Proceedings of the 2006 Winter Simulation Conference
L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, and R. M. Fujimoto, eds.

A HYBRID METHOD FOR SIMULATION FACTOR SCREENING

Hua Shen
Hong Wan

School of Industrial Engineering
Purdue University
West Lafayette, IN 47907-2023, U.S.A.

ABSTRACT

Factor screening is performed to eliminate unimportant factors so that the remaining important factors can be more thoroughly studied in later experiments. Controlled Sequential Bifurcation (CSB) and Controlled Sequential Factorial Design (CSFD) are two new screening methods for discrete-event simulations. Both methods use hypothesis testing procedures to control the Type I Error and power of the screening results. The scenarios at which each method is most efficient are complementary. This paper proposes a two-stage hybrid approach to combine CSB and CSFD. The new method usually has the same error control as CSB and CSFD. The efficiency, on the other hand, is usually much better than either component method.

1 INTRODUCTION

Screening experiments allow the researcher to eliminate obviously unimportant so that more detailed investigations can focus on the most influential ones. Many strategies have been proposed for factor screening purpose (Trocine and Malone 2000, 2001 and Campolongo et al. 2000). However, most research has concentrated on designs for physical experiments, which typical involves less than 25 factors and do not take advantage of the sequential nature of simulation experiments. In addition, because of the high cost of conducting physical experiments, the traditional screening methods usually emphasize using fewest number of runs to estimate as many effects as possible, the correctness of the results is considered secondary.

CSB (Wan et al. 2003, 2006a) is a new group screening method specifically designed for stochastic simulation experiments. Factors are tested in groups. If the group effect is unimportant, all factors in the group will be considered as unimportant; if the group effect is important, the factors in the group will be split into two smaller subgroups for further testing. CSB is the first screening method to control the probabilities of misclassifications. With qualified hypothesis testing procedure (Wan et al. 2006a, 2006b) at each bifurcation step, CSB can control the Type I Error for each factor (i.e., the probability of an unimportant factor being classified as important) and the power at each bifurcation step (i.e., the probability of a critical group being identified) under heterogeneous variance conditions. Since CSB can eliminate unimportant factors in groups, it is specifically well suited for the cases with a large number of factors and a small percentage of them being important. Wan et al. (2006b) later proposed an improved version of CSB, called CSB-X, using a fold-over design. CSB-X relaxes the assumption of main-effects model and gives the same error control for main effects as in CSB even when two-factor interactions and quadratic terms exist.

Although CSB methods are attractive for many simulation applications, they also have serious limitations: (1) The methods can only screen main effects and the results can be misleading when higher-order interactions exist; (2) The signs of main effects are assumed to be known to avoid effect cancellation, but this knowledge is not always available in practice; (3) In CSB methods, simulation observations generated in previous bifurcation steps may not be useful in the later screening stages and new observations are usually needed at each bifurcation step; and (4) The efficiency of CSB methods is sensitive to the index order of factors (important factors are preferably clustered) and the variances of the response surface. In reality, the optimal setting is rarely achieved since prior information is often faulty.

CSFD (Shen and Wan 2005) was proposed to overcome these limitations of CSB. CSFD combines qualified hypothesis testing procedure with a sequential traditional factorial design to provide simultaneous Type I Error and power control for each interested effect under heterogeneous variance conditions (the power control is stronger than CSB). CSFD can screen any main effects and interactions without assuming the directions of effects to be known *a priori*. In addition, unlike CSB methods, it can utilize all previously generated observations in the later screening process. In most cases, after the first few effects are classified, there is enough data to classify all of the remaining effects. On the other hand, when the number of factors is large and interactions exist, CSFD would have to repeat a huge factorial design and the simulation effort would be prohibitive.

The structure of CSB (CSB-X) and CSFD is demonstrated in Table 1 and Table 2 respectively. Numerical evaluation shows that there exists a complementary relationship between CSB and CSFD methods (Wan et al. 2006a, Shen and Wan 2005), i.e., the strength of CSB methods is usually the weakness of CSFD, and vice versa. This complementary relationship inspires us to propose a hybrid method that combines CSB and CSFD to achieve better efficiency. The underlying idea is to apply CSFD to screen those likely important effects (typically a small percentage of all effects) and CSB (CSB-X) to screen those likely unimportant effects. Since both methods would be conducted in their favorable configurations, the efficiency of the screening process could be significantly improved. The challenge is to coordinate different procedures and provide overall error control of the screening results.

The paper is organized as follows: The underlying response model and the objective of screening are discussed in Section 2. Section 3 describes the proposed hybrid method and its error control properties. Section 4 presents empirical evaluations of the hybrid method and compares it with the existing methods. Conclusion and future research are discussed in Section 5.

2 MODEL DESCRIPTION

Suppose there are L factors. A general linear model including all main effects and interactions is shown below:

$$Y = \beta_0 + \sum_{i=1}^{L} \beta_i z_i + \sum_{i<j} \beta_{ij} z_i z_j + \sum_{i<j<k} \beta_{ijk} z_i z_j z_k + \cdots + \beta_{12\cdots L} z_1 z_2 \ldots z_L + \varepsilon.$$

Here $\beta = \{\beta_1, \beta_2, \ldots, \beta_{12\cdots L}\}$ is the effect coefficient vector and $\mathbf{z} = (z_1, z_2, \ldots, z_L)$ stands for the deterministic level settings. In practice, the interested effects can be any subset of β. Heterogeneous variances are allowed and the error term, ε, is assumed to be a $\text{Nor}(0, \sigma^2(\mathbf{z}))$ random variable whose variance is unknown and may depend on $\mathbf{z}$. Screening experiment will classify each factor as "important" or "unimportant". We want to simultaneously control the Type I Error $\leq \alpha$ for those effects $\leq \Delta_0$ (unimportant effects), and the power $\geq \gamma$ for those effects $\geq \Delta_1$ (critical effects). For those effects between Δ_0 and Δ_1, we consider them important but no error control will be offered for the screening results. Here the parameters Δ_0 and Δ_1 are the thresholds of importance and criticality respectively; α and γ are user-specified error control parameters.

Consider a typical complex simulation model with a large number of factors, possible important interactions, and little prior knowledge of the system. Neither CSB (CSB-X) nor CSFD alone will be both effective and efficient. CSB (CSB-X) cannot screen interactions and the scattered important factors may impede the elimination of unimportant ones in group. CSFD will require a huge factorial design; even if the design only repeats for a few times, the number of runs will still be too many. The proposed hybrid method is to target this situation. The sparsity of effects principle (Myers and Montgomery 2002) is still assumed to be valid, namely, only a small percentage of factors are responsible for most of the response variation; otherwise, screening experiments would be unnecessary.

3 HYBRID SCREENING PROCEDURE

3.1 Hybrid Procedure

FF-CSB (Sanchez et al. 2005) is the first effort on the hybrid screening approach. The structure of FF-CSB is given in Table 3. FF-CSB still assumes main-effects response model. In order to drop the assumption of known effect directions in CSB, FF-CSB adds a prescreening stage in which a saturated or nearly-saturated fractional factorial experiment is conducted to estimate the directions and magnitudes of the effects. All factors are then divided into positive and negative groups and within each group factors are sorted. In the second stage, the original CSB procedure is applied on the "positive" and "negative" groups separately. Numerical result shows that even with the extra effort in prescreening, FF-CSB is generally more effective and efficient than CSB.

We extend the above hybrid strategy by integrating the prescreening, CSB-X and CSFD procedures into one screening method. CSB-X is used since it has superior performance than CSB (Wan et al. 2006b). The generic structure of the hybrid method is given in Table 4. It consists of two phases. Phase 1 is to obtain the initial estimates of all desired effects and all factors are explicitly assigned into one of three groups: all factors associated with one or more potentially important main or interaction effects will be assigned to group IMP; the rest of the factors, the potentially unimportant ones, will be assigned to either group POS (positive factor) or group NEG (negative factor). The cut-off value that divides potentially important and unimportant effects is called the threshold of factor assigning. The prescreening design used in Phase 1 should be able to estimate all desired effects with a small number of simulation runs. In Phase 2, CSFD is applied on group IMP and CSB-X is applied on groups POS and NEG separately. Factors in groups POS and NEG will first be sorted within each group so that CSB-X procedure can achieve its best efficiency.

Table 1: Structure of CSB and CSB-X

Initialization:
Create an empty LIFO queue for groups. Add the group $\{1,\ldots,K\}$ to the LIFO queue.

While queue is not empty, do
Remove: Remove a group from the queue.
Test:
Unimportant:
If the group is unimportant, then classify all factors in the group as unimportant.
Important (size=1):
If the group is important and of size 1, then classify the factor as important.
Important (size>1):
If the group is important and the size is greater than 1, then split the group into two subgroups such that all factors in the first subgroup have smaller indices than those in the second subgroup. Add each subgroup to the LIFO queue.
End Test
End While

Table 2: Structure of CSFD

Initialization:
Form a queue of effects of interests. Select a factorial design. Generate $N = n_0$ replications of observations.

While queue is not empty, do
Remove: Remove an effect from the queue.
Compute: Compute sample mean and sample variance of the effect coefficient. Sample size = N.
While the effect is not classified, do
If the effect cannot be classified with the specified error control, then
Generate new replication(s). Update sample size N and sample mean.
End If
End While
End While

Table 3: Structure of FF-CSB

Initialization:
Create two empty LIFO queues for groups, NEG and POS.

Phase 1:
Conduct a saturated or nearly-saturated fractional factorial experiment and estimate $\hat{\beta}_1,\ldots,\hat{\beta}_k$. Order the estimates so that $\hat{\beta}_{[1]} \leq \ldots \leq \hat{\beta}_{[z]} < 0 \leq \hat{\beta}_{[z+1]} \ldots \leq \hat{\beta}_{[K]}$. Add factors $\{[1],\ldots,[z]\}$ to the NEG LIFO queue, and factors $\{[z+1],\ldots,[K]\}$ to the POS LIFO queue.

Phase 2:
Apply CSB on two LIFO queues, NEG and POS, separately.

Table 4: Structure of Hybrid Method

Initialization:
Create three empty groups: IMP, POS, and NEG.

Phase 1:
Prescreen: Select a prescreening procedure to estimate the coefficients of all effects of interest.
Divide: Assign factors related to potential important effects to group IMP; assign other factors to either group POS or NEG based on the directions of their estimated effect coefficients.

Phase 2:
Sort: Sort factors in groups POS and NEG respectively based on estimated effect coefficients.
CSB-X: Apply CSB-X to classify factors in groups POS and NEG separately.
CSFD: Apply CSFD to classify factors in group IMP (main effects and interactions).

3.2 Error Control of Hybrid Method

Because of the stochastic nature of the response, factors could be assigned to the wrong group. For example, important (unimportant) factors can be assigned to unimportant (important) groups, and positive factors can be assigned to NEG or vice versa. No mis-assignment of factors would affect the Type I Error control of the hybrid method since for any effect to be classified as important, it must be tested individually by CSB-X or CSFD in Phase 2.

However, mis-assignments of factors associated with critical effects could seriously affect the power control of the hybrid method. For example, if a factor associated with a critical interaction effect is assigned to an unimportant group, there is no chance that this interaction could be classified as important in Phase 2 since CSB-X cannot screen interactions. This prompts us to be conservative in the selection of the threshold of factor assigning in Phase 1. On the other hand, we do not want to be too conservative as well: a too small threshold value results in that many unimportant factor are assigned to group IMP and Phase 2 CSFD may have a large factorial design to repeat. In the empirical evaluation, we choose the threshold of factor assigning to be $\Delta_0/2$ rather than using the threshold of importance Δ_0. We will have more discussion of the selection the threshold in next section.

4 EMPIRICAL EVALUATION

Numerical experiments are conducted to compare the performance of the hybrid method to CSFD and FF-CSB. Because of its superiority over CSB, we use CSB-X procedure in FF-CSB and the hybrid method. Table 5 lists the experiment parameters. In all cases, the presented results are the averages of 1000 independent trials. Fractional factorial experiments are used as prescreening procedure (Resolution III designs for main-effects models and Resolution V designs for second-order models). Unless stated otherwise, only one replication is used in prescreening procedures. For CSB-X and CSFD procedures in Phase 2, different initial sample sizes are tried and for each case the result with the minimal number of simulation runs required for screening is presented for comparison. For the relationship of initial sample size and the overall efficiency of CSB-X and CSFD, please refer to Shen and Wan (2006).

4.1 Main-Effects Model

We first consider the main-effects cases with 200 and 500 factors respectively. For both cases, the effect coefficients are randomly generated and the distribution of the absolute values of effect coefficients is as follows: 2.5% of them are equal to $\Delta_1 = 4$; 2.5% of them are uniformly distributed on $(\Delta_0, \Delta_1) = (2, 4)$; 2.5% of them are equal to $\Delta_0 = 2$; 2.5% of them are uniformly distributed on $(0, \Delta_0) = (0, 2)$; and all others are zeros. Factors with non-zero effects are randomly distributed. Each non-zero coefficient has equal probability to be positive or negative.

A general method has been proposed (Shen and Wan 2005, Wan and Ankenman 2006) to construct large-scale Resolution III factorial designs. For 200-factor and 500-factor experiments, these designs need 256 and 512 simulation runs respectively in one replication to provide an independent estimate for each main effect in Phase 1. The same method is used to construct the factorial design used in the Phase 2 CSFD procedure. The size of this factorial design depends on how many factors are assigned to group IMP.

Table 6 presents the average numbers of simulation runs required by CSFD, FF-CSB, and the hybrid method for selected scenarios. The hybrid method is the most efficient one in all cases. The numbers in the parentheses are the relative savings of the simulation effort by the hybrid method compared with CSFD. When the variance is large,

Table 5: Simulation Experiment Parameters

Parameter	Value
L	50, 200, 500
Δ_0	2
Δ_1	4
α	0.05
γ	0.95
σ	$m*$(1 + size of the group effect)
m	0.01, 0.1, 0.3, 1

Table 6: Simulation Runs Required for Cases with Main-Effects Model

Case	Variance Factor	CSFD	FF-CSB	Hybrid
200-Factor	$m = 0.01$	512	392	336 (34.4%)
	$m = 0.1$	559	798	371 (33.6%)
	$m = 0.3$	792	2817	475 (40.0%)
	$m = 1.0$	1807	22523	1475 (18.4%)
500-Factor	$m = 0.01$	1024	1379	656 (35.9%)
	$m = 0.1$	1304	4500	734 (43.7%)
	$m = 0.3$	1678	26986	998 (40.5%)
	$m = 1.0$	4169	275101	4064 (2.5%)

the efficiency of the hybrid method approaches that of CSFD. This is because with larger variances the effectiveness of the prescreening procedure drops, which then affects the efficiency of both CSB-X and CSFD procedures in Phase 2 of the hybrid method. The benefit of incorporating CSFD into the hybrid method (compared with FF-CSB) becomes more obvious when the variance increases.

Selected P(DI)'s, i.e., the percentage of times that each effect is declared important, are presented in Table 7 for the 200-factor case. The three methods have similar effectiveness results when variance is small ($m = 0.01$) and all meet the error control requirements. When variance is large, CSFD and the hybrid method still have similar effectiveness and the classification results are much more conservative than the error control requirements. But FF-CSB fails to meet the specified error control for some effects (highlighted in Table 7).

Given $\Delta_0/2$ as the threshold of factor assigning, Tables 8 and 9 give the average numbers and percentages of mis-assignments in Phase 1. "IMP to UNIMP" stands for assigning potentially important factors to unimportant groups, and "UNIMP to IMP" stands for the opposite. "Potentially important" means the absolute value of effect coefficient is no less than the threshold of factor assigning. For example, in the 500-factor case with $m = 1.0$, when prescreening sample size is 1, "3.96 (9.2%)" means that in average 3.96 potentially important factors are assigned to unimportant groups, which is 9.2% of the total number of potentially important factors. We can see that when variance is not too large, few mis-assignments happen. Furthermore, mis-assignments of critical factors are even less likely (Table 9). In the same case above, out of the 12 critical factors, the average number of critical factors assigned to unimportant groups is 0.005; and for the 13 important but not critical factors, the number is 0.395.

Tables 8 and 9 also show that the larger the prescreening sample size, the less mis-assignments. When there are less mis-assignments, both the effectiveness and efficiency of CSB-X and CSFD procedures in Phase 2 improve. The optimal prescreening sample size is unknown. However, since the prescreening only accounts for a small percentage of the total simulation effort in main-effects models, if little knowledge is known on the variance, using two or three replications in prescreening could be a safer approach.

Table 10 shows the influence of the threshold of factor assigning on the dividing of the factors and the efficiency of the hybrid method. It is based on the 500-factor case with $m = 1.0$. What the table does not show is that unless the threshold is extremely large, different thresholds have little impact on the effectiveness results. For each threshold value, columns 2-4 give the average numbers of factors assigned to each group in Phase 1, columns 5-6 give the average numbers of mis-assignments, and the simulation runs required by CSB-X and CSFD procedures in Phase 2 are given in columns 7 and 8. When the threshold is too small, lots of unimportant factors are assigned to group IMP; thus CSFD procedure will have a large design to repeat and CSB-X's ability to eliminate unimportant factors in group would help little. If the threshold is too large, many important factors would be assigned to unimportant groups; this not only may result in misclassifications of critical effects but also significantly affect the efficiency of the CSB-X procedure. As shown in Table 10, $\Delta_0/2$ seems to be a good choice of the threshold of factor assigning.

4.2 Second-Order Model

We now compare CSFD and the hybrid method on a 50-factor case where second-order interactions exist. Main effect coefficients are randomly generated in the same way as those in main-effects models except that the percentage of each non-zero effect category is increased from 2.5% to 5%. The probability that a second-order interaction exists is assumed to be 0.2, if both parent factors are important; 0.05, if only one parent factor is important; and 0, if neither parent factor is important. The probability of a non-zero interaction coefficient being positive (or negative) is 0.5 and the distribution of the absolute values of non-zero interaction effects is as follows: 25% of them are equal to $\Delta_1 = 4$; 25% of them are uniformly distributed on $(\Delta_0, \Delta_1) = (2, 4)$; 25%

Table 7: Selected P(DI)'s of 200-Factor Case with Main-Effects Models

Effect	$m = 0.1$			$m = 0.3$			$m = 1.0$		
	CSFD	FF-CSB	Hybrid	CSFD	FF-CSB	Hybrid	CSFD	FF-CSB	Hybrid
$\beta_9 = 4.0$	1.000	0.974	1.000	1.000	0.957	1.000	1.000	0.955	0.990
$\beta_{19} = 4.0$	1.000	0.965	1.000	1.000	0.956	1.000	1.000	**0.943**	0.996
$\beta_{63} = 4.0$	1.000	0.958	1.000	1.000	**0.943**	1.000	1.000	**0.947**	0.995
$\beta_{77} = -4.0$	1.000	1.000	1.000	1.000	0.996	1.000	0.998	0.966	0.994
$\beta_{123} = -4.0$	1.000	1.000	1.000	1.000	0.991	1.000	0.999	0.955	0.998
$\beta_{127} = -3.39$	1.000	0.843	0.999	0.998	0.745	0.933	0.896	0.721	0.841
$\beta_{71} = 3.35$	1.000	0.773	0.994	0.994	0.745	0.880	0.877	0.720	0.790
$\beta_{17} = 2.88$	0.018	0.353	0.207	0.197	0.398	0.383	0.349	0.359	0.397
$\beta_{118} = 2.74$	0.000	0.233	0.011	0.025	0.325	0.176	0.203	0.285	0.232
$\beta_4 = 2.38$	0.000	0.046	0.000	0.000	0.095	0.022	0.028	0.099	0.081
$\beta_{25} = 2.0$	0.000	0.001	0.000	0.000	0.008	0.000	0.001	0.035	0.007
$\beta_{55} = 2.0$	0.000	0.000	0.000	0.000	0.013	0.000	0.003	0.017	0.007
$\beta_{140} = 2.0$	0.000	0.025	0.000	0.000	**0.051**	0.000	0.000	0.024	0.000
$\beta_{96} = -2.0$	0.000	0.025	0.000	0.000	0.048	0.001	0.001	0.021	0.007
$\beta_{144} = -2.0$	0.000	0.017	0.000	0.000	0.043	0.000	0.002	0.022	0.003
$\beta_{174} = 1.61$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.001
$\beta_{10} = 1.28$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\beta_{35} = -0.88$	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
$\beta_{182} = -0.48$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\beta_{39} = -0.35$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Simulation Runs	559	798	371	792	2817	478	1807	22294	1474
Initial Sample Size	2	6	1/2/3*	3	20	1/3/5*	6	60	1/8/10*

*The order of the initial sample sizes is "Prescreen/CSB-X/CSFD".

Table 8: Mis-Assignments in Phase 1 (Main-Effects Models)

Case	Variance Factor	Prescreening Sample Size	Mis-Assignment		Simulation Runs
			IMP to UNIMP	UNIMP to IMP	
200-factor	$m = 0.1$	1	0.00 (0.0%)	0.08 (0.0%)	371
	$m = 0.3$	1	0.14 (0.8%)	0.32 (0.2%)	478
	$m = 1.0$	1	1.23 (6.8%)	40.7 (22.4%)	1474
		2	0.70 (3.9%)	15.7 (6.6%)	1545
		3	0.47 (2.6%)	6.76 (3.7%)	1666
500-factor	$m = 0.1$	1	0.02 (0.0%)	0.20 (0.0%)	734
	$m = 0.3$	1	0.77 (1.8%)	0.79 (0.2%)	998
	$m = 1.0$	1	3.96 (9.2%)	119.4 (26.1%)	4064
		2	2.53 (5.9%)	51.8 (11.3%)	3800
		3	1.92 (4.5%)	24.5 (5.4%)	4063

Table 9: Mis-Assignments of Important Factors with $m = 1.0$ (Main-Effects Models)

Case	Prescreening Sample Size	Mis-Assignments	
		Critical Factors	Important but not Critical Factors
200-factor	1	0.002 (0.04%)	0.088 (1.76%)
	2	0.000 (0.00%)	0.013 (0.26%)
	3	0.000 (0.00%)	0.002 (0.04%)
500-factor	1	0.005 (0.04%)	0.395 (3.29%)
	2	0.000 (0.00%)	0.099 (0.83%)
	3	0.000 (0.00%)	0.026 (0.22%)

Table 10: Efficiency of the Hybrid Method with Different Thresholds of Factor Assigning, 500-factor case, $m = 1.0$

Threshold	Number of Factors			Mis-Assignment		Simulation Runs		Total runs
	IMP	POS	NEG	IMP to UNIMP	UNIMP to IMP	CSFD	CSB-X	
$0.25 \times \Delta_0$	304	98	98	2.77	259.7	5131.8	170.9	5814.7
$0.30 \times \Delta_0$	269	116	115	2.96	226.5	4846.1	198.6	5556.7
$0.35 \times \Delta_0$	238	132	130	3.13	195.9	3226.1	246.7	3984.8
$0.40 \times \Delta_0$	209	146	145	3.23	167.9	3005.7	323.8	3841.5
$0.45 \times \Delta_0$	182	160	159	3.80	142.1	3019.5	416.0	3947.6
$0.50 \times \Delta_0$	158	172	170	3.96	119.4	3021.3	530.2	4063.5
$0.55 \times \Delta_0$	137	182	180	4.63	99.0	2872.2	733.1	4117.3
$0.60 \times \Delta_0$	119	191	190	4.84	81.7	2521.6	981.4	4015.0
$0.65 \times \Delta_0$	103	199	198	4.06	67.8	2383.1	1328.2	4223.3
$0.70 \times \Delta_0$	89	206	205	4.77	54.6	2368.0	1817.4	4697.4
$0.75 \times \Delta_0$	77	213	210	5.08	44.1	2339.3	2459.9	5311.2

of them are equal to $\Delta_0 = 2$; 25% of them are uniformly distributed on $(0, \Delta_0) = (0, 2)$. The results presented in this section are based on a randomly generated case where there are 10 non-zero main effects and 11 non-zero interactions. CSFD method and the prescreening procedure of the hybrid method run a 2_V^{50-38} factorial design, (4096 runs in each replication), to provide a set of independent estimates of all main effects and second-order interactions. For details on the construction of this design, please refer to Sanchez and Sanchez (2005).

The effectiveness results are similar with those in main-effects models. Table 11 shows that the advantage of the hybrid method over CSFD is even more obvious when second-order interactions are considered. In this 50-factor case, the hybrid method could save more than 40% of simulation effort compared to CSFD and the performance is not affected by the change of variances. Compared to the main-effects model, the second-order model requires a much larger prescreening factorial design. For this 50-factor case, it is 4096 runs, which is more than half of the total simulation runs. Therefore, when the number of factors is large and interactions exist, having more than one replication in prescreening is not recommended. On the other hand, the significant increase of the sample size within one replication gives more accurate effect estimations. This is why the percentages of mis-assignments in Table 11 are significantly smaller than those in Tables 8 of main-effects models. In fact, in this 50-factor case, no factors related to critical effects are assigned to unimportant groups in any of the 1000 trials. This improvement of effectiveness in prescreening makes it possible for the hybrid method to take full advantage of the strength of CSB-X and CSFD procedures to obtain the best efficiency.

5 CONCLUSION

The hybrid method introduced here combines prescreening, CSB-X and CSFD to achieve better overall performance than all its component methods in general circumstances. The prescreening stage eliminates the requirement of prior knowledge of the system and allows both CSB-X and CSFD to perform in their optimal conditions. The hybrid framework allows the incorporation of other screening/analysis methods depending on the practical requirement. Future research will concentrate on: (1) exploring a variety of pre-screening strategies for different scenarios; (2) studying the overall error control of the hybrid method both theoretically and numerically; (3) understanding more completely the selection of the threshold of factor assigning; (4) implementing the hybrid method to practical problems; and (5) extending the hybrid method to include more procedures.

ACKNOWLEDGMENTS

This research was partially supported by Purdue Research Foundation (PRF) and Naval Postgraduate School Award N00244-06-C-0002.

REFERENCES

Bettonvil, B., and J. P. C. Kleijnen. 1997. Searching for important factors in simulation models with many factors: sequential bifurcation. *European Journal of Operational Research* 96(1): 180–194.

Campolongo, F., J. P. C. Kleijnen, and T. Andres. 2000. Screening Methods, In *Sensitivity Analysis*. ed. A. Saltelli, K. Chan, E. M. Scott. New York: John Wiley & Sons Inc.

Myers, R. H. and D. C. Montgomery. 2002. *Response surface methodology: process and product optimization*

Table 11: Screening Results when Two-factor Interactions Exist

Variance Factor	CSFD	Hybrid Method						
		Mis-Assignment		Simulation Runs				Relative Saving
		IMP to UNIMP	UNIMP to IMP	Prescreen	CSB-X	CSFD	Total	
$m = 0.1$	8192.0	0.00 (0.00%)	0.00 (0.00%)	4096	16.3	591.6	4703.9	42.6%
$m = 0.3$	8384.5	0.00 (0.00%)	0.08 (0.44%)	4096	24.1	807.4	4927.5	41.2%
$m = 1.0$	12390.4	0.05 (0.28%)	0.60 (3.33%)	4096	40.8	1924.6	6061.5	51.1%

using designed experiments, 2nd Edition. New York: John Wiley & Sons Inc.

Sanchez, S. M., H. Wan, and T. W. Lucas. 2005. A two-phase screening procedure for simulation experiments. In *Proceedings of the 2005 Winter Simulation Conference*, 223-230.

Sanchez, S. M., and P. J. Sanchez. 2005. Very large fractional factorial and central composite designs. *ACM Transactions on Modeling and Computer Simulation* 15(4): 362-377.

Shen, H., and H. Wan. 2005. Controlled sequential factorial design for simulation factor screening. In *Proceedings of the 2005 Winter Simulation Conference*, 467-474.

Shen, H., and H. Wan. 2006. Controlled sequential factorial design for simulation factor screening. Working paper. Available online via `<http://web.ics.purdue.edu/˜hwan/CSFDsubmitted.pdf>`.

Trocine, L., and L. Malone. 2000. Finding important independent variables through screening designs: a comparison of methods. In *Proceedings of the 2000 Winter Simulation Conference*, 749–754.

Trocine, L., and L. Malone. 2001. An overview of newer, advanced screening methods for the initial phase in an experimental design. In *Proceedings of the 2001 Winter Simulation Conference*, 169–178.

Wan, H., and B. Ankenman. 2006. Two-stage controlled fractional factorial screening for simulation experiments. Working Paper.

Wan, H., B. Ankenman, and B. L. Nelson. 2003. Controlled sequential bifurcation: a new factor-screening method for discrete-event simulation. In *Proceedings of the 2003 Winter Simulation Conference*, 565-573.

Wan, H., B. Ankenman, and B. L. Nelson. 2006a. Controlled sequential bifurcation: a new factor-screening method for discrete-event simulation. *Operations Research*, forthcoming.

Wan, H., B. Ankenman, and B. L. Nelson. 2006b. Simulation factor screening with controlled sequential bifurcation in the presence of interactions. Working Paper. Available online via <http://web.ics.purdue.edu/˜hwan/WanAnkenmanNelsonCSBX.pdf>.

AUTHOR BIOGRAPHIES

HUA SHEN is a doctoral candidate in the School of Industrial Engineering at Purdue University. His dissertation topic is sequential factor-screening methods for discrete-event simulation. The other projects in which he has participated include supply chain management and statistical consulting service. His research interests include experimental design and quality control, simulation of manufacturing systems, and simulation output analysis. His email address is <shenh@purdue.edu>.

HONG WAN is an Assistant Professor in the School of Industrial Engineering at Purdue University. Her research interests include design and analysis of simulation experiments, simulation optimization; simulation of manufacturing, healthcare and financial systems; quality control and applied statistics. She has taught a variety of courses and is a member of INFORMS and ASA. Her e-mail and web addresses are <hwan@purdue.edu> and <http://web.ics.purdue.edu/˜hwan/index.htm>.