RELIABILITY-DIRECTED COMPUTER-AIDED DESIGN SYSTEM

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study

Abstract.

A theoretical apporoach and applied techniques for designing analogus engineering devices and systems with due account of random variations in system parametrs and reliability specifications are considered. For solving this problem a so-called operational/parametric approach is used. This approach is based on the computer-aided simulation of system capability and availability, parameter deviations and techniques of optimal parametric synthesis in terms of reliability criteria. Special attention is paid to algorithms that reduce the labour content of parameters optimisation problems. For seeking a numerical solution of the parametric design problem a computer-aided reliability-oriented design system is proposed.

1. Introduction

The design process consists of group of particular tasks such as analysis or synthesis one. Any technical object can be stated as a pair $W=<X,S>$, where $X=(x_1,...,x_n)$ are parameters and S is the object structure. We can consider a function $\Phi=\Phi(W,Q)$ as a criteria of object's operation quality (here Q is the operation conditions).

The synthesis problem can be formulated as an optimization task

$$\Phi(W,Q) \to \underset{W \in \Omega_W}{extr} \Rightarrow W_Q^0,$$

where Ω_w is the possible set of object variations and W_Q^0 is the optimal object under the conditions Q. The analysis task can be divided to the parametric and structural ones

$$\Phi(X,S,Q) \to \underset{W \in \Omega_X}{extr}\ \underset{W \in \Omega_S}{extr} \Rightarrow X_Q^0, S_Q^0,$$

where Ω_X is the set of possible parameters and Ω_S is the set of possible structures.

Therefore, the synthesis of engineering systems consists of two basic parts: developing of structure (structural synthesis) and internal parameter values choosing (parametric synthesis).

The studies have shown that the engineering system parameters are subject to random variations and the variations may be considered as non-stationary stochastic processes. The conventional methods for choosing parameters (for parametric synthesis) generally do not take account of parameter production and field deviations of parameters from their design values. As a result, the engineering systems designed in such a manner are not optimal in the sense of their gradual failure reliability.

This paper proposes the approach and some algorithms for seeking a numerical solution of the parametric optimization problem with a stochastic (reliability) criterion, which has made possible to implement and extend the concepts discussed in [1], [2], [3].

On the basis of the proposed methods and algorithms a computer-aided reliability-oriented design system called CARD has been developed. The CARD system builds mathematical models and calculates ratings of component parameters so that achieve the highest precision, acceptability (manufacturing yield) or reliability of engineering systems under design.

2. Parametric synthesis problem

Let $S(\boldsymbol{x})$ be a system which depends on a set of n parameters $\boldsymbol{x}=(x_1,..., x_n)$. We say that system $S(\boldsymbol{x})$ is acceptable if $\boldsymbol{Y}(\boldsymbol{x})$ satisfy the conditions (1):

$$\mathbf{a} \le \mathbf{Y}(\mathbf{x}) \le \mathbf{b} \qquad (1)$$

where $\boldsymbol{Y}$, $\boldsymbol{a}$ and $\boldsymbol{b}$ are m-vectors of system responses(output parameters) and their specifications, e.g. $Y_1(\boldsymbol{x})$ - average power, $Y_2(\boldsymbol{x})$ -delay, $Y_3(\boldsymbol{x})$ - gain.
The inequalities (1) define a region D in the space of design parameters

$$D = \{\mathbf{x} | \mathbf{a} \le \mathbf{Y}(\mathbf{x}) \le \mathbf{b}\} \qquad (2)$$

D is called the tolerance margin domain (region of acceptability) for S.

Fig.1 illustrates such a region. The values given for a and b are the specifications for the system.

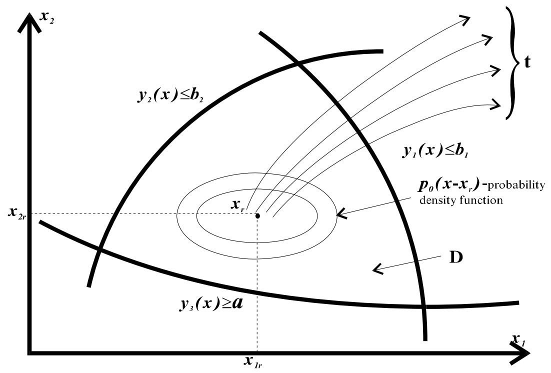

Fig. 1. Region of acceptability ***D*** defined by system response functions.

As it was mentioned above, the engineering system parameters are subject to random variations (aging, wear, temperature variations) and the variations may be considered as stochastic processes:

$$\mathbf{X}(t) = \{X_1(t), \ldots, X_n(t)\}.$$

In general the optimal parametric design (synthesis) problem can be stated as follows. Given the characteristics of random processes $\mathbf{X}(t)$ of system parameters variations, a region of admissible deviation- D and a service time T, find such a deterministic vector of parameter ratings (nominals) $\boldsymbol{x}_r = (x_{1r}, \ldots, x_{nr})$ that the probability

$$P_r(\mathbf{x}_r, T) = P_r\{[X_1(t) - x_{1r}, \ldots, X_n(t) - x_{nr}] \in D, \forall t \in [0, T]\}$$

be maximized.

Any optimization technique requires, first, a method of objective function calculation and, second, an extremum searching method which allows to find a solution with a minimum cost.

3. Reliability estimation

The proposed method of reliability estimation, called "the method of critical sections", is based on the following fundamental ideas.

As known, any random process can be presented as a set of random values, or as an ensemble of functions $y_\omega(t)$ in some functional space, where functions $y_\omega(t)$ depend on the parameter ω which characterizes the realization or the selective function of a random process. The entire set of this functions will define the output parameter degradation process.

The probability $P_{rt}(D_Y)$ of matching to given constraints $D_Y = \{Y / a \leq Y \leq b\}$ at the time t for any t-section of output parameters space

$$P_{rt}(D_Y) = \int_a^b f_t(y)dy,$$

where $f_t(y)$ is a one-dimensional distribution density of a random process.

Let us select from the entire set of random processes a subset S_μ of such realizations that their values will belong to the numeric ensemble D at the times $t_1, t_2, \ldots t_\mu$. The value of the probability index corresponding to this subset can be defined as

$$P_r(S_\mu) = \underbrace{\int_a^b \ldots \int_a^b}_{\mu} f_{t1,\ldots,t\mu}(y_{t1}, \ldots, y_{t\mu})dy_1 \ldots dy_\mu, \qquad (3)$$

where $f_{t1,\ldots,t\mu}$ is the joint distribution density of random values for t_1-,...,t_μ- sections.

If the number of t-sections within $[0;T]$ is large enough, the $P_r(S_\mu)$ may be considered as a probability of system non-fault operationality.

Usage of equation (3) is very difficult, but it can be simplified by applying some constraints to the selective functions. For example, for smooth processes we can suppose that in order to determine acceptability of any realization it will suffice to determine acceptability of this realization only for few t-sections (called critical sections). In usual practice the number of such critical sections is not more than three for real engineering devices.

Let the random parameter changing process $Y(t)$ be monotonous. In this case in order to any it realization $y(t)$ lie in the region of acceptable changes $[a,b]$ during the time interval T, it is necessary and enough that they lie in this region in the boundary (critical) sections $t=0$

and $t=T$. The conditions of lying of $Y(t)$ in the region of acceptable values during time T will be as follows:

$a \le Y(0) \le b, \qquad a \le Y(T) \le b,$

where $Y(0)$ and $Y(T)$ are random values appeared on the corresponded t-sections of process $Y(t)$.

The probability of lying of $Y(t)$ inside $[a,b]$ during given time can be stated as

$$P_r(T) = P_r\{[\, a \le Y(0) \le b] \cap [a \le Y(T) \le b]\}$$

If the tendency of parameter changing is known, then using some allowances we can write

$$P_r(T) = \int_a^{\infty} f_0(y)dy - \int_b^{\infty} f_T(y)dy, \quad \text{for } \frac{dy}{dt} \ge 0,$$

$$P_r(T) = \int_a^{\infty} f_T(y)dy - \int_b^{\infty} f_0(y)dy, \quad \text{for } \frac{dy}{dt} < 0,$$

where $f_0(y)$ and $f_T(y)$ are the probability density functions at the sections $t=0$ and $t=T$ respectively.

An important problem of system design is to choose the nominal design $\boldsymbol{x}_r$, so that the "yield" is maximized. The yield is the probability that the system will work, i.e., pass specifications (1) at the time $t=0$. Now suppose that a joint probability density function (PDF) for internal parameters $p(\boldsymbol{x})$ is given which characterizes the random variations of the parameters at $t=0$. The designer usually has design control on the nominal $\boldsymbol{x}_r$ of this distribution. To emphasize this dependence of the PDF on the nominal design, we write the probability density function as $p(\boldsymbol{x} - \boldsymbol{x}_r)$. In terms of $p(\boldsymbol{x} - \boldsymbol{x}_r)$ the yield is

$$P_r(\boldsymbol{x}_r) = \int_D p(\boldsymbol{x} - \boldsymbol{x}_r)dx$$

(D - is the region of acceptability). Thus the design problem is to choose $\boldsymbol{x}_r$ so that $P_r(\boldsymbol{x}_r)$ is maximum.

The practical algorithm of the stochastic criterion calculation is based on the conventional Monte Carlo method.

At the beginning, the random vector of parameters is generated (this vector means random manufacturing device realization), and then the internal parameters degradation is simulated using degradation model. For example, parameters variations can be approximated as follows

$$X(t) = \sum_{k=0}^{m} x_r u_k(t)$$

where x_k is a random variable; $\{u_k(t)\}^m{}_{k=0}$ are continues deterministic functions of time.

The Monte Carlo method approximates $P_r(x_r, T)$ by the ratio of number of acceptable realizations (falling in region D)-N_a to the total number of trials - N.

$$P_r = {N_a}/{N} ,$$

Unfortunately, often the region D is unknown. It is given only implicitly through system's equations and the systems response functions. If we do not know the region D, then a Monte Carlo evaluation of probability $P_r(\boldsymbol{x}_r, T)$ at particular nominal value $\boldsymbol{x}_r$ requires N system analyses for each trial set of parameter $\boldsymbol{x}_r$. Typically, hundreds of trials are required to obtain a reasonable estimate for $P_r(\boldsymbol{x}_r, T)$.

Optimization requires the evaluation of our probability $P_r(\boldsymbol{x}_r, T)$ for many different values of the nominal values of the parameters $\boldsymbol{x}_r$. Therefore to make practical the use of Monte Carlo techniques in statistical system design, it is necessary to reduce the number of system analysis required during optimization.

As a solution, the following two-steps technique and the corresponding algorithms can be used for practical reliability optimization.

4. Optimization techniques

The first step consists in replacing the original stochastic criterion with a certain deterministic one, allowing nearby optimum solutions to be obtained. The two such objective functions are possible. One of them is a so-called a "minimal serviceability reserve" that can be presented in the general form:

$$F(\mathbf{x}) = \min_{i=1,m}\left[\frac{a_i - Y_i(\mathbf{x})}{w_i} - 1\right],$$

where $Y_i(\boldsymbol{x})$ - the i-th output value, a_i - the i-th constraint ($Y(\boldsymbol{x}) \le a$) and w_i - the i-th weight coefficient.

From this, we have a following optimization problem:

$$\mathbf{x}_r = \arg\max_{x \in D} F(\mathbf{x}).$$

It means that such a nominal point should be found that will have the largest distance from the acceptability region margins.

An other method which can be used for the reliability optimization is so-called "equal densities method". This method is of combined type, that uses statistical data and a deterministic optimization technique.

At the first step we should estimate distribution density function (DDF) for output parameter. As can be shown analytically, probability maximum will be achieved, if DDF will be shifted such, that both lower and upper constraints will cut equal densities on DDF [1]. Advantages of this approach are fairly clear, but there is one serious restriction - this method may be applied only in case of one output parameter.

Now the first design step is completed. At the same time the next design step must be made if the reliability index that was achieved by using deterministic methods is not high enough. This step is a direct probability optimization, i.e., methods of stochastic optimization should be used here.

First, it should be pointed out that most of optimization methods have the highest convergence speed when they start at a "good" initial point. Therefore, it would be most natural to get a previous solution as an initial point for the next design step.

As it was mentioned above, the stochastic methods are very time-consuming. And now some techniques that allow us to decrease computational cost will be considered. The first method, we dwell on, is the "correlated samples method".

It is clear that the optimization process needs only the value of difference ΔP between to points probabilities, not probability values. And the variance of ΔP is estimated to be

$$\sigma^2\left\{\Delta\hat{P}\right\} = \sigma^2\left\{\hat{P}_1\right\} + \sigma^2\left\{\hat{P}_2\right\} - 2R\left\{\hat{P}_1;\hat{P}_2\right\}\sigma\left\{\hat{P}_1\right\}\sigma\left\{\hat{P}_2\right\},$$

where R is the correlation coefficient between two estimates. When the samples are independent, the R is equal to zero and the variance

$$\sigma^2\left\{\Delta\hat{P}\right\} = \sigma_I^2\left\{\Delta\hat{P}\right\} = \sigma^2\left\{\hat{P}_1\right\} + \sigma^2\left\{\hat{P}_2\right\}.$$

If a positive correlation can be achieved, R will be more than zero and, therefore,

$$\sigma^2\left\{\Delta\hat{P}\right\} < \sigma_I^2\left\{\Delta\hat{P}\right\},$$

i. e., for the same precision, simulation with correlated samples will require the less number of model runs, than independent samples. Intuition suggests that the positive correlation can be achieved by use the equal random influences for both device realizations to be compared.

The next approach is based on the supposition that the device operation state do not change inside the little region near the previously checked point. Therefore, if a simulated point exists such that the distance from it to the point to be checked is less than a definite value, it is not need to perform the new system simulation.

In practical algorithm the internal device parameters quantization is accomplished. And every generated random point can be assigned to the one of the existing quants. The system simulation will be performed if no early checked points are exist within this quant. Each newly simulated point is presented as a vector of quant coordinates with the acceptability flag (0 or 1), so a database of checked quants can be build, and it is not necessary to make a system simulation more than one time per quant.

The experimental results show that the method in general is highly effective when compared to a conventional Monte Carlo technique, especially in conjunction with the "correlated samples".

The next way to decrease total design time on the phase of statistical optimization is to use modern supercomputing technologies and parallel processing. The easiest implementation of this idea would be multithreading programming on computers with symmetric multiprocessors (SMP) architecture and operating systems that can assign different threads to different processors (like Windows NT or modern clones of Unix). But computational power of conventional SMP systems is very limited - usually they consist of not more than two or four processors. Systems with massive parallel processing (MPP) architecture can contain much more processors (up to few thousands) but are very expensive.

It seems more applicable for most installations usage of distributed processing technologies. In this case computational tasks can be distributed over the set of networked workstations. And, by the way, here each computer can use multithreading and SMP architecture. Now the CAD system to be developed is modified for usage of parallel Monte Carlo method. The implementation of this technology is based on PVM (Parallel Virtual Machine) software package. The work is still in progress.

5. Interactive system for design optimization

All techniques described above were included in the computer-aided reliability-directed system called SPORA. The system SPORA was developed for parametric synthesis of analogous engineering devices with respect to reliability requirements. SPORA is designed to permit a user to observe, interrupt, diagnose, modify and restart a computation as it progress, resulting in very substantial savings not only in computing time, but olso in the overall time needed to carry out a design. For example, when a design or optimization procedure is not succeeding in an attempt to meet specifications, the failure can be identified in an interactive CAD system by observing the output. The designer may therefore stop the computation and, making use of the heuristic information displayed on the screen, the designer could,

- modify the structure of the design,
- relax the constraint specifications,
- reset parameters of the procedure such as scaling, weights etc.,
- change problem formulation or algorithms.

This involvement in the optimization process put the designer in an ideal position to perform tradeoffs.

The system uses a widely distributed SPICE-like circuit simulation program, that allows to simulate a large class of analogous devices in direct current, frequency and time domains. SPORA also consists of features for nominal design, design centering, tolerances assignment, etc. The system has special graphic postprocessor for the best presentation of design results. SPORA is now in service and used for the reliability-oriented design of electronic equipment.

The SPORA system has been tested on a number of complex designs involving integrated circuits, filters and control systems.

6. Design example

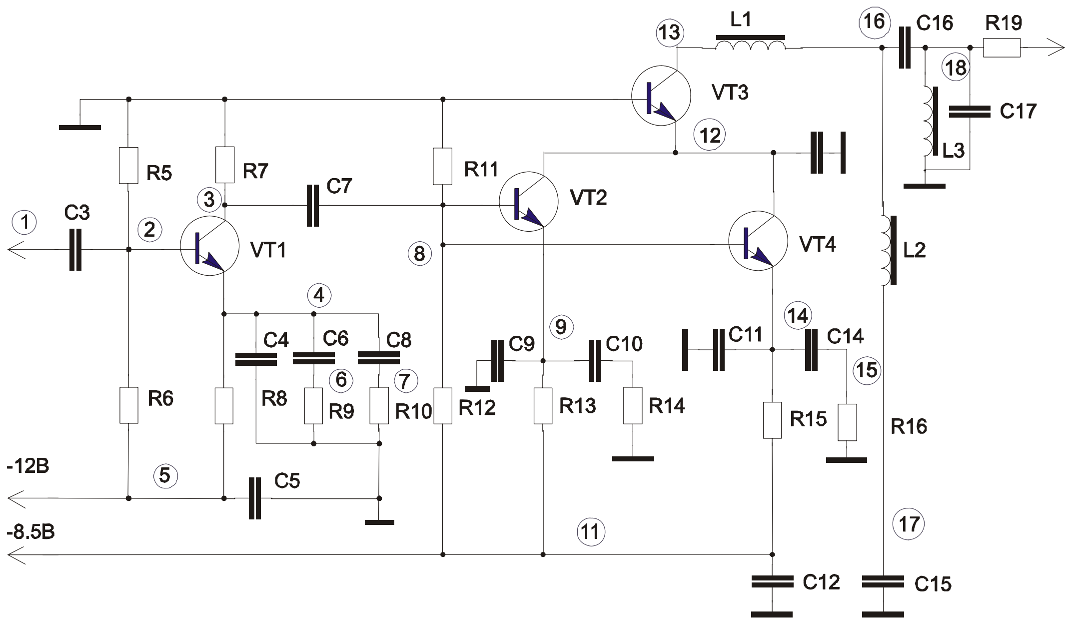

Fig. 2 Band-width amplifier

<u>Requirements:</u>

Frequency band: 800...1800 MHz

Amplifier ratio: 25±2 DB

Probability (manufacturing yield) >0.9

Table 1. Initial nominal values ($P_r = 0.44$)

L1	C4	C9	C10	C11	C13	C14	C17
0.01m	0.05p	20.6p	15p	25p	10p	1.5p	1.5p

Table 2. Nominal values after first optimization step ($P_r = 0.7$)

L1	C4	C9	C10	C11	C13	C14	C17
0.03m	5.6p	8.2p	12p	8.2p	2.2p	12p	1.5p

Table 3. Optimal values ($P_r = 0.92$)

L1	C4	C9	C10	C11	C13	C14	C17
0.012	6.5p	8.5p	10p	8.9p	2.4p	11p	1.4p

7. Conclusion

A theoretical approach and applied techniques for designing analogous engineering devices and systems with due account of random variations in systems parameters and reliability specifications were considered. For solving this problem we use a so-called operational/parametric approach based on the computer-aided simulation of system capability and availability, parameters deviations and techniques of optimal parametric synthesis with respect to reliability criteria.

Under this approach the optimal parametric synthesis task is formulated as an optimization problem with a stochastic criterion.

The replacement of original stochastic criterion with a certain deterministic one is used in order to reduce computational cost of statistical algorithms. Moreover, a few techniques for decreasing the number of model runs in Monte Carlo method were implemented.

On the basis of the proposed methods and algorithms a computer-aided reliability-oriented design system called SPORA has been developed. The SPORA system builds mathematical models and calculates ratings of component parameters so that achieve the highest precision, acceptability (manufacturing yield) or reliability of engineering systems under design.

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