Annual Risk Assessment for Overload Security

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***Abstract*—This paper presents an approach to assess the cumulative risk associated with overload security for the purposes of midterm power system planning. The work is motivated by a need to refine bulk power system reliability assessment to meet the needs of the restructured industry. There are two main contributions to the work. First, the assessment is performed over a year-long trajectory of hourly operating conditions, resulting in reliability assessment of all expected conditions and not just a limited number of snapshots. Secondly, the assessment is quantified by a risk index comprised of summed products of probability and consequence. This index is a good indicator of the actual reliability level, it is decomposable, and it can be effectively integrated into economic decision making paradigms. The work is illustrated using the 1996 IEEE Reliability Test System.**

***Index Terms*—Decision, overload security, planning, probabilistic risk, reliability, sequential trajectory.**

I. Introduction

THE RECENT evolution of the electric power industry has brought about new needs in terms of assessing the reliability of the transmission system. Perhaps the most important of these include its accurate assessment and the need to integrate reliability into economic decision making. These needs exist at the operational level, and we have so addressed them in previous work [1]–[3]. In this paper, we address them in terms of the one year planning problem. Although we have also addressed voltage security [4], we limit the scope of this paper to the assessment of only circuit overload.

There are today a number of commercial software packages that include the influence of circuit overload in a reliability assessment scheme. All programs develop probabilistic indices characterizing the power system reliability level, although some use analytical approaches, sometimes called contingency enumeration, while others use Monte Carlo simulation. Some of the most well known in North America include TRELSS [5], TPLAN, PROCOSE [6], and CREAM. The approaches for assessing circuit overload for planning purposes used in these and other programs have rested on two main assumptions. These are

1) The circuit overload reliability level is indicated by a measurement of the amount of load shed necessary to avoid circuit overload; loss of load probability (LOLP) and expected unserved energy (EUE) are two of the most common measurements used.
2) Measurements taken on one or a limited number of selected base cases are sufficient to indicate the reliability of the system.

In this paper, we report on an approach that avoids these two assumptions. Our approach is predicated on a desire to provide a measure of *risk*, a probabilistic expectation, as the product of probability and monetary consequence of each outcome, summed over all possible outcomes. An important attribute of using this measure is that it reflects event likelihood and consequence, the two factors which, according to industry-developed disturbance-performance criteria [7], determine reliability level.

In measuring risk, it is essential that we distinguish between an *outcome* and a *decision*. One important distinction is that an outcome is an unavoidable result of a decision. Based on this distinction, we categorize transmission reinforcement, unit commitment, economic dispatch, and load interruption as decisions. In the context of overload assessment, the outcome of these decisions are the effects on the circuits. These effects, which include equipment damage and equipment unavailability, are random because they are heavily dependent on weather and on loadings, the randomness of the latter caused mainly by uncertainties in demand and equipment outages. In contrast to the commonly made assumption 1, our assessment is in terms of the probability and monetary impact of these effects, given a decision, where the decision includes transmission reinforcement and policies on unit commitment, redispatch and load interruption. Calculation of the risk index has the distinct advantage of providing a uniform basis of comparing various decisions. On the other hand, reliability evaluation of circuit overload, using a load interruption-based index like LOLP or EUE requires that the load interruption policy remain fixed throughout the study, and that it accurately reflect the load interruption policy used by the operator during the time period studied. This is undesirable because it removes a degree of freedom in the decision space, and because there is no guarantee that the programmed load interruption policy is the same as the one that will actually be used. An important implication of our evaluation approach is that the hard limits on circuit flows are not modeled. Rather, high flows approaching or exceeding the circuit limits are reflected by very high values of risk.

The second assumption given above, which results in what we call the "snapshot" model, normally means that the most stressed conditions are modeled in order to identify the lowest level of reliability. This can result in highly conservative decisions requiring high cost solutions to satisfy loading and outage conditions that very rarely occur. In addition, it can miss some important reliability problems altogether that occur during off-peak or partial peak load conditions when weak network

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topologies, weak unit commitment patterns, or unforeseen flow patterns are more likely to occur. There are also inter-temporal constraints, such as water reservoir capacities and steam turbine start-up/shut-down times, and these can affect reliability in ways that the snapshot model cannot capture. Therefore we embrace the so-called "sequential" model where we evaluate a series of hourly snapshots, sequential in time, and sum the resulting indices to obtain the final assessment. We refer to the resulting indices as *cumulative risk*. In contrast to the snapshot model which only evaluates a limited number of nonsequential network configurations and loading conditions, the sequential approach evaluates a *trajectory* of operating conditions over time, where the trajectory is formed based on the forecasted load variation, maintenance schedules, unit commitment strategy, and operating policies in place. This approach has been advocated in [8], but there, simulations of hundreds or even thousands of trajectories are required to satisfy the adopted Monte Carlo approach for computing the reliability indices. Because simulation of even a single trajectory can be computationally intensive, we propose an approach that requires simulation of only the expected trajectory. We refer to the model used to obtain this expected trajectory as the *sequential mean-variance* (SMV) model.

We will describe the SMV model in Section II. Section III summarizes the approach taken in computing *component overload risk* for transmission lines and for transformers. This is the hourly risk associated with a single circuit given the current flowing through that circuit and statistics describing the factors that affect the performance of that circuit. It is computed in advance and then utilized in the cumulative risk calculation. Section IV describes the overload risk calculation which is applied at each hour of the trajectory simulation. An example using the 1996 IEEE Reliability Test System (RTS) is provided in Section V. Conclusions are given in Section VI.

II. SMV Model Description

The SMV model first uses the expected annual load curve, sampled hourly,[1] to arrange the maintenance and unit commitment schedules, then employs time invariant variances to represent normally distributed load uncertainties. The expected annual load curve can be obtained from load forecasting, or it can be obtained from the load curve of the previous year, with an appropriate scaling to account for load growth. There are various methods to identify the maintenance, unit commitment schedule and load forecasting error. We propose a feasible one for each in order to show the effectiveness of our overall framework. For the maintenance schedule arrangement, we apply the equal LOLP criterion by utilizing the effective load carrying capacity [9]. For the unit commitment, we employ the priority list method based on the piecewise linear fuel consumption curve, considering hydro-thermal coordination [10]. Our method for unit commitment also results in an economic dispatch calculation for the generators in each hour. This provides us an hourly base case for which we can solve the power flow equations.

For load forecasting error identification, we first employ time series analysis to identify the structure and parameters of an ARIMA (autoregressive integrated moving average) model used to represent the load series [11]. This provides a load value for each hour. We assume that each hourly load value used in our trajectory has associated with it some error. This error characterizes the potential for deviation away from the load forecast for which the system coordinator (perhaps the independent system operator) is unable to make effective and economically efficient adjustments. We assume that such adjustments would be possible given more than a one-day advance warning by using the day-ahead electricity market, but they would not be possible for advance warning less than one day. Therefore, we use the estimated error of a one-day forecast in our work. This estimated error is computed by averaging the errors of a day-ahead load forecast as compared with historical data, over one year. Other reasoning could be used to identify this error, if appropriate.

For each hour, we use the load curve value as the mean load and the error as the standard deviation of the load in order to represent normally distributed load uncertainty. Allocation among buses is done according to assumed load sharing factors, but statistical correlation between loads may also be employed if data is available.

The result of this modeling effort is a series of 8760 samples, one per hour over a year, for which we know the committed generation units, their dispatch and a probability density function (pdf) for the load. We denote the series of 8760 samples as Ω. Let's consider a single hour, h, a single contingency state, s, and a single branch, b. If we can obtain the pdf for the flow on branch b, denoted by $\Pr(I_b|h, s, \Omega)$ and if we have a function $Risk(TOL|I_b)$ which gives the expected monetary impact of each flow I_b on branch b, the component risk, then we can compute the thermal overload (TOL) risk for the particular contingency state s in hour h as

$$Risk(TOL|h, s, b, \Omega) = \int_{-\infty}^{\infty} \Pr(I_b|h, s, \Omega) Risk(TOL|I_b) dI_b. \quad (1)$$

The total risk for this branch in hour h over all contingency states is then

$$Risk(TOL|h, b, \Omega) = \sum_s \Pr(s) Risk(TOL|h, s, b, \Omega). \quad (2)$$

From (2), we may sum over all branches to obtain total risk for a particular hour, or we may sum over all hours to obtain the cumulative risk for a particular branch. These kinds of calculations reflect the decomposition capability of this approach and are attractive for identifying the reasons for high risk. In addition, we may evaluate total cumulative risk as

$$Risk(TOL|\Omega) = \sum_h \sum_b Risk(TOL|h, b, \Omega). \quad (3)$$

[1]We have used a 1 hour time step as it is the longest interval for which the load may be assumed reasonably constant. We have used a 1 year study period because of our perception that new facility construction requiring $5+$ years to plan and build is no longer common in the industry. Rather, there is tendency to utilize existing transmission where feasible and reject large-scale transmission requests when not. As a result, transmission reinforcements for small-scale transmission requests are most often considered. Typically, these transmission reinforcements have relatively short completion times, so that a 1 year interval can be appropriate in many cases. When longer simulation time is needed, one can string together multiple one year simulations.

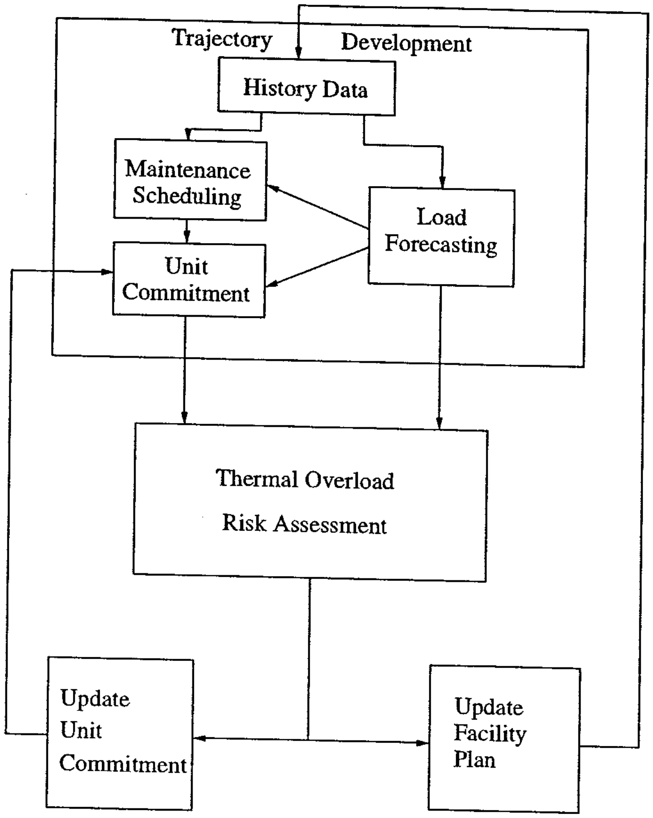

Fig. 1. Annual thermal overload risk assessment framework.

These calculations, together with those required to obtain $P_r(I_b|h, s, \Omega)$, are referred to as thermal overload risk assessment. Its use, together with the trajectory development, are illustrated in Fig. 1. From this figure, we also observe that the results of assessing the risk of a trajectory are used to update the unit commitment (or other operating policies) and/or the facility plan as needed to reduce risk. These updates correspond to different decisions and are therefore re-evaluated to determine their effect on risk.

We turn our attention to computing $Risk(TOL|I_b)$ in Section III and then $\Pr(I_b|h, s, \Omega)$ in Section IV.

III. Component Risk

Equation (1) requires $Risk(TOL|I_b)$, which is the expected monetary impact on branch b due to overload given the flow on branch b. If branch b is a transmission line, then, depending on the weather conditions, conductor type, and flow duration, the flow I_b causes conductor heating which can result in one or both of the following:

- Loss of clearance due to sag: Here, the thermal expansion of the conductor results in sag. In the worst case, the line can touch an underlying object, resulting in a permanent fault and subsequent outage.
- Loss of strength due to annealing: Annealing, the recrystallization of metal, is a gradual and irreversible process when the grain matrix established by cold working is consumed causing loss of tensile strength.

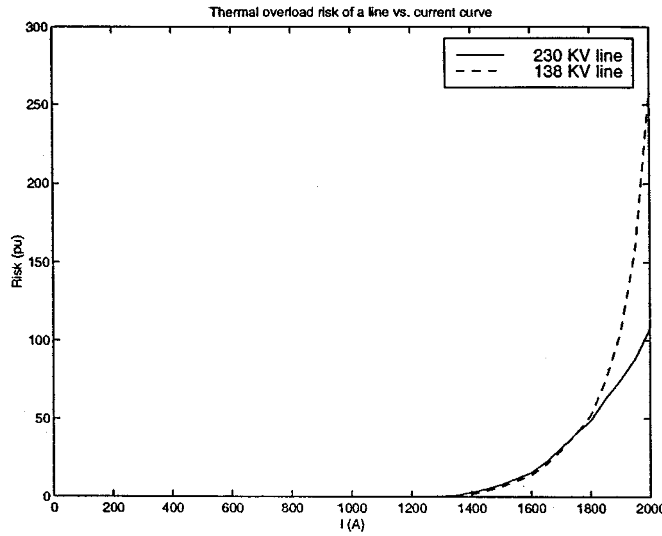

Fig. 2. The thermal overload risk vs. line current curve.

In [12], we have shown how to use weather statistics to obtain $f(\theta|I_b)$, the pdf for conductor temperature θ. This can be used to obtain the desired risk expression as

$$Risk(TOL|I_b) = \int_\theta f(\theta|I_b)[Im_{L1}(\theta) + Im_{L2}(\theta)]\, d\theta \quad (4)$$

where $Im_{L1}(\theta)$ and $Im_{L2}(\theta)$ express the monetary impact on the transmission line of sag and annealing, respectively, as a function of conductor temperature, also described in [12]. Equation (4) can be evaluated for a range of flows, resulting in a component risk curve for branch b, as shown in Fig. 2, where the pdfs for ambient temperature and wind speed are typically chosen. The same pdf for ambient temperature is also used in transformer risk assessment. The two curves for Fig. 2 are per unitized on a base equal to the cost of reconductoring 1 mile of the line. This base value is estimated based on discussions with utility engineers as \$108 000 for a 230 kV line and \$60 606 for a 138 kV line.

If branch b is a transformer, then depending on the ambient temperature, transformer type and aging rates of insulation materials (paper and oil), and flow duration, higher flow I_b causes winding hottest spot temperature to increase which can result in transformer loss of life and/or failure. We can then use an expression just like (4) to evaluate the thermal overload risk, except here, θ represents the hottest spot temperature, and Im_{L1} and Im_{L2} represent the monetary impact on the transformer of failure and loss of life, respectively, as described in [13] and [14]. With these modifications, we can evaluate eqt. (4) for a range of flows, resulting in a component curve for branch b, as shown in Fig. 3. Here, 1.0 pu risk equals the cost to rebuild the transformer. It is chosen to be \$1 000 000 in [13] and [14].

The risk evaluation of both lines and transformers, as a function of loading, must also account for the impact on the *system* caused by outage of the circuit due to high loading. In some cases, circuit outage has very little system impact, but in other cases, it results in cascading leading to islanding and/or widespread outages. There are various approaches that one can take

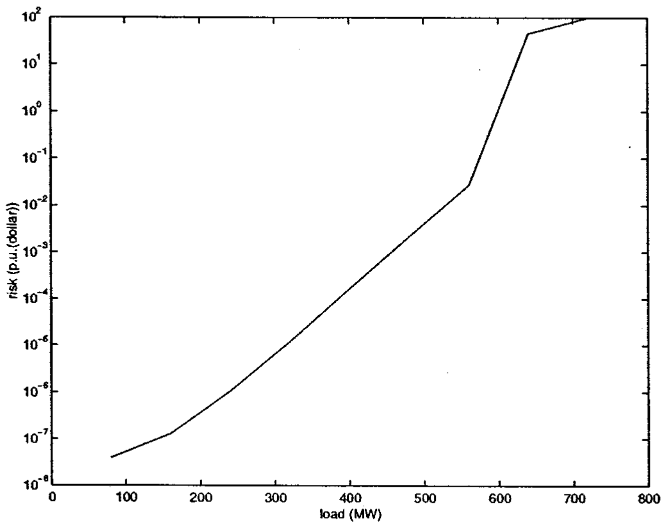

Fig. 3. The thermal overload risk vs. transformer load curve.

to evaluate this impact. For example, one could detect the extent of cascading overloads by performing a series of power flow solutions, each time removing any additional overloaded circuits. More rigorous analysis would require representation of system dynamics. Here, we have accounted for this impact very simply, but conservatively, by assigning any circuit failure, as represented by Im_{L1} in (4), to have an impact K times the cost of replacing the equipment, where K is a very large number. In the component risk curves shown in Figs. 2 and 3, we have assigned $K = 100$. The practical result of this is that circuit loadings causing any significant probability of failure contribute very large risk.

The component risk curves for both lines and transformers clearly depend on the weather statistics. One can significantly enhance the analysis accuracy by using different weather descriptions for different times of the day and for different seasons. For example, one might divide the 24 hour period into four 6 hour intervals, late morning, afternoon, evening, early morning, and one might divide the year into the four seasons of winter spring, summer and fall. Of course, this would require 16 component risk curves for every line and transformer. However, these curves may be computed and stored in advance of the trajectory simulation, so that their number does not affect the processing time. In our work, in order to illustrate the idea with the simplest approach, we have used the same weather statistics for all component risk curves. The parameters chosen for these statistics are provided in [12]–[14] .

IV. Probability Densities for Circuit Flows

The pdfs of currents can be identified by probabilistic load flow methods. The probabilistic load flow proposed in [15] uses DC power flow and convolution to deal with load uncertainties. The stochastic load flow (also called AEP method) proposed in [16] linearizes the power system around the expected point (which is obtained by iterations in order to account for the nonlinear nature of the power flow equations), and then applies linear transformation of Gaussian distributions. Some refinements for these two methods have also been proposed [17], [18]. In addition, efforts have been made to perform risk assessment for power system planning in [19]. In this paper, we linearize the system around the operating point at every hour, then use a convolution method to obtain pdfs of current flows of all lines and transformers. We then combine these pdfs with component risk curves to get the decomposed risk assessment for every line and every transformer in every hour, as expressed by (1)–(3).

A. Assumptions

We assume all loads are normally distributed random variables at every hour. Each hourly bus load is assigned a mean and variance equal to a fixed percentage of the total load forecasted mean and variance. We also assume the covariance matrix of loads is available. In practice, this covariance matrix can be estimated by statistical methods.

Generator outages are also considered. We assume that each bus is a single independent generating company. Therefore, if a unit is outaged, other units at the same bus will increase power to make up for the generation loss. When the outaged generation exceeds the remaining capacity at the bus, we assume the excess is picked up by other generators according to a specified load following policy, which could also include load shedding. In the study illustrated in this paper, we choose a single generator to perform all load following.

For the line contingencies, we include all single line outages and all common mode outages when two lines are built along the same corridor. We also assume the reactive power flow through a line remains constant at its precontingency value after a contingency.

We perform the assessment of each hour assuming there are no forced outages at the beginning of the hour, implying that in each hour's contingency assessment, outaged components are re-energized before the next hour. This is convenient because it allows us to set a single yearly trajectory *a priori*. Doing otherwise results in a very large number of possible trajectories, requiring multiple simulations in order to converge to a statistically significant result. We believe that the highly increased computation time would not provide a commensurate increase in value to the information content of the result.

B. Analytical Development

From the DC power flow formulation, we can obtain the following expressions for branch flows corresponding to any outage state s and the normal state 1.

$$P_l(s) = A(s)^T B_{ps}^{-1}(P_G - P_D) \tag{5}$$

$$P_l(1) = A(1)^T B_{p1}^{-1}(P_G - P_D) \tag{6}$$

where

- P_G is the vector of real power generator levels at each bus.
- P_D is the vector of real power load levels at each bus.
- B_{ps} is the B-matrix for outage state s.
- $A(s)$ is the connection matrix of the network for outage state s, having rows and corresponding to buses (excluding the swing bus) and columns corresponding to branches.
- $P_l(s)$ is the vector of branch power flows for outage state s.

Subtracting (5) from (6) we get

$$P_l(s) = P_l(1) + [X_l(s) - X_l(1)](P_G - P_D) \qquad (7)$$

where $X_l(s) = A^T(s)B_{ps}^{-1}$. Since $X_l(s)$ are independent of generation and load level, we can calculate and store them beforehand to save computation time.

If we set P_G and P_D to be their expected values for the hour, and use a full AC power flow solution to obtain $P_l(1)$, then (7) provides the expected flows for all branches at the hour. We will use this below in obtaining the distribution of flows due to uncertainty in generation.

Now we define ΔP_G and ΔP_D as the vectors of random variables corresponding to generation and load levels, respectively. We describe each component of ΔP_G with a two state probability mass function. We describe each element of ΔP_D with a normal distribution having a mean equal to 0 and a standard deviation derived from our load model assumption. The vector of random variables corresponding to variations in branch flows at outage state s are then given as

$$\Delta P_L(s) = X_l(s)(\Delta P_G - \Delta P_D) \qquad (8)$$

and the vector of random variables corresponding to the branch flows

$$P_L(s) = P_l(s) + \Delta P_L(s). \qquad (9)$$

Substitution of (8) into (9) yields

$$\begin{aligned} P_L(s) &= (P_l(s) + X_l(s)\Delta P_G) - X_l(s)\Delta P_D \\ &\triangleq P_{LG} + P_{LD}. \end{aligned} \qquad (10)$$

Here P_{LG} is the vector of random variables corresponding to branch flows due to variation in generation, given by

$$P_{LG}(s) = P_l(s) + X_l(s)\Delta P_G. \qquad (11)$$

The mean of $P_{LG}(s)$ is $P_l(s)$. Also, P_{LD} is the vector of random variables corresponding to branch flows due to variations in loads, given by

$$P_{LD}(s) = -X_l(s)\Delta P_D. \qquad (12)$$

The mean of $P_{LD}(s)$ is zero.

The covariance matrix for $P_{LD}(s)$ is obtained from

$$cov(P_{LD}(s)) = X_l(s) cov(\Delta P_D) X_l^T(s) \qquad (13)$$

and the diagonal elements of (13) are the line flow variances.

The pdfs for the elements of $P_{LG}(s)$s can be obtained by a convolution algorithm. In order to facilitate speed of this algorithm while maintaining reasonable accuracy, we have used segmentwise cluster-based convolution. The algorithm is described in [20].

The flowchart for thermal overload risk assessment is shown in Fig. 4. For the first hour, we form the generation random variable ΔP_G, i.e., we obtain their pdfs. After the first hour, we use convolution (when some unit is started) and deconvolution (when some unit is shut down) to update ΔP_G. Then for each hour and each credible contingency, we linearize the system, calculate the pdfs of line flows contributed by generation and by load by using (11) and (12), respectively. Then we convolve the two pdfs to get the pdfs for active flows, which is the term $\Pr(P_b|h, s, \Omega)$. This term can be transformed into $\Pr(I_b|h, s, \Omega)$ based on the assumption that the reactive flow remains constant. It can then be used in (1), together with the composite risk, to obtain the risk assessment for a specific contingency state, line, and hour.

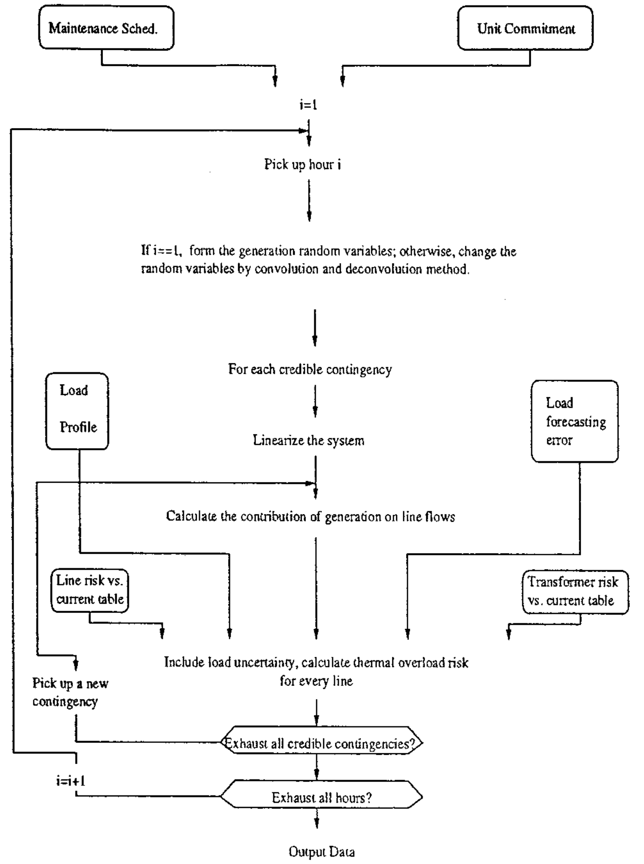

Fig. 4. The flowchart for thermal overload risk assessment.

V. CASE STUDY

A. Example System Description

The IEEE RTS 96 system is shown in Fig. 5. It has 24 buses, 38 lines, 32 generation units. The expected load profile of the next year is shown in Fig. 6, obtained from [21].

B. Determination of System Trajectory and Load Forecasting Error

In our program, the maintenance schedule is arranged by applying equal LOLP criterion [9]; the unit commitment is arranged by applying priority list method [10]. The one day ahead load forecasting error is identified by time series analysis [11]. The day ahead error is 1.92% according to our calculation. There are a number of methods and variations of them available for each of these modules. So our selected implementations of maintenance scheduling, unit commitment, and load forecasting error may be replaced or modified. However,

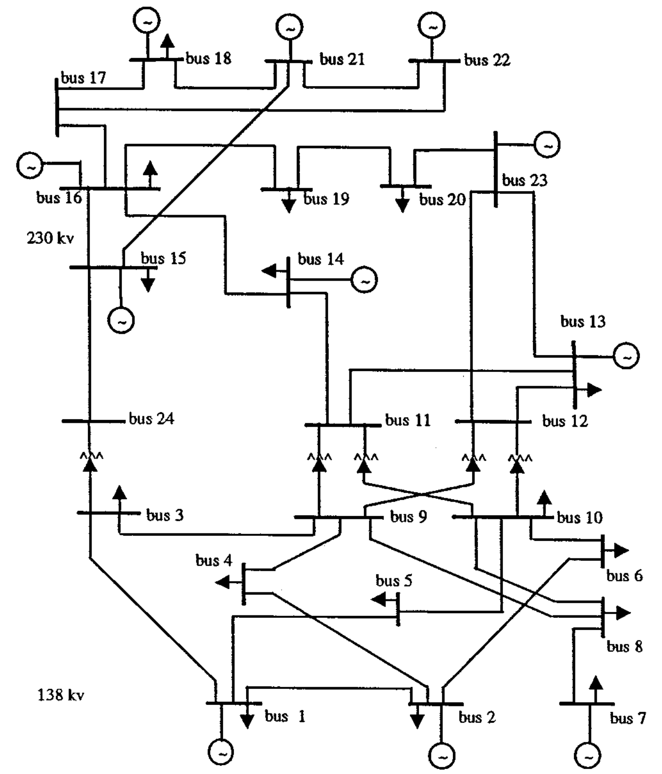

Fig. 5. The IEEE RTS 96 system.

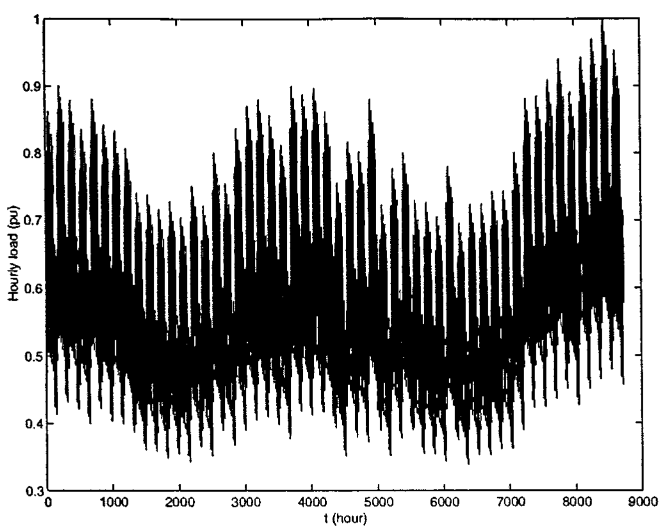

Fig. 6. The expected load profile.

it is our integration of them for the purpose of cumulative risk assessment that is of significance.

C. Analysis of Calculation Results

For the IEEE RTS'96, the thermal overload risk during a whole year is shown in Fig. 7. Here, we can see the 1798th hour has a peak risk which is much higher than other hours. Reference to Fig. 6 indicates that this peak risk occurs at an off-peak loading season.

The risk curve for the day of peak risk hour 1798 (hour 22 of this day) is shown in Fig. 8, and the corresponding daily load profile is shown in Fig. 9. Here, we see that this peak risk occurs

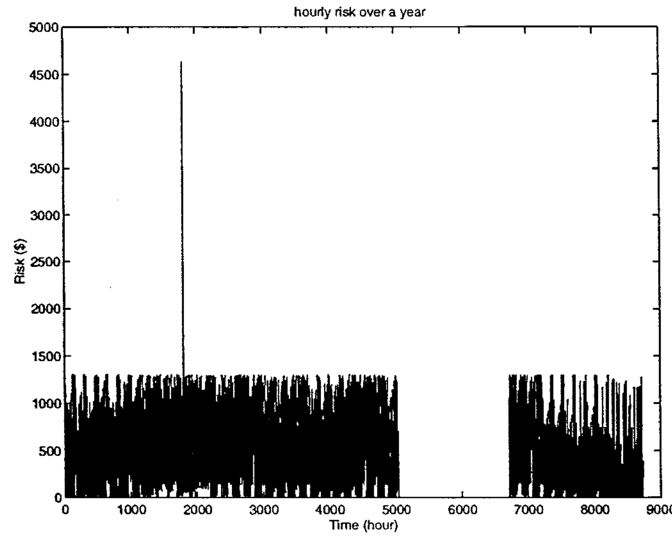

Fig. 7. Hourly thermal overload risk over a year.

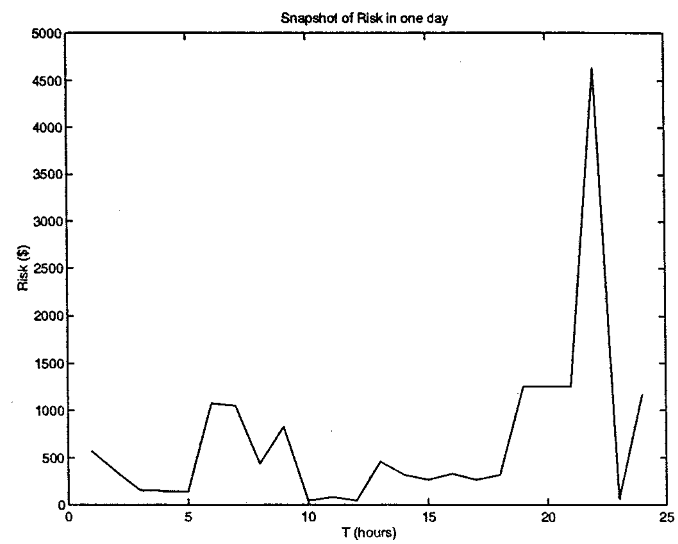

Fig. 8. Risk curve of the day with the peak risk hour.

at a partial peak condition for the day. One can observe from Fig. 8 that the load decreases a little from hour 21 to hour 22. We checked the unit commitment and found that this small decrement triggers 2 generation units with capacity 197 MW each at bus 13 to be shut down, even though the loads at buses 7 and 8 are still significant. This results in long distance power transfer, and it causes high thermal overload risk ultimately. If we were to assess the overload reliability using snapshot models, we would be unlikely to capture this condition, occurring at an off-peak loading season at a partial peak loading hour, and caused by a unit commitment transition. This result could be reason to modify the unit commitment strategy for this hour or revise the unit commitment algorithm itself.

There is a period which has almost no risk between hour 5401 and hour 6668. This is because during this time period, generation is distributed more evenly so that customers do not have to require power transfer from a long distance.

The annual risk suffered by severe lines is listed in Table I. All other lines have less than $1 risk. There are 46 network states,

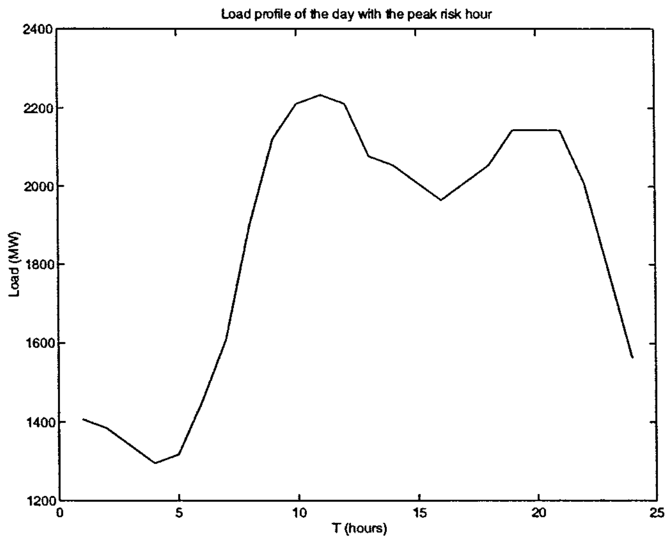

Fig. 9. Load profile of the day with the peak risk hour.

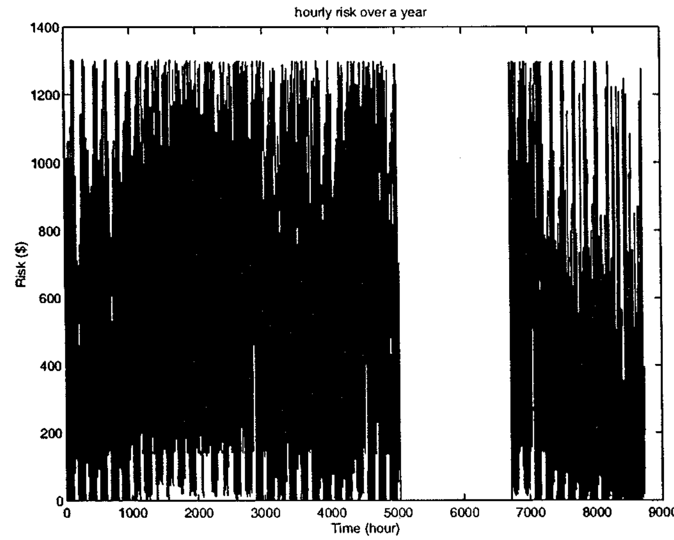

Fig. 10. Hourly thermal overload risk over a year after unit commitment adjustment.

TABLE I
THE ANNUAL RISK SUFFERED BY SEVERE LINES

Overloaded line	Risk ($)
11–13	145
14–16	2333
15–16	979
16–17	2796207
16–19	1300
17–18	139006

TABLE II
THE ANNUAL RISK FOR DIFFERENT OUTAGES

Outage	Risk ($)
Line 14–16	1300
Line 15–16	217
Line 16–19	979
Line 17–18	2333
Common mode B	145
Common mode D	2934996

including the normal state, one-line outages, common mode outages. The states which cause high risk are listed in Table II.

The cumulative annual risk is $2 939 971. We can see from Table I that line 16–17 and line 17–18 suffer severe risk. The owner of these two lines should receive some compensation for their high risk. We can also see from Table II that common mode D contributes the most to the annual risk. Therefore, if we can build the double lines from bus 15–21 on separated towers, the risk will be significantly reduced.

Risk may be decomposed among hours as indicated in Figs. 7 and 8. Risk may also be decomposed among components, as indicated in Table I, which shows the components that *incur* the most risk. Finally, risk may be assigned to different components, and subsequently to the owners of these components, as indicated in Table II, which shows the components that *cause* the most risk.

According to our unit commitment results, bus 7's generation units are frequently shut down due to high marginal cost of generation power. However, the local area of bus 7 and bus 8 is a load center, so bus 7 generation shut down results in long distance power transfer from the 230 KV network to the 138 KV network. Therefore, if we constrain-on bus 7's generation units (except for maintenance), we are likely to reduce the risk [9]. Calculation of our program for this case provides the risk curve shown in Fig. 10. We can see that the peak risk at hour 1798 has been eliminated. However, the cumulative annual risk is $2 904 812, only $35 159 less. This is reasonable because the main problem is located at bus 13 in the 230 KV network. Some minor adjustments in the 138 KV network will have limited influence on the cumulative risk.

VI. CONCLUSION

We have proposed the sequential mean variance (SMV) model together with a risk index to assess power system reliability over a mid-term planning period. We have shown that the SMV model enables assessment of loading periods and inter-temporal affects that may not be captured by so-called snapshot models. Yet, it does so with reduced computational requirements relative to the sequential Monte Carlo model. The strength of the method lies in its ability to identify *a-priori* high-risk situations encountered during an expected trajectory of yearly operating conditions, and then to avoid or mitigate these conditions using short-term operational or reinforcement measures (see footnote 1). This is in contrast to long-term facility planning needs, where one thinks of performing design that is robust to a wide range of possible trajectories. The risk index used in the hourly assessment provides a compact evaluation of the hour's reliability level for overload that does not require the representation of the operator's load shedding policy, considered here to be a decision which could be assessed by the risk index. This risk assessment is performed based on linearization around the operating point and convolution between random variables. The risk index can be presented as cumulative over time, it can be decomposed according to which agent incurs it, and it can be assigned to the agent that causes it. Having units of dollars, it becomes possible to directly include reliability assessment in economic decision making strategies. Our proposed framework is shown to be conducive to facility planning and unit commitment adjustment. It is also possible to use a similar approach for assessment of voltage security [4] using optimization methods [22], [23], and a paper on our completed work on this subject is now being prepared.

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