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IMPACT OF LOAD UNCERTAINTY ON GENERATION SYSTEM RELIABILITY

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วิทยานิพนธ์ฉบับนี้เกี่ยวข้องกับการกำหนดกำลังการผลิตไฟฟ้าโดยอาศัยเกณฑ์ความเสี่ยงของระบบไฟฟ้ากำลังซึ่งได้รับการกำหนดไว้ตั้งแต่เริ่มต้น การกำหนดเกณฑ์ความเสี่ยงซึ่งอาศัยวิธีการตัดสินใจและวิธีการความน่าจะเป็นนั้น เป็นการดำเนินการเพื่อให้มั่นใจว่า การจัดหากำลังการผลิตไฟฟ้าเป็นไปอย่างพอเพียงและต่อเนื่อง ตลอดระยะเวลาการวางแผนกำลังการผลิตไฟฟ้าในระยะยาว ด้วยเหตุที่กำลังการผลิตที่ต้องการนี้ขึ้นอยู่กับความต้องการไฟฟ้าที่พยากรณ์ไว้ในอนาคต วิทยานิพนธ์ฉบับนี้จึงพิจารณาผลของความไม่แน่นอนเนื่องจากการพยากรณ์ความต้องการใช้ไฟฟ้าไว้หลายรูปแบบ ได้แก่ แบบจำลองความคลาดเคลื่อนของการพยากรณ์แบบปกติ การพยากรณ์ต่ำเกินไป และ การพยากรณ์สูงเกินไป ในการศึกษาจะมีการเปรียบเทียบผลระหว่างการใช้เกณฑ์ความเสี่ยงที่อาศัยการกำหนดกำลังการผลิตสำรองเป็นร้อยละของความต้องการใช้ไฟฟ้า และการใช้ดัชนีความเชื่อถือได้ เช่น LOLE เป็นต้น ผู้วิจัยได้ทำการพัฒนาโปรแกรมคอมพิวเตอร์สำหรับวางแผนกำลังการผลิตในระยะยาว ซึ่งได้ผ่านการทดสอบกับระบบ IEEE - RTS จากนั้นจึงนำไปใช้จำลองกับระบบที่ใช้ในทางปฏิบัติ เช่น การผลิตไฟฟ้าของประเทศไทย และประเทศพม่า ผลจากการทดสอบได้นำไปสู่ข้อเสนอแนะในการกำหนดกำลังการผลิตไฟฟ้าที่เหมาะสมต่อไป

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This thesis focuses on the determination of generation capacity based on a predefined risk criterion. The predefined criteria, based on deterministic and probabilistic methods, is set to ensure continuous and adequate power supply for long-term generation expansion planning. Since the required generation capacity highly depends on the future forecasted demand, the thesis considers the impact of various load uncertainty types, i.e. normal, under, and over forecasted models. In this thesis the results from basic percentage reserve criteria and probabilistic indices, e.g. Loss of Load Expectation etc., are compared. A long-range generation expansion planning program has been developed and tested with the IEEE-RTS system. Then it is used to simulate several scenarios for practical test systems, i.e. Myanmar and Thailand generation systems, from which suggestion on reserve criteria is proposed.

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Field of study Electrical Engineering Advisor's signature..................................
Academic year 2004

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CHAPTER I

INTRODUCTION

1.1 Background

The basic functional zones of generation Hierarchical Level (HL I), composite (HL II) and distribution systems (HL Ш) can be used to analyze and plan for system development. In an HL I study, the total system generation is examined to determine its adequacy to meet the total system load requirement. The HL I model is shown in Fig.1.1.

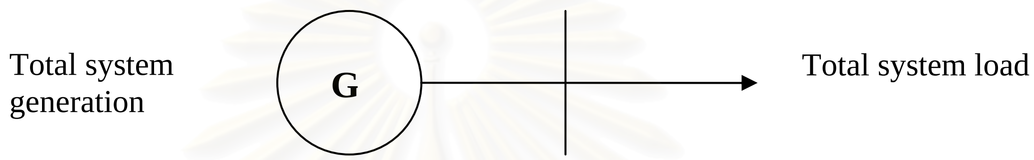


Fig 1.1 Basic model for HL I study

To supply electricity of high quality and reliability with least interruption we should consider extending generation to meet with forecasted load for long term planning. To perform generation system reliability evaluation more efficiently and accurately we should consider impact of uncertainties in the forecasted peak loads. In addition we should determine the required amount of system generating capacity and provide an excess capacity or reserve margin to ensure continuous and adequate power supply. All these considerations are important in power system operation and planning.

Both deterministic and probabilistic methods have been applied extensively to determine the required level of capacity reserve to be maintained by a system. A basic goal of a probabilistic technique is to maintain the system risk as close as possible to but lower than an allowable risk at all time.

There is considerable reluctance to apply probabilistic techniques such as Loss of Load Expectation (LOLE) approaches to small isolated power systems, containing small numbers of generating units. Some of the more frequently cited [1] are the lacks of system operating information contained in the conventional probabilistic risk index and the unavailability of appropriate data on generating unit performance and on the actual load demand. The reluctance by system planners of small isolated systems to accept probabilistic methods in their present form dictates a need to create a bridge between the deterministic methods and the prevalent probabilistic techniques. This can be achieved using a well-being framework in which the deterministic techniques are embedded in the conventional probabilistic indices.

In addition to reliability index based on the sense of risk, e.g. LOLE, a system well-being index [2] which is defined as healthy, marginal, and at risk status are illustrated by application to practical power systems [3]. These indices can be obtained by a technique which takes into account system well-being of factors such as generating unit sizes and their forced outage rates, annual load growth and load forecast uncertainty.

Reference [4] discusses the operating benefits from load management taking into account both deterministic and probabilistic aspects of the system. System cost savings can be achieved by using interruptible load to reduce system spinning reserve. The system may transfer from the risk state to the healthy state by committing additional generating unit(s).The problem of generation expansion planning is to determine the amount of new generation facility to be constructed so that the sum of fixed and variable costs of generation facilities is minimized over a certain period of time [5].Reference [6] provides an alternative approach in dealing with uncertainty modeling by fuzzy number in electrical power generation reliability evaluation.

One of the main tasks for an electric utility is to adequately supply the demand. The supply generation usually takes 5-10 years to complete the construction. Therefore we need to forecast the demand into the future. Then a required amount of generation capacity is planned for such demand. The forecasted demand contains uncertainty in its value. If the demand is forecasted too high it consequently requires too much generation capacity causing over investment and finally high electricity price. In contrast if the forecasted demand is lower than what actually happens in the future it may cause inadequate generation capacity and face high risk of interruption. Therefore the load forecast uncertainty is an important parameter which has to be considered in generation expansion planning study.

Generation expansion planning takes into account all concerned parameters, e.g. forecasted demand, generation and load uncertainties to adequately supply the demand. The most important uncertainty in any expansion plan is that uncertainty still exists at the time the actual decision has to be made for additional generating units. The unit additions incorporating load forecast uncertainty are at a different rate from that determined without recognizing uncertainty. In general, the reserve required to satisfy the future uncertain load is always higher than that required for an equivalent known load.

Load forecast uncertainty can be incorporated in general generation system reliability evaluation. Risk indices, e.g. Frequency and Duration (F&D), Loss of Load Expectation (LOLE) can be calculated with the consideration of load uncertainty. In this thesis, impact of load uncertainty comprising normal, over forecast, and under forecast models on the generation reserve capacity has been analyzed with application for long-term generation planning problems.

In this thesis, basic deterministic and probabilistic based methods are applied to find the capacity reserve for different predefined risk index, i.e. LOLE, etc. Then the results will be analyzed with different generation and demand scenarios obtained from Myanmar generation System and Thailand generation System. Finally suggestion on reserve criteria for Thailand and Myanmar generation system will be proposed.

This thesis is organized into six chapters. Chapter 2 describes the concept of system modeling i.e. generating unit model, load model, and uncertainty models. Chapter 3 explains the calculation methodology of risk indices concept. A method to develop a completed capacity outage probability table which is an important tool to calculate the risk indices is reviewed. Chapter 4 presents the system expansion studies and concept by using probabilistic method. Chapter 5 interprets the simulation results of practical test system, i.e. Myanmar generation system and Thailand generation system. Finally the conclusion is drawn in Chapter 6.

1.2 Objectives of Research

1) To study generation system expansion taking into account uncertainties of both generation and demand.
2) To determine and compare generating reserve capacity, based on specified criteria and various load uncertainty scenarios.
3) To compare generation system risks obtained from both deterministic and probabilistic criteria.

1.3 Scope of the Study

1) Focusing on generation system expansion.
2) Collecting unit performance based on actual data from Electricity Generation Authority of Thailand (EGAT), IEEE, etc.
3) Using actual load during 1993-2003 for Thailand generation system study.

1.4 Expected Contribution

1) This thesis provides useful information and resources for future generation expansion planning.
2) The results will suggest suitable options for improving generation system reliability taking into account all concerned parameters, e.g. generating unit forced outage rate, forecasted demand, and generation and load uncertainties.
3) Appropriate generating reserve capacity for a general system can be determined by comparing generation system risks obtained from both deterministic and probabilistic criteria.

CHAPTER II

SYSTEM MODELING

2.1 Introduction

A model is a structure that a system can use to simulate or anticipate the behavior of something else. To measure risk precisely mathematical models of uncertainty, are called probability models. During eighteenth and nineteenth centuries, it was believed that variability or uncertainty in an observed phenomenon could be attributed to a failure to identify and control its causes. Problems in power system analysis, such as load flow, optimal power flow, fault current calculation, contingency evaluation, and penalty factor calculations, generally relies on the use of power system's modeling.

Generation system reliability evaluation also relies upon two main types of models, i.e. generation and load. This chapter will discuss the concepts of generating unit modeling, load modeling and uncertainty models in the forecasted peak loads, which will be used in generation system reliability assessment, of which the details will be presented in the next chapter.

2.2 Generation System Reliability Evaluation Concept

In power system reliability evaluation, the generation model can be developed through a capacity outage probability table which represents the capacity outage states of the generation system together with the probability of each state. The load model can either be the daily peak load variation curve (DPLVC), which only includes the peak loads of each day, or the load duration curve (LDC) which represents the hourly variation of the load. Generation and load models are combined to form an appropriate risk model as shown in Fig 2.1.

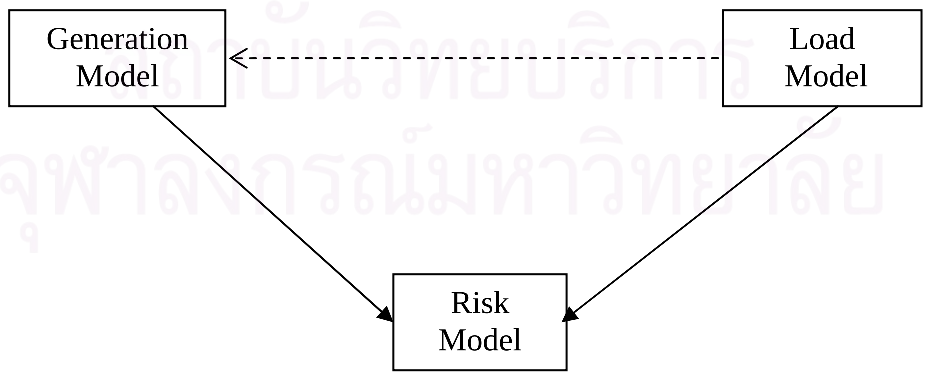


Fig.2.1 Conceptual tasks for HL I evaluation

2.3 Generating Unit Modeling

The generation system model can be used directly as an indication of system generating capacity adequacy. A loss of load will occur only when the capacity of the generating capacity remaining in service is exceeded by system load.

Risk in the system can be calculated if the unavailability of each generating unit is known. The unavailability or the probability of finding a generating unit in the failed state in the future is known as the unit forced outage rate (FOR).

The concept of unavailability as illustrated in equation 2.1 is associated with the simple two-state model shown in Fig 2.2. This model is directly applicable to a base load generating unit which is either operating or forced out of service. In most capacity reserve studies [1-3], generating units are represented by a two-state model.

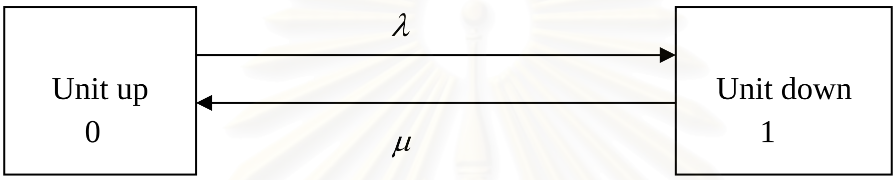


Fig 2.2 Two state model for a base load unit

The steady state probability of each state can be represented by the unavailability and the availability as described by equations 2.1 and 2.2 respectively.

$$\text{Unavailability (FOR)} = U = \frac{\lambda}{\lambda+\mu} = \frac{r}{m+r} = \frac{r}{T} \qquad (2.1)$$

$$\text{Availability (A)} = 1\text{-}U \qquad (2.2)$$

where

λ = expected failure rate,
μ = expected repair rate,
m = mean time to failure = MTTF = $1/\lambda$,
r = mean time to repair = MTTR = $1/\mu$, and
T = cycle time = 1/f.

The parameters λ and μ are state transition rates since they represent the rate at which the system transits from one state to the other.

The operating cycle of a generating unit at down and up states are shown in Fig 2.3. The system down state is tolerable provided it does not happen too frequently or last too long. A system repair or replacement action is performed during these down states. The system may suffer failures, particularly during bad weather, and cause the interruption of supply to customers until the system can be restored to an operating (up) state.

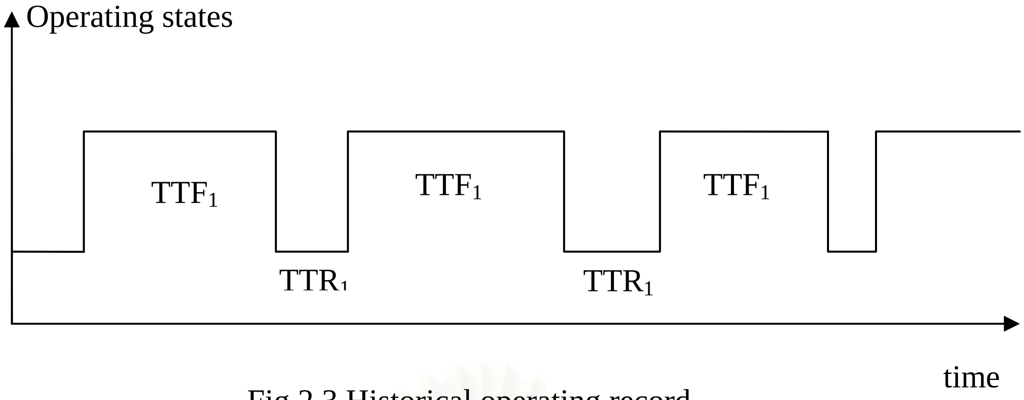


Fig 2.3 Historical operating record

If the utility collect data long enough so that we can find their mean values as mean time to failure (MTTF) and mean time to repair (MTTR) of which shown in Fig 2.4. In some cases, MTTR can be days while MTTF can be years.

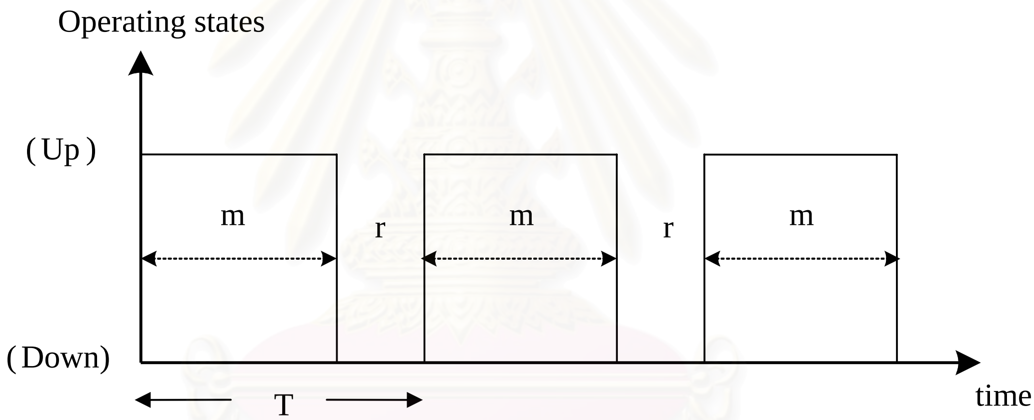


Fig 2.4 Mean time to failure and mean time to repair

As an example that parameters λ and μ will be used to develop the generation model or COPT. Consider a system data containing five 40MW units each with a FOR of 0.1.

Table 2.1 Generation model for the five-unit system

State	Capacity out of service (MW)	Individual probability	Cumulative probability
1	0	0.59049	1
2	40	0.32805	0.40951
3	80	0.0729	0.08146
4	120	0.0081	0.00856
5	160	0.00045	0.00046
6	200	1.00E-05	1.00E-05

2.4 Load Modeling

In power system reliability analysis, there are a number of possible load models, e.g. load duration curve and individual state load model etc. In this thesis we use three types of load model i.e. daily peak load variation curve, load duration curve, and individual state load.

One of the simplest load model used in generation reliability analysis is represented by variation of daily peak load. The individual daily peak load can be arranged in descending order to form a cumulative load model which is known as the daily peak load duration curve as shown for an example in Fig 2.5. We need to know the peak load for this model. The unit of daily peak load variation curve is in days. This model can be used to calculate risk index, e.g. loss of load expectation (LOLE).

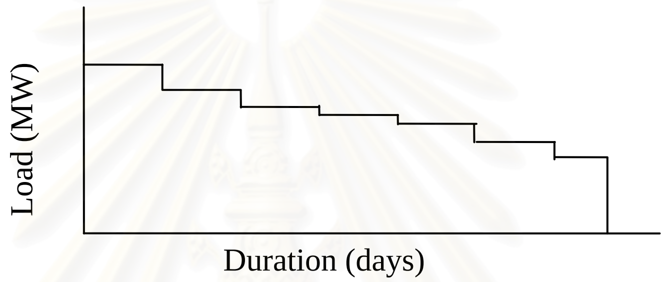


Fig.2.5 Daily peak load variation curve (DPLVC)

2.4.1 Load duration curve

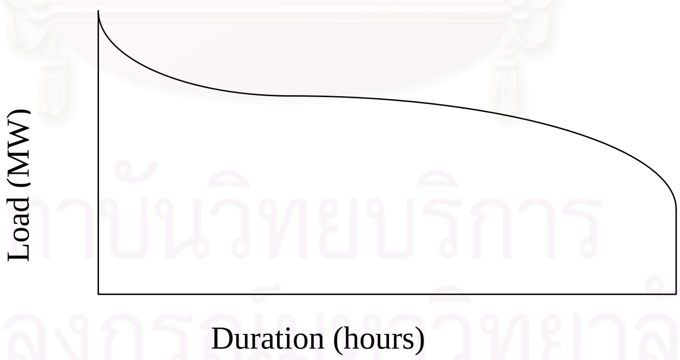


Fig.2.6 Load duration curve (LDC)

The model shown in Fig 2.6 is known as load duration curve since it is developed from individual hourly load values. In this case the area under the curve represents the energy required in the given period. This model is used to find one of the reliability indices, i.e. expected energy not supply (EENS). The unit of load duration curve is in hours.

2.4.2 Individual state load model

An individual state load model is shown in Table 2.2.

Table 2.2 load data

No. of occurrences (day)	load (MW)
12	890
83	850
107	750
11	720
47	690
365	500

The information in Table2.2 can be rearranged to be an LDC as shown in Fig 2.6. For simplicity, we can use a straight line instead of a ladder type LDC to calculate risk index. It should be noted that we can calculate the load factor from the above information as described by equations 2.3 and 2.4.

$$\text{Load factor} = \text{Average load / Peak load} \quad (2.3)$$

$$\text{Average Load} = \text{Energy / Hour} \quad (2.4)$$

From the load data shown in Table 2.2, we obtain

$$\text{Average load} = \{(890*12) + (850 * 83) + (750 * 107) + (720 * 116) + (690 * 47) + (500 * 365)\} / \{365+ (12+ 83+107+116+47)\}$$

$$= 630.$$

Load factor = 630 / 890 = 0.7

To simplify the hourly load curve, we can use a two state load model, i.e. low and peak load level, as shown in Fig 2.7. The element e is called as exposure factor. The daily load model contains a peak load level of mean duration of e day and a fixed low load of 1-e day shown in Fig. 2.7.

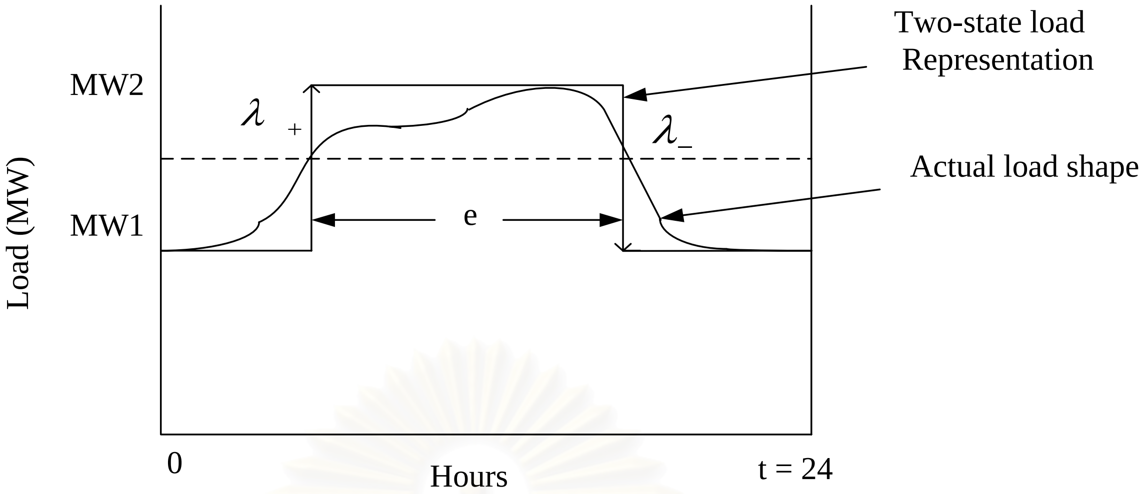


Fig.2.7 Daily load model

To calculate the e factor, we can find area under the actual load curve which is energy demand (MWh).

From the Fig. 2.7, Low load (L0) is MW1 and peak load (L1) is MW2.
We can calculate e by applying the following equation (2.5) derived from equation (2.6).

$$\text{energy} = MW1 * e * t + MW2 * (1-e) * t \tag{2.5}$$

$$e = (\text{energy} - MW2 * t) / (MW1 * t - MW2 * t) \tag{2.6}$$

If e = 1, the load is constant and normally represented by its daily peak value as in the conventional LOLE calculation approach. For normal calculation, the e factor is considered to be the same for every day during the considering period. Its magnitude is between 0 and 1, otherwise arbitrarily chosen. There is no clear rule for how to choose e in a given case. However most of the results are not too sensitive to the value of e [7]. λ_+ is the transition rate from low load to high low and λ_- is the transition rate from high load to low load.

The model represents the daily load cycle as a sequence of peak loads L_i, each of a mean duration of e days interspersed with periods averaging (1-e) days of a fixed, light load L_0. The load cycle for a specified period is illustrated in Fig.2.8. The sequence of peak loads is random.

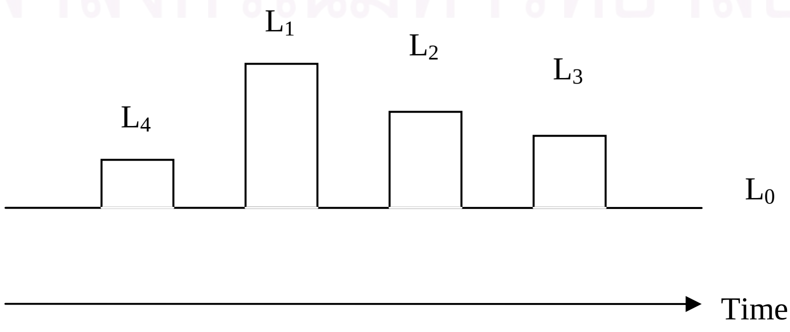


Fig.2.8 Period load model

The parameters required to completely define the individual load model for a specified period are shown in Table 2.3.

Table 2.3 Parameters for individual state load model

Number of load levels	N	
Peak loads	L_i, i=1,……, N	$L1>L2>…..>L_N$
Low load	L_0	
Number of occurrences of L_i	$n(L_i)$, i = 1,……,N	
Period	$D=\sum_{i=1}^{N} n(Li)$	
	Peak load L_i	Low load L_0
Mean duration	e	1-e
Probability	$p(Li)=\frac{n(Li)}{D}e$	$p(L_0)=1-e$
Upward load Departure rate	$\lambda_+(L_i)=0$	$p(L_0)=1-e$
Downward load Departure rate	$\lambda_-(L_i)=\frac{1}{e}$	$\lambda_-(L_0)=0$

The load model can either be the daily peak load variation curve (DPLVC), which only includes the peak load of each day, or the load duration curve (LDC) which represents the hourly variation of the load.

2.5 Uncertainty in the Forecasted Peak Loads

Uncertainty is the difference between a measured, forecasted, estimated or calculated value and the true value that is sought. Uncertainty includes errors in observation and calculation. The forecasted peak load normally differs from the actual value due to unforeseen factors, e.g. economic growth, weather changes etc. Some uncertainty can be described by a probability distribution whose parameters can be determined from past experience, future load modeling, and possible subjective evaluation.

It is difficult to obtain sufficient historical data to determine the statistical distribution describing the load forecast uncertainty. However, published data has suggested that the uncertainty can be reasonably described by a normal distribution. The distribution mean is the forecast peak load.

The probability density function f(x) of a normal distribution is defined by the equation (2.7).

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}}\exp[-\frac{(x-\mu)^2}{2\sigma^2}] \qquad -\infty < x < \infty \qquad (2.7)$$

The constants $\mu(-\infty < \mu < \infty)$ and $\sigma^2(\sigma^2 > 0)$ are the parameters of the normal distribution. The graph of f(x) which is a bell-shaped curve shown in Fig 2.9. The graph of a normal density function f(x) is symmetric around the mean μ .

If x (random variable) has a normal distribution with mean μ and variance σ^2, then the standardization

$$Z = \frac{(x-\mu)}{\sigma}$$ of x has the standard normal distribution. That is mean $\mu = 0$

and variance $\sigma^2 = 1$.

By integrating f(x) with random variable x start from $-\infty$ until ∞ we get the value of area under the curve of each interval. The area of each class interval represents the probability of the load is the class interval mid-value.

The normal distribution is often used to model variation when the distribution is symmetric.

The uncertainty in load forecasting using normal distribution can be included in the computation by dividing the load forecast density function into class intervals, the number of which depends upon the accuracy desired. The value at the middle point of each interval can be represented for its class. Fig.2.9 shows the seven-step interval representation for the forecasted load density function.

Parameter x in figure 2.9 represent the forecasted peak load, x = 0 and its deviation defined according to the standard score, i.e. x = -3,-2,-1, 0,1,2,3. The area under the curve represents the occurring probability of each interval also shown in figure 2.9.

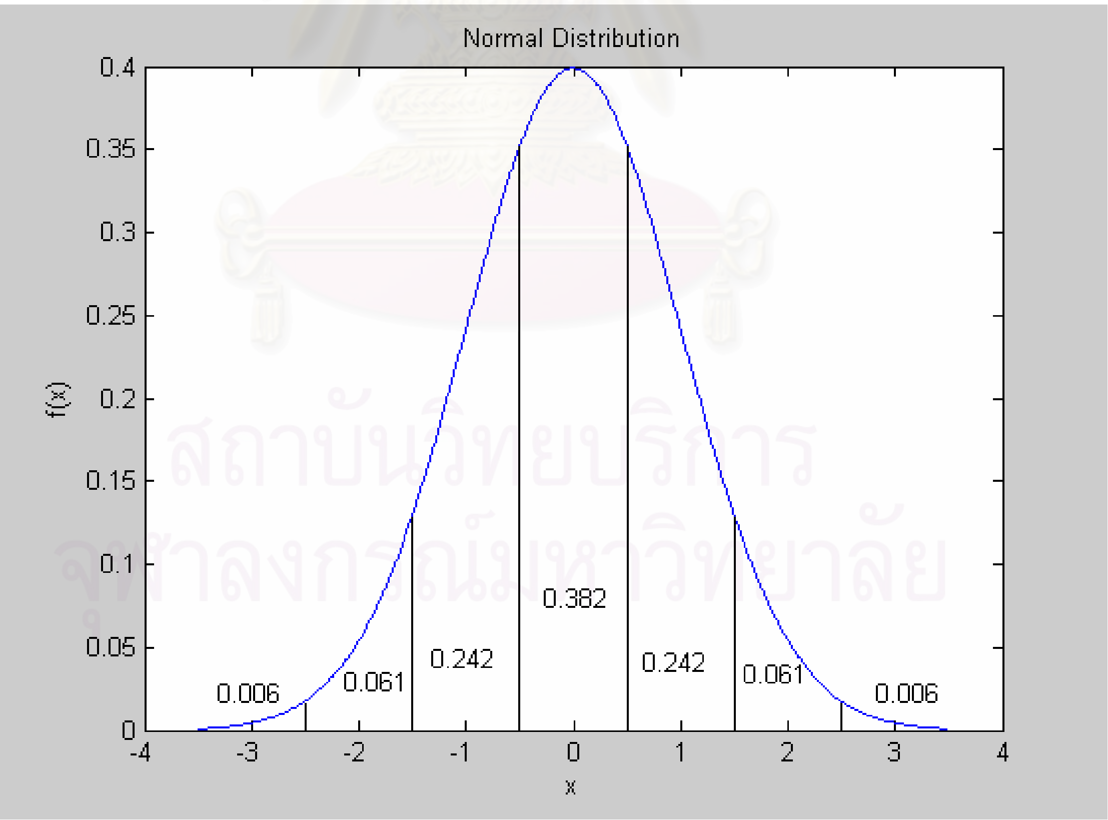


Fig.2.9 Approximation of the forecasted peak load

According to Fig.2.9, the actual and the forecasted loads are the same at mean or the standard score of 0. The standard scores of 1, 2 and 3 mean that the actual load to be occurred in the future may be more than the forecasted value, and vice versa for -1,-2 and -3. If the peak load of 50MW is forecasted, and assuming that the standard deviation of 2% error is assumed, the error of one standard deviation will be $50 \times 2/100 = 1$ MW. Therefore, the uncertainty of the forecasted peak load for -1,-2,-3 according to Fig 2.9 are 49, 48, 47MW and for +1, +2, +3 are 51, 52, 53MW respectively.

2.5.1 Over forecast load model

Since the future peak demand is normally forecasted based on a methodology used by each utility, its accuracy may be different according to the employed technique. There might be a chance the forecasted results are frequently either too high or too low compared to the actual values to be occurred in the future.

Assume that we can track down all the concerned records and found out that the forecasted peak loads were normally higher than the actual peak load i.e. over forecasted load. In this regard, we use Rayleigh distribution [9] instead of the normal density function as described in the previous section to model the uncertainty of which the general formula can be described by equation (2.8).

$$f_x(x) = \frac{2}{b}(x-a)e^{-(x-a)^2/b} \tag{2.8}$$

for $-\infty < a < \infty$ and $b > 0$

The mean and variance of this function are shown in Equation (2.9) and (2.10) respectively.

$$\bar{x} = a + \sqrt{\frac{\pi b}{4}} \tag{2.9}$$

$$\sigma_x^2 = \frac{b(4-\pi)}{4} \tag{2.10}$$

To compare with the normal distribution presented in the previous section, we assume the parameters a and b of equation (2.8) to be as -3.5 and 6 respectively, of which the density function is illustrated in Fig.2.10.

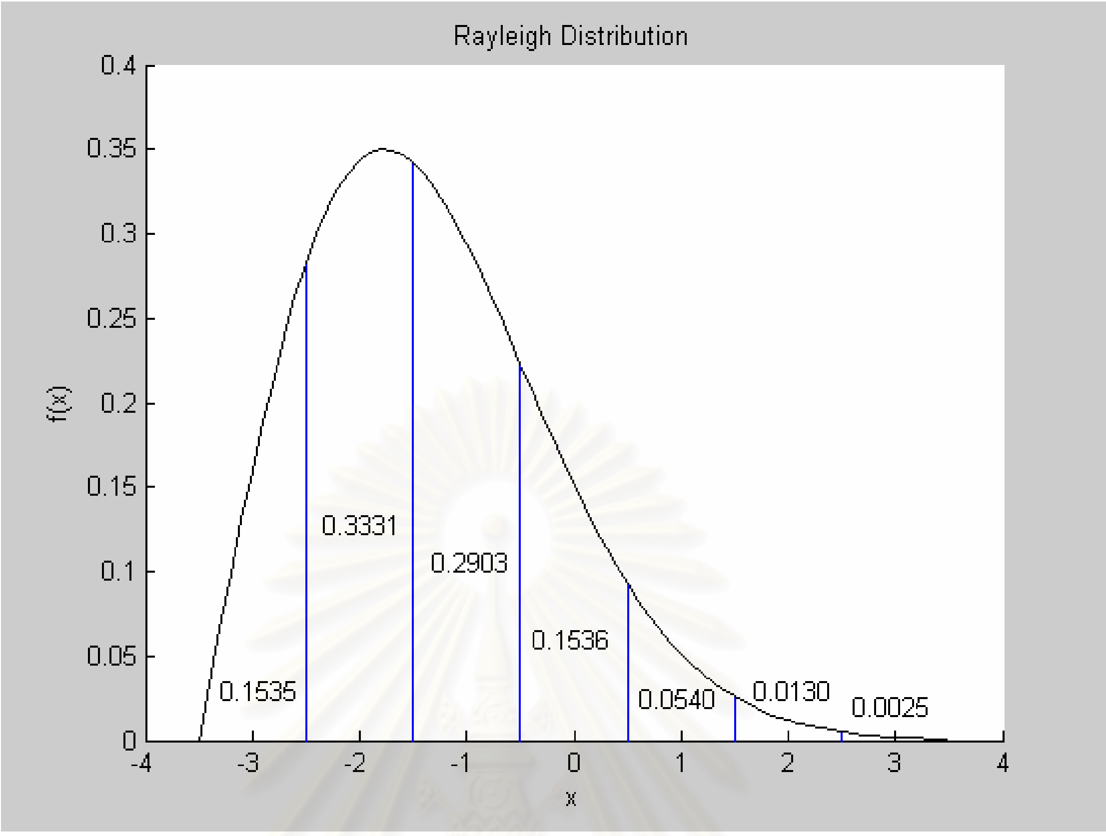


Fig.2.10 Seven-step approximation of the Rayleigh distribution

2.5.2 Under forecast load model

If the forecasted load is less than the actual peak load, we call it to be under forecasted. A Rayleigh distribution function can also be used to model the under forecast uncertainty which is illustrated in Fig.2.11. The parameters used are still the same as in the case of over forecasted except the signs of the standard deviation (x) are different.

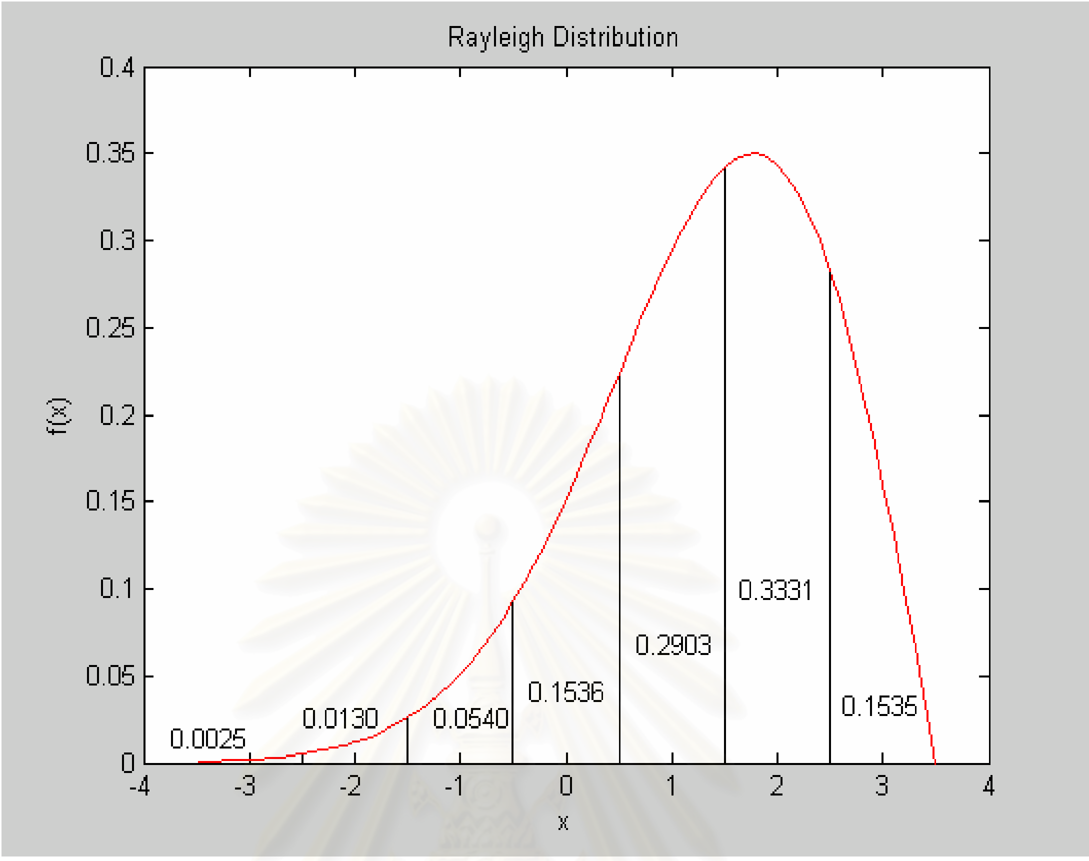
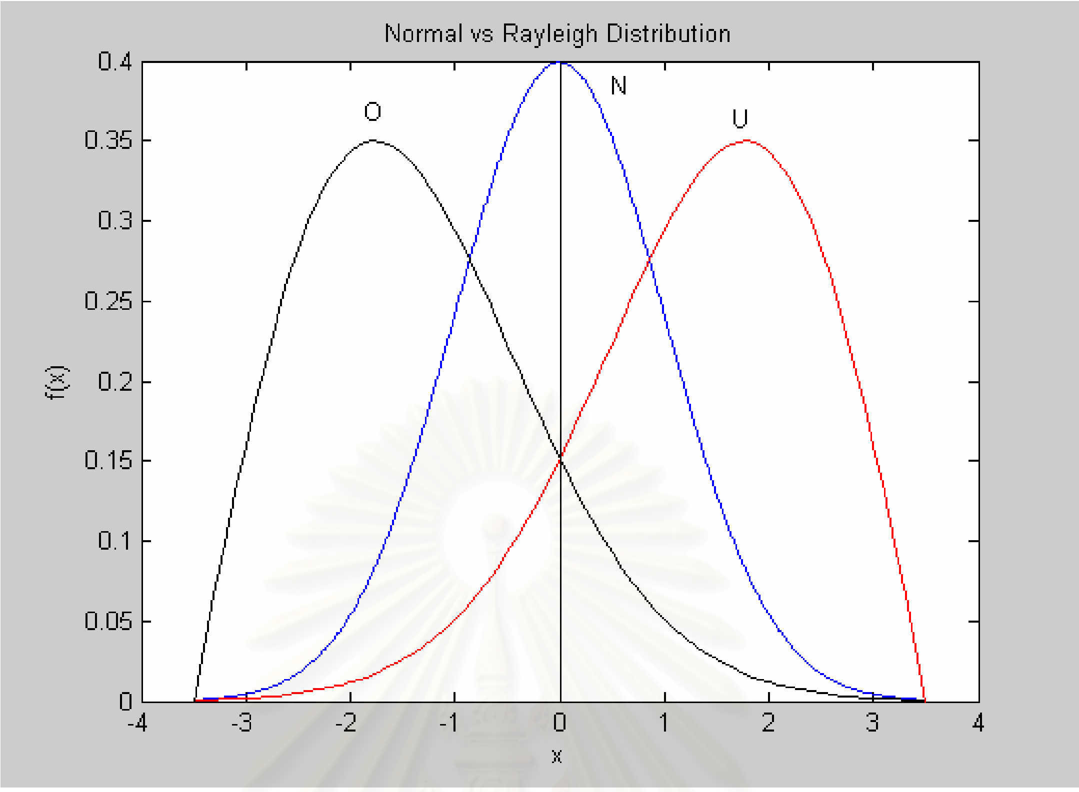


Fig.2.11 Seven-step approximation of the Rayleigh distribution

As mentioned before the normal distribution is symmetric for both sides, lower and higher of the forecasted peak load. Generally our forecasted value, e.g. peak load, may be either higher or lower than the actual value. The forecast uncertainty, comprising normal, over forecast and under forecast models are shown for comparison in Fig 2.12. By simulation using the different uncertainty models, we may expect to see different results as described below.



Figs 2.12 Comparison among normal, over forecast, and under forecast models

The forecast error is the difference between the forecasted and the actual values. We can see different results in case of with and without uncertainty consideration based on a simple example. Suppose that the actual peak load to be occurred in a considered future year is 9,000 MW and 10% of peak load is employed for determining reserve capacity. If we did over forecast the peak to be 10,000MW, the minimum installed capacity will be 11,000MW compared to the required 9,900 MW in the case of accurate load forecast. However if we forecasted the peak load to be 8,000MW, the minimum installed capacity might be just 8,800MW which may cause inadequate capacity for the considering year. This kind of impact will be considered based on both deterministic and probabilistic methods in this thesis.

CHAPTER III

CALCULATION METHODOLOGY

3.1 Introduction

The generating capacity reliability evaluation is examined to determine the adequacy generation to meet the total system load requirement. In an HL I study the generation model and load model have been discussed in chapter 2. Generation model is represented through the system capacity outage probability table (COPT) which is combined with the system load characteristics to give expected risk indices, e.g. LOLE, EENS, and F&D.

This chapter will discuss about the risk index concept of LOLE, EENS and F&D, capacity outage probability table development, risk indices calculation and calculation examples.

3.2 Risk Indices Concept

A loss of load will occur when the capability of the generating capacity remaining in service is exceeded by the system load level. The loss of load expectation (LOLE) is the average number of days on which the daily peak load is expected to exceed the available generating capacity. Therefore it indicates the expected number of days on which a load loss or deficiency will occur. It does not indicate the severity of the deficiency and neither does it indicate the frequency nor the duration of loss of load. Despite these shortcomings, it is the most widely used criterion in generation-planning studies [10-12].

The basic expected energy curtailed concept can also be used to determine the expected energy produced by each unit in the system and therefore provides a relatively simple approach to production cost modeling. The expected energy not supplied (EENS) is the expected energy which can not be supplied in a given period due to insufficient installed capacity. If the unavailability of the generating units is known, the risk of the system can be calculated. The area under the load duration curve represents the energy required for the system load demand in the specified time period.

The frequency and duration criterion is an extension of the LOLE index in that it also identifies the expected frequency of encountering a deficiency (F) and the expected duration of the deficiencies (D). It therefore contains an additional physical characteristic which makes it sensitive to further parameters of the generating system, and so it provides more information to power system planners. The criterion has not been used very widely in generation system reliability analyses, although it is extensively used in network studies.

All the mentioned indices are of HL I type and can be obtained via the combination of the generation and load models. The next section will present the development of the COPT which is considered as a generation model to obtain all the indices.

3.3 Capacity Outage Probability Table (COPT)

The term 'capacity outage' indicates a loss of generation which may or may not result in a loss of load. This condition depends upon the generating capacity reserve margin and the system load level. The generation model required in the loss of load approach is sometimes known as a capacity outage probability table. The expression for a state of exactly X MW on forced outage after a unit of capacity C MW and forced outage rate U is added are shown in equation (3.1).

$$p(X) = p'(X)(1-U) + p'(X-C)U \qquad (3.1)$$

where

$p'(X)$ is the individual state probability before the unit is added, and
$p(X)$ is the individual state probability after the unit is added.

The above expression is initialized by setting $p'(X)=1.0$ for $X \leq 0$ and $p'(X) = 0$ otherwise. The primed values represent similar quantities before the unit is added. In Equations (3.1) if X is less than C

$$p'(X-C) = 0$$

The procedure is initiated with the addition of the first unit (C_1). The following equation (3.2) is used to give the cumulative state probabilities.

$$P(X) = P(Y) + p(X) \qquad (3.2)$$

where

$P(X)$ is the cumulative state probability , and
Y denotes the capacity outage state just larger than X MW.

The units can be combined using basic probability concepts. This approach can be extended to a simple but powerful recursive technique in which units are added sequentially to produce the final model. These concepts can be illustrated by a simple numerical example.

Suppose that we look at a system consisting of two 25 MW units and one 50 MW unit with forced outage rates of 0.02 as given in Table 3.1.

Table 3.1 System data

Unit no.	Capacity (MW)	Failure rate λ (f/day)	Repair rate μ (r/day)	FOR
1	25	0.01	0.49	0.02
2	25	0.01	0.49	0.02

We can obtain the COPT based on sample calculation which is shown below.

Step 1 Add the first 25 MW unit

Since the first unit is a two-state model, therefore there are only two states of which their probability and outage capacity are shown in table 3.2.

Table 3.2 Add the first 25 MW unit

State No. i	Cap. outage (MW)	Probability $p(X)$
1	0	0.98
2	25	0.02

The next 25 MW generating unit can be added to this table by considering that it also has only two states, i.e. in and out of service. The unit can be in service with probability of 1-0.02 = 0.98 and it can be out of service with probability of 0.02.

Step 2 Add the second 25 MW unit

Based on the information in the previous step, equation 3.1 is then applied to obtained table 3.3.

Table 3.3 Individual and cumulative probability calculation

(1) Cap. outage X (MW)	(2) $p^{'}(X)(1-U)$	(3) $p^{'}(X-C)U$	(4) Col(2)+Col(3) $p(X)$	(5) Cumulative Pb $P(X)$
0	0.98×0.98	0×0.02	0.9604	1.0000
25	0.02×0.98	0.98×0.02	0.0392	0.0396
50	0×0.98	0.02×0.02	0.0004	0.0004

From column (1) of table 3.3, 50MW outage is resulted from the failure of both units. In column (2) $p^{'}(X)$ obtained from table 3.2, i.e. 0.98 and 0.02 for 0 and 25 MW respectively. For X = 50 MW the capacity outage for $p^{'}(X) = 0$ because $X > 0$.

In column (3) X is less than C so $p^{'}(X-C) = 0$ for 0 MW. For 25, and 50MW outages $X-C$ = 25-25 = 0 and, 50-25 = 25, this probability of each state is taken from table 3.2.

Column (4) individual probability in table 3.3 is calculated by using equation 3.1. By summation column (2) and (3), it gets individual probability of each capacity out is shown in column (4).

$$P(X) = P(Y) + p(X) = 0.0004 + 0.0392$$

= 0.0396 that shown in column (5).

With the above calculation procedure, we can obtain the generation capacity model or capacity outage probability table of two identical units which can be combined to give the capacity outage probability table as shown in table 3.4. The above technique is ideally suited to digital computer application.

Table 3.4 Capacity Outage Probability Table (COPT)

State No. i	Cap. outage X (MW)	Individual probability $p(X)$	Cumulative probability $P(X)$
1	0	0.9604	1.0000
2	25	0.0392	0.0396
3	50	0.0004	0.0004

The 50 MW generating unit is to be added to this table 3.4 by considering that it can exist in two states. It can be in service with probability of 1-0.02 = 0.98 and out of service with probability of 0.02. Column (2) shows the 50 MW extend unit in service. Therefore 0.98 multiply with the individual probability before 50 MW unit is added. Column (3) shows the 50 MW extend unit out of service shown in table3.5.

Table 3.5 Capacity outage probability table for the three unit system

(1) Cap. outage X (MW)	(2) $p^{'}(X)(1-U)$	(3) $p^{'}(X-C)U$	(4) Col(2)+Col(3) Ind pb $p(X)$	(5) Cumulative Pb $P(X)$
0	0.9604 × 0.98	0 × 0.02	0.9412	1
25	0.0392 × 0.98	0 × 0.02	0.0384	0.058792
50	0.0004 × 0.98	0.9604 × 0.02	0.0196	0.020392
75	0 × 0.98	0.0392 × 0.02	0.000784	0.000792
100	0 × 0.98	0.0004 × 0.02	0.000008	0.000008

From the Table 3.5 we can say that the probability of capacity outage 50 MW is 0.020392. The cumulative probability values decrease as the capacity on outage increases.

The table can be truncated by omitting all capacity outages for which the cumulative probability is less than a specified amount, e.g. 10^{-8}. This also results in a considerable saving in computer time as the table is truncated progressively with each unit addition.

3.4 Risk Indices Calculation

The development of the capacity models followed by the load models and the subsequent convolution to create the system of LOLE, EENS and F&D risk indices calculation are presented in this section.

3.4.1 LOLE calculation

Figure 3.1 shows a typical system relationship between load, installed and reserve capacity.

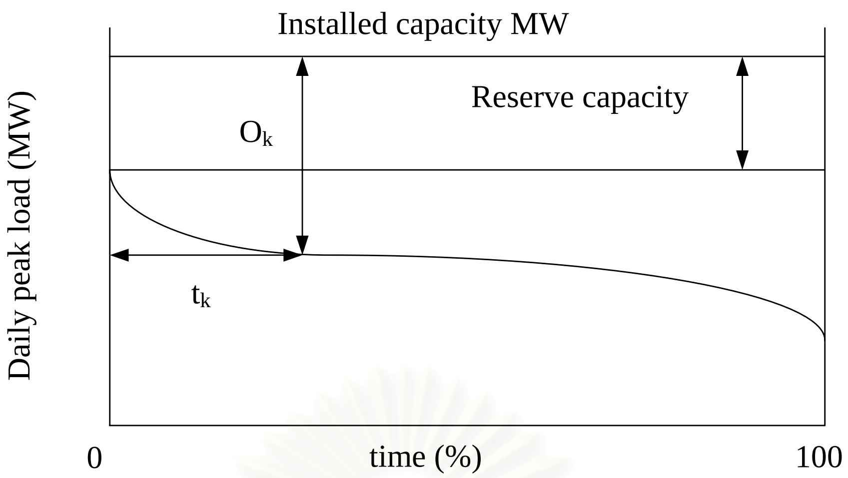


Fig.3.1 Relationship between load, installed and reserve capacity

Any capacity outage less than the reserve capacity will not contribute to the system LOLE. Outages of capacity in excess of the reserve will result in varying numbers of time units during which loss of load could occur.

A particular capacity outage will contribute to the system LOLE by an amount equal to the product of the probability of existence of the particular outage and the number of time units in the study interval that loss of load would occur if such a capacity outage was to exist. The total LOLE for the study interval is shown in equation (3.3).

$$LOLE = \sum_{k=1}^{n} p_k t_k \tag{3.3}$$

where

p_k = individual probabilities associated with capacity outage states,

O_k = magnitude of the *k*th outage in the system capacity outage probability table,

t_k = number of time units in the study interval that an outage magnitude of O_k would result in a loss of load, and

n = number of states of the system COPT.

The LOLE index can be obtained using the daily peak load variation curve. The load model is shown in Fig.3.1 as a continuous curve for a period of 100%.

If 100% of the time is 365 days, then

$$\text{LOLE} = \frac{365}{100} * \text{LOLE (\%)} = \text{LOLE day/yr.}$$

Generally the daily peak load variation curve (DPLVC) is used to evaluate LOLE indices giving a risk expressed in number of days the peak load will exceed the available capacity. The period of study could be a week, a month or a year.

When a daily peak load variation curve is used for annual calculation, the LOLE is in day per year. If the load characteristic in figure 3.1 is the hourly load duration curve, the value of LOLE is in hours.

3.4.2 EENS Calculation

The capacity outage probability model is convolved with the period load duration curve to obtain the expected energy not supplied due to unit forced outages. The load duration curve for a period of 8760 hours is shown in figure 3.2.

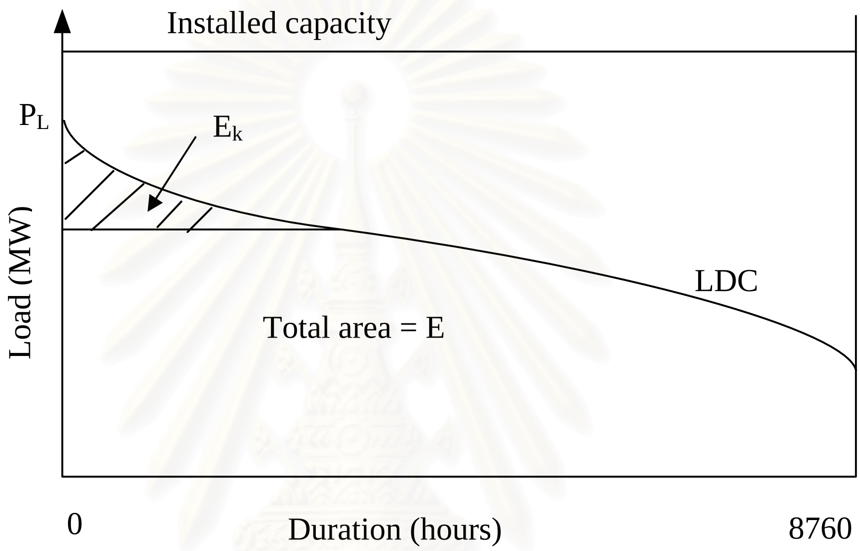


Fig.3.2 Load Model

The energy demanded E is the total area under the load duration curve. The formula used to determine the expected energy not supplied after each unit has been added to the capacity probability table of the system is:

$$EENS = \sum_{k=1}^{N} E_k \, p_k \tag{3.4}$$

where

N = total number of capacity states in the current system capacity-probability table,
E_k = area under load duration curve above a load equal to the capacity of the k^{th} capacity state and
p_k = probability of the k^{th} capacity state.

3.4.3 F&D Calculation

The system described in table 3.1 contains the basic data required for both the LOLE and the F&D methods. The F&D requires additional system data. Capacity outage probability table (COPT) as shown in section 3.3 can be added additional column to form a more complete capacity model.

The expression for a state of exactly X MW on forced outage after a unit of capacity C MW and forced outage rate U is added are shown in equations (3.5) and (3.6).

$$\lambda_+(X) = \frac{p'(X)(1-U)\lambda'_+(X) + p'(X-C)U(\lambda'_+(X-C)+\mu)}{p(X)} \tag{3.5}$$

$$\lambda_-(X) = \frac{p'(X)(1-U)(\lambda'_-(X)+\lambda) + p'(X-C)U(\lambda'_-(X-C))}{p(X)} \tag{3.6}$$

The $\lambda_+(X)$ and $\lambda_-(X)$ parameters are the upward and downward capacity departure rates respectively after the unit is added. The prime values represent similar quantities before the unit is added. In equations (3.5) and (3.6), if X is less than C

$$\lambda'_+(X-C) = 0 \qquad \lambda'_-(X-C) = 0$$

The procedure is initiated with the addition of the first unit (C_1). In this case

$$\lambda_+(0) = 0 \qquad \lambda_-(0) = \lambda_1$$

$$\lambda_+(C_1) = \mu_1 \qquad \lambda_-(C_1) = 0$$

$$\lambda_+(X) = \lambda_-(X) = 0 \quad \text{for } X \neq 0, C_1$$

The individual capacity state probability is calculated as mentioned in equation (3.1).The individual frequency can be used the following equation (3.7).

$$f(X) = p(X)\{\lambda_+(X) + \lambda_-(X)\} \tag{3.7}$$

Equation (3.8) and (3.9) can also be used to calculate the cumulative state probability and frequency respectively.

$$P(X) = P(Y) + p(X) \tag{3.8}$$

$$F(X) = F(Y) + p(X)(\lambda_+(X) - \lambda_-(X)) \tag{3.9}$$

where

$F(X)$ is the cumulative state frequency, and
Y denotes the capacity outage state just larger than X MW.

The above algorithms are suited for computer application. The period T is the system cycle time and is equal to the sum of the mean time to failure (MTTF) and mean time to repair (MTTR).

$$\text{Cycle time } T = m + r = \frac{1}{f} \tag{3.10}$$

The average duration of a particular capacity condition can be obtained as follows:

Average duration = probability of the condition / frequency of the condition (3.11)

The generation capacity models can be combined with the load to obtain system risk indices. The individual state load model which described in section 2.4.2 is used to examine and illustrate the calculation of F&D indices.

Normally the low load level does not contribute substantially to the negative margins and is sometimes omitted from the calculation. This can be easily done by assuming that the low load level is zero.

If low load level is included cumulative probabilities associated with the margin states increases slightly depending on the value of the low load level and the cumulative frequencies associated with the margin states decreases slightly as the load level transitions do not add to the frequency when the available capacity level is less than the low load level.

Reserve or margin, is the difference between the available capacity and the system load. A negative margin represents a state in which the system load exceeds the available capacity and describes a system failure condition.

A cumulative margin state contains all states with a margin less than or equal to the specified margin. A margin state m_k is the combination of the load state L_i and the capacity state C_n where

$$m_k = C_n - L_i. \tag{3.12}$$

The individual load state model shown in table 2.2 in section 2.4.2 is used to calculate the probability and also upward $\lambda_+(L_i)$ and downward $\lambda_-(L_i)$ load departure rates of all load levels.

$P(m)$ and $F(m)$ are the cumulative probability and frequency associated with the specified margin m which is used in computer program are described by equations (3.13) and (3.14) respectively.

$$P(m) = \sum_{i=1}^{N} p(L_i)P(X_i) \tag{3.13}$$

$$F(m) = \sum_{i=1}^{N} p(L_i)(F(X_i) + P(X_i)(\lambda_-(L_i) - \lambda_+(L_i))) \tag{3.14}$$

$$D(m) = \frac{P(m)}{F(m)} \tag{3.15}$$

$$T(m) = \frac{1}{F(m)} \tag{3.16}$$

where

$p(L_i)$ is the probability of each load level , $\sum p(L_i) = 1.0$,
$P(X_i)$ is the cumulative probability of the complete COPT generation with outage capacity X MW, and
$F(X_i)$ is the cumulative frequency of the complete COPT generation with outage capacity X MW.

P(m) and F(m) are cumulative probability and frequency respectively associated with the specified margin m. D is duration and cycle time T. The negative margin provides the basic reliability index.

3.5 Calculation Examples

3.5.1 LOLE Calculation Example

Consider a system containing twelve 5MW units each with a forced outage rate of 0.01 as shown in table 3.6. The forecasted peak load of the system is 50 MW.

Table 3.6 System data

No.	Capacity (MW)	Unit number	FOR
1	5	12	0.01

The forecast daily peak loads is a straight line from 100 to 70%. Consider time period is 100 percent. The system load model is represented by the daily peak load variation curve shown in figure 3.3.

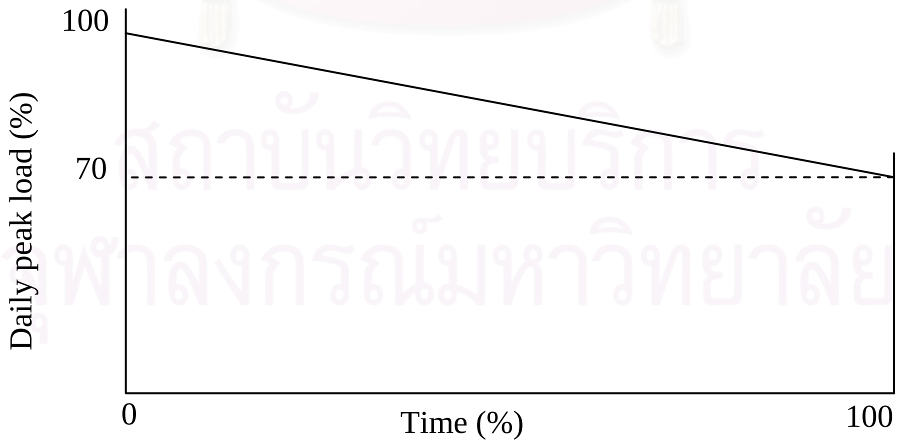


Fig. 3.3 System load model (DPLVC)

By using equation (3.1) and (3.2) as mentioned in section 3.3, we get the capacity outage probability table for this system as shown in table 3.7.

Table 3.7 Generation model (COPT)

State	Cap. outage (MW)	Individual probability	Cumulative probability
1	0	0.8864	1
2	5	0.1074	0.11362
3	10	0.0060	0.0061745
4	15	2.0097E-4	0.00020562
5	20	4.5676E-6	4.6423e-006
6	25	7.3820E-8	7.4697e-008

Table 3.8 LOLE calculation

State No	Cap. outage (MW)	Cap. in (MW)	Individual probability	Total time t_k(%)	(4) × (5) LOLE
1	0	60	0.8864	0	0
2	5	55	0.1074	0	0
3	10	50	0.0060	0	0
4	15	45	2.0097E-4	33.33	0.0067
5	20	40	4.5676E-6	66.67	3.0451E-4
6	25	35	7.3820E-8	100	7.3820E-6
				$\sum$ LOLE = 0.007	

For the case of the available capacity is equal or greater than the peak load 50MW, the time units in the study period is 0.

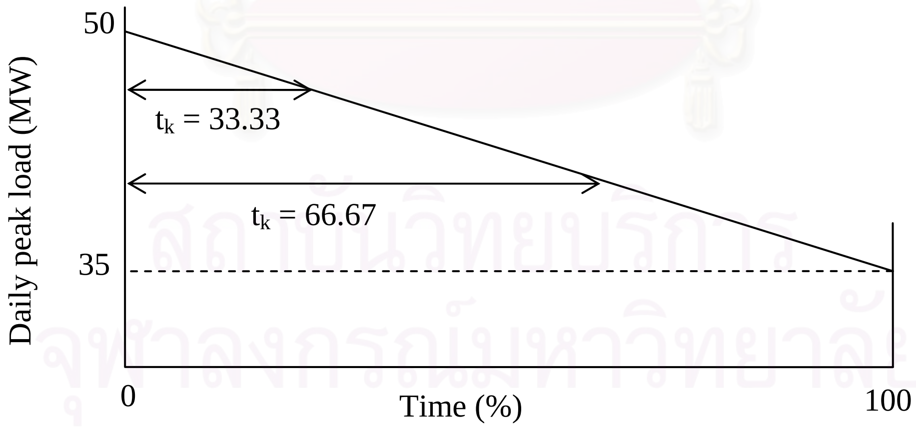


Fig 3.4 Time periods during which loss of load occurs

Next we can calculate minimum power by multiplying load factor and peak load. If the available capacity is less than peak load, we can calculate t_k by using similar triangular rule as shown in figure 3.4.

t_k = ((peak load – cap. in) × period) / (peak load – min. power)

For the capacity in 45 MW

t_k = ((50-45) × 100) / (50 – 35) = 33.33

For the capacity in 40 MW

t_k = ((50-40) ×100) / (50-35) = 66.67

The last case if the available capacity is less than peak load and minimum power, t_k= period. Probability values less than 10^{-8} have been neglect. Therefore the available capacity of less than 35MW probability is equal to zero. p_k is the individual probability shown in column (4) of table 3.8.

From equation 3.3, we can obtain

$$LOLE = \sum_{k=1}^{n} p_k t_k$$

The LOLE is 0.007 % of the time base units. If the daily peak load curve is based on an annual basis, the LOLE is 0.007 × 365 /100 = 0.0256 day per year.

The above example is calculated for the LOLE without uncertainty. System consists of twelve 5MW units, each with forced outage rate of 0.01. The following tables (3.9-3.11) show the LOLE calculation with 2% uncertainty by using normal, over and under forecast uncertainty consideration.

Table 3.9 normal distribution uncertainty model

(1) Number of Standard Deviations from the mean	(2) Load (MW)	(3) Probability of The load in Col.(2)	(4) LOLE (days/year) for the load in Col.(2)	(3) × (4)
-3	47	0.006	0.011256	6.75E-05
-2	48	0.061	0.016233	0.00099
-1	49	0.242	0.021007	0.005084
0	50	0.382	**0.02559**	0.009775
1	51	0.242	0.172389	0.041718
2	52	0.061	0.313543	0.019126
3	53	0.006	0.449369	0.002696
			Total	**0.07945747**

Table 3.9 shows the LOLE calculation with 2% uncertainty by using normal density function. The LOLE value without uncertainty is 0.02559 day/year and with uncertainty is 0.07945747 day/year. Therefore we can see that the LOLE value include uncertainty is higher more than the LOLE without uncertainty.

Table 3.10 over forecast uncertainty model

(1) Number of Standard Deviations from the mean	(2) Load (MW)	(3) Probability of The load in Col.(2)	(4) LOLE (days/year) for the load in Col.(2)	(3) × (4)
-3	47	0.154	0.011256	0.001728
-2	48	0.333	0.016233	0.005407
-1	49	0.29	0.021007	0.006098
0	50	0.154	**0.02559**	0.003931
1	51	0.054	0.172389	0.009309
2	52	0.013	0.313543	0.004076
3	53	0.003	0.449369	0.001123
			Total	**0.03167243**

Table 3.10 shows the LOLE calculation with 2% uncertainty by using over forecast. The LOLE value without uncertainty is 0.02559 day/year and with uncertainty is 0.03167243 day/year. Therefore we can see that the LOLE value include uncertainty is higher more than the LOLE without uncertainty. Moreover the LOLE value by using over forecast is less than by using normal density function.

Table 3.11 under forecast uncertainty model

(1) Number of Standard Deviations from the mean	(2) Load (MW)	(3) Probability of The load in Col.(2)	(4) LOLE (days/year) for the load in Col.(2)	(3) × (4)
-3	47	0.003	0.011256	2.81E-05
-2	48	0.013	0.016233	0.000211
-1	49	0.054	0.021007	0.001134
0	50	0.154	**0.02559**	0.003931
1	51	0.2903	0.172389	0.050045
2	52	0.333	0.313543	0.104441
3	53	0.154	0.449369	0.068978
			Total	**0.22876809**

Table 3.11 shows the LOLE calculation with 2% uncertainty by using under forecast. The LOLE value without uncertainty is 0.02559 day/year and with uncertainty is 0.22876809 day/year. Therefore we can see that the LOLE value

considers uncertainty by using under forecast is the highest value compare with normal, over forecast and without uncertainty case.

3.5.2 EENS Calculation Example

A system consists of two 25MW units and one 50 MW unit with forced outage rates of 0.02 as shown in table 3.12. Individual state load data is shown in table 3.13.

Table 3.12 System data

No.	Capacity (MW)	Unit number	FOR
1	25	2	0.02
2	50	1	0.02

Table 3.13 Load data

Peak Load	No of occurrences
65	8
55	4
50	4
46	4
0	20

From table 3.13, we can draw the load duration curve (LDC) shown in figure 3.5 for a period of 480 hours (20 days).

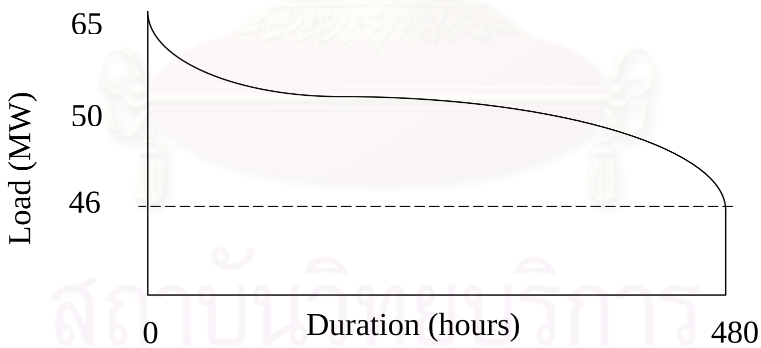


Fig.3.5 Load duration curve

The COPT before adding any unit contains only one level (a capacity of 0.0 with a probability of 1.0). The expected energy not supplied before any units have been considered is therefore equal to the expected energy of the load for the 480 hour period under consideration represented by the area under the LDC (above a load of 0.0 MW).The total required energy in this period is

$$EENS_0 = 26976 \text{ MWh} \times 1.0 = 26976 \text{ MWh}.$$

The expected energy output of the first level of the priority list is obtained by adding the capacity model of unit #1 25MW. The individual probability is from the capacity outage probability table. If the system contained only Unit 1, the EENS can be calculated as shown in table 3.14.

Table 3.14 EENS with Unit 1

Cap. Out (MW)	Cap. in (MW)	Individual probability	Energy curtailed (MWh)	Expectation (MWh)
0	25	0.98	26,476	25,946
25	0	0.02	26,976	539
			$EENS_1$	26486

The expected energy not supplied is then determined using equation (3.4) i.e.

$$EENS = \sum_{k=1}^{N} E_k \, p_k$$

$EENS_1$ = 26,476 × 0.98 + 26,976 × 0.02 = 26,486

26,476 MWh, 26,976 MWh are the areas under the load duration curve of figure 3.5 above load of 25 MW and 0 MW respectively.

The expected energy produced by Unit 1 = $EENS_0 - EENS_1$
= 26,976-26,486 = 490 MWh

Then the next unit in the priority list, unit #2 is added to the system as shown in table 3.15.

Table 3.15 EENS with Units 1 and 2

Cap. Out (MW)	Cap. in (MW)	Individual probability	Energy curtailed (MWh)	Expectation (MWh)
0	50	0.9604	140	134
25	25	0.0392	26476	1037
50	0	0.0004	26976	10
			$EENS_2$	1183

The expected energy not supplied at this priority level is determined using equation (3.4).

$EENS_2$ = 140 × 0.9604 + 26,476 × 0.0392 + 26,976 × 0.0004 = 1,183 MWh

The expected energy supplied by Unit 2 = $EENS_1 - EENS_2$
= 26,486 – 1,183 = 25,303 MWh.

Next the individual probability of capacity model of unit #3 is combined with the individual probability of capacity model of table 3.15 to determine the final system individual probability shown in column 3 of table 3.16.

Table 3.16 EENS with Unit 1, 2 and 3

Cap. Outage (MW)	Cap. in (MW)	Individual probability	Energy curtailed (MWh)	Expectation (MWh)
0	100	0.9412	0	0
25	75	0.0384	0	0
50	50	0.0196	140	2.744
75	25	0.0008	26,476	21.18
100	0	0.0000	26,976	0
			$EENS_3$	23.92

The expected energy not supplied is then:

$EENS_3 = 0\times0.9412 + 0 \times0.0384 + 140 \times 0.0196 + 26476 \times 0.0008 + 26976\times0$
$= 23.92$

The expected energy output of unit #3 is

$EENS_2 - EENS_3 = 1183\text{-}23.92 = 1159$ MWh

Table 3.17 Summary of EENS

Priority Level	Unit capacity (MW)	EENS(MWh)	Expected energy output(MWh)
1	25	26,486	490
2	25	1,183	25,303
3	50	23.92	1,159

The expected energy not supplied for the system is 23.92 MWh.
Expected energy produce by each unit is shown in column 4 of table 3.17. If we know the expected energy produced by each unit and its production cost, we can calculate the total production cost of system ($/MWh).

3.5.3 F&D Calculation Example

Consider further the system data as shown in table 3.18. The load model presented can be characteristic as the individual state load model as shown in table 3.19.

Table 3.18 System data

No.	Capacity (MW)	Unit number	λ (per day)	μ (per day)
1	25	2	0.01	0.49
2	50	1	0.01	0.49

Table 3.19 Load data

Load level Li (MW)	No. of occurrences
57	12
52	83
46	107
41	116
34	47
31	365

From table 3.19 load data, we can draw the individual state load model as shown in figure 3.6.

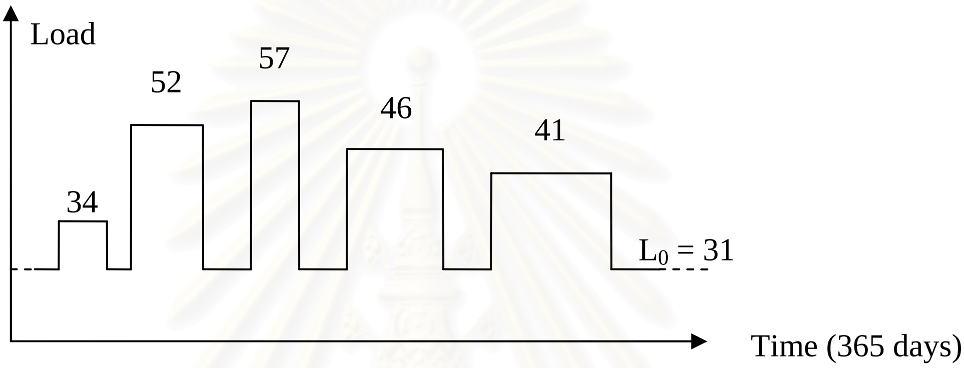


Fig 3.6 System Load Model

As mentioned in section 3.4.3 from equation (3.5)-(3.6) i.e.

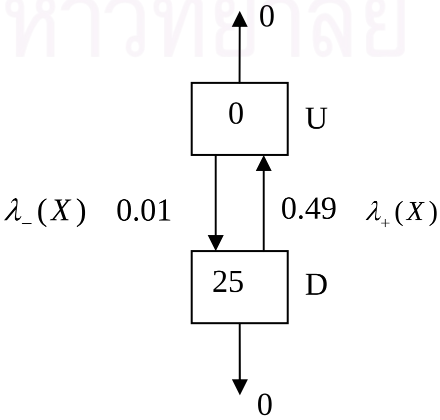
$$\lambda_+(X) = \frac{p'(X)(1-U)\lambda'_+(X) + p'(X-C)U(\lambda'_+(X-C)+\mu)}{p(X)}$$

$$\lambda_-(X) = \frac{p'(X)(1-U)(\lambda'_-(X)+\lambda) + p'(X-C)U(\lambda'_-(X-C))}{p(X)}$$

The procedure is initiated with the addition of the first unit (C_1). In this case

$\lambda_+(X) = \lambda_-(X) = 0 \quad$ for $X \neq 0, C_1$

<u>Step 1</u> Add the first 25 MW unit



$\lambda_+(0) = 0 \qquad \lambda_-(0) = \lambda_1 = \lambda$

$\lambda_+(C_1) = \mu_1 \qquad \lambda_-(C_1) = 0$

Fig 3.7 upward and downward capacity departure rate

Table 3.20 Add the first unit C = 25MW

State No. i	Cap. outage (MW)	Probability $p(X)$	$\lambda_+(X)$ (occur/day)	$\lambda_-(X)$ (occur/day)
1	0	0.98	0	0.01
2	25	0.02	0.49	0

<u>Step 2</u> Add the second unit C = 25 MW

Table 3.21 use the same concept as mentioned in section 3.4.3.

Table 3.21 Individual and cumulative probability calculation

(1) Cap. outage X (MW)	(2) $p'(X)(1-U)$	(3) $p'(X-C)U$	(4) Col(2)+Col(3) $p(X)$	(5) Cumulative Prob $P(X)$
0	0.98 × 0.98	0 × 0.02	0.9604	1.0000
25	0.02 × 0.98	0.98 × 0.02	0.0392	0.0396
50	0 × 0.98	0.02 × 0.02	0.0004	0.0004

From equations (3.5) and (3.6) as mentioned in section 3.4.3, i.e. if X is less than C

$$\lambda'_+(X-C) = 0 \qquad \lambda'_-(X-C) = 0$$

If not, X value is greater or equal to C, $\lambda_+(X-C)$ and $\lambda_-(X-C)$ get from the previous table 3.20.

Table 3.22 $\lambda_+(X)$ calculation

(1) Cap. outage X (MW)	(6) $p'(X)(1-U)$ $(\lambda_+(X))$	(7) $p'(X-C)U$ $(\lambda'_+(X-C)+\mu)$	(8) Col(2) + Col(3)	(9) Col(8)/Col(4) $\lambda_+(X)$ (occur/day)
0	0.9604 × 0	0 ×(0+0.49)	0	0
25	0.0196 × 0.49	0.0196 × (0+0.49)	0.019208	0.49
50	0 × 0	0.0004×(0.49+0.49)	0.000392	0.98

Table 3.23 $\lambda_-(X)$ calculation

(1) Cap. outage X (MW)	(10) $p'(X)(1-U)$ $(\lambda_-(X)+\lambda)$	(11) $p'(X-C)U$ $(\lambda'_-(X-C))$	(12) Col(2)+ Col(3)	(13) Col(12)/Col 4 $\lambda_-(X)$ (occur/day)
0	0.9604 × (0.01+0.01)	0 ×0	0.019208	0.02
25	0.0196 × (0 + 0.01)	0.0196 × 0.01	0.000392	0.01
50	0 × (0 + 0.01)	0.0004 ×0	0	0

<u>Step 3</u> Add the third unit C = 50 MW

The below table 3.24 is the same with table 3.5 as mentioned in section 3.4.3.

Table 3.24 Individual and cumulative probability calculation

(1) Cap. outage X (MW)	(2) $p^{'}(X)(1-U)$	(3) $p^{'}(X-C)U$	(4) Col(2)+Col(3) Ind prob. $p(X)$	(5) Cumulative prob. $P(X)$
0	0.9604 × 0.98	0 × 0.02	0.9412	1
25	0.0392 × 0.98	0 × 0.02	0.0384	0.058792
50	0.0004 × 0.98	0.9604 × 0.02	0.0196	0.020392
75	0 × 0.98	0.0392 × 0.02	0.000784	0.000792
100	0 × 0.98	0.0004 × 0.02	0.000008	0.000008

In equations (3.5) and (3.6) as mentioned in section 3.4.3, i.e. if X is less than C

$$\lambda_{+}^{'}(X-C)=0 \qquad \lambda_{-}^{'}(X-C)=0$$

Table 3.25 $\lambda_{+}(X)$ calculation

(1) Cap. outage X (MW)	(6) $p^{'}(X)(1-U)$ $(\lambda_{+}(X))$	(7) $p^{'}(X-C)U$ $(\lambda_{+}^{'}(X-C)+\mu)$	(8) Col(2)+ Col(3)	(9) Col8/Col4 $\lambda_{+}(X)$ occur/day
0	0.941192 × 0	0 × (0+0.49)	0	0
25	0.038416 × 0.49	0 × (0+0.49)	0.018824	0.4900
50	0.000392 × 0.98	0.019208 ×(0+0.49)	0.009796	0.4998
75	0 × 0	0.000784 × (0.49+0.49)	0.000768	0.9800
100	0 × 0	0.000008 × (0.98+0.49)	0.000012	1.47

Table 3.26 $\lambda_{-}(X)$ calculation

(1) Cap. outage X (MW)	(10) $p^{'}(X)(1-U)$ $(\lambda_{-}(X)+\lambda)$	(11) $p^{'}(X-C)U$ $(\lambda_{-}^{'}(X-C))$	(12) Col(2)+ Col(3)	(13) 12 / 4 $\lambda_{-}(X)$ occu/day
0	0.941192 × (0.02+0.01)	0 × 0	0.028236	0.0300
25	0.038416 × (0.01+0.01)	0 × 0	0.000768	0.0200
50	0.000392 × (0+0.01)	0.019208 × 0.02	0.000388	0.0198
75	0 × (0+0.01)	0.000784 × 0.01	0.000008	0.0100
100	0 × (0+0.01)	0.000008 × 0	0	0

As an example we will explain for capacity out X = 50MW in table 3.25. In Col (6) $p^{'}(X)(1-U)(\lambda_{+}(X))$ = 0.000392 is obtained from the table 3.24 in Col (2) of X= 50 MW. $\lambda_{+}(X)$ = 0.98 is already calculated from table 3.22 in Col (9) at X = 50MW.

For Col (7) $p^{'}(X-C)U(\lambda_{+}^{'}(X-C)+\mu)$ is from table 3.24 in Col (3) 0.9604 × 0.02 = 0.019208 and $\lambda_{+}^{'}(50-50)+0.49$, $\lambda^{'}_{+}(0)=0$ is already obtained from table3.19 in Col (9) of 0MW capacity outage. μ is given in table 3.18.

Col (8) obtains by combining Col (6) and (7). Col (9) that is $\lambda_{+}(X)$ is by dividing Col (8) and Col (4) $p(X)$.

$$\lambda_{+}(X)=\frac{p'(X)(1-U)\lambda'_{+}(X)+p'(X-C)U(\lambda'_{+}(X-C)+\mu)}{p(X)}$$

$$Col(9)=\frac{Col(6)+Col(7)}{Col(4)} = 0.4998$$

$\lambda_{-}(X)$ also calculate the similar way like $\lambda_{+}(X)$ so that easy to understand.

$$Col(13)=\frac{Col(10)+Col(11)}{Col(4)} = 0.0198$$

The individual capacity state probabilities are given in Col (4). They can be combined directly with the values in Col (9) and Col (13) to give the individual state frequencies.

$$f(X)=p(X)\{\lambda_{+}(X)+\lambda_{-}(X)\}$$

$$= 0.941192\ \{0 + 0.03\} = 0.028236$$

These values can also be used to give the cumulative state probabilities and frequencies using the following equations respectively.

$$P(X)=P(Y)+p(X)$$

$$= 0.000008 + 0.000776 = 0.000792$$

$$F(X)=F(Y)+p(X)(\lambda_{+}(X)-\lambda_{-}(X))$$

$$= 0.000012 + 0.000784\ (0.98-0.01) = 0.000772$$

Finally we get complete capacity model as shown in table 3.27.

Table 3.27 Complete generation model

State	Cap.out X (MW)	Individual Probability p(X)	$\lambda_{+}(X)$ (occ/day)	$\lambda_{-}(X)$ (occ/day)	Individual Frequency f(X)occ/day	Probabilty P(X)	Frequency F(X) (occ/day)
1	0	0.94119	0	0.03	0.028236	1	0

2	25	0.038416	0.49	0.02	0.019592	0.058808	0.028236
3	50	0.0196	0.4998	0.0198	0.010184	0.020392	0.01018
4	75	0.000784	0.98	0.01	0.000776	0.000792	0.000772
5	100	8.00E-06	1.47	0	1.18E-05	8.00E-06	1.18E-05

By using equations from table 2.3 parameters for individual state load model as shown in section 2.2 the probability and also upward and downward load departure rate of each load level and low load level are calculated to modify the load data as shown in table3.28.

$$D = \sum_{i=1}^{N} n(Li) = 12 + 83 + 107 + 116 + 47 = 365 \text{ days}$$

$$p(Li) = \frac{n(Li)}{D} e \quad , \quad p(L_0) = 1 - e$$

$$p(L1) = \frac{n(L1)}{D} \times 0.5 = \frac{12}{365} \times 0.5 = 0.016438 \quad , \quad p(L_0) = 1 - 0.5 = 0.5$$

$$\lambda_+(L_i) = 0 \qquad \lambda_-(L_i) = \frac{1}{e} = 2 \qquad \lambda_-(L_0) = 0$$

Table 3.28 Modified load data

Level No. i	Load level Li (MW)	No. of occurrences	Probability $p(Li)$	$\lambda_+(L_i)$	$\lambda_-(L_i)$
1	57	12	0.016438	0	2
2	52	83	0.1137	0	2
3	46	107	0.14658	0	2
4	41	116	0.1589	0	2
5	34	47	0.064384	0	2
6	31	365	0.5	2	0

A margin state m_k is $C_n - L_i$. A negative margin represents a state in which the system load exceeds the available capacity and depicts a system failure condition. The first negative margin is -2 MW that just higher state is greater or equal to zero and just lower state is less than zero.

In Col (3) it shows each load combines with first negative margin that is -2.

From equations (3.13),

$$P(m) = \sum_{i=1}^{N} p(L_i) P(X_i)$$

P(-2) = 0.003343

$p(Li)$ is the probability of load show in Col(4) of table 3.25. $P(X_i)$ as shown in Col (6) is obtained from the complete generation model of 50 MW and 75 MW capacity outage probability as shown in Table 3.27. The cumulative probability of the first negative margin Col (7) gets by multiplying Col (5) and Col (6). From equations (3.14),

$$F(m) = \sum_{i=1}^{N} p(L_i)(F(X_i) + P(X_i)(\lambda_-(L_i) - \lambda_+(L_i)))$$

F(-2) = 0.007098 occur / day

$F(X_i)$ is the cumulative frequency of 50 MW and 75 MW outage capacity as shown in table 3.27. $\lambda_-(L_i)$ and $\lambda_+(L_i)$ is from table 3.25 Col (5) and (6). By using the cumulative frequency of first negative margin equation, the result is shown in Col (10) table 3.29.

The duration index is the cumulative probability divided by the cumulative frequency of the first negative margin. From equations (3.15),

$$D(m) = \frac{P(m)}{F(m)}$$

$$D(-2) = \frac{0.003343}{0.007098} = 0.4709 \text{ days}$$

Cycle time of first negative margin is from equations (3.16),

$$T(m) = \frac{1}{F(m)}$$

$$T(-2) = \frac{1}{0.007098} = 140.88 \text{ days}$$

Table 3.29 Calculation of P(m) and F(m)

(1) i	(2) L_i	(3) L_i +m	(4) X_i	(5) $p(Li)$	(6) $P(X_i)$	(7) Col(5)*Col(6)
1	57	55	50	0.016438	0.0204	0.000335
2	52	50	50	0.113699	0.0204	0.002319
3	46	44	75	0.146575	0.0008	0.000116
4	41	39	75	0.158904	0.0008	0.000126
5	34	32	75	0.064384	0.0008	0.000051
6	31	29	75	0.5	0.0008	0.000396
						0.003343

(1) i	(8) $\lambda_-(L_i)$ - $\lambda_+(L_i)$	(9) Col(6)*Col(8)	(10) $F(X_i)$	(11) Col(9)+Col(10)	(12) Col(5)*Col(11)
1	2	0.040784	0.010180	0.050964	0.000838
2	2	0.040784	0.010180	0.050964	0.005795
3	2	0.001584	0.000772	0.002356	0.000345
4	2	0.001584	0.000772	0.002356	0.000374
5	2	0.001584	0.000772	0.002356	0.000152

6	-2	-0.001584	0.000772	-0.000812	-0.000406
					0.007098

3.5.4 F&D calculation with normal, over, under forecast uncertainty consideration

Similar to LOLE uncertainty calculation procedure, we can calculate F&D including uncertainty. By using normal distribution model, the result is shown in table 3.30. The probability of seven individual values of load uncertainty is shown in Col (3), and weighted by the calculated frequency for the load as shown in Col (4).

Table 3.30 Calculation frequency include uncertainty (normal distribution)

(1) No of SD from mean	(2) Load (MW)	(3) Probability of the load in Col.(2)	(4) Freq (occur/day) in Col.2	(3)*(4)
-3	[54 49 43 38 31]	0.006	0.001571	0.00000943
-2	[55 50 44 39 32]	0.061	0.001571	0.00009585
-1	[56 51 45 40 33]	0.242	0.007098	0.00171770
0	[57 52 46 41 34]	0.382	***0.007098***	0.00271141
+1	[58 53 47 42 35]	0.242	0.007098	0.00171770
+2	[59 54 48 43 36]	0.061	0.007098	0.00043297
+3	[60 55 49 44 37]	0.006	0.007098	0.00004259
			Total	**0.00672765**

From table 3.30 it shows that the frequency value without uncertainty is 0.007098 and if uncertainty (2%) of normal distribution is taken into account, it will be 0.00672765.

Next we will see the result of over forecast uncertainty in table 3.31.

Table 3.31 Calculation frequency include uncertainty (rayleigh distribution)

(1) No of SD from mean	(2) Load (MW)	(3) Probability of the load in Col.(2)	(4) Freq (occur/day) in Col.2	(3)*(4)
-3	[54 49 43 38 31]	0.105	0.001571	0.000165
-2	[55 50 44 39 32]	0.254	0.001571	0.000399
-1	[56 51 45 40 33]	0.273	0.007098	0.00194
0	[57 52 46 41 34]	0.199	***0.007098***	0.001412
+1	[58 53 47 42 35]	0.107	0.007098	0.000758
+2	[59 54 48 43 36]	0.044	0.007098	0.000312
+3	[60 55 49 44 37]	0.018	0.007098	0.00013
			Total	**0.00511513**

The frequency without including uncertainty is 0.007098 and in case of 2% over forecast it will be 0.00511513.As shown in table 3.31, we found that over forecast uncertainty value is lower than uncertainty normal distribution.

Furthermore by using under forecast uncertainty modeled by Rayleigh distribution we get the result as shown in table3.32.

Table 3.32 Calculation frequency include uncertainty (Rayleigh distribution)

(1) No of SD from mean	(2) Load (MW)	(3) Probability of the load in Col.(2)	(4) Freq (occur/day) in Col.2	(3)*(4)
-3	[54 49 43 38 31]	0.018	0.001571	0.00002875
-2	[55 50 44 39 32]	0.044	0.001571	0.00006898
-1	[56 51 45 40 33]	0.107	0.007098	0.00075806
0	[57 52 46 41 34]	0.199	***0.007098***	0.00141178
+1	[58 53 47 42 35]	0.273	0.007098	0.00193987
+2	[59 54 48 43 36]	0.254	0.007098	0.00180075
+3	[60 55 49 44 37]	0.105	0.007098	0.00074670
			Total	**0.00675489**

The frequency without including uncertainty is 0.007098 and in case of 2% under forecast uncertainty based on rayleigh distribution, it will be 0.00675489. As shown in table 3.32, we found that under forecast uncertainty provide highest risk value than uncertainty of normal distribution and over forecast uncertainty.

Finally, we may conclude at this stage that if we take into account load forecast uncertainty, the results may be $U_o < U_N < U_u$.

where

Uo = the value calculated based on over forecast uncertainty model
U_N = the value calculated based on normal distribution uncertainty model
Uu = the value calculated based on under forecast uncertainty model

CHAPTER IV

SYSTEM EXPANSION STUDIES

4.1 System Expansion Concept

A fundamental problem in system planning is the correct determination of reserve capacity. In the past, most utilities used percentage reserve margin criteria to determine their required reserve capacity. If the defined percentage reserve margin is too low, excessive interruption may occur. If too high percentage reserve margin is applied, more added capacity will be required and excessive cost will arise. The main goal of generating capacity expansion planning is to establish how many MW of new generator units must be installed for a reliable supply of the predicted load. At present, generation capacity expansion planning widely uses probabilistic criteria as mentioned before. Figure 4.1 shows the effect of added units to the system.

The adequacy of the system capacity in the successive year can be measured based on an acceptable level of risk (R_a) expressed in the reliability risk index LOLE. If the calculated risk LOLE is above the acceptable risk (R_a), we will add the unit until the calculated risk LOLE arrive equal to or below the acceptable risk (R_a).

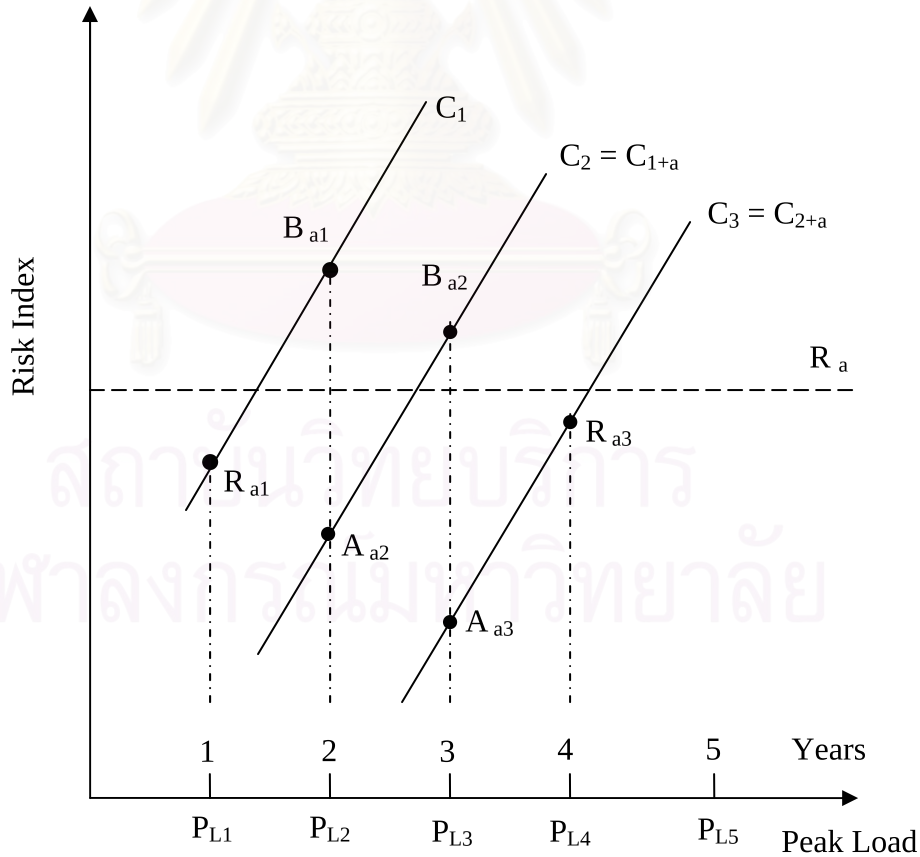


Fig 4.1 System expansion concept

From figure 4.1 we can see that the installed system capacity C_1 for the first year at peak load P_{L1} provides risk index of R_{a1} which is below and complied with the defined risk criteria of R_a. Therefore, it does not need any more added capacity for this year. For the next year, we will increase the forecasted peak load according to our forecasted load growth which is P_{L2}. In this year the calculated risk with existing capacity from the previous year is B_{a1} which is above R_a . Therefore we need to add more capacity of "a" MW so the installed capacity is increased to be $C_2 = C_{1+a}$, which provides risk index of A_{a2} to comply with R_a, i.e. A_{a2} is below R_a. Therefore, it does not need any more added capacity for this year. For the next year, we will increase the forecasted peak load according to our forecasted load growth which is P_{L3}. In this year the calculated risk with existing capacity from the previous year is B_{a2} which is above R_a. Therefore we need to add more capacity of "a" MW so the installed capacity is increased to be $C_3 = C_{2+a}$ which provides risk index of A_{a3} to comply with R_a, i.e. A_{a3} is below R_a. Therefore, it does not need any more added capacity for this year. For the next year, we will increase the forecasted peak load according to our forecasted load growth which is P_{L4}. P_{L4} provide risk index of R_{a3} to comply with R_a. R_{a3} is below R_a hence it does not need any more added capacity for this year.

The procedure of generation capacity expansion program is shown in figure 4.2. The added capacity for each unit can be arbitrarily defined by system planners. After added units the program need to calculate again COPT and required risk indices as mentioned in chapter 3.

We have mentioned generation system and load model as an input data in sections 2.1 and 2.2 respectively. Users can provide number of study periods, and defined planning criteria of LOLE, percentage of load increase and sizes of generating unit added capacity and other concerned parameters. Starting from the first year of the study period the developed program will check the obtained LOLE whether it passes the criteria to meet the load requirement. If not, add the capacity sequentially as selected.

The above procedure does not include uncertainty model. However, the uncertainty models i.e. normal, over, and under forecast uncertainty, can be included in the process. We can use the same way to calculate one of reliability index F&D instead of using LOLE which is already shown in section 3.5.4.

The procedure in figure 4.2 is based on probabilistic consideration. The deterministic criterion based on a percentage reserve margin is also used for comparison in this thesis.

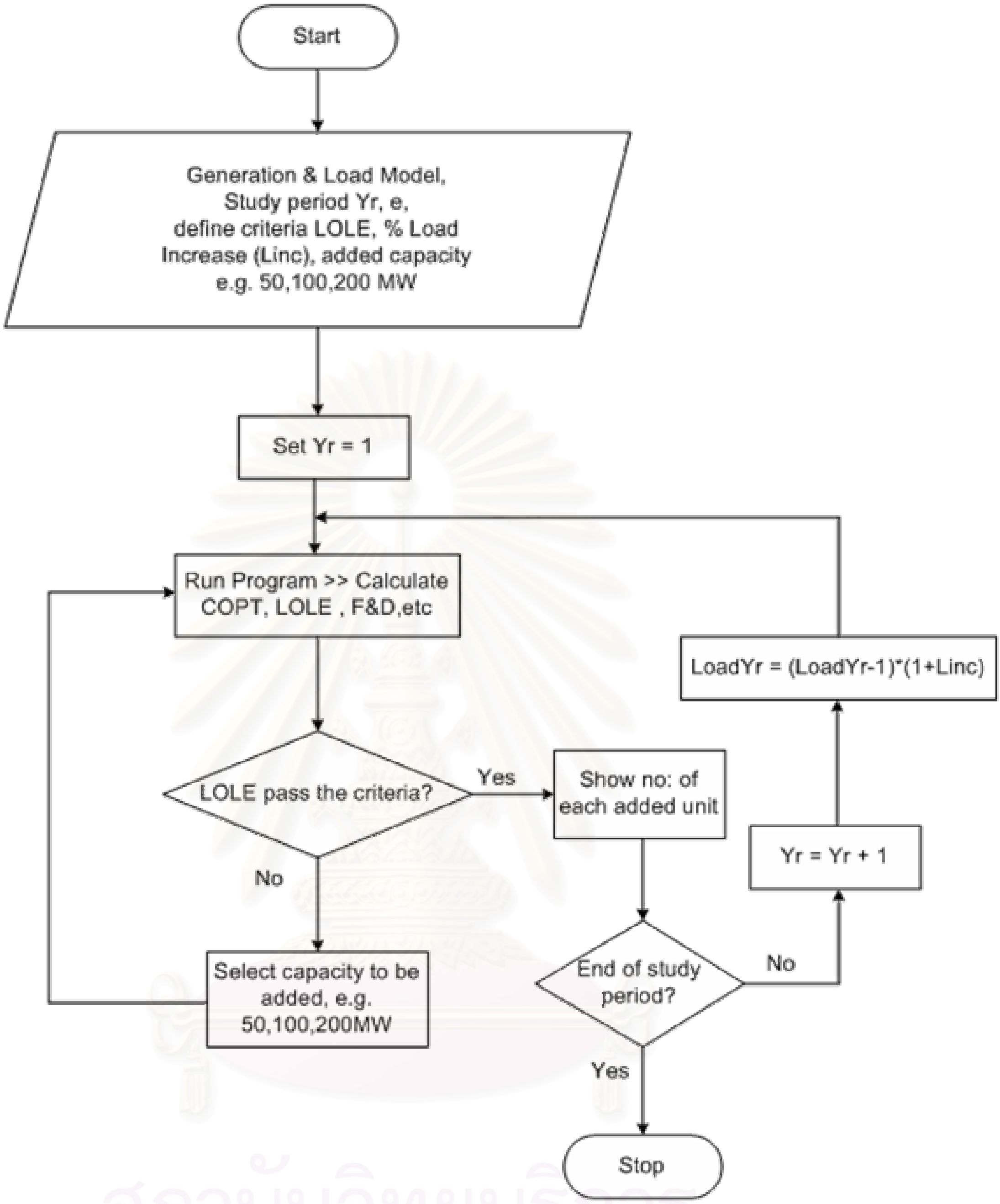


Fig.4.2. Flow chart for generating capacity expansion planning

Two basic deterministic criteria are as follows:

$$CRM = CLU + X \times PL \tag{4.1}$$

$$CRM = CLU + X \times IC \tag{4.2}$$

$$CR = CRM + PL \tag{4.3}$$

where

CR = capacity reserve,
CLU = capacity of the largest unit,
PL = peak load,
IC = installed capacity, and
X = multiplication factor – usually 5-15 %
CRM = capacity reserve margin

Equations (4.1) and (4.2) do not provide the same reserve requirement for a given value of X. Since installed capacity (IC) is normally greater than peak load (PL), therefore equation (4.2) creates a higher reserve requirement. In practice equation (4.1) may be used since we normally forecast the system peak load first. Then determine the required amount of generating capacity.

However, the basic objective in each case is the same, i.e., to provide sufficient capacity to protect the loss of the largest unit and incorporate a cushion against unforeseen load variations. The basic weakness of a deterministic approach is that it does not incorporate any explicit recognition of the actual risk. The criteria described by equation (4.1) and (4.2) obviously respond to the capacity of the largest generating unit.

The following tables and figures are used as the forecasted peak load data for practical system i.e. Myanmar and Thailand generation system. The actual peak load starting from Year 1 is 890 MW and on the rate of 10% load growth expected for a number of years ahead for the future is described in table 4.1

Table 4.1 Load growth at 10% of the forecasted peak load

Year number	Year	Forecast peak load (MW)
1	2003	890
2	2004	979
3	2005	1076
4	2006	1183
5	2007	1301
6	2008	1431
7	2009	1574
8	2010	1731
9	2011	1904
10	2012	2094
11	2013	2303

From the table 4.1 we can plot the forecast load as shown in figure 4.3. This data is used for forecast future load growth of Myanmar generation system.

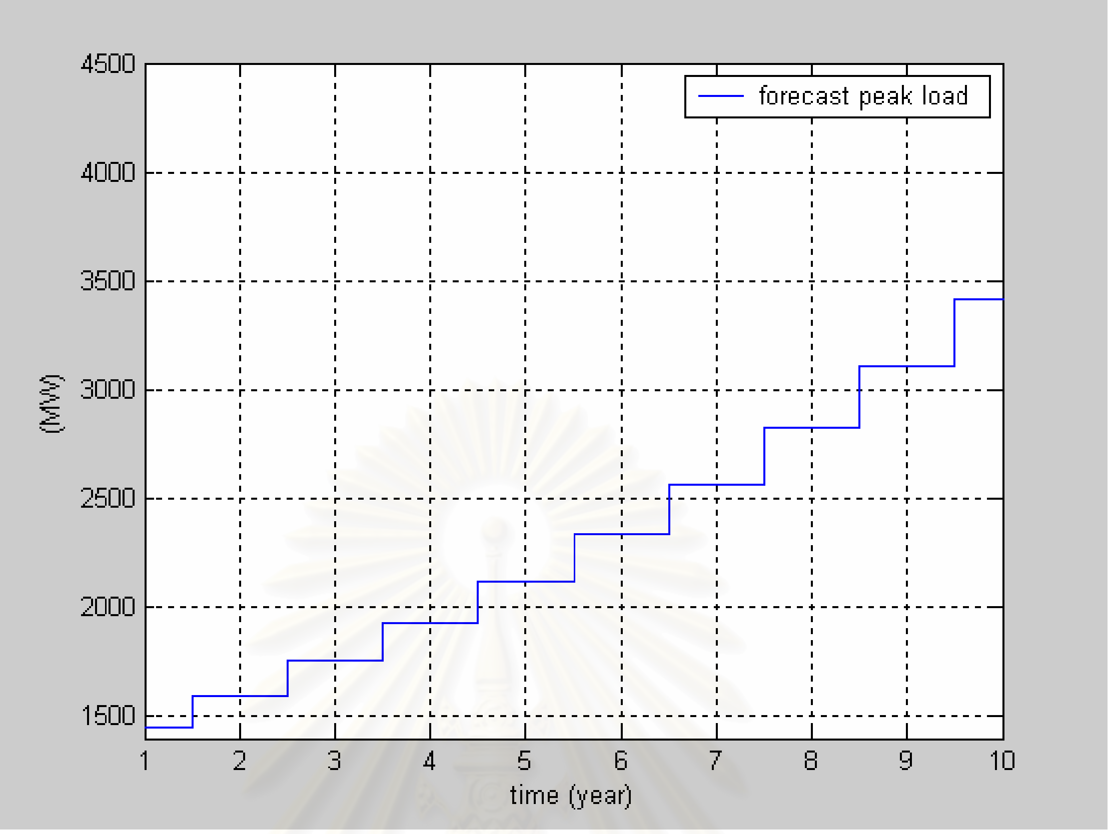


Fig 4.3 forecasted peak load growth for future system expansion analysis

The actual forecasted loads from the records of EGAT for the years 1993 to 2003 is shown in table 4.2.

Table 4.2 Actual load growth data

Peak generation of national grid (MW)		
Year number	Year	Actual peak load (MW)
1	1993	9735
2	1994	10911
3	1995	12168
4	1996	13881
5	1997	14993
6	1998	14464
7	1999	14267
8	2000	17275
9	2001	16445
10	2002	18724
11	2003	18788

From the table 4.2 we can plot the actual forecasted load as shown in figure 4.4. This data is used for actual forecasted load growth data of Thailand generation system.

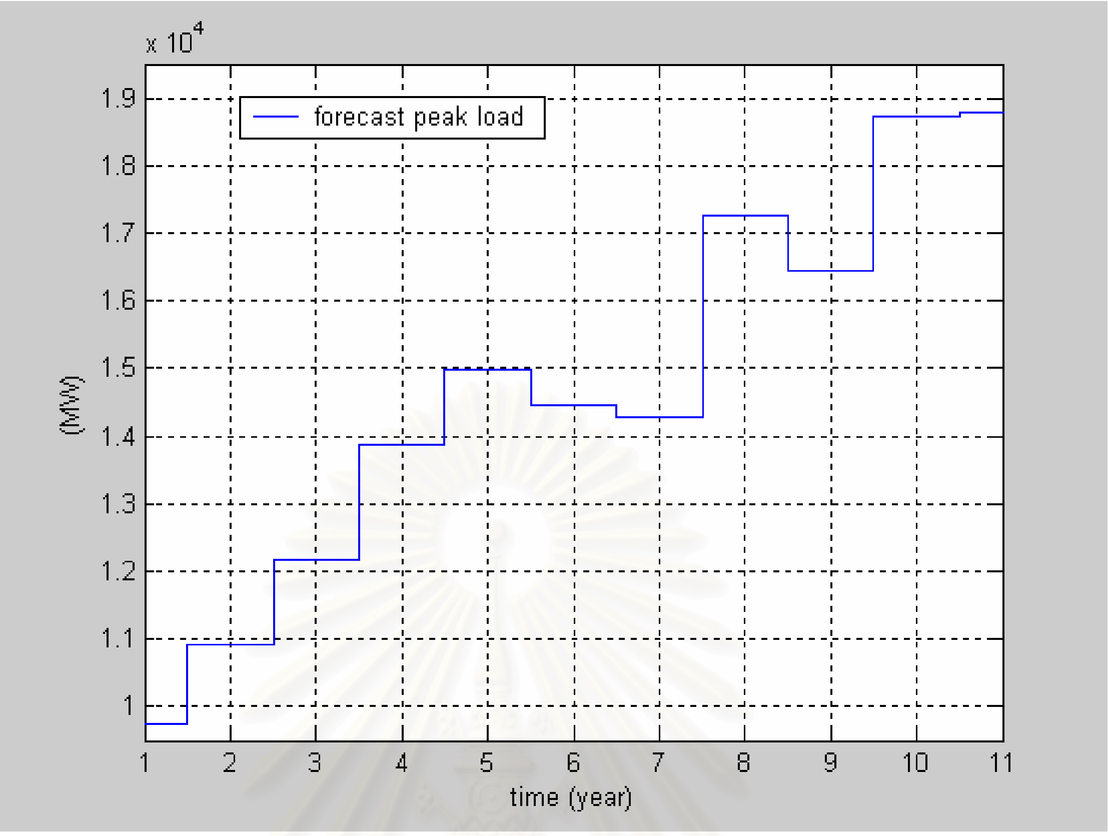


Fig 4.4 Actual peak load growth of past years system expansion analysis

Based on the load information for Myanmar and Thailand systems, to be presented in more details in the next chapter, we will use the proposed concept from all the previous chapters to analyse the required amount of reserve capacity.

CHAPTER V

SIMULATION RESULTS

5.1 Introduction

The objective of the chapter is to get a reliable expansion plan which complies with acceptable risk index. A developed program has been tested with the IEEE – RTS and a sample test system [7] to check its accuracy. Then several simulations have been conducted on actual systems, i.e. Myanmar generation system and Thailand generation system. Finally suggestion on reserve criteria for Myanmar Generation System and Thailand Generation System were proposed based on the simulation results.

5.2 Sample Test System Studies

The concept of capacity expansion analysis can be illustrated using the system with five 40 MW units, containing a total installed capacity = 200 MW described in table 5.1. Assuming that only new 50 MW unit with forced outage rates of 0.01 are available to meet a projected future load growth of 10% per year.

Table 5.1 Generation system

No	Unit size (MW)	No of unit	Forced outage rate	Expected failure rate λ (f/day)	Expected repair rate μ (r/day)
1	40	5	0.01	0.01	0.99

The daily peak load variation curve using a straight line from the 100% to 40% points is assumed in the analysis. It is firstly assumed that the installed capacity of 200MW is adequate for a system peak load of 160 MW. The risk criterion (LOLE) is 0.15 days/year is then set as the required target. If calculated LOLE is higher than the risk criterion (LOLE), then unit additions will be required as shown in Fig 5.1. This expansion result can be shown in Table 5.2

Table 5.2 Generation expansion results based on probabilistic method

Year	System capacity (MW)	Peak load (MW)	LOLE (days/year)
1	200	160	0.1506
2	200	176	2.8473
2 *	250	176	0.05
3	250	193.6	0.1262
4	250	213	0.9496
4 *	300	213	0.0156
5	300	234.3	0.1091
6	300	257.7	0.553
6 *	350	257.7	0.0101
7	350	283.4	0.1261
8	350	311.8	1.07
8 *	400	311.8	0.0266
9	400	343	0.2006
9 *	450	343	0.0058
10	450	377.3	0.1272

* Generation is added to meet the criteria.

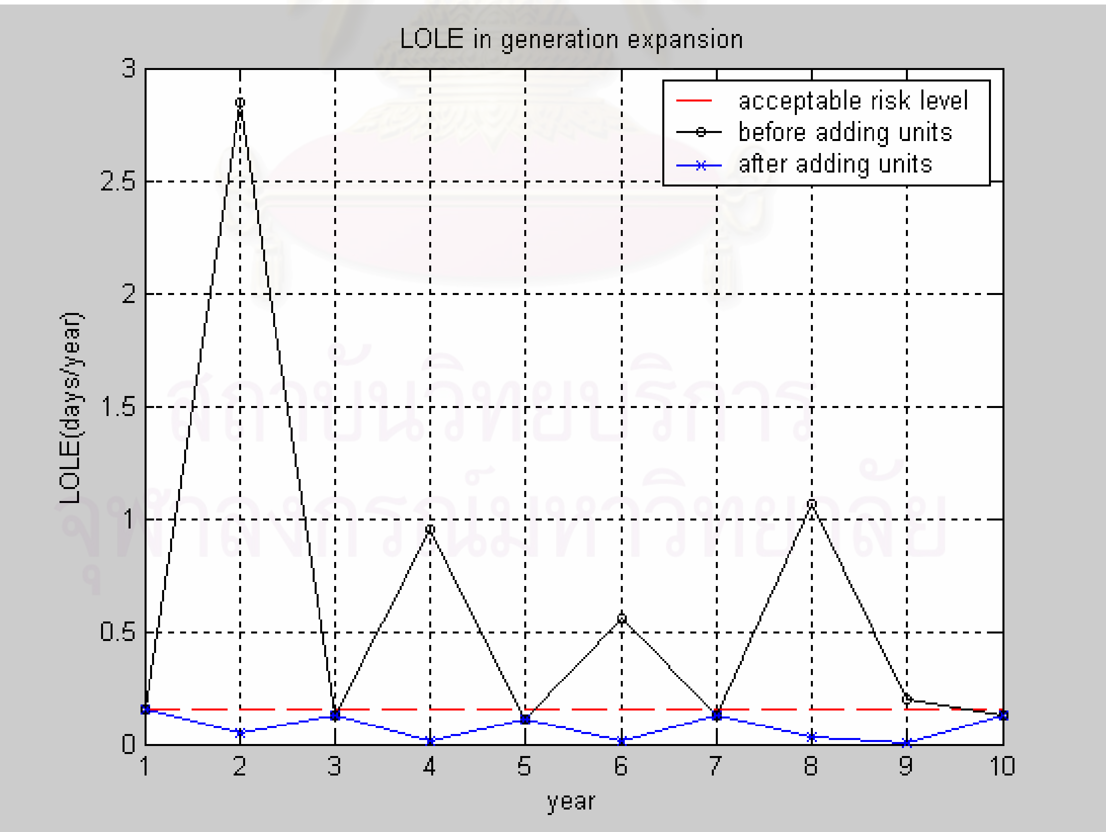


Fig.5.1 System expansion result (LOLE $\leq$ 0.15 day/year)

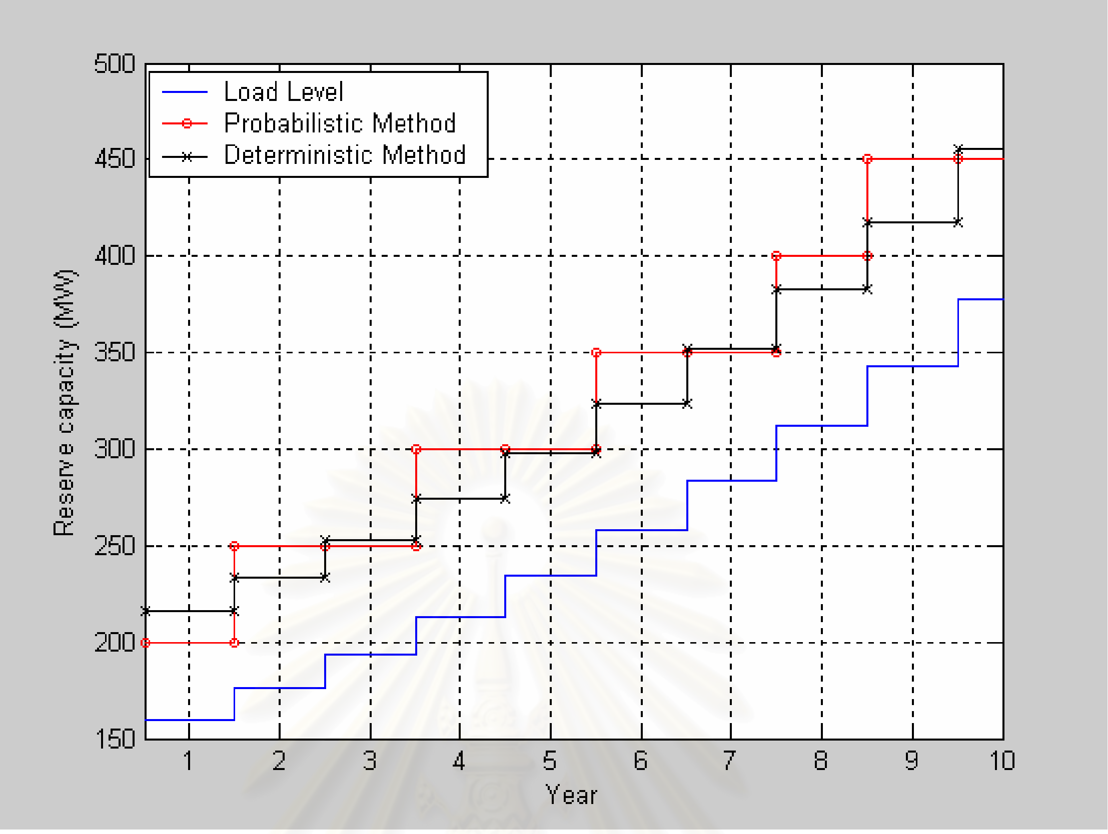


Fig.5.2 Compare the reserve capacity with both deterministic and probabilistic method

As shown in Fig.5.2 the first year begins when the peak load is 160MW with 10 % increase for each year. For the deterministic method we can get reserve capacity according to equation (4.1) and (4.3). In this example we consider only 50 MW as the largest unit plus 10% of peak load as the reserve criteria. For a probabilistic based method we can get the step line starting from the total installed capacity of 200MW, with additional added 50MW units if it does not pass LOLE criteria. Finally, we can compare the reserve capacity with both deterministic and probabilistic methods as shown in Fig 5.2.

From the result at years no.1 and 10 the reserve capacity based on the deterministic method is higher than the one based on the probabilistic method. However the reserve capacity based on probabilistic method is higher than deterministic method for the other years.

In this thesis we will explore, according to different uncertainty scenarios mentioned in section 2.3, the impact on the required reserve capacity obtained from both methods for Myanmar generation system and Thailand generation system is shown in sections (5.3) and (5.4) respectively.

5.3 Myanmar Generation System

The electricity requirements are being fulfilled by generation from hydro power plants and thermal power plants consisting of gas turbines and diesel power stations. The area of Electricity Supply in the Union of Myanmar can be defined into two parts:

(1) Area of supply from the national grid system.
(2) Area of supply outside the grid system.

The national grid system covers the southern and central parts of the country. Electricity generation within this system is about 95% percent of the total generation of the whole country.

At present, the major electric power stations feed electricity into the national grid system (the interconnected system) with 230KV, 132 KV and 66 KV transmission lines and substations. At the moment, the transmission system is capable of handling the power generated in the grid system. However, as more power stations are commissioned, further reinforcement of the transmission network will be required in the near future.

Up to now, onshore natural gas is used to supply the demand of natural gas related economic sectors. Major industrial activities are presently in the area between Yangon and Mandalay and therefore, a natural gas pipeline network is laid as a domestic energy infrastructure in these areas, which play an important role in the industrial development in Myanmar.

The electricity generation had increased from about 2,676 GWh in 1991-92 to about 5,674 GWh in year 2002-2003. The peak demand also increased to about 350 MW in 1991-92 to 860 MW in 2002-2003. In order to overcome the insufficient power supply situation and to meet the future power demand, we need to plan to have sufficient reserve capacity in the Grid System.

Table 5.3 presents 58 units generation system containing a total of 1340MW installed capacity. The load information as shown in table 5.4 is first considered without uncertainty. The load model for a 365 day period is shown in table 5.4.The forecast peak load is 890 MW, and the risk criterion (LOLE) is 1 day/year. An exposure factor (e) of 0.5 was used and low load level of 500 MW is assumed as shown in table 5.4. The daily load variation curve is assumed to be a straight line at a load factor of 70%. Assume that the system has been decided to add additional 25 MW units, if required, with forced outage rates of 0.02 to meet a projected future load growth of 10% per year.

The annual added capacity for the next 11 years is shown in figure 5.3. In this thesis we assume the information as shown in table 5.3 for our simulation for Myanmar generation system.

The Data of Myanmar Power Station 17/9/2004

Table 5.3 *Myanmar Electrical Power Enterprise (MEPE)*

No.	Name and Type of Power Station	Unit No.	Capacity	Install Capacity (MW)	FOR	$/MWh
	Hydro Power stations					
1	Law Pi Ta	6	28	168	0.02	0.50
2	Bi Lu Chaung(1)	2	14	28	0.02	0.50
3	Kin Tar	2	28	56	0.02	0.50
4	Se Daw Gyi	2	12	24	0.02	0.50
5	Zaw Gyi(1)	3	6	18	0.02	0.50
6	Zaw Gyi(2)	2	6	12	0.02	0.50
7	Zaung Thu	2	10	20	0.02	0.50
8	Ta Phan Seik	3	10	30	0.02	0.50
9	Paung Long	4	70	280	0.02	0.50
10	Maw La Mying	2	6	12	0.02	0.50
	Total	28	190	648		
	Gas Power Plants					
11	Kyun Chaung	3	18	54	0.08	30
12	Mann	2	18	36	0.08	30
13	Shwe Taung	3	18	54	0.08	30
	Diesel Power Plants					
14	Myan Aung	1	18	18	0.08	35.0
15	Myan Ag	1	16	16	0.08	30.0
	Combined Cycle Power Plants					
16	Ywama (gas)	2	18	36	0.29	5.0
17	Ywama (steam)	3	10	30	0.29	5.0
18	Tar Kay Ta	3	19	57	0.29	5.0
19	Tar Kay Ta	1	35	35	0.29	5.0
20	Alon	3	33	99	0.29	5.0
21	Alon	1	54	54	0.29	5.0
22	Hlaw Kar	3	33	99	0.29	5.0
23	Hlaw Kar	1	54	54	0.29	5.0
24	Ta Hton	1	18	18	0.29	5.0
25	Ta Hton	2	16	32	0.29	5.0
	Total	*58*	*568*	*1,340*		

Table 5.4 Assumed Myanmar load data

Peak (MW)	No. of occurrences (day)
890	12
850	83
750	107
720	116
690	47
500	365

The simulation results are shown in the following figures. Figure 5.3 show the effects of adding a group of 25 MW units to the existing 58 unit system to meet a projected future load growth of 10 % per year. The risk index is the annual LOLE value. The peak load in the first year is 890 MW. It can be seen from the figures that the installed capacity of 1,340 MW is adequate for the first and second years. The system standard risk indices of LOLE = 1 day/year is used.

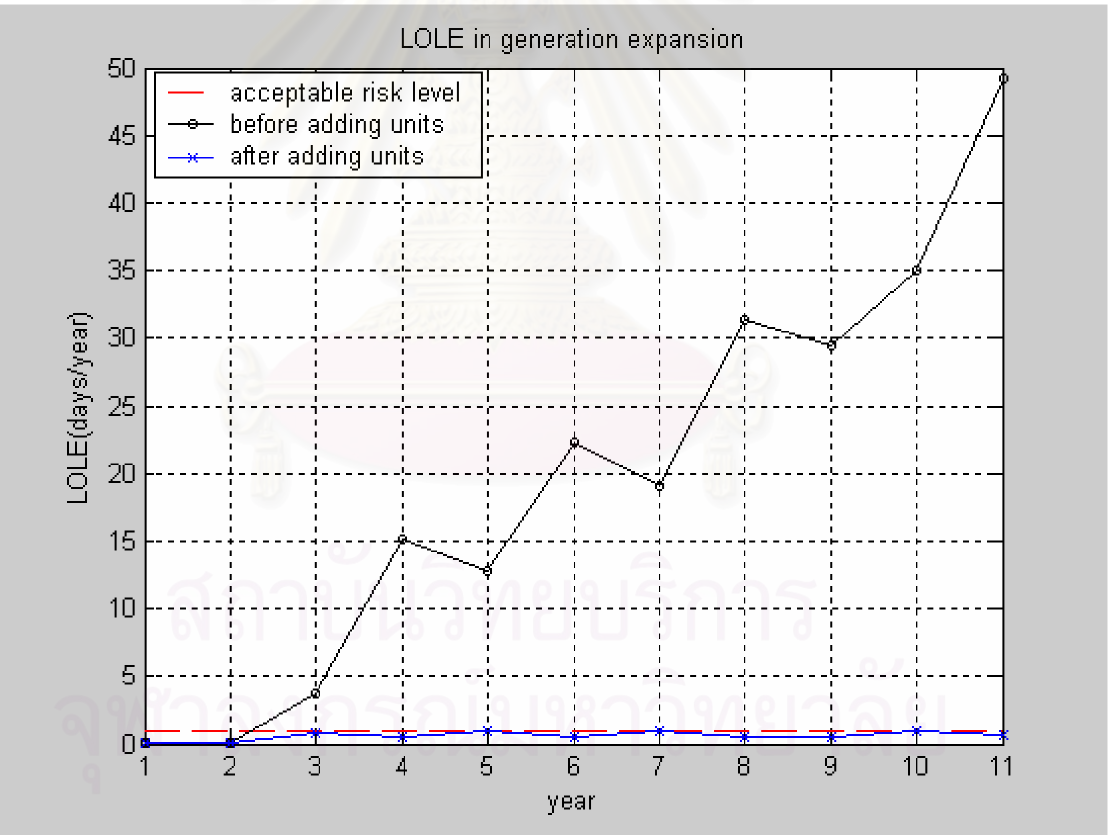


Fig 5.3 Risk from system expansion (LOLE $\leq$ 1day/ year)

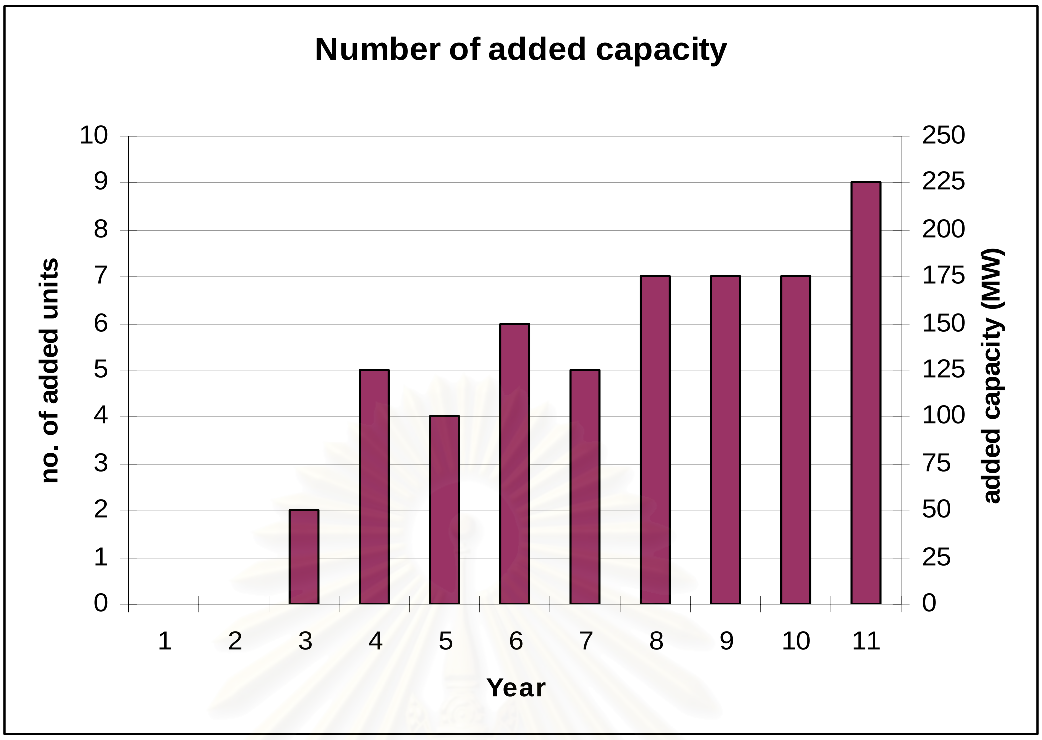


Fig 5.4 Number of added units (25 MW each)

From figure 5.4 we can see the required added capacity for each year. The system does not require any more units in the first and second year. However, in the third year, the system needs two additional 25 MW units to comply with the defined criteria.

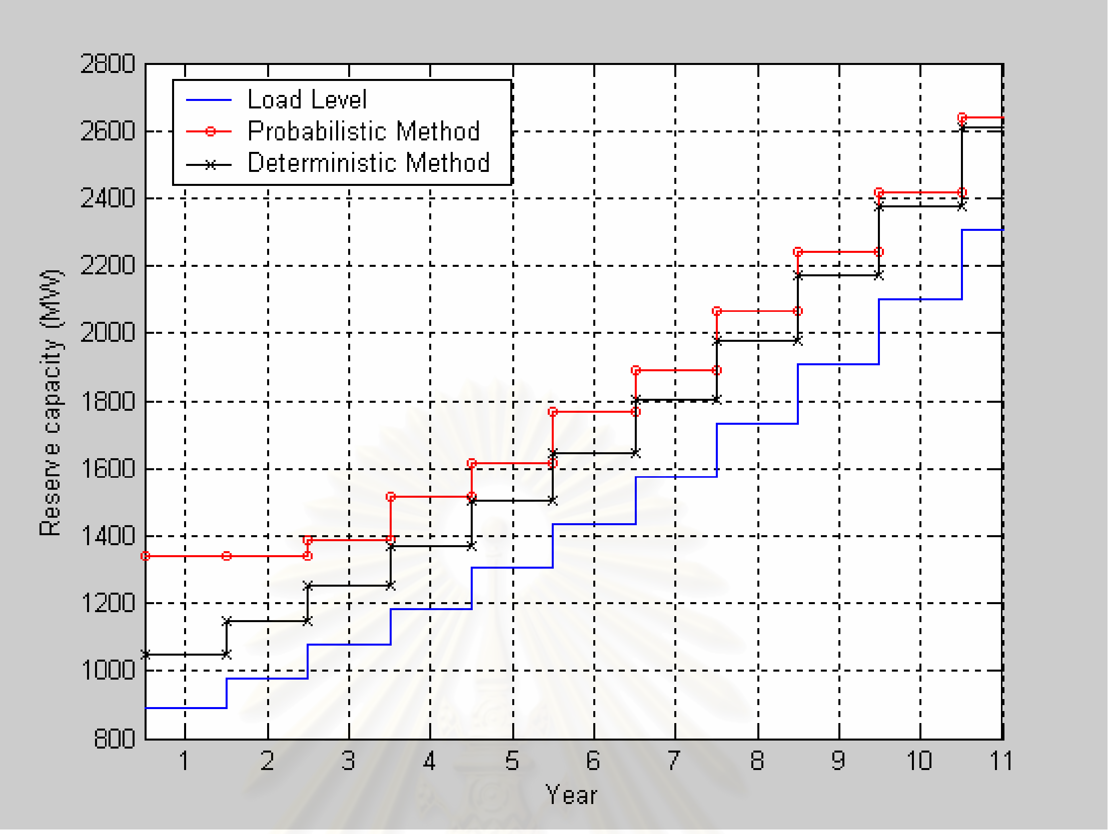


Fig 5.5 Compare the reserve capacity with probabilistic and deterministic method

As shown in figure 5.5 we can see the reserve capacity with probabilistic method and deterministic method. Installed capacity based on Probabilistic method is higher than the installed capacity based on deterministic method for 1-11years. The first year which starting from the peak load of 890MW with 10 % increase each year. By using probabilistic method we can get the step line starting from total installed capacity of 1,340 MW, which can be added with a unit of 25 MW if it does not pass LOLE criteria. The results show that the capacity of over 2200 MW is needed in the final year.

The impact of load forecast uncertainty is now then considered. We consider three cases, i.e. 2%, 4%, and 6% as standard deviation from the forecasted load. The normal density function is firstly analysed.

Figures (5.6), (5.7) and (5.8) are represented for 2% uncertainty case with normal distribution mentioned in section 2.3 .The planning criteria LOLE is 1day/yr, and added unit's capacity is 25 MW.

5.3.1 Impact of Load Uncertainty (Normal density function)

a) 2% uncertainty

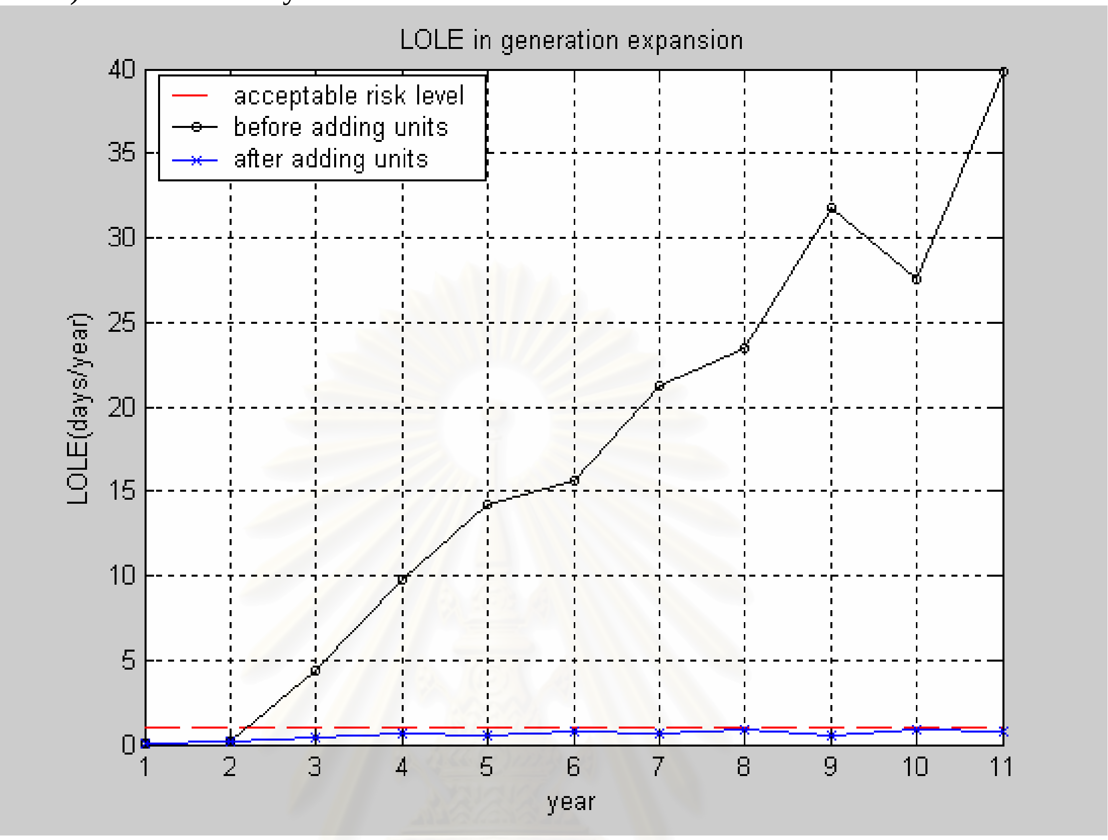


Fig 5.6 Risk from system expansion (LOLE $\leq$ 1 day / year)

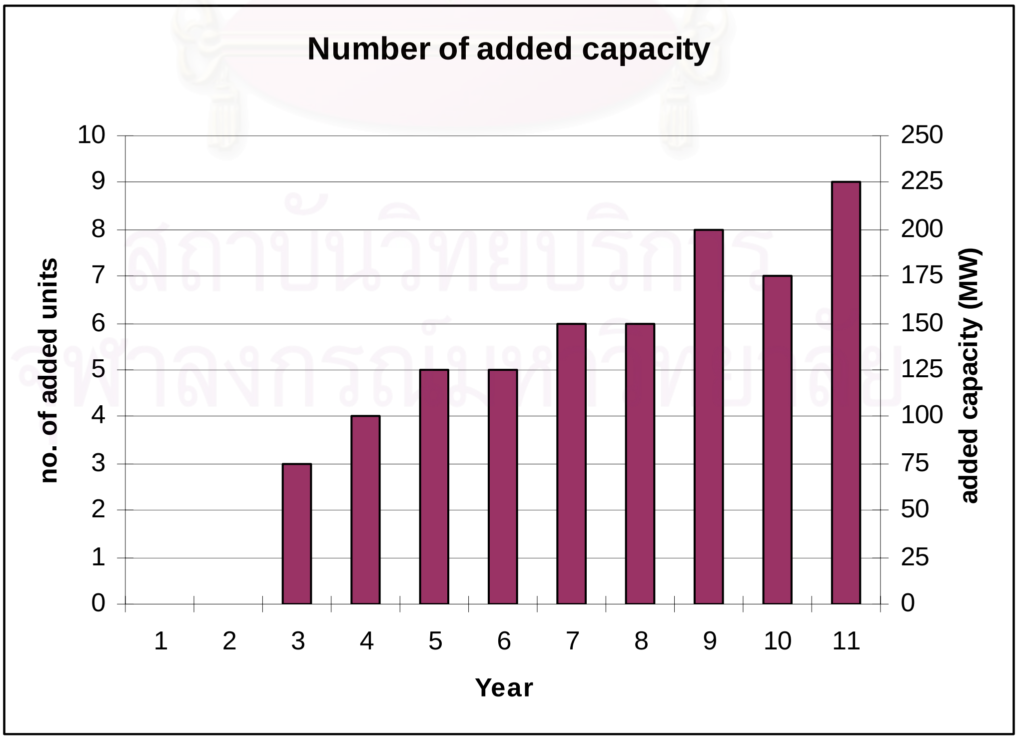


Fig 5.7 Number of added units (25 MW each)

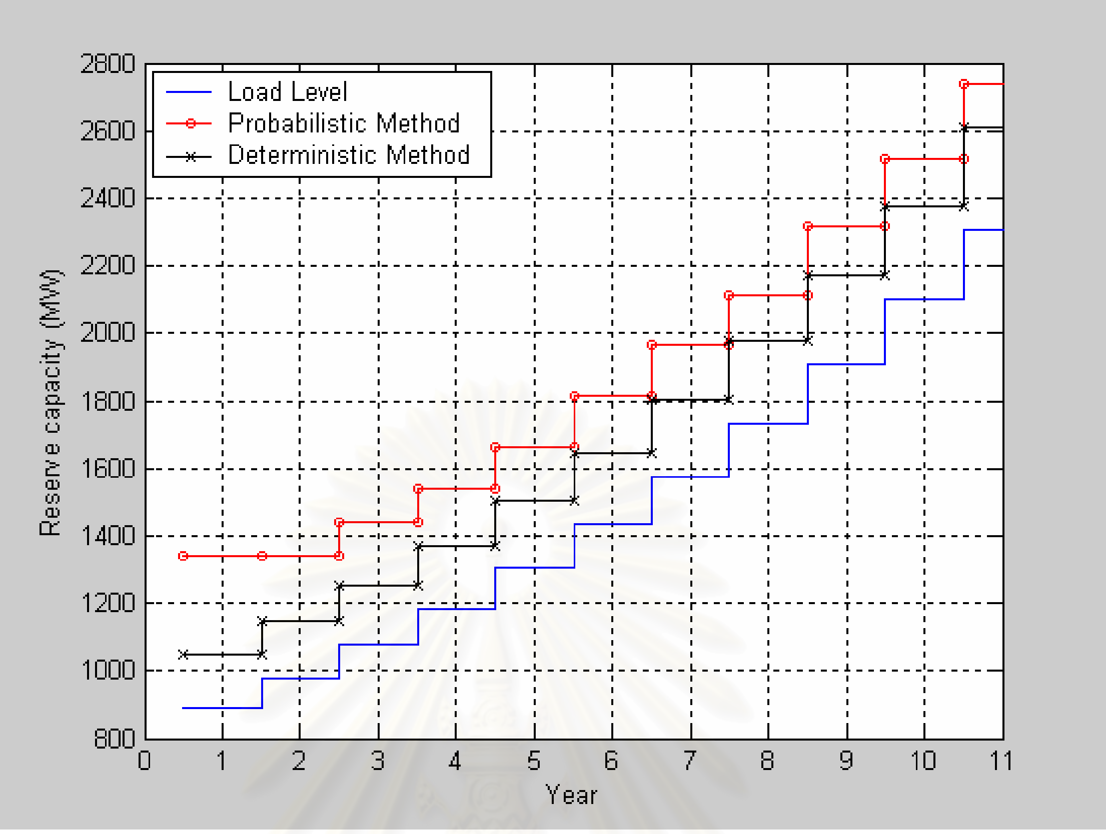


Fig 5.8 Installed capacity

b) 4% uncertainty

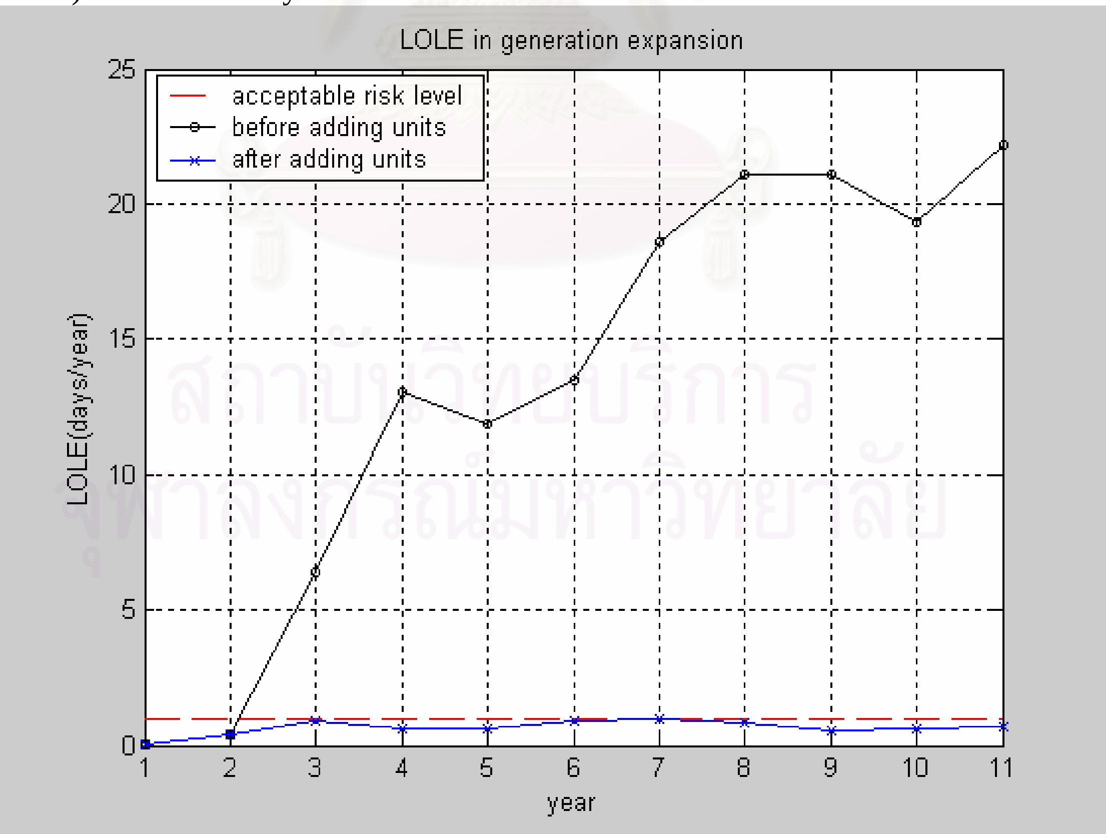


Fig 5.9 Risk from system expansion (LOLE $\leq$ 1 day / year)

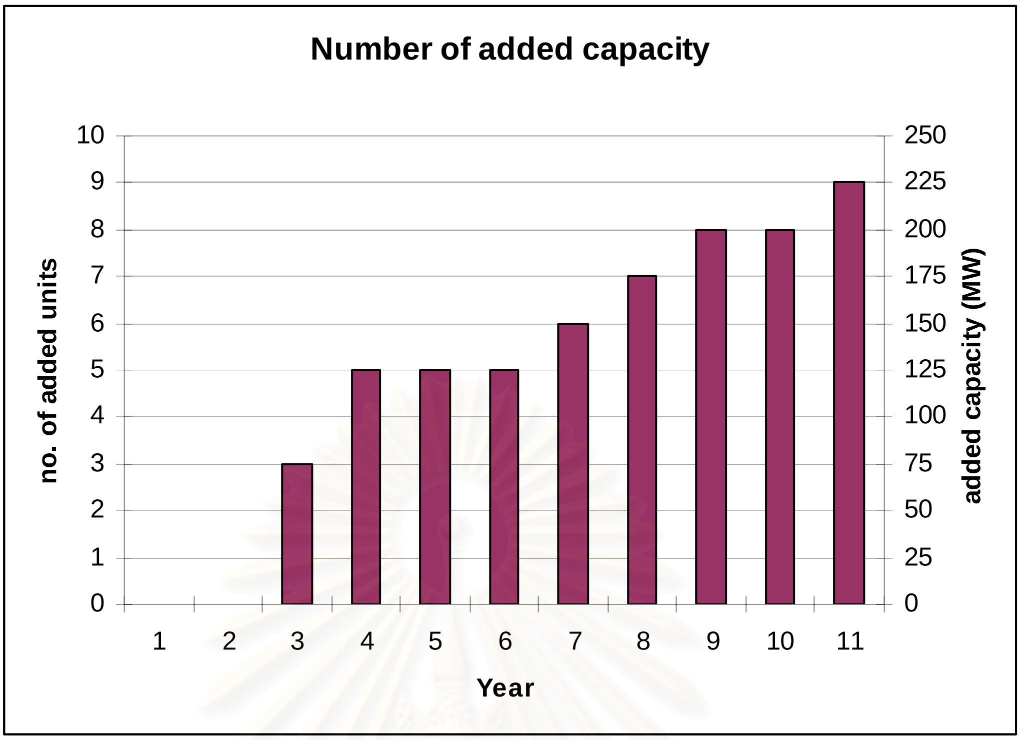


Fig 5.10 Number of added units (25 MW each)

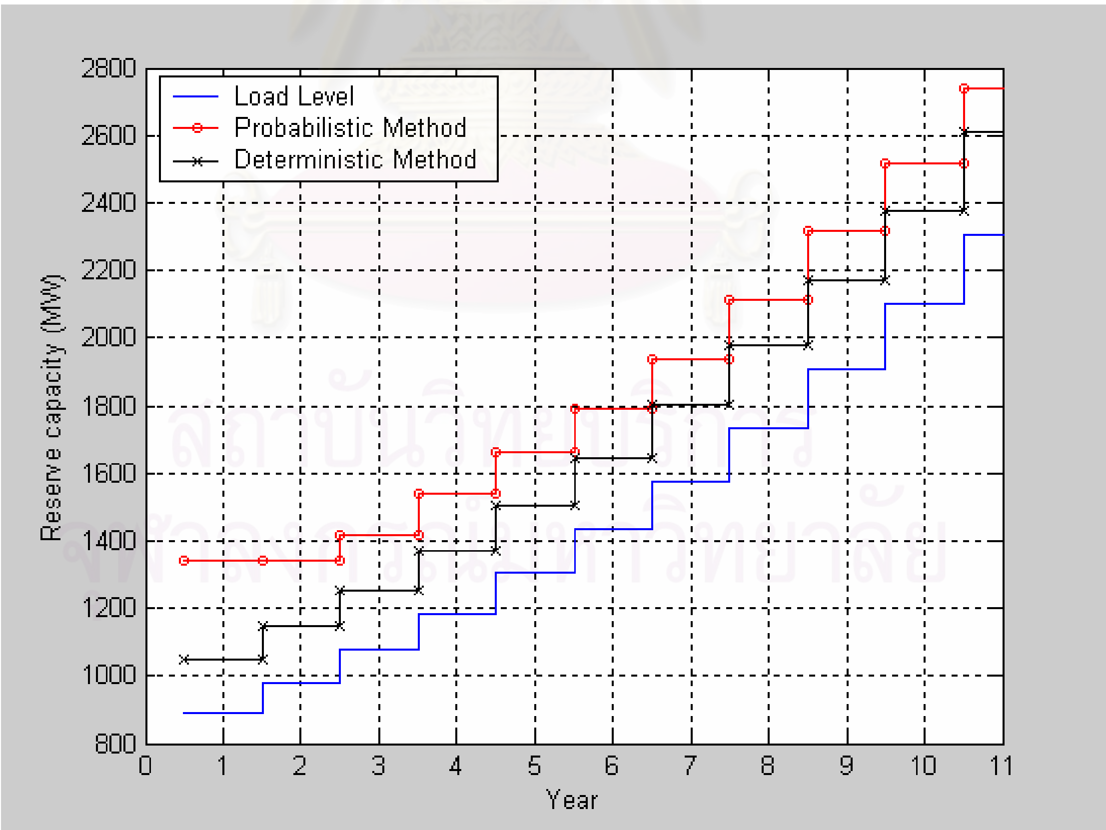


Fig 5.11 Installed capacity

c) 6% uncertainty

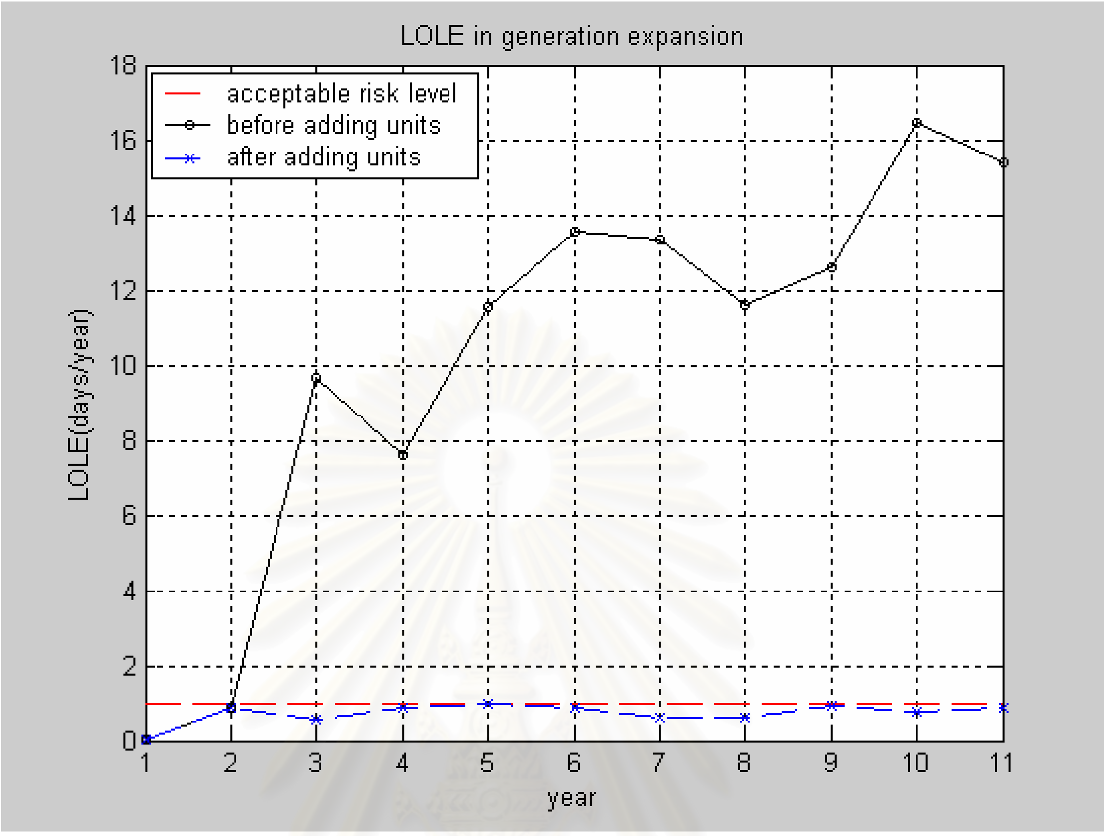


Fig 5.12 Risk from system expansion (LOLE ≤ 1 day / year)

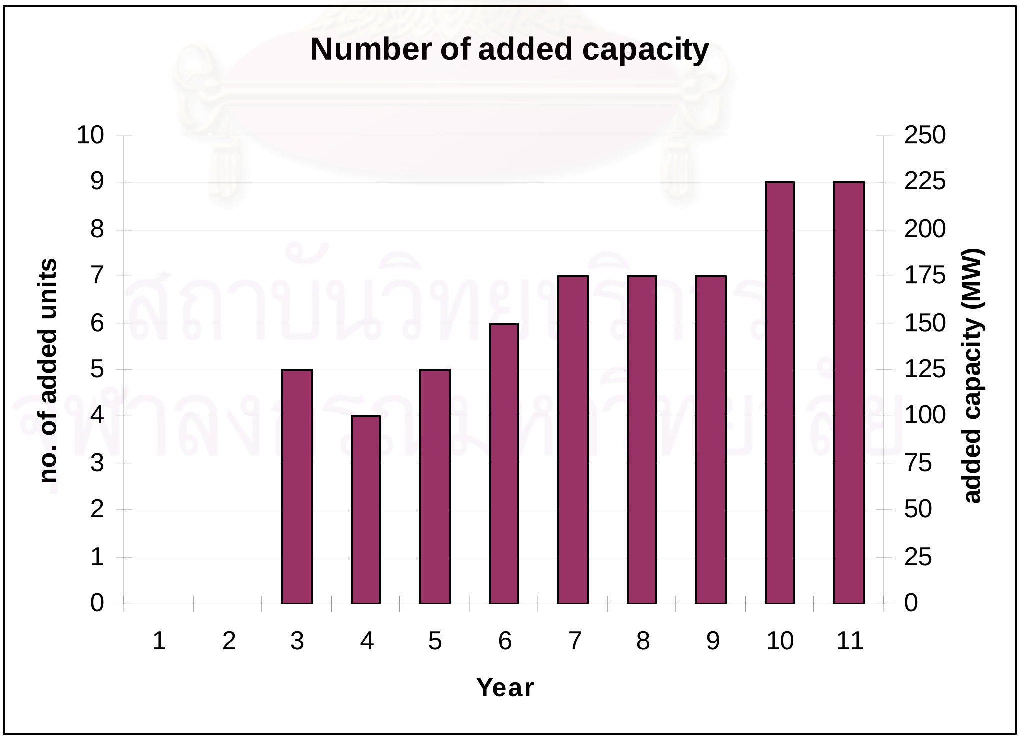


Fig 5.13 Number of added units (25 MW each)

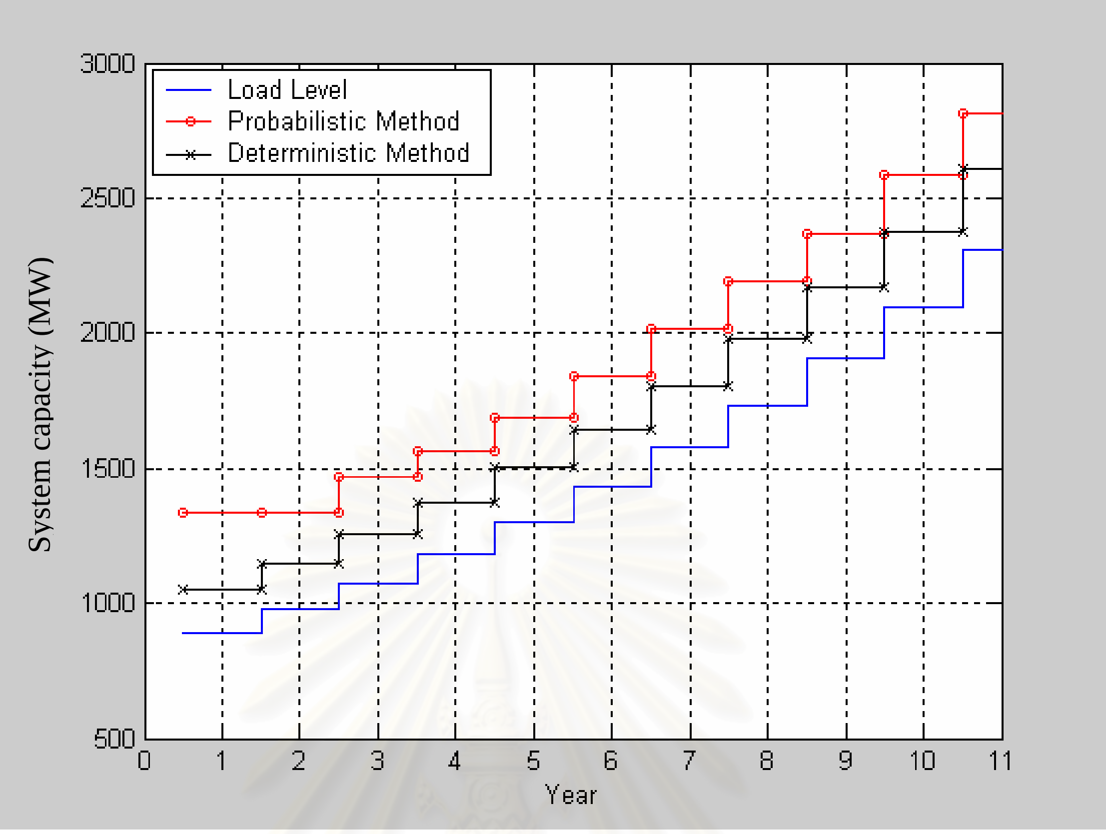


Fig 5.14 Installed capacity

From the above results based on normal density function, we can conclude that without uncertainty, the system requires less capacity compared with the cases of taking into account uncertainty. Similarly if we compare between 2% and 4% uncertainty cases we can see the latter case requires more capacity. Therefore the higher uncertainty, the more added capacity required.

The following subsections present the load forecast uncertainty for over and under forecasted cases. The detailed results of all the cases, different LOLE criteria and different added unit sizes, are shown in appendix A.

5.3.2 Impact of Load Uncertainty (Over forecast)

a) 2% uncertainty

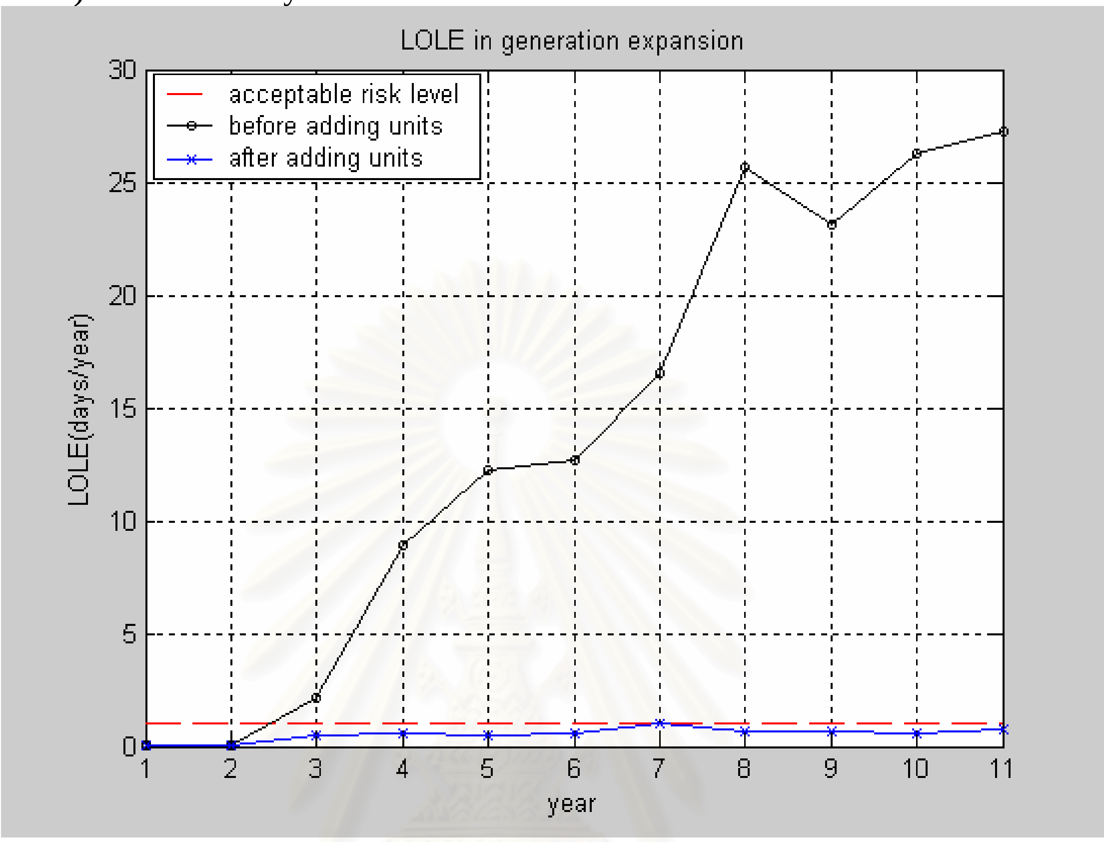


Fig 5.15 Risk from system expansion (LOLE ≤ 1 day / year)

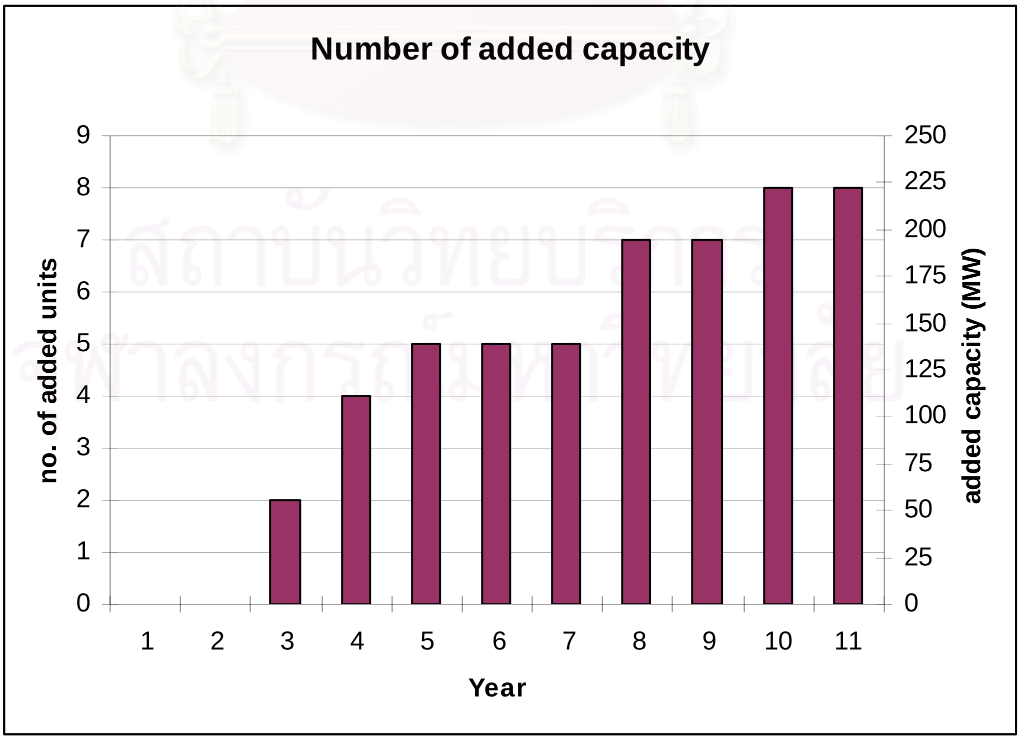


Fig 5.16 Number of added units (25 MW each)

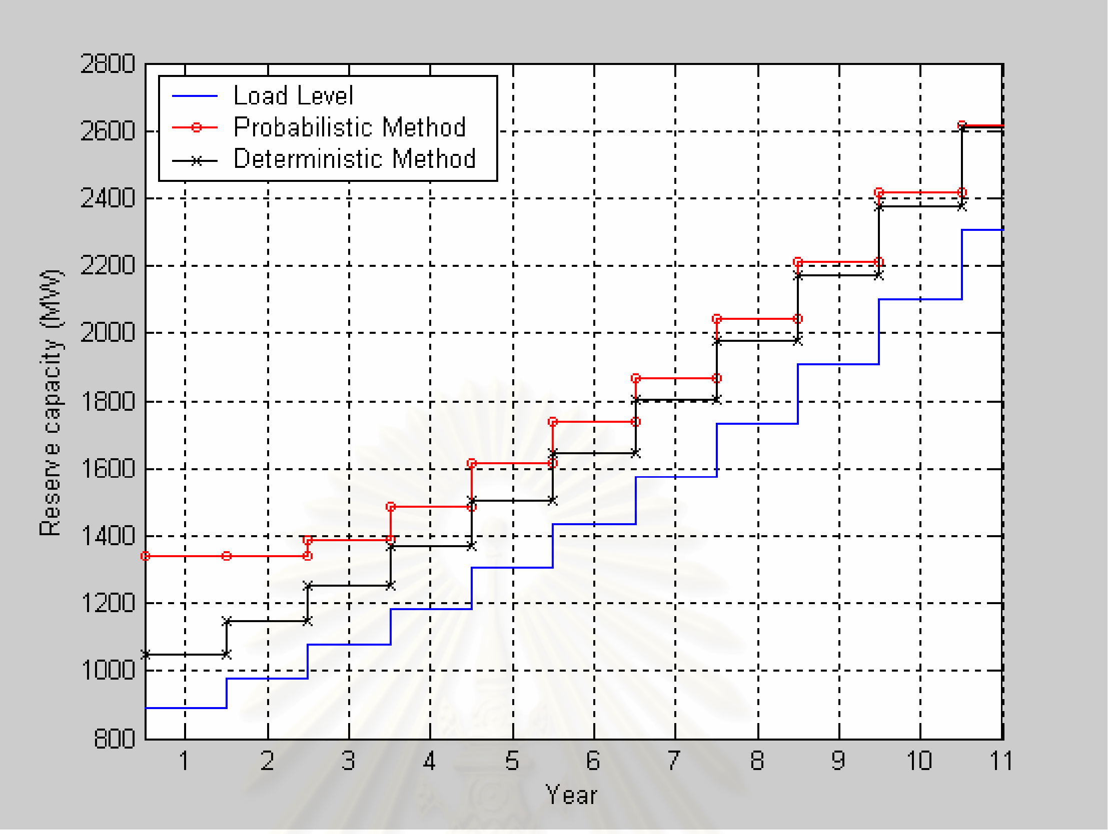


Fig 5.17 Installed capacity

b) 4% uncertainty

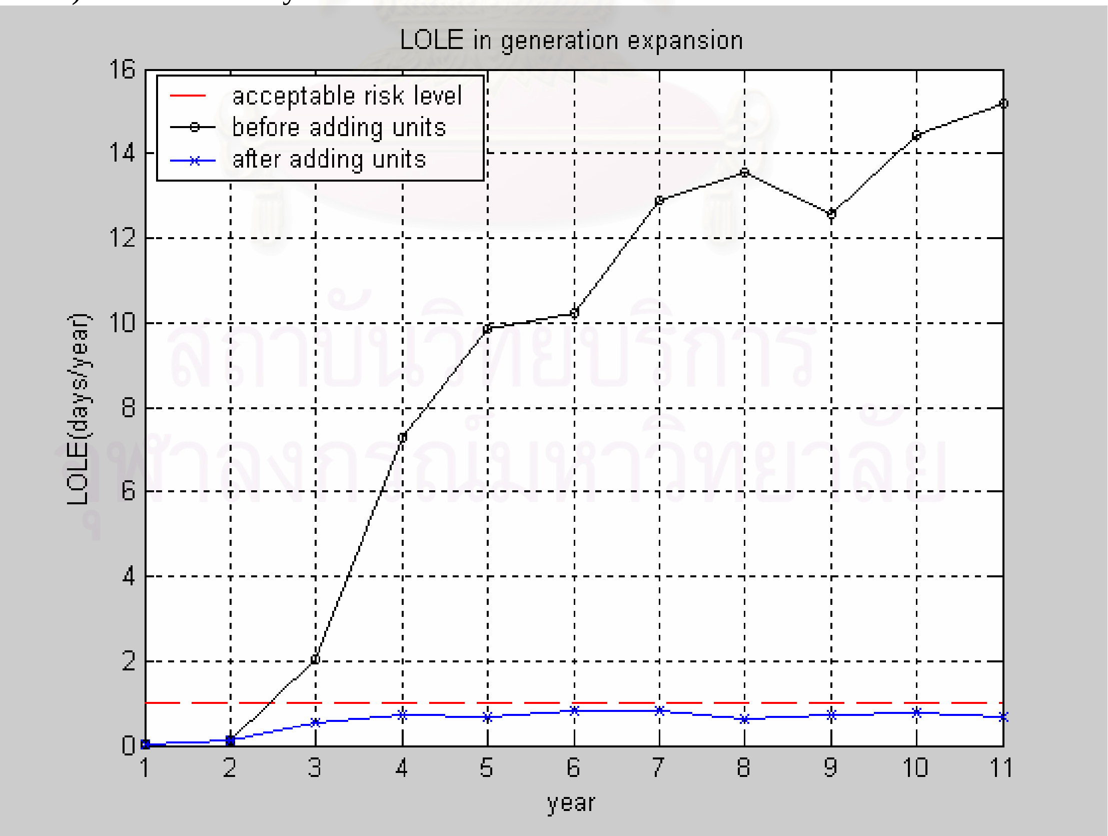


Fig 5.18 Risk from system expansion (LOLE ≤ 1 day / year)

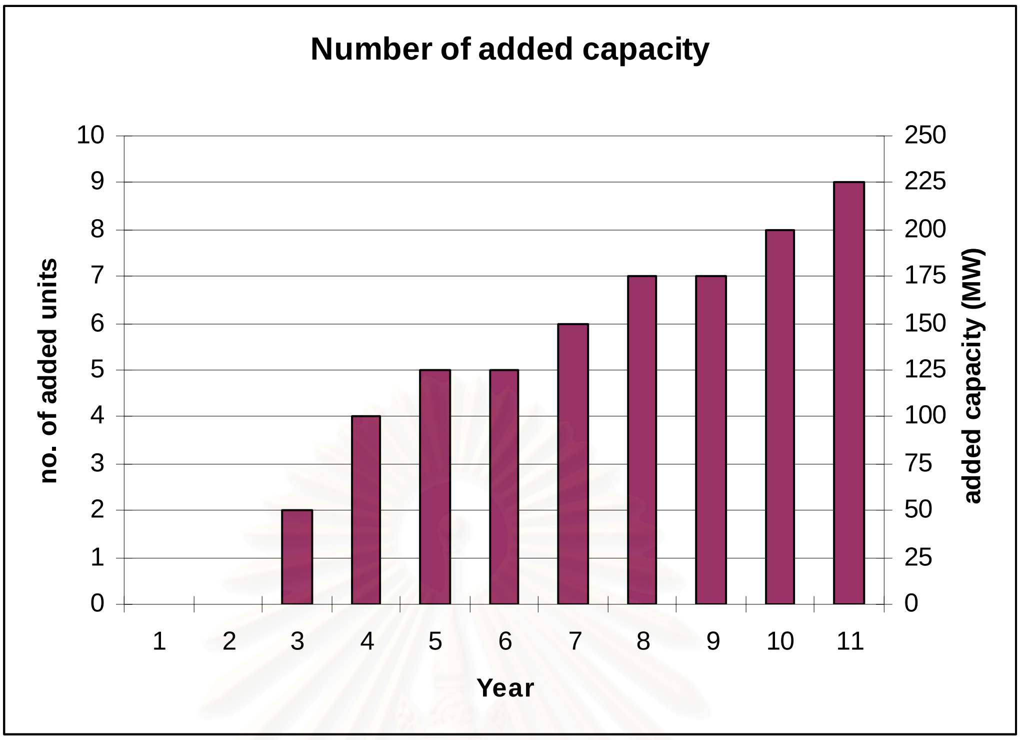


Fig 5.19 Number of added units (25 MW each)

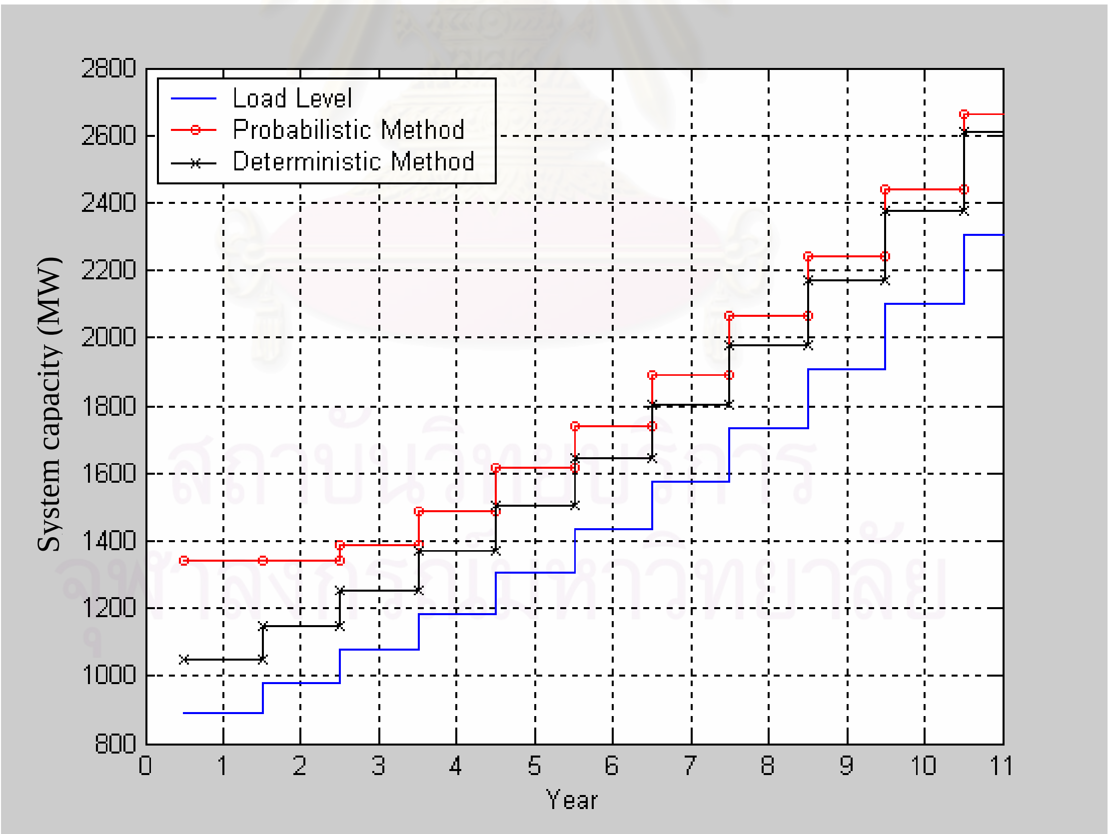


Fig 5.20 Installed capacity

c) 6% uncertainty

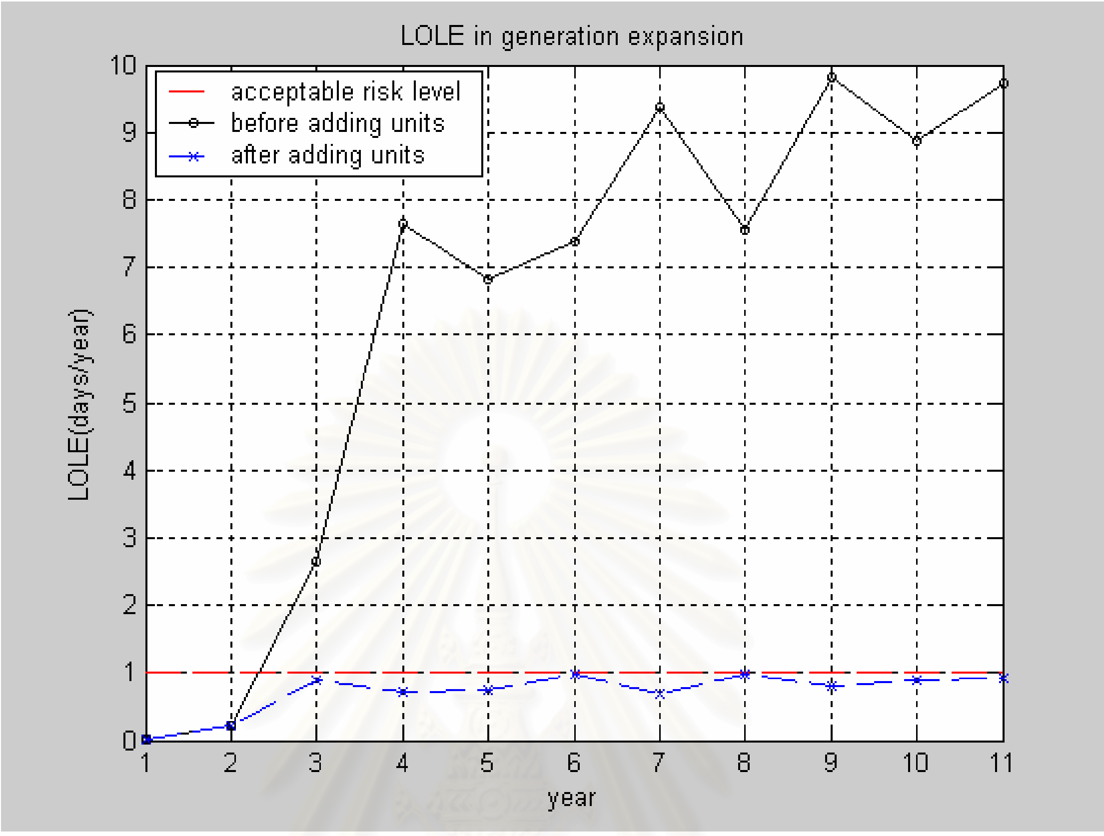


Fig 5.21 Risk from system expansion (LOLE $\leq$ 1 day / year)

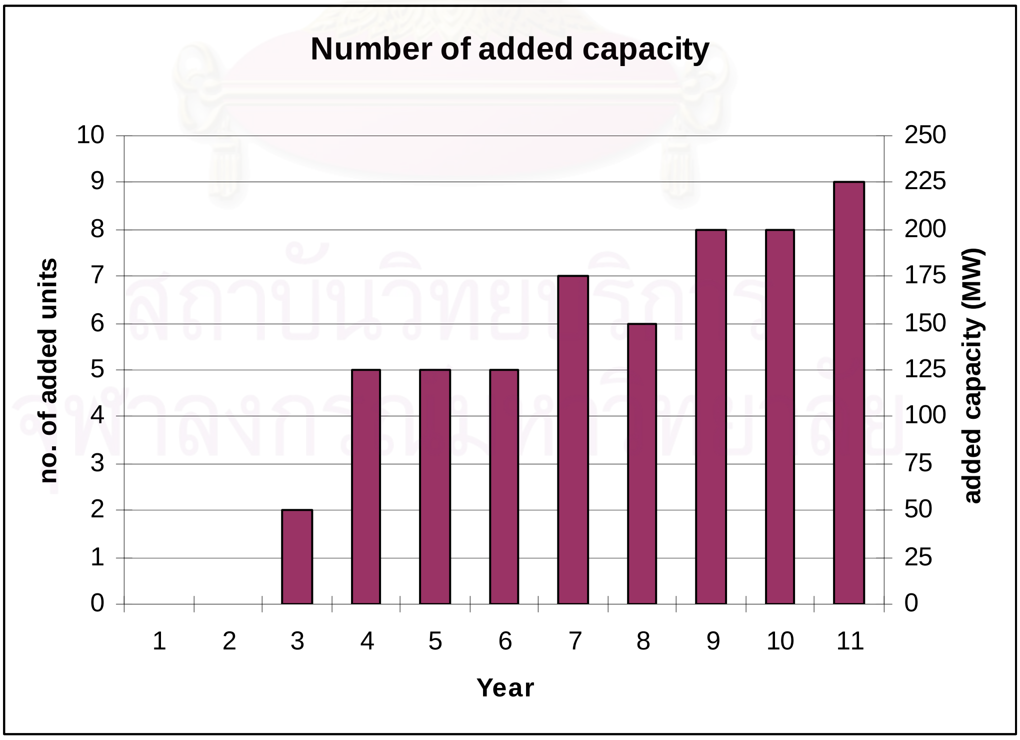


Fig 5.22 Number of added units (25 MW each)

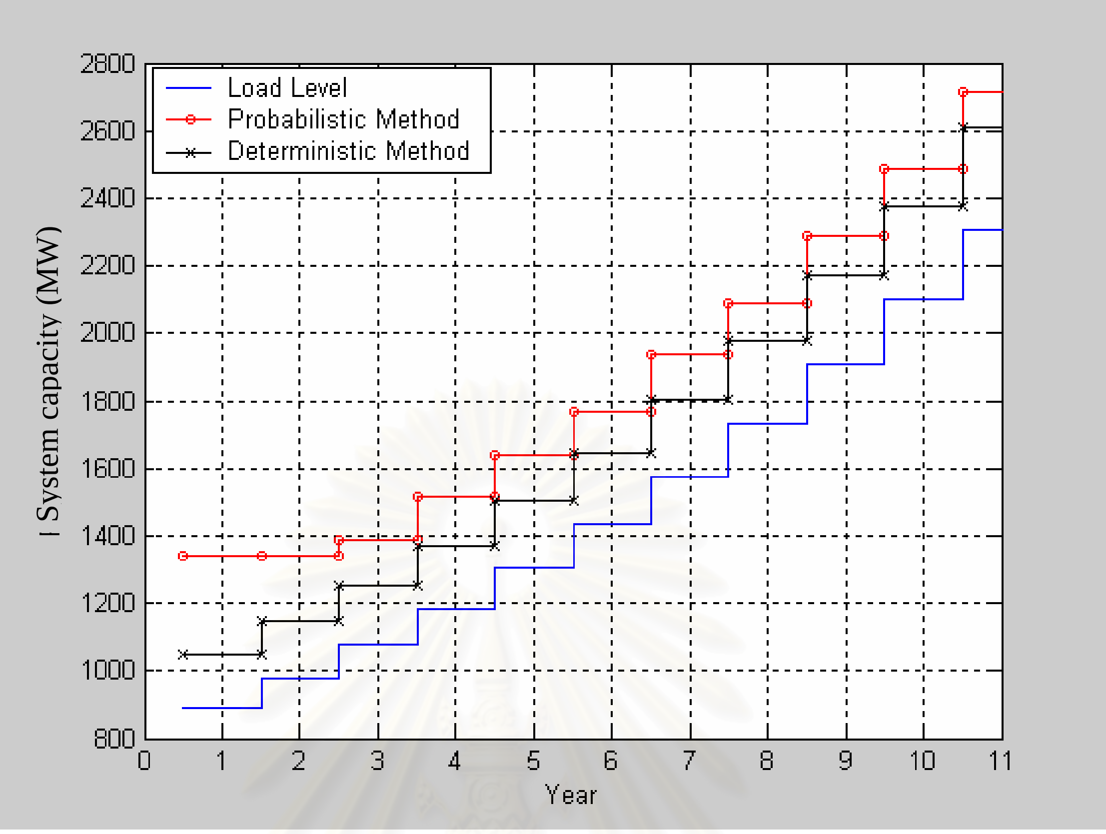


Fig 5.23 Installed capacity

The above results show that, since the over forecast means that the forecasted load is higher than actually happened. Therefore the risk is lower than the normal density function case. We can see clearly if we compare 2% of normal and over forecast, the normal case requires a little more capacity than the over forecast.

5.3.3 Impact of Load Uncertainty (Under forecast)

a) 2% uncertainty

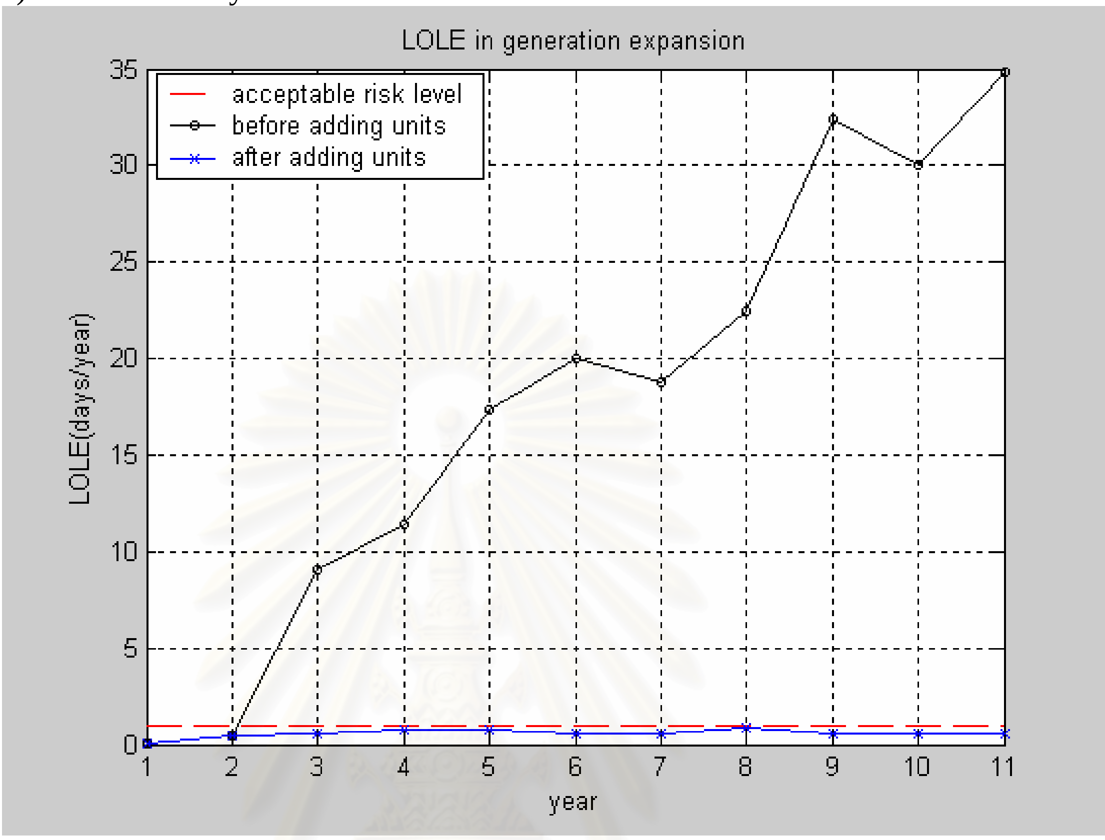


Fig 5.24 Risk from system expansion (LOLE $\leq$ 1 day / year)

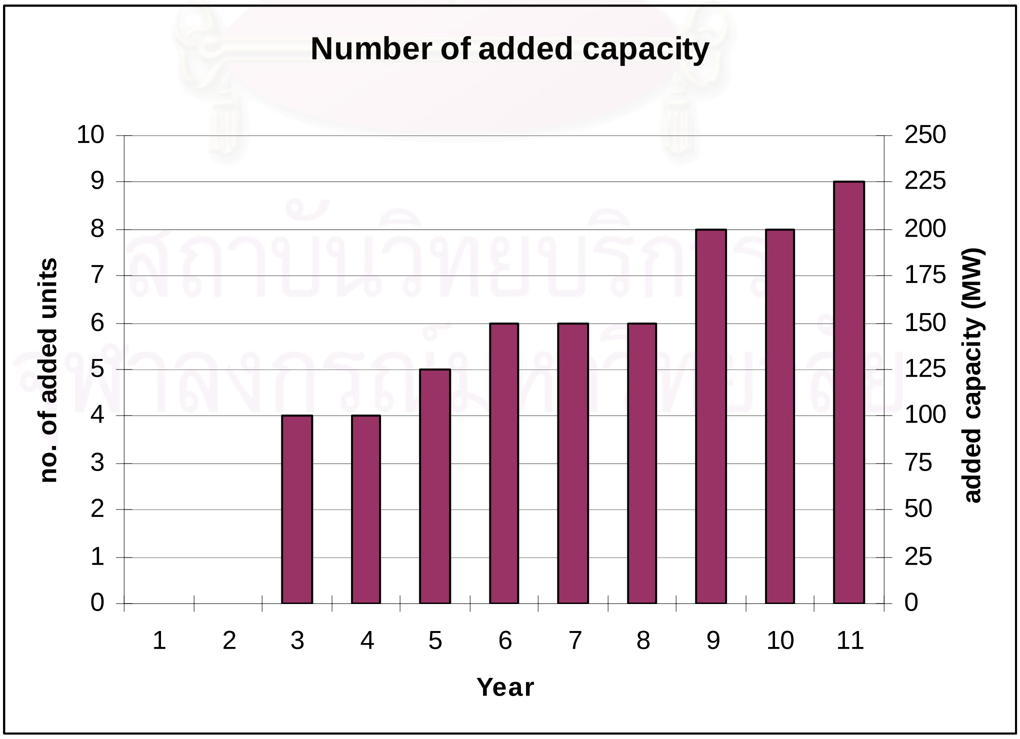


Fig 5.25 Number of added units (25 MW each)

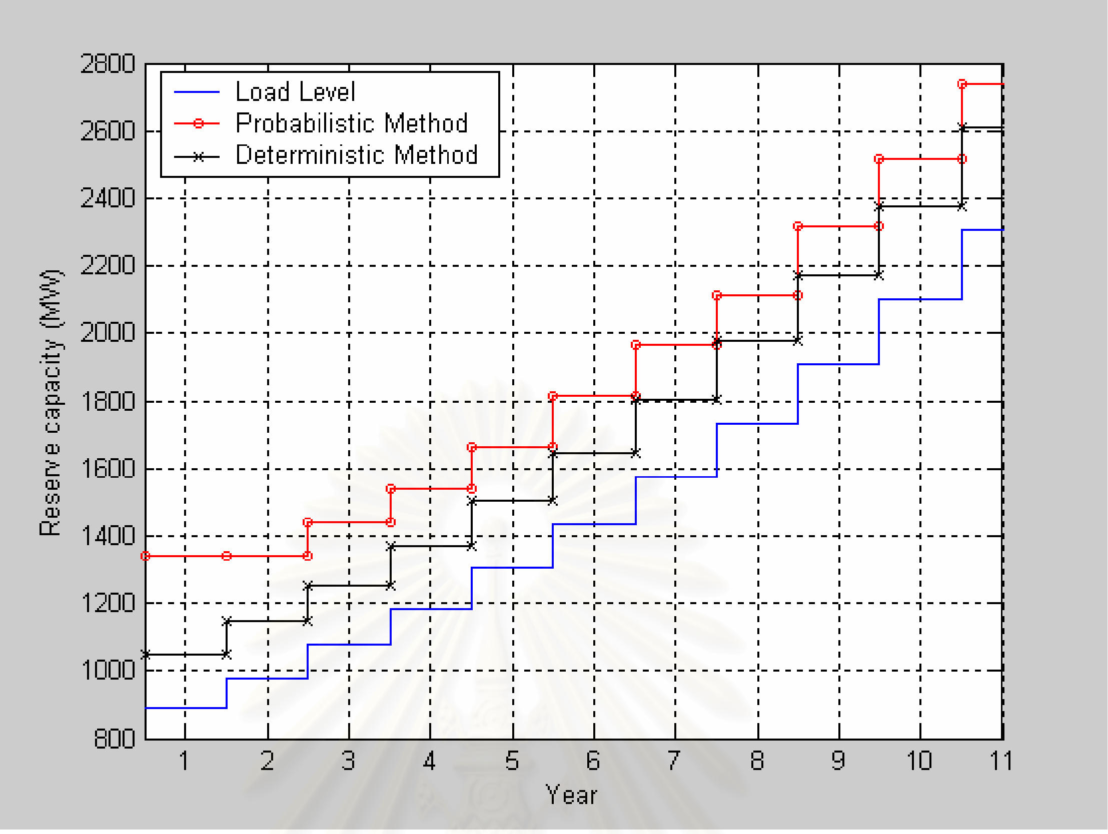


Fig 5.26 Installed capacity

b) 4%uncertainty

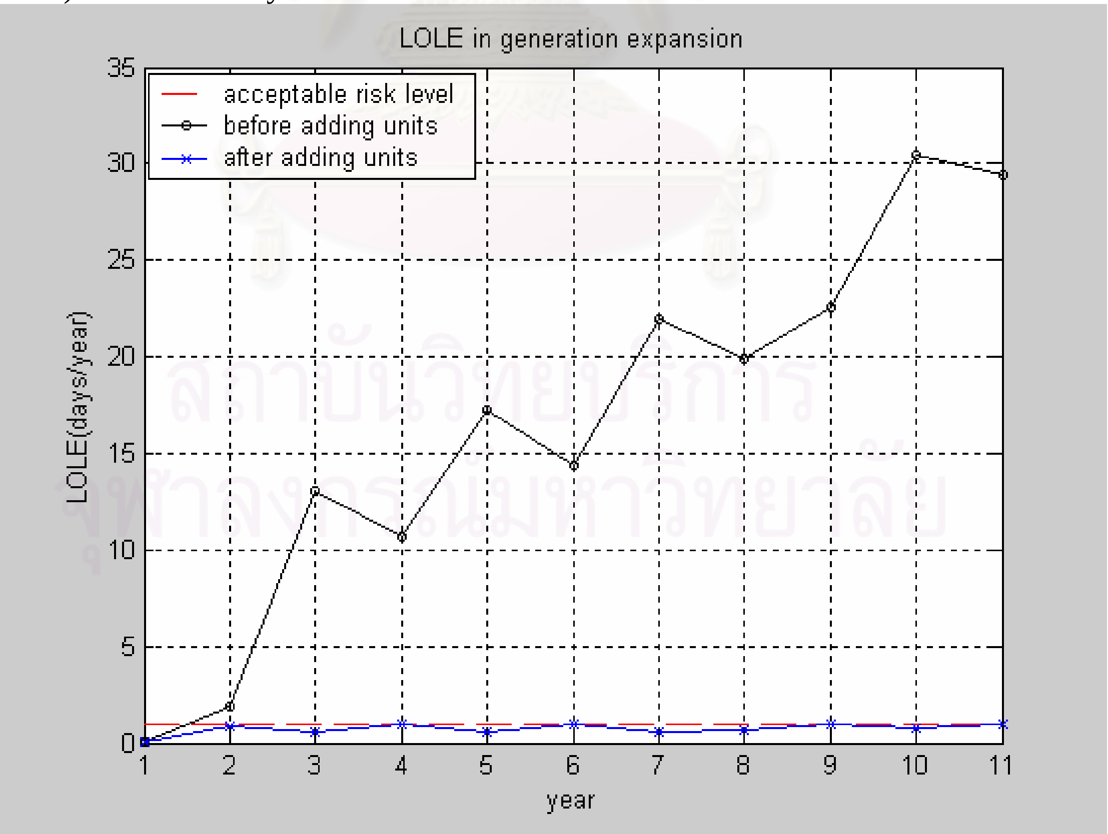


Fig 5.27 Risk from system expansion (LOLE $\leq$ 1 day / year)

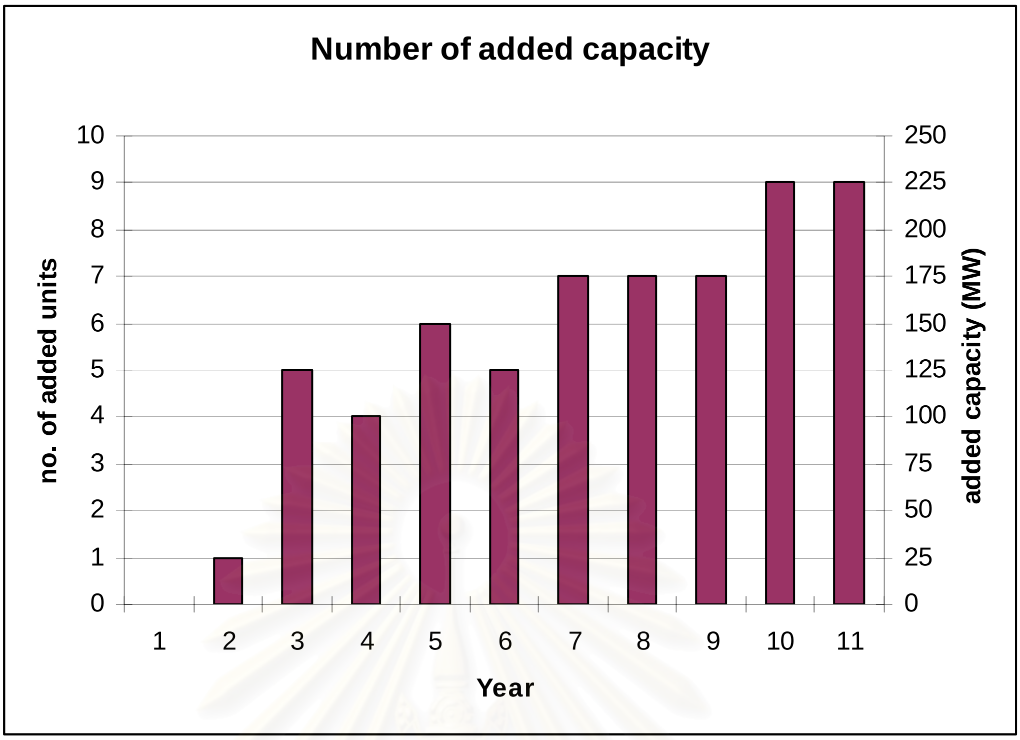


Fig 5.28 Number of added units (25 MW each)

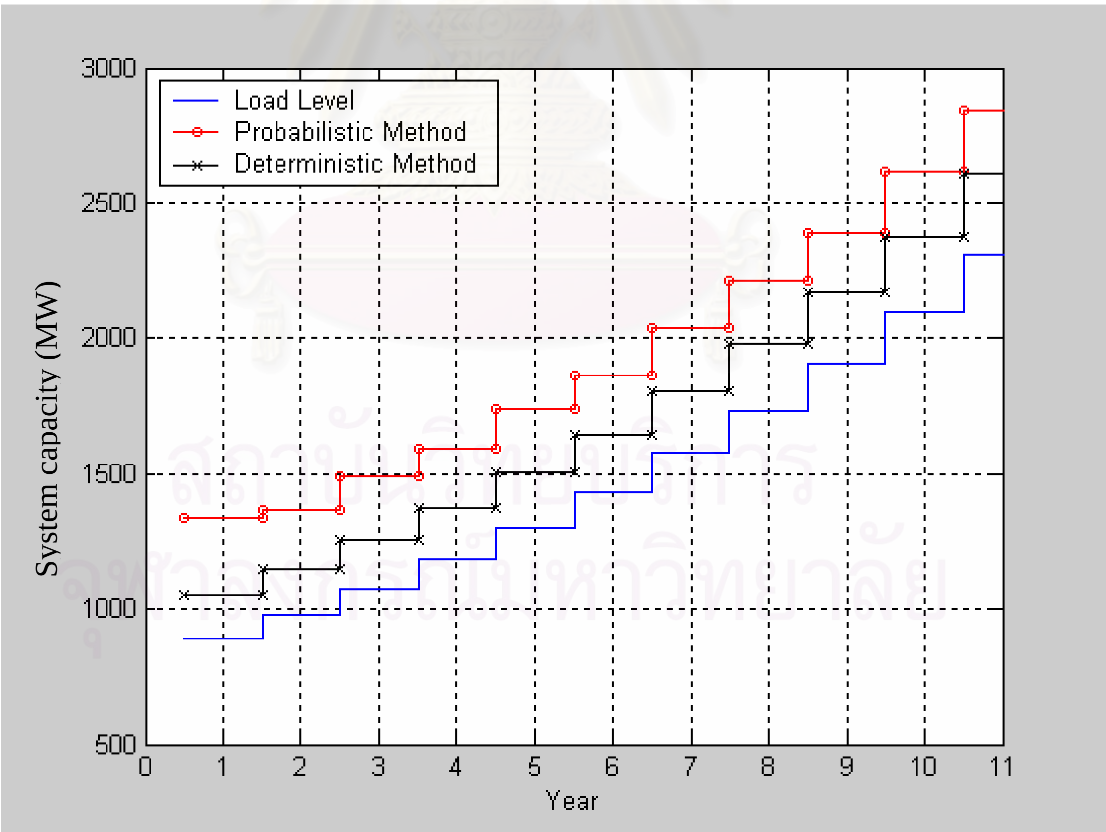


Fig 5.29 Installed capacity

c) 6% uncertainty

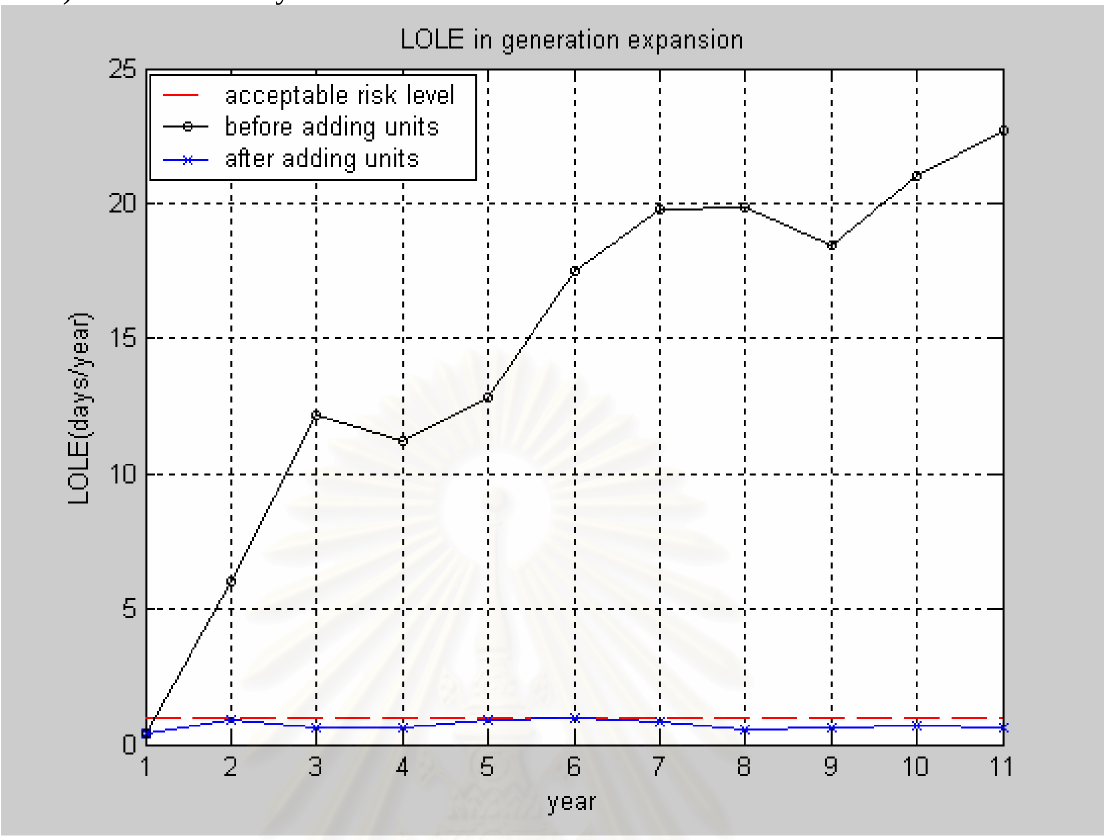


Fig 5.30 Risk from system expansion (LOLE ≤ 1 day / year)

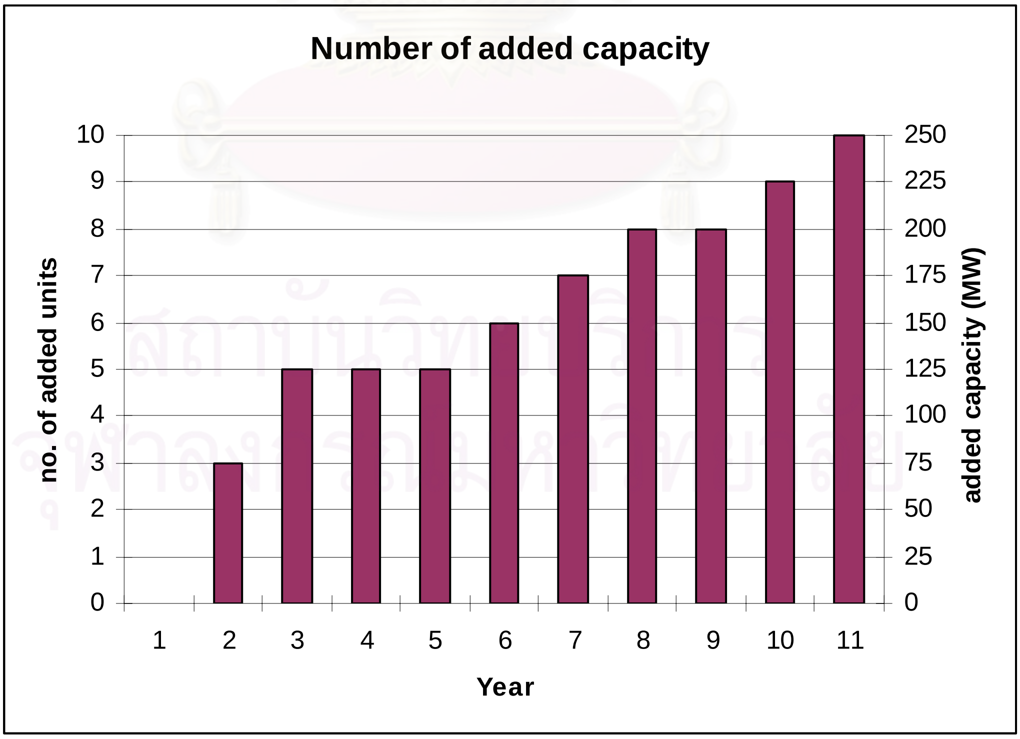


Fig 5.31 Number of added units (25 MW each)

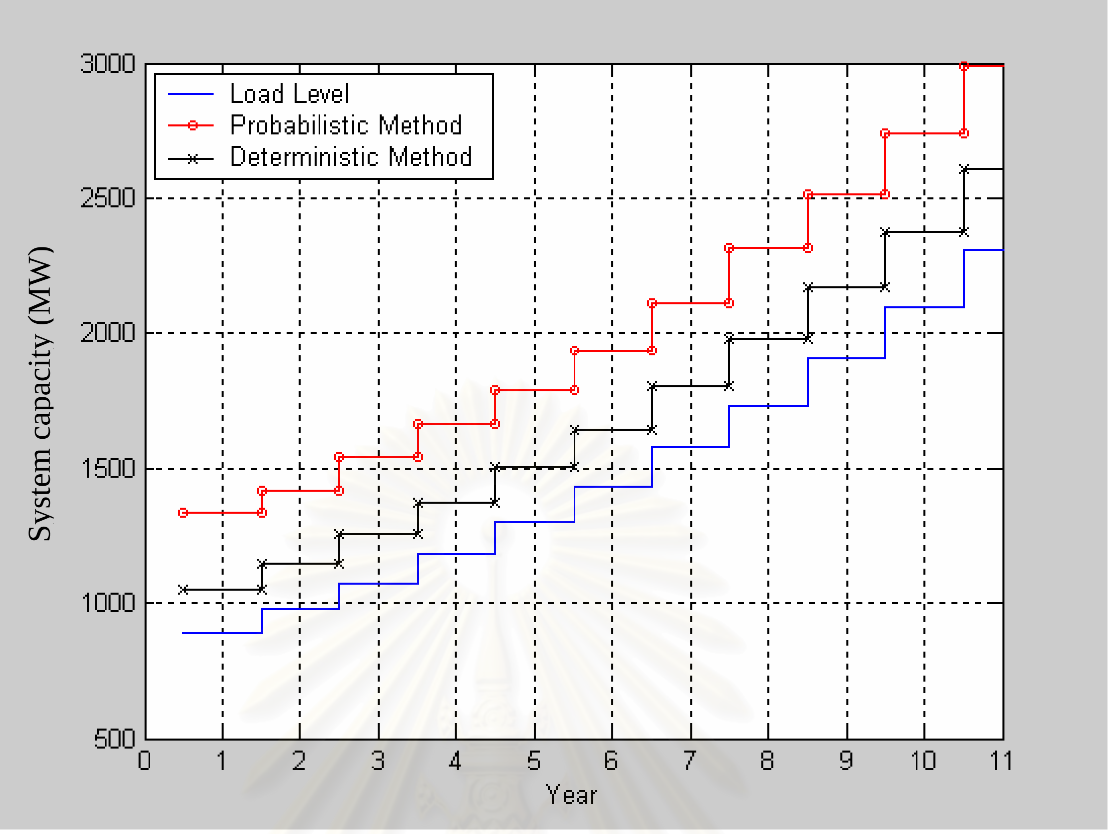


Fig 5.32 Installed capacity

5.3.4 Result Comparison

The above simulation results for the Myanmar system are analysed and compared in this section. Firstly we compare the cases of without uncertainty and with normal density function for the uncertainty model.

Figure 5.34 show the higher uncertainty the higher reserve capacity is required, especially for the years number 3-11. When we consider the reserve margin as percentage of peak load, we can find that for the case of no uncertainty, it requires more than 15% of peak load reserve.

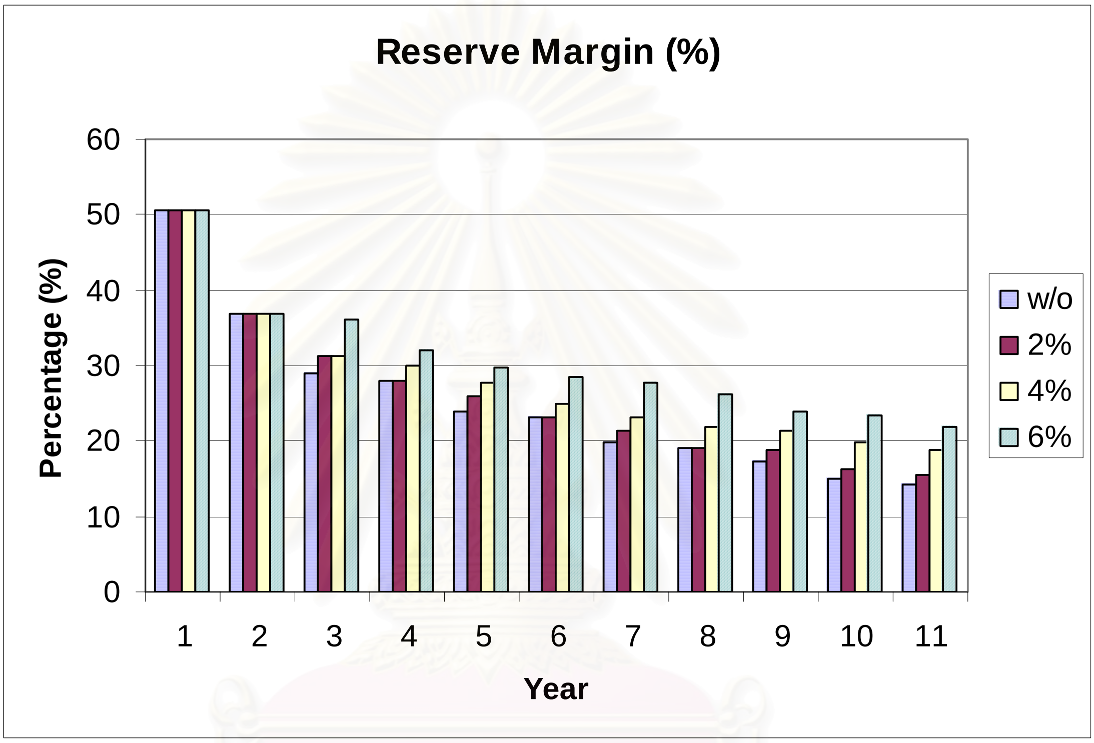


Fig 5.33 Reserve margin (%) in percentage of peak load

The comparison of the average reserve margin (2-11) year for the cases of with and without uncertainty is shown in figure 5.34. We found that average reserve margin of without uncertainty case is approximately 23% for each year. When the uncertainty is taken into account, the average reserve margin percentage is required about 24-29%. The average uncertainty reserve margin (%) is about 26% for normal density function case.

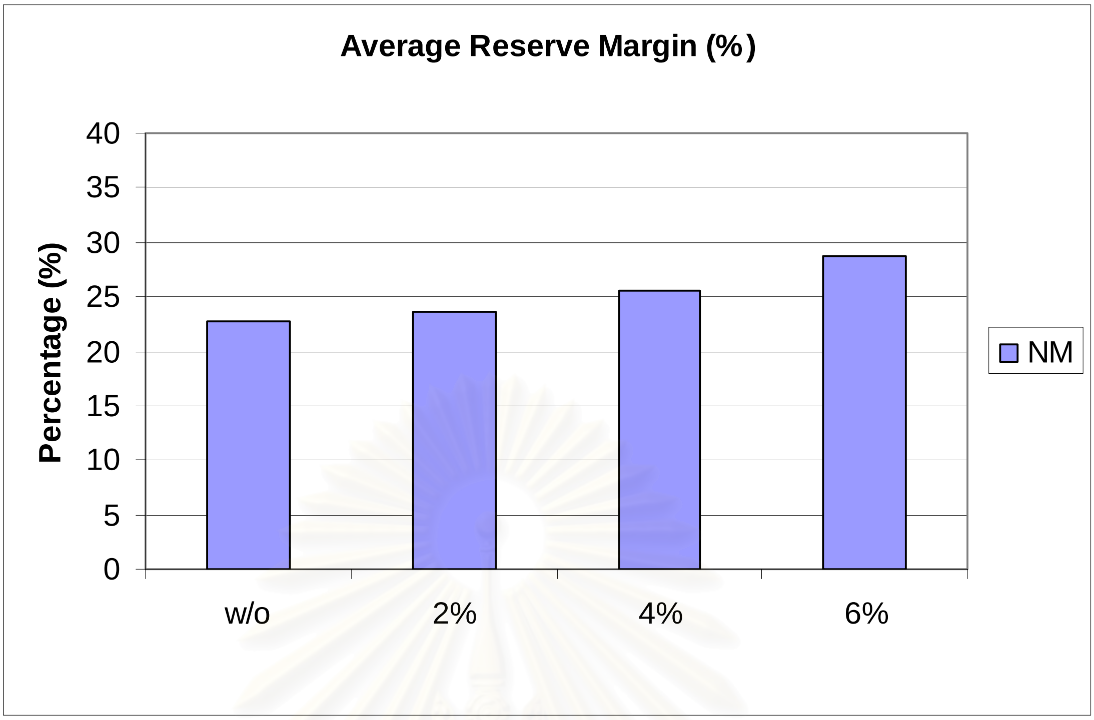


Fig 5.34 Comparison of the average reserve margin

For the over forecast cases, similar results are summarized in figures 5.35-5.36. However the average reserve margin is about 22-24 % which is less than the normal uncertainty cases. The average uncertainty (%) reserve margin of over forecast case is about 23%.

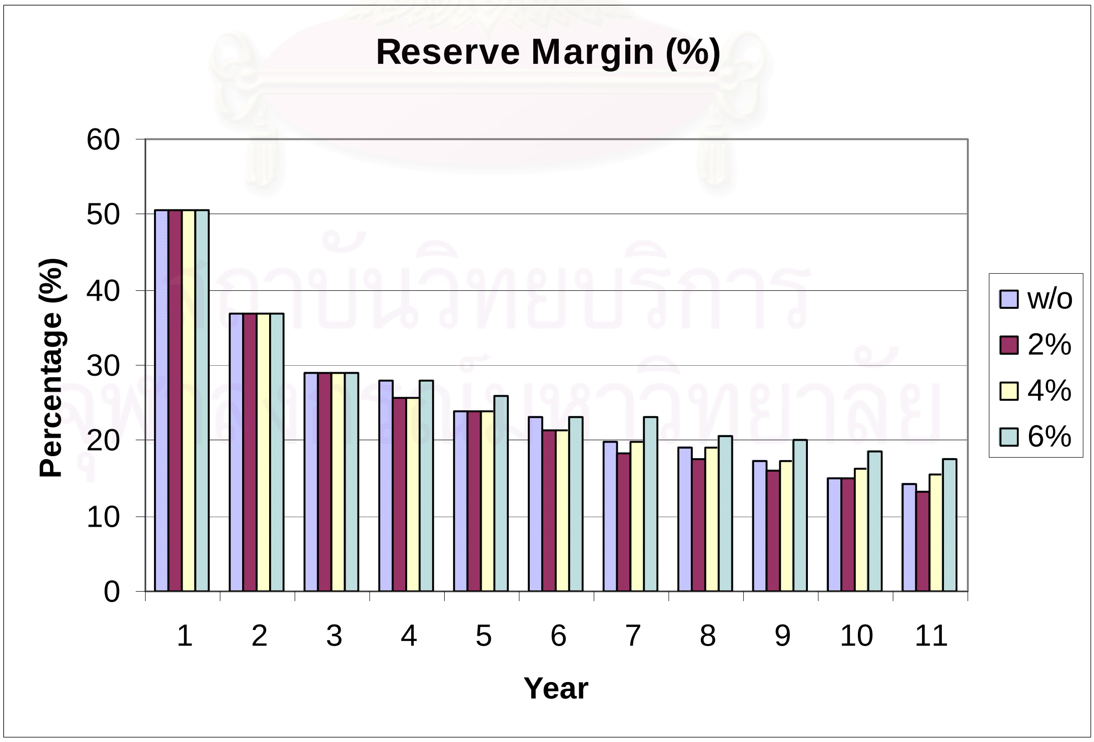


Fig 5.35 Reserve margin (%) in percentage of peak load

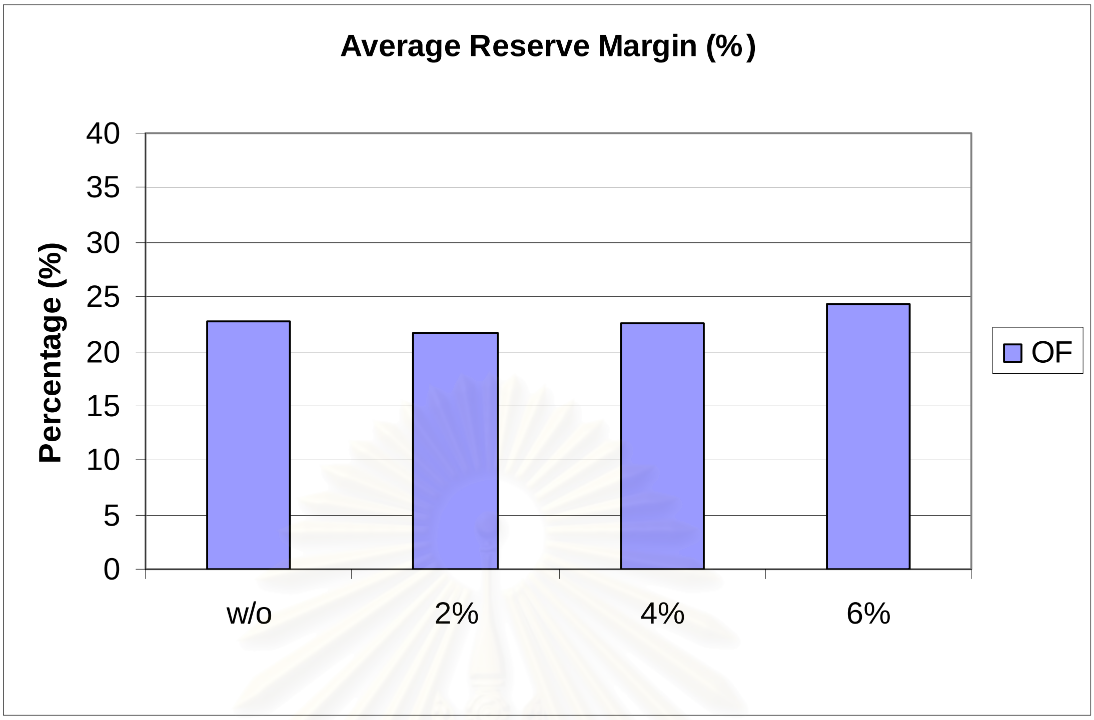


Fig 5.36 Comparison of the average reserve margin

For the under forecast cases, similar results are summarized in figures 5.37-5.38. However the average reserve margin is about 26-36 % which is the highest required reserve capacity case. The average uncertainty (%) reserve margin of under forecast is about 31%.

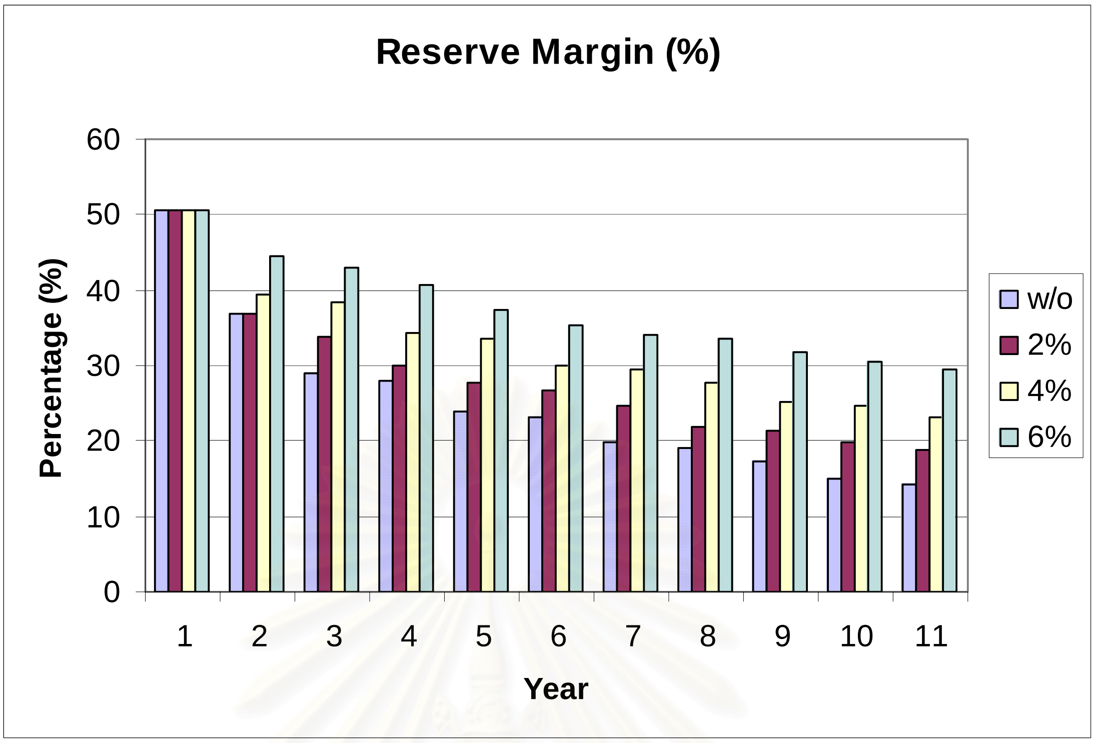


Fig 5.37 Reserve margin (%) in percentage of peak load

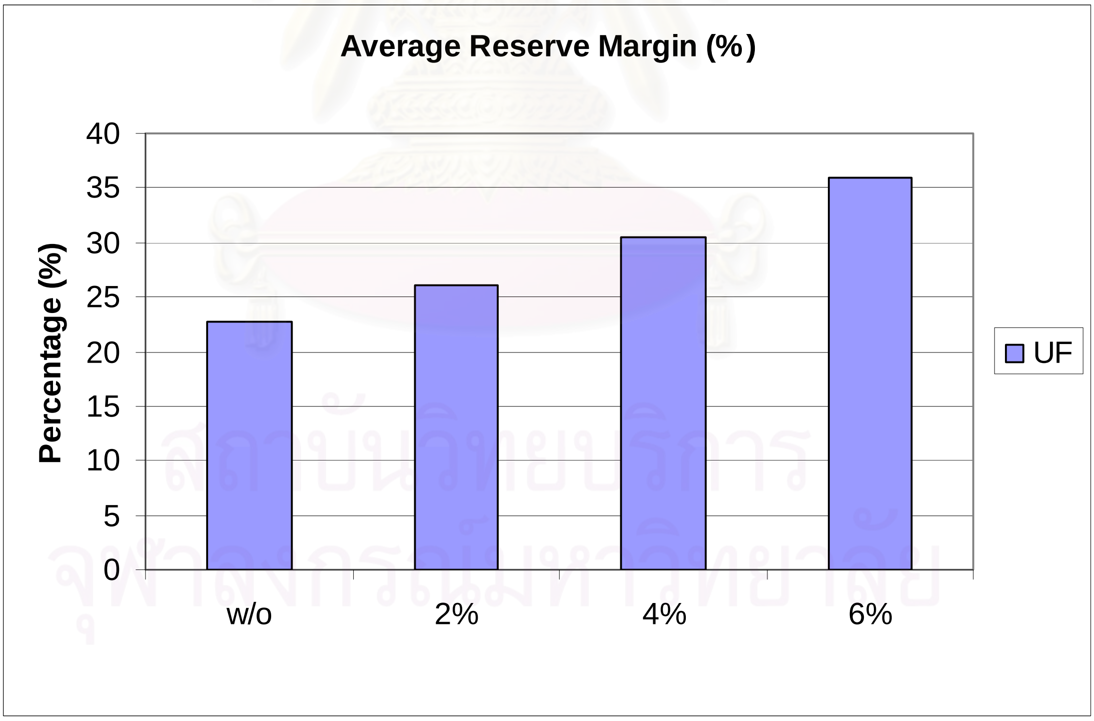


Fig 5.38 Comparison of the average reserve margin

As a conclusion for Myanmar system, the planning criteria of LOLE = 1day/yr, with new added capacity of 25 MW, we can suggest that if the uncertainty of the forecasted load is neglected the required reserve capacity is about 23% of the peak demand. However if we take into account the forecast uncertainty a higher percentage value should be used instead. Myanmar generation system should use the average reserve margin percentage is about 23% for the over forecast, 26% for the normal density function, and 31% for the under forecast case. It should bare in mind that if the risk criteria is changed, the suggestion should be adjusted according. Detailed results of the changed criteria, LOLE ≤ 3 day/year, and another risk of the new added capacity are shown in appendix A.

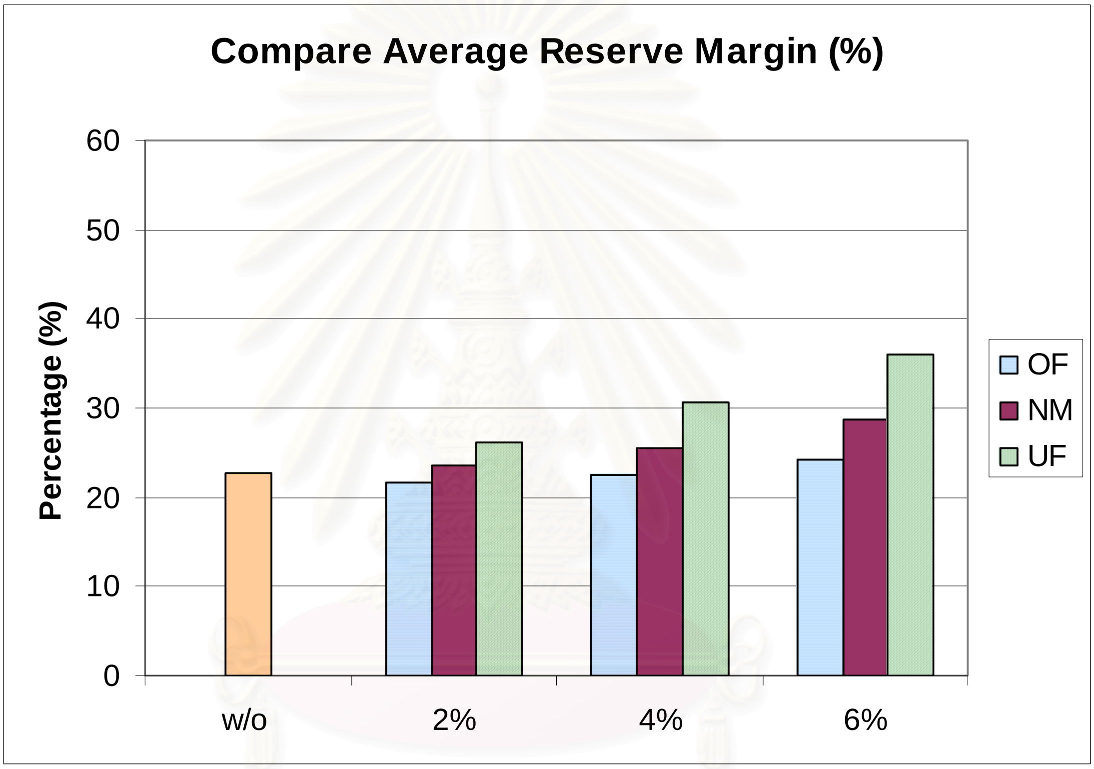


Fig 5.39 compare average reserve margin with three uncertainty models

5.4 Thailand Generation System

The Electricity Generation Authority of Thailand (EGAT) has been primarily responsible for power generation and transmission, where as the Metropolitan Electricity Authority (MEA) and the Provincial Electricity Authority (PEA) share the responsibility of distributing electricity to Bangkok and the provinces, respectively.

Thailand electricity consumption of national grid in 2000 was 87,932 GWh, an increase of 8 % over 1999. The total of national grid installed capacity in 2000 was 22,593 MW, up 11.7% over the previous year. The installed capacity was shared by government or state electric utilities and private power producers. Power plants are thermal, combined cycle, hydro, SPP’s cogeneration and others.

At present, EGAT has a 26,387 MW installation capacity base. In 2003 the peak demand was 19,326MWs which is lower than EGAT’s predication by 274MWs. The real peak demand has been consistently lower than what’s been forecasted.

In this thesis we use the 1993 EGAT generation data as shown in table 5.5 with actual peak demand from 1993 to 2003 which are described in table 5.6. We will conduct expansion planning with consideration of uncertainties for 11 years, with each newly added unit capacity of 200 MW. The simulation results of other added capacity of 300, 400, 500 MW each are shown in appendix B.

Table 5.5 presents 117 units generating system with a total capacity of 11,660 MW. The individual state load model for a 365day period is assumed and shown in table 5.7. Assuming that we start at the year 1993 of which the forecasted peak load is 9,735MW. The risk criterion (LOLE) is set at 1 day/year. An exposure factor e of 0.5 was used with low load level of 5,746 MW as shown in table 5.7. The daily load variation curve is assumed to be a straight line at a load factor of 70 %. Assume that the system has been decided to add additional 200 MW unit, if required, with forced outage rates of 0.045 to meet the actual load during 1994-2003. The annual added capacity for each of the next 11 years is shown in figure 5.40.

Table 5.5 Reliability Information of EGAT's Power Plants [14]

No	Power Plants	No of Unit	Capacity (MW)	FOR
	Thermal Plants			
1.	Bang Pakong			
		1	550	0.0052
		1	550	0.0028
		1	600	0.1271
		1	600	0.0174
2.	North Bangkok			
		1	75	0.0252
		1	75	0.0135
		1	90	0.0173
3	South Bangkok			
		1	200	0.0642
		1	200	0.0274
		1	310	0.0088
		1	310	0.0195
		1	310	0.0018
4	Khanom PPB.			
		1	75	0.0082
		1	75	0.0795
5	Surat Thani			
		1	30	0.0661
6	Krabi			
		1	15	0.0378
		1	15	0.0886
7	Mae Moh			
		1	75	0.0342
		1	75	0.0137
		1	75	0.0234
		1	150	0.0381
		1	150	0.0211
		1	150	0.0203
		1	150	0.0198
		1	300	0.0336
		1	300	0.0309
		1	300	0.0540
		1	300	0.0214
	Total	28	5,795	
	Combined Cycle Plants			
1	Bang Pakong			
	Block#1			
	GT-11	1	60	0.0546
	GT-12	1	60	0.1260

	Combined Cycle Plants (Continued)			
	GT-13	1	60	0.0128
	GT-14	1	60	0.0170
	ST-10	1	140	0.2534
	Block#2			
	GT-21	1	60	0.0320
	GT-22	1	60	0.0152
	GT-23	1	60	0.0148
	GT-24	1	60	0.0651
	ST-20	1	140	0.0591
	Block#3			
	GT-31	1	110	0.0506
	GT-32	1	110	0.0613
	ST-40	1	110	0.0266
	Block#4			
	GT-41	1	110	0.0495
	GT-42	1	110	0.0407
	ST-40	1	110	0.0189
2	Rayong			
	Block#1			
	GT-11	1	110	0.0386
	GT-12	1	110	0.0405
	ST-10	1	110	0.0289
	Block#2			
	GT-21	1	110	0.0244
		1	110	0.0226
		1	110	0.0392
	Block#3			
	GT-31	1	110	0.0344
	GT-32	1	110	0.0201
	ST-30	1	110	0.0508
	Block#4			
	GT-41	1	110	0.0315
	GT-42	1	110	0.0136
	ST-40	1	110	0.0000
3	Nam Phong			
	Block#1			
	GT-11	1	125	0.0048
	GT-12	1	125	0.0031
	ST-10	1	125	0.0168
	Total	31	3,115	
	Hydro Plants			
1.	Bhumidbol			
		1	70.0	0.0268
		1	70.0	0.0308
		1	70.0	0.0627
		1	70.0	0.0129

	Hydro Plants (continued)			
		1	70.0	0.0227
		1	70.0	0.0143
		1	115.0	0.0320
2.	Sirikit			
		1	125.0	0.0145
		1	125.0	0.0214
		1	125.0	0.0301
3.	Srinagarind			
		1	120.0	0.0026
		1	120.0	0.0025
		1	120.0	0.0045
		1	180.0	0.0176
		1	180.0	0.0231
4.	Tha Thung Na			
		1	20	0.0007
		1	20	0.0004
5.	Khao Laem			
		1	100	0.0309
		1	100	0.0237
		1	100	0.0087
6.	Kaeng Krachan			
		1	15	0.0055
7.	Bang Lang			
		1	25	0.0167
		1	25	0.0106
		1	25	0.0146
8.	Rajjaprabha			
		1	80.0	0.2200
		1	80.0	0.0808
		1	80.0	0.0062
9.	Chulabhorn			
		1	20.0	0.0121
		1	20.0	0.0430
10.	Ubolratana			
		1	10	0.0127
		1	10	0.0074
		1	10	0.0195
11.	Nam Phung			
		1	5	0.0016
		1	5	0.0013
12.	Sirindhorn			
		1	10	0.0431
		1	10	0.0054
		1	10	0.0184
13.	Huai Kum			
		1	5	0.0029
14.	Mae Ngat			

		1	5	0.0096
		1	5	0.0100
15.	Ban Santi			
		1	5	0.0229
		41	2,470	
	Gas Turbine Plants			
1.	Lan Krabu			
		1	15	0.0203
		1	15	0.0371
		1	15	0.0251
		1	15	0.0000
		1	20	0.0058
		1	20	0.0070
		1	20	0.0053
		1	20	0.0672
2.	Songkhla			
		1	20	0.5288
3.	Hat Yai			
		1	15	0.2414
		1	15	0.4980
		1	15	0.5322
4.	Surat Thani			
		1	15	0.5831
		1	15	0.4639
		1	15	0.5831
5.	Nakhon Ratchasima			
		1	15	0.2498
6.	Udon Thani			
		1	15	0.3562
	Total	17	280	
	Grand capacity	117	11,660	

Table 5.6 Actual load growth data [15]

Peak generation of national grid (MW)		
Year number	Year	Actual peak load (MW)
1	1993	9,735
2	1994	10,911
3	1995	12,168
4	1996	13,881
5	1997	14,993
6	1998	14,464
7	1999	14,267
8	2000	17,275
9	2001	16,445
10	2002	18,724
11	2003	18,788

Table 5.7 Individual state load model

Load level (MW)	No. of occurrences
9,735	12
9,000	83
8,500	107
7,200	116
6,385	47
5,746	365

The simulation results are shown in figures 5.40-5.42. Figure 5.40 shows the impact of adding a group of 200 MW units to the 117 unit system to meet the future loads during 1993-2003 or years 1-11. The risk index is the annual LOLE value. The peak load in the first year is 9,735 MW. It can be seen that the installed capacity of 11,660 MW is adequate for the first year to meet the criteria LOLE of 1 day/year.

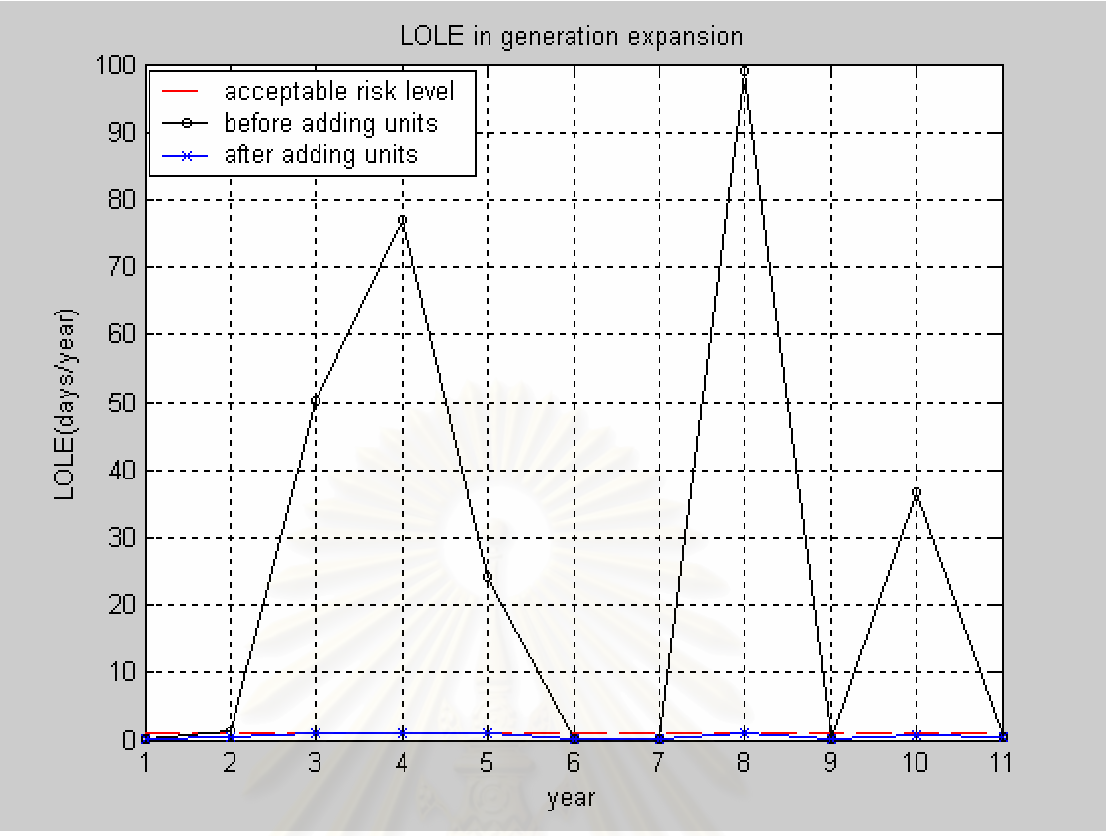


Fig 5.40 Risk from system expansion (LOLE ≤ 1day/year)

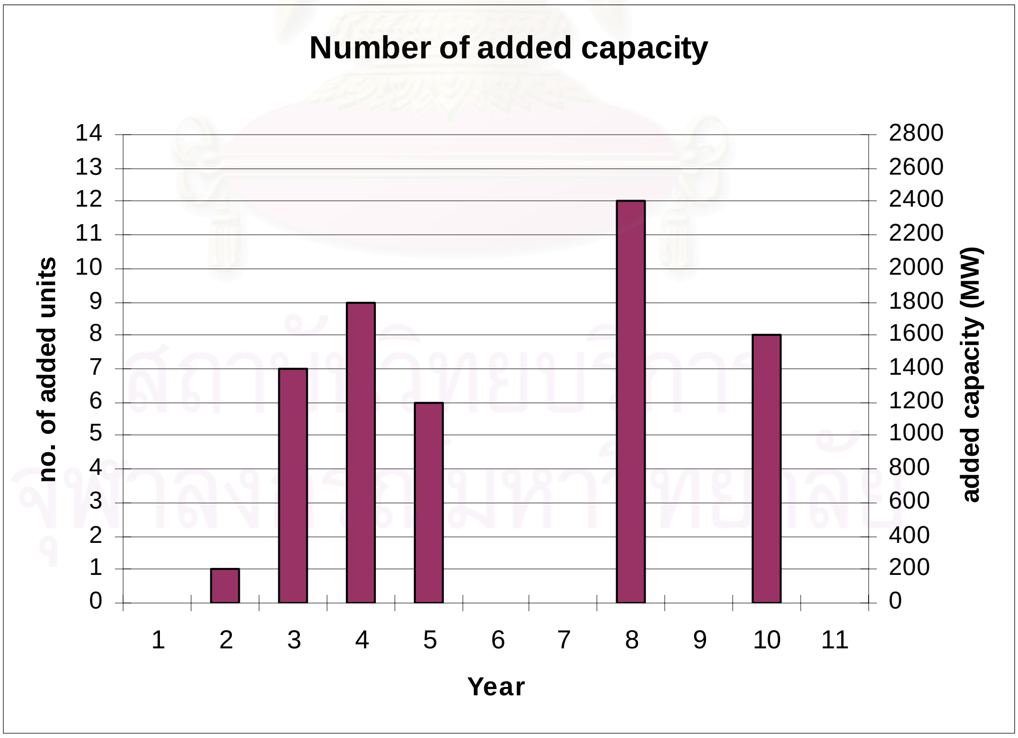


Fig 5.41 Number of added units (200MW each)

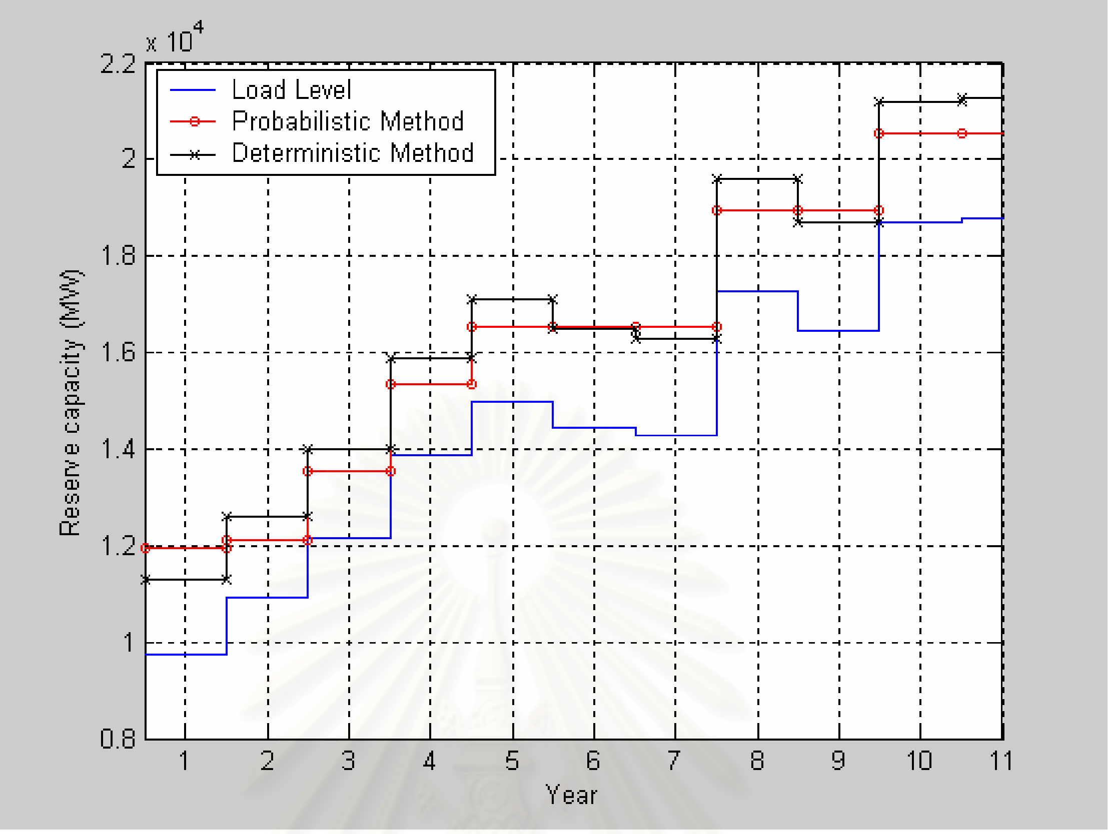


Fig 5.42 Compare the reserve capacity with both deterministic and probabilistic method

Figure 5.41 shows the required added capacity for each year. The system needs to add a 200 MW unit in the second year whereas it requires highest added units for the 8th year.

Figure 5.42 shows the Compare the reserve capacity with both deterministic and probabilistic method**.** From the result at the years 2, 3, 4, 5, 8, 10, and 11 the reserve capacity based on the deterministic method is higher than the reserve based on the probabilistic method. However the reserve capacity based on probabilistic method is higher than deterministic method for the other years..

The next section will describe the impact of load uncertainty. The computation of the LOLE considering load forecast uncertainty is shown with 2% , 4% ,6% uncertainty standard deviation from the forecasted peak load.

5.4.1 Impact of Load Uncertainty (Normal density function)

a) 2% Standard deviation
The results are shown in figure 5.43-5.45.

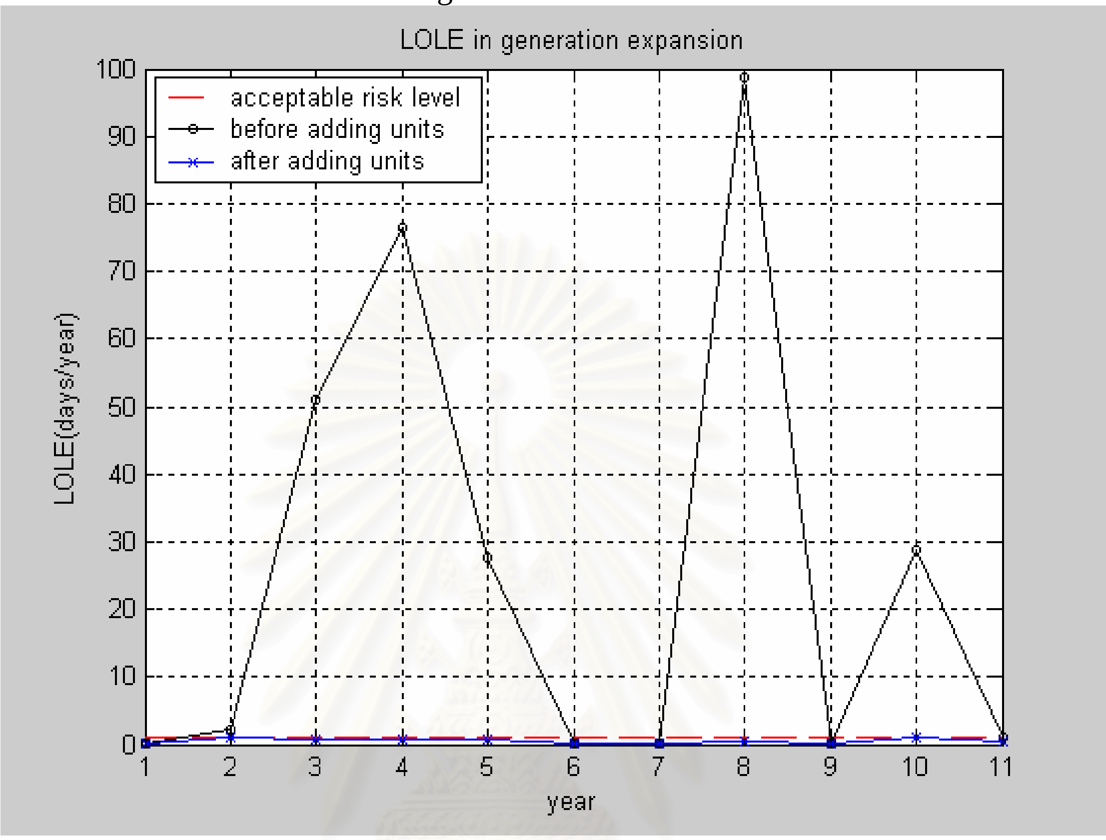


Fig 5.43 Risk from system expansion (LOLE ≤ 1 day/ year)

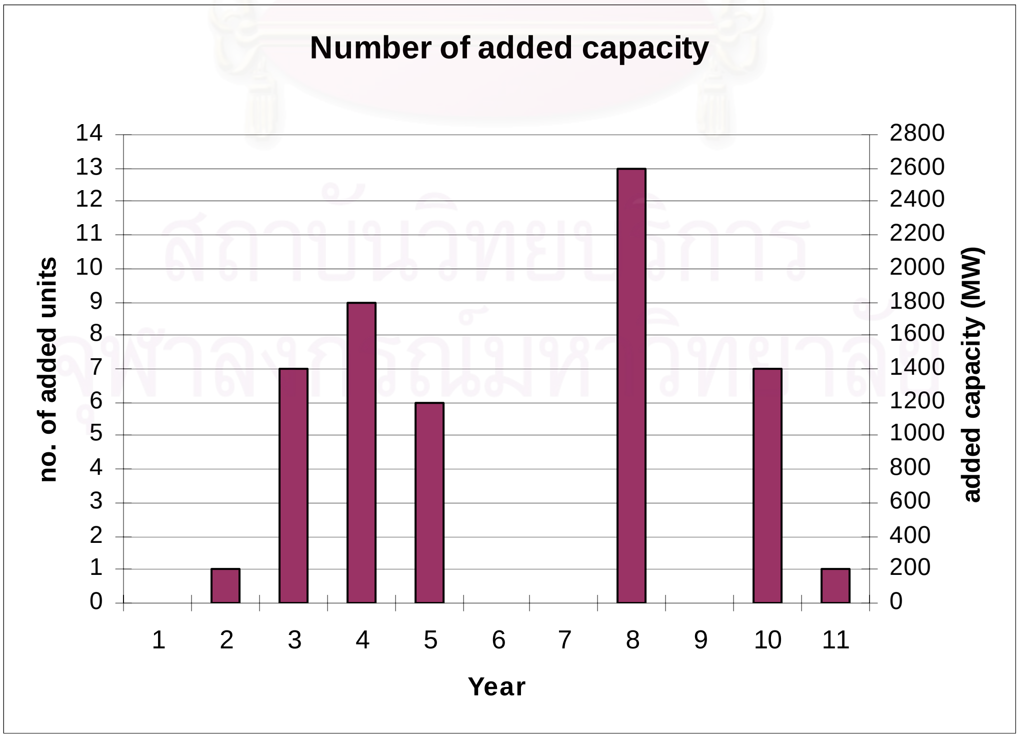


Fig 5.44 Number of added units (200MW each)

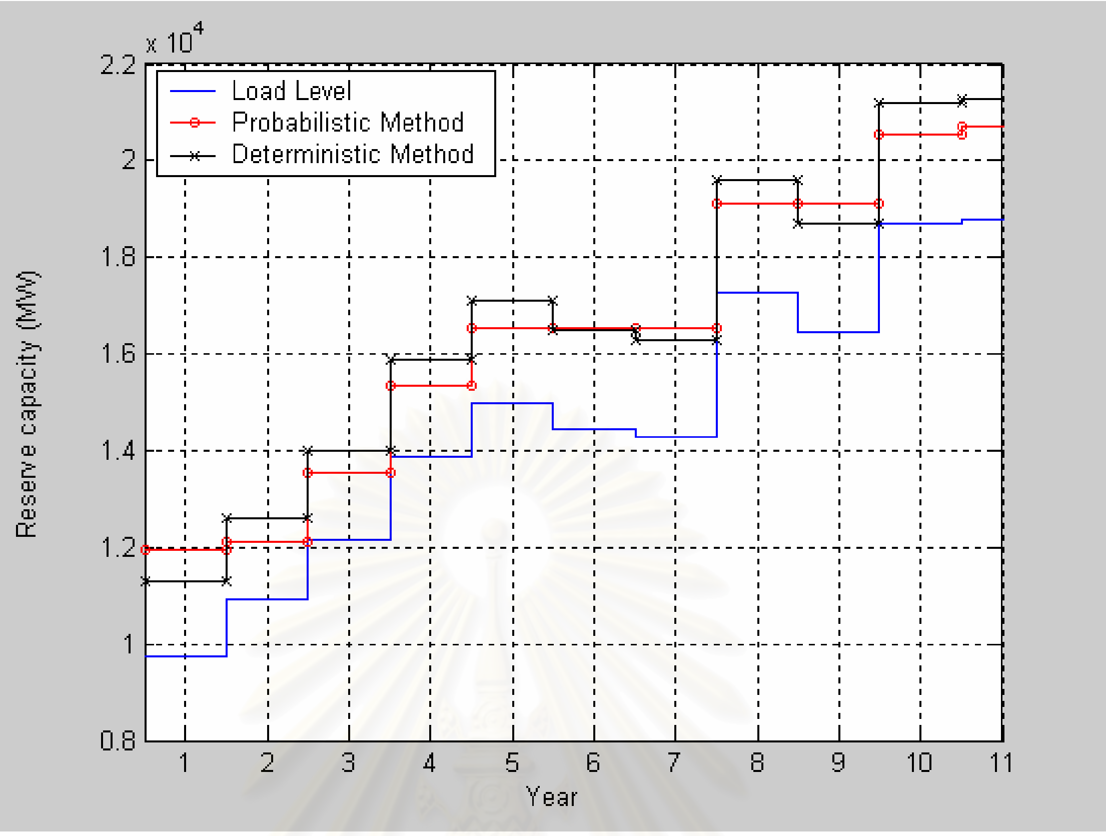


Fig 5.45 Compare the reserve capacity with both deterministic and probabilistic method

The results show that the uncertainty causes higher reserve capacity requirement as figure 5.44 reveals that more units is needed compared to figure 5.41.

From Fig 5.45 we can see that deterministic based installed capacity is higher than installed capacity probabilistic based method at years 2,3,4,5, 8, 10 and 11.

b)4% standard deviation

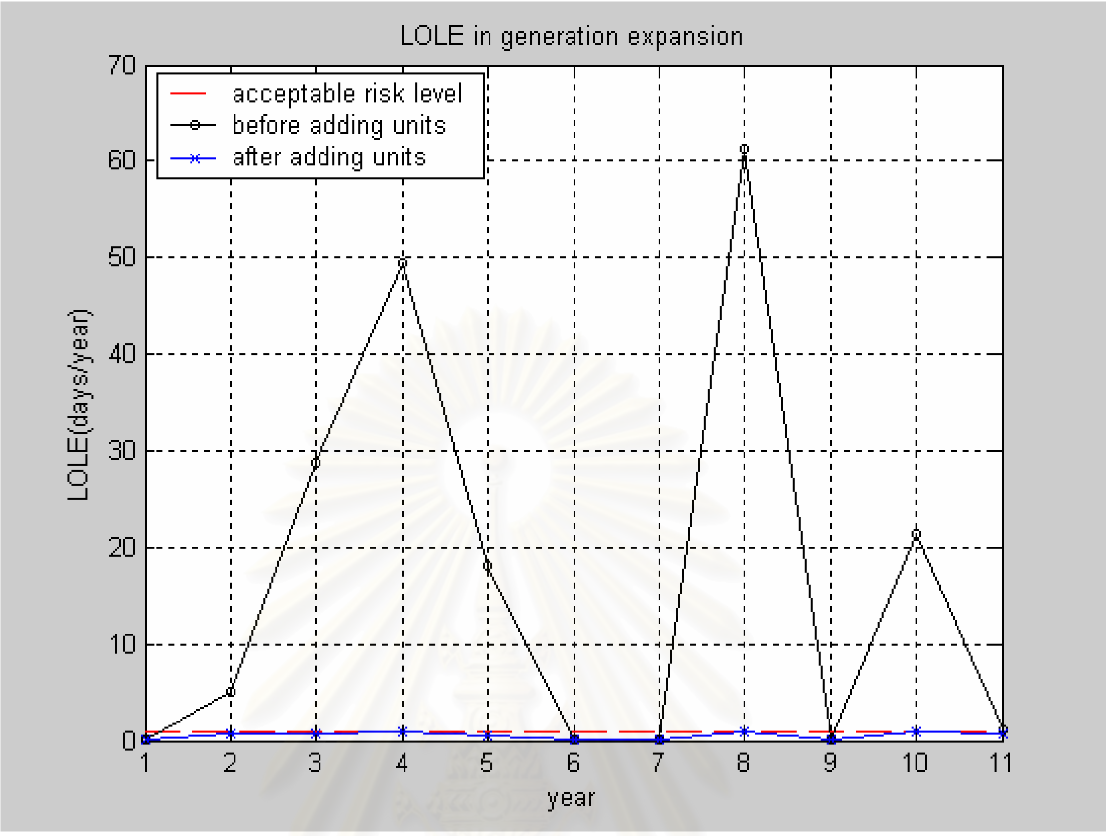


Fig 5.46 Risk from system expansion (LOLE ≤ 1 day/ year)

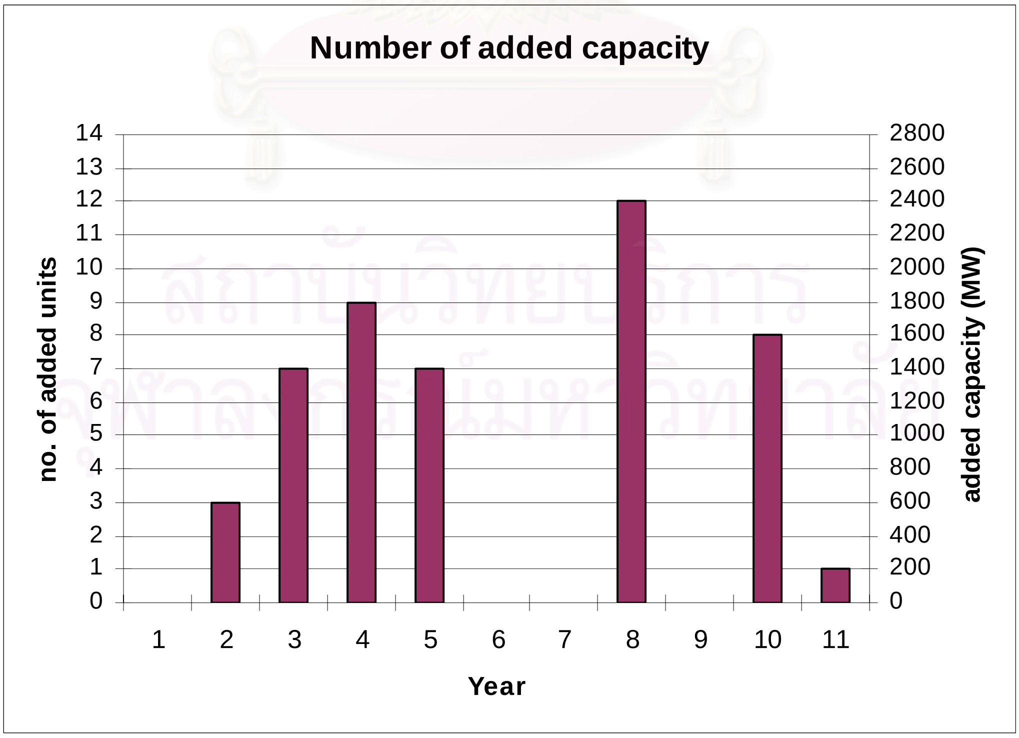


Fig 5.47 Number of added units (200MW each)

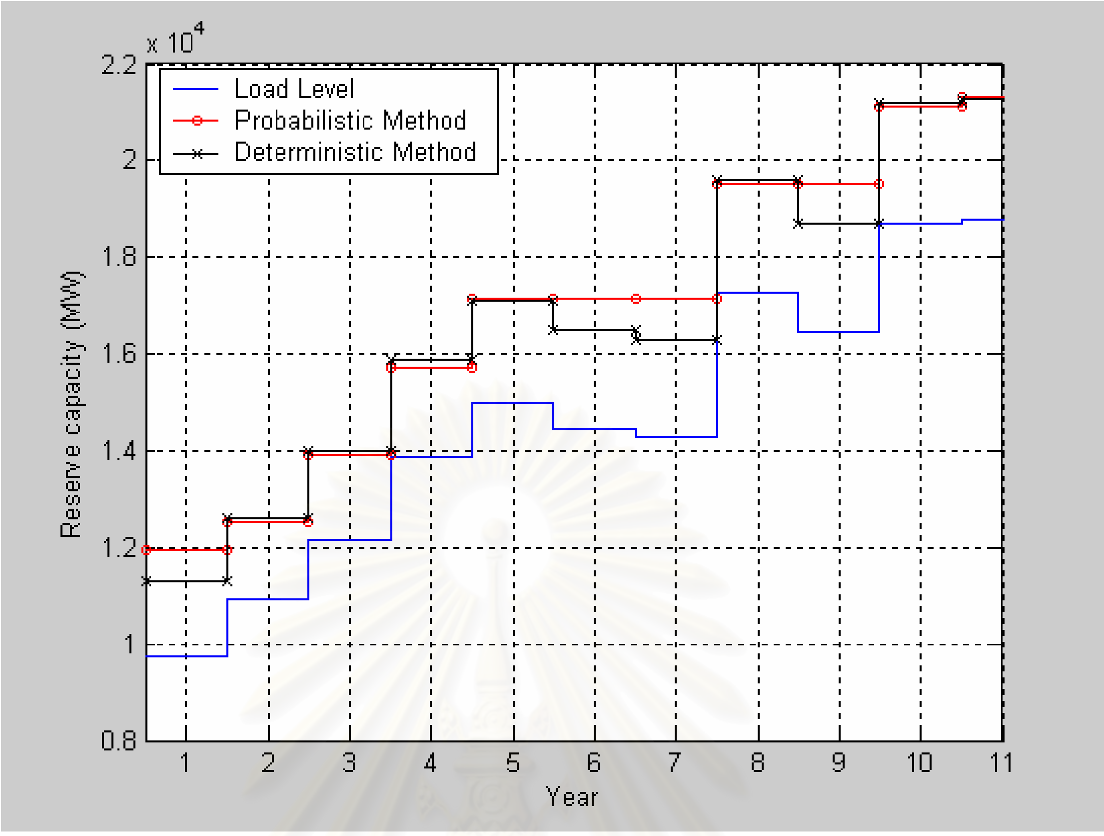


Fig 5.48 Installed capacity

The results show that this case requires higher capacity than the previous case (2%).

c) 6% standard deviation

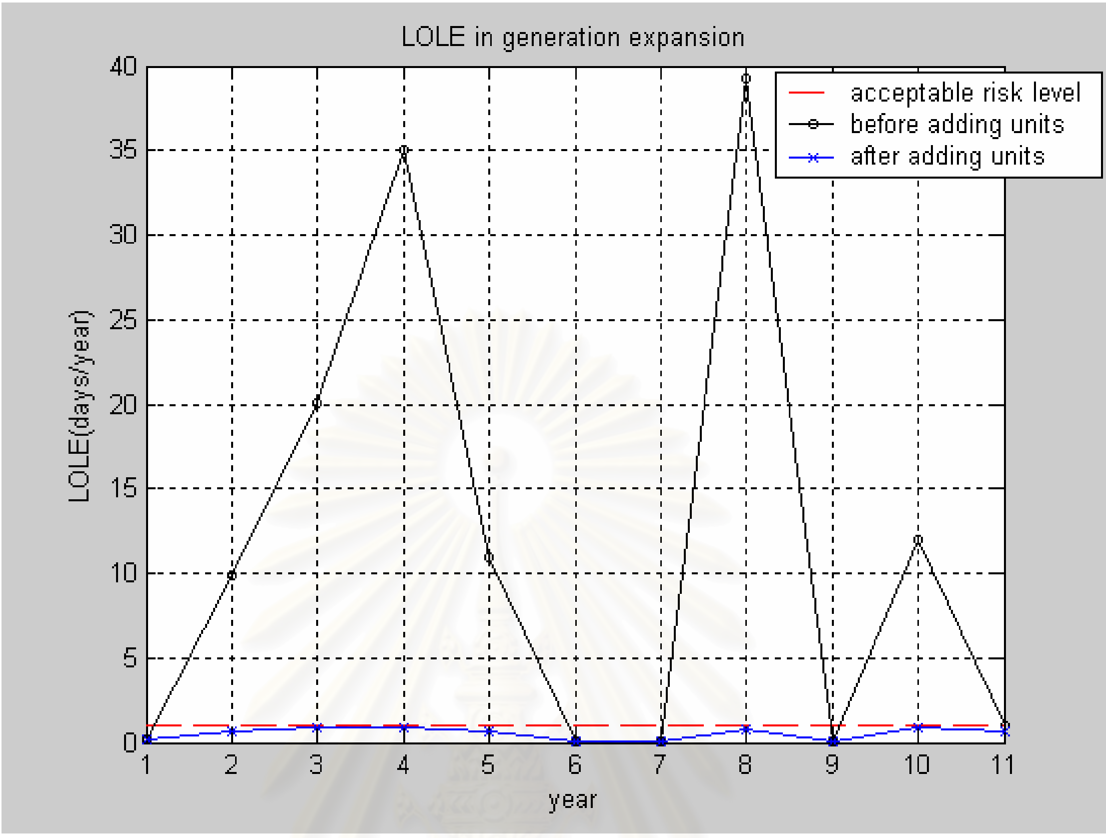


Fig 5.49 Risk from system expansion (LOLE ≤ 1 day/ year)

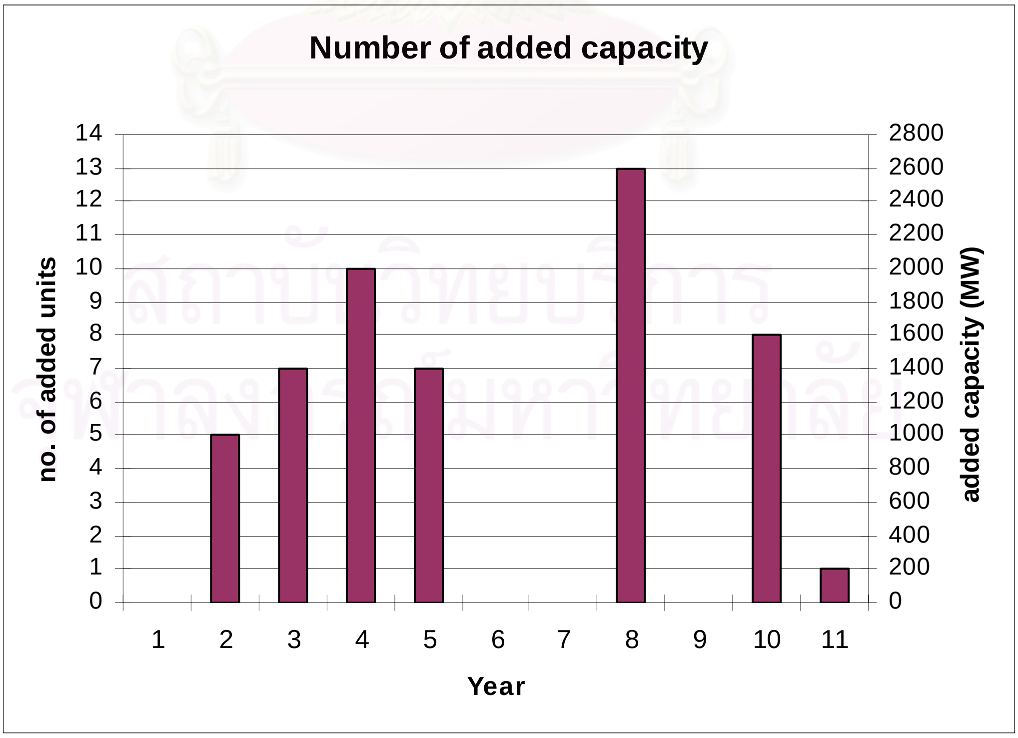


Fig 5.50 Number of added units (200MW each)

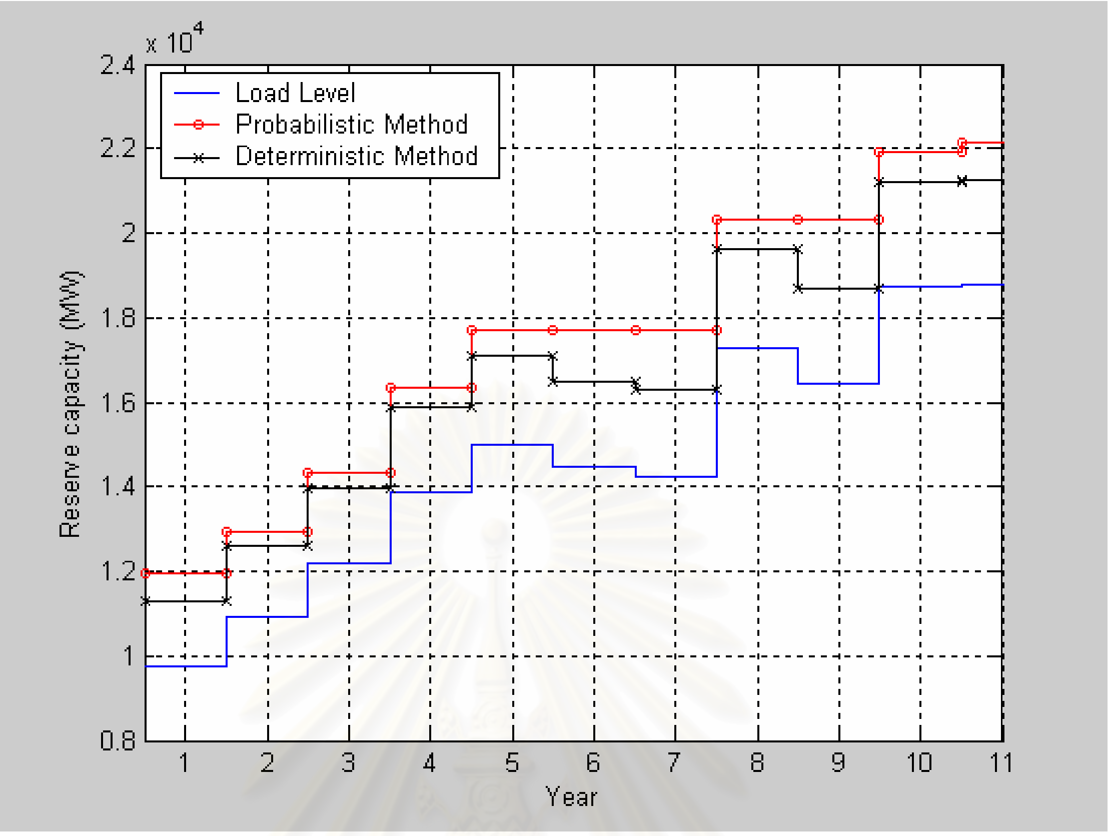


Fig 5.51 Installed capacity

All the normal density function cases (2, 4, and 6%) show that higher uncertainty causes higher required capacity.

From the above results based on normal density function, we can conclude that without uncertainty, the system requires less capacity compared with the cases of taking into account uncertainty. Similarly if we compare between 2% and 4% uncertainty cases we can see the latter case requires more capacity. Therefore the higher uncertainty, the more added capacity required.

The following subsections present the load forecast uncertainty for over and under forecasted cases. The detailed results of the over and the under forecast cases are shown in appendix B.

5.4.2 Impact of Load Uncertainty (Over forecast)

a) 2% uncertainty

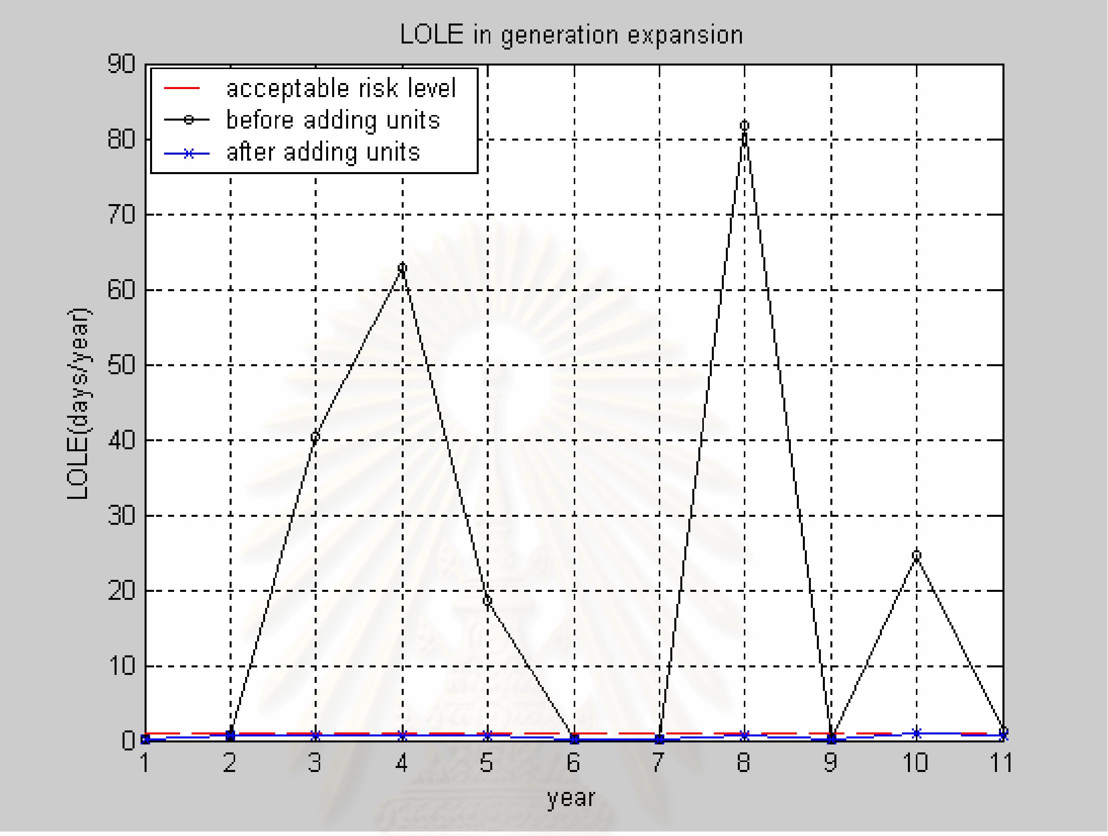


Fig 5.52 Risk from system expansion (LOLE ≤ 1 day/ year)

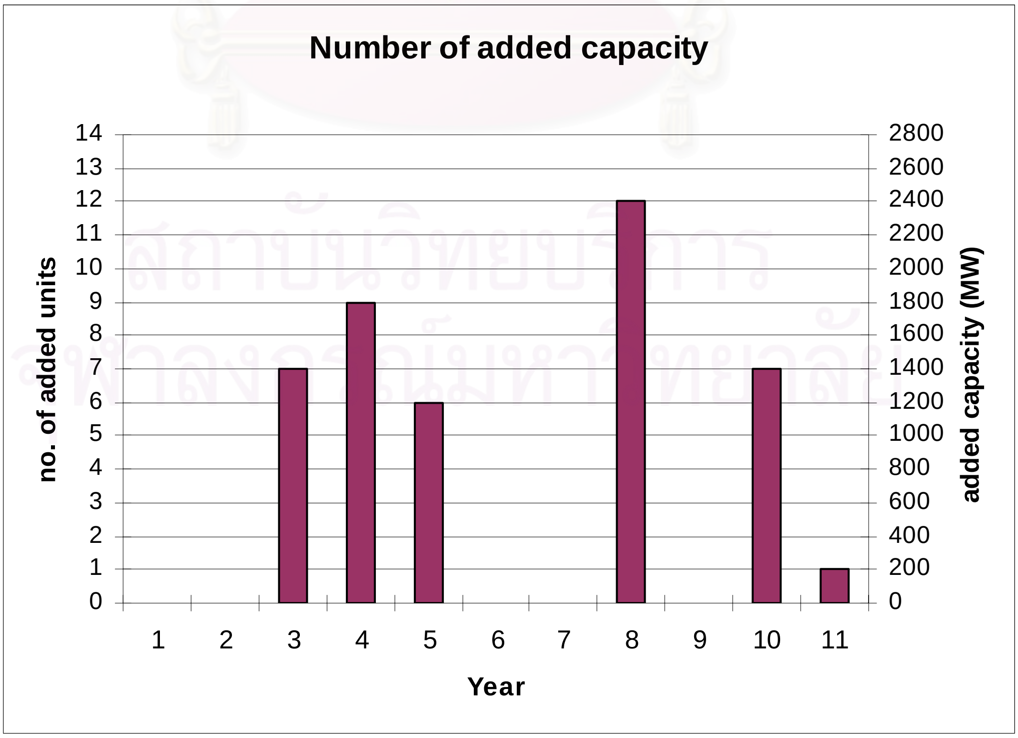


Fig 5.53 Number of added units (200MW each)

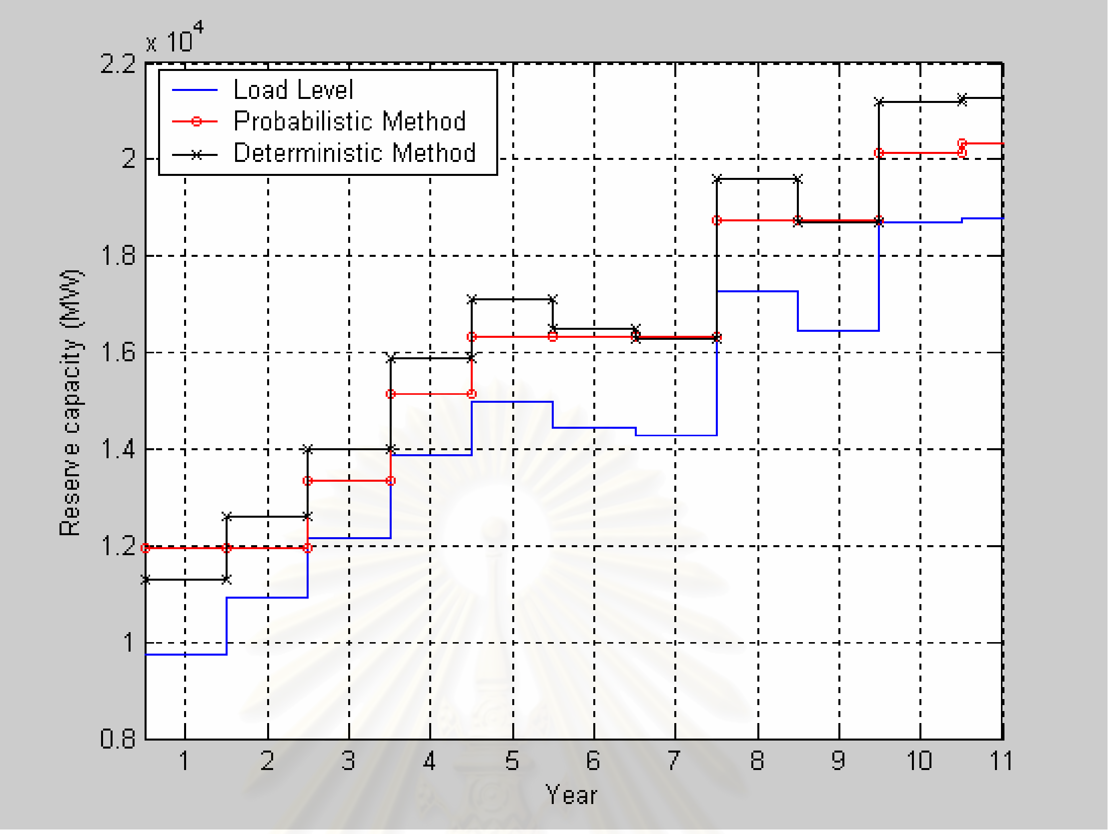


Fig 5.54 Compare the reserve capacity with both deterministic and probabilistic method

From figure 5.54 reserve capacity based on deterministic method is mostly higher than the one based on probabilistic method.

b) 4% uncertainty

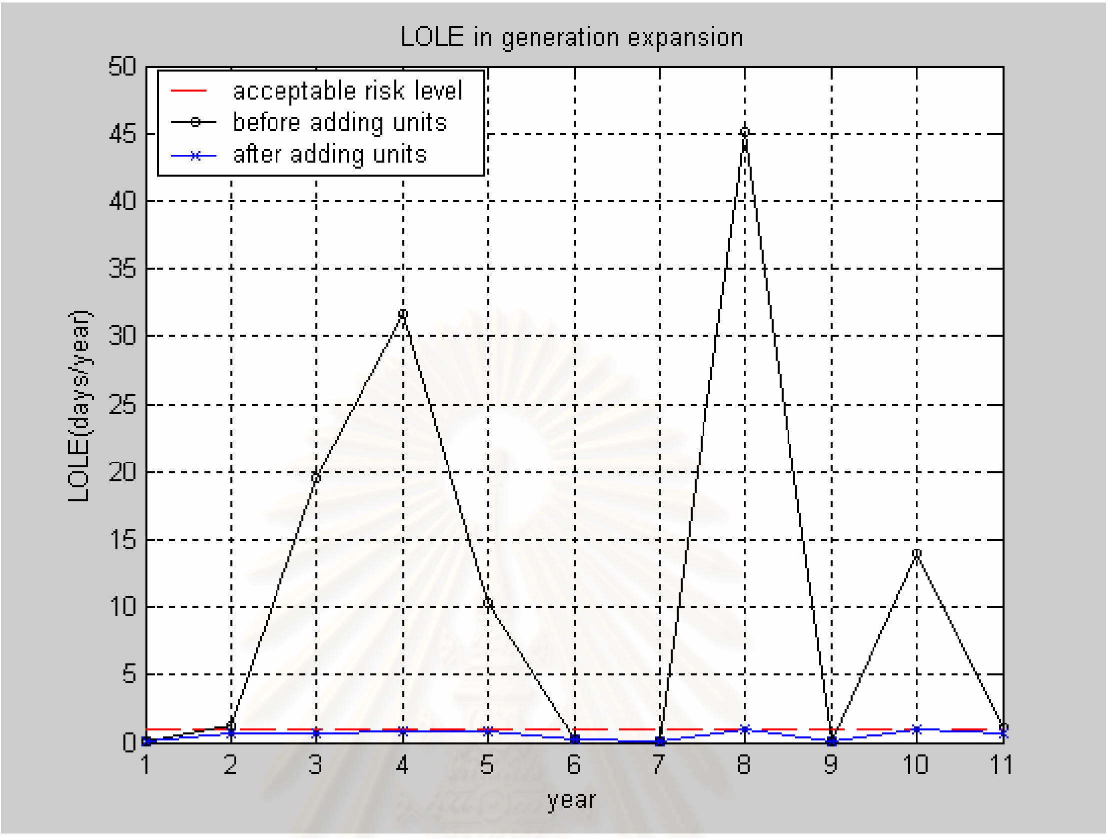


Fig 5.55 Risk from system expansion (LOLE ≤ 1 day/ year)

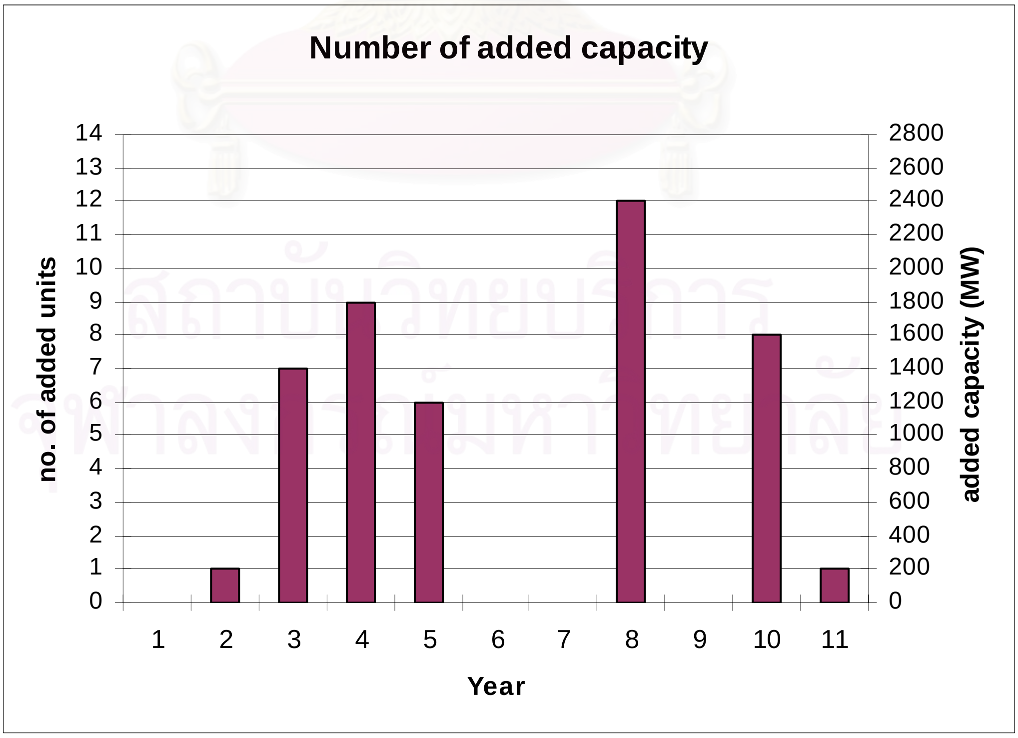


Fig 5.56 Number of added units (200MW each)

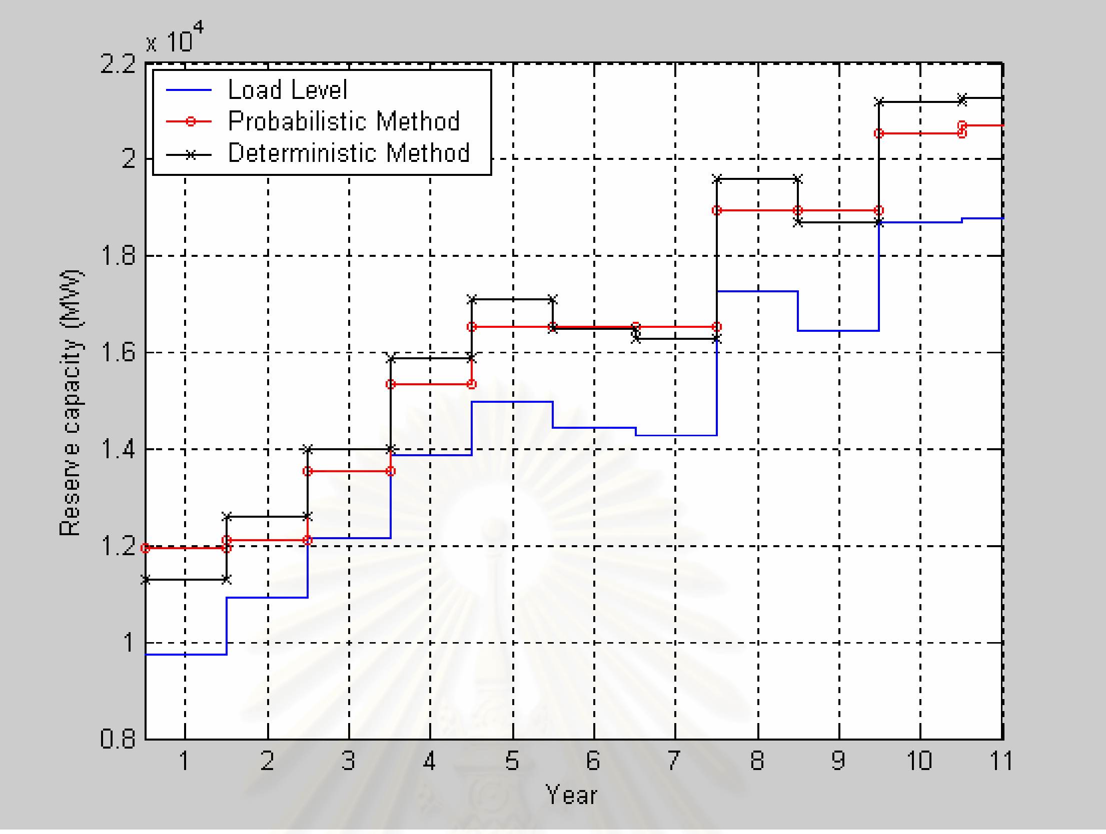


Fig 5.57 Compare the reserve capacity with both deterministic and probabilistic method

c) 6% uncertainty

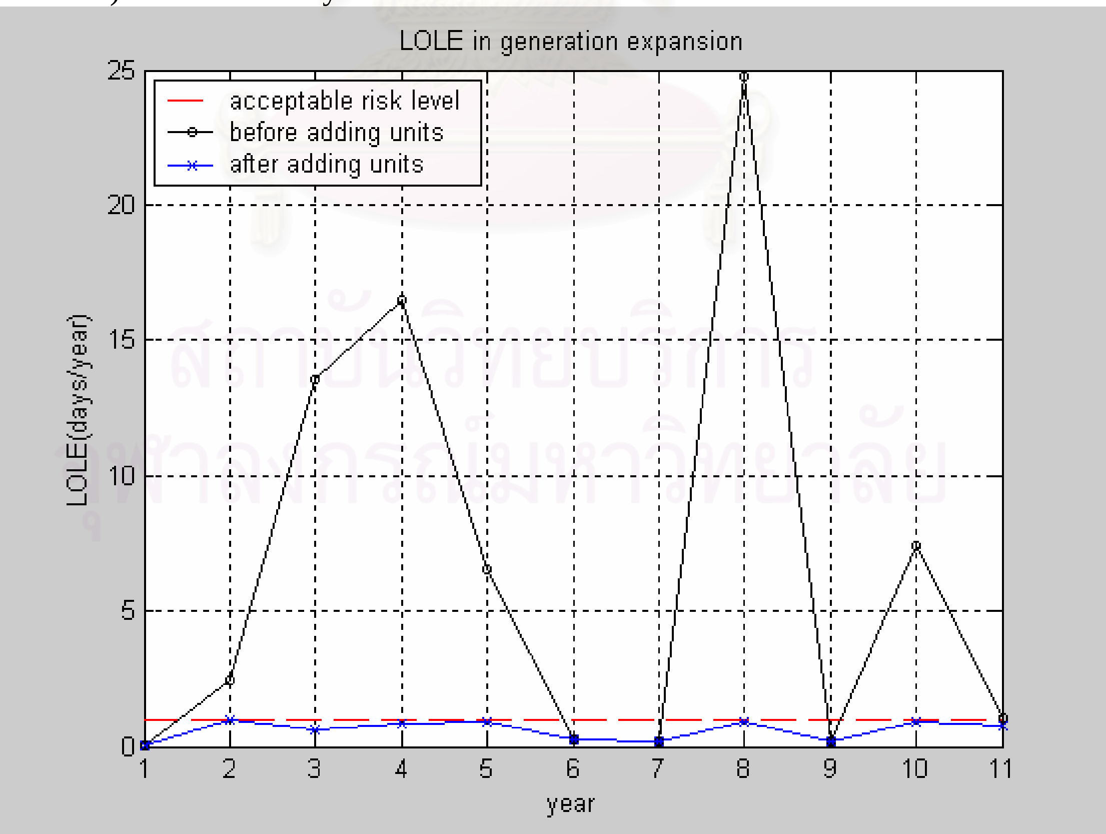


Fig 5.58 Risk from system expansion (LOLE $\leq$ 1 day/ year)

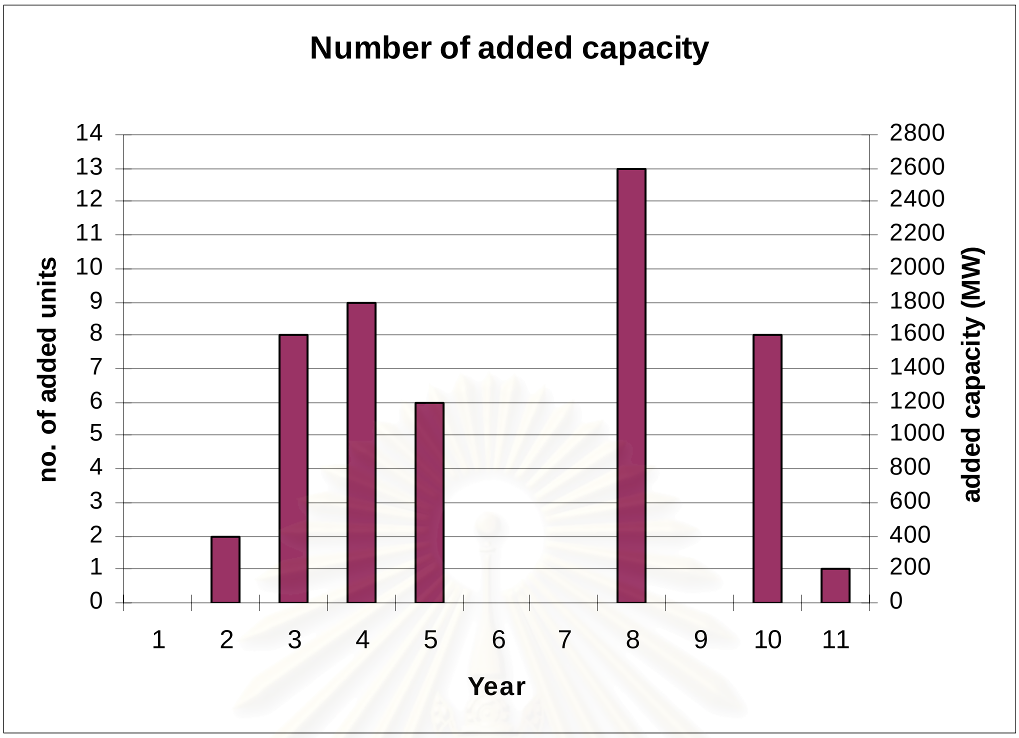


Fig 5.59 Number of added units (200MW each)

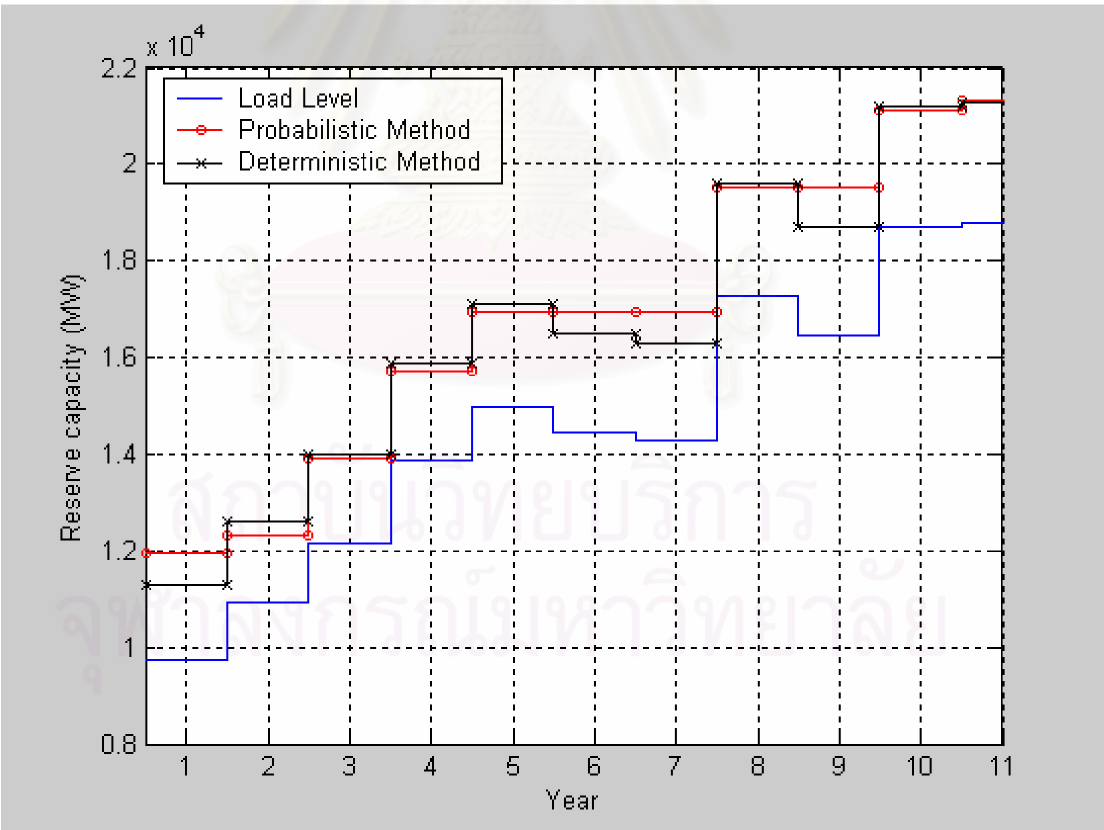


Fig 5.60 Compare the reserve capacity with both deterministic and probabilistic method

5.4.3 Impact of Load Uncertainty (Under forecast)

a) 2% uncertainty

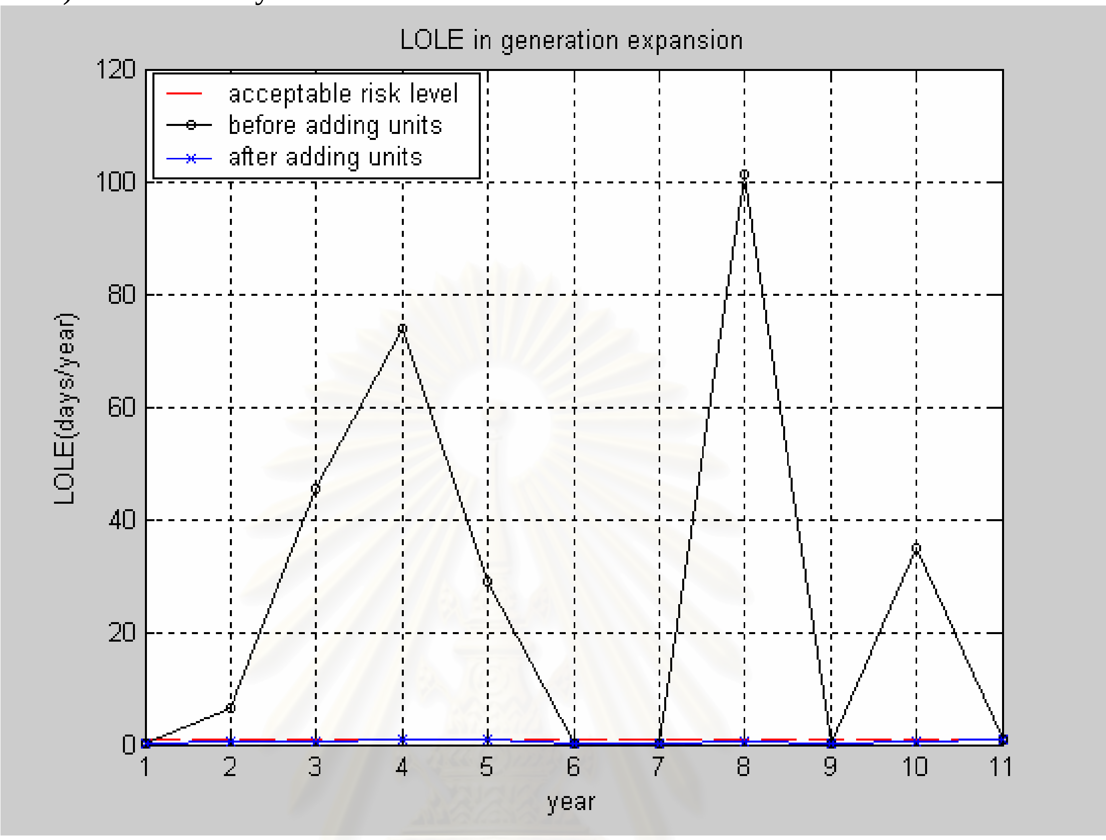


Fig 5.61 Risk from system expansion (LOLE ≤ 1 day/ year)

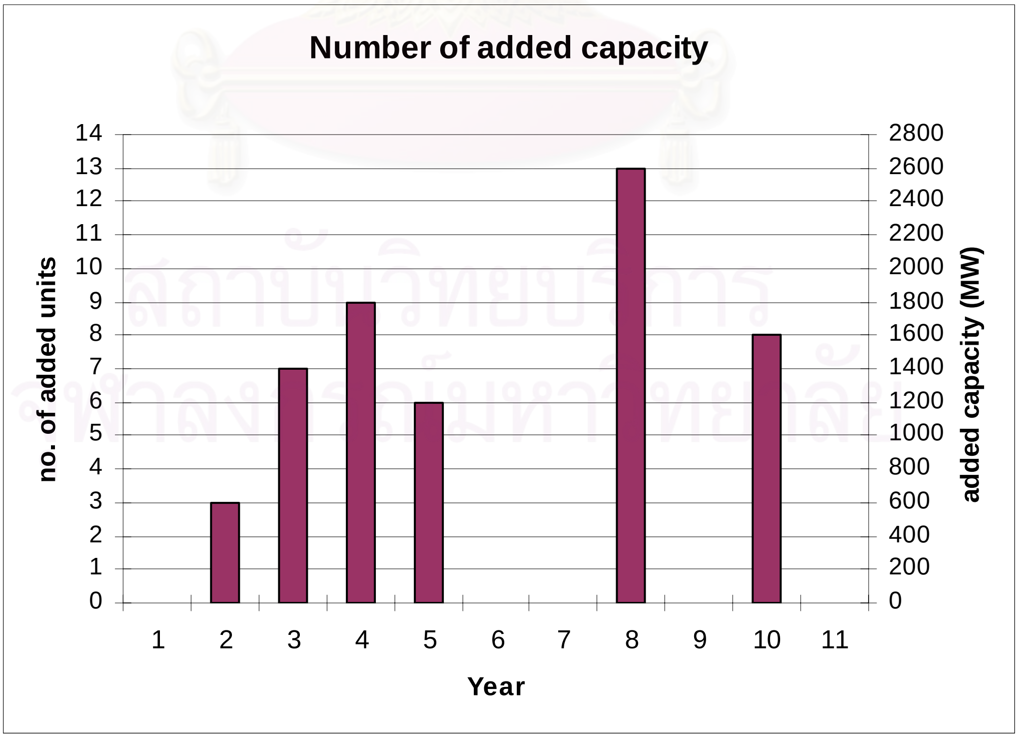


Fig 5.62 Number of added units (200MW each)

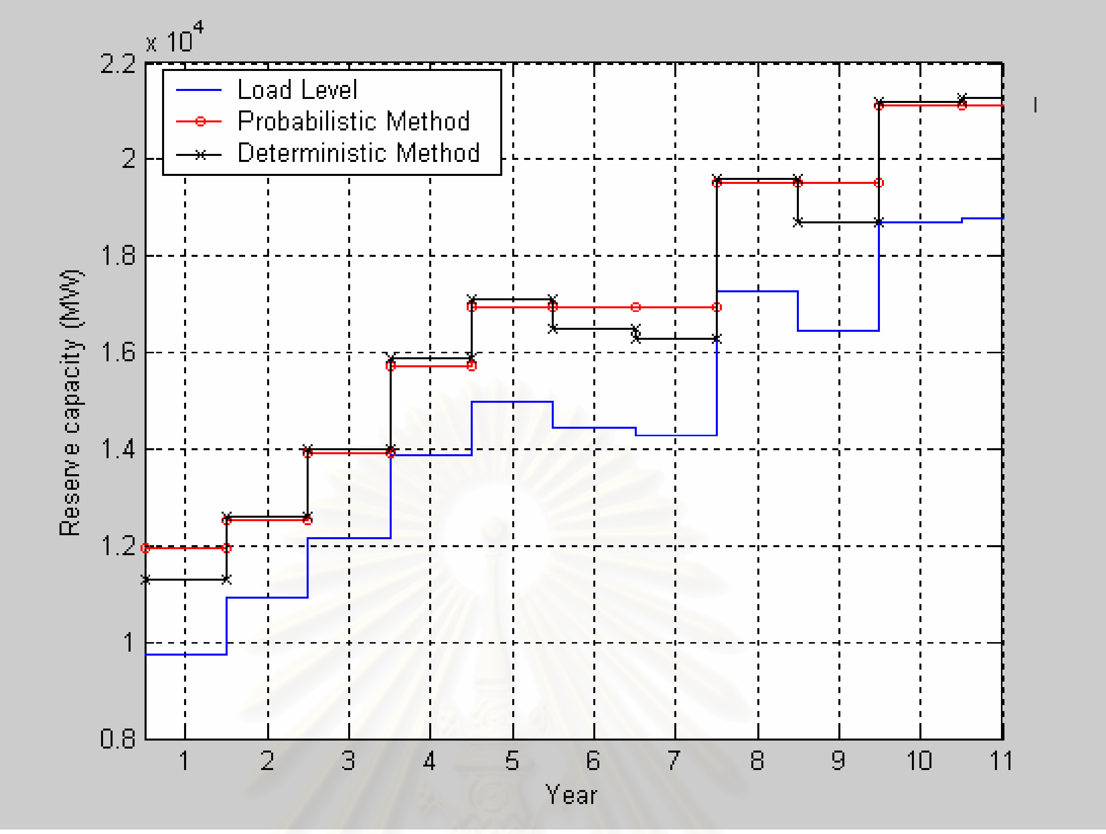


Fig 5.63 Compare the reserve capacity with both deterministic and probabilistic method

b)4% uncertainty

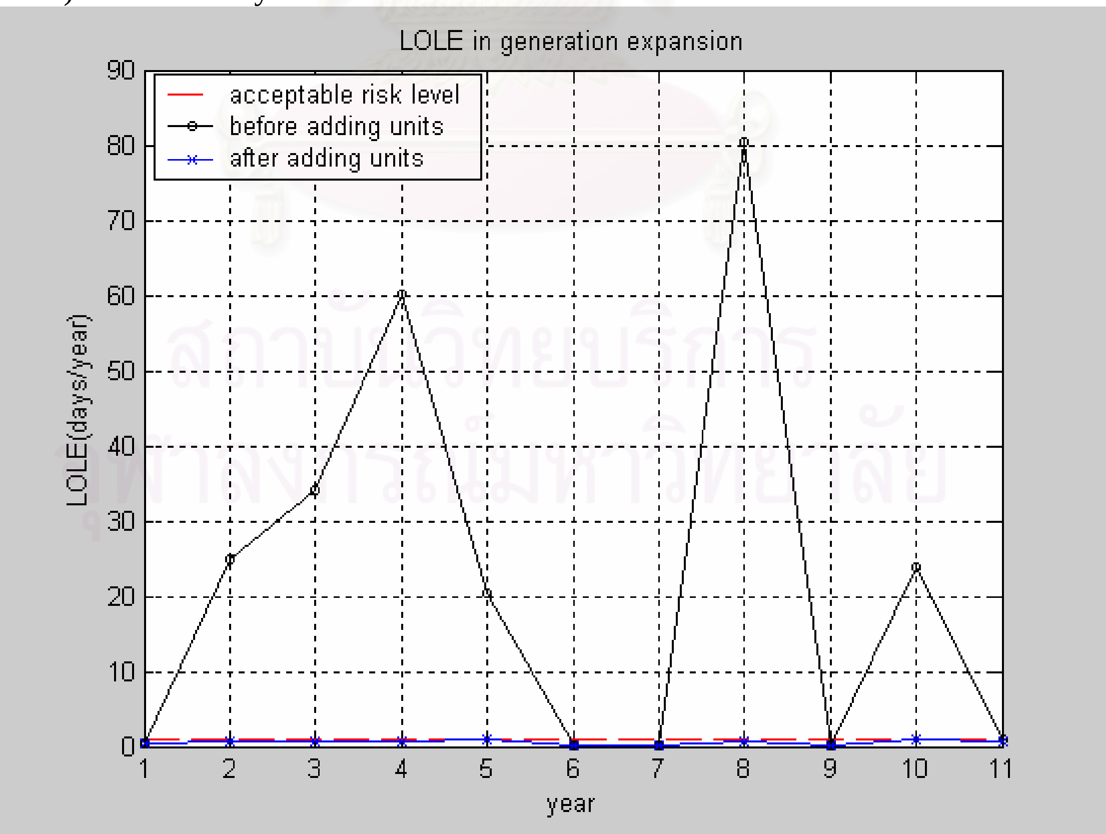


Fig 5.64 Risk from system expansion (LOLE $\leq$ 1 day/ year)

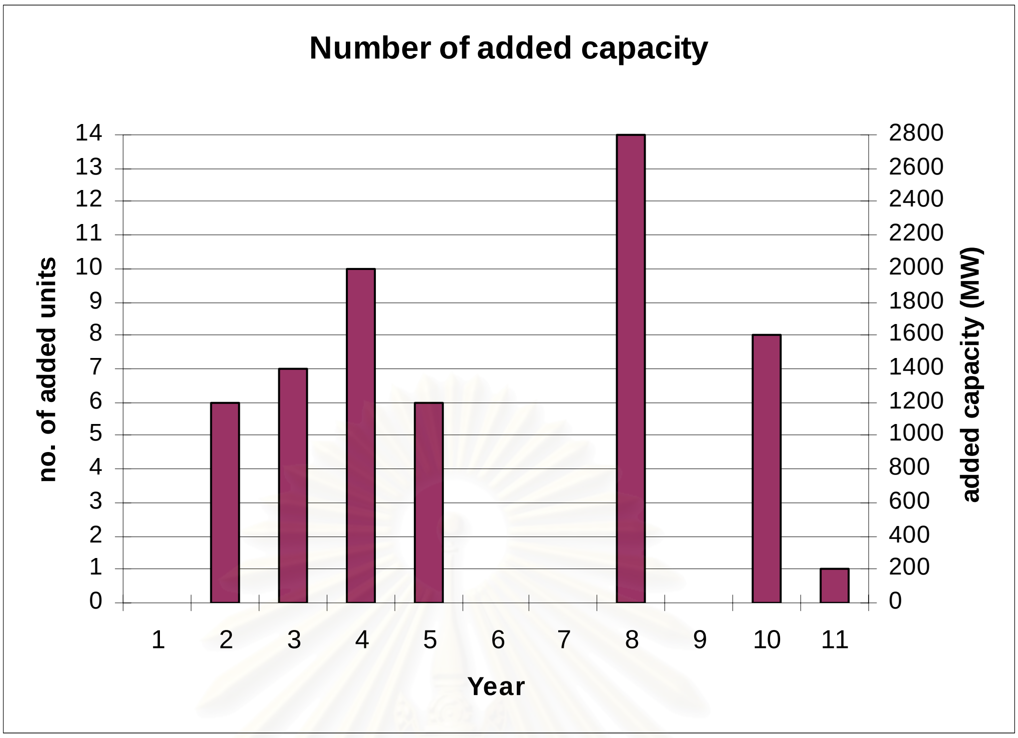


Fig 5.65 Number of added units (200MW each)

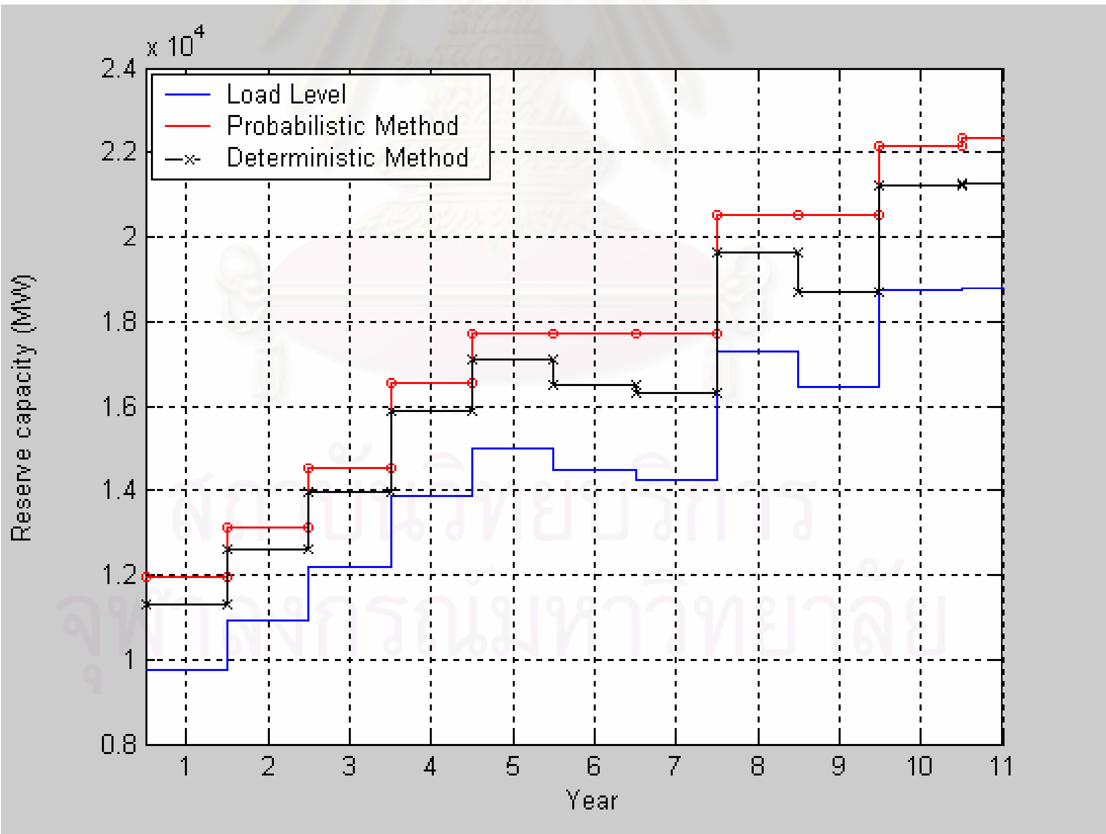


Fig 5.66 Compare the reserve capacity with both deterministic and probabilistic method

c) 6% uncertainty

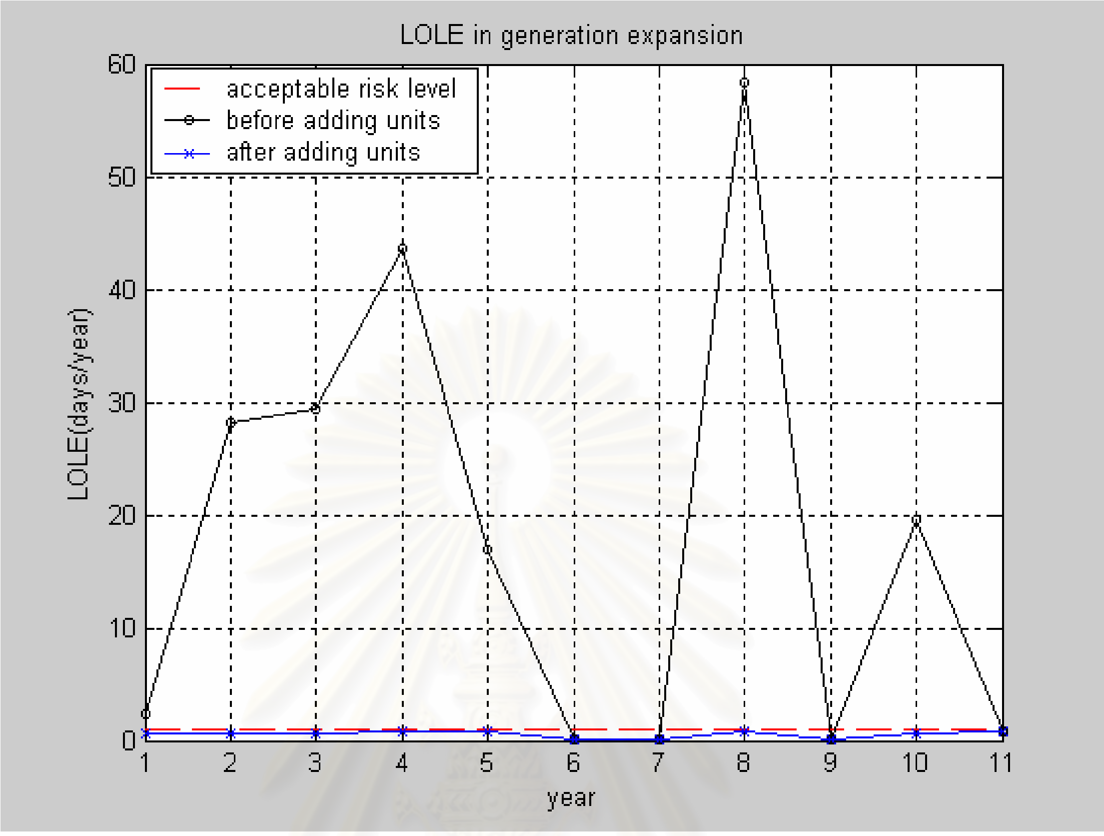


Fig 5.67 Risk from system expansion (LOLE ≤ 1 day/ year)

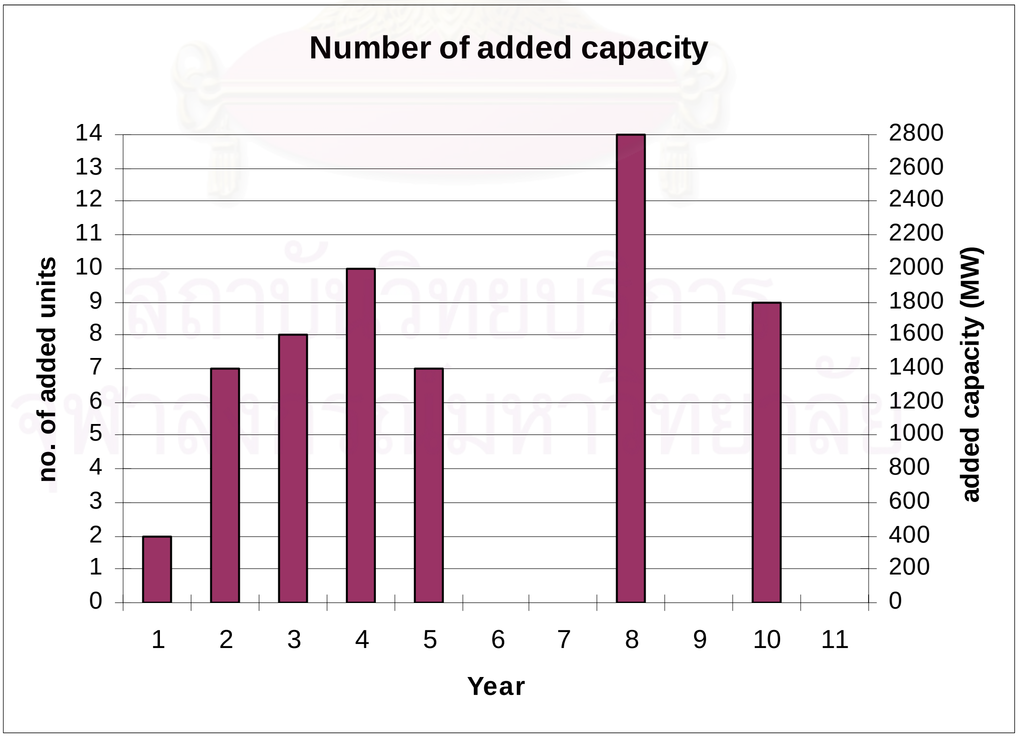


Fig 5.68 Number of added units (200MW each)

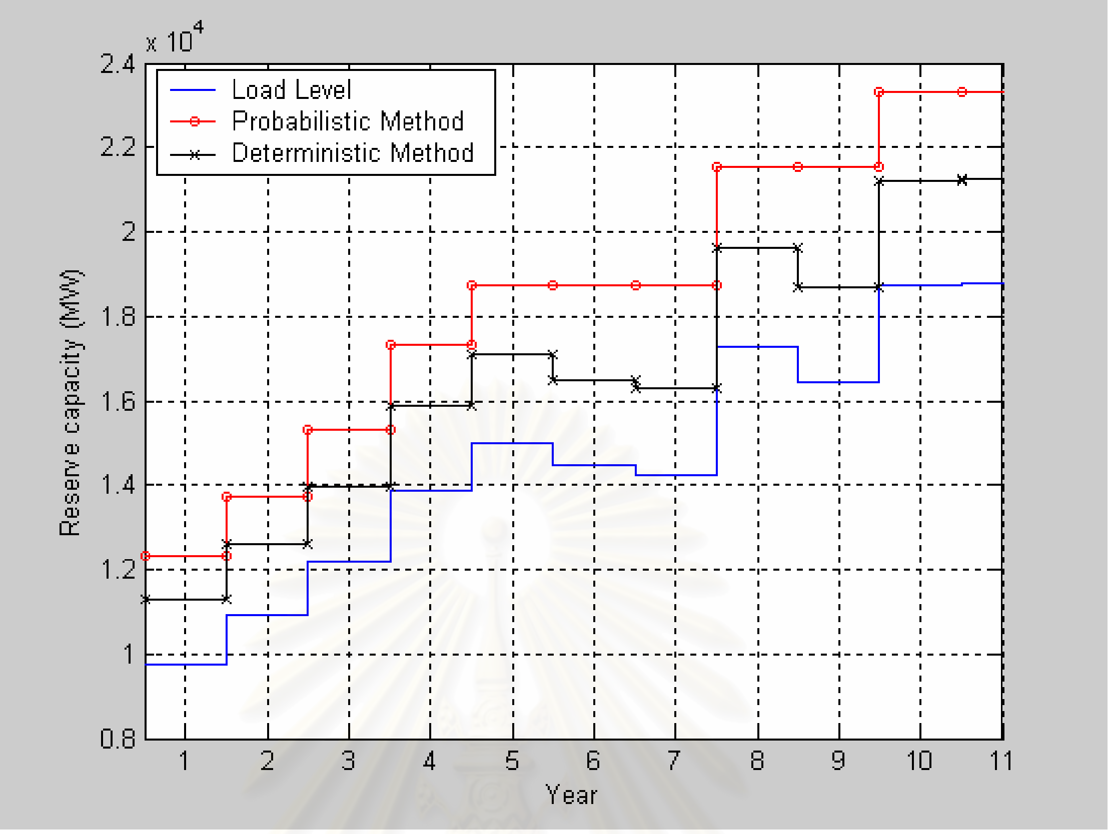


Fig 5.69 Compare the reserve capacity with both deterministic and probabilistic method

5.4.4 Result Comparison

The above simulation results for the Thailand system are analysed and compared in this section. Firstly we compare the cases of without uncertainty and with normal density function for the uncertainty model.

Figure 5.70 show the higher uncertainty the higher reserve capacity is required, especially for the years number 2-11. When we consider the reserve margin as percentage of peak load, we can find that for the case of no uncertainty, it requires more than 8% of peak load reserve.

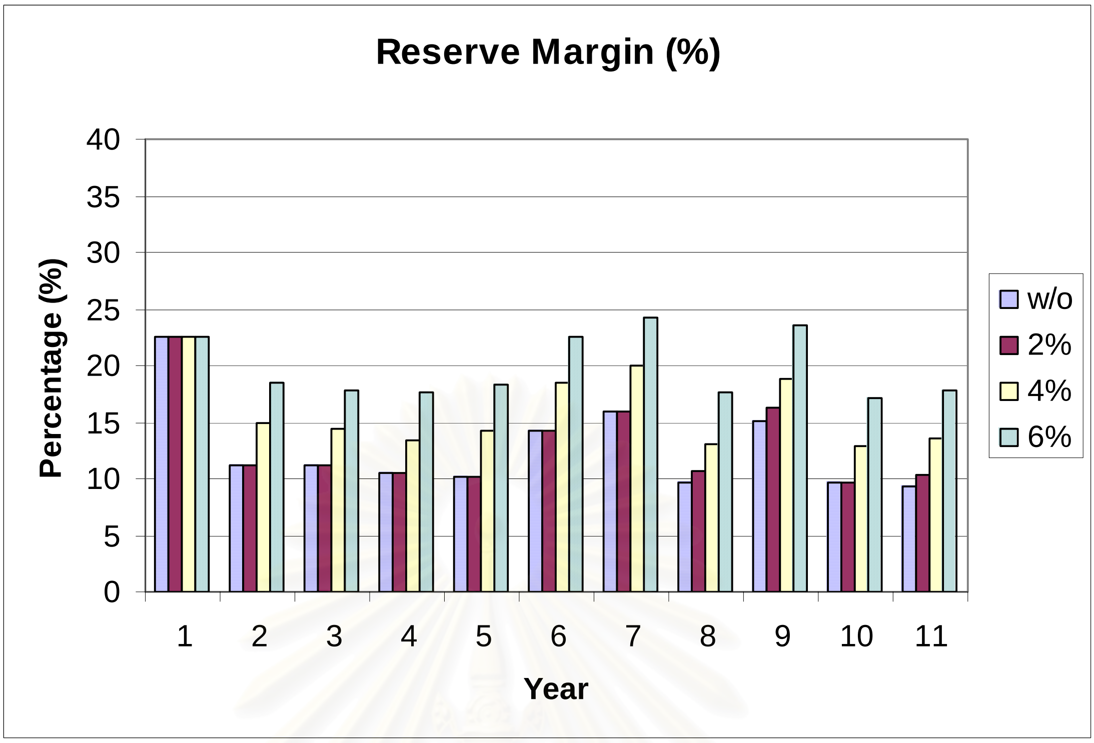


Fig 5.70 Reserve margin (%) in percentage of peak load

The comparison of the average reserve margin (2-11) year for the cases of with and without uncertainty is shown in figure 5.71. We found that for each year is approximately 12% for the case of without uncertainty case. However when uncertainty is taken into account the percentage average reserve margin requires about 12-20%. The average uncertainty percentage reserve margin of normal density function is about 16%.

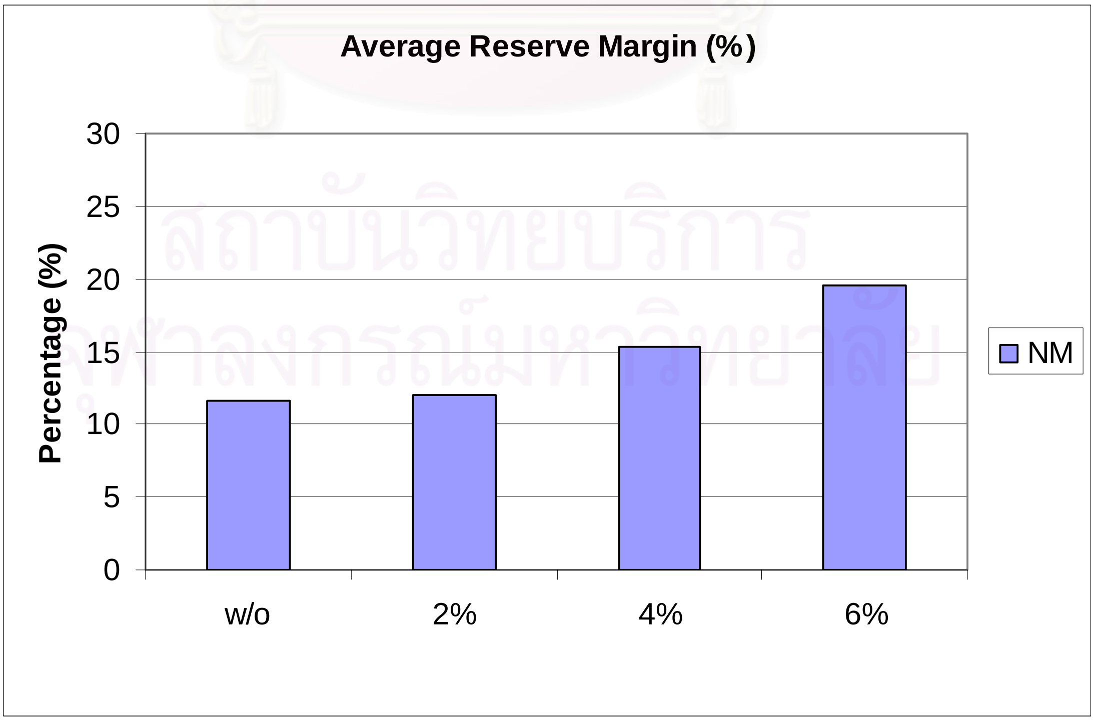


Fig 5.71 Compare average reserve margin

For the over forecast cases, similar results are summarized in figures 5.72-5.73. However the average reserve margin is about 10-15 % which is less than the normal uncertainty cases. The average uncertainty percentage reserve margin of over forecast is about 12%.

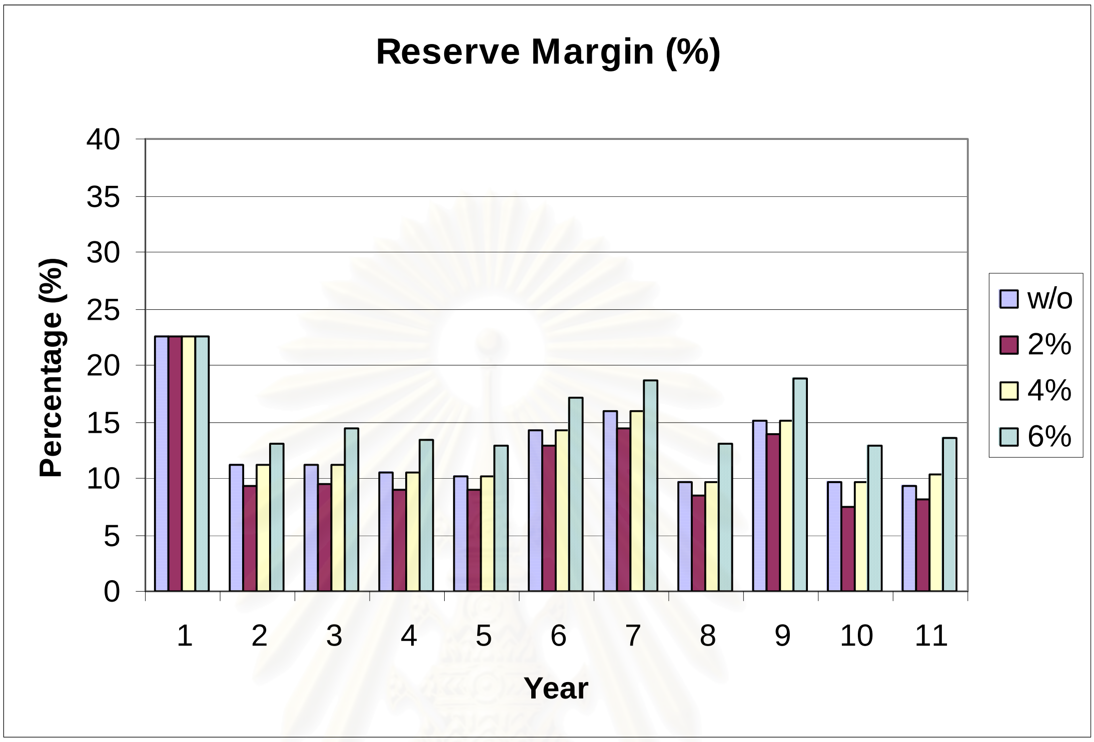


Fig 5.72 Reserve margin (%) in percentage of peak load

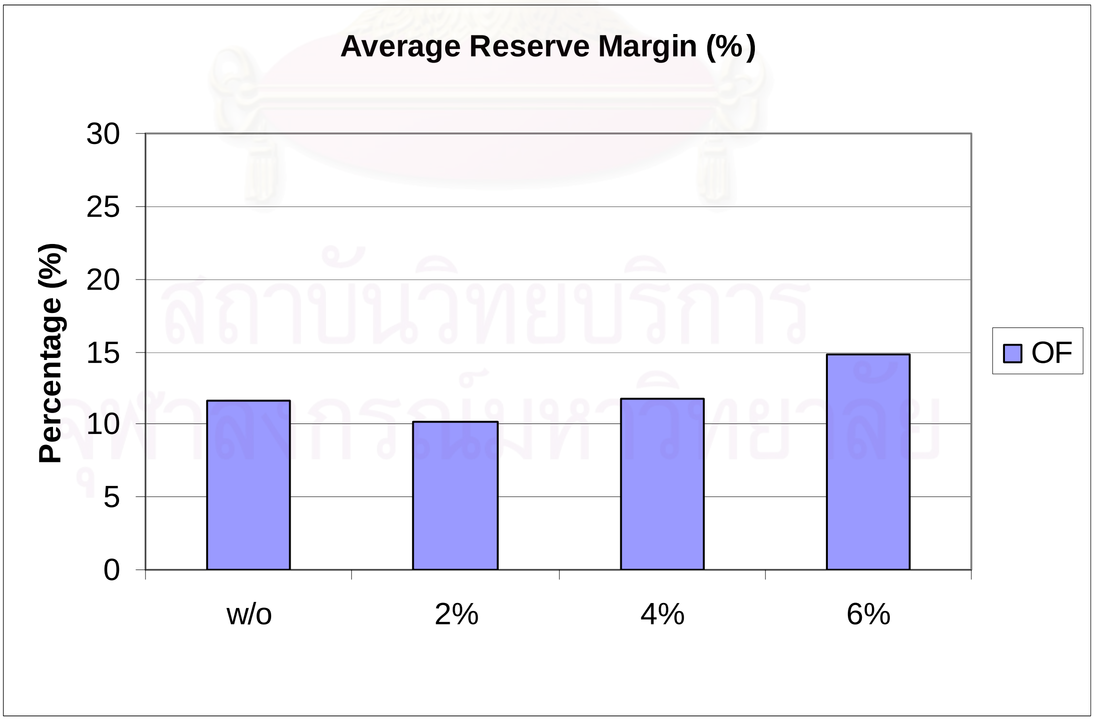


Fig 5.73 Comparison of the average reserve margin

For the under forecast cases, similar results are summarized in figures 5.74-5.75. However the average reserve margin is about 15-27 % which is the highest required reserve capacity case. The average uncertainty percentage reserve margin is about 21% required.

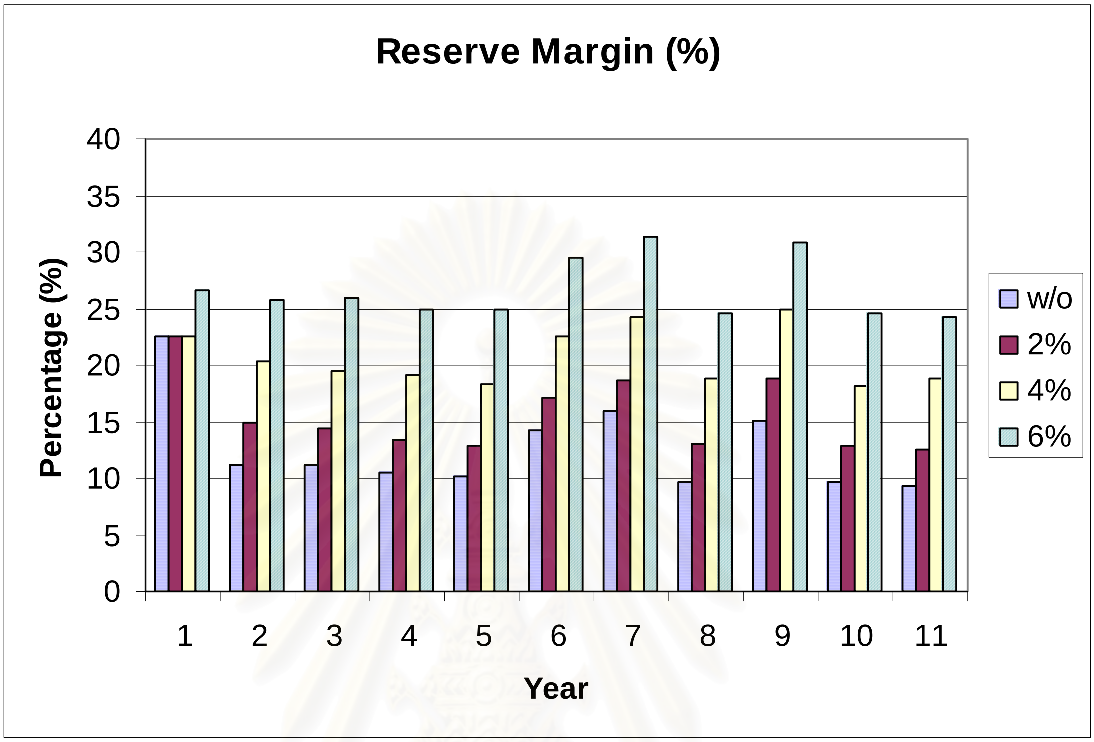


Fig 5.74 Reserve margin (%) in percentage of peak load

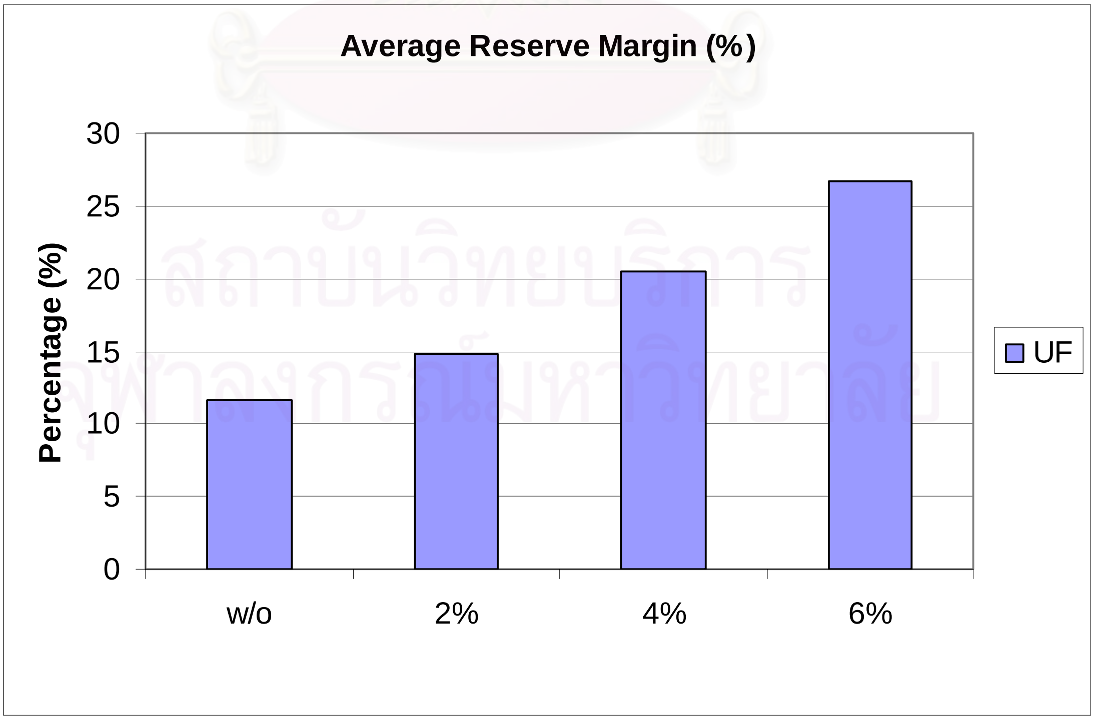


Fig 5.75 Comparison of the average reserve margin

As a conclusion for Thailand system, the planning criteria of LOLE = 1day/yr, with new added capacity of 200 MW, we can suggest that if the uncertainty of the forecasted load is neglected the required reserve capacity is about 12% of the peak demand. However if we take into account the forecast uncertainty a higher percentage value should be used instead. Thailand generation system should use the average reserve margin percentage is about 12% for over forecast, 16% for normal density function and 21% for under forecast case. It should bare in mind that if the risk criteria is changed, the suggestion should be adjusted according. Detailed results of the changed criteria, LOLE ≤ 3 day/year, and another risk of the new added capacity are shown in appendix B.

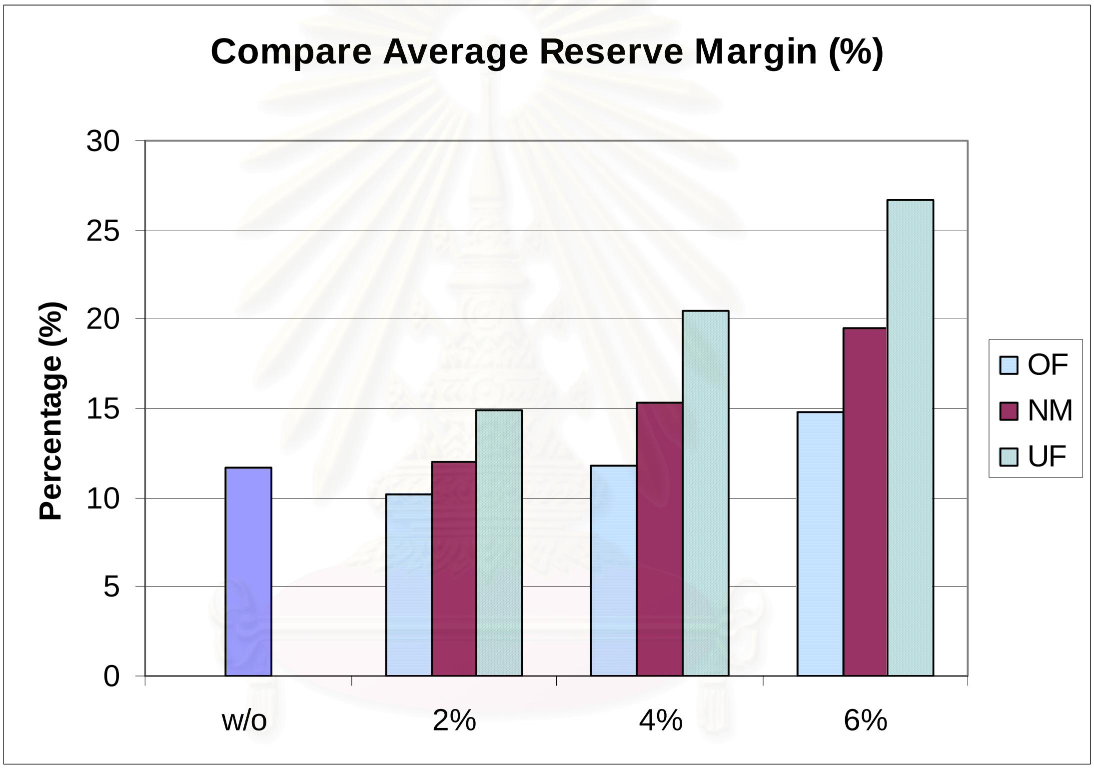


Fig 5.76 Compare average reserve margin with three uncertainty models

CHAPTER VI

CONCLUSION

This thesis presents system generation capacity requirement determination based on predefined risk criteria, which is based on either deterministic or probabilistic methods.

We have described the comparison of reserve capacity requirement with both methods in the previous chapter. Normally the reserve based on deterministic method is higher than the one based on probabilistic method in the case of over forecast and vice versa for under forecast. For the case of normal density function both method sometime require similar reserve capacity amount. Similarly the reserve capacity by using the probabilistic method is higher than the reserve by using deterministic method. However some case show that deterministic method need more reserve. If reserve capacity is higher, the reliability of the system is better but on the other hand it will be costly because the system requires more additional added capacity.

The electric power supply industry now combined effect of considerable uncertainty in predicting future demand. Since the required generation capacity highly depends on the forecasted demand into the future, this thesis also consider the impact of various load uncertainty types, i.e. normal, under and over forecasted models. So that by applying different uncertainty model which gives the different percentage reserve requirement. If over forecast case, the less reserve capacity required. The reserve by using normal density function is higher than the reserve by applying over forecast. For under forecast case is the highest reserve capacity required compared with normal and over forecast. The higher uncertainty the higher reserve capacity will be required.

Compare added capacity 25MW with percentage reserve margin of without and uncertainty cases for Myanmar Generation System is described in the following figures 6.1 and table 6.1.

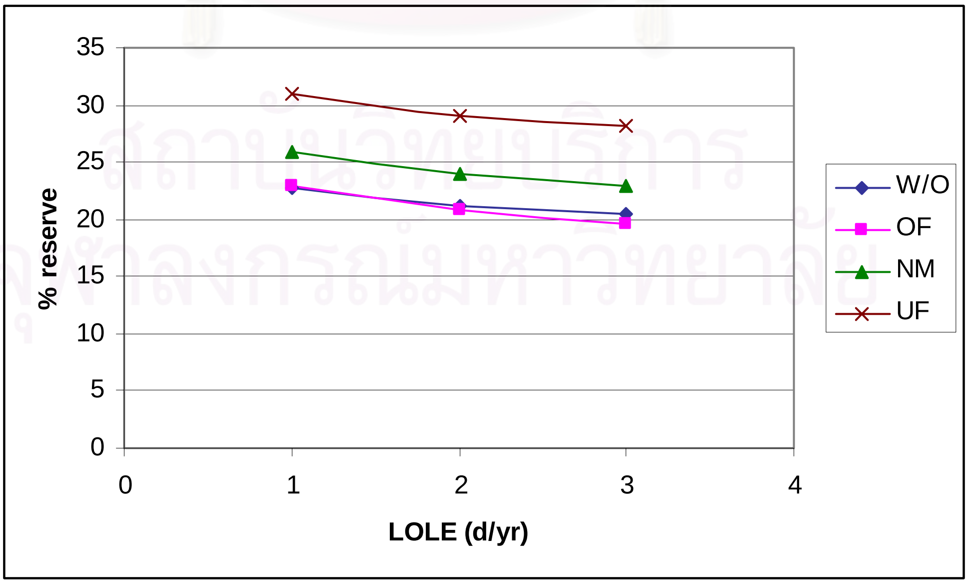


Fig 6.1 Average reserve margin (%) of without and uncertainty models with different risk criteria

Table 6.1 Compare average reserve (%) with different risk criteria

Average Reserve (%)				
LOLE (day/year)	(Without)	Over forecast uncertainty	Normal distribution uncertainty	Under forecast uncertainty
1	22.6	22.8	25.9	30.9
2	21.1	20.8	24.0	29.0
3	20.4	19.5	22.9	28.2

Compare added capacity 200MW with percentage reserve margin of without and uncertainty cases for Thailand Generation System is described in the following figures 6.2 and table 6.2.

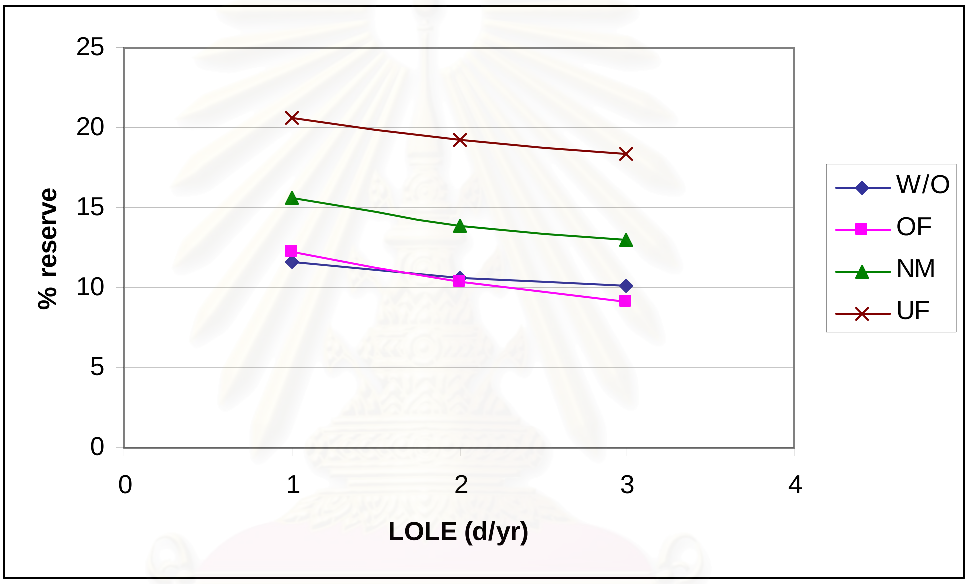


Fig 6.2 Average reserve margin (%) of without and uncertainty models with different risk criteria

Table 6.2 Compare average reserve (%) with different risk criteria

Average Reserve (%)				
LOLE (day/year)	(Without)	Over forecast uncertainty	Normal distribution uncertainty	Under forecast uncertainty
1	11.6	12.2	15.6	20.6
2	10.6	10.4	13.8	19.2
3	10.1	9.1	12.9	18.4

We can conclude that without uncertainty, the system requires less capacity compared with the cases of taking into account uncertainty. The uncertainty causes higher reserve capacity requirement reveals that more units are needed compare with without uncertainty. However if we take into account the forecast uncertainty a higher percentage value should be used instead. The LOLE criteria is higher, the less percentage average reserve is required. If risk is changed the suggestion should be adjusted according.

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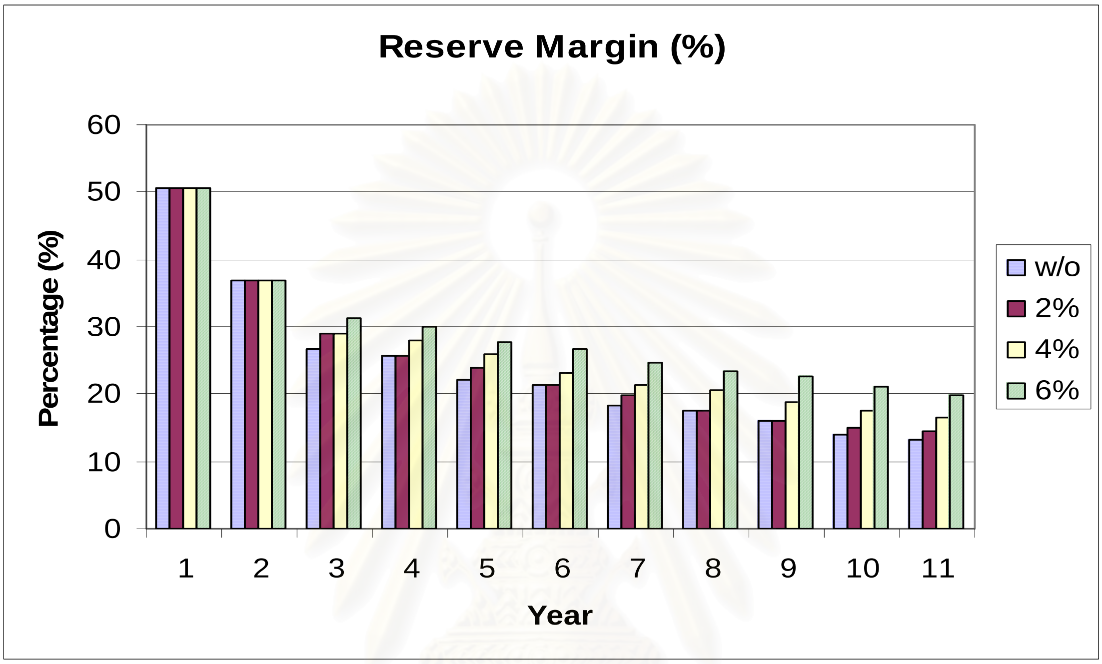
APPENDICES

APPENDIX A

Myanmar Generation expansion planning

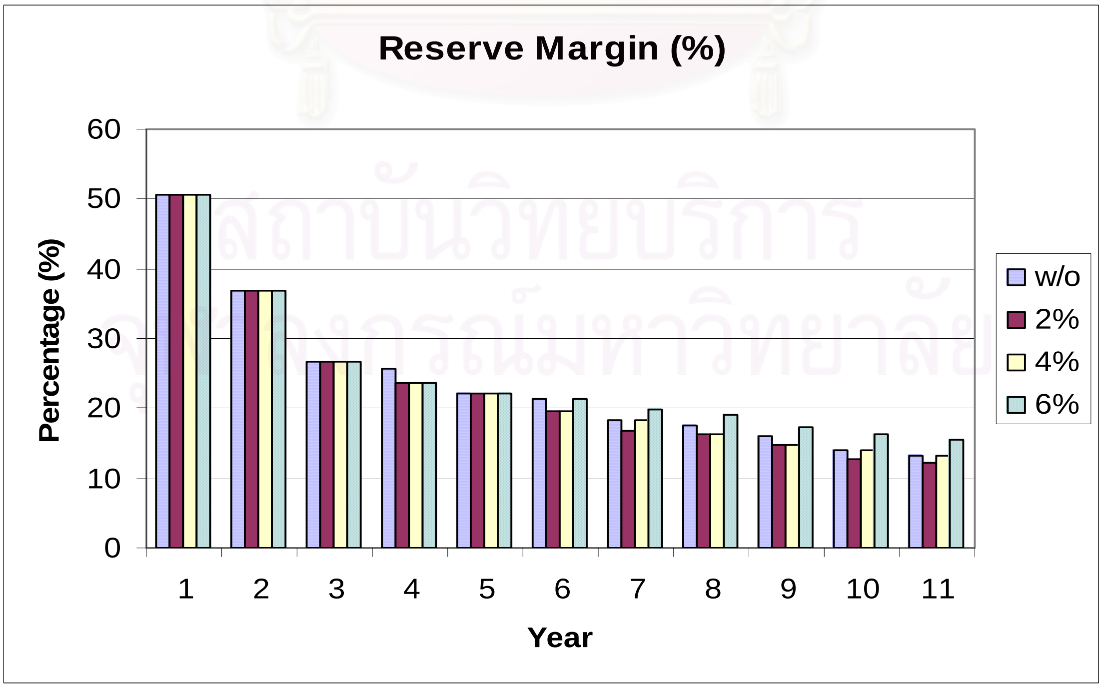
<u>Planning criteria =2day/yr, added capacity = 25MW</u>

Normal density function (NM)



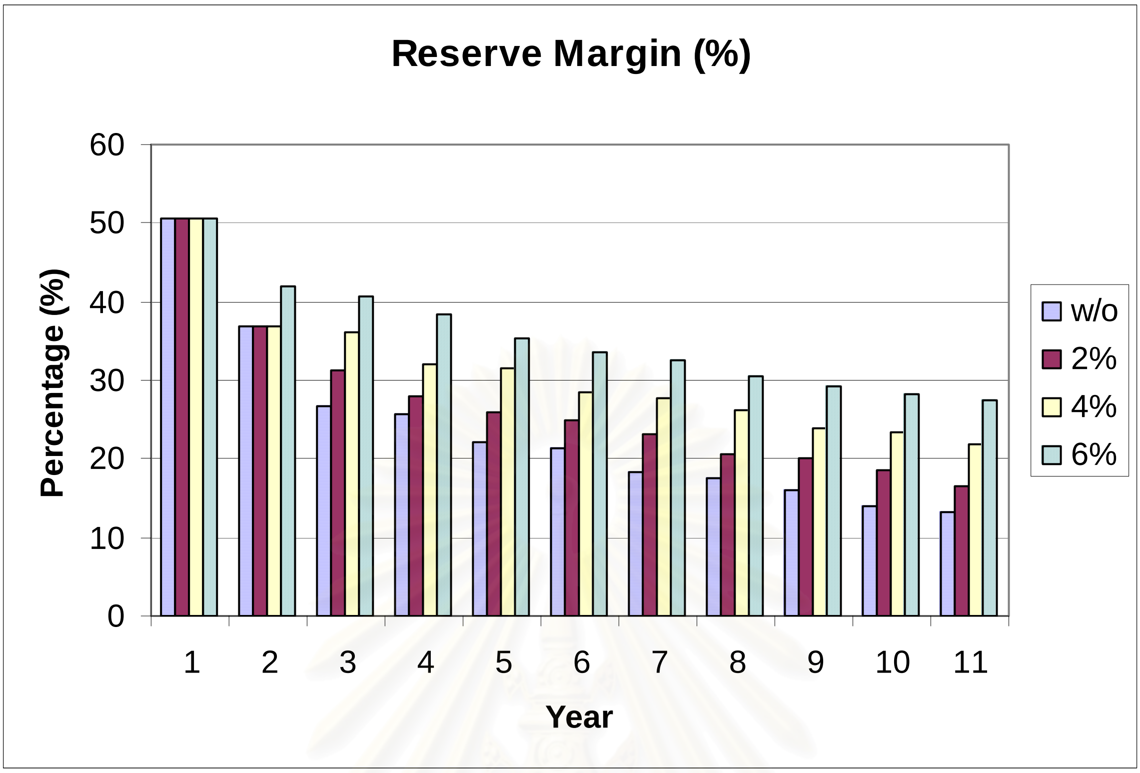
FigA.1 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigA.2 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigA.3 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

* Average (2-11) year

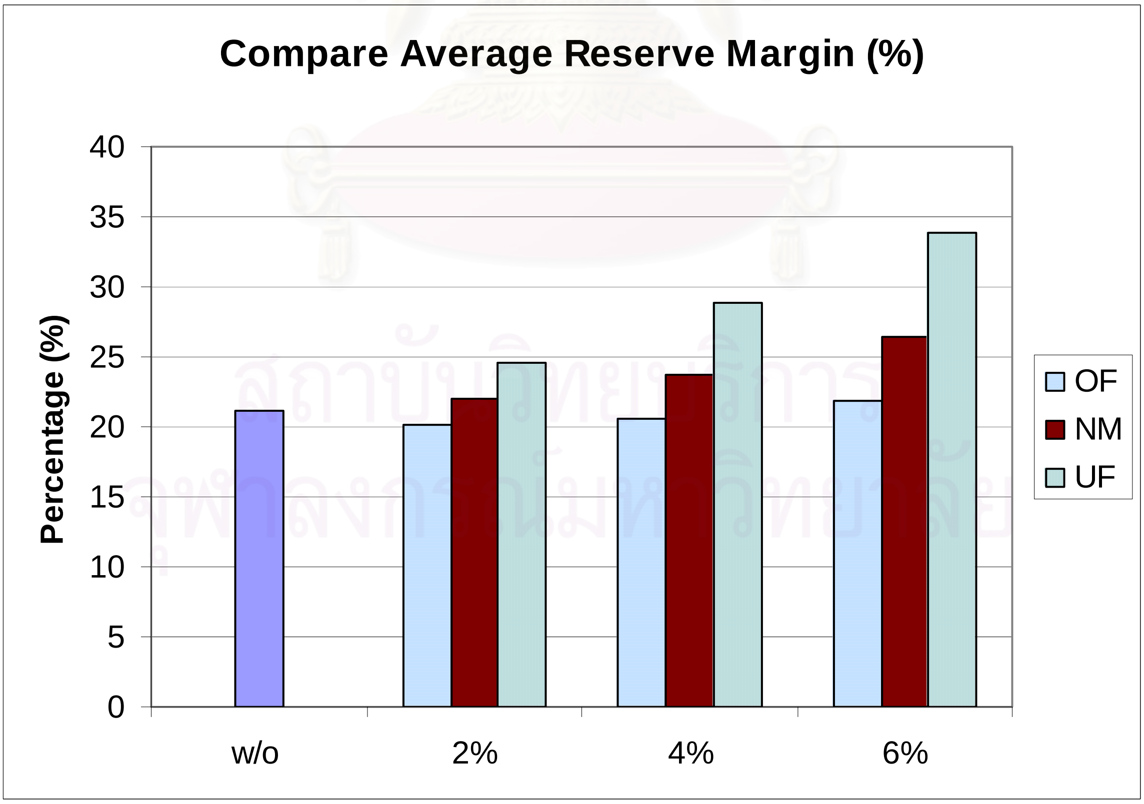
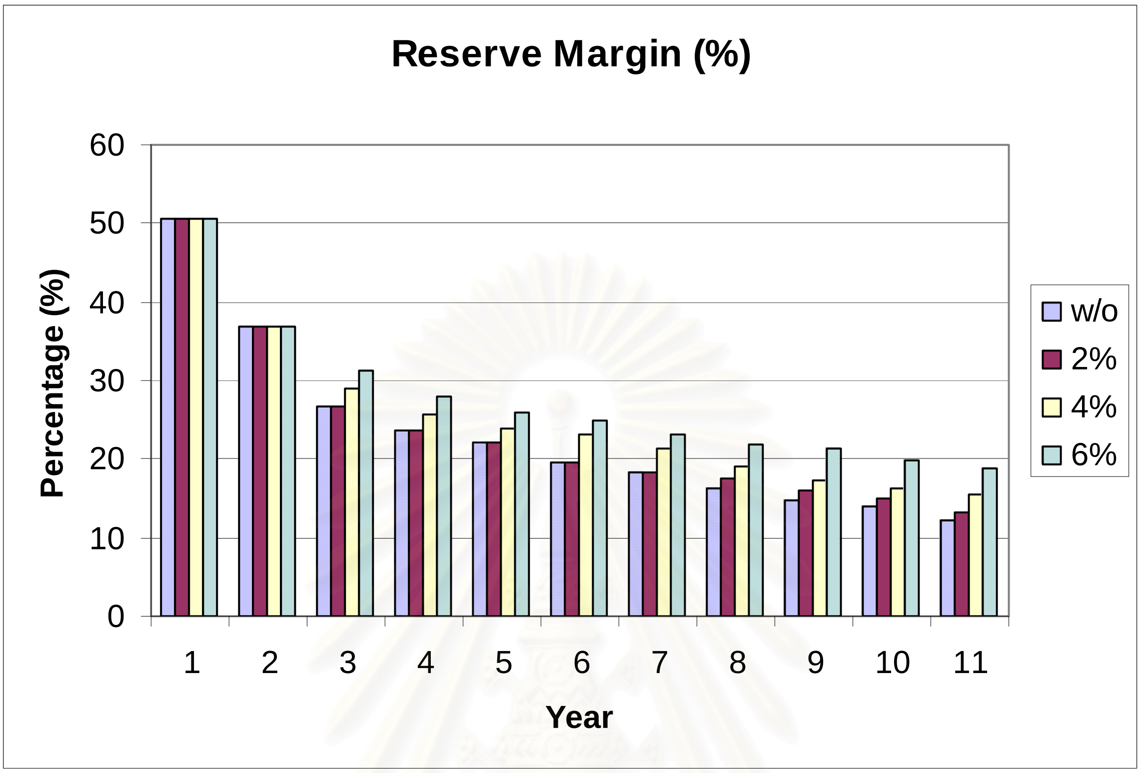


Fig A.4 Compare average percentage reserve margin with without and three uncertainty models

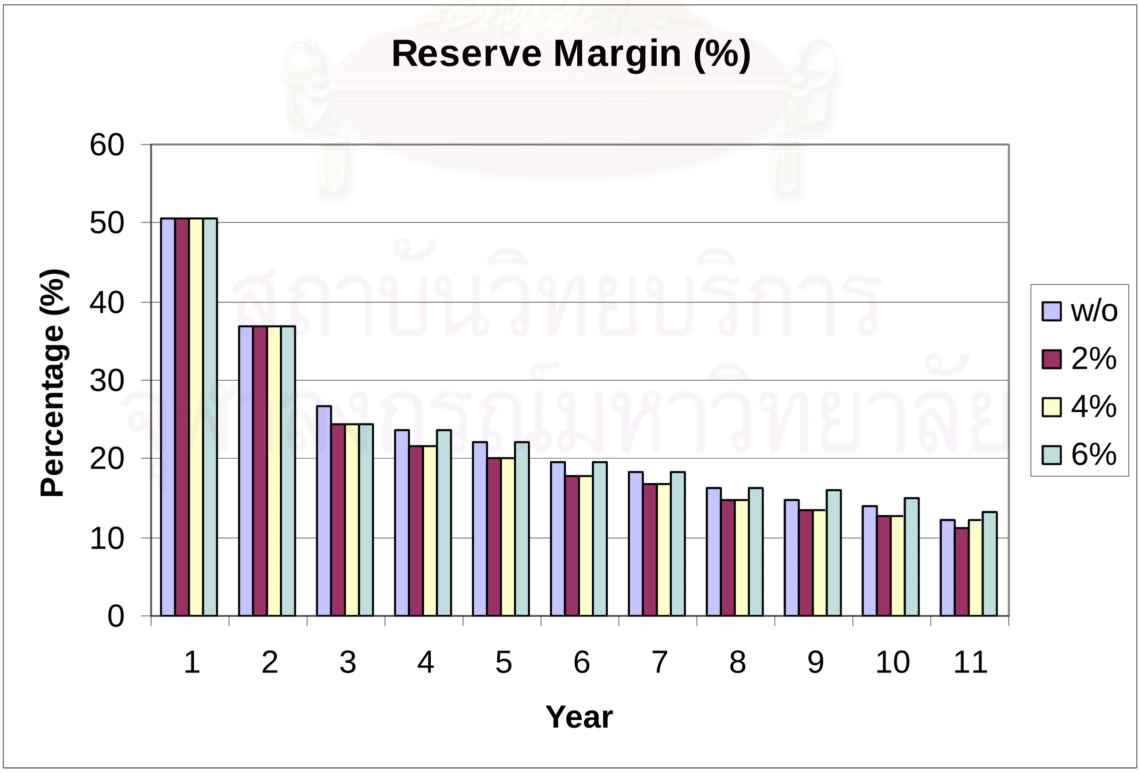
Planning criteria =3day/yr, added capacity = 25MW

Normal density function (NM)



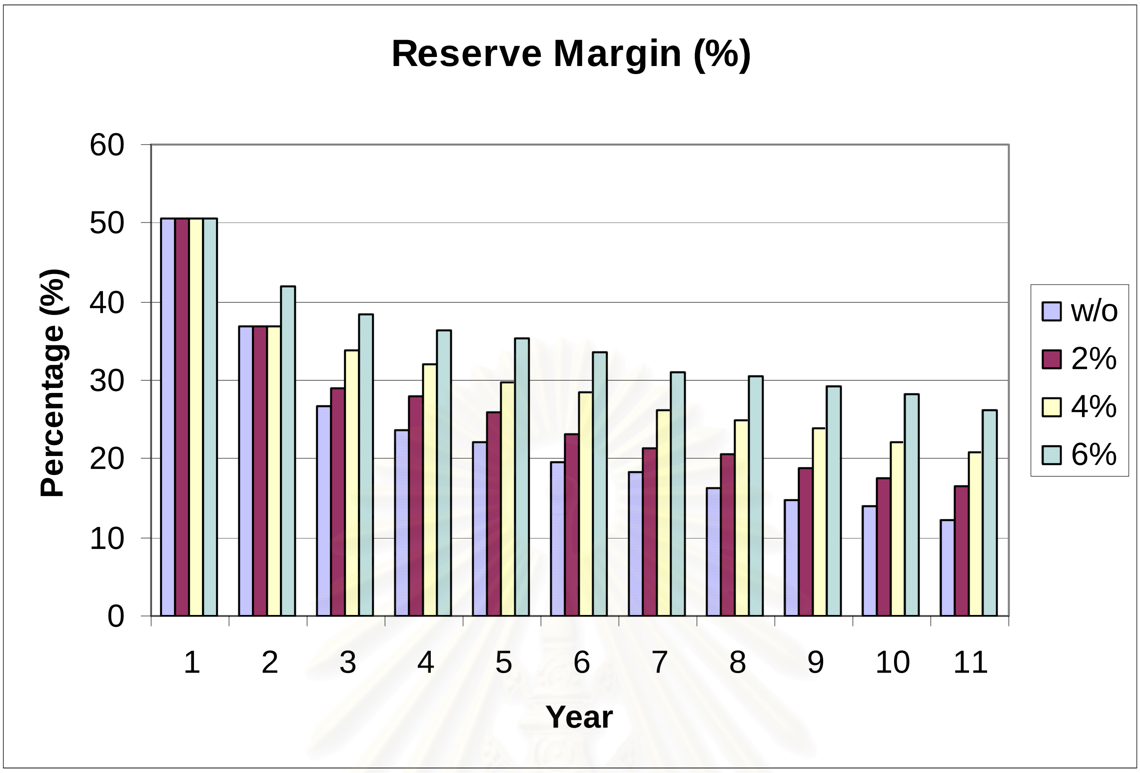
FigA.5 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigA.6 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigA.7 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

* Average (2-11) year

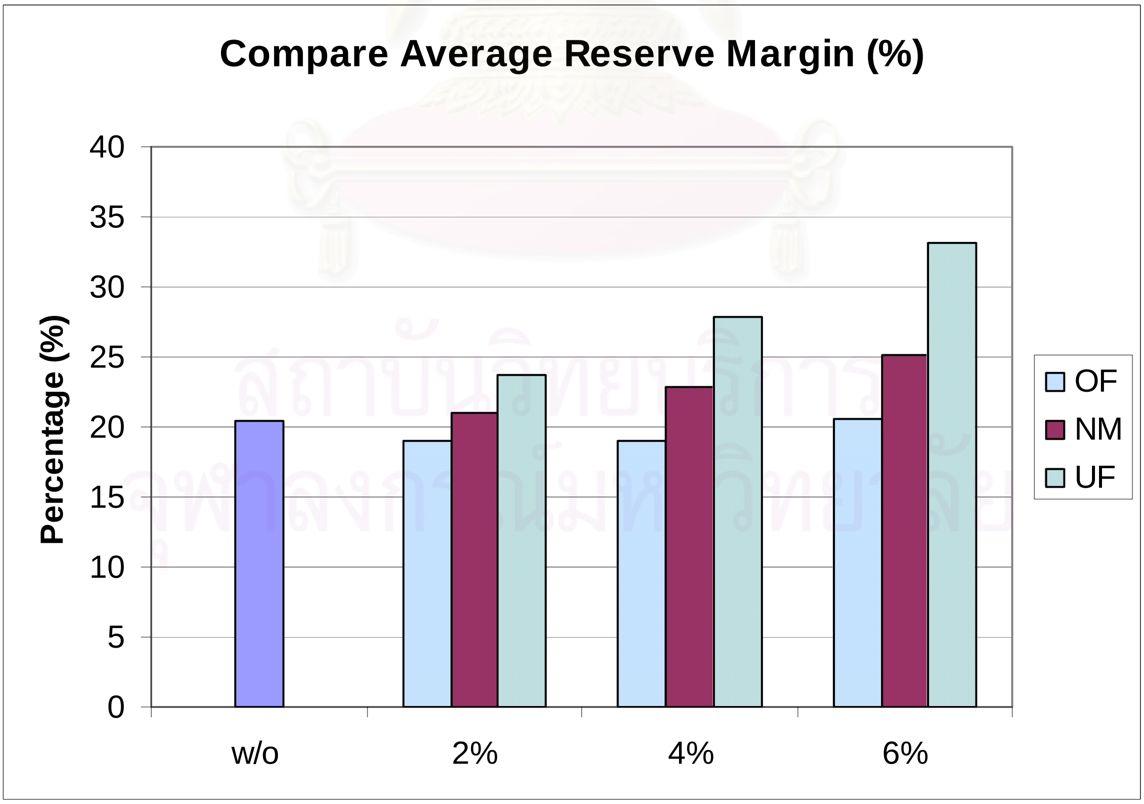
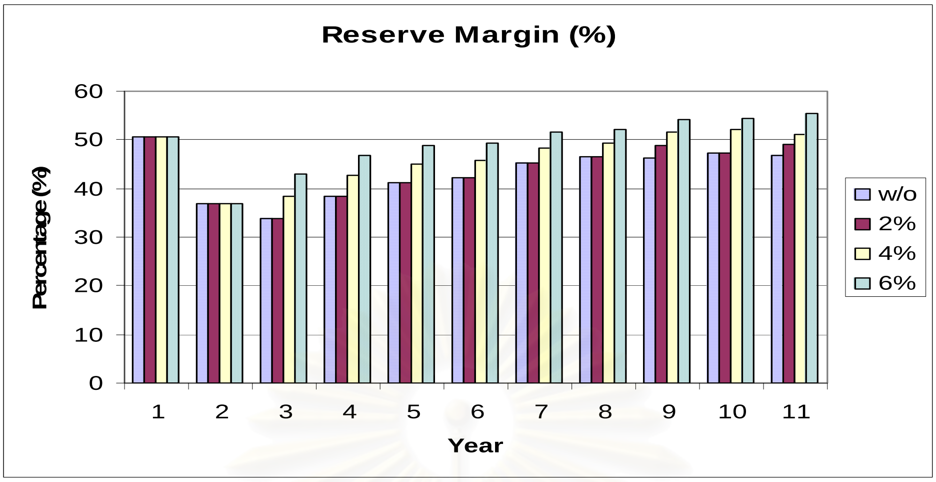


Fig A.8 Compare average percentage reserve margin with without and three uncertainty models

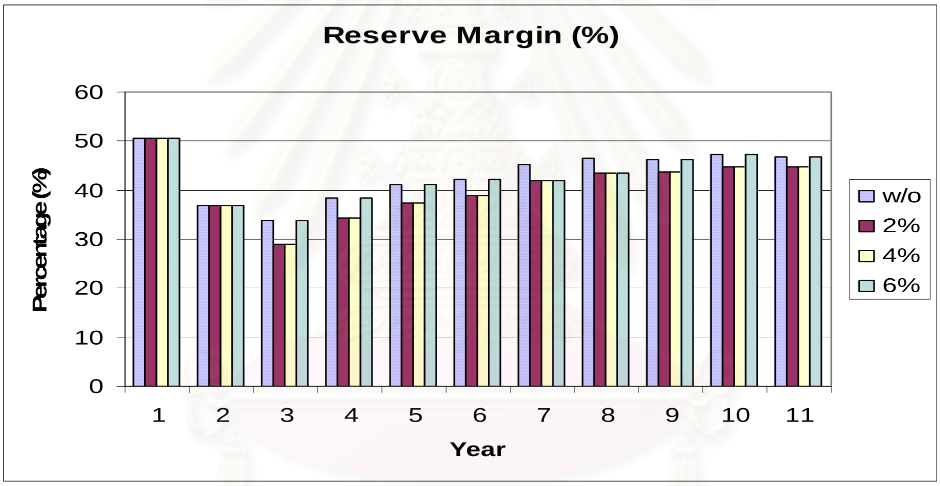
Planning criteria =1day/yr, added capacity = 50MW

Normal density function (NM)



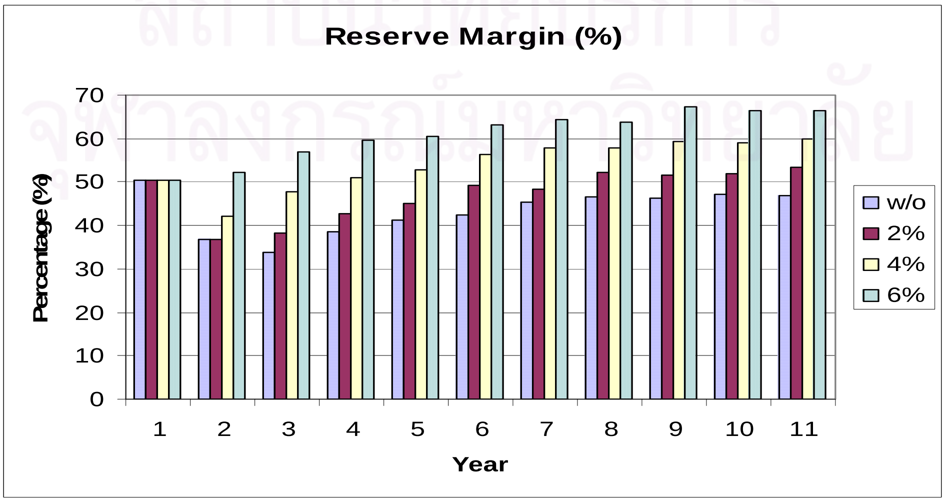
FigA.9 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigA.10 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigA.11 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

* Average (2-11) year

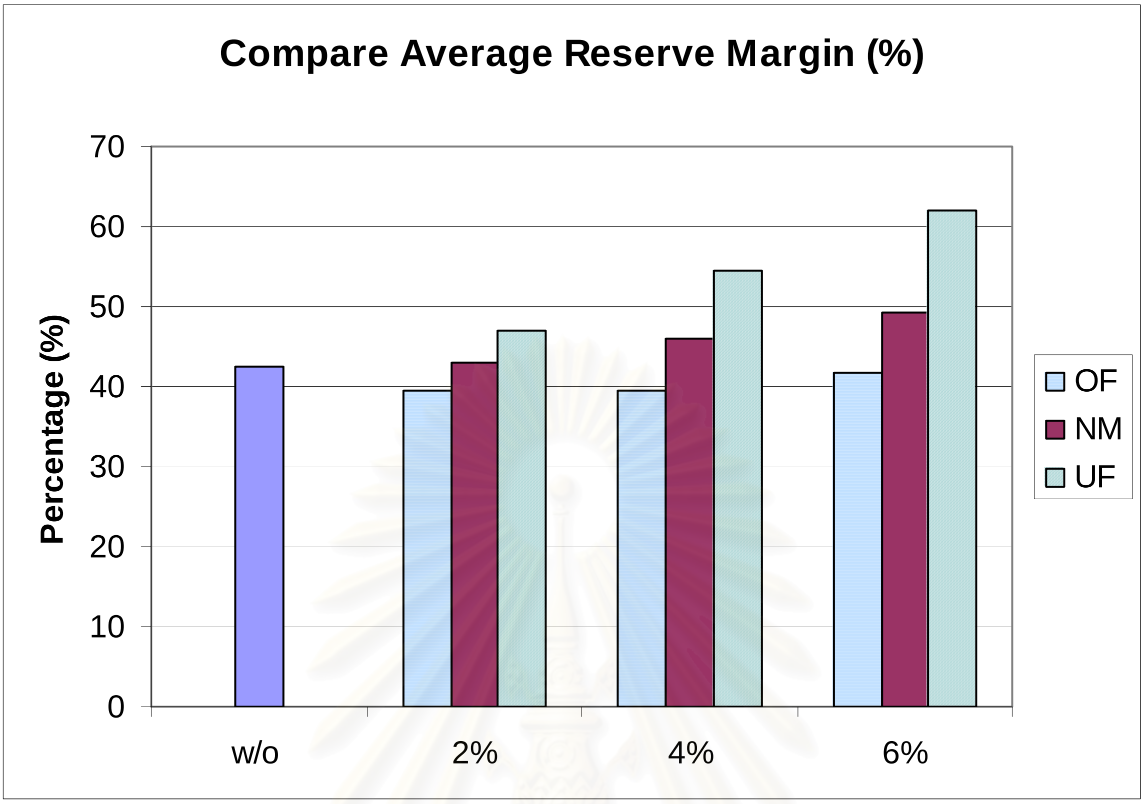
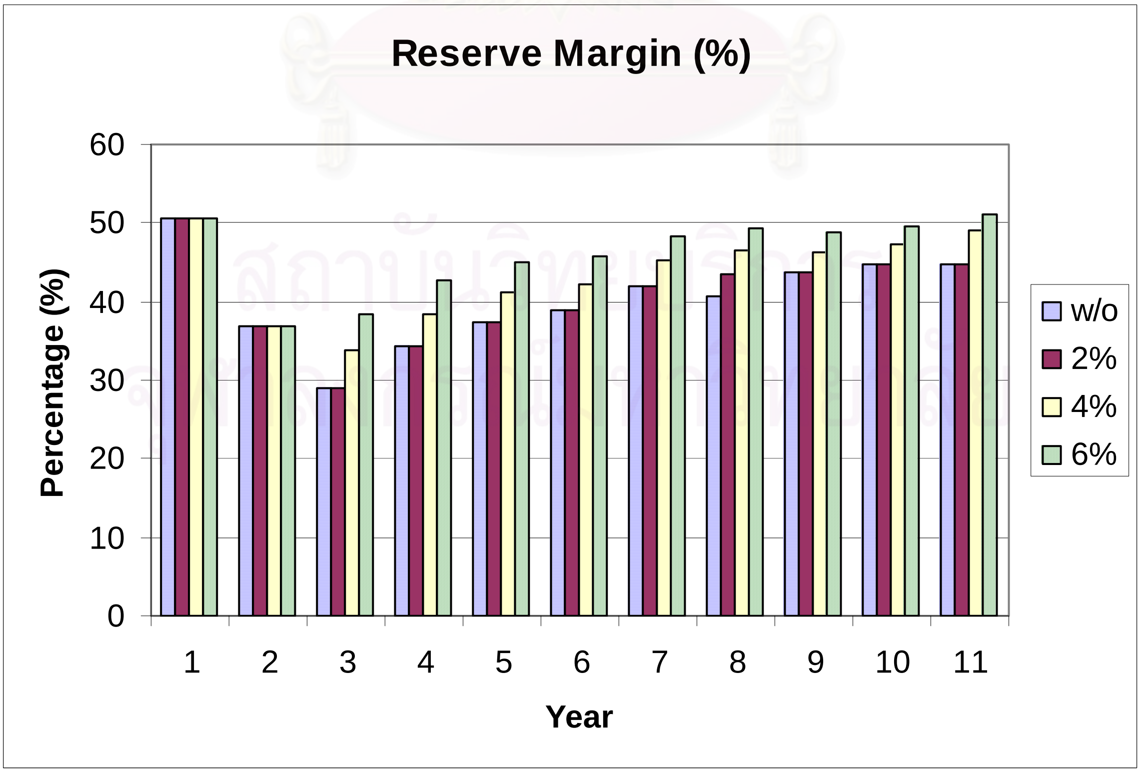


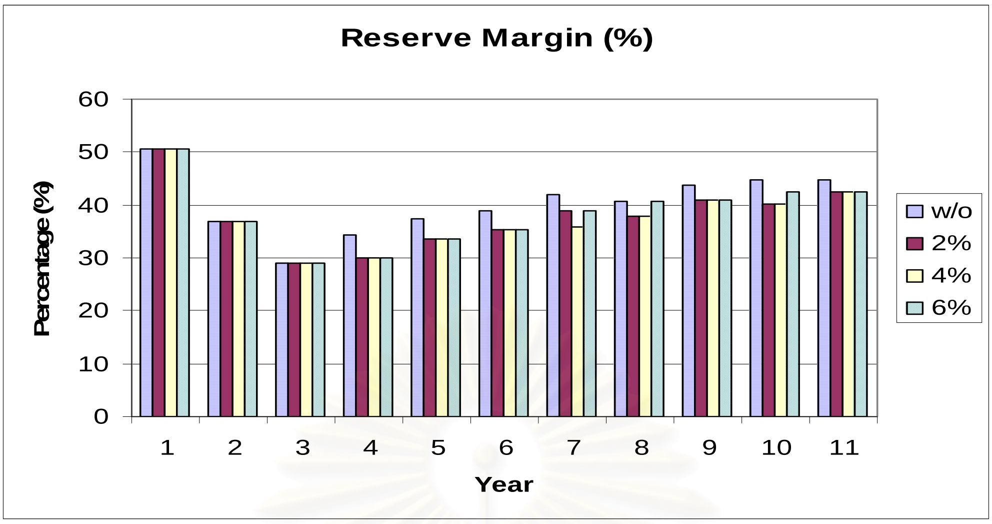
Fig A.12 Compare average percentage reserve margin with without and three uncertainty models

Planning criteria =2day/yr, added capacity = 50MW

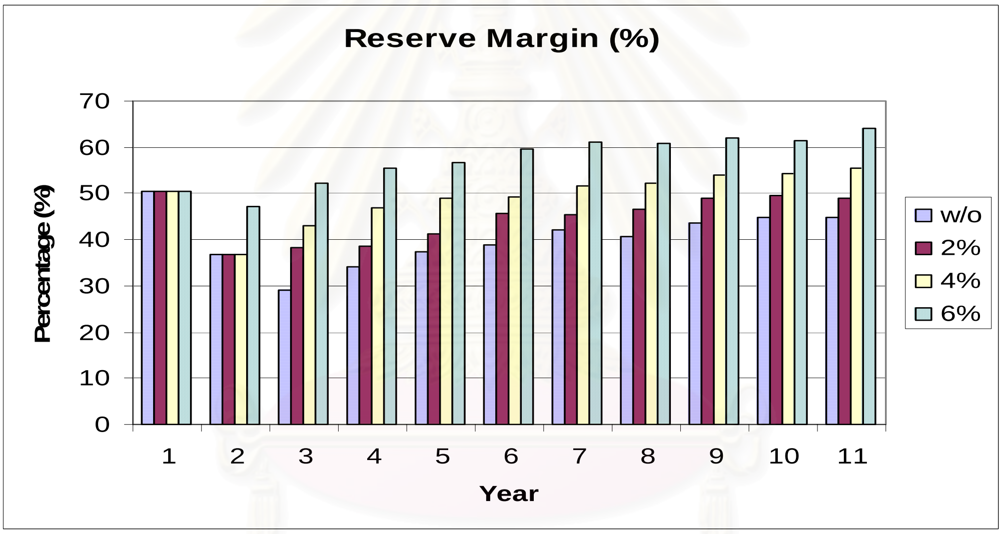
Normal density function (NM)



FigA.13 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty
Over forecast (OF)



FigA.14 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty
Under forecast (UF)



FigA.15 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

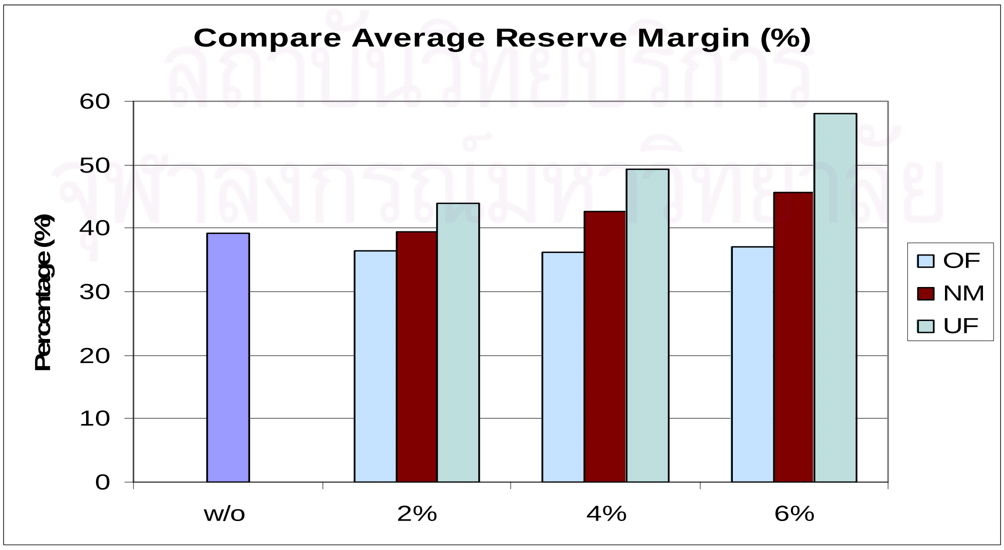
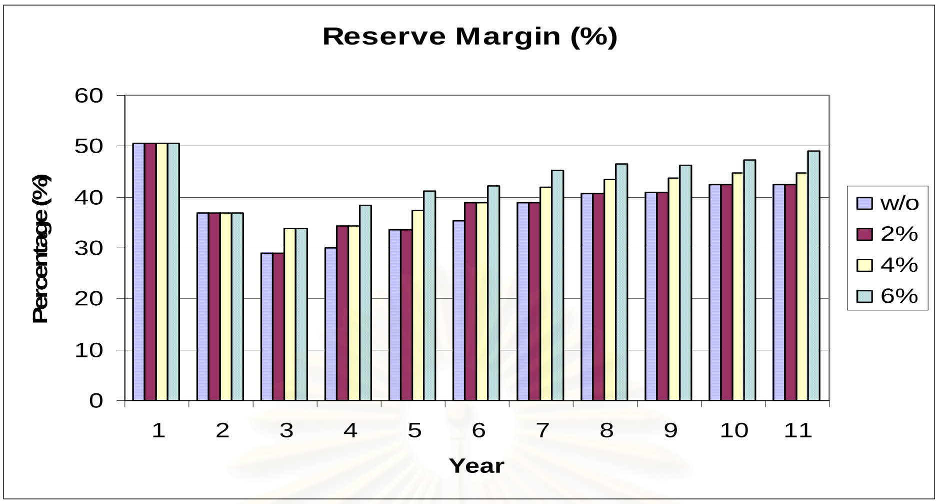


Fig A.16 Compare average percentage reserve margin with without and three uncertainty models

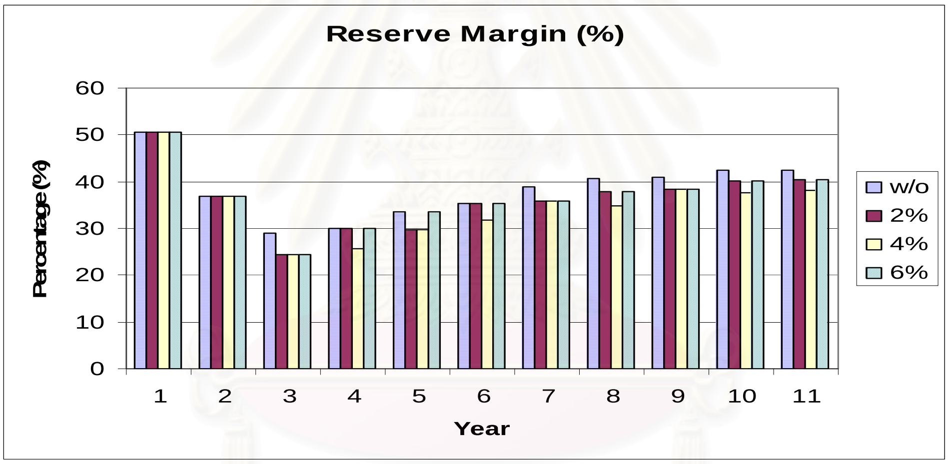
Planning criteria =3day/yr, added capacity = 50MW

Normal density function (NM)



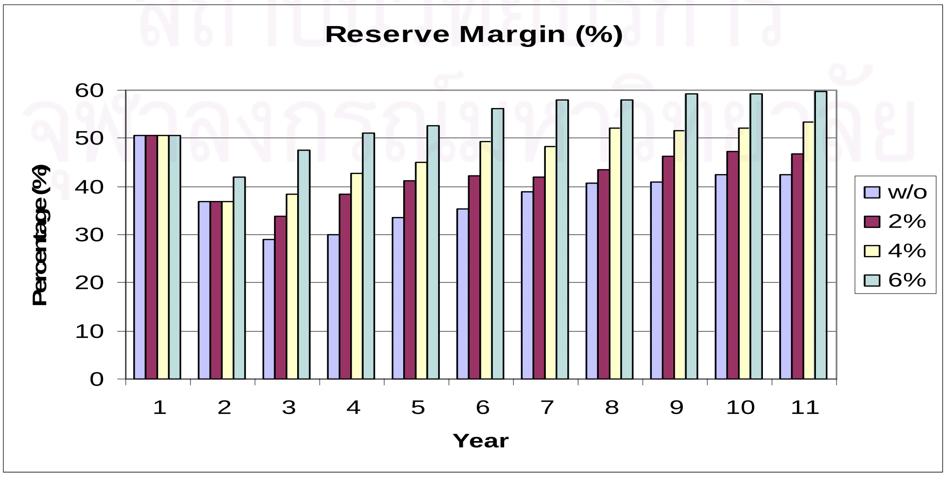
FigA.17 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigA.18 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigA.19 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

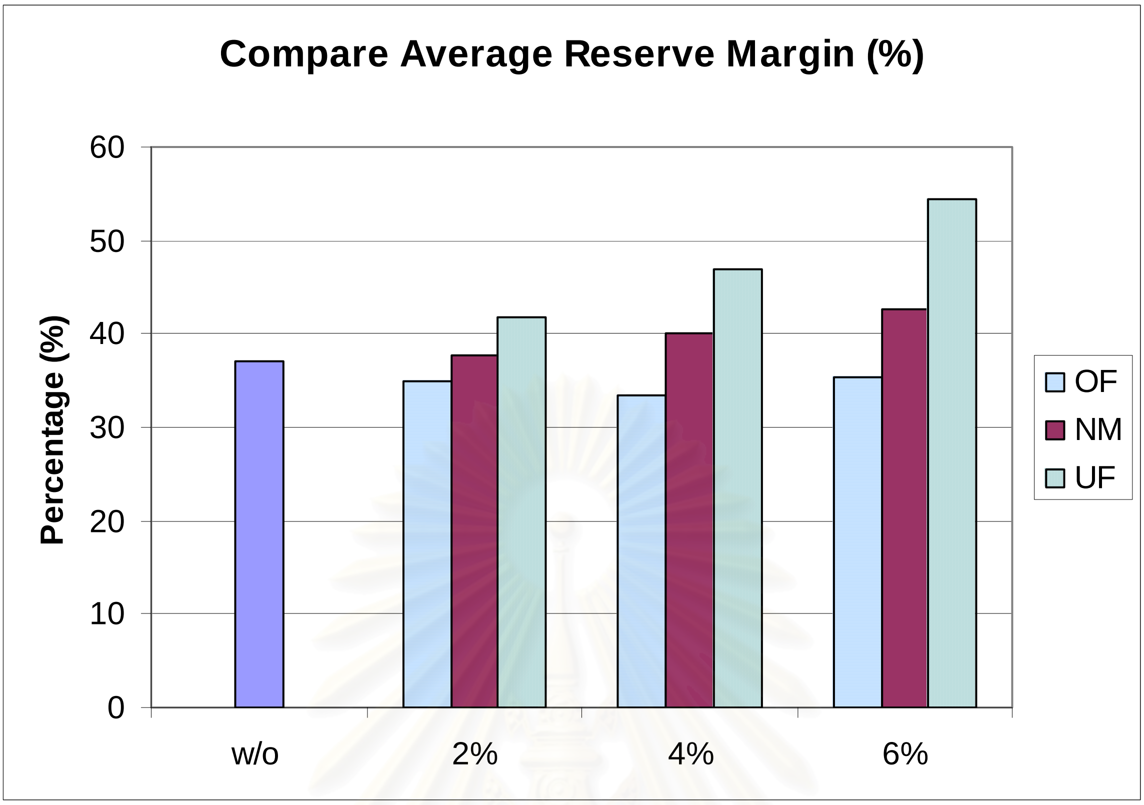


Fig A.20 Compare average percentage reserve margin with without and three uncertainty models

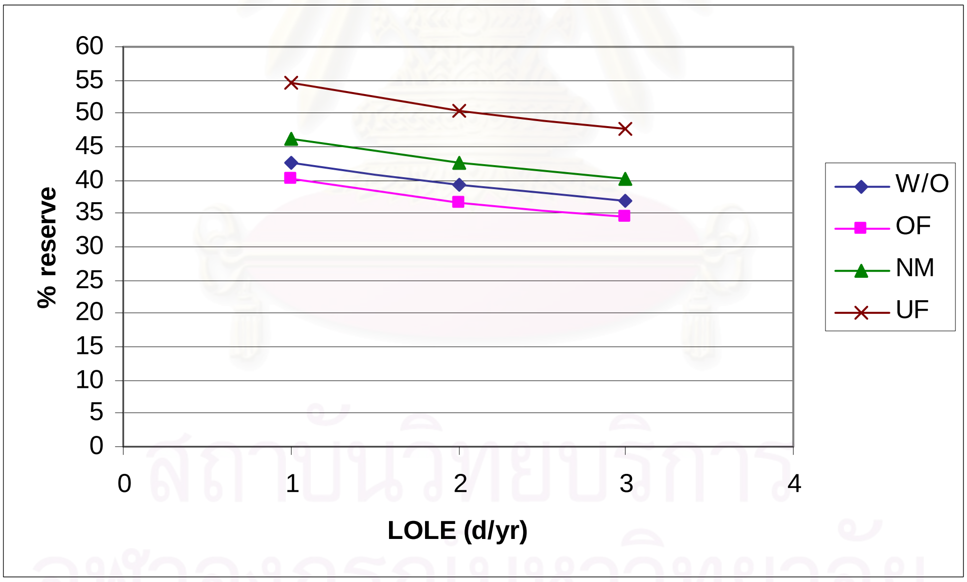


Fig A.21 Average reserve margin (%) of without and uncertainty models with different risk criteria

Table A.1 Compare average reserve (%) with different risk criteria

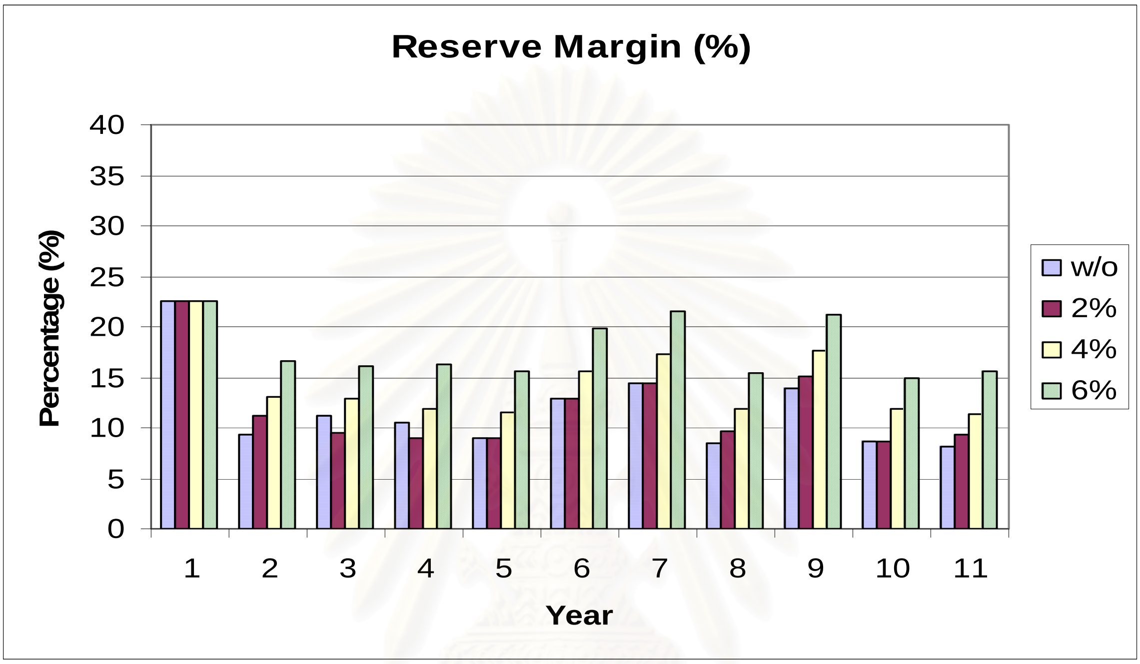
	Average Reserve (%)			
LOLE (day/year)	(Without)	Over forecast uncertainty	Normal distribution uncertainty	Under forecast uncertainty
1	42.4	40.2	46.1	54.4
2	39.2	36.5	42.6	50.4
3	37.0	34.4	40.1	47.7

APPENDIX B

Thailand Generation expansion planning

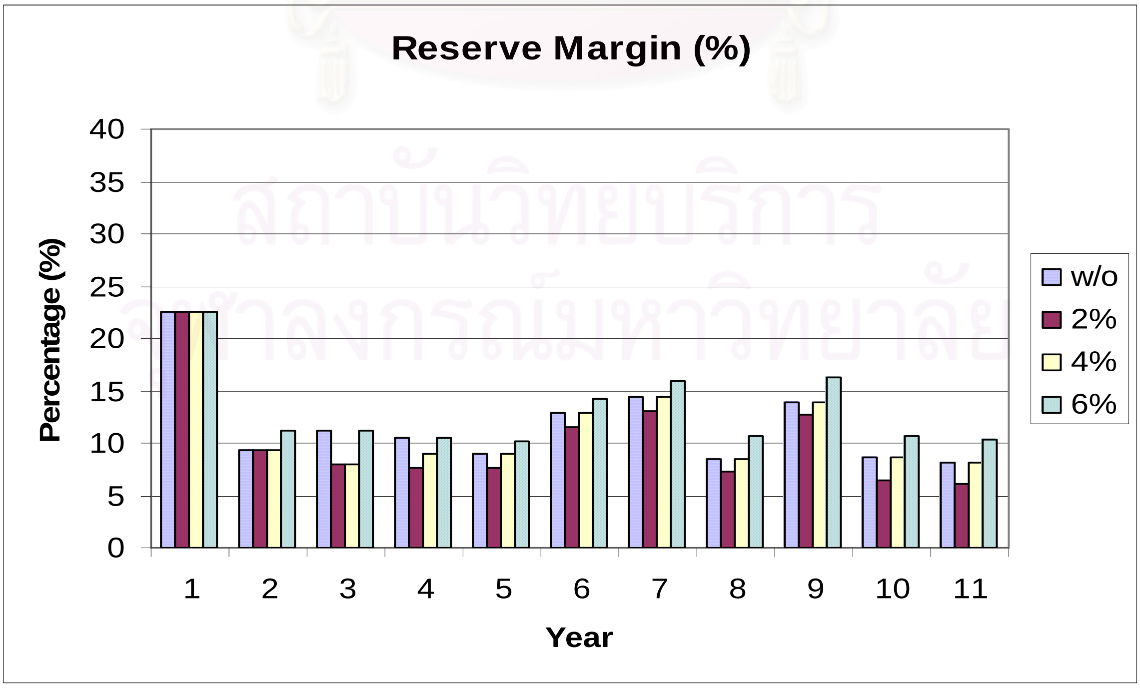
Planning criteria =2day/yr, added capacity = 200MW

Normal density function (NM)



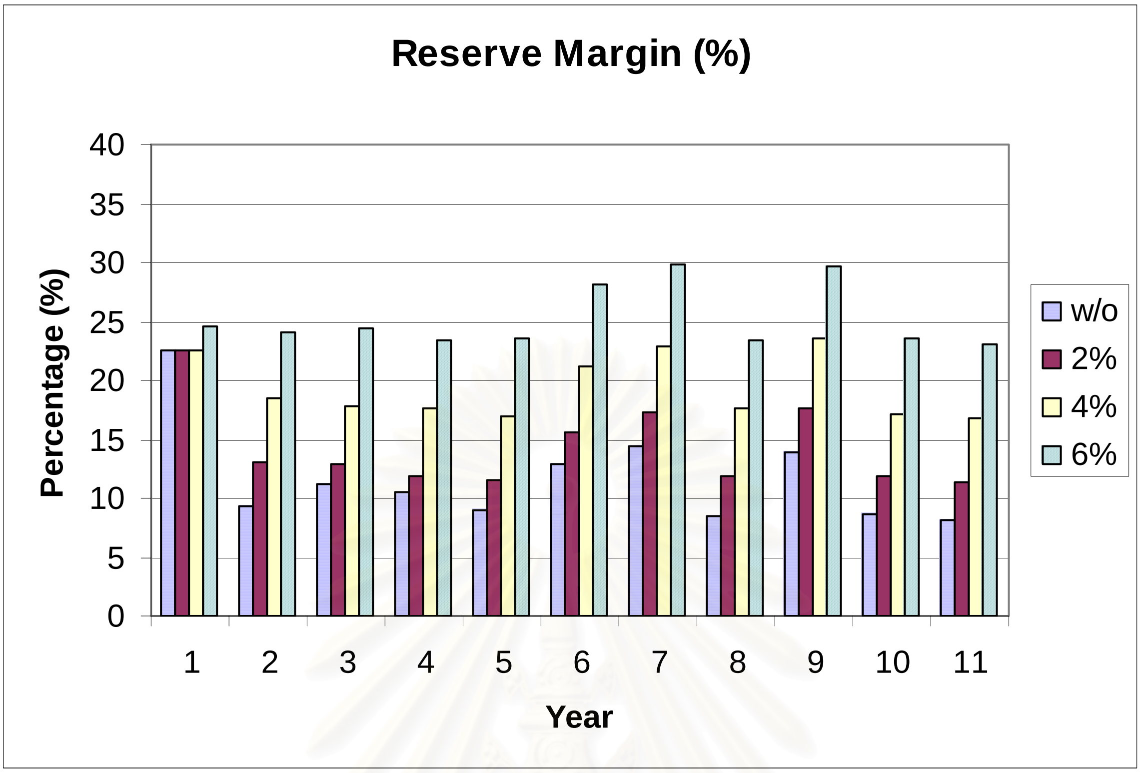
FigB.1 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigB.2 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigB.3 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

Average (2-11) year

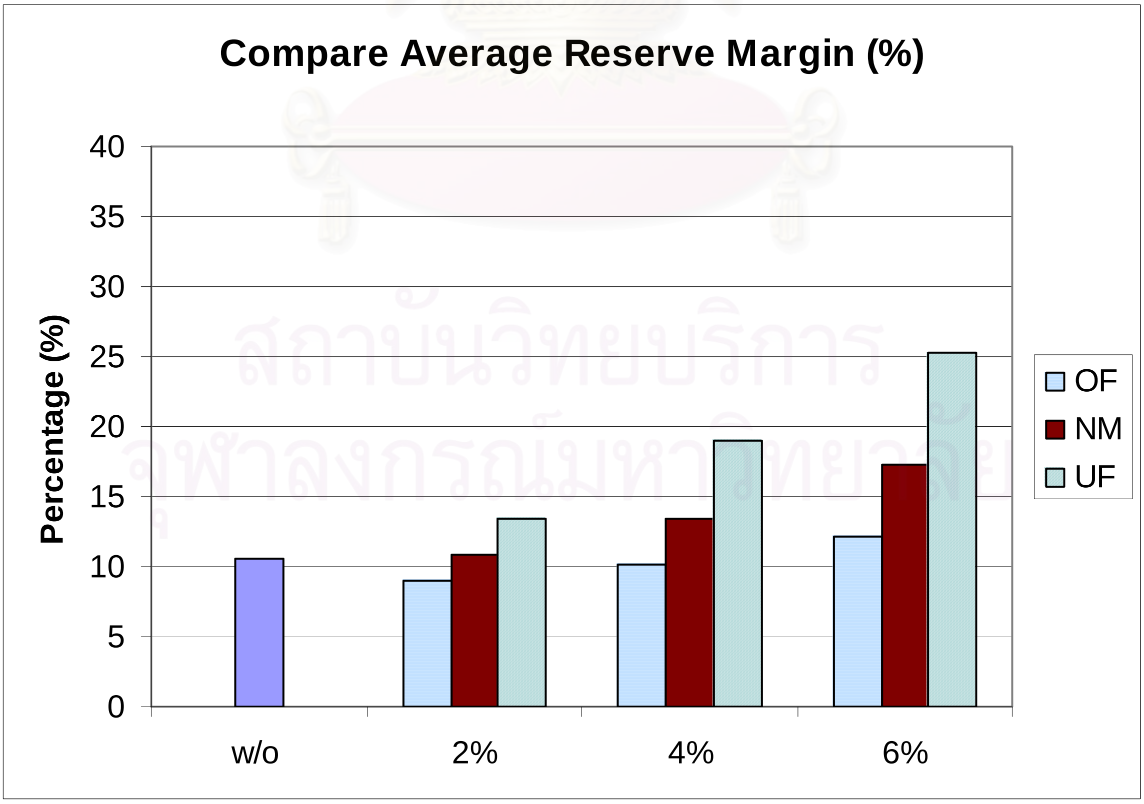
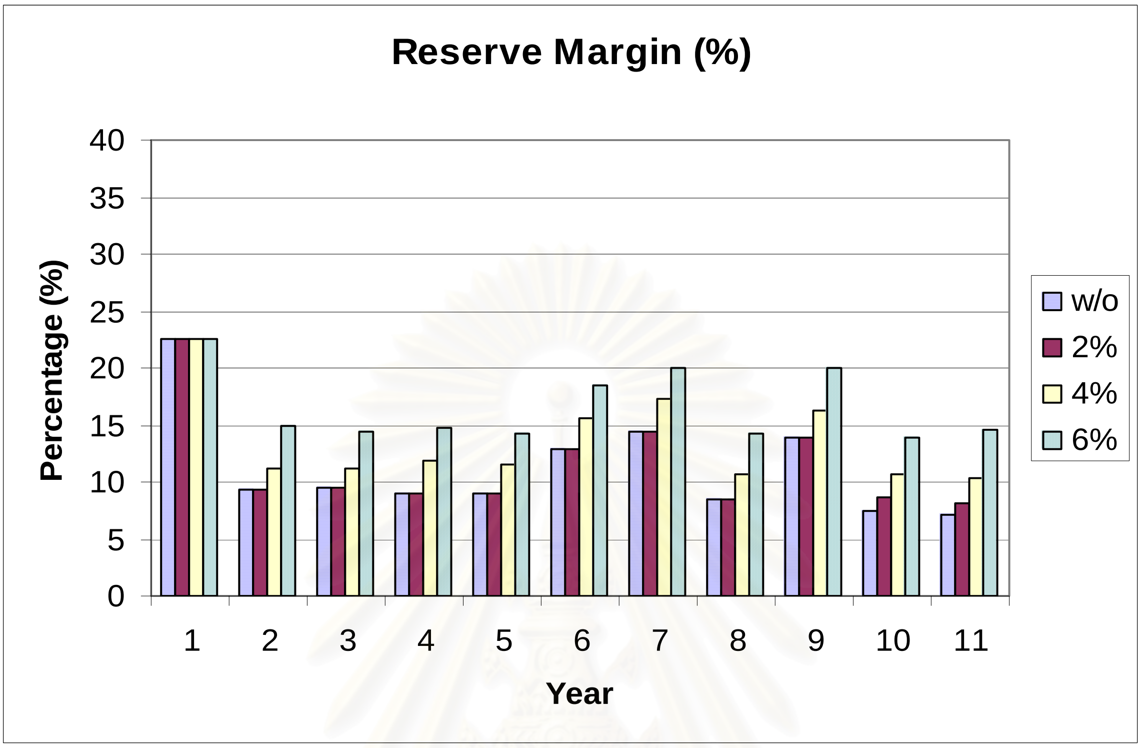


Fig B.4 Compare average percentage reserve margin with without and three uncertainty models

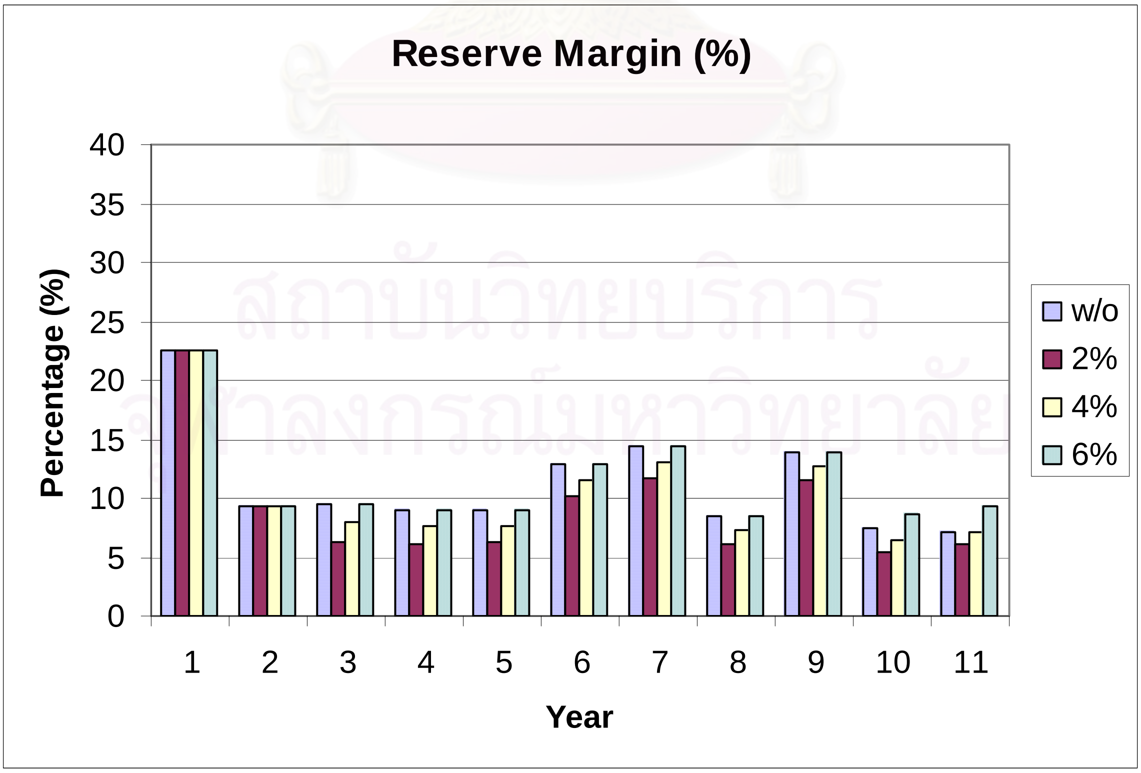
Planning criteria =3day/yr, added capacity = 200MW

Normal density function (NM)



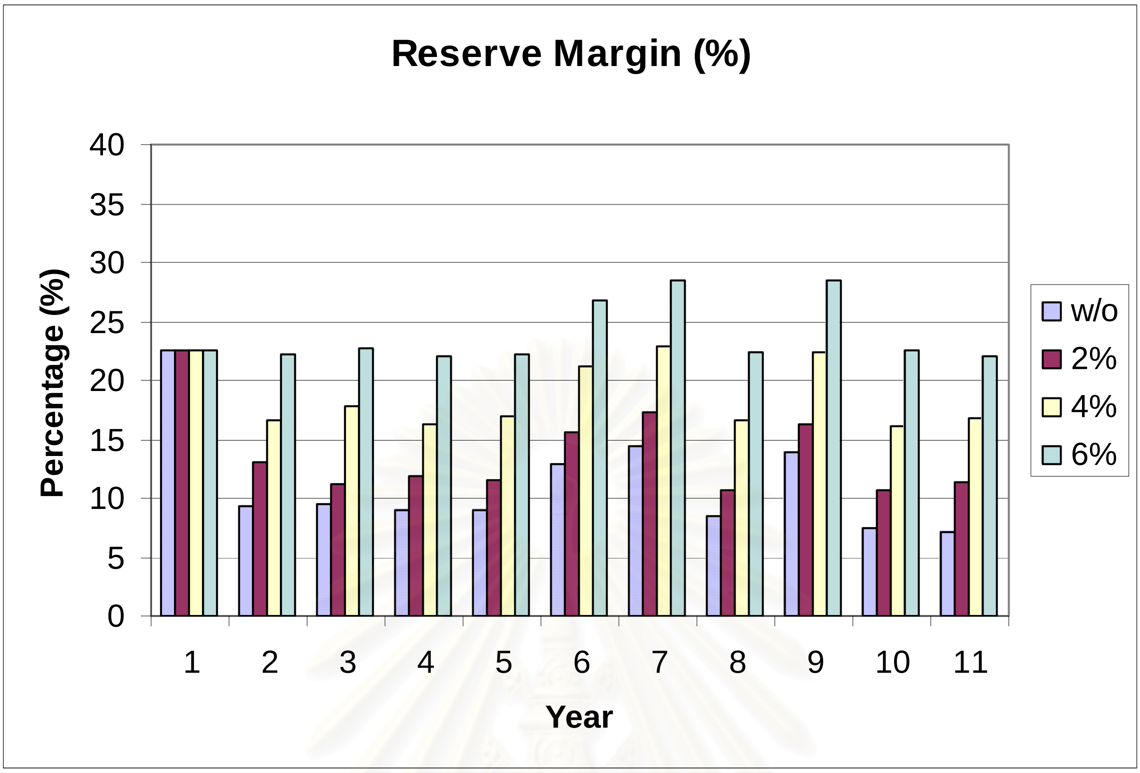
FigB.5 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigB.6 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigB.7 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

* Average (2-11) year

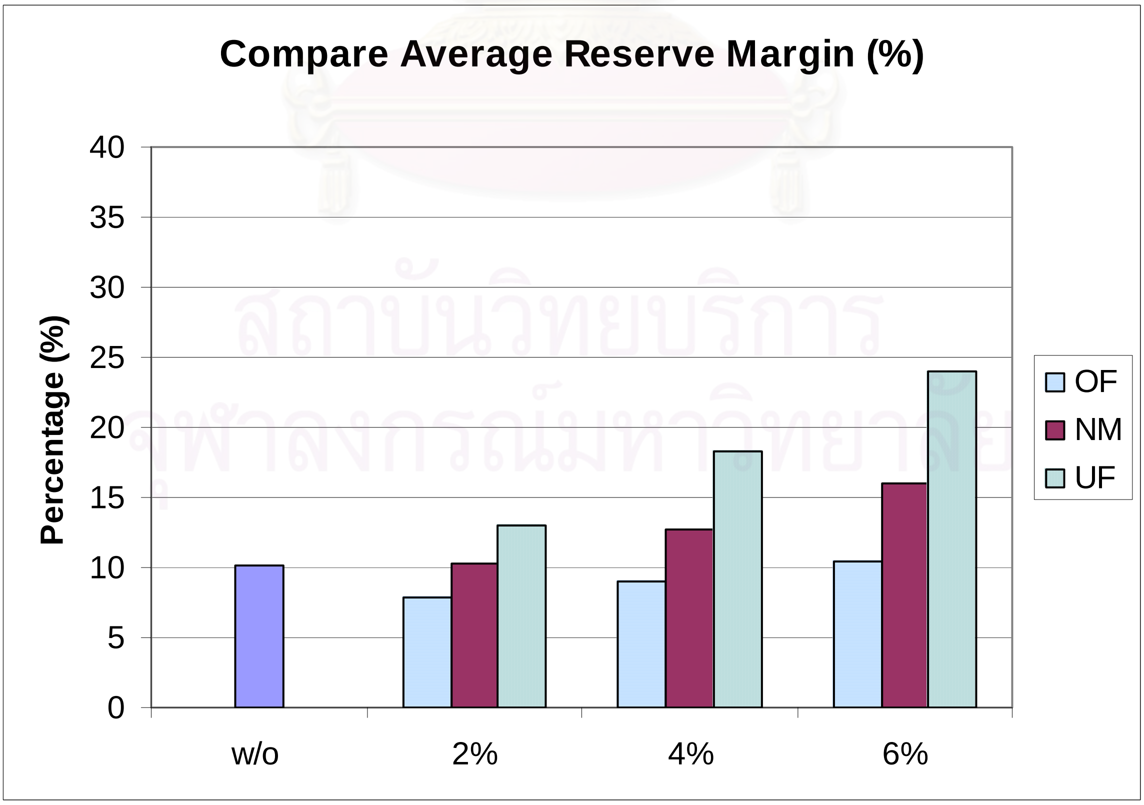
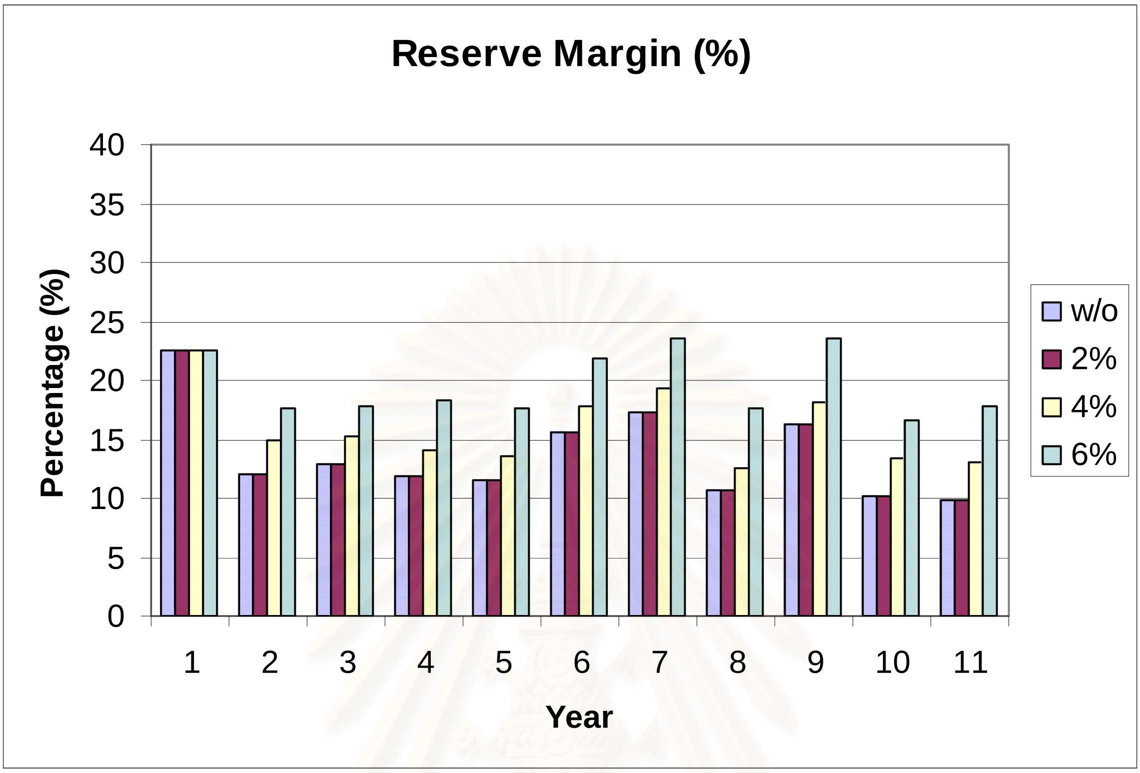


Fig B.8 Compare average percentage reserve margin with without and three uncertainty models

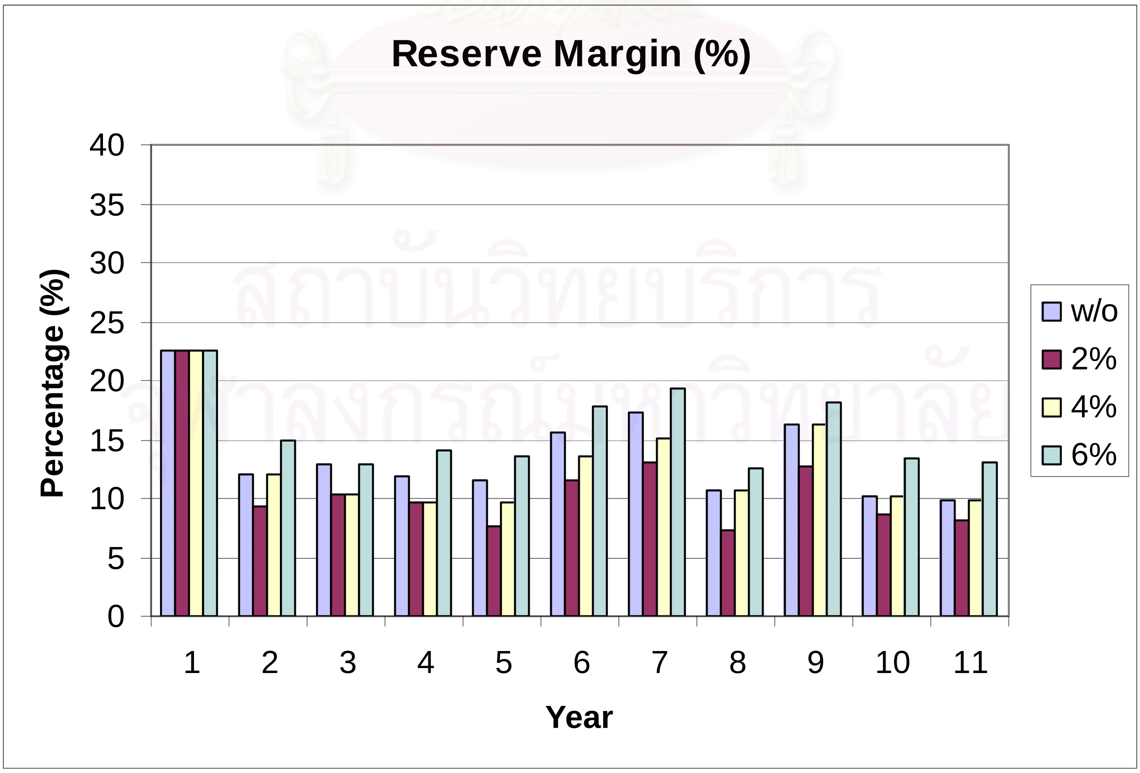
Planning criteria =1day/yr, added capacity = 300MW

Normal density function (NM)



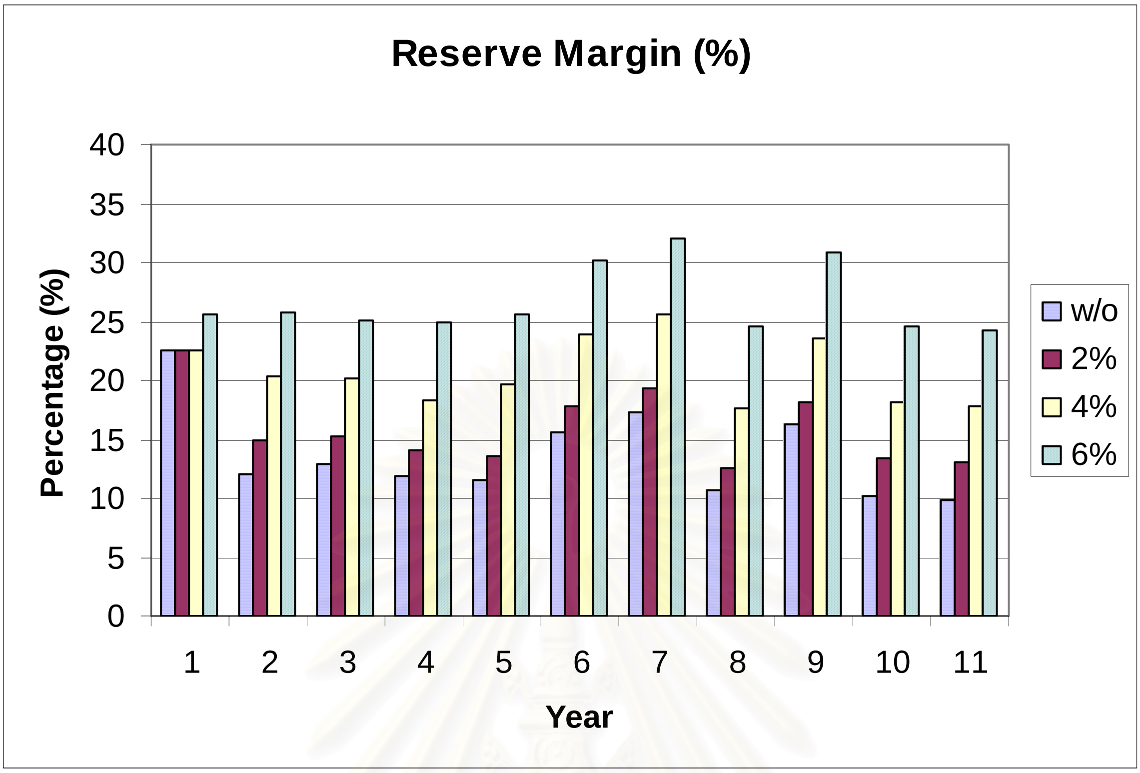
FigB.9 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigB.10 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigB.11 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

* Average (2-11) year

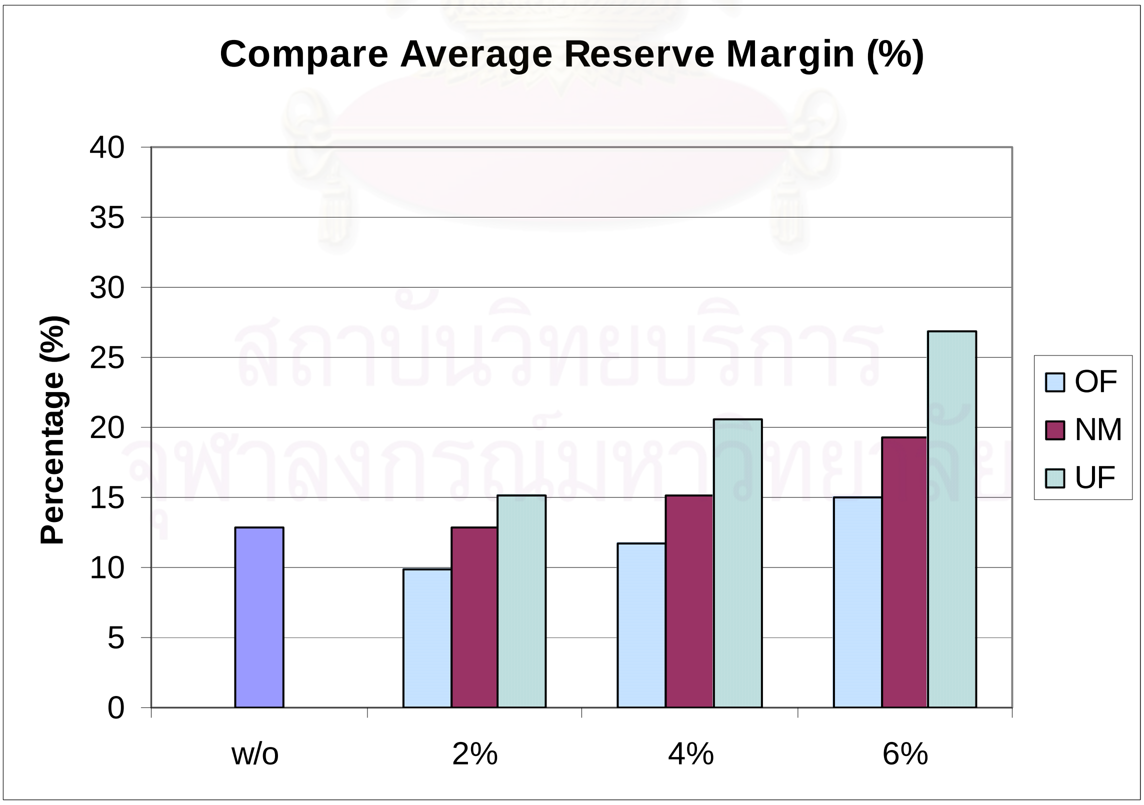
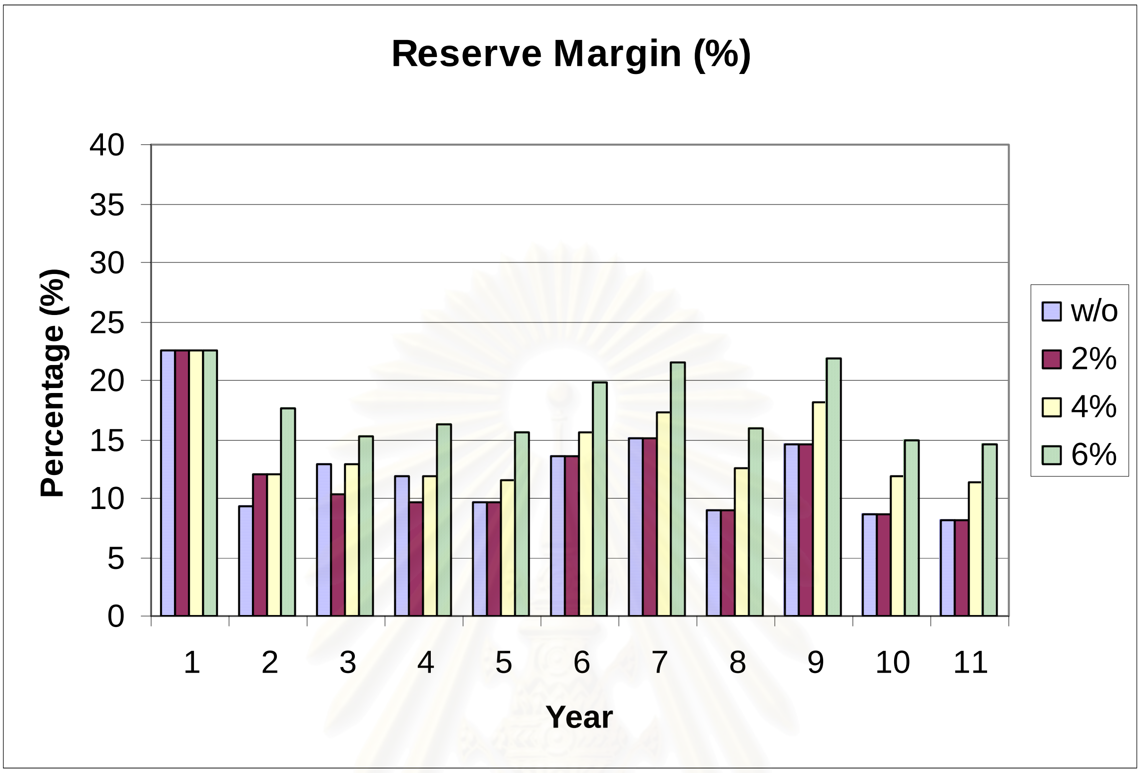


Fig B.12 Compare average percentage reserve margin with without and three uncertainty models

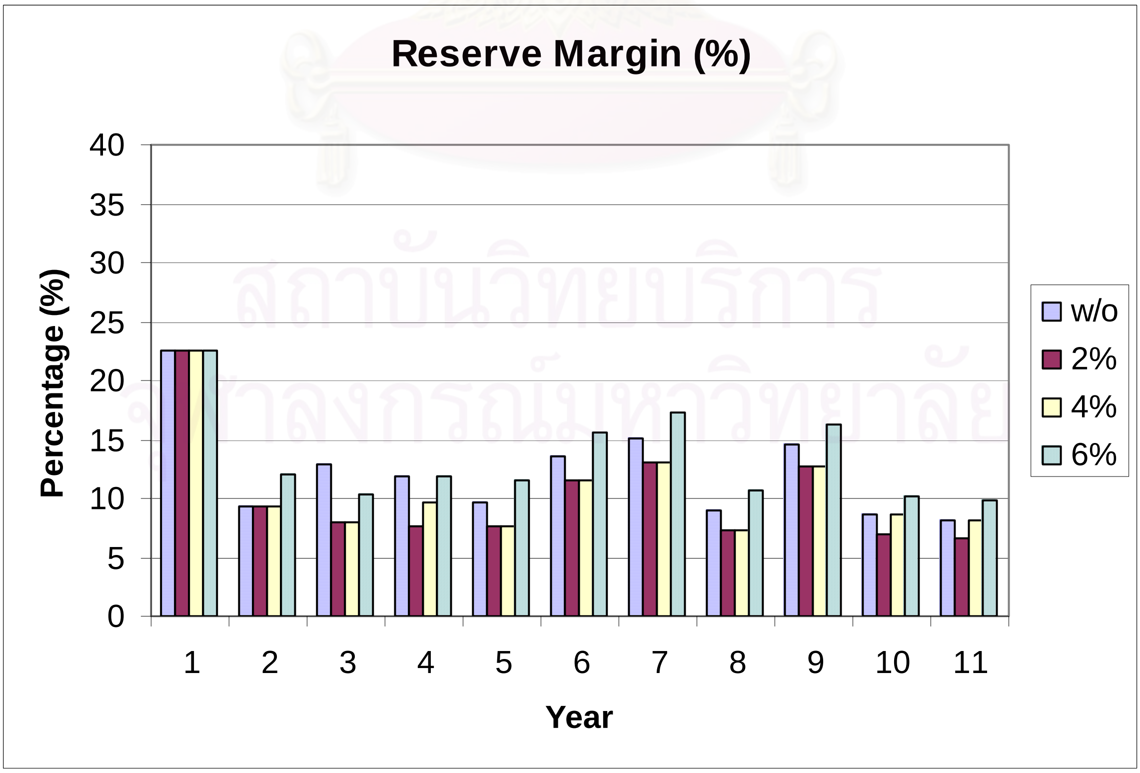
Planning criteria =2day/yr, added capacity = 300MW

Normal density function (NM)



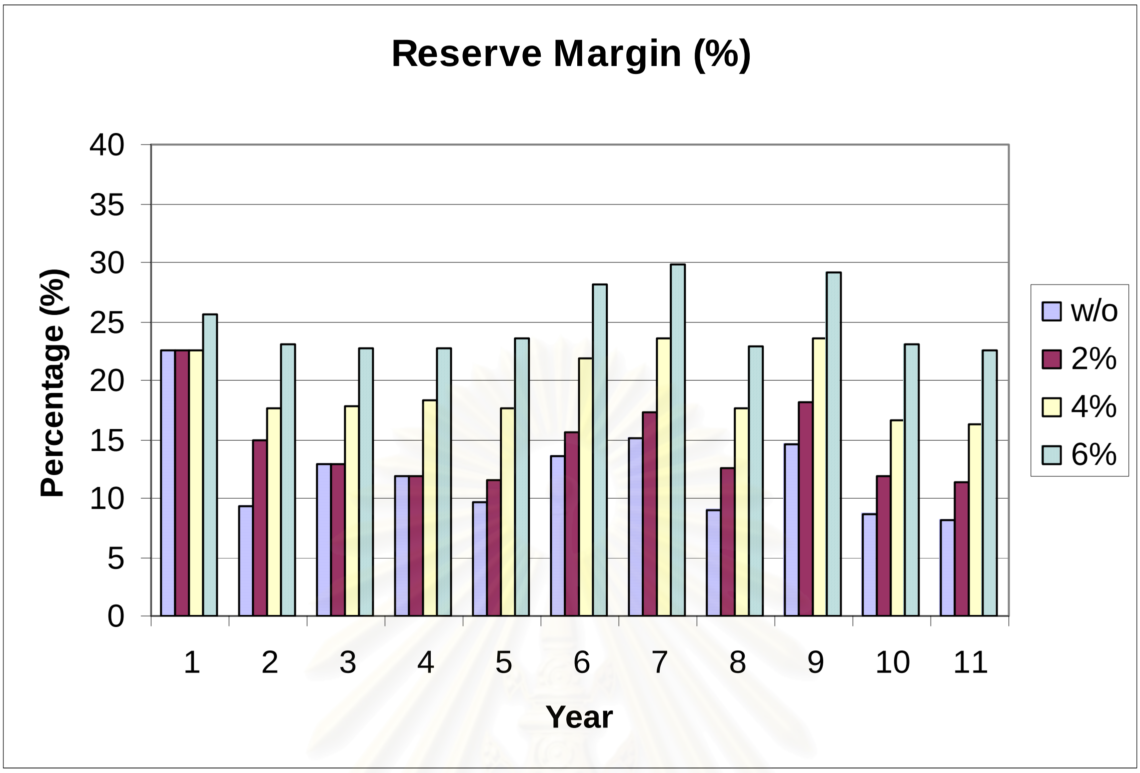
FigB.13 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigB.14 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigB.15 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

* Average (2-11) year

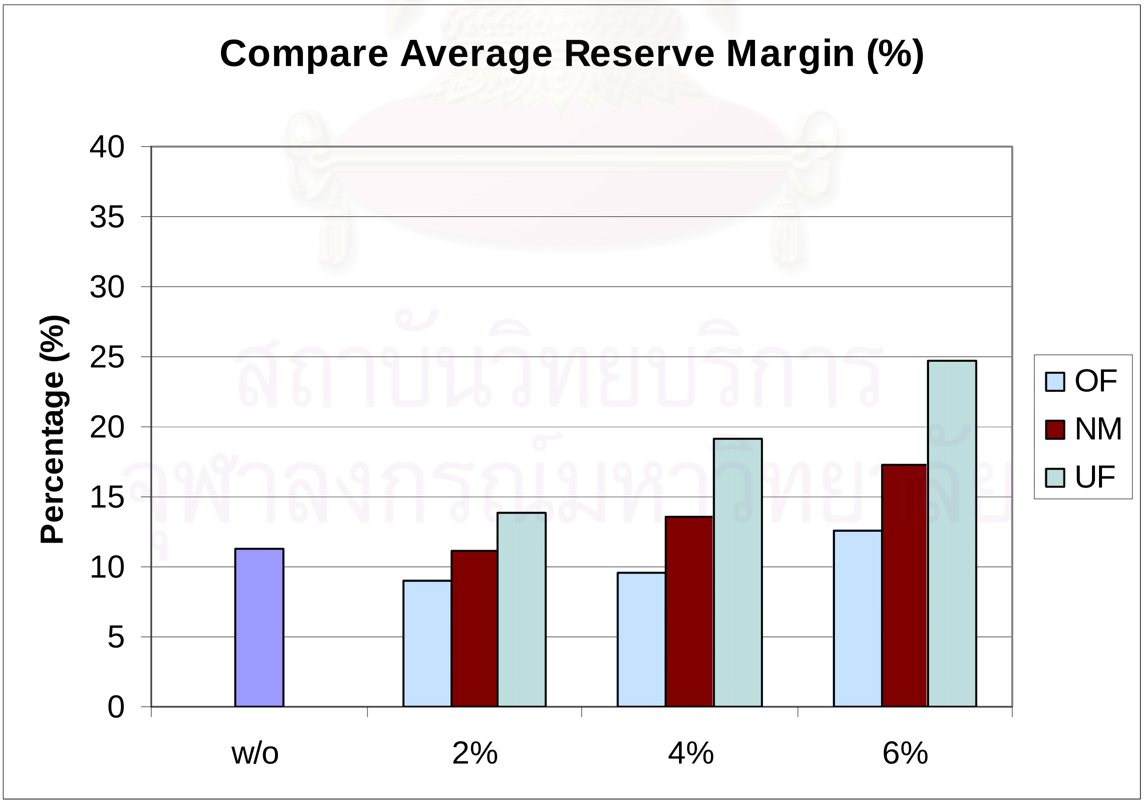
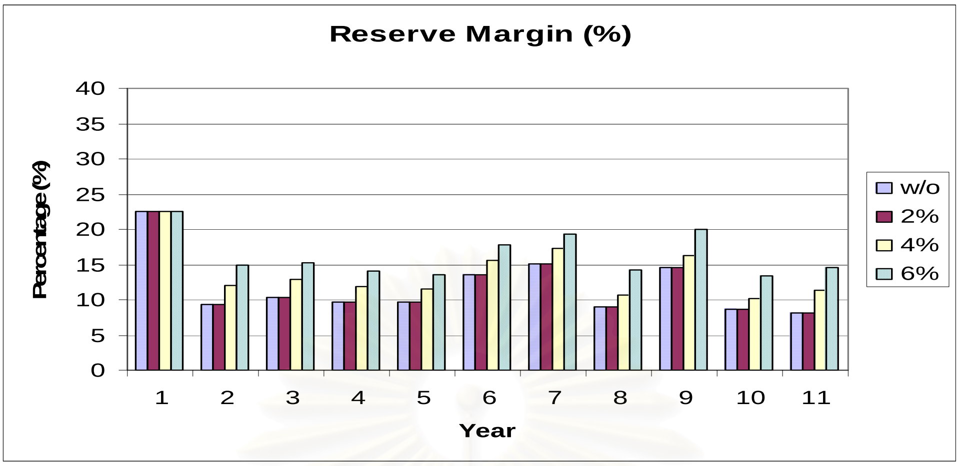


Fig B.16 Compare average percentage reserve margin with without and three uncertainty models

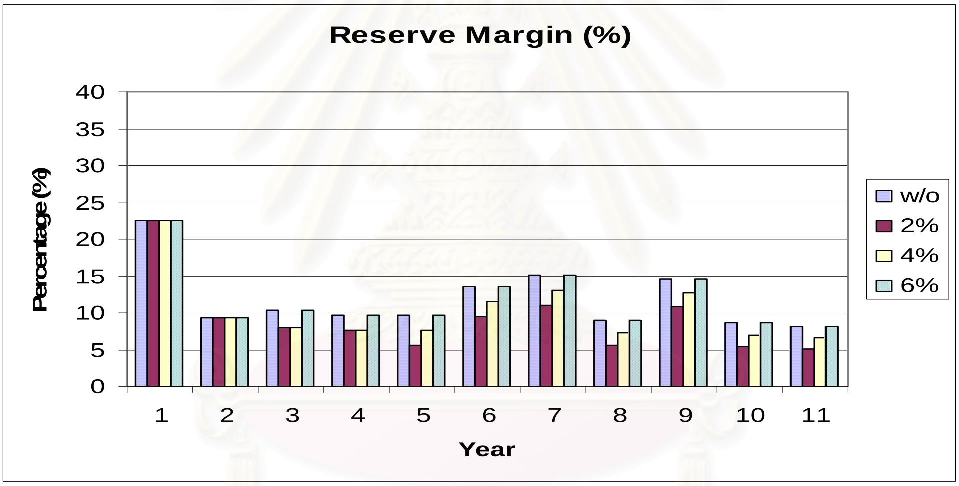
Planning criteria =3day/yr, added capacity = 300MW

Normal density function (NM)



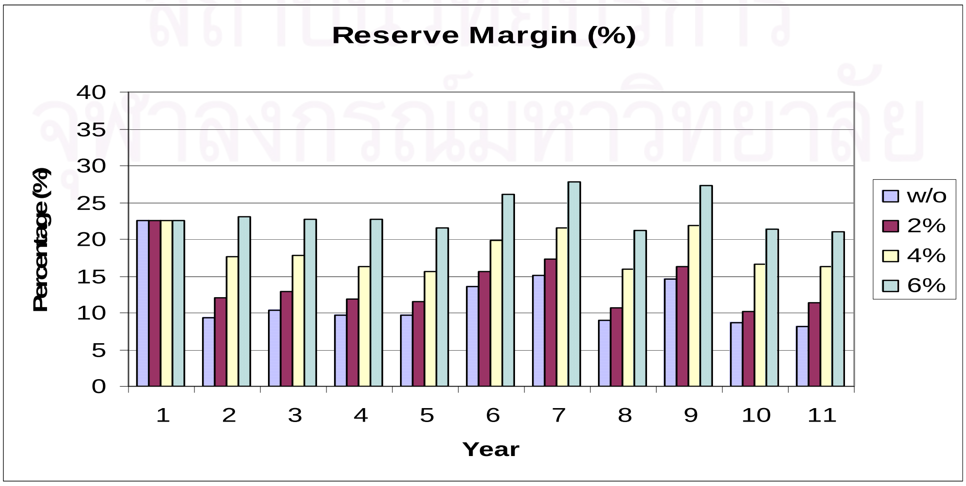
FigB.17 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigB.18 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigB.19 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

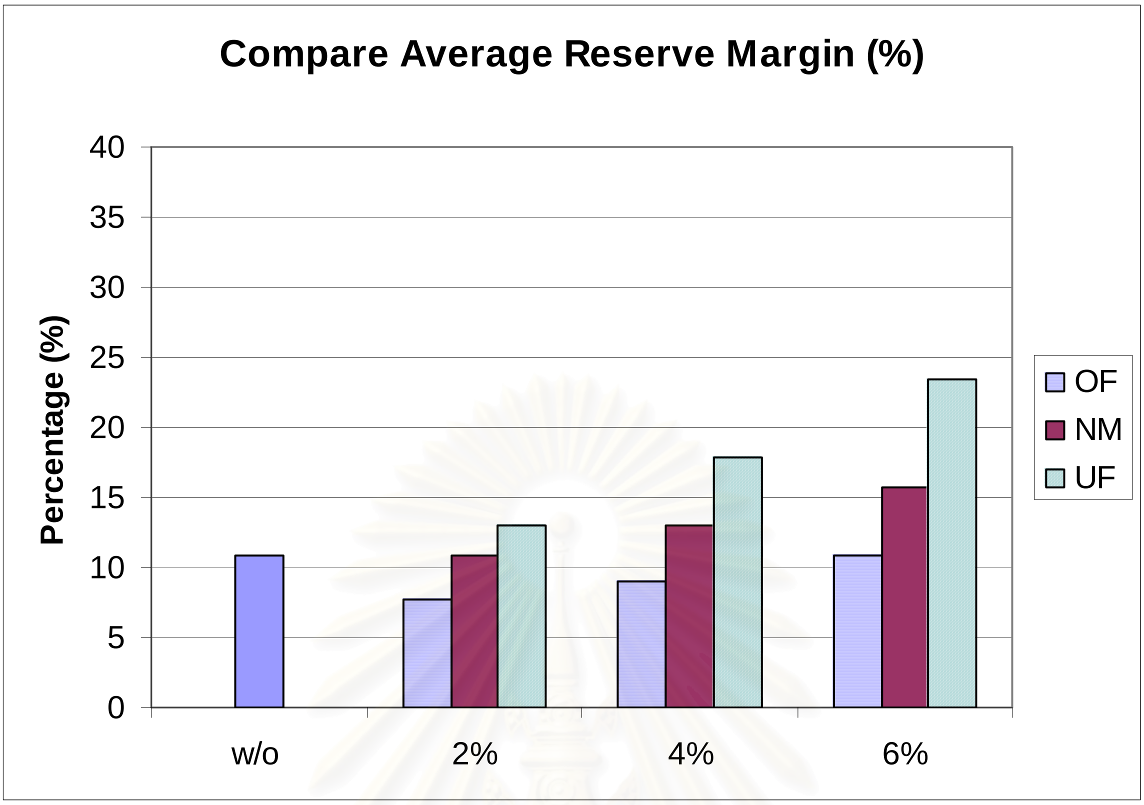


Fig B.20 Compare average percentage reserve margin with without and three uncertainty models

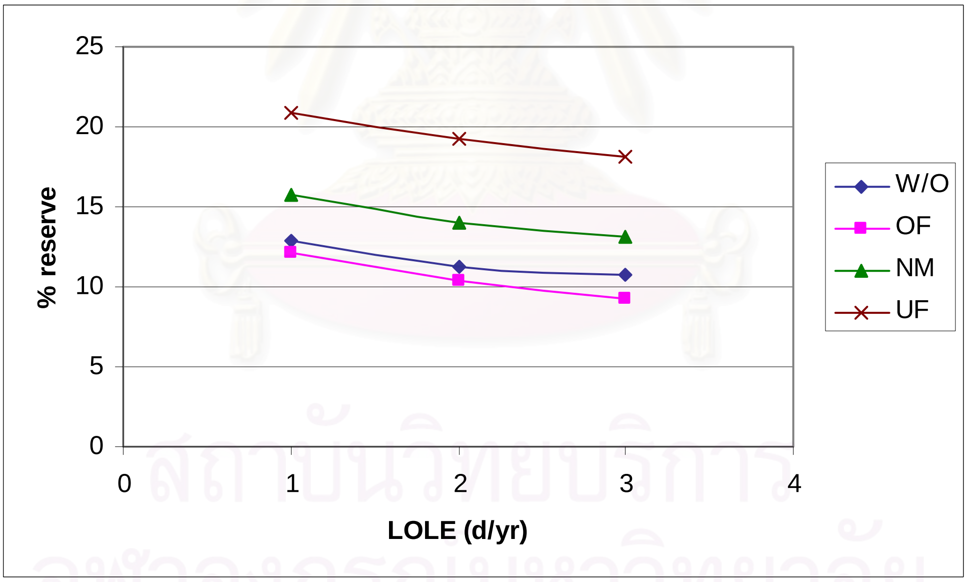


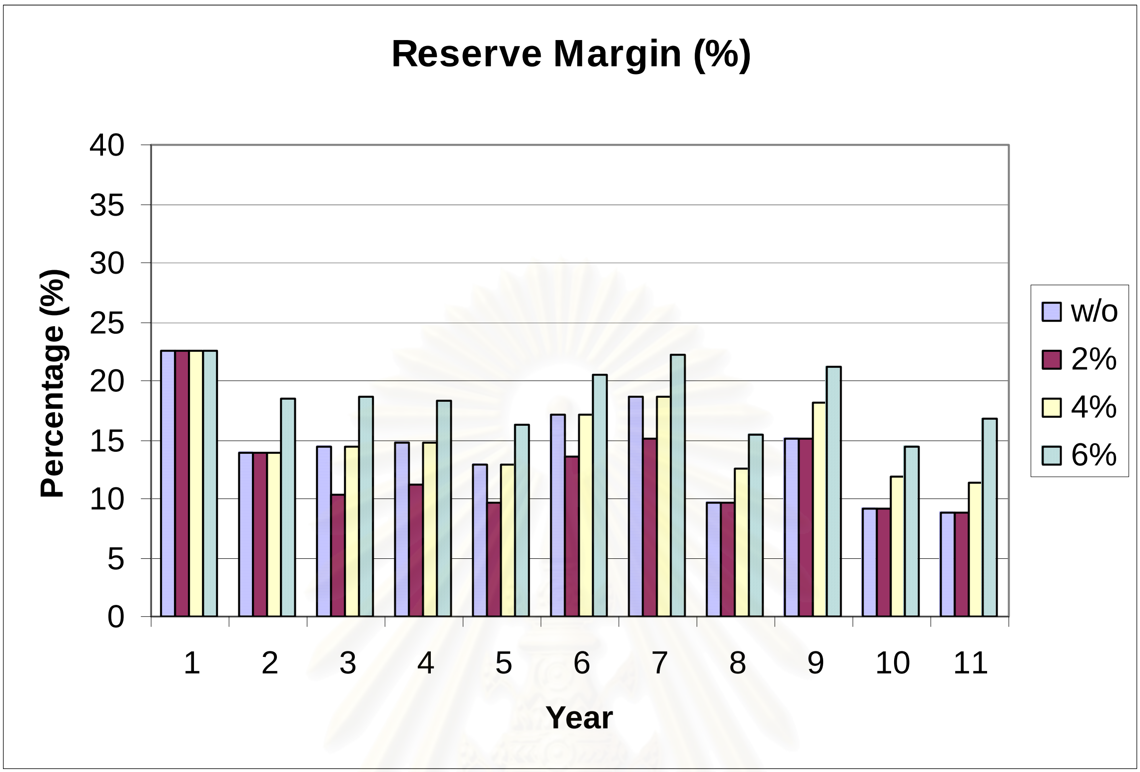
Fig B.21Average reserve margin (%) of without and uncertainty models with different risk criteria

Table B.1 Compare average reserve (%) with different risk criteria

Average Reserve (%)				
LOLE (day/year)	(Without)	Over forecast uncertainty	Normal distribution uncertainty	Under forecast uncertainty
1	12.8	12.1	15.7	20.8
2	11.2	10.4	13.9	19.2
3	10.8	9.2	13.1	18.1

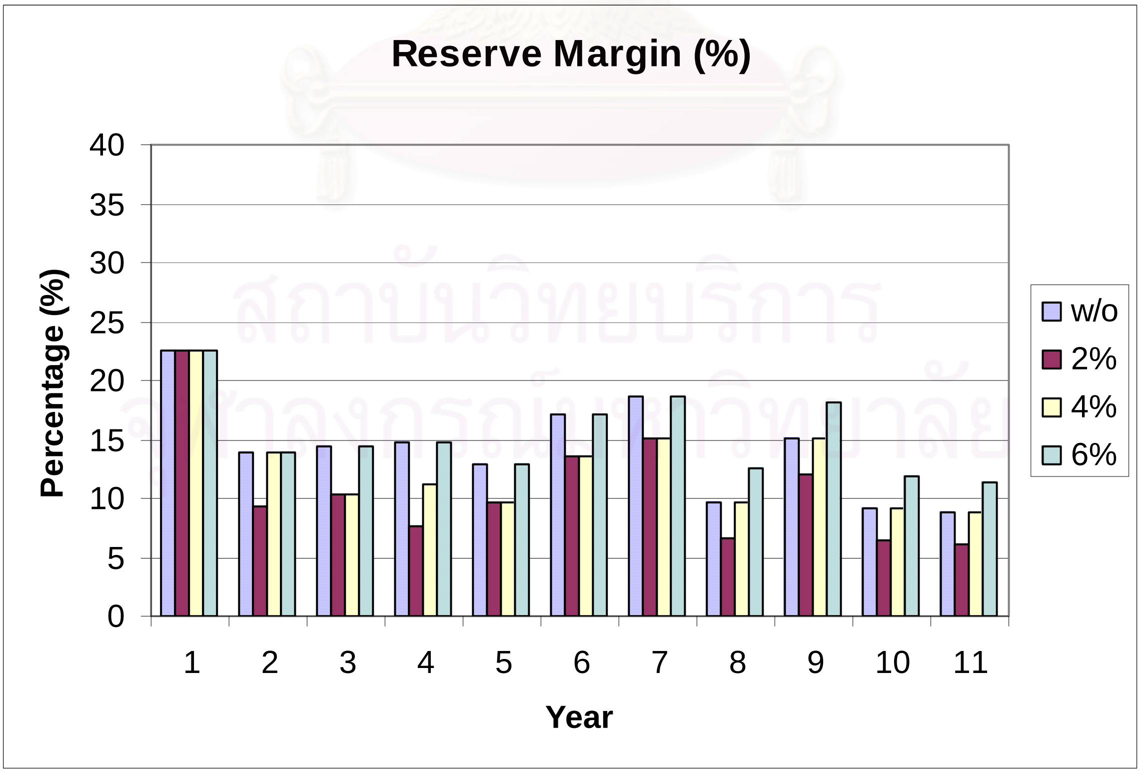
Planning criteria =1day/yr, added capacity = 500MW

Normal density function (NM)



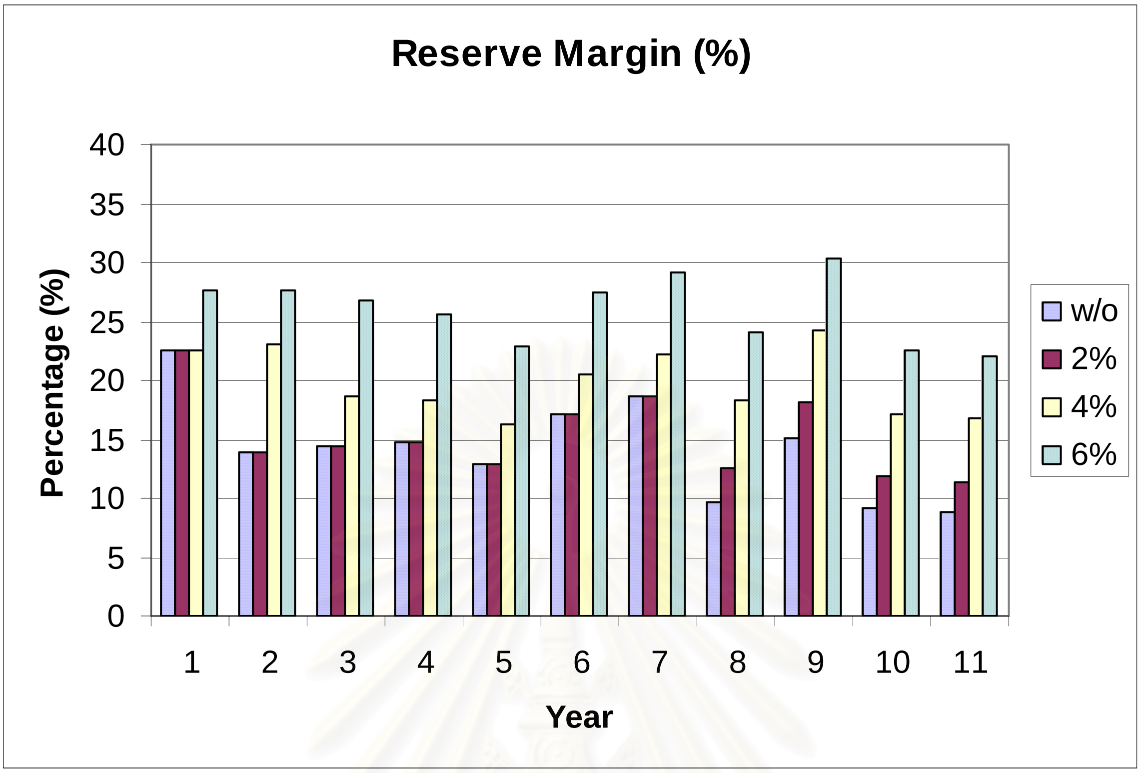
FigB.22 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigB.23 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigB.24 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

Average (2-11) year

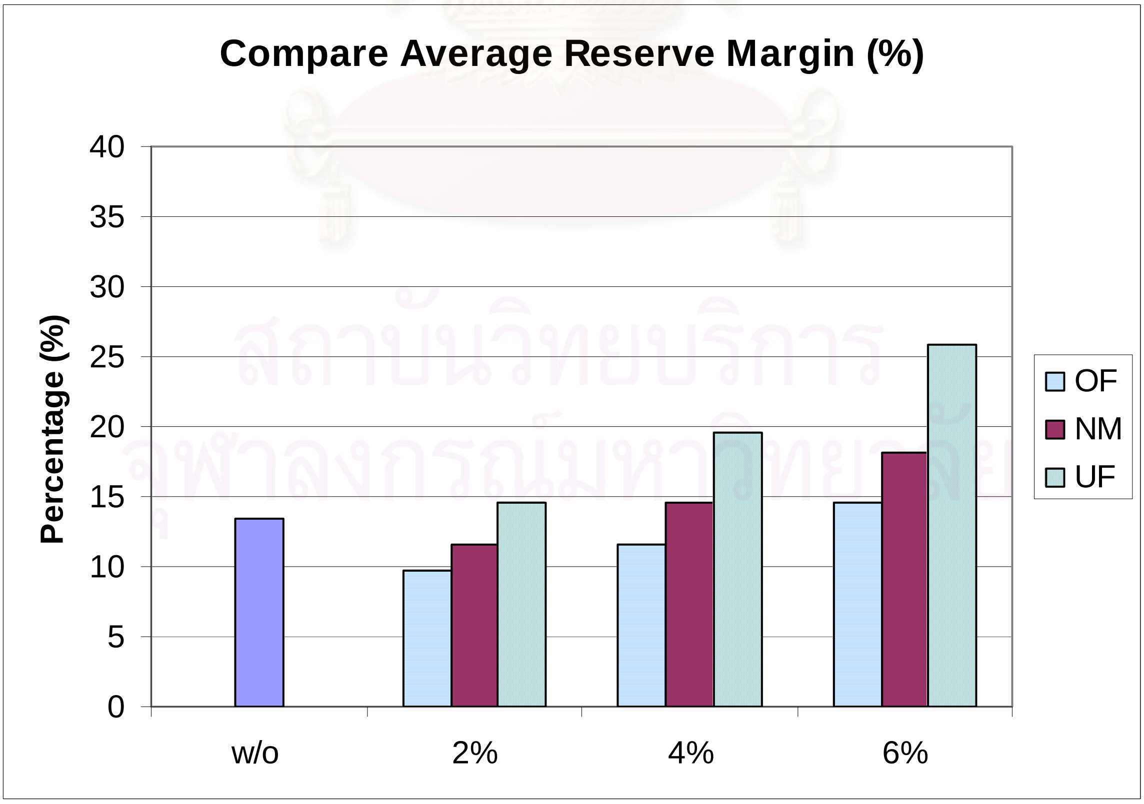
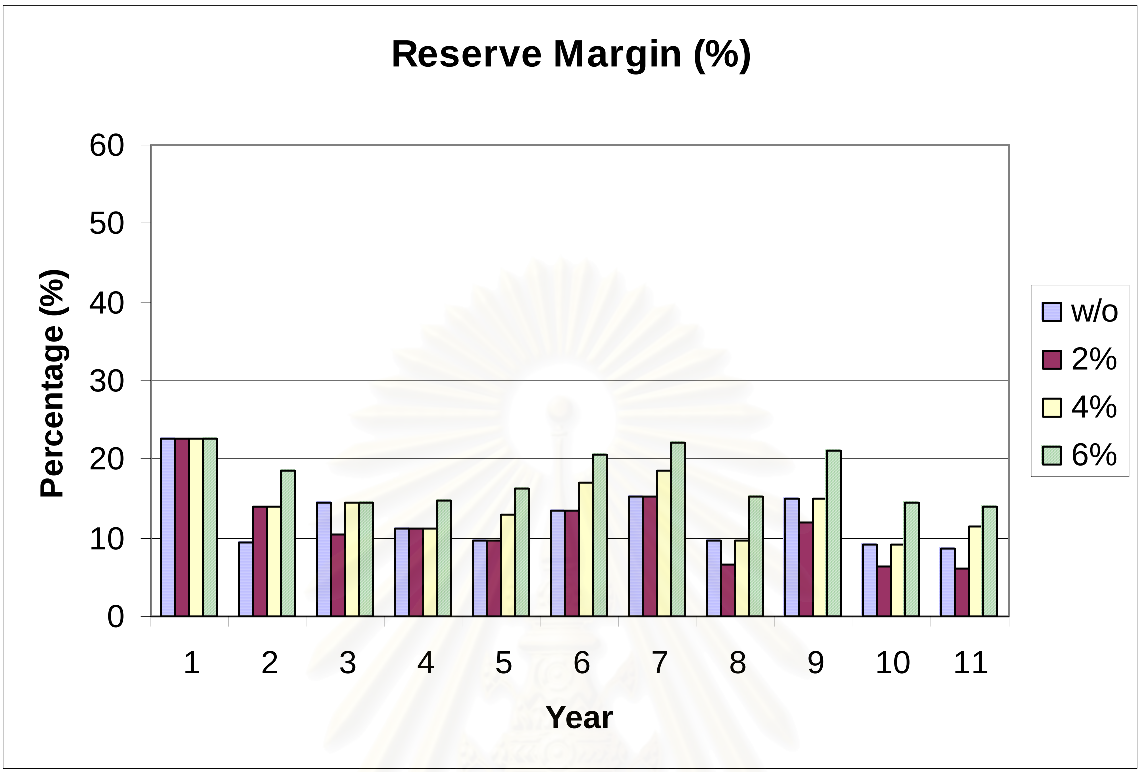


Fig B.25 Compare average percentage reserve margin with without and three uncertainty models

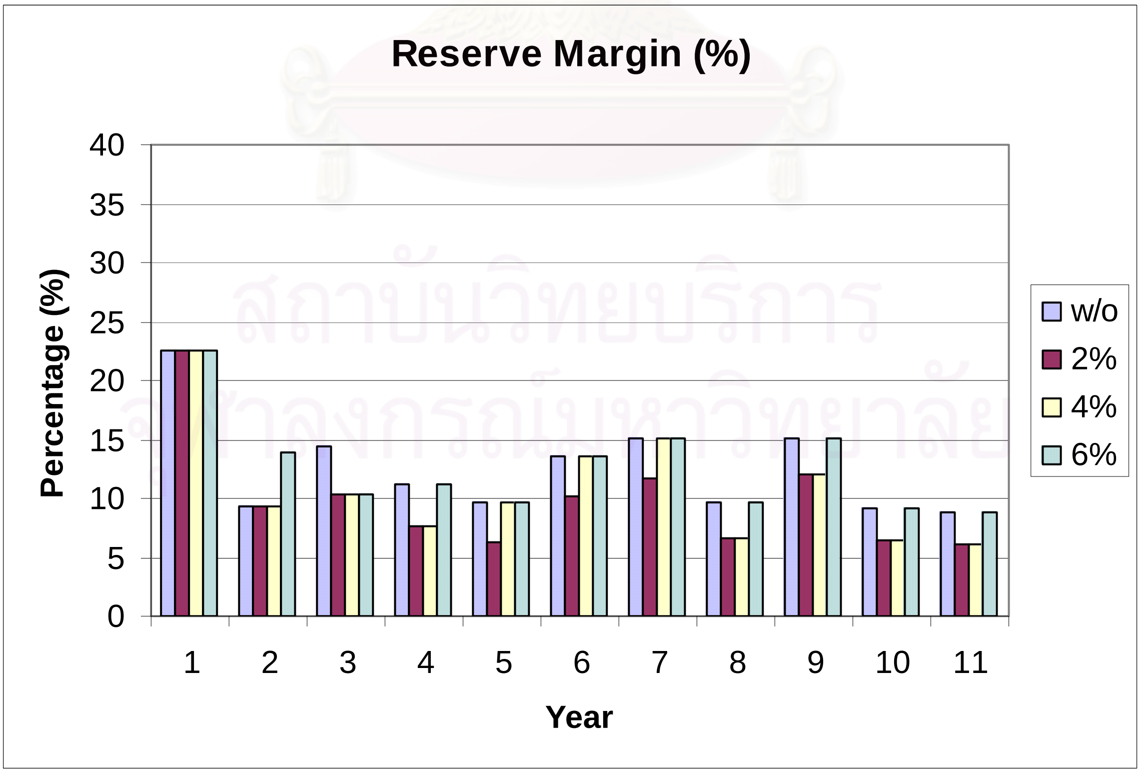
Planning criteria =2day/yr, added capacity = 500MW

Normal density function (NM)



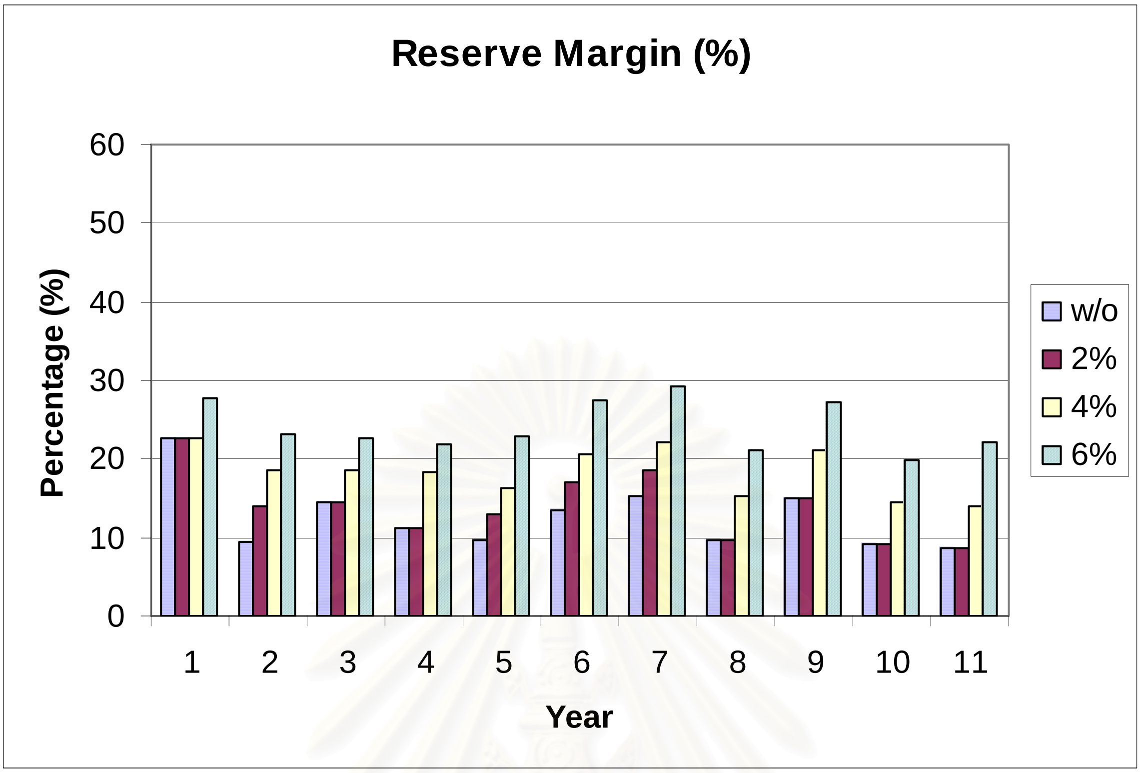
FigB.26 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigB.27 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigB.28 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

Average (2-11) year

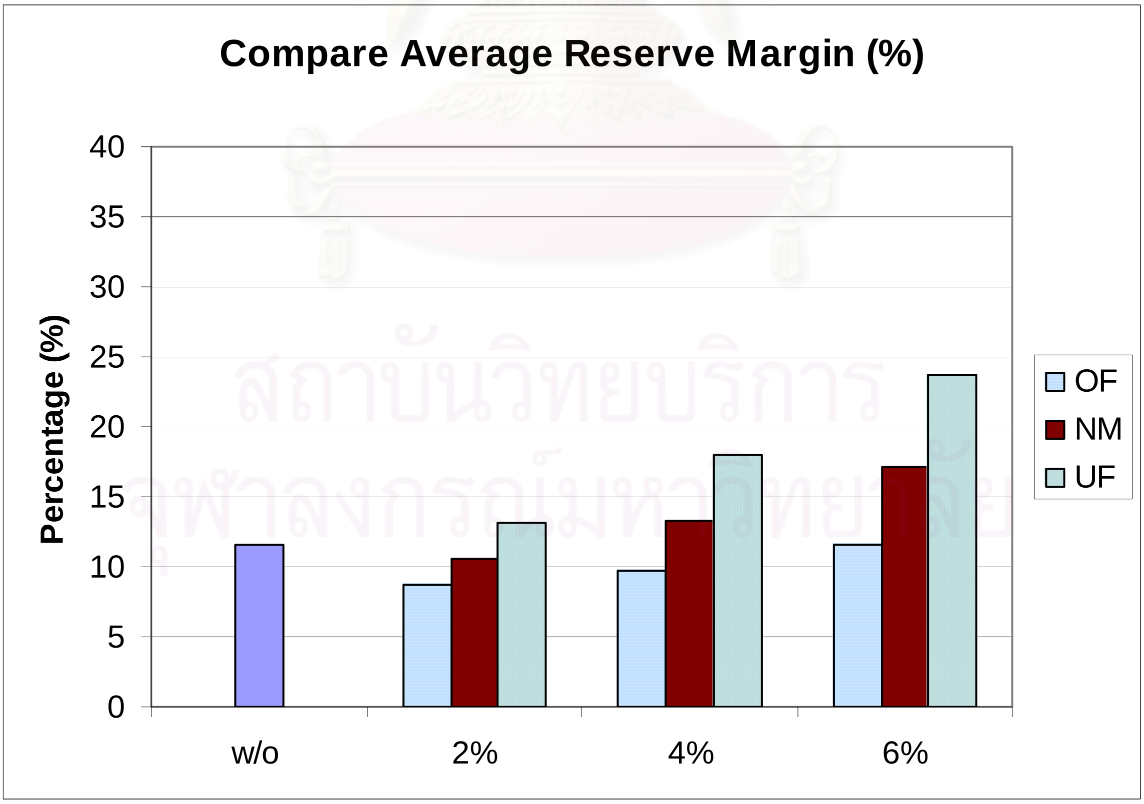
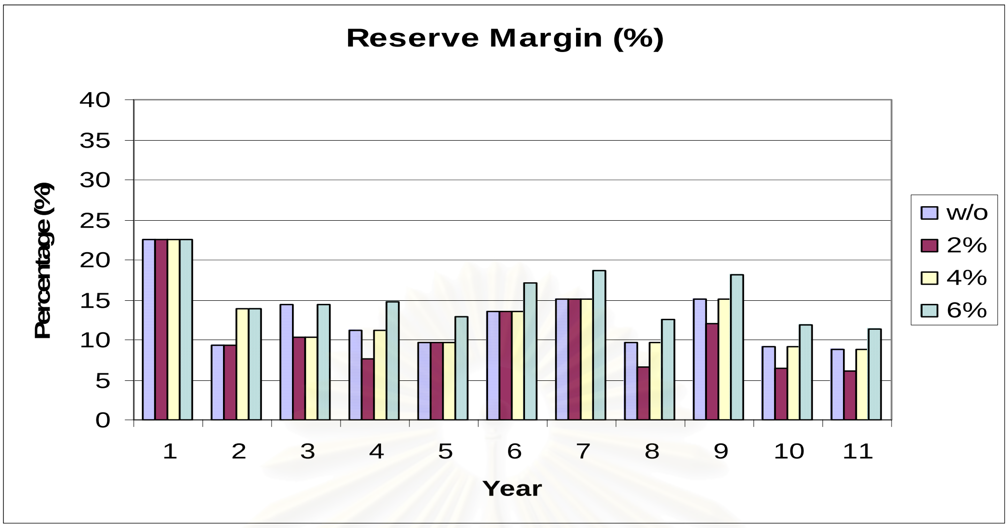


Fig B.29 Compare average percentage reserve margin with without and three uncertainty models

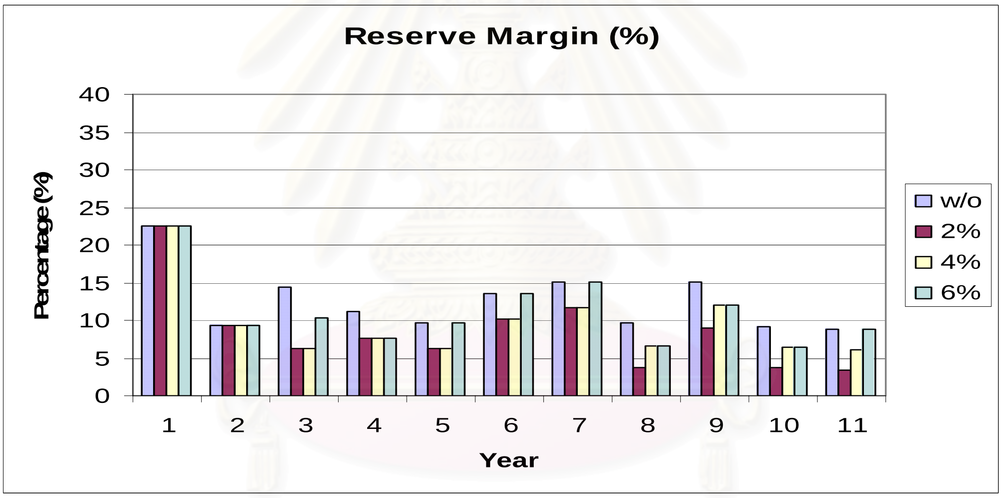
Planning criteria =3day/yr, added capacity = 500MW

Normal density function (NM)



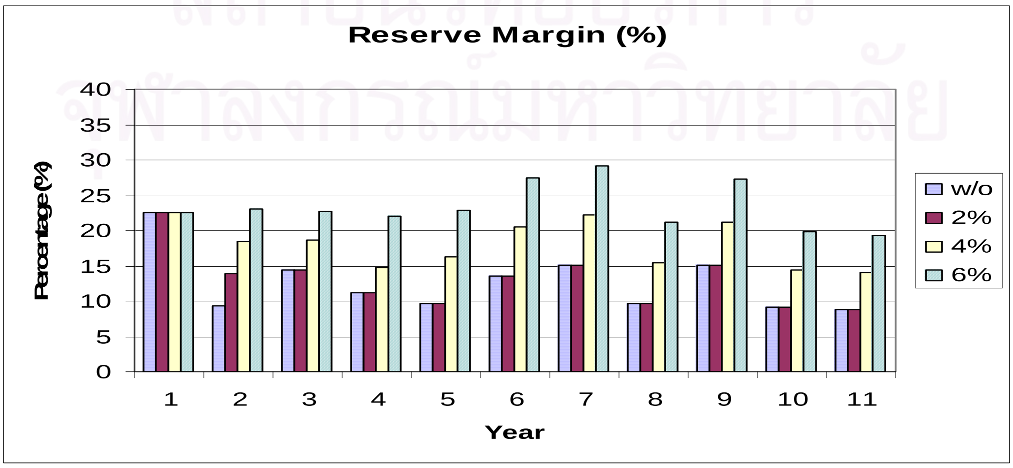
FigB.30 Compare percentage reserve margin with without, and NM (2%, 4%, 6%) uncertainty

Over forecast (OF)



FigB.31 Compare percentage reserve margin with without, and OF (2%, 4%, 6%) uncertainty

Under forecast (UF)



FigB.32 Compare percentage reserve margin with without, and UF (2%, 4%, 6%) uncertainty

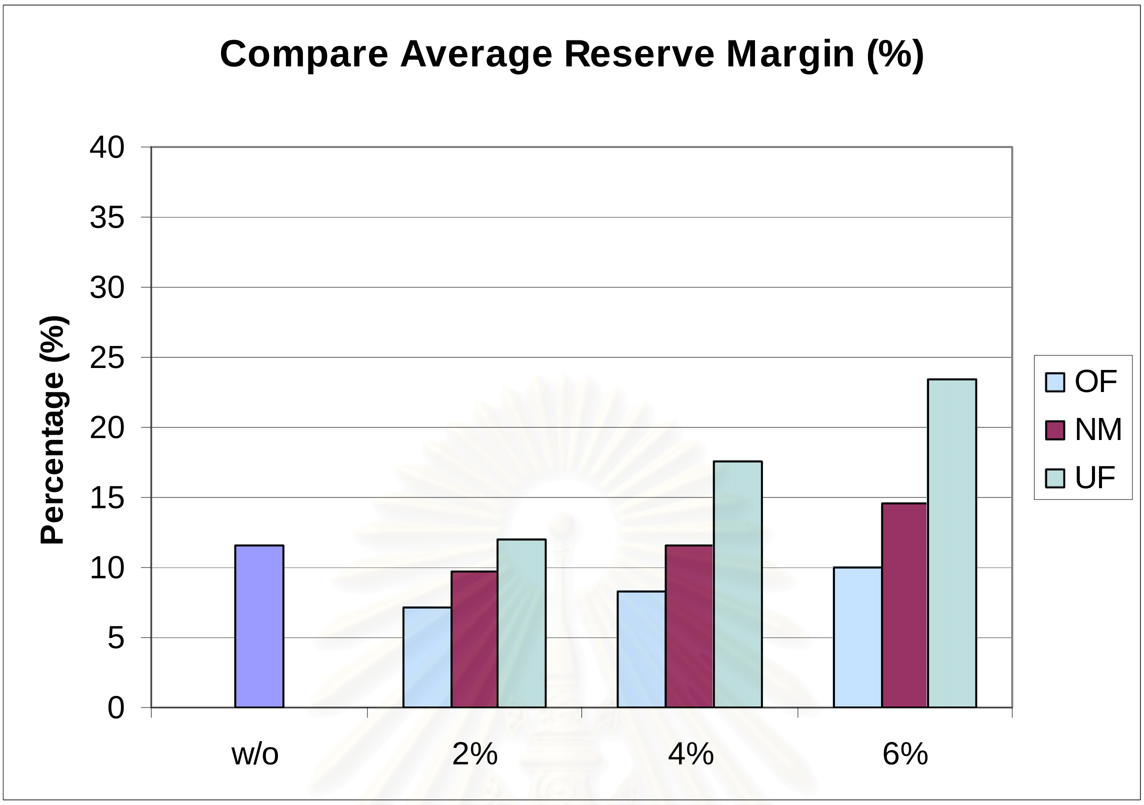


Fig B.33 Compare average percentage reserve margin with without and three uncertainty models

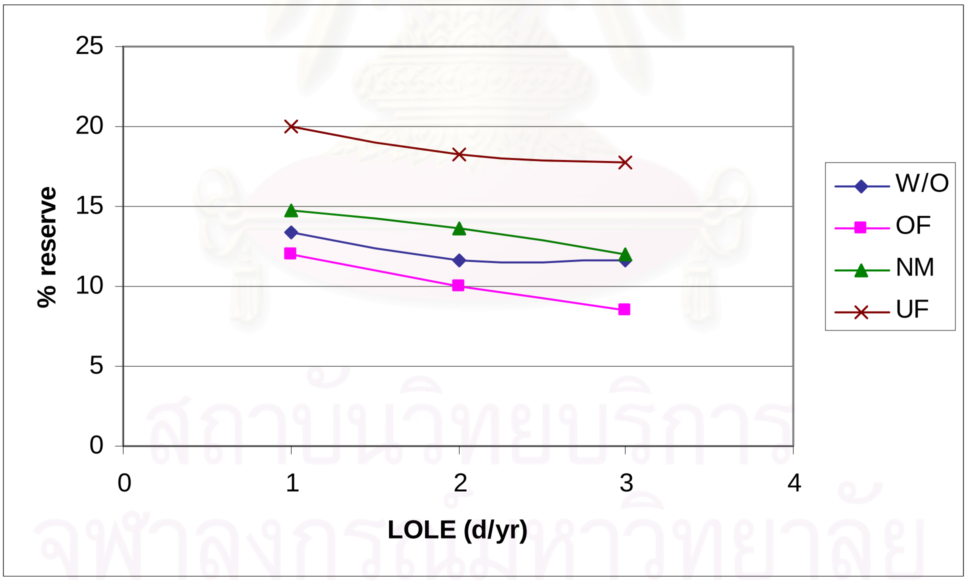


Fig B.34 Average reserve margin (%) of without and uncertainty models with different risk criteria

Table B.2 Compare average reserve (%) with different risk criteria

	Average Reserve (%)			
LOLE (day/year)	(Without)	Over forecast uncertainty	Normal distribution uncertainty	Under forecast uncertainty
1	13.4	11.9	14.8	19.9
2	11.5	9.9	13.6	18.2
3	11.5	8.4	11.9	17.7

Biography

Htet Zarni Kyaw was born in Phyu, Myanmar in 1980. In 2002, she received her Bachelor of Engineering (B.E) degree from the Mandalay Technological University (MTU), Myanmar. At present she is a government service under Ministry of Science and Technology. Her research interest includes the area under power system operation and planning.