270,816 41,135	281,596 41,050
2030	341,032 44,424	314,385 45,050	323,885 44,750
2036	393,335 49,655	365,050 50,015	379,850 49,985

concerned with the economic and Nation Development as well as considering fuel diversification to dependency on any one power - source; (ii) Economic: developing appropriate costs for power generation to engender long-term economic competitiveness and energy efficiency; and (iii) Ecological: the reduction of environmental seeking lessened co_2 in electricity generation process.

In 2036, the demand capacity will need to be 70,335 MW and will have a present capacity of 37,612 MW, a further capacity of 57,459 MW, and a removed capacity (2018–2036) as 24,736 MW. These are shown as follows:

-Generating and retired capacity between 2018 until 2036

-Present capacity 37,612 MW (end of 2017)

-New capacity more over 57,459 MW

-Removed capacity 24,736 MW

-Further demand capacity 70,335 MW in 2036

The results from stochastic optimized model and forecasting in long-term are power plant technology installed and environmental affect cost.

In the end, we will have summary of generating capacity expansion planning classify by technology in time period shown in Table 10 and 11. The forecasted results with the MLR and NN models in electricity consumption are shown in Table 12. The production of renewable energy will be used instead of oil and gas production to consider the impact on the environment and cost.

4. Conclusion

The following targets for 2036's installed capacity: 57,600 MW for renewable; and wind, solar, and small-hydro were set at 3,000 MW, 6,000 MW, and 5,100 MW, respectively. The current status of renewable energy sources in Thailand makes these goals ambitious. The installed capacity for wind power tripled from 2014 to 2017 to 627.82 MW. The capacity for solar power nearly doubled to 2,692.26 MW of 2014–2017. Thailand is halfway to its 6,000 MW goal for installed solar capacity by 2036. Both the demand and supply of solar power are growing and the future will require upward revisions. The pivot to renewable power sources will satisfy the stochastic optimization model. Thailand has shown great potential for continuing growth of the renewable energy sector.

Based on the limitations of the long-term electricity generation planning established by the government, the current study produced a power generation system operation plan model that can calculate realistic operation and construction costs, moreover it can be solve the optimization for generation in best value.

In the future, if any researchers want to use the proposed stochastic model, it must be consideration factors in the topography that affects the production of renewable energy. A constrain will be adjust according to the efficiency of electricity production in each country; hydro power, solar and wind power plant. For sustainability, enough production capacity of electrical should be increased without the need to purchase energy from different countries, will be decrease a risk in uncertainty and must be improve the model.

Fig. 8 shows forecasting results of electricity consumption from 2018-2036. In Fig. 9 shows the types of power plant of Thailand in future.

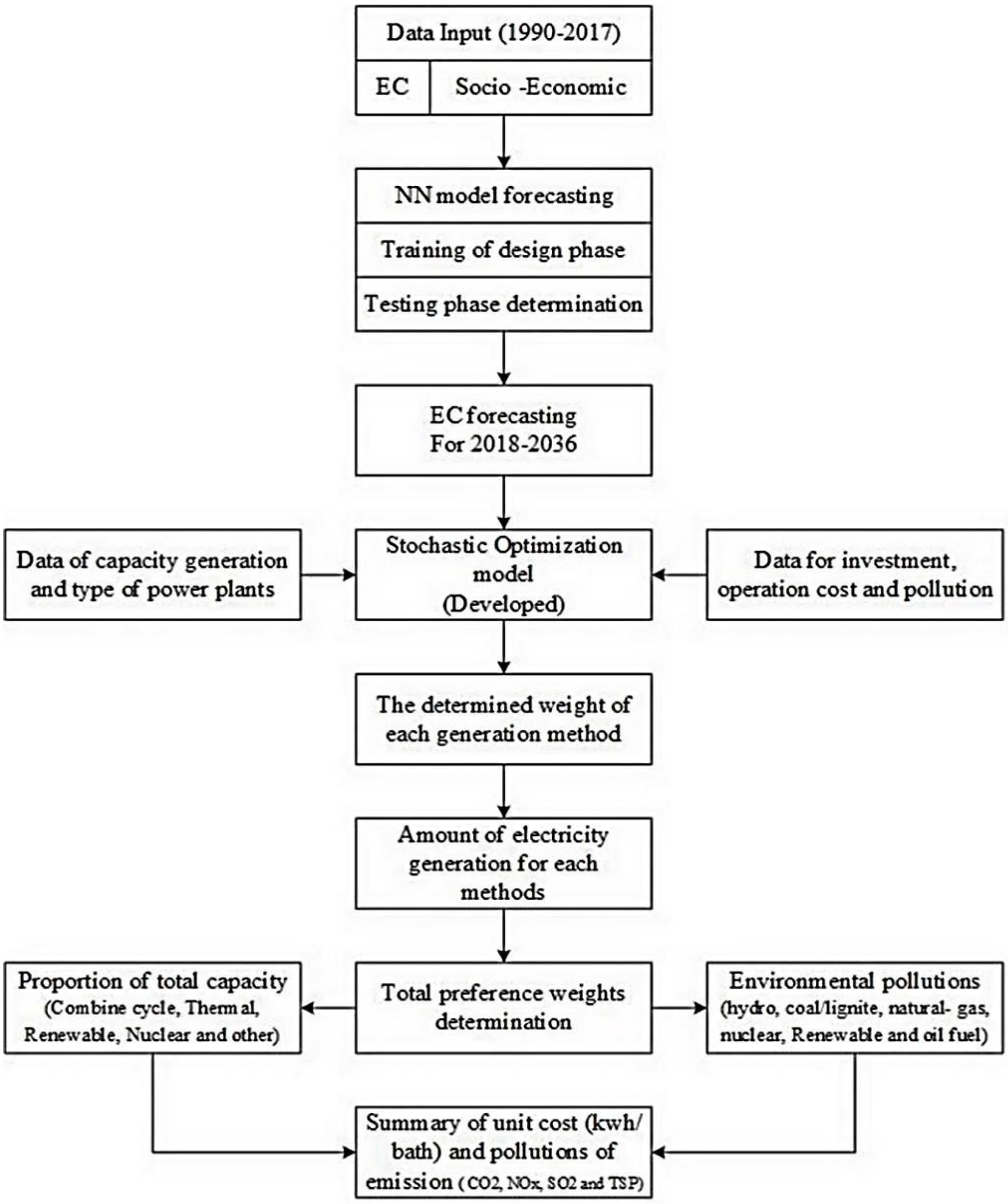

Figure.7 Flowchart for long-term of EC forecasting and stochastic optimization method

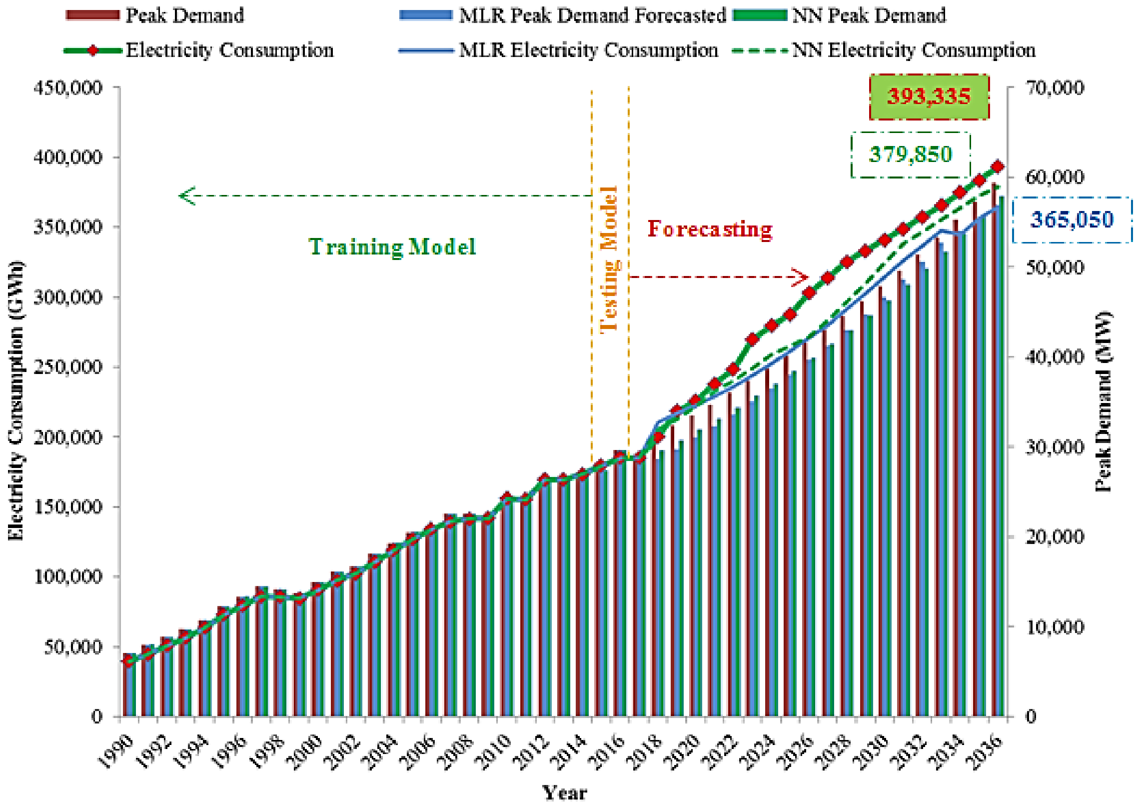

Figure.8 Forecasting results of electricity consumption.

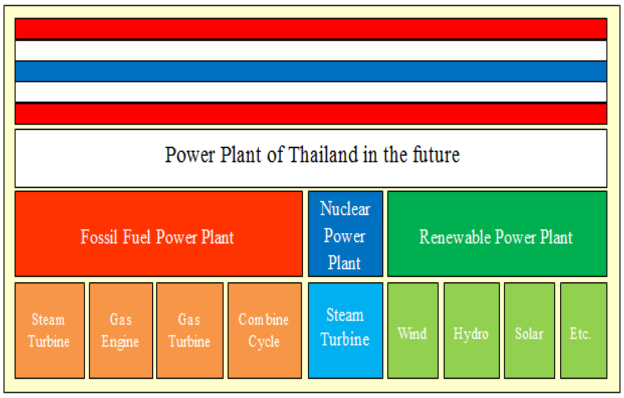

Figure.9 Thailand types of power plants in the future

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