CHAPTER III
SHORT-TERM OPERATING STRATEGY BASED ON DETERMINISTIC CRITERION

3.1 Introduction

One of the objectives in short-term operation of vertically integrated utilities is how to schedule generation to meet all of the forecasted demand over the considered time horizon with minimum operating cost. The system operator has responsibility to seek the best operating strategy which satisfies the prevailing constraints, e.g. power and spinning reserve balance, minimum and maximum generation unit constraints, transmission limit, ramp-rate constraint, fuel constraint, and minimum up and down time limits. The problem becomes much more complicated since, in the actual planning problem, the operator also faces the system uncertainty caused by demand forecast error and generating unit unavailability [79].

Several approaches have been used to solve the unit commitment (UC) optimization problem, e.g. priority ordering [59], dynamic programming [60], Lagrange Relaxation (LR) [49], [80], mixed-integer linear programming (MILP) [63], [64] evolutionary programming [81], combination of LR and evolutionary programming [82] and simulated annealing [83], [45]. Detailed survey on unit commitment problems can be found in [26]. Among the developed unit commitment methods, one of the most popular methods is based on LR technique, which has many advantages on the others, e.g. the ability to solve large scale UC problem, ease of incorporating various constraints, and fast computation time [28]. However, LR method has main disadvantage due to the non-convexity of the UC problem hence it needs heuristic procedure to find the feasible solution which may be suboptimal. Meanwhile, the MILP has ability to guarantee the optimal convergence solution of the problem. The most successful method to solve MILP problem are branch-and-bound and cutting plane algorithm [51]. In the early development, a key drawback of the MILP algorithm was its high computation time and memory requirement. In recent years, efficient MILP software having ability to cope with large-scale UC problems have been developed and commercialized [75].

In generation scheduling, spinning reserve strategy has considerable impact on the operating cost. The reserve capacity is generally scheduled to account for load forecast uncertainty and possible outage of generating units. The spinning reserve requirement set in most UC solving methodology is based on deterministic criteria e.g. a fraction of demand, largest generator/line contingency or maximum on-line generator during a dispatch period. A probabilistic reserve criterion, even though is more complicated, can be applied to obtain a proper schedule of the spinning reserve capacity to meet acceptable risk, e.g. Expected Unserved Energy-EUE, unit commitment risk, etc. The level of risk index is usually specified by system operator based. Another key factor having the significant impact on the UC decision is the load uncertainty. This uncertainty is embedded in the load forecast error due to two basic reasons i.e. inherent error in weather forecast, and inability to exactly predict load from the available information [79]. Impact of the weather temperature forecast uncertainty on the load forecast results has been investigated using Bayesian Load Forecasting method [22]. A simple way to represent the load uncertainty is using load forecast distribution and variance.

Many approaches in the previous works dealt with the techniques based on scenario analysis [40], [22] to solve the load uncertainty embedded on the UC problem. In the scenario analysis method, the uncertainty the future demand is modeled by a number of deterministic sub-problems [41]. In the other related paper [22], this method is also called decision tree analysis, which concludes that load uncertainty imposes additional risk on short-term planning, thereby increases Expected Cost of Uncertainty (ECOU). However all the mentioned papers did not take into account the cost of uncertainty resulting from generating unit unavailability.

3.2 Problem Formulation

3.2.1 UC Problem in the Vertically Integrated Utility

Unit commitment problem in vertically integrated system can be formulated as minimization of operation cost over the schedule time horizon by considering the prevailing constraints. This formulation has been presented in Chapter 2 subsection 2.2. Spinning reserve requirement in (2.4) is set as a percentage of the demand.

3.2.2 Load Uncertainty Model

Load uncertainty, in general, results from forecast error. Consequently it is embedded in power system planning problems. In short-term operation, if the actual demand is lower than the forecasted value, some unit may be unnecessary committed thereby resulting in higher operating cost than necessary. In contrast, if the actual demand is higher than the forecasted value, insufficient resources may be scheduled to meet reliability requirement.

Load uncertainty can be determined, based on historical forecasting performance, by a probability distribution function. In this dissertation a discrete normal distribution comprising three load levels, i.e. low, medium and high, will be used to represent the load uncertainty. Let's assume that the mean value of the forecasted demand at interval time t is $FD(t)$ with standard deviation of $\sigma (t)$. In general, the longer lead time we consider, the higher uncertainty will be implicitly embedded in the forecasted value [79], [53]. Suppose that the predefined standard deviations of the first and last hours of the study horizon are denoted by $\sigma(1)$ and $\sigma(T)$ respectively. The discrete normal distribution function of demand uncertainty is depicted in Figure 3.1.

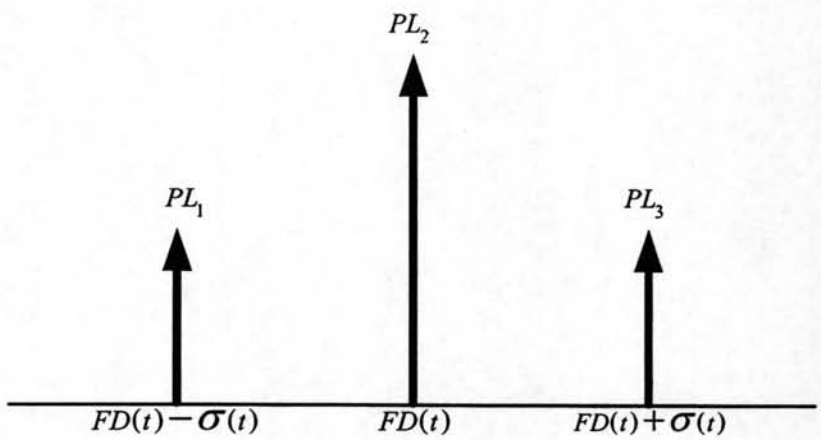


Figure 3.1 Discrete normal distribution function of forecasted demand

With the assumption that the standard deviation increases linearly with the considered lead time, the standard deviation in each considered hour, i.e. the first to the last, can be approximated by

$$\sigma(t) = \sigma(1) + \frac{\sigma(T) - \sigma(1)}{T-1}(t-1), \quad \forall t \in [1,T] \quad (3.1)$$

Based on (3.1), the demand at low, medium, and high levels can be generated as described by

$$\begin{aligned} D^{t}_{LL} &= FD(t) - \sigma(t)FD(t), \\ D^{t}_{ML} &= FD(t), \qquad \forall\, t \in [1,T] \quad (3.2) \\ D^{t}_{HL} &= FD(t) + \sigma(t)FD(t), \end{aligned}$$

All the three discrete loads shown in , i.e. *FD(t)-σ(t)FD(t)*, *FD(t)*, and *FD(t)+ σ(t)FD(t)*, will be considered as low, medium, and high load in a UC consideration. To represent the possibility of its occurrence in the future, each load level is assigned with a weight of, *PL*. The occurrence probability of the demand at low, medium, and high levels is denoted by PL_1, PL_2, PL_3 respectively.

3.2.3 Generating Unit Unavailability Model

Any generating units may be forced out during operation. In this dissertation a two-state Markov model as shown in Figure 3.2 is used to estimate its unavailability. A more detailed model [32] may be used if utilities have collected unit's data accordingly.

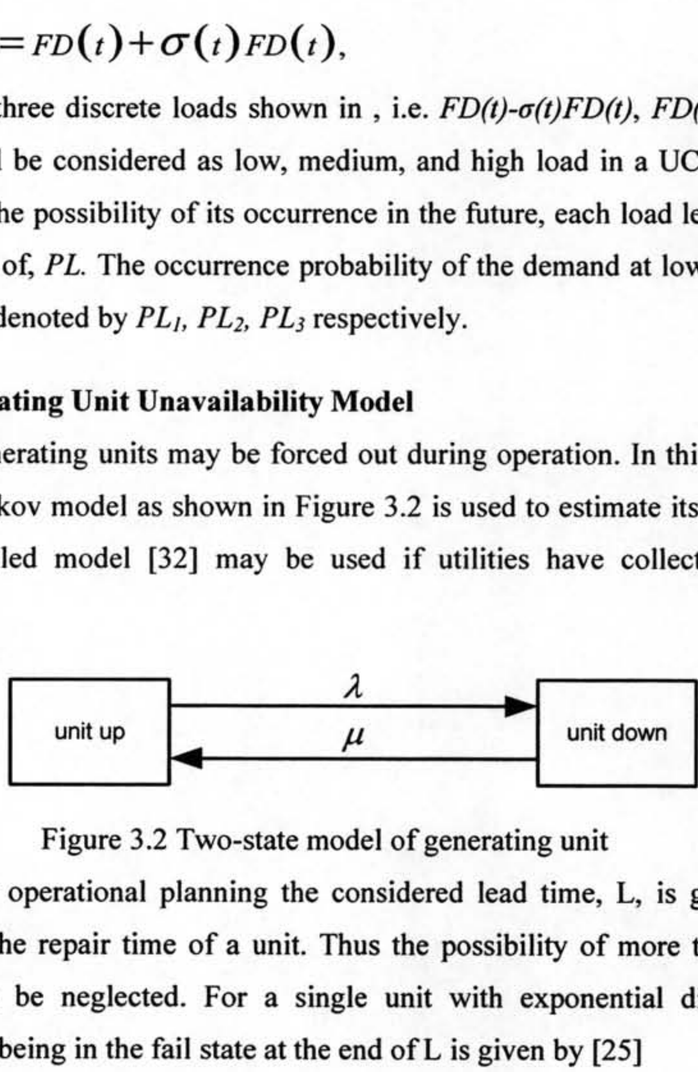


Figure 3.2 Two-state model of generating unit

In daily operational planning the considered lead time, L, is generally much smaller than the repair time of a unit. Thus the possibility of more than one repair during L can be neglected. For a single unit with exponential distribution, the probability of being in the fail state at the end of L is given by [25]

$$\text{P[unit down at L]} \approx \text{P}[t_{up} \le L] = 1 - e^{-\lambda L} \quad (3.3)$$

where t_{up} is the up-time and λ is the failure rate of the unit. If $\lambda L << 1$, then

$$\text{P[unit down at L]} \approx \lambda L \quad (3.4)$$

The product λL is called the Outage Replacement Rate (ORR) of the considered unit. The ORR of specificed unit at a specified lead time can be expressed as

$$ORR(i,t) = \lambda_i L \text{ .... } (3.5)$$

where *ORR (i,t)* is outage replacement rate of unit *i*, λ_i is the expected failure rate of unit *i*, and *L* is the considered lead time of unit *i*.

3.3 Methodology

3.3.1 Operating Strategy Determination

The objective of this chapter is to find the best operating strategy and it's associated expected total cost by considering demand uncertainty and generating unit unavailability. The uncertainty on the supply side is considered via generating unit's ORR, whereas the demand will be considered through the forecast error distribution function. The demand uncertainty will be accomplished using the concept of decision analysis. The basic form of decision analysis method for solving short-term generation scheduling problem for a specific spinning reserve requirement is shown in Figure 2.4.

Given a set of forecasted demand for the next 24 hours, i.e. considered as the lead time, the aim of this chapter is to analyze the impact of system uncertainty on the associated total cost under vertically integrated utility structure. The total cost is composed of generation cost and risk cost. The impact will be evaluated using various spinning reserve (SR) strategies, defined based on a deterministic criteria. In this work, we will consider three SR strategies, i.e. low, medium, and high. From a given forecasted load data, it is assumed that there is a certain error around each forecasted value which can be represented by a three-discrete distribution function, denoted as low load (LL), medium load (ML), and high load (HL).

The scenarios take into account the combination of all possible loads and spinning reserve strategies, which are shown in Table 3.1. Since three spinning reserve strategies and three possible load levels are considered, there are nine possible scenarios. For each scenario, the UC has to be determined to obtain generation cost (GC) and risk cost (RC) as shown in the decision tree of Figure 3.3. For each scenario, the optimal UC decision is determined using a developed program based on MILP method [64]. With the obtained UC decision, economic dispatch calculation is done for each load level to calculate its relevant generation cost (GC). With the same number of committed units under each UC decision, the expected unserved energy for each interval can also be calculated to obtain risk cost (RC), shown on the right hand side of Figure 3.4. The expected total cost of each UC decision can be obtained by adding up both of the generation cost and risk cost and then weighted by each load level probability. With various spinning reserve strategy, the best scenario which results in the minimum total cost will be selected. The detail flowchart of this proposed method is shown in Figure 3.4.

Table 3.1 The verified scenarios for deterministic criterion

SR strategy	Load level	UC decision	Scenario#
Low (SR_L)	Low (LL)	UC (SR_L,LL)	1
	Medium (ML)	UC (SR_L,ML)	2
	High (HL)	UC (SR_L,HL)	3
Medium (SR_M)	Low (LL)	UC(SR_M,LL)	4
	Medium (ML)	UC(SR_M,ML)	5
	High (HL)	UC(SR_M,HL)	6
High (SR_H)	Low (LL)	UC(SR_H,LL)	7
	Medium (ML)	UC(SR_H,ML)	8
	High (HL)	UC(SR_H,HL)	9

For simplicity, the created scenarios are indexed as shown in last column of Table 3.1, meanwhile the sequence of the considered load level, i.e. LL, ML, and HL, is indexed as j=1, 2, and 3 respectively. Then, the associated generation cost and risk cost as shown in the last column of Figure 3.3 are symbolized as GC_{jk} and RC_{jk} respectively.

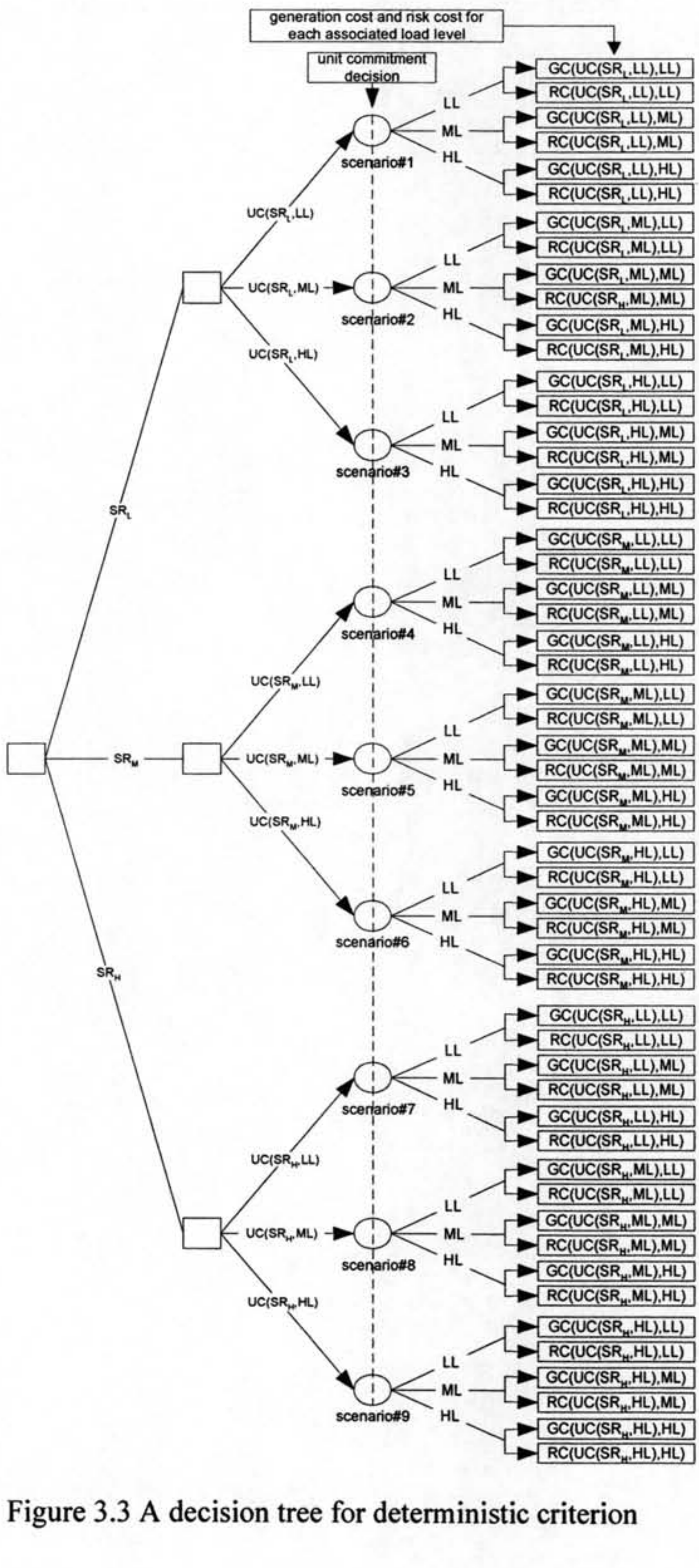


Figure 3.3 A decision tree for deterministic criterion

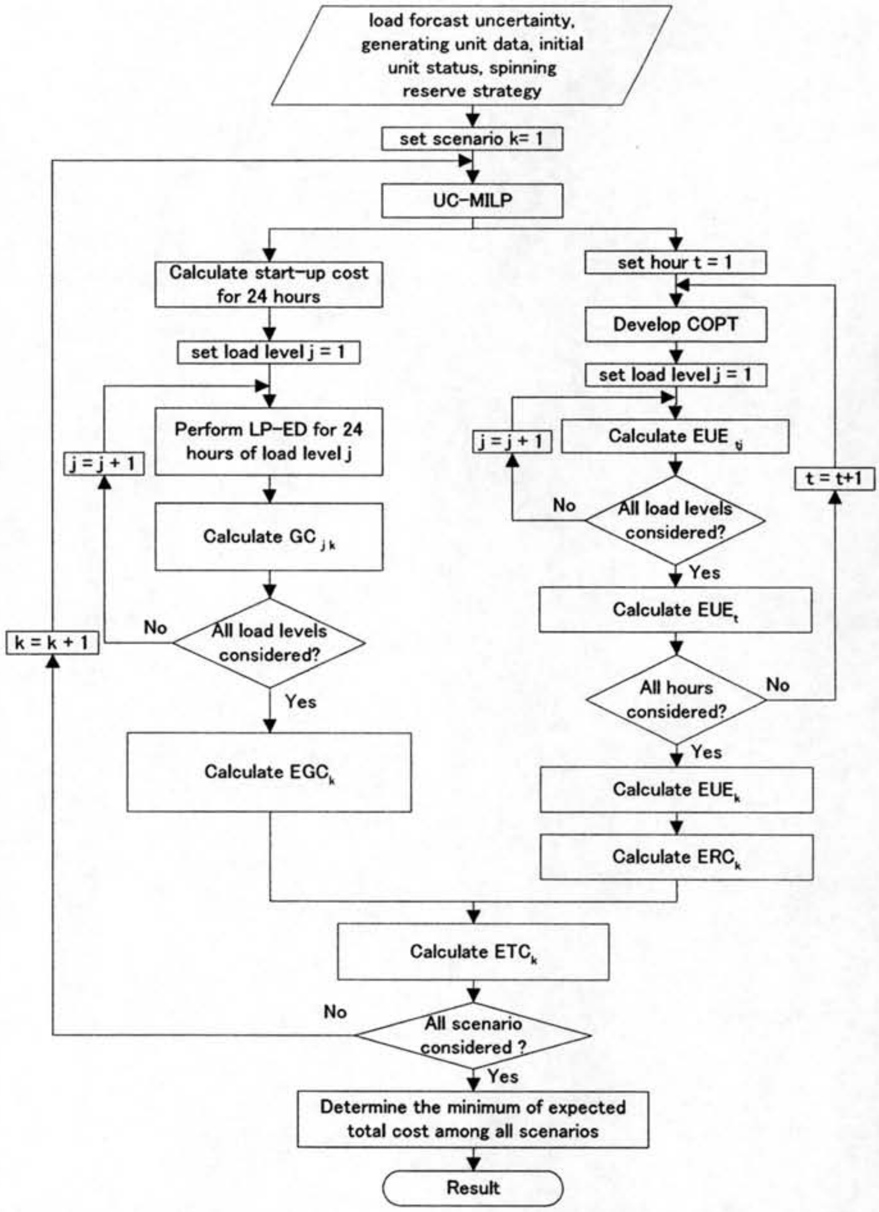


Figure 3.4 Flowchart of the proposed method based on deterministic criterion

3.3.2 Expected Generation Cost Calculation

Once a scenario is generated with a specified load demand and associated spinning reserve requirement, then these data is used as input to determine the UC decision. A mixed-integer linear programming (MILP) method is utilized to solve the conventional UC problem, called as UC-MILP module. In order to meet with the requirement of the MILP method, the UC problem is linearized as proposed in [64]. The objective function formulation is to minimize the generation cost as stated in (2).

Once the UC decision is generated from the UC-MILP module, economic dispatch is conducted to calculate the generation cost.

For a given scenario k at load level j, economic dispatch is calculate based on linear programming method (LP-ED) to obtain the dispatched power and fuel cost of each committed unit. The generation cost for the related load level, denoted by GC_{jk}, can be obtained by adding up the fuel cost and start-up cost from each committed unit. The total expected generation cost of scenario k by taking into account load uncertainty, which denoted by EGC_k, is given by

$$EGC_k = \sum_{j=1}^{3} PL_j GC_{jk} \quad \forall k \in [1,9] \quad (3.6)$$

where PL_j is the occurrence probability of load level j. The flowchart of expected generation cost calculation is shown on the left side of Figure 3.4.

3.3.3 Expected Risk Cost Calculation

Once a UC decision is obtained from the UC-MILP module, this information can be used to calculate the risk cost. The risk cost function is defined by the worth of damage cost on customer side due to electricity shortage. It can be obtained by multiplying the expected unserved energy and the predefined EUE price. The initial step for each time interval is setting up the capacity outage probability table (COPT) [25] based on the ORR of the committed units. Suppose that the number of states in the developed COPT is NS. Each state represents an expected generation outage, the remained in-service capacity CR_s and the probability PR_s corresponding to the state [84]. The EUE for each hour t can be calculated by

$$EUE_{tj} = \sum_{s=1}^{NS} PR_s LOSS_s \left(LOAD_{tj} - CR_s\right) \quad \forall t \in [1,T] \quad (3.7)$$

where $LOSS_s$ is obtained by

$$LOSS_s = \begin{cases} 1, & if\ CR_s < LOAD_{tj} \\ 0, & otherwise \end{cases} \quad (3.8)$$

with all considered load levels, the total EUE for the considered interval or hour is given by

$$EUE_t = \sum_{j=1}^{3} EUE_{tj} PL_j \quad \forall t \in [1,T] \quad (3.9)$$

Therefore the total EUE for the scheduling time horizon of scenario k is given by

$$EUE_k = \sum_{t=1}^{T} EUE_t, \ \forall k \in [1,9] \quad (3.10)$$

Finally, based on the obtained total EUE and the predefined EUE price (\$/MWh), the expected risk cost of scenario k, denoted by ERC_k, can be calculated by

$$ERC_k = EUE_k EUE\_price, \ \ \forall k \in [1,9] \quad (3.11)$$

The expected risk cost calculation is presented on the right side of flowchart in Figure 3.4.

Since the calculation of COPT which involves a large number of units generally requires long computation time, a modified generating unit using efficient round-off model as proposed in [85] is implemented in this work. The further reduction of computation time requirement can be achieved by omitting the outage levels for which the cumulative probability is less than a predefined limit, e.g., 10^{-7}.

3.3.4 Expected Total Cost Calculation

As explained in the previous section, we can obtain the expected total cost, of scenario k, called ETC_k, as shown in (3.12).

$$ETC_k = EGC_k + ERC_k, \forall k \in [1,9] \quad (3.12)$$

To obtain the best expected total cost among developed scenarios, the above procedure is repeated for other scenarios. The best scenario taking into account uncertainty on both generation and demand side can be determined by selecting the scenario which provides minimum total cost as defined in (20)

$$\text{The best cost} = \min\{ETC_1, ..., ETC_9\} \quad (3.13)$$

3.4 Numerical Results

The proposed method has been implemented to solve a modified IEEE 24-bus system [80] comprising 26 generating units as shown in Appendix A. The reliability data used in the chapter is based on the modified actual information from a utility in Thailand. Details of all the generating units data are shown in Appendix A. A base case demand of 24 hour period is shown in Table A.4. Three spinning reserve strategies based on deterministic criteria are set at 8%, 10%, and 12% of each of the load demand in each hour. Each reserve level represents low, medium and high spinning reserve strategy. The quadratic fuel cost function has been linearized to two segments approximation. A fixed start-up cost, i.e. cold and hot start-up, is applied in our analysis. Meanwhile, the demand uncertainty is modeled by low, medium, and high load level with its associated probability. The load forecast uncertainty is represented by the standard deviation (SD) – or σ in (3.1) –, e.g. 2 % of the expected values, and the occurrence probability of each load level, representing by low, medium, and high load, is shown in Figure 3.1.

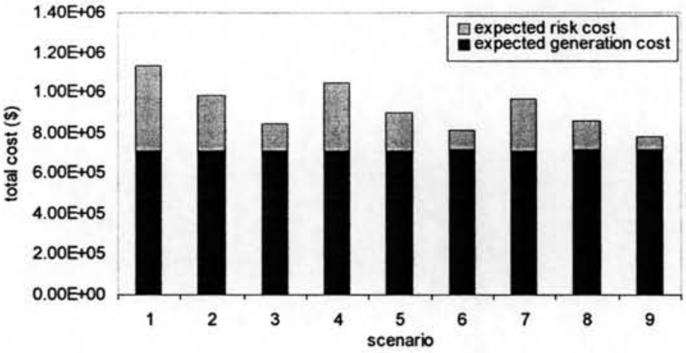
The UC-MILP and economic dispatch model has been developed using TOMLAB/CPLEX v10.0 [75]. The optimality of the solution in the TOMLAB/CPLEX is reflected by MIPGAP parameter which represents the absolute relative distance between the best integer solution and the best LP solution. In this chapter, the execution of CPLEX was terminated if the MIPGAP of the objective function is within 0.5% of the optimal solution.

3.4.1 Sensitivity Analysis

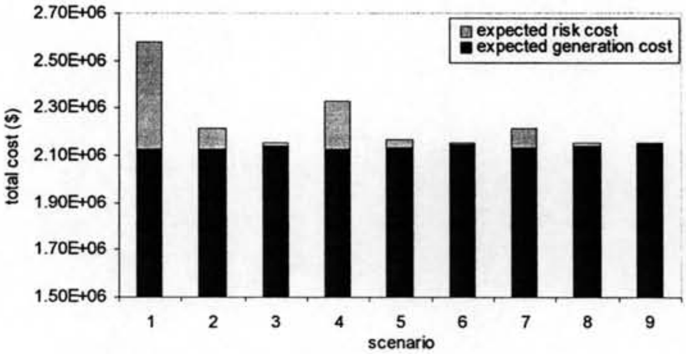
Several test cases have been conducted on the base system, with varied system size, standard deviation, EUE price, and probability of each possible load, to verify the impact from each parameter on the investigating strategy.

a) Impact of number of units

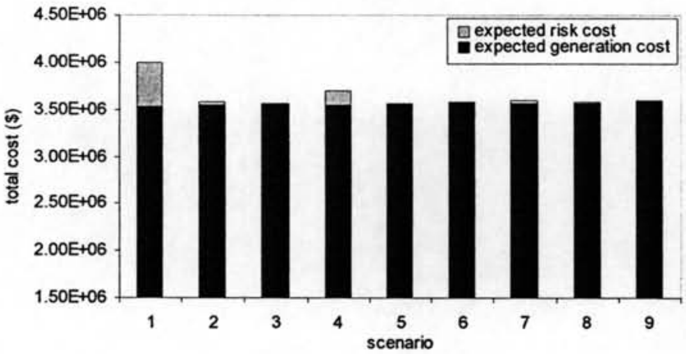
In this sensitivity analysis, the IEEE test system is duplicated to be 26-unit, 78-unit and 130-unit system representing small, medium, and large-scale system. The load forecast error represented by SD is assumed to be 1% of the forecast value in the first hour and linearly increased to 4% in the last hour. Meanwhile, occurrence probability of load level is assumed to be 0.2, 0.6, and 0.2 which represent probability of low, medium, and high load levels respectively. The EUE is priced at 2,000 \$/MWh, which is close to the result of study based on the actual data as reported in [86]. The simulation results of all scenarios as presented in Table 3.1 are shown in Figure 3.5.



(a) 26-unit system



(b) 78-unit system



(c) 130-unit system

Figure 3.5 Comparison of total cost for scenarios

It can be seen from Figure 3.5 that the generation cost of each scenario is a little different whereas the risk cost is highly different from each other. It clearly shows that the risk cost plays an important role especially in case of small systems. The details of the EUE result which implies risk cost of each scenario is depicted in Figure 3.6.

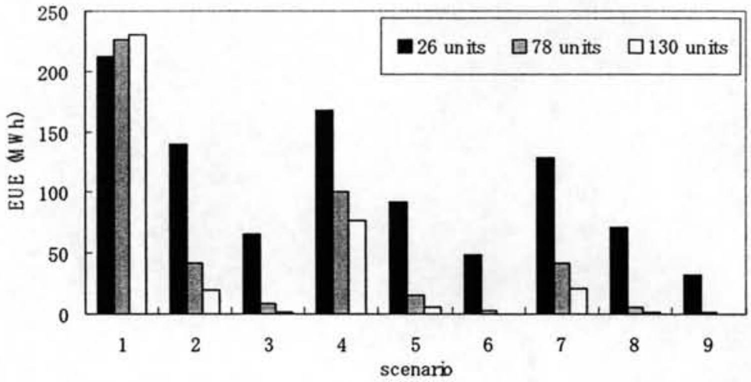


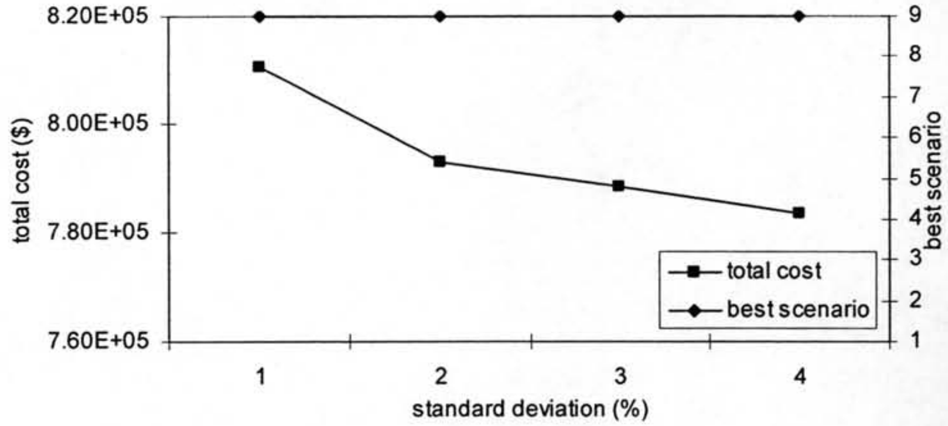
Figure 3.6 The EUE for scenarios of the various cases

In the case of applying low spinning reserve strategy, the risk costs are 37.4%, 28.1%, and 15.4% of the total cost for the cases of scenario# 1st – 3rd, respectively. Since different load levels require different number of units to be committed, therefore it creates different risk or EUE even though the same percentage of the spinning reserve strategy is applied. At higher spinning reserve strategy, the percentage of the risk cost compared to the total cost tends to decrease. For example, scenario# 7th to 9th, the contribution of risk cost to the total cost decreases to 26%, 16% and 8% respectively. However as higher SR strategy is employed the generation cost tends to increase since more units will be committed. Therefore the balance between the decrease of risk cost and the increase of generation cost will determine the best strategy to be used. It is found from the results shown in Figure 3.6 that the best strategy for the small 26-unit system is the 9th scenario, i.e. scheduling high spinning reserve to meet the expected high load.

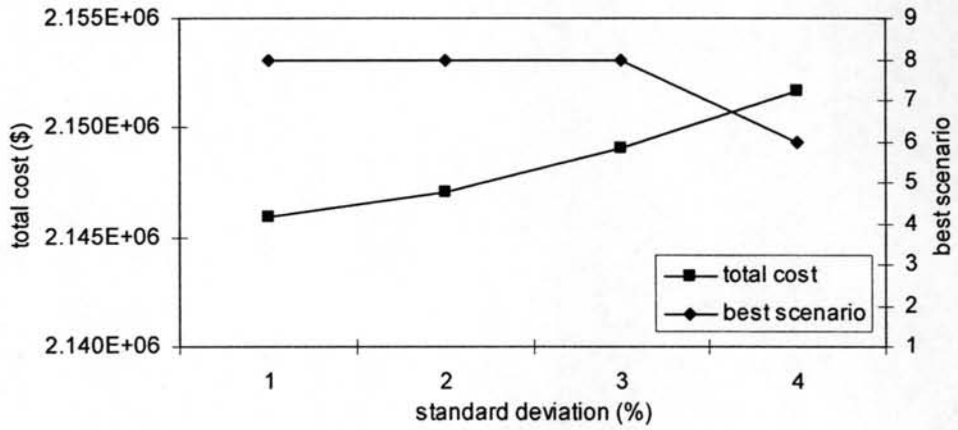
In cases of 78-unit and 130-unit system, scenario# 6th and 7th provide the best strategies respectively. It shows that the best strategy tends to require lower percentage of spinning reserve as the system becomes larger.

b) Impact of load forecast error

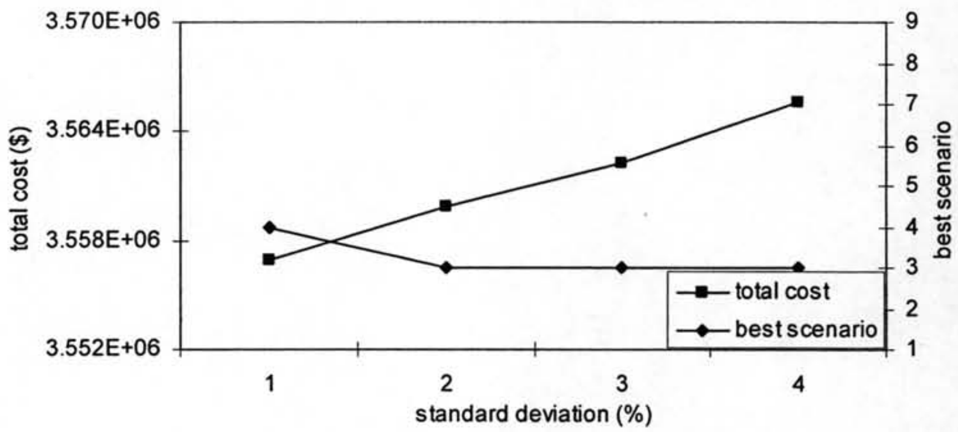
As mentioned in section 3.3, the impact of the load forecast error is analyzed through the variation of standard deviation (SD) values. In this analysis, it is supposed that the SD is assumed to be 1% of the forecasted value in the first hour, and is treated as either a constant value for the whole lead time of 24 hours or linearly increased to 2–4% in the last hour. The simulation results are shown in Figure 3.7 .



(a) 26-unit system



(b) 78-unit system



(c) 130-unit system

Figure 3.7 Correlation between standard deviation and the best scenario

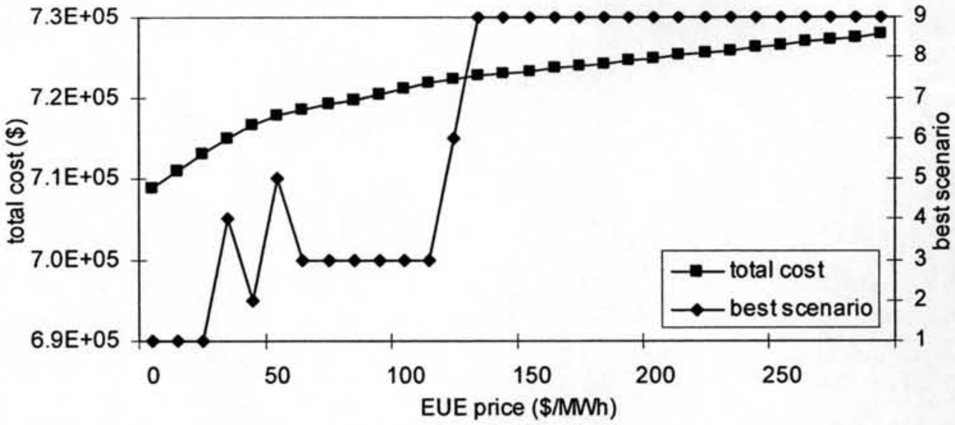
It can be seen from Figure 3.7 (a) that for a small 26-unit system, scenario# 9^{th} of high spinning reserve strategy, is always the most appropriated strategy. It can be clearly understood that since the high SR will diminish the EUE which contributes fairly high percentage of the total cost for a small system, the high SR as of scenario # 9^{th} therefore provides the best strategy. With higher forecast error, i.e. higher SD, the total cost obtained from the best strategy tends to decrease. However, as the system becomes larger, lower reserve strategy tends to be more appropriated, since the risk cost contribution to the total cost is relatively small. It can be seen in Figure 3.7 (b) that the 78-unit system should applies either medium or high spinning reserve strategy, i.e. scenarios # 6^{th} and 8^{th}, whereas in the case of 130-unit system, Figure 3.7 (c), the low and medium spinning reserve strategies, i.e. scenarios # 3^{rd} and 4^{th}, should be applied.

c) Impact of EUE price

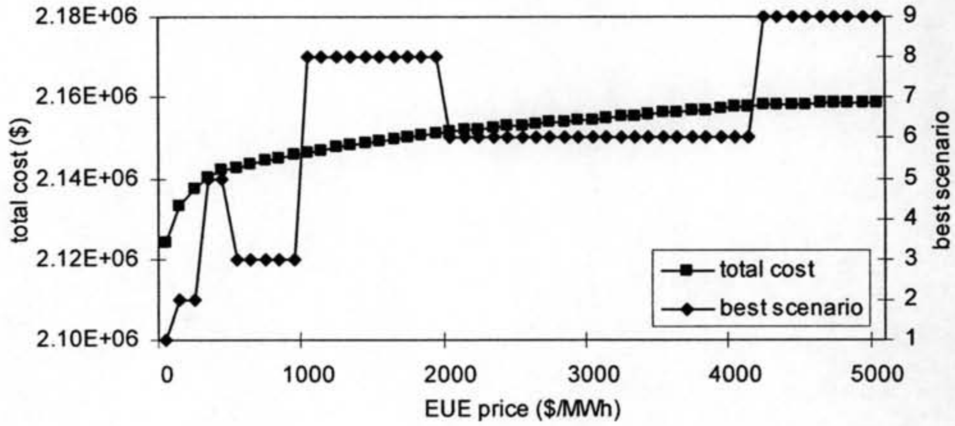
EUE price is varied to verify its impact on the operating strategy. The results are shown in Figure 3.8. Unsurprisingly, higher EUE price causes the higher total cost. As is seen from Figure 3.8(a), the selected scenario is sensitive to the change of EUE price, especially at a relatively low price up to 130\$/MWh. In case of EUE price is higher than 130\$/MWh, the best scenario is always found at scenario# 9^{th}, which requires high spinning reserve to keep the risk cost at a reasonable level.

For the larger 78-unit system, the best strategy tends to require higher spinning reserve for higher EUE prices. For the large system of 130 units, the results of the EUE are very small as shown in Figure 3.6, even for low and medium spinning reserve strategies.

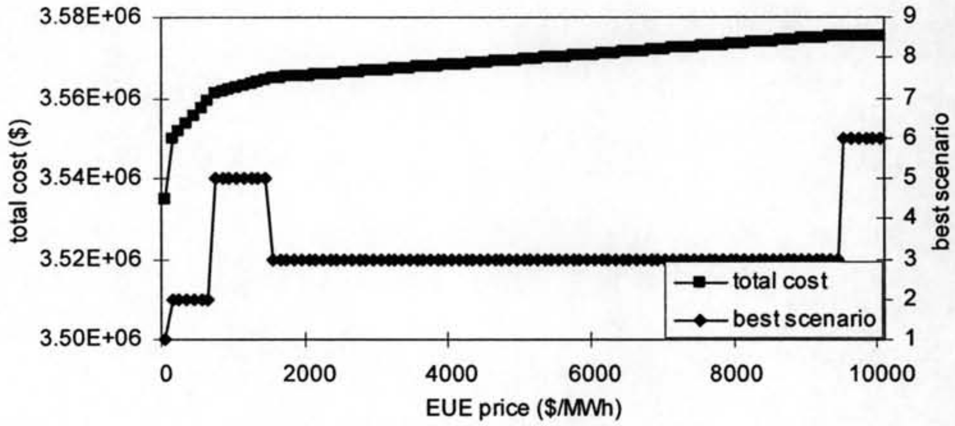
It can be noticed that if the risk cost is neglected from our consideration, i.e. EUE price is set at zero, the lower spinning reserve strategy will be preferred. However, if the higher EUE price is employed, the higher spinning reserve strategy will be more appropriate in the UC decision.



(a) 26-unit system



(b) 78-unit system



(c) 130-unit system

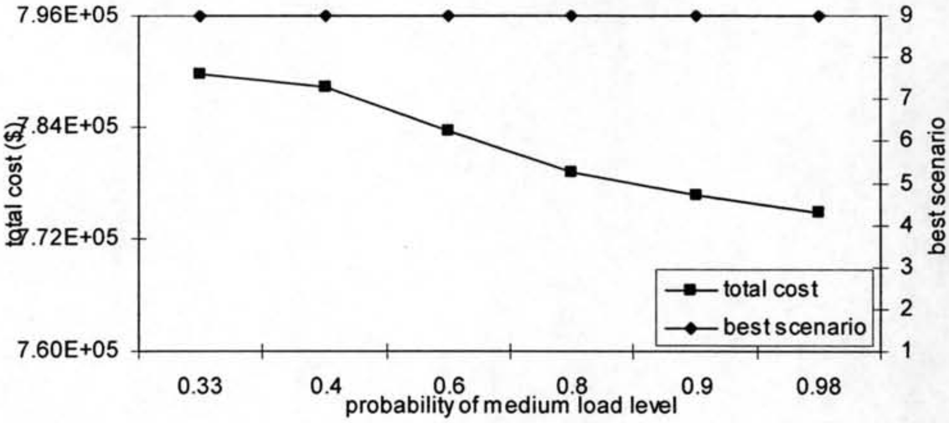
Figure 3.8 Correlation between EUE price and the best scenario

d) Impact of load uncertainty

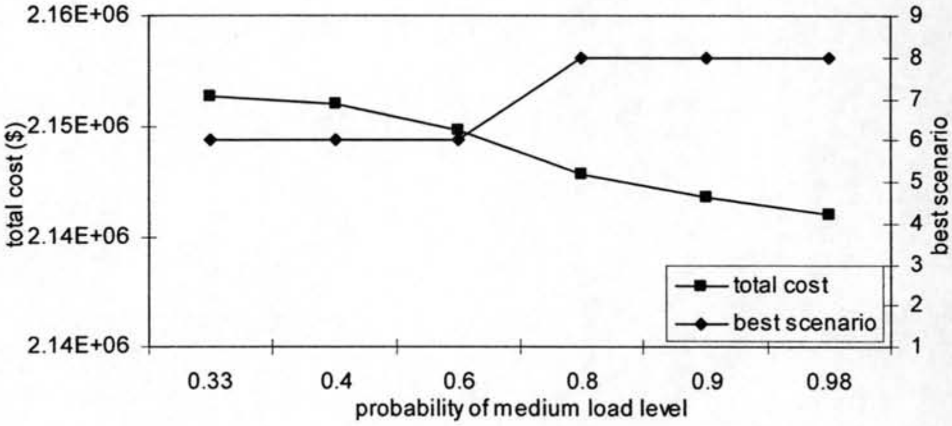
In this sensitivity analysis, the probability of the future demand is varied meanwhile other parameters such as standard deviation for the first and last hour is fixed at 1% and 4% respectively, and EUE price is defined at 2,000$/MWh. Since the medium load level is the forecasted load value, the probability of the medium load occurrence will be varied to reflect the accuracy of the forecasted load. In this test the probability of the medium or the forecasted load occurrence will be varied from 0.33 - 0.98, whereas the probability of the other two load levels will be adjusted accordingly. The sets of the probability for the occurrence of low, medium, and high load levels, according to the model presented in Figure 3.1, to be analyzed in this case are (0.01, 0.98, 0.01), (0.05, 0.90, 0.05), (0.10, 0.80, 0.10), (0.20, 0.60, 0.20), (0.30, 0.40, 0.30), and (0.33, 0.33, 0.33). The simulation results are depicted in Figure 3.9.

It can be seen that the raise of the probability of the medium load level, better accuracy of the forecasted load, leads to the decrease of the expected total cost. In these cases, the reduction of the total costs of the best accurate forecasted load, with the probability of 0.98, compared to the least accurate forecasted load, probability of 0.33, for the 26-unit, 78-unit, and 130-unit systems are 1.90%, 0.40%, and 0.29% respectively. It was found that risk cost play an important role on the total cost difference especially in the smaller systems.

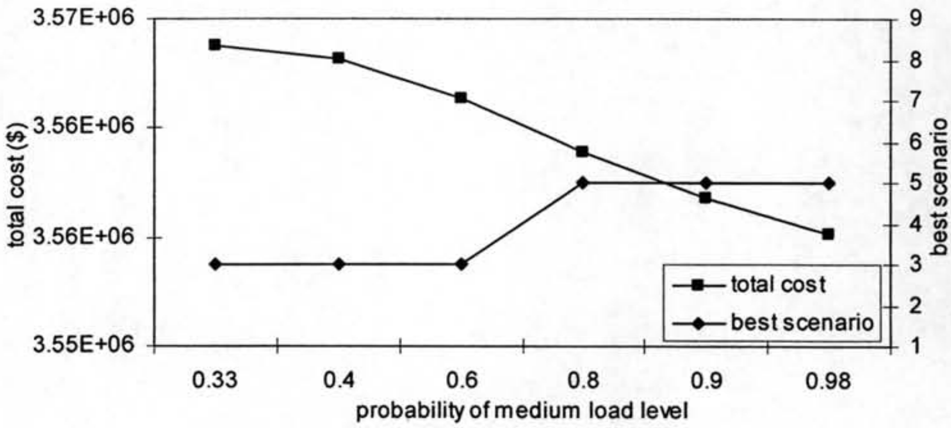
It can also be found from the results that the accuracy of the load forecast has the impact on the expected total cost. The better load forecast accuracy will result in the lower expected total cost.



(a) 26-unit system



(b) 78-unit system



(c) 130-unit system

Figure 3.9 Relationship between probability of load level and the best scenario

3.4.2 Determination of Cost of Demand Uncertainty

In this analysis, the cost of uncertainty is defined as the difference between the considered costs, i.e. the generation and total cost, with and without taking into account demand uncertainty. The cost without taking into account uncertainty can be calculated by running the unit commitment problem of the considered system based on the forecasted demand at a specified spinning reserve strategy. Meanwhile, by taking into account demand uncertainty, the considered cost is obtained among the scenarios which give minimum total cost as stated by equation (3.13). Since three spinning reserve strategies are involved in this equation, hence the difference between the cost without taking into account uncertainty and the cost obtained from the best scenario resulted from equation (3.13) is caused from the different both of load level and spinning reserve strategy. Accordingly, to evaluate the impact of demand uncertainty only, the best scenario is selected among the scenarios which utilize similar spinning reserve strategy. In this analysis, we focus on the scenarios which utilize spinning reserve strategy at 12% of the demand, i.e. scenarios#7-9.

As a reference value for determining the cost of demand uncertainty, i.e. the generation cost and total cost which is generated from UC solution based on the forecasted demand, are shown in Table 3.2. To analyze the impact of the considered probability parameters, i.e. occurrence probability of load level and standard deviation of the forecasted demand, the cost of demand uncertainty is calculated with various values of probability parameter. In this analysis, the cost of demand uncertainty is investigated from the viewpoint of both generation cost and total cost.

Table 3.2 Costs of UC solution at forecasted demand

Test system	Generation cost ($)	Total cost ($)
26 unit system	714,920	849,478
78-unit system	2,139,100	2,145,268
130-unit system	3,559,400	3,560,906

The cost of demand uncertainty for a specific value of standard deviation and occurrence probability excluding risk cost can be formulated as

$$\Delta GC = EGC_{best\_scenario} - GC_{UC\_normal} \quad \text{.......................................} (3.14)$$

where ΔGC denotes cost of uncertainty without taking into account risk cost, $EGC_{best\_scenario}$ is the expected generation cost of the corresponding best scenario, GC_{UC_normal} is the generation cost resulted from the UC solution based on the forecasted demand.

Meanwhile, the cost of demand uncertainty taking into account risk cost can be determined as

$$\Delta TC = ETC_{best\_scenario} - TC_{UC\_normal} \quad \text{..} \quad (3.15)$$

where ΔTC denotes cost of uncertainty taking into account risk cost, $EGC_{best\_scenario}$ is the expected total cost of the corresponding best scenario, GC_{UC_normal} is the total cost resulted from the UC solution based on the forecasted demand.

The cost of demand uncertainty without taking into account risk cost for various test system are shown in Figure 3.10 to Figure 3.12. It is found that, higher value of standard deviation and smaller value of occurrence probability of medium load level results in an increase of cost of demand uncertainty. We also found that, the cost of uncertainty decreases when the occurrence probability of medium load level is decreased. The reason is because by considering demand uncertainty, the utilities have to commits more units to cover the possibility of higher demand. In the case of 26-unit system, at the highest probability of medium load level, i.e. 0.98, the increase of standard deviation from 1 to 4% results in the increase of generation cost as of 0.33%. Meanwhile, at a larger test system, i.e. at 78-unit and 130-unit systems, the increase of standard deviation in the same value of occurrence probability gives much smaller increase of generation cost, i.e. 0.004% and 0.003% respectively. It means that even though the standard deviation of the forecasted demand is high but if the forecasted demand is accurate in the term of highly probability of medium of load level, it will not have significant impact to the increase of generation cost, especially in a large system. On the other side, at the worst accurate of forecasted demand, with the probability of 0.33, the increase of standard deviation from 1 to 4% will significantly boost the increase of cost of uncertainty. It can be found that the increase of cost of uncertainty due to the increase of standard deviation at the worst accurate of forecasted demand is about 0.45%, 0.13%, and 0.09% for 26-unit, 78-unit, and 130-units systems respectively.

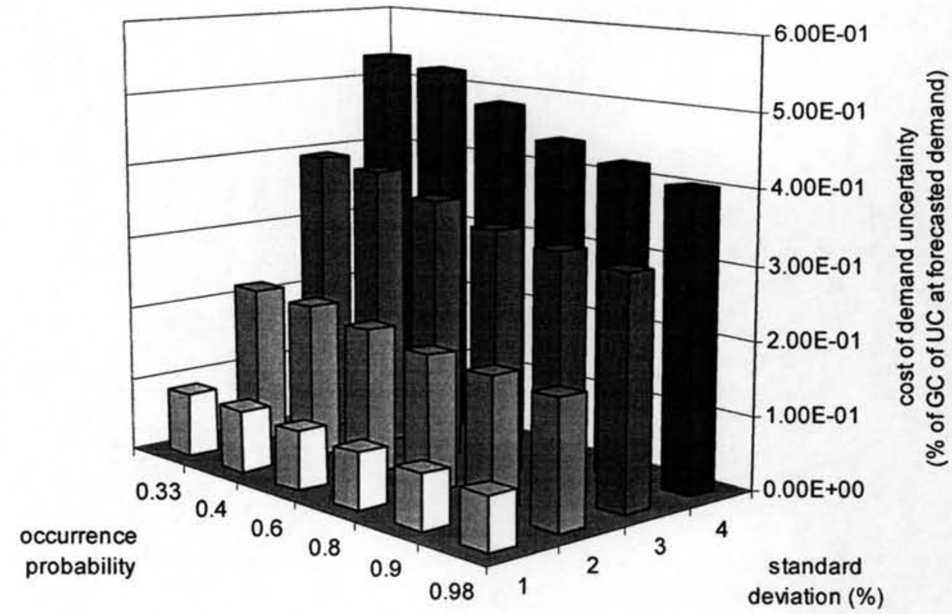


Figure 3.10 Cost of uncertainty excluding risk cost of 26-unit system

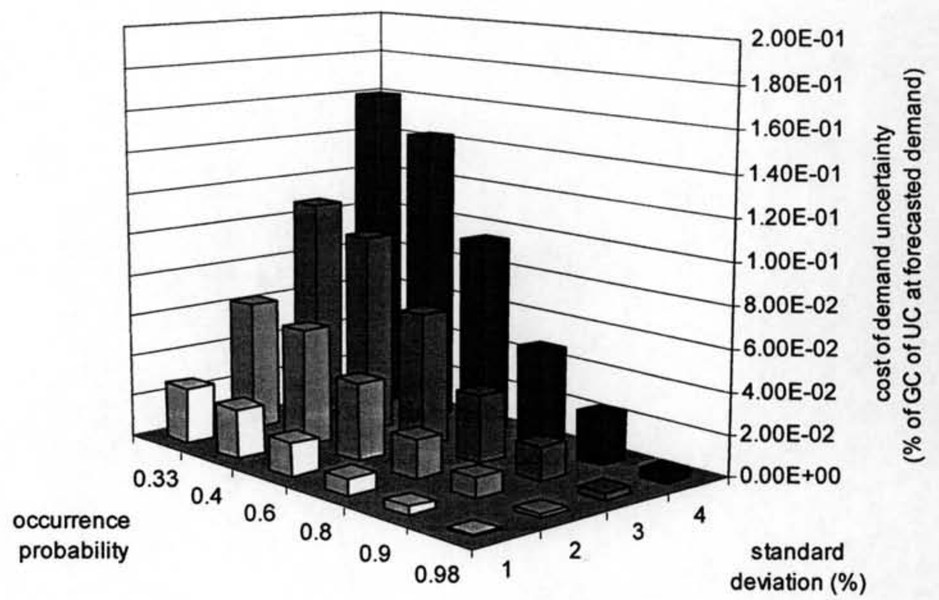


Figure 3.11 Cost of uncertainty excluding risk cost of 78-unit system

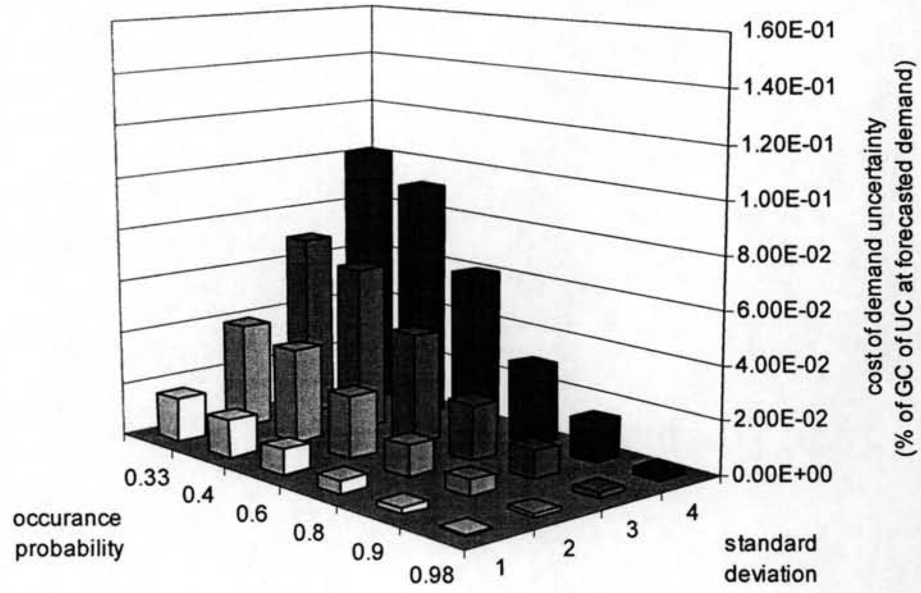


Figure 3.12 Cost of uncertainty excluding risk cost of 130-unit system

If the risk cost is included in the determination of cost of uncertainty, the results for various test systems is shown in Figure 3.13 to 3.15. For the case of small system size, i.e. 26-unit system, as shown in Figure 3.13, the inaccuracy of the forecasted demand leads the cost of uncertainty by taking into account risk cost being negative. It is also found that at higher uncertainty of the forecasted demand, i.e. at higher standard deviation and smaller probability of medium load level, the cost of uncertainty tends to be more negative. It means that the consideration of demand uncertainty in the scheduling process leads the reduction of total cost. The reason is because by considering demand uncertainty, the system might commit more units to cover the uncertain demand in the future therefore the reserve is increased. As a further consequence, the risk cost will reduce. Since the risk cost plays an important role in the total cost for small system size hence the reduction of risk cost will significantly cause the reduction of total cost.

In the case of larger system size, the inaccuracy of the forecasted demand leads to the higher impact of demand uncertainty on the total cost. This fact can be seen from Figure 3.14 and Figure 3.15 which show that at the increase of standard deviation and the decrease of probability of medium load level has significant effect to the increase of cost of uncertainty. At the smallest occurrence probability of medium load level, the increase of standard deviation from 1% to 4% leads the increase of cost of uncertainty as of 0.36% and 0.28% for 78-unit and 130-unit system respectively.

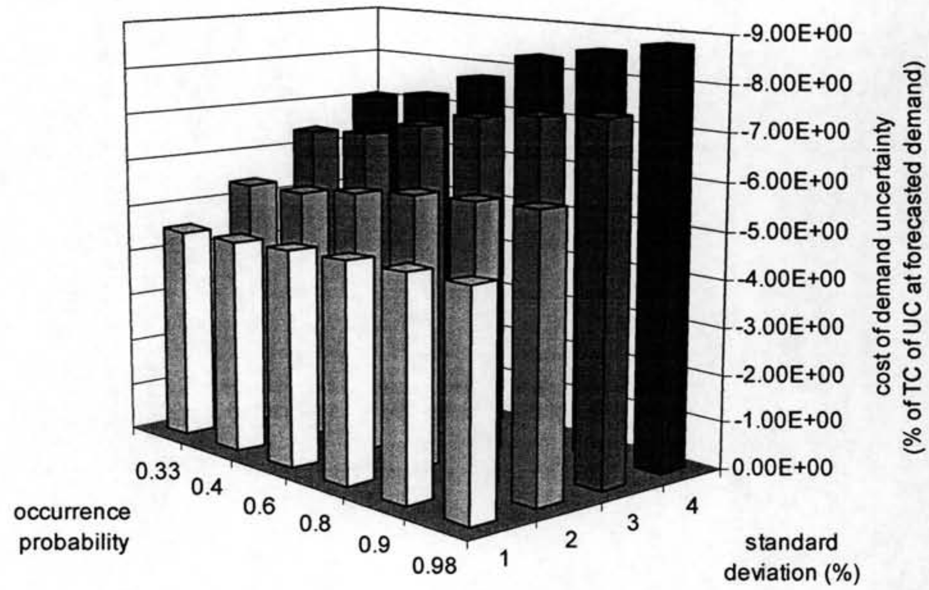


Figure 3.13 Cost of uncertainty including risk cost of 26-unit system

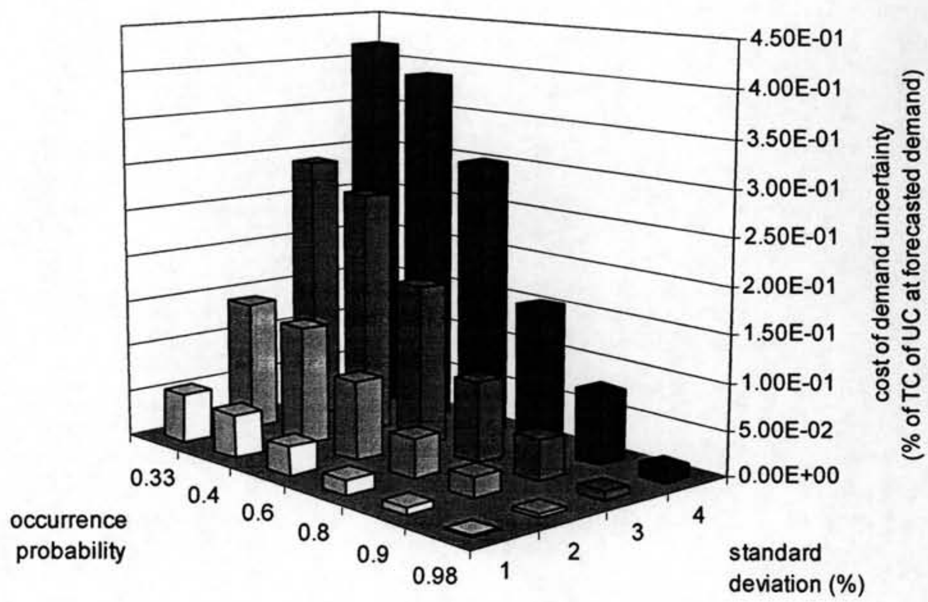


Figure 3.14 Cost of uncertainty including risk cost of 78-unit system

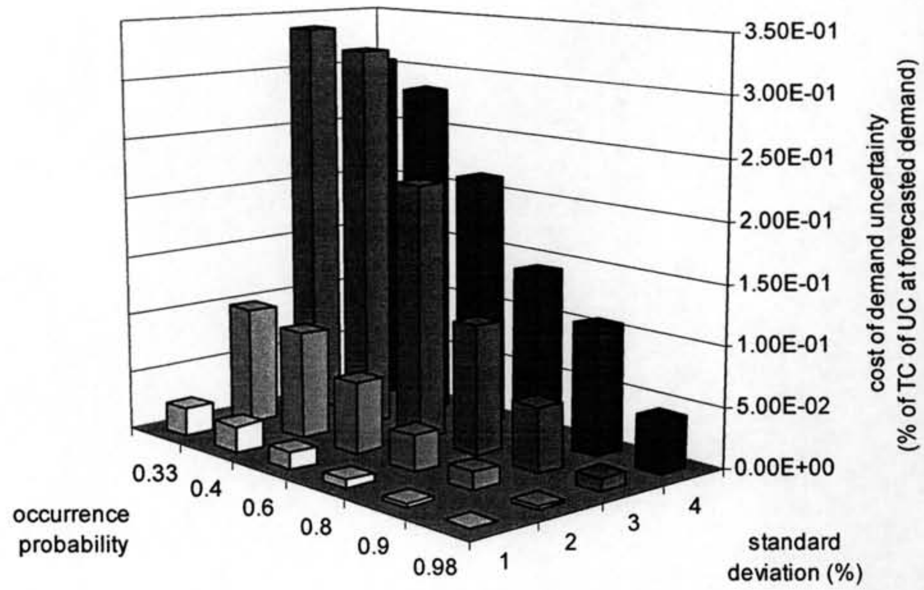


Figure 3.15 Cost of uncertainty including risk cost of 130-unit system

3.5 Conclusion

An approach to incorporate the load forecast uncertainty and generating unit unavailability in the determination of the best short-term operating strategy has been presented in this chapter. The best strategy is selected among the developed scenarios which are created based on decision analysis method. The effectiveness of the proposed method has been tested using a modified of IEEE 24-bus system and its replication. The sensitivity analysis has been conducted, which shows that the degree of sensitivity to the evaluated parameter is different among the investigated system sizes, hence the determination of the best strategy should be suited correspondingly. The results prove that the proposed method has a capability to solve a realistic short-term planning problem taking into account system uncertainties. Utilities may simulate in the same way as presented in this chapter to define the best spinning reserve strategy for their systems, according to their specified conditions, e.g. system size, load forecast error in the past, EUE price.