Cost of Reliability Analysis Based on Stochastic Unit Commitment

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***Abstract*—This paper presents a model for calculating the cost of power system reliability based on the stochastic optimization of long-term security-constrained unit commitment. Random outages of generating units and transmission lines as well as load forecasting inaccuracy are modeled as scenario trees in the Monte Carlo simulation. Unlike previous reliability analyses methods in the literature which considered the solution of an economic dispatch problem, this model solves an hourly unit commitment problem, which incorporates spatial constraints of generating units and transmission lines, random component outages, and load forecast uncertainty into the reliability problem. The classical methods considered predefined reserve constraints in the deterministic solution of unit commitment. However, this study considers possible uncertainties when calculating the optimal reserve in the unit commitment solution as a tradeoff between minimizing operating costs and satisfying power system reliability requirements. Loss-of-load-expectation (LOLE) is included as a constraint in the stochastic unit commitment for calculating the cost of supplying the reserve. The proposed model can be used by a vertically integrated utility or an ISO. In the first case, the utility considers the impact of long-term fuel and emission scheduling on power system reliability studies. In the second case, fuel and emission constraints of individual generating companies are submitted as energy constraints when solving the ISO's reliability problem. Numerical simulations indicate the effectiveness of the proposed approach for minimizing the cost of reliability in stochastic power systems.**

***Index Terms*—Expected energy not supplied, load shedding, loss-of-load-expectation, power system reliability, random outages, security-constrained unit commitment, stochastic programming.**

NOMENCLATURE

Variables:

ET	Emission type representing SO_2 or NO_x considered in the paper.
$E_{e,i}^{ET}(\cdot)$	Emission function of unit i (type ET).
$EENS$	Expected energy not supplied value for the system.
$F_{c,itp}(\cdot)$	Production cost function of unit i at time t at weekly interval p.
$F_{f,i}(\cdot)$	Fuel consumption function of unit i.
i	Index of unit.
I_{itp}^s	Commitment state of unit i at time t at weekly interval p in scenario s.
l	Index of transmission line.
$\overline{LOLE}$	Expected quantity of loss-of-load-expectation for all S scenarios.
$LOLE^s$	Loss-of-load-expectation of scenario s.
$LOLE_b^s$	Loss-of-load-expectation at bus b of scenario s.
$LS_{b,tp}^s$	Load shedding at bus b at time t at weekly interval p in scenario s.
LS_b^s	Total load shedding at bus b in scenario s.
$LSIDX_{tp}^s$	Load shedding index at time t at weekly interval p in scenario s. 1 if load shedding happens, otherwise 0.
σ_{LOLE}	Estimated standard deviation of LOLE.
m	Index of unit fuel group.
n	Index of unit emission group.
p	Index of weekly interval.
$P_{i,tp}^s$	Real power generation of unit i at time t at weekly interval p in scenario s.
$PL_{l,tp}^s$	Power flow on line l at time t at weekly interval p in scenario s.
SU_{itp}^s	Startup cost of unit i at time t at weekly interval p in scenario s, which is a function of total off time.
SD_{itp}^s	Shutdown cost of unit i at time t at weekly interval p in scenario s, which is a function of total on time.
$SU_{f,itp}^s$	Startup fuel consumption of unit i at time t at weekly interval p in scenario s, which is a function of total off time.
$SD_{f,itp}^s$	Shutdown fuel consumption of unit i at time t at weekly interval p in scenario s, which is a function of total on time.
$SUET_{e,itp}^s$	Startup emission of unit i at time t at weekly interval p in scenario s, which is a function of total off time.
$SDET_{e,itp}^s$	Shutdown emission of unit i at time t at weekly interval p in scenario s, which is a function of total on time.
t	Index of time in one week.
$\overline{\lambda}_{u,i}^s$, $\underline{\lambda}_{u,i}^s$	Lagrangian multipliers corresponding to upper/lower fuel limit for unit i in scenario s.
$\overline{\lambda}_{g,m}^s$, $\underline{\lambda}_{g,m}^s$	Lagrangian multipliers corresponding to upper/lower fuel limit for unit group m in scenario s.
$\overline{\mu}_{u,i}^{ET,s}$	Lagrangian multipliers corresponding to the type ET emission limit for unit i in scenario s.

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$\overline{\mu}_{g,n}^{ET,s}$ Lagrangian multipliers corresponding to the type ET emission limit for unit group n in scenario s.
μ_{itp}^{s} Lagrangian multipliers corresponding to scenario bundle constraints for unit i at time t at weekly interval p in scenario s.
μ_{LOLE}^{s} Lagrangian multipliers corresponding to LOLE constraints for scenario s.

Constants:

B_b Set of units which are connected to bus b.
DR_i Ramp-down rate limit of unit i.
$E_{g,n}^{ET,\max}$ Upper emission limit of emission group n (type ET).
$E_{u,i}^{ET,\max}$ Upper emission limit of unit i (type ET).
$F_{g,m}^{\min}$ Lower fuel consumption limit of unit group m.
$F_{g,m}^{\max}$ Upper fuel consumption limit of unit group m.
$F_{u,i}^{\min}$ Lower fuel consumption limit of unit i.
$F_{u,i}^{\max}$ Upper fuel consumption limit of unit i.
L_b Set of transmission lines which are connected to bus b.
$LOLE_{fix}$ Predefined upper limit of LOLE.
σ_{fix} Predefined required standard deviation of LOLE.
M Predefined threshold of the large positive value.
NG Number of units.
NL Number of transmission lines.
NM Number of fuel groups.
NN Number of emission groups.
NP Number of weeks under study.
NT Number of hours at each weekly interval (168 h).
P_s Probability of scenario s.
$P_{b,tp}^{s}$ System demand at bus b at time t at weekly interval p in scenario s.
$P_{D,tp}^{s}$ System demand at time t at weekly interval p in scenario s.
pv_b^s VOLL of bus b in scenario s.
S Number of scenarios.

I. Introduction

RELIABILITY implies a continuous supply of energy to end users when taking into account scheduled and unscheduled outages. As electric power continues to play a momentous role in the national economy, power companies are faced with an increasing fuel cost for supplying the hourly load and maintaining a certain level of reliability. Meanwhile, power companies are also seeking ways to improve profitability in competitive power markets. In such environments, generating plants and transmission networks are operated closer to their limits which could make them more vulnerable to outages and lead to lower reliability margins [1]–[6].

A power system contingency could leave an unbalance between demand and supply. If sufficient spinning/non-spinning reserves are available, the deficiency may be mitigated without requiring any load shedding by system operators.

The earliest and most easily computed criterion for the evaluation of power system reliability is a deterministic criterion which includes the percent generation reserve margin and loss-of-the-largest-generating-unit methods [3], [8]. It is, however, difficult to determine the percent reserve value properly in a volatile power system. When the percentage is designated to be large, power system reliability can be guaranteed but the total operating cost will be excessively large. On the other hand, a smaller percentage of generation reserve could provide an economical generation schedule, but the power system reliability could be relatively vulnerable. There are other disadvantages of the percent reserves approach. It is insensitive to unforeseen load changes and forced outage rates of generation and transmission equipment, lacks any consideration for unit sizes.

The loss-of-the-largest-generating-unit method provides a degree of sophistication over the percent generation reserve margin method by reflecting the effect of unit size on spinning/non-spinning reserve requirements. This approach explicitly recognizes the impact of a single outage by considering the loss of the largest generating unit. However, the approach is not very economical because the largest generating unit is not often on outage during the scheduling horizon. Furthermore, the redundancy could become excessive as larger units are added to power systems. The largest unit could be insufficient when simultaneous outages occur. It is also difficult to take transmission network structure and demand fluctuations into account when applying this method.

A more complicated method based on loss-of-load-expectation (LOLE) examined the probabilities of component outages that resulted in the expected number of days per year of capacity shortages. LOLE takes the stochastic characteristic of component outages into consideration. Reference [9] used the value of service (VOS) reliability approach to determine an optimal reliability state. It incorporated LOLE and customer outage cost information into economic dispatch. Reference [10] simulated generation unit outages as well as load forecasting uncertainties in calculating the power system security. If the system risk in a scheduling interval was greater than the predefined system risk level, the unit commitment (UC) problem was recalculated by updating Lagrangian multipliers. The over-commitment of spinning reserve was further reduced by a heuristic postprocessing reduction procedure. In practice, an acceptable system risk level may be hard to define when considering the system reliability and economics simultaneously. The approach did not consider transmission network constraints.

As computational requirements for LOLE indices and expected-energy-not-supplied (EENS) matrices are complicated by their nonlinear and combinatorial nature, [11] defined LOLE and EENS explicitly in terms of unit commitment and dispatch variables as well as forced outage rates. The advantages of the technique were the computational efficiency for calculating LOLE indices as well as EENS matrices, and the impact of probabilistic characteristics on market-clearing results. The approximation of outages could ignore the geographical and temporal information. Furthermore, outages of transmission lines were not considered.

Reference [12] used a preselected set of contingencies to calculate the optimal mix of preventive and corrective security actions. Demand side corrective actions were introduced and the objective was to minimize the sum of operation costs and payments to demands which were proportional to the amount of energy not supplied. Furthermore, exercise fee payments to demand side corrective actions could result in higher LOLE and EENS. The major issues are the selection of a sufficient set of contingencies and the proper amount of exercise fee which is paid for demand side corrective actions.

References [13] and [14] introduced the costs of normal state operation and contingencies into the objective function. A series of preselected contingencies was determined and involuntary load shedding was applied for deriving a feasible solution. A limited number of contingencies with larger probabilities were included because of the exponential growth in the number of contingency combinations. The critical issue remains to be the selection of a sufficient set of contingencies.

Reference [14] presented a probabilistic method to assess the operating reserve requirements in a power system. That is, the generation system was classified into different system operating states, healthy, marginal, and at risk. It combined deterministic criteria with probabilistic indices to monitor the system well-being. A risk index designated as the generating system operating state risk was defined as the probability of residing in an undesirable operating state. Reference [15] further evaluated the effect of stand-by units, interruptible loads, and postponable outages on generating system operating health. Generating units were committed to the system at a particular load level to satisfy either a specified risk or an acceptable system health probability or both. Additional details of the reliability evaluation method were given in [16].

This paper focuses on the cost of reliability by considering the stochastic nature of power systems. The paper presents a stochastic security-constrained unit commitment (SCUC) model for calculating the cost of reliability. One obvious difference between this work and the previous works is that the reliability model is solved here with an hourly unit commitment problem instead of an economic dispatch problem. The proposed study coordinates the hourly unit commitment with random outages, fuel consumptions, and emission allowance within a single reliability problem. Instead of applying $\mathrm{N}-1$ or other deterministic contingency criteria, we apply the Monte Carlo method to simulate possible contingencies in stochastic SCUC. Random disturbances, such as outages of generation units and transmission lines as well as load forecasting inaccuracies, are modeled as scenario trees in the Monte Carlo simulation. It is viewed that the number of Monte Carlo simulations for the reliability evaluation within a given accuracy level is independent of the size of system. A scenario-based technique is adopted in this paper to control a goodness-of-fit of approximation between computation time and solution accuracy.

With the introduction of LOLE and EENS indices in the stochastic SCUC model, we determine implicitly the probabilistic spinning/non-spinning reserves as a tradeoff between reliability and economics. In other words, the optimal spinning/non-spinning reserves are determined by economically penalizing the operation of power systems for the expected cost of energy not supplied. If the cost of providing the next megawatt of power is higher than the benefit of providing such services to customers, power suppliers may prefer the involuntary load shedding. This condition implies that the level of spinning/non-spinning reserves is determined by comparing the cost of supplying the reserves with the expected cost of not supplying the load, thus limiting redundant reserve capacities. On the other hand, if the LOLE requirement is not binding, system operators would raise spinning/non-spinning reserve levels, as expensive as they could be, to meet power system reliability indices.

The proposed model can be utilized by traditional vertically integrated utilities when minimizing the expected operating cost. It can also be utilized by an ISO in centralized energy markets when minimizing the expected payment for energy purchases. For the sake of presentation, we consider in this paper the model for a vertically integrated utility and apply the generation cost functions in the objective function to illustrate the proposed methodology. When considering the ISO model, the only difference would be in the input data for representing generator bids as opposed to their cost functions. The same methodology discussed in this paper will apply to both power system models.

In the proposed model, we are more concerned with the expected value of objective function as a decision tool rather than the actual cost of operation of power systems with contingencies. LOLE and EENS indices provide useful information on long-term operating decisions which will accordingly assist the ISO or the utility personnel in making a tradeoff decision between economics and reliability at the presence of uncertainties and limited supply of fuel and emission allowance.

The rest of the paper is organized as follows. Section II provides the stochastic reliability evaluation. Section III presents the solution methodology of the stochastic long-term model with the formulation of uncertainty of generation components (units and transmission lines) as well as the inaccuracy of load forecasting with Monte Carlo method. Section IV presents and discusses a modified IEEE 118-bus system with 54 units and 91 loads. The conclusion is drawn in Section V.

II. Stochastic Reliability Evaluation

In electric power systems, certain customers may have specific reliability requirements and should pay corresponding rates for managing reliability. However, a more responsive calculation of spinning/non-spinning reserve levels could avoid excessive customer payments. The LOLE index is the expectation that the available generation supply would not meet the hourly system load. It can also be expressed as the expected number of days that the power system would fail to supply load demands. LOLE for bus b in scenario s is defined in (1) as

$$LOLE_b^s = \sum_{p=1}^{NP}\sum_{t=1}^{NT} prob\left(\sum_{i\in \mathrm{B}_b} P_{i,tp}^s + \sum_{l\in L_b} PL_{l,tp}^s - P_{b,tp}^s < 0\right). \quad (1)$$

Here the function $prob[\cdot]$ refers to the probability of load not supplied at a certain bus. Spinning/non-spinning reserve requirements based on random outages can be satisfied by constraining LOLE to be less than or equal to a predefined value.

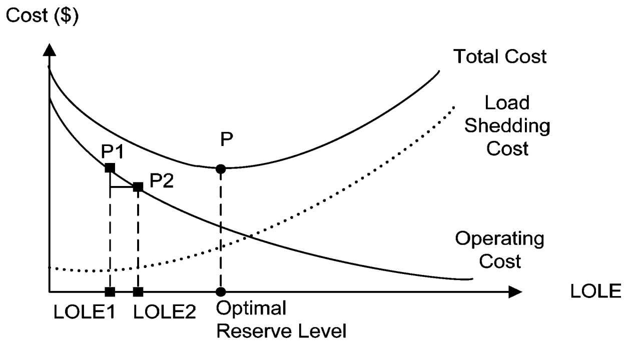

Fig. 1. Variation of cost as a function of LOLE.

The EENS index is the average energy not supplied when there is a loss-of-load. The EENS is expressed as

$$EENS = \sum_{s=1}^{S} P_s \cdot \sum_{b=1}^{NB}\sum_{p=1}^{NP}\sum_{t=1}^{NT} LS_{b,tp}^{s}$$

$$LS_{b,tp}^{s} = \begin{cases} 0, & \text{if } P_{b,tp}^{s} - \sum_{i\in \mathrm{B}_b} P_{i,tp}^{s} - \sum_{l\in L_b} PL_{l,tp}^{s} \le 0 \\ P_{b,tp}^{s} - \sum_{i\in \mathrm{B}_b} P_{i,tp}^{s} - \sum_{l\in L_b} PL_{l,tp}^{s}, & \text{otherwise.} \end{cases} \quad (2)$$

We represent the system reliability in the stochastic SCUC by adding the cost of EENS to the objective function and the LOLE limit to the set of constraints. The cost of EENS is calculated by multiplying EENS with the load shedding price for compensating customers. The load shedding price is also referred as the value of lost load (VOLL) and expressed in $/kWh.

The magnitude of VOLL, which impacts the cost of EENS, can influence the operating cost as well as spinning/non-spinning reserve deployments. A higher VOLL will result in smaller load shedding, which leads to additional deployment of reserves, and vise versa. VOLL depends on many factors including the types of customers interrupted, actual load demand at the time of outage, duration of outage, and the time in which the outage occurs. There are several ways to approximate VOLL including gross national product/total energy consumption, survey method, case studies of blackouts, preparation cost of customer, direct and indirect methods [17]–[19]. In this paper, we regard VOLL as an input and demonstrate the impact of VOLL on the system reliability as well as the total operating cost.

Fig. 1 illustrates the nature of operating and load shedding costs and the total cost as a function of LOLE. Lower LOLE may result in higher operating costs for supplying additional reserves. Accordingly, load shedding and its cost will be lower. The total cost decreases first in Fig. 1 as LOLE increases. However, the total cost will increase gradually due to the additional cost of load shedding. At the minimum total cost, the marginal cost of supplying additional reserves is equal to the marginal cost of reducing LOLE.

For a fixed VOLL in Fig. 1, we calculate the incremental load shedding cost as $(OC_{p1} - OC_{p2})/(LS_{p2} - LS_{p1})$, where OC_{p1} and LS_{p1} are operation cost and load shedding at p1. The incremental load shedding cost represents the marginal cost of a small incremental LOLE (i.e., LOLE2-LOLE1).

There are many uncertain factors such as fuel prices and load shedding costs that could influence operating cost curves and optimal long-term solutions. In our reliability formulation, spinning/non-spinning reserve levels are implicitly represented by load shedding costs, operating costs, and upper bounds of LOLE. In the following, we illustrate the way LOLE constraints and stochastic behavior of power systems are represented in the long-term SCUC model, optimal reserves are determined, and reliability costs are calculated. We will present a few examples in our case study section.

III. Stochastic Long-Term Model

The possible number of contingency scenarios could be enormous in the stochastic modeling of power systems. An alternative is to consider a limited number of contingencies with larger probabilities using $\mathrm{N}-1$ or other contingency criteria. However, this deterministic alternative may introduce approximated results with potentially damaging consequences to power systems. The Monte Carlo method is the other alternative for simulating the stochastic model of power systems. The scenario-based approximation is used in our Monte Carlo simulation for calculating the cost of reliability based on the long-term SCUC model.

A. Scenario Techniques in Monte Carlo Method

In order to calculate LOLE and EENS, we generate a set of scenarios for simulating uncertainties in stochastic power systems. The advantage of applying the Monte Carlo method is that the required number of samples for a given accuracy level is independent of the size of power system and therefore is suitable for larger scale systems.

In the paper, we apply a two-state continuous-time Markov chain model to represent available and unavailable states of a component [21], [30]. The on/off conditions of available units are determined by solving the SCUC problem. We could apply a four-state Markov chain model given in [17] which includes in service, forced out in period of need, forced out but not needed, and reserve shutdown. However, the model in [17] assumes that the unit commitment states of each component are determined when applying the Markov chain model, which is not a necessary assumption in our model. Thus, we resort to the two-state Markov chain model in Fig. 2 to represent the available and unavailable states of generating units.

Random outages of generation units are simulated for a specified time period with the assumption that the power system is at its normal state at the beginning of period. Assume the availability of the ith generating unit is p_i and its unavailability is $q_i = 1 - p_i$. Using μ_i and λ_i, we represent the ith component's

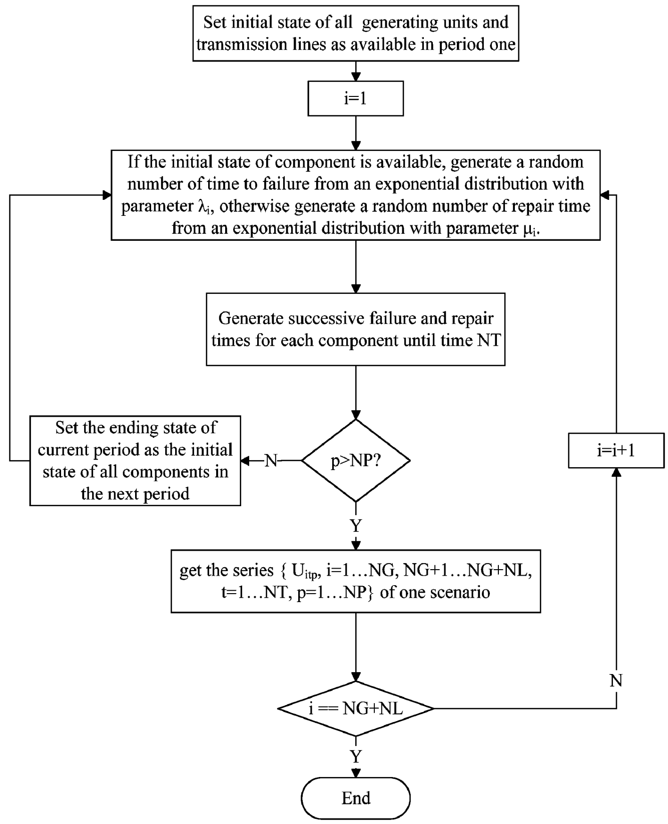

Fig. 2. Generating unit state simulation with Monte Carlo method.

repair and failure rates in a period, and apply a two-state continuous-time Markov chain model for representing the ith component. The associated conditional probabilities for component i are defined as follows [21]:

$$\begin{aligned} p(\varphi_t = 1|\varphi_{t0} = 1) &= p_i + q_i \cdot e^{-(\mu_i+\lambda_i)\cdot(t-t0)} \\ p(\varphi_t = 0|\varphi_{t0} = 1) &= q_i - q_i \cdot e^{-(\mu_i+\lambda_i)\cdot(t-t0)} \\ p(\varphi_t = 1|\varphi_{t0} = 0) &= p_i - p_i \cdot e^{-(\mu_i+\lambda_i)\cdot(t-t0)} \\ p(\varphi_t = 0|\varphi_{t0} = 0) &= q_i + p_i \cdot e^{-(\mu_i+\lambda_i)\cdot(t-t0)}. \end{aligned} \quad (3)$$

We use the Monte Carlo method to simulate component outages during the scheduling period $\{\mathrm{U_{itp}}, \mathrm{i} = 1\ldots\mathrm{NG}, \mathrm{t} = 1\ldots\mathrm{NT}, \mathrm{p} = 1\ldots\mathrm{NP}\}$ in which $\mathrm{U_{itp}} = 1$ indicates that the ith component is available at time t and period p while $\mathrm{U_{itp}} = 0$ indicates otherwise. Fig. 2 depicts the generating unit simulation while a similar procedure can be devised for transmission line outages [29].

The proposed stochastic model can include hydro and gas generating units. The states of generating units are first classified according to their availabilities. If a unit is available, it may be either committed (in service) or decommitted (not in service) as shown in Fig. 3. The latter state indicates that the unit is available but not in operation for economic reasons. The Monte Carlo methods simulate unit outages in each scenario and calculate unit commitment states by solving the stochastic SCUC problem. The parameters used for the Monte Carlo simulation are failure and repair rates of each power system component.

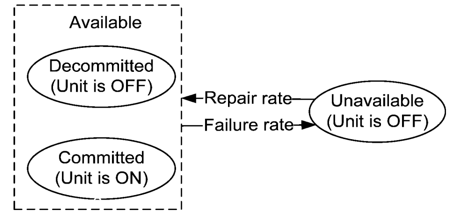

Fig. 3. Transition states of system components.

The power system components are assumed independent in our scenario-based simulation and the simultaneous effects of outages are presented in scenario trees. The generators and transmission lines that are on outage at certain hours cannot supply any energy or reserves.

Our stochastic model provides an hourly commitment solution. Hence, we consider a set of weekly peak loads and generate hourly load values accordingly in each scenario. The load forecasting uncertainty is represented by a normal distribution in which the mean value is the forecasted peak load. The normal distribution is divided into a discrete number of intervals and the load in the midpoint of each interval represents the probability for that interval. To simplify the calculation, a seven-step distribution $(0, \pm\sigma, \pm 2\sigma, \pm 3\sigma,)$ is often used where σ, standard deviation, is 2% of the expected load [22]. Such a model will encompass more than 99% of load uncertainty.

The computational requirements for a scenario-based optimization model depend on the number of scenarios. Thus an effective scenario reduction method could be very essential for solving large scale systems. The scenario reduction technique results in a scenario-based approximation with a smaller number of scenarios and a reasonably good approximation of the original system. Accordingly, we determine a subset of scenarios and a probability measure based on the subset that is the closest to the initial probability distribution in terms of probability matrices [25]. The basic idea of scenario reduction is to choose a set of scenarios that could be deleted by measuring a distance of probability distributions as a probability metric. Efficient algorithms based on backward and fast forward methods were developed in our previous work [29].

Using the Monte Carlo simulation, a very large number of scenarios are generated. However, S scenarios are retained after the scenario reduction, which are determined by the estimated standard deviation of LOLE. Here we introduce the following stopping criterion (4) while taking into account the accuracy:

$$\begin{aligned} &\sigma_{LOLE} = \frac{1}{S}\sqrt{\sum_{s=1}^{S}\frac{(LOLE^s - \overline{LOLE})^2}{S-1}} \\ &\sigma_{LOLE} < \sigma_{fix}. \end{aligned} \quad (4)$$

When the estimated standard deviation of LOLE, σ_{LOLE}, is less than the predefined boundary σ_{fix}, it means that enough scenarios are calculated to guarantee the accuracy of results. The value of σ_{fix} is given as an input which does impact the scenario reduction results. The standard deviation of results will decrease as the number of samples increases. Thus, the smaller the $\sigma_{\rm fix}$, the more scenarios are to be kept after the scenario reduction. Usually a $\sigma_{\rm fix}$ of 0.05 or 0.01 could be used. In the paper, we use 0.05 as the criterion and introduce a variance reduction technique, i.e., Latin hypercube sampling, to speed up the convergence. Other variance reduction techniques (such as antithetic variates, control variates, importance sampling) could also be applicable [26].

After scenario reduction, S deterministic scenarios with their corresponding probability P_s are considered for analyses. The possible optimal solution for the original stochastic problem could be the average of S optimal solutions. However, averaging may result in a suboptimal or even infeasible solution for the original stochastic problem. The bundle constraint is then introduced to develop a "well-hedged" solution to the original problem. The bundle constraint is stated as: if two scenarios s and s' are indistinguishable from the beginning to time τ on the basis of information available at time τ, then the decision rendered for the two scenarios must be identical from the beginning point to time τ, which will be presented as coupling constraint in our stochastic model [23], [24].

B. Stochastic Long-Term Solution

The objective for optimizing the cost of reliability in stochastic power systems problem is described as follows:

$$\min \sum_{s=1}^{S} P_s \sum_{p=1}^{NP}\sum_{t=1}^{NT}\left\{\sum_{i=1}^{NG}\left[F_{c,itp}\left(P_{itp}^s\cdot I_{itp}^s\right)+SU_{itp}^s+SD_{itp}^s\right] + \sum_{b=1}^{NB} pv_b^s \cdot LS_b^s\right\}. \quad (5)$$

The objective function (5) is composed of production cost, startup and shutdown costs of individual units, and the cost of EENS. The concept of utilizing scenarios adds another dimension to the solution that is different from that of the deterministic long-term SCUC solution.

The stochastic SCUC model could be utilized by a traditional vertically integrated utility and a centralized energy market (with ISOs). It is quite natural to model long-term fuel and emission constraints for a utility. The set of utility constraints includes the system power balance, ramping up and down, minimum up and down time, real power generation limits, fuel constraints for individual and groups of units, emission constraints for individual and groups of units, DC network security constraints, and phase shifter angles limits. In ISO applications, SCUC is utilized as a clearing tool in the day-ahead energy market in which GENCO's energy constraints are considered. That is, GENCOs submit energy limits which indicate that the daily sum of hourly generation for individual units, or the entire GENCO, would not exceed a prescribed level. The energy constraint is usually a linear function of GENCO's power that is generated by a group of units. In our model, a combination of fuel and emission constraints, which is a quadratic function of power generation by a group of units, represents the energy constraint for a GENCO [27]–[29]. The extra set of constraints introduced in this paper is the load shedding possibility at each bus and each time period in each scenario, the sum of load shedding power and its limit at each bus (6), and the LOLE constraint (7)

$$\begin{aligned} 0 \le LS_{b,tp}^s - \left(P_{b,tp}^s - \sum_{i\in B_b} P_{i,tp}^s - \sum_{l\in L_b} PL_{l,tp}^s\right) \\ \le M\cdot\left(1-LSIDX_{tp}^s\right) \\ 0\le LS_{b,tp}^s \le M\cdot LSIDX_{tp}^s \qquad (6) \\ LS_b^s = \sum_{p=1}^{NP}\sum_{t=1}^{NT} LS_{b,tp}^s, \quad \forall t,\forall p,\forall s \quad LSIDX_{tp}^s\in\{0,1\} \end{aligned}$$

$$LOLE^s = \frac{\sum_{p=1}^{NP}\sum_{t=1}^{NT} LSIDX_{tp}^s}{NT\cdot NP} \le LOLE_{fix}, \quad \forall s. \quad (7)$$

The optimal spinning/non-spinning reserve requirements are implicitly determined in our model because we add a penalty item for EENS to the objective function and include LOLE as a constraint. In (8), $B(s,P,\tau)$ represents a fraction of scenario s from the beginning to time τ in the Pth period. Constraint (8) indicates that if two scenarios s and s' are indistinguishable from the beginning point to time τ in the Pth period on the basis of information available at time τ, then the decision made for scenario s (here decision includes the unit commitment status) must be the same as that of scenario s' from the beginning to time τ in the P period

$$\begin{aligned} B(s,P,\tau)=B(s',P,\tau)=\Omega_{P\tau}\Rightarrow I_{itp}^s = I_{itp}^{s'} = c_{itp} \\ i=1\cdots NG, (p,t)\in\{P,\tau\}. \qquad (8) \end{aligned}$$

A multiplier μ_{itp}^s is associated with constraints on each I_{itp}^s. The corresponding penalty term $\mu_{itp}^s(I_{itp}^s - c_{itp})$ is added to the objective function. The target value c_{itp} in (9) is assumed the weighted average of the decision which would satisfy $B(s,P,\tau)=B(s',P,\tau)$

$$c_{itp} = \frac{\sum_{s\in B(s,P,\tau)=\Omega_{P\tau}} P_s\cdot I_{itp}^s}{\sum_{s\in B(s,P,\tau)=\Omega_{P\tau}} P_s}. \quad (9)$$

Then the dual problem of objective function (5) is separated into S disjoint problems each corresponding to a scenario for long-term SCUC problem (10) with other constraints listed above except the coupling constraint (8)

$$\begin{aligned} \min \quad P_s\left\{\sum_{p=1}^{NP}\sum_{t=1}^{NT}\left\{\sum_{i=1}^{NG}\left[F_{c,itp}\left(P_{itp}^s\cdot I_{itp}^s\right) + SU_{itp}^s + SD_{itp}^s\right]\right\}\right. \\ + \sum_{(s,p,t)\in\{B(S,P,\tau)\}}\sum_{i=1}^{NG}\mu_{itp}^s\left(I_{itp}^s - c_{itp}\right) \\ \left. + \sum_{b=1}^{NB} pv_b^s\cdot LS_b^s\right\} \\ s=(1,\cdots,S). \qquad (10) \end{aligned}$$

Reference [28] presents an efficient hybrid method for the solution of deterministic long-term SCUC. It divides the original problem into a master problem and several small-scale subproblems corresponding to each period. Fuel and emission constraints as coupling constraints over a long-term horizon are considered in the master problem, pseudo penalty price signals for fuel and emission are calculated and used directly by the adjustment signals for the reallocation of long-term fuel and emission constraints. The LR is used for the solution of deterministic long-term SCUC (10) with constraints mentioned above except the coupling constraint (8). The relaxed coupling constraints transform the original problem into easier-to-solve subproblems, each representing a traditional short-term SCUC problem without fuel and emission constraints. The LR is formulated as (11) subject to constraints (6), and others mentioned earlier. Starting with initial penalty multipliers, S deterministic long-term problems are solved.

If the results satisfy fuel/emission allowance and constraint (8), this feasible solution is stored for the future use and the duality gap is calculated and compared with the designed limit, otherwise penalty multipliers are updated by the subgradient method and the process is repeated. The iteration will stop either the duality gap limitation is satisfied or the maximum iteration number reaches. An optimal solution is selected among feasible solutions as shown in Fig 4. Since the problem stated in (5) is not convex, there is no guarantee that coupling constraints will be entirely satisfied, i.e., scenario solutions I_{itp}^s and weighted average c_{itp} will be the same. Accordingly, the bundle constraint (8) must satisfy the stopping criterion, which is the weighted total violation of bundle constraints, ought to be below a certain threshold for a fast convergence while maintaining a relatively high accuracy. More details on the stochastic simulation of power systems are presented in [29].

IV. Numerical Examples

A modified IEEE 118-bus system is studied in this section to demonstrate the application of the proposed method for calculating the reliability of a vertically integrated utility based on the stochastic long-term SCUC solution. The same methodology applies to an ISO. The one-line diagram and test data for the 118-bus system are given in http://www.motor.ece.iit.edu/data/ltscuc which include the failure and repair rates for generators and transmission lines. The maximum curtailment is set to be the same as the load value at designated buses, shown in (11) at the bottom of the next page.

Fuel and emission groups are listed in Table I. VOLL is given as input. Generating units, which are burning coal, oil, and gas, are represented as fuel group (FGroup) 1, 2, and 3 respectively, and generating units with emission constraints are listed in emission groups (EGroup) 1, 2 and 3. The coal fuel group has upper and lower fuel supply constraints, while the oil fuel group has the upper limit fuel constraint, and the gas fuel group has the lower limit fuel constraint respectively. The entire emission allowance and fuel consumption constraints over eight weeks, which are the same for different scenarios, are listed in Tables II

$$\begin{aligned}
\min \ P_s \Bigg\{ & \sum_{p=1}^{NP}\sum_{t=1}^{NT}\Bigg\{\sum_{i=1}^{NG}\left[F_{c,itp}\left(P_{itp}^s\cdot I_{itp}^s\right)+SU_{itp}^s+SD_{itp}^s\right] \\
&+\sum_{i=1}^{NG}\overline{\lambda}_{u,i}^s\cdot\left[\sum_{p=1}^{NP}\sum_{t=1}^{NT}\left(F_{f,itp}\left(P_{itp}^s\cdot I_{itp}^s\right)+SU_{f,itp}^s+SD_{f,itp}^s\right)-F_{u,i}^{\max}\right] \\
&-\sum_{i=1}^{NG}\underline{\lambda}_{u,i}^s\cdot\left[\sum_{p=1}^{NP}\sum_{t=1}^{NT}\left(F_{f,itp}\left(P_{itp}^s\cdot I_{itp}^s\right)+SU_{f,itp}^s+SD_{f,itp}^s\right)-F_{u,i}^{\min}\right] \\
&+\sum_{m=1}^{NM}\overline{\lambda}_{g,m}^s\cdot\left[\sum_{i\in m}\sum_{p=1}^{NP}\sum_{t=1}^{NT}\left(F_{f,itp}\left(P_{itp}^s\cdot I_{itp}^s\right)+SU_{f,itp}^s+SD_{f,itp}^s\right)-F_{g,m}^{\max}\right] \\
&-\sum_{m=1}^{NM}\underline{\lambda}_{g,m}^s\cdot\left[\sum_{i\in m}\sum_{p=1}^{NP}\sum_{t=1}^{NT}\left(F_{f,itp}\left(P_{itp}^s\cdot I_{itp}^s\right)+SU_{f,itp}^s+SD_{f,itp}^s\right)-F_{g,m}^{\min}\right] \\
&+\sum_{i=1}^{NG}\sum_{ET}\overline{\mu}_{u,i}^{ET,s}\cdot\left[\sum_{p=1}^{NP}\sum_{t=1}^{NT}\left(E_{e,i}^{ET}\left(P_{itp}^s\cdot I_{itp}^s\right)+SUET_{e,itp}^s+SDET_{e,itp}^s\right)-E_{u,i}^{ET,\max}\right] \\
&+\sum_{n=1}^{NN}\sum_{ET}\overline{\mu}_{g,n}^{ET,s}\cdot\left[\sum_{i\in n}\sum_{p=1}^{NP}\sum_{t=1}^{NT}\left(E_{e,i}^{ET}\left(P_{itp}^s\cdot I_{itp}^s\right)+SUET_{e,itp}^s+SDET_{e,itp}^s\right)-E_{g,n}^{ET,\max}\right] \\
&+\sum_{(s,p,t)\in\{B(S,P,\tau)\}}\sum_{i=1}^{NG}\mu_{itp}^s\cdot\left(I_{itp}^s-c_{itp}\right)+\mu_{LOLE}^s\cdot\left(LOLE^s-LOLE_{fix}\right)+\sum_{b=1}^{NB}pv_b^s\cdot LS_b^s\Bigg\} \\
s = \{1,\cdots,S\} & \qquad (11)
\end{aligned}$$

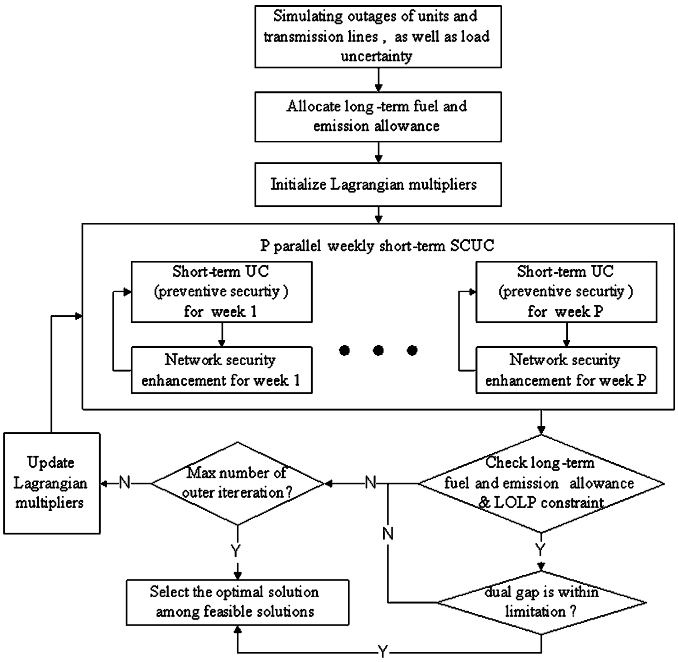

Fig. 4. Flowchart of the proposed algorithm for reliability calculation.

TABLE I
FUEL AND EMISSION GROUPS

	Units
FGroup1 (Coal)	4 5 7 10 11 14 16 19 20 21 22 23 24 25 26 27 28 29 30 34 35 36 37 39 40 43 44 45 47 48 51 52 53
FGroup2 (Oil)	31 32 33 38 41 42 46 49 50 54
FGroup3 (Gas)	1 2 3 6 8 9 12 13 15 17 18
EGroup1	10 11 16 21 22 23 24 28 29 30 34 35 36
EGroup2	31 32 33
EGroup3	8 9 15 17 18

TABLE II
LONG-TERM GROUP FUEL CONSUMPTION CONSTRAINTS

Fuel	Take-or-Pay Contract (MBtu)	Available (MBtu)
Coal (FGp1)	65,000,000	75,000,000
Oil (FGp2)	-	7,000,000
Gas (FGp3)	9,000,000	UNLIMITED

TABLE III
LONG-TERM GROUP EMISSION ALLOWANCE CONSTRAINTS

Emission	Max allowance (lbs)
SO_2 (EGP1)	8,000,000
SO_2 (EGP2)	200,000
SO_2 (EGP3)	1,600,000
NO_x (EGP1)	3,500,000
NO_x (EGP2)	500,000
NO_x (EGP3)	700,000

and III. The system is tested in an eight-week case study. The annual peak load of the system is 6000 MW and the weekly peak load as a percentage of annual peak load are listed in Table IV.

We simulate the frequency and the duration of outages of generators and transmission lines based on forced outage rates and rates to repair. The load forecasting inaccuracy is represented by a seven-step normal distribution. For each accuracy level, the computation time for the scenario-based problem depends on the number of scenarios. Scenario reduction is adopted to reduce the total number of scenarios as a tradeoff between the calculation speed and the accuracy. The original scenario tree has 100 scenarios, each with a probability of 0.01. After reduction, only 12 scenarios are left with probabilities shown in Table V. Table VI presents the results for different LOLE values. To demonstrate the efficiency of proposed model, four LOLE limits ranging from one day to 15 days in ten years, are used in SCUC. For comparison, a deterministic case is also calculated using the 20% of load as reserve. All EENS results presented are for the whole eight weeks. As shown, our reliability-constrained model accommodates the designated LOLE while reducing the cost by adjusting the generating unit commitment and dispatch. For example, it is possible to reduce the LOLE from ten days per ten years to five days per ten years by increasing the operating cost by $109.5*10^4$, i.e., $(9136.7 - 9027.2)*10^4$ and reducing the load shedding by 771.85 MWh, i.e., (1692.7-920.85).

When the designated LOLE constraint is set loosely at 15 days per ten years, economical coal-burning units would supply most of the load with a smaller generation reserve. Accordingly, the operating cost is low and the involuntary load shedding is significant. As LOLE is decreased to five days or even

TABLE IV
WEEKLY PEAK LOAD AS PERCENTAGE OF ANNUAL PEAK LOAD

Week	1	2	3	4
Peak Load%	86.2%	90.0%	90.0%	88.0%
Week	5	6	7	8
Peak Load%	88.0%	84.1%	83.2%	80.6%

TABLE V
PROBABILITIES OF EACH SCENARIO AFTER SCENARIO REDUCTION

Scenario	1	2	3	4	5	6
Probability	0.01	0.01	0.28	0.01	0.01	0.39
Scenario	7	8	9	10	11	12
Probability	0.01	0.01	0.01	0.01	0.01	0.24

TABLE VI
COMPARISON OF RESULTS FOR DIFFERENT LOLE

Proposed LOLE (in 10 years)		1 day	5 days	10 days	15 days	Deterministic
OPERATING COST ($*10^4$\$)		9623.9	9136.7	9027.2	8880.1	9225.7
EENS (MWh)		532.21	920.85	1692.7	3714.1	4220.2
Calculated LOLE (in 10 years)		0.85 day	4.97 days	6.95 days	14.27 days	16.2 days
Min Reserve (MW)		905.33	579.98	471.25	382.28	508.4
Fuel ($*10^3$ MBtu)	Coal	72,443	74,059	74,112	74,279	73,258
	Oil	6,475	5,945	4,904	4,426	6,037
	Gas	12,111	9,675	9,572	9,784	11,579
Ems SO_2 ($*10^3$lbs)	EGp1	7,545.3	7,574.1	7,617.7	7,619.9	7,562.3
	EGp2	194.02	136.11	120.42	118.07	174.57
	EGp3	1,534.6	943.37	942.81	948.72	1,325.8
Ems NO_x ($*10^3$lbs)	EGp1	3,029.6	3,018.1	3,046.7	3,047.6	3,089.2
	EGp2	93.61	74.44	64.17	47.23	83.19
	EGp3	653.83	377.35	353.12	361.49	547.53

one day per ten years, more reserve capacity is required to guarantee the required level of power system reliability. The minimum reserve requirement of one day per ten years is 905.33 MW which is about twice as much as that of ten days per ten years. Thus economical coal-burning units as well as expensive oil- and gas-burning units are committed to supply hourly loads and reserves. Accordingly, the operating cost increases due to a smaller chance for considering the involuntary load shedding.

Fuel allocation and emission allowance are included in the stochastic SCUC model. Table VI shows that at the higher LOLE, economical coal-burning units supply most of the load, thus the coal consumption is relatively higher with a smaller operating reserve. However at the lower LOLE, expensive oil- and gas-burning units are committed to supply reserves which result in a higher oil and gas consumption and a slightly lower coal consumption.

The deterministic model when considering the 20% of load as reserve has a slightly lower operating cost as compared with the stochastic case of one day per ten years LOLE. Also, it has an unacceptably high LOLE and load shedding implications, i.e., 16.2 days per ten years and 4220.2 MWh, respectively. If we lower the deterministic reserve criterion to 10% of load, the minimum reserve requirement will drop from 508.4 MW to 254.21 MW. Accordingly, the operating cost will be lower. However, a lower reserve criterion will increase the EENS and LOLE from 4220.2 MWh and 16.2 days in ten years to 7040.2 MWh and 31.7 days in ten years, respectively. Though the application of deterministic criterion is attractive for its simplicity, it does not provide an adequate assessment of power system reliability. In such cases, even a reserve criterion of 20% of the load can not result in a good enough reliability solution because the deterministic criterion neglects the stochastic nature of power system outages. That is, if more than one component is on outage at some hours, even a higher reserve of 20% of the load may not be enough to ensure the reliability of the power system.

Fig. 5, which is conceptually the same as Fig. 1, illustrates the relationship of LOLE and EENS with operating costs. Fig. 5 shows that a smaller LOLE requirement, such as one day per ten years, will result in higher operating costs and a smaller involuntary load shedding (EENS). In Fig. 5, as LOLE is set higher, the operating cost will drop while the involuntary load shedding will be higher. Fig. 5 also shows the incremental cost of load shedding. $\Delta 1$ is the incremental cost of load shedding when LOLE changes form one day to five days per ten years, $\Delta 2$ is for five days to seven days per ten years, and $\Delta 3$ is for seven days to 15 days per ten years, respectively. The corresponding incremental costs are 12.536$/kWh, 1.419$/kWh and 0.7277$/kWh according to the method discussed in Section II. The reason for higher $\Delta 1$ is that more expensive generating units are committed when the LOLE is changed from five days to one day per ten years. In this case, additional gas and oil are consumed for satisfying the one day per ten years LOLE criterion. As discussed in Section II, the incremental load shedding cost is equal to the cost of marginal generation when there is sufficient generation to supply loads. Thus, the incremental load shedding cost will drop monotonically by increasing LOLE as shown by $\Delta 1$, $\Delta 2$, and $\Delta 3$. Table VI also shows that the smaller LOLE will result in the commitment of more expensive generating units and higher operating costs.

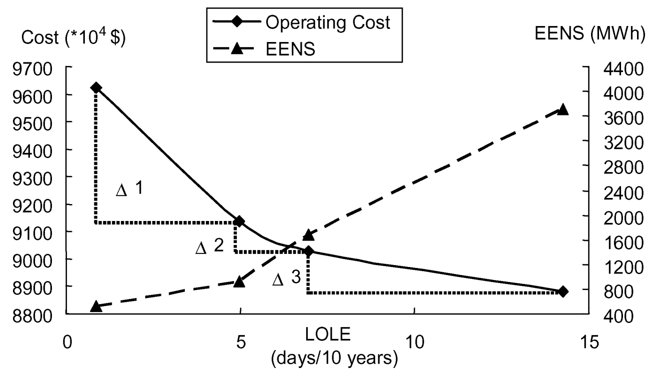

Fig. 5. Operating cost and load shedding as a function of LOLE.

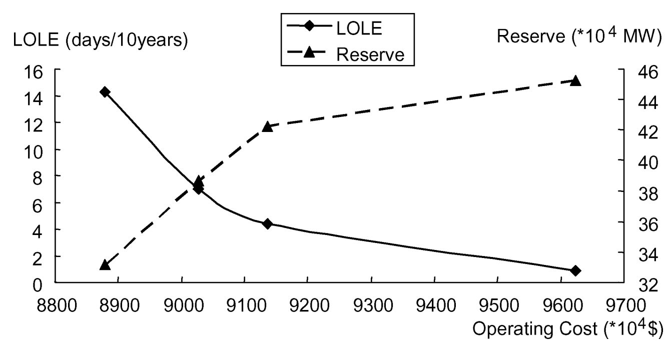

Fig. 6. Relationship among operating cost, LOLE, and reserve.

Fig. 6 illustrates the relationship among operating cost, LOLE and reserve. The reserve here refers to the sum of spinning and non-spinning reserves. A sharp increase in reserve requirement from 15 days to five days in ten years indicates a good tradeoff between reliability and economics when considering a lower LOLE of five days in ten years. Fig. 7 shows the total costs when assuming the VOLL (i.e., cost of load shedding) at 10$/kWh and 5$/kWh. The total cost in Fig. 7 decreases first and then increase as the LOLE increases. A higher load shedding cost will result in a smaller load shedding deployment, when minimizing the total cost, which leads to the additional deployment of reserves. Accordingly, LOLE will be smaller since additional reserve is considered. In Fig. 7, the optimal operating point (marked with an asterisk) occurs at a LOLE of 3.5 days per ten years when VOLL is set at 10$/kWh. As we lower VOLL to 5$/kWh, the optimal operating point occurs at around five days per ten years. In Fig. 7, the total cost at the optimal point increases by about 4% when VOLL is set higher at 10 $/kWh.

Fig. 8 illustrates the impact of fuel price on LOLE when VOLL is set at 10$/KWh. As fuel price increases by 30%, LOLE rises from 3.5 days to 4.5 days per ten years, which implicitly results in a smaller deployment of reserves. The reason is that higher fuel prices will lead to higher marginal generation costs when the load shedding cost is fixed; thus load shedding is preferred for minimizing the total cost. The results illustrate that the optimal operating cost will be higher for a higher fuel price. Higher fuel prices will also result in a higher LOLE which necessitates an optimal fuel scheduling and energy exchanges with

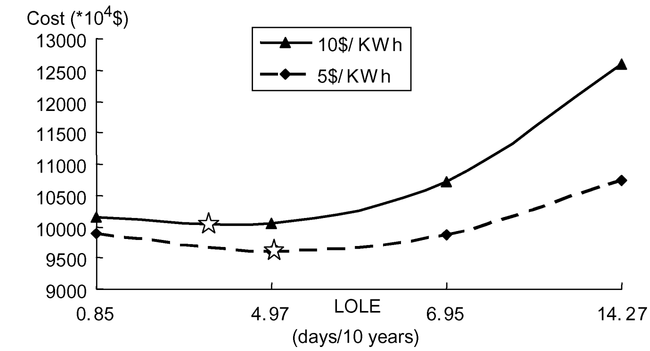

Fig. 7. Total cost as a function of LOLE and VOLL.

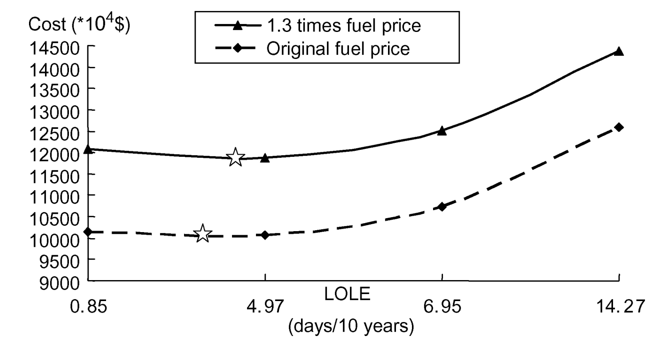

Fig. 8. Impact of fuel price on LOLE.

other zones when minimizing the total cost and maximizing the reliability.

This case is tested on a 3.1 GHz personal computer. The CPU time for solving the stochastic SCUC model is about 40 h for each LOLE value which can be reduced dramatically by parallel processing of scenarios. That is, in this case if parallel processing of scenarios is used, the CPU time is about $(40/12) = 3.3$ h. The time can be further reduced with the decomposition strategy introduced in [28] by parallel processing of weeks in each scenario. Since the proposed model is applied to the long-term reliability evaluation, the computation time may not be of a major concern.

V. Conclusions

This paper considers the reliability cost analysis by applying the stochastic model of the long-term SCUC. The probabilistic reliability criteria, i.e., LOLE as a constraint and EENS cost are introduced in the objective function of the SCUC problem. The optimal operating point of power systems is based on the minimum total cost which includes operating and EENS costs. This optimal point is influenced by power system characteristics, generating unit and transmission line constraints, fuel prices, and load shedding costs. The optimal reserve level is implicitly determined by this optimal point which indicates that the marginal cost of additional reserves at the optimal point is equal to the marginal cost of reducing EENS at that point. The study can be used for the scheduling of fuel contracts as well the maintenance outage of components in a vertically integrated utility. The same formulation applies to long-term applications in an ISO while satisfying short term constraints in electricity markets.

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