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A ROBUST DESIGN TUTORIAL

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ABSTRACT

This tutorial describes a framework for discrete event simulation which synthesizes Taguchi's robust design philosophy and a response surface metamodeling approach. We show how the use of a loss function which incorporates both system mean and system variability can be used to efficiently and effectively carry out system optimization and improvement efforts. The results can yield new insights into system behavior, and may recommend system configurations which differ substantially from those selected by analysis solely of the mean response. Issues of model validation and model complexity can also be addressed. The tutorial is meant for both practitioners and researchers. We assume a knowledge base at the level of Chapters 11 and 12 of *Simulation Modeling and Analysis* (Law and Kelton, 1991), but will review essential elements and distribute illustrative examples at the session.

1 INTRODUCTION

What is robust design? It is a system optimization process which springs from a view a system should not be evaluated on the basis of mean performance alone. In addition to exhibiting an acceptable mean performance, a "good" system must be relatively insensitive to uncontrollable sources of variation present in the system's environment. The robust design approach was pioneered by Genichi Taguchi for quality planning and engineering product design activities (Taguchi and Wu 1980; Taguchi 1986, 1987). He found that it was often more costly to control causes of manufacturing variation than to make a process insensitive to these variations, and through the use of simple experimental designs and loss functions was often able to greatly improve product performance by "building in" the quality.

In the simulation context, robust design can be viewed from two slightly different perspectives. One view is that simulation is used primarily as a surrogate for a real system, because of the cost and time required to make and observe changes in a real system. From this perspective, application of the Taguchi strategy proceeds in a straightforward manner: the total time required to perform the experiment is greatly reduced, but the designs and analyses used are the same as those which would be applied to a physical system if cost and time permitted. Applications have included the product designers' uses of computer models for experimentation in place of physical prototypes, particularly in the semiconductor industry (Sacks et al. 1989, Welch et al. 1990). These experiments have typically involved Monte Carlo simulation, although clearly robustness can be used as a criteria for evaluating discrete-event simulation systems as well. Those who use simulation to study systems primarily because of the difficulty of experimenting on the real system may realize the benefits of improved performance and decreased cost cited by many manufacturers if they decide to evaluate performance in terms of robustness.

A larger view of the simulation process is also possible. A simulation model is constructed assuming a variety of system inputs (e.g., distributional forms and characteristics, simplifying assumptions, level of detail) which are unlikely to be completely accurate. Model verification and validation are important issues in the field, as is simulation sensitivity analysis. From this perspective, one can view robust design as a process of simulation optimization, where the "best" answer is not overly sensitive to small changes in the system inputs. If robust systems are identified, then the actual results are more likely to conform to the anticipated results after implementation.

The robustness criteria can be applied to rank a discrete number of alternatives, which result from changing the settings of some or all of the inputs to the simulation model (or system). Alternatively, if some or all of the input factors are quantitative, one can construct metamodels of the simulation which describe how the system performance varies as a function of the input factors. There are many approaches to metamodeling (Barton, 1992), but response surface metamodels work well in the robust design context. Metamodels provide much more information about the underlying system than haphazard investigation of a few alternatives. Thus, if the goal of the analyst is to optimize or improve the model's performance, and flexibility exists in the settings of the parameter levels (as in prospective studies), then building a metamodel is appropriate. The actual number of configurations studied, and the form (linear, quadratic, etc.) of the resulting metamodel are dependent on the experimental design chosen. Note that first-order models may not suffice for complex discrete-event simulations: performance is often highly nonlinear, even over a relatively restricted range of factor settings.

The construction of metamodels is facilitated by the use of experimental design techniques. Simulation analysts have the luxury of controlling all inputs to the simulation (including random number seeds, etc.): this means they have more flexibility in designing the experiment, and more opportunities for exploiting the additional degree of control, than do those experimenting directly on real systems.

In this tutorial our focus is on the robust design process for discrete-event simulation experiments. We begin with an overview of the robust design strategy. We then discuss tactical issues, such as appropriate experimental designs, metamodel construction, robust design identification, analysis, and conclude with a summary of the insights into system behavior that can be achieved under a robust design approach.

2 PHILOSOPHY AND OVERVIEW

Taguchi's philosophy and strategy have been widely praised in both the applied statistics and manufacturing communities, (Pignatiello and Ramberg 1991) but many of the methods and tactics he advocates are often controversial (Box 1988, Ramberg, Pignatiello and Sanchez 1991, Nair et al. 1992). The approach described in this paper (see also Sanchez et al 1993, Sanchez, Ramberg and Sanchez 1994) combines Taguchi's strategy and response-surface metamodeling techniques, which we feel is particularly beneficial when analyzing complex simulation experiments because of the additional insights available.

2.1 Factor Classification

In systems where stochastic variation is present, the response exhibits random fluctuation or variation. In order to achieve systems or products for which the variation around the target value is low, several steps are necessary. First, one must identify factors in the system which are anticipated to affect the system response. Factors are classified as *parameters*, *noise factors*, or *artificial factors*.

The parameters are the decision factors—those which are controllable in the real world setting modeled by the simulation. Noise factors are not easily controllable or controllable only at great expense in the real-world setting. (Parameters should not be confused with distributional characteristics, such as the mean processing time μ_t characterizing a machine in a manufacturing system simulation. The factor μ_t would be a parameter if one could select one of several machines or methods to employ, but it would be a noise factor if the mean processing time varied across similar machines in a group.) Noise factors include sources of variation within the real-world system (i.e., within a manufacturing plant) as well as exogenous factors (such as customer and supplier characteristics). Finally, artificial factors are those simulation-specific variables such as the initial state of the system, the warm-up period (truncation point), termination conditions (run duration), and random number stream(s) (seed, antithetic switch).

The distinction between parameters and noise factors is often recognized in simulation experiments, but rarely used to develop the experimental design or affect the analysis of the simulation results. However, as we discuss in Section 3.1, the classification is important. It is necessary for determining system robustness, and also presents an opportunities for reducing the number of runs required by concentrating sampling efforts on assessing parameter effects. This additional layer of control possible by the artificial factors can also be exploited in the experimental design (Schruben et al. 1992). This is not new—it is the basis of many variance reallocation techniques.

2.2 Performance Evaluation

The analyst begins by specifying some performance characteristic of special interest, and an associated target value τ. Common measures are related to system throughput or system states, such as the waiting time or number of customers in queueing systems, although cost could also be used as a performance measure. In general, the pattern of the performance characteristic's fluctuation around the target value will differ across these configurations. The cost of this fluctuation must be measured in order to optimize or improve the system. Taguchi's philosophical view is that the overall cost should include the costs incurred by end-users of the system. In this context, the evaluation criterion is often referred to as the *loss to society*, or the *long term business loss.*

An ideal configuration would result in the performance characteristic's mean equal to τ and its variance equal to zero. Thus, a numerical method for trading off performance mean and variability is needed. There are many possibilities, including so-called *signal-to-noise ratios* which are based on ratios of (mean performance$-\tau)^2$ to performance variability across the noise space. Taguchi uses many variants of a S/N ratio, most which remain proprietary. Unfortunately, this construction is not amenable to analysis using response surface metamodels.

Instead, we utilize a quadratic loss function, which (in many cases) is a reasonable surrogate for the 'true' underlying loss function which may be difficult or impossible to specify exactly. Let $\mathbf{x}$ and $Y(\mathbf{x})$ denote a vector of parameter settings and the associated performance characteristic respectively, and let Ω denote the noise factor space. Then, assuming that no loss is incurred when $Y(\mathbf{x})$ achieves the ideal state (τ), the quadratic loss function can be written as:

$$\ell(Y(\mathbf{x})) = c\,[Y(\mathbf{x}) - \tau]^2 \tag{1}$$

where the scaling constant c can be used to convert losses into monetary units to facilitate comparisons of systems with different capital costs. It follows from equation (1) that the expected loss associated with configuration $\mathbf{x}$ is

$$E(loss) = c\left[\sigma^2 + (\mu - \tau)^2\right]. \tag{2}$$

While conceptually straightforward, the use of a loss function to incorporate system variability into the performance evaluation represented a major shift in perspective within the manufacturing community. No longer was it acceptable to think about optimizing mean performance without regard to performance variability: a "good" product was also robust. The quantification of robustness, instead of the 0/1 loss function often implicitly used to represent products which were within/outside specification limits, also provided impetus to management and manufacturing to continually improve product quality. We believe that for many types of applications, a similar change in perspective should occur within the discrete-event simulation community. If simulation is being used to identify "good" systems (e.g., plant layouts, scheduling and control mechanisms), where variability is not constant across alternative system designs, then a loss function such as that in equation (2) is a better descriptor of the system's desirability than solely the of the performance characteristic. For example, a single-server queue will have the same mean waiting time for customers/jobs under the FIFO and LIFO queue disciplines, but the variability is quite different. In general, the configuration with the best mean need not be associated with the lowest loss.

2.3 Stages of Analysis

Taguchi's three-stage approach for quality improvement activities consists of *system design*, *parameter design*, and *tolerance design*. In the simulation context, system design corresponds to building and validating a functional model, such as one representing an existing real-world system or a prospective new facility, process, or product. During the parameter design stage, the analyst attempts to "optimize" or "improve" the performance of the simulation model by judiciously selecting settings for some of the decision factors in the model. In the tolerance design stage, the analyst can study the systems in more depth for a particular parameter configuration (e.g., that selected in stage 2). The simulation's sensitivity to sources of noise in the system, as well as to the values of distributional characteristics used to generate random inputs, can be investigated.

The three stages are less clearly distinct in the simulation setting than in the manufacturing environment for which they were initially developed, since tolerance design can be used to provide insights into system modeling and validation. In this tutorial we shall concentrate on the issues of parameter design and tolerance design stages. We point out how questions regarding system complexity and the benefit of further data for estimating input distributions can be addressed in stage 3, but otherwise leave the system design and modeling issues aside.

3 EXPERIMENTAL DESIGNS

Choosing an experimental design means specifying the levels of all parameters, noise factors, and artificial factors for each run of the simulation. An appropriate total sample size must also be determined. In order to evaluate the expected response variability across the noise space, a crossed parameter×noise factor plan can be used. This means that the same experimental plan for the noise factors is used for each run of the parameter plan.

3.1 Basic Plans

Complete and fractional factorials are often used. Among these, two-level designs are popular choices because of their simplicity and efficiency. They permit the evaluation of the linear parameter effects, as well as interaction or synergistic effects.

For a two-level factorial or fractional factorial experiment involving k parameters, the factor levels should be chosen to cover the range of interest. For noise factor plans, the levels should be chosen so that the mean and variance of the two-point sampling distribution are equal to the mean and variance of the underlying distribution. In the case of two-level sampling of continuous factors (or discrete factors whose distributions can be closely approximated by continuous distributions), this corresponds to one standard deviation below and one standard deviation above the mean. In the case of equally likely Bernoulli outcomes, this corresponds to the two factor levels. For discrete distributions where $\mu \pm \sigma$ does not yield valid factor levels, the outcomes can be sampled (approximately) proportional to their probability of occurrence. If the factor is a mean estimated from data, then the upper and lower bounds of a 95% confidence interval ean be used (Wild and Pignatiello 1991).

Other orthogonal designs have been advocated for response surface metamodeling. For example, one might want to minimize the bias or mean-squared error of the regression coefficients (Donahue, Houck and Myers 1992). Central composite designs are good for fitting second-order metamodels. These designs are discussed for simulation experiments by Tew (1992) or Hood and Welch (1993); experimental design texts such as Box and Draper (1987), Box, Hunter, and Hunter (1988) or Montgomery (1991) contain details and alternative designs. Two-level plans are not sufficient if quadratic effects are anticipated.

3.2 Artificial Factor Plans

A well established field in simulation is that of variance reallocation (or variance reduction), where researchers have established methods of reducing the variance of the *estimators* of mean responses in order to increase power for hypothesis testing purposes. Unequal response variance at different system configurations is recognized as pervasive. It often influences the experiment design and analysis (e.g., varying run lengths for different system alternatives), but has rarely been incorporated into the system evaluation. In the robust design context, variance reallocation schemes hold promise for further increasing the efficiency of experimentation. Rather than using all independent random number streams, one can use a common/antithetic sampling strategy (Schruben and Margolin 1978, Tew and Wilson 1991, 1994). This reallocates variance among the coefficient estimates. The implications for parameter design are that The artificial factor plan should be chosen in order to induce correlations which reallocate variance from the interesting terms (parameters) to the uninteresting terms (noise factors) (Schruben et al. 1992). The artificial factor plan is typically embedded in the noise factor plan, e.g., through the choice of random number streams used during a simulation run.

3.3 Frequency Domain Plans

If the number of noise factors is large, even a saturated factorial plan for the noise factors may result in an unwieldy experimental design after crossing it with the parameter plan. One way to cut down the size of the experiment is to first screen the noise factors and then employ a highly fractionated factorial design. Another efficient way to collect the data is to oscillate each noise factor sinusoidally within a simulation run at unique, carefully selected frequency. This allows examination of the system across a range of noise factor combinations without a prohibitively large number of runs (Moeeni, Sanchez and Vakharia 1994a; Sanchez, Moeeni and Sanchez 1994). Such oscillation forms the basis of frequency domain experimentation in the simulation field (Schruben and Cogliano, 1987; Sanchez and Buss, 1987), although the analysis differs. Indexing by time, rather than by entity, is recommended (Mitra and Park, 1991).

In the tolerance design stage, the analyst is interested in determining what portions of the total system variability can be attributed to the noise factors, and a frequency domain approach could be used for factor screening purposes. During the parameter design stage, we are interested in what the performance variability is at a particular parameter configuration: the fact that noise factors are varying across the noise space is important, while estimates of their specific effects are not. In both cases, care should be taken to select driving frequencies which will not result in confounding and to choose frequencies resulting in cycles sufficiently long to affect the system response (Jacobson, Buss and Schruben 1991). Discrete factors can be handled either by oscillating their probabilities of realizing particular levels, or by discretizing the sinusoidal function (Sanchez and Sanchez, 1991).

3.4 Correlated Factor Plans

If the noise factors are correlated in the real world system, it might be that a factorial or fractional factorial design could not be conducted over the entire range of interest. For example, a queueing system might be unstable if all noise factors were held at their high levels. If this situation was unlikely to occur in practice because of correlation among the variables, then a sampling scheme which made use of the underlying dependence structure would seem more appropriate. If the noise factors are normally distributed, the analyst can sample at axial points on the elliptical contours of the joint distributions (Sanchez 1994).

3.5 Combined Array Plans

Recent work suggests that in some circumstances, a crossed parameter×noise factor plan may not be the most efficient in terms of the total number of observations (runs) required. An alternative is a combined plan, where a single design matrix (such as a factorial) is used with columns divided among parameters and noise factors. As Myers, Khuri and Vining (1992) suggest, this can be used if one can specify a priori which of the many possible interaction terms are potentially important. It may mean that the experiment can be conducted using a smaller total number of simulation runs than a crossed plan would require.

4 RESPONSE SURFACE METAMODELS

The response Y is a random function of the parameters $\{X_i\}$, the noise factors $\{W_j\}$, the artificial factors $\{A_k\}$, and the inherent variability of the system. The form of the metamodels fit to the simulation outputs, and the metamodel uses, differ between the parameter design and tolerance design stages.

4.1 Parameter Design Metamodels

In this stage, we seek to characterize the system behavior as a function of the parameters alone. For every combination of parameter configuration i and noise configuration j, we first compute (after suitable truncation to remove initialization bias) the sample average $\overline{Y}_{ij}$ and sample variance s_{ij}^2 for the run. Then we compute summary measures across the noise space for each parameter configuration i:

$$\begin{aligned}\overline{Y}_{i\cdot} &= \frac{1}{n_w}\sum_{j=1}^{n}\overline{Y}_{ij},\\ \overline{V}_{i\cdot} &= \frac{1}{n_w-1}\sum_{j=1}^{n_w}\left(\overline{Y}_{ij}-\overline{Y}_{i\cdot}\right)^2+\frac{1}{n_w}\sum_{j=1}^{n}s_{ij}^2\end{aligned}$$

where n_w is the number of points in the noise factor plan. Regression is used to fit two initial metamodels: one for the performance mean, and one for the performance variability (Sanchez et al. 1993; see also Vining and Myers, 1990). The terms in the initial metamodels depend on the experimental design used. For discrete-event simulation experiments we recommend a design which allows for fitting at least a quadratic effect. We obtain models such as

$$\begin{aligned}\mu &\approx \hat{\beta}_0+\hat{\beta}_1X_1+\ldots+\hat{\beta}_kX_k+\hat{\beta}_{1,2}X_1X_2 \quad (3)\\ &\quad +\ldots+\hat{\beta}_{k-1,k}X_{k-1}X_k+\ quadratic\end{aligned}$$

$$\begin{aligned}\log(\sigma^2) &\approx \hat{\gamma}_0+\hat{\gamma}_1X_1+\ldots+\hat{\gamma}_kX_k \quad (4)\\ &\quad +\hat{\gamma}_{1,2}X_1X_2+\ldots+\hat{\gamma}_{k-1,k}X_{k-1}X_k\\ &\quad +\ quadratic\end{aligned}$$

The logarithmic transformation is used for stability purposes. If the quadratic is an important term in either metamodel, further experimentation is needed to determine the parameter(s) from which it arises.

4.2 Tolerance Design Metamodels

In this stage, metamodel construction is slightly different. First, for tolerance design experiments all factors are treated as noise factors and we assume that the factor ranges are sufficiently small that a linear metamodels suffice. If we fit models of the response mean and standard deviation, then we obtain

$$\begin{aligned}\mu &\approx \hat{\beta}_0+\hat{\beta}_1W_1+\ldots\hat{\beta}_kW_k,\\ s &\approx \hat{\gamma}_0+\sum_{j=1}^{w}\hat{\gamma}_jW_j\end{aligned}$$

where the $\{\beta_j\}$ and $\{\gamma_j\}$ are the least-squares regression coefficients. By treating these coefficients as fixed, the overall variance can be approximated by

$$\sigma^2 \approx \hat{\gamma}_0^2+\sum_{j=1}^{w}(\hat{\beta}_j^2+\hat{\gamma}_j^2)Var(W_j). \quad (5)$$

5 ANALYZING THE RESULTS

The initial metamodels constructed for either the parameter design or tolerance design stages should be assessed and may need to be refined. The experimental plans are typically unreplicated because of the cost of experimentation. This means that the analyst may have only a single degree of freedom for error in the initial regression metamodels, so heavy reliance should not be placed on the raw p-values or t-values. An option offered by many statistical packages (or which can be done manually) is a normal probability plot, which can be used to graphically assess whether or not any effects larger than the noise thresh-hold of the the experiment. Normal probability plots work well when 15 or more parameter or interaction effects are estimated. If the regression metamodels can be simplified by eliminating unimportant terms, then pooling increases the degrees of freedom for the error estimate and allows formal tests of the statistical significance of the remaining metamodel coefficients.

5.1 Parameter Design Analysis

The information resulting from the parameter design metamodels of equations (3) and (4) can easily be combined using the quadratic loss function (equation (2)) to identify robust configurations. The metamodels themselves provide detailed information regarding the system performance: they indicate which parameters affect the mean, which affect the variance, and which influence both aspects of performance.

For many simulation models, the presence of interaction terms and the relationship between the mean and the variability of the performance characteristic make it difficult to achieve the target value with the most robust product design. In these cases, contour plots may be useful for selecting candidate product designs. For example, one can first use the mean metamodel to identify several configurations for which the average performance characteristic is on target, and then use the the metamodel of $\log(\sigma^2)$ to select a configuration which is fairly robust.

Often the results suggest configurations which were not among those initially tested. In such cases, further experimentation is beneficial in order to confirm the performance characteristic's behavior before committing to a particular configuration. However, the secondary experiment may be much smaller than the initial experiment if several of the parameters do not appear in the revised metamodels: they can be set at their most economical levels and screened from further experimentation.

We emphasize that the decision in the robust design framework can be very different than that made on the basis of mean performance alone. Even for queueing systems, where performance mean and variability tend to have high positive correlation, complex interactions among parameters may affect that relationship. One example (Sanchez, Ramberg and Sanchez 1994) of a job-shop simulation a job-shop with three products, five machine groups, and varying processing time distributions, product mix percentages, etc. showed that two configurations could have the same mean response to two decimal places, yet variances which differed by over a factor of two. The configurations corresponding to the best means were dramatically inferior to the low loss designs: one job shop configuration which was among the best in terms of mean performance had a 36% higher loss then the low-loss configuration, yet it used more machines.

5.2 Tolerance Design Analysis

Several types of questions can be addressed in the tolerance design stage. First, one can assess the overall mean and variability for a particular configuration, e.g., that chosen at the end of the parameter design stage. If the parameters can be perfectly controlled at their chosen settings, then the overall mean and variance can just be estimated by the parameter design metamodels. However, if variation in the parameter settings around their nominal values is anticipated, an additional experiment will provide a better picture of the system's capabilities.

Other questions concern the relative effects of the noise factors. The term $(\hat{\beta}_j^2 + \hat{\gamma}_j^2)Var(W_j)$ in equation (5) is called the *transmitted variance* for noise factor W_j. This indicates the amount of variability in the noise factor which is passed along to variance in the response. Depending on the magnitudes of $\hat{\beta}_j$ and $\hat{\gamma}_j$, variation in W_j can be amplified or dampened by the system. The term $\hat{\gamma}_0^2$ in equation (5) is called the *inherent variance*: it is the smallest variance achievable if all noise factors investigated in the experiment have variances driven to zero. (For Monte Carlo simulations, all randomness has been removed during experimentation and every $\hat{\gamma}_i$ can be replaced by zero.)

Once transmitted variances have been computed for all noise factors, the relative importance of these sources of variation on the output is apparent. This information can be used to evaluate proposed changes to the system. For example, is it cost-effective to pay more for raw materials, machine maintenance, or training in order to improve the consistency of these factors? Alternatively, is it possible to relax controls slightly and allow more variation in the inputs without adversely affecting the system behavior? If the standard deviation of a noise factor W_j can be reduced by a factor of a_j without affecting the mean performance, then its transmitted variance is reduced by a factor of a_j^2 and the overall system variability is reduced by the amount $(1 - a_j^2)Var(W_j)$. The conversion constant c from equation (2) can be used to express the overall performance change in dollars. A comparison with the cost of implementing the proposed change then shows whether or not such implementation would further improve the system performance. If changes in the noise factor variance also affect the system mean, then both the mean and variance components should be included in the cost assessment via equation (2).

Tolerance design can also aid in simulation modeling and validation. If the distributional characteristics used to generate random components of the simulation model are themselves estimates, and if the system is highly sensitive to those characteristics, then the simulation may not mimic the true system behavior adequately. Once again, the analyst can use tolerance design to obtain feedback regarding the modeling process. This allows model refinement efforts to be expended in accordance to factor sensitivity.

6 CONCLUDING REMARKS

The approach outlined in this paper integrates the concepts of robust design with response surface metamodeling and system optimization efforts for discrete-event simulation. Simulation is a useful and powerful tool for addressing many complex problems, such as the design and analysis of manufacturing systems, communications systems, transportations systems, and service organizations (Law and Kelton, 1991). While typical analyses of complex systems like these emphasize average performance (e.g., average throughput, average time in system, average number in queue), we argue that the use of a loss function which also incorporates the variability of the performance measure will guide the analyst toward better system designs. The loss function also facilitates the comparison of alternatives with different capital expenditure requirements. Another key aspect is the analysis of expected performance over noise factor variation. The distinction between parameters and noise factors allows the analyst to more efficiently construct an experiment designed to gain detailed information about parameter effects and interactions—the potential metamodel terms.

The simulation arena is amenable to analysis using robust design strategies since all factors are controllable by the analyst. The efficiency gained by designed experimentation is particularly beneficial for complex simulation models, since each realization of system performance corresponds to the results of a (potentially lengthy) run. Simulation-specific artificial factors can also be incorporated into the design to improve the precision of the metamodel coefficients.

The robust design philosophy and joint metamodeling approach have a synergistic relationship: they typically provide the analyst with more information than would result from either a loss comparison of only the configurations tested, or from a single metamodel which directly measures system loss or cost. In the latter case, if a metamodel shows that expected loss decreases as factor X increases, the root cause remains unknown. Perhaps the response mean is closer to the target. Perhaps the response variance is smaller. It could be that both the mean and variance improve, or that an improvement in one aspect is partially offset by a degradation in the other. However, separate construction of metamodels for the system mean and variability facilitate the identification of new designs which may be even better than those considered in the experimental framework. Finally, metamodels of the system sensitivity to noise factors can be used to aid in simulation modeling and to guide system optimization and improvement efforts.

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