Proceedings of the 1998 Winter Simulation Conference
D.J. Medeiros, E.F. Watson, J.S. Carson and M.S. Manivannan, eds.

RISK ANALYSIS OF ROBUST SYSTEM DESIGN

E.G.A. Gaury
J.P.C. Kleijnen

Department of Information Systems and Auditing/Center for Economic Research (CentER)
School of Management and Economics
Tilburg University (Katholieke Universiteit Brabant)
P.O. Box 90153, 5000 LE Tilburg, NETHERLANDS

ABSTRACT

Robustness has become a popular issue in engineering. For products, Taguchi suggests to adjust the design so that product performance is insensitive to the effects of uncontrolled environmental variations. For systems (to be distinguished from products), we propose to adjust the design so that the risk of getting poor performance is minimized. This risk is evaluated by simulating the system over a sample of environmental scenarios: this procedure yields an estimate of the probability distribution of the outcome. We illustrate this risk/uncertainty approach to robustness through the comparison of four pull production-control systems, including Kanban and Conwip. We conclude that the traditional approach consisting of optimizing the design of a system for a specific environment (base scenario) may be risky.

1 INTRODUCTION

Taguchi's principle of robust product design is simple: instead of trying to eliminate or reduce the causes of product performance variability, adjust the design of the product so that it is insensitive to the effects of uncontrolled (noise) variation. However, this formulation of the parameter design problem (PDP) seems to be biased. Indeed, the terms 'effects' and 'insensitivity' refer to sensitivity analysis and design of experiments. Thus, formulating the PDP in these terms is already deciding for a solution procedure. In this paper we use a more general formulation: instead of trying to eliminate or reduce the causes for product performance variability, we adjust the design of a product or process (system) so that it performs well in many environments. This formulation raises two managerial issues, namely what is good performance, and in which environments should the product/system perform well? These issues, however, are not specific to the PDP: they arise during any product/system design process. A possible approach to the reformulated PDP is *risk analysis*: designers do not know with certainty in which environment the product/system will be used. The purpose of risk analysis is to derive an estimate of the output probability from a sample of scenarios. In fact, in simulation-based design, two sources of uncertainty may coexist: (a) the *system uncertainty*, also called intrinsic or aleatory uncertainty, is intrinsic to the simulation model (random number streams) and differentiates stochastic models from deterministic ones, and (b) analysts uncertainty, also called subjective or epistemic uncertainty, is due to the limited availability of data on the model inputs (parameters of distributions, for instance). We consider both sources of uncertainty.

This paper is organized as follows. First, we summarize Taguchi's approach to parameter selection for product design and its application to system design. Second, we propose a new approach based on risk management. Third, we analyze some differences between the two approaches. Fourth, we illustrate our approach by comparing four pull production-control systems, using stochastic simulation models and risk analysis.

2 PARAMETER DESIGN

2.1 Taguchi's Approach

Robust design consists of searching for a product design that guarantees low variations in the performance level when the environment changes, instead of designing a product that is optimal for a single specific environment (noise configuration). This quality-improvement approach, also known as parameter design, has been stated and popularized by Taguchi (Taguchi and Phadke 1984;

Taguchi 1986). Later, Mayer and Benjamin (1992) gives the following six steps for robust design:

i- *Identify factors and specify targets*

Distinguish between (a) design factors, which are independent variables of the model with values (presumably) within the control of the designer, and (b) noise factors, which are not within the control of the designer. Define performance measure(s) and possible target values. Taguchi proposes robustness measures called signal to noise (S/N) ratios that aggregate information on the average performance and its variability (location and dispersion); see step iii.

ii- *Formulate the design of experiment (DOE): crossed arrays*

Design factors are varied according to an orthogonal array (Taguchi 1959), called *inner array*. For each combination in this array, noise factors are systematically varied according to another orthogonal array called *outer array*. Thus, if there are m and n factor combinations in the design and noise arrays respectively, then m x n runs have to be examined (see Table 1). In the following, this DOE for robustness study is called a crossed array.

iii- *Execute the runs and compute the performance statistics*

Execute the m x n runs. Then, for each combination of design factors compute the S/N ratios, which measure the effect of systematic noise variations on the performance of the product. Concretely, if the smaller Y the better, then $S/N_i = -10 \log(1/n \sum y_{ij}^2)$. If the larger Y the better, then $S/N_i = -10 \log(1/n \sum 1/y_{ij}^2)$. And, if the closer Y to target the better, then $S/N_i = 10 \log(\bar{y}^2 / s^2)$.

iv- *Find parameter settings that maximize S/N*

Perform an analysis of variance (ANOVA) using S/N ratios as response. Identify design factors with a significant effect on S/N. Then, set these factors at levels that maximize S/N.

v- *Tune performance to target*

Perform a second ANOVA using the performance measure(s) averaged over the n noise combinations, as response. Identify design factors with significant effects on performance measure(s), among factors that have a negligible effect on S/N (identified in step iv). Adjust the former factors to improve performance.

vi- *Perform confirmation runs*

Does the model perform as predicted? If not, assumptions are not valid (for instance, ignoring factor interactions may be wrong). Go back to ii.

2.2 Literature Review

The contribution of Taguchi to robust design is undeniable. However, his choices for robust design implementation are not unanimously accepted. For instance, Nair (1992) reports on a thorough panel discussion that criticized the use of S/N ratios and crossed arrays. Yet, there seems to be consensus about the fundaments of robust design: conducting experiments in order to study the effects of controllable factors on both the location and the dispersion of the response. Thus, Pignatiello and Ramberg (1987) propose to distinguish the strategic aspect (namely, Taguchi's philosophy of robustness) and the tactical issues (for instance, S/N ratios and DOE).

Many tactical alternatives can be found in the literature. Table 2 shows that researchers sometimes prefer using loss functions or studying the location and dispersion of the performance separately (instead of S/N ratios). Moreover, crossed designs, such as shown in Table 1, may be replaced by combined designs, that is, a single array that does not distinguish noise factors from design factors.

Taguchi originally proposed his technique for product design. Later, researchers have also applied robust design to simulated systems. For instance, Wild and Pignatiello (1991), Dooley and Mahmoodi (1992), Benjamin, Erraguntla, and Mayer (1995), and Sanchez *et al.* (1996) propose simulation-based methodologies for the design of robust jobshop manufacturing systems. Simulation allows

Table 1: Experimental Strategy for Robust Design: Crossed Arrays

						Outer array			
					1	j	n		
					-	…	-	N_l	
					…	…	…	…	
		D_1	…	D_k	-	…	+	N_1	
	1	-	…	-		…		S/N_1	
Inner array	i	…	…	…	…	y_{ij}	…	S/N_i	S/N ratios
	m	+	…	-		…		S/N_m	

Table 2: Literature on Strategic Issues for Robustness Studies

Reference	# Design/ Noise factors	Measure of robustness	Design of Experiments
Sanchez *et al.* (1996)	5 / 2	quadratic loss function	comparison: - combined: 2^{7-2} + two center points - crossed: (2^{5-1} + center points) x 2^2
Mayer and Benjamin (1992)	4 / 2	close-to-target S/N	crossed: 2^{4-1} x 2^2
Lim *et al.* (1996)	4 / 6	smaller-the-better S/N for flowtime and larger-the-better for throughput	crossed: L_{27}^{*} x L_8^{**} * : 3^{13-10} ** : 2^7
Dooley et Mamoodi (1992)	2 / 4	signal-to-noise ratios of the performance mean and dispersion.	2^2 x 2^{4-1}
Sanchez *et al.* (1993)	4 / 1	$\overline{\mathrm{Y}}(x)$, $\log(S(x))$	2^{4-1} x 2^1, replicated four times
Moeeni, Sanchez, and Vakharia (1997)	7 / 34	quadratic loss function	2^{7-1} & noise factors oscillations***, replicated four times *** : frequency domain experiments

the use of larger samples than crossed and combined arrays. Next, we discuss two recent examples of alternative experimental techniques.

2.3 Experimental Alternatives to Taguchi

Moeeni, Sanchez, and Vakharia (1997) proposes an original approach – based on simulation and *Frequency Domain Experiments* (FDE) – to design robust Kanban systems. FDE consists of generating levels x_{ij} for each noise factor x_i and for each noise configuration $j = 1\ldots m$, according to a sinusoidal function:

$$x_{ij} = \tfrac{1}{2}(u_i + l_i) + \tfrac{1}{2}(u_i - l_i)\cos(2\pi.\omega_i.j), \qquad (1)$$

for $i = 1,\ldots,n$ and where u_i and l_i are the upper and lower bound of factor x_i respectively, ω_i is the oscillation frequency of x_i. $\omega_i = T_i/m$, where T_i is the driving integer for x_i. Jacobson, Buss, and Schruben (1991) proposes an algorithm for determining the driving integers so that main effects, quadratic effects, and two-factor interactions are not confounded. Moeeni, Sanchez, and Vakharia (1997) uses FDE to measure the robustness of a Kanban system design.

FDE has originally been designed for sensitivity analysis (Schruben and Cogliano 1981): the effect of each input factor can be measured by the contribution of its characteristic frequency to the output. This contribution is determined through discrete Fourier analysis. Previous research also used sinusoidal functions to examine sensitivity to inputs. The approach is known as the Fourier Amplitude Sensitivity Test (Cukier *et al.* 1973), and is used for uncertainty analyses (Morgan and Henrion 1990, p209). Factor values change in a similar way as FDE:

$$x_{ij} = \mathrm{E}[x_i] + v_i \sin(\omega_i.s_j), \qquad (2)$$

where v_i is the half-spread of the variations (x_{ij} varies within $[\mathrm{E}[x_i] - v_i; \mathrm{E}[x_i] + v_i]$), $\{\omega_i\}$ is a set of frequencies so that factors are not correlated, and s_j is a parameter to discretize the sinusoidal function and has equally space values. So (1) and (2) are equivalent.

Kalagnanam and Diwelar (1997) propose an optimization procedure for the design of robust systems based on simulation and Monte Carlo methods, which they apply to the design of a chemical tank reactor. They do not consider system uncertainty: the simulation model is deterministic. The robustness of the system is not studied for a few extreme environments only, as in experimental arrays, but for a large sample of environments. They compare four sampling techniques: Monte Carlo, Latin Hypercube, Median Latin Hypercube, and Hammersley points. We give a brief description of these techniques in section 3.

In Moeeni, Sanchez, and Vakharia (1997) and Kalagnanam and Diwelar (1997), the sampling techniques are used to measure the effect of noise factors on the performance. However, unlike experimental arrays, these techniques also provide estimates of the output distribution. Thus, it is possible to quantify the probability of the output. This is the core of uncertainty/risk analysis. Next, we propose to reformulate the design parameter problem.

3 RISK ANALYSIS

During the design process, the environment in which the product/system will be used is not known with certainty. Moreover, the environment may vary during the product/system lifetime (for instance, the demand rate for finished goods in a manufacturing plant may fluctuate). Designing a product/system for a specific environmental scenario does not guarantee good performance for other environments: there is a risk associated with the chosen design; another design may lead to a lower risk. Thus, we reformulate the parameter design problem as follows: adjust the design of the system so that the risk of getting poor performance is minimized. This approach can be considered as *risk management* and uses risk/uncertainty analysis techniques to quantify the risk.

By definition, risk involves an 'exposure to a chance of injury or loss' (Morgan and Henrion 1990, p. 1). Thus, quantifying risk requires determining the output probability. Risk/uncertainty analysis consists of sampling each unknown parameter (namely, noise factor according to Taguchi's terminology) from statistical distribution functions, combining the sampled values into scenarios (factor combinations), and conducting a simulation experiment for each scenario. The outcome of this procedure is an estimated probability distribution of the performance measures. Among the many sampling techniques, Monte Carlo sampling is probably best known. Basically, the principle is to select values at random from the distribution per input. Other techniques try to yield better samples than Monte Carlo sampling. Latin Hypercube sampling (Iman and Shortencarier 1984), for instance, is stratified sampling that divides the range of each input parameter into non-overlapping intervals of equal probability; from each interval, one value is selected at random according to the probability distribution in that interval. A refined technique is Median Latin Hypercube sampling, which selects systematically the middle value of the intervals; thus, the sample of each input parameter depends only on the sample size. Hammersley points are designed using a procedure based on "low discrepancy" pseudo-random numbers; for details, we refer to Hammersley (1960) and Kalagnanam and Diwekar (1997).

A choice between two systems can be made by comparing their performance probability distributions. Such a comparison is based on preference criteria, which are often synthesized in a utility function, that is, a mathematical expression that assigns values to all possible choices. In investment theory the utility function is the expression of preferences with respect to perceived risk and expected return. The higher the values of the utility function, the better. Preferences, however, are individual perceptions: a preference may not be unanimous. First- and second-order stochastic dominance tests identify probability distributions that are unanimously preferred by all decision-makers with monotone utility functions and monotone, strictly concave utility functions respectively; see Wolfstetter (1996) and section 5.

Risk management is popular in finance and investment problems, and compulsory for the design of potentially dangerous systems, such as nuclear and waste isolation plants (Helton *et al.* 1997), and certain industrial activities, such as chemical industry (Palle 1994); also see Brehmer, Eriksson, and Wulff (1994). However, to our knowledge, it has not been used to design stochastic systems such as production-control systems. For such systems, we think that risk management is an attractive alternative to Taguchi's robust design.

4 RISK ANALYSIS VERSUS ROBUST DESIGN

4.1 Physical versus Simulation Experiments

Mayer and Benjamin (1992) points out the main differences between product design and system design. In product design, robustness is achieved through prototypes and physical experiments; goods are generally produced in large quantities. In system design, a robustness study has to be performed on models using simulation experiments. Moreover, only a small number of systems are to be implemented. Thus, for feasibility reasons (it may not be easy to reproduce a specific environment) and cost reasons (prototypes usually are expensive), product design can use only small experiments, whereas system design is limited only by time constraints (any type of environment can be simulated, and the major experimental cost is time).

Originally, robust design addressed product design problems: it is a method designed for physical experimentation. Now, physical experimentation is rarely possible for systems. Risk/uncertainty analysis, however, is designed for simulated experiments. Thus, the second approach seems better suited for system parameter design.

4.2 Sampling

Most robustness studies consider at most three levels for each environmental parameter. Then, mathematical techniques are used to choose the combinations of parameter values to be simulated. Risk analysis, on the other hand, uses a large sample size for each parameter. For instance, Latin Hypercube Sampling (LHS) requires a sample size of 100 at least. Moreover, DOE selects extreme parameter value combinations, whereas risk analysis samples values for each parameter over the whole domain. The probability distribution functions, from which each parameter is sampled, are specified by the analyst, possibly with the support of experts.

4.3 Dispersion versus Risk

Robust design is based on the estimation of the performance's location and dispersion over environmental variations. Any deviation from the mean is penalized (quadratic loss function): dispersion does not differentiate good and bad performance. We, however, are interested only in "bad" performance, that is, in performance below a prespecified target.

5 COMPARISON OF PULL PRODUCTION-CONTROL SYSTEMS (PPCSS) USING A RISK CRITERION

Next, we illustrate the risk approach through the comparison of four pull production-control systems. We do not intend to solve the design parameter problem, which is an optimization problem, but simply show how risk analysis can be used to compare the performances of production systems. We leave the optimization problem for further research.

In pull systems, the occurrence of finished goods delivery triggers production: a station cannot start production without an authorization, which conveys the information about a finished good delivery. Limiting the number of authorizations sets an upper bound for the Work-In-Progress (WIP) level. For production lines, pull systems can be specified by the way demand information flows through the production system (Gstettner and Kuhn 1996). Kanban is a system in which information flows from a station to its immediate predecessor only (Monden 1993). In a Conwip system, information is sent directly from the finished goods inventory, to the first station; within the line, stations do not need authorizations to produce (Spearman, Woodruff, and Wallace 1990). In a Hybrid Kanban/Conwip system, the information paths used in Kanban and Conwip are combined (Bonvik, Couch, and Gershwin 1997): it is a Conwip system for which stations within the line need authorizations to produce. Figure 1 shows models of these three pull systems using the same symbols as in Gstettner and Kuhn (1996).

Bonvik, Couch, and Gershwin (1997) compares various pull systems for a four-stage production line inspired by a Toyota factory. The simulation model of this line randomly selects processing times from lognormal distributions; times between failure and times to repair are exponentially distributed. The system is feeding an assembly line, which is modeled as a deterministic demand process. Thus, the demand interarrival time is constant, and any demand that cannot be satisfied from stock is lost. For this system, those authors perform a search for the best configuration (that is, the number of authorizations circulating along each information path) with the objective of achieving a high service level (namely, 99.9%), while minimizing the inventory level. Gaury, Pierreval, and Kleijnen (1998) proposes a generalization of Hybrid systems based on evolutionary principles. They illustrate the approach through the same model and the same objective as in Bonvik, Couch, and Gershwin (1997). An optimization procedure based on an evolutionary algorithm yields a pull system that is significantly different from Hybrid Kanban/Conwip. In the following, we call this new system *generic*.

Both Bonvik, Couch, and Gershwin (1997) and Gaury, Pierreval, and Kleijnen (1998) do not account for robustness issues. Thus, we propose to compare the robustness of the best pull systems found in those two papers, but we use risk analysis. The uncertain parameters are the various processing time averages and variances, the average times between failures and times to repair, and the demand rate; altogether 17 parameters. The *base scenario* is the set of values used for these parameters in Bonvik, Couch, and Gershwin (1997). We choose to study the robustness to environmental variations within a range of ±5% around the base scenario. LHS is used to generate a sample of 100 environmental scenarios. We assume that these scenarios are equally probable. Thus, each parameter has a uniform distribution. For each scenario, we run a simulation corresponding to one month of production, that is 22 days with two shifts per day. All simulation runs use the same initial conditions. In Bonvik, Couch, and Gershwin (1997), the objective was to achieve a 99.9% service level, while minimizing the Work-In-Progress (WIP) level. We use the monthly WIP level and the monthly proportion of shifts with a service level below 99.9% as performance measures. A shift with a service

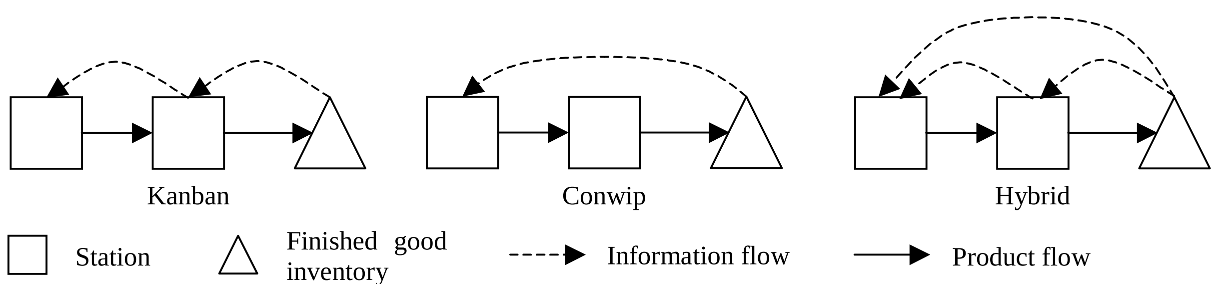

Figure 1: Three Types of Pull Systems

level below 99.9% is seen as a disaster (risk terminology): we want to minimize the probability of a disaster over the environmental sample.

Figures 2 and 3 show the cumulative probability of the outcome in terms of monthly disaster proportion and WIP, for the best configurations of Kanban, Conwip, Hybrid, and generic found in Bonvik, Couch, and Gershwin (1997) and Gaury, Pierreval, and Kleijnen (1998). The cumulative probability functions of the monthly disaster proportions show strong similarities. The theory of *stochastic dominance* (Wolfstetter 1996) can be used to rank the four PPCSs, as follows. Let X and Y be two random variables. X first-order stochastically dominates Y ($X \geq_{FSD} Y$) if

$$\Pr\{X>z\} \geq \Pr\{Y>z\}, \text{ for all } z.$$

X is *unanimously preferred* to Y by all agents with monotone increasing utility functions if and only if $X \geq_{FDS} Y$.

X second-order stochastically dominates Y ($X \geq_{SSD} Y$) if

$$\int_a^k \Pr\{X > x\}dx \geq \int_a^k \Pr\{Y > y\}dy, \text{for all } k.$$

X is *unanimously preferred* to Y by all agents with monotone increasing and strictly concave utility functions if and only if $X \geq_{SSD} Y$. Y is said to be "stochastically more risky" than X. The strictly concave condition on the utility function expresses the risk aversion of the agent.

We compute dominance tests for the monthly disaster proportions: Conwip second-order stochastically dominates all the other systems; Hybrid second-order stochastically dominates Kanban and Generic; it is not possible to choose unanimously between Kanban and Generic.

The monthly WIP distributions show large differences among PPCSs (Figure 3). Hybrid and Kanban lead to high probabilities of low WIP levels, whereas Conwip and Generic lead to high probabilities of high WIP levels. So we can rank the four PPCSs – according to the WIP levels averaged over the LHS scenarios – from best to worst: 1. Hybrid, 2. Kanban, 3. Generic, and 4. Conwip.

In summary, Conwip is less risky than the three other systems in terms of service performance, but at the cost of a higher WIP level. Hybrid seems to be a good compromise. It is interesting to note that when robustness issues are not considered, the ranking of the four PPCSs is: 1. Generic, 2. Hybrid, 3. Conwip, and 4. Kanban. This means that Generic is a system that is well adapted to the base scenario, but it looses its advantage over the other systems whenever the environment is uncertain. This illustrates clearly the importance of considering robustness issues in systems design.

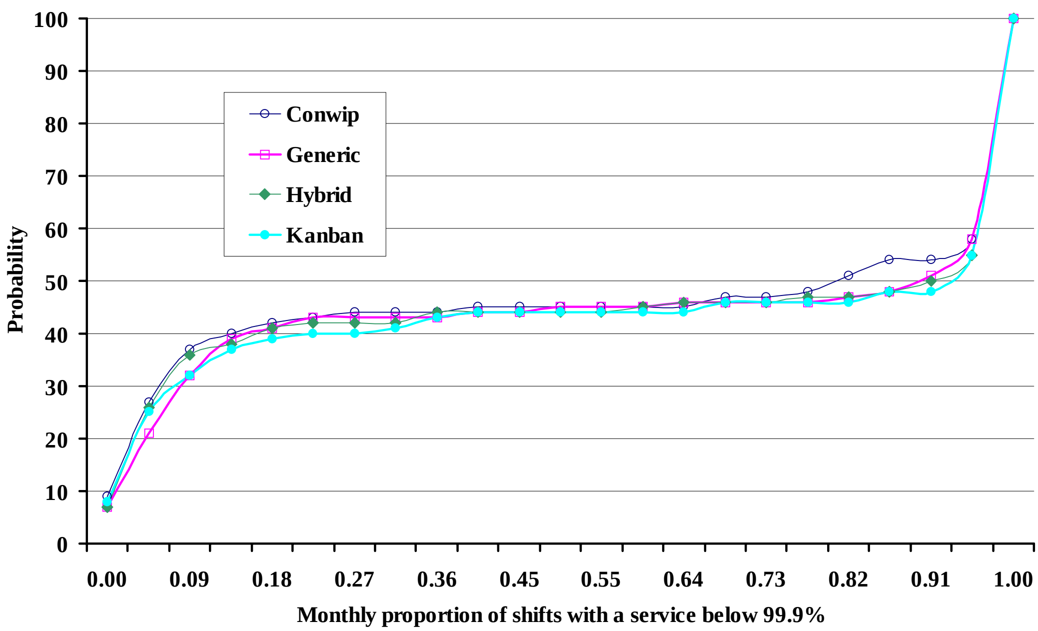

Figure 2: Cumulative Probability Functions of the Monthly Disaster Proportion for Four PPCSs

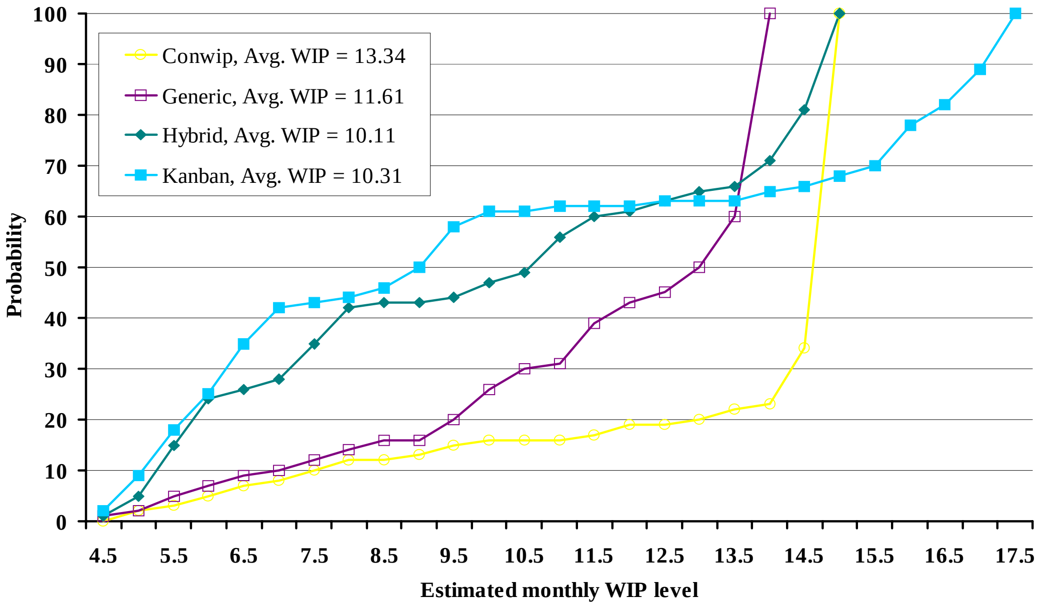

Figure 3: Cumulative Probability Functions of the Monthly WIP Level for Four PPCSs

6 CONCLUSION

In this paper we examined the robustness issue for system design. We discussed the extension of the approach proposed by Taguchi for product design to system design using simulation. We proposed a different procedure based on risk analysis. This procedure uses Monte Carlo sampling to build scenarios for the uncertain environmental parameters. Simulating the scenarios yields a measure of the risk of getting poor performance. We believe this procedure is an advantageous alternative to Taguchi's robust design, even though the former needs more experiments. An analysis of the robustness of several PPCSs illustrated the approach and showed how risk analysis combined with stochastic simulation can be used to compare systems. It also demonstrated the importance of robust design: designing a system for a specific environment – ignoring environmental variations and uncertainties – may be risky.

REFERENCES

Benjamin, P.C., M. Erraguntla, and R.J. Mayer. 1995, Using simulation for robust system design. *Simulation* 65(2), 116-128.

Bonvik, A.M., C.E. Couch, and S.B. Gershwin. 1997. A comparison of production-line control mechanisms. *International Journal of Production Research* 35(3), 789-804.

Brehmer, B., E.A. Eriksson, and P. Wulff. 1994. Risk management (feature issue). *European Journal of Operational Research* 75: 477-566.

Cukier, R.I, C.M. Fortuin, K.E. Schuler, A.G. Petschek, and J.H. Schaibly. 1973. Study of the sensitivity of coupled reaction systems to uncertainties in rate coefficients: I Theory. *Journal of Chemical Physics* 59: 3873-3878.

Dooley, K.J., and F. Mahmoodi. 1992. Identification of robust scheduling heuristics: application of Taguchi methods in simulation studies. *Computers and Industrial Engineering* 22(4): 359-368.

Gaury, E.G.A., H. Pierreval, and J.P.C. Kleijnen. 1998. New species of hybrid pull systems. CentER Discussion Paper No. 9831, Tilburg University, Netherlands.

Gstettner, S., and H. Kuhn. 1996. Analysis of production control systems Kanban and Conwip. *International Journal of Production Research* 34(11): 3253-3274.

Helton, J.C., D.R. Anderson, M.G. Marietta, and R.P. Rechard. 1997. Performance assessment for the waste isolation pilot plant: from regulation to calculation for 40 CFR 191.13. *Operations Research* 45(2): 157-177.

Iman, R.L., and M.J. Shortencarier. 1984. A FORTRAN 77 program and user's guide for the generation of Latin Hypercube and random samples for use with computer models. NUREG/CR-3624, SAND83-2365, Sandia National Laboratories, Albuquerque, New Mexico.

Jacobson, S.H., A.H. Buss, and L.W. Schruben. 1991. Driving frequency selection for frequency domain simulation experiments. *Operations Research* 39(6): 917-924.

Kalagnanam, J.R., and U.M. Diwekar. 1997. An efficient sampling technique for off-line quality control. *Technometrics* 39(3): 308-319.

Lim, J.-M., K.-S. Kim, B.-J. Yum, and H. Hwang. 1996. Determination of an optimal configuration of operating policies for direct-input-output manufacturing systems using the Taguchi method. *Computers and Industrial Engineering* 31(3/4): 555-560.

Mayer, R.J., and P.C. Benjamin. 1992. Using the Taguchi paradigm for manufacturing system design using simulation experiments. *Computers and Industrial Engineering* 22(2): 195-209.

Moeeni, F., S.M. Sanchez, and A.J. Vakharia. 1997. A robust design methodology for Kanban system design. *International Journal of Production Research* 35(10): 2821-2838.

Monden, Y. 1993. *Toyota Production System*, 2nd edition, Norcross: Institute of Industrial Engineers.

Morgan, M.G., and M. Henrion. 1990. *Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy and policy analysis*. Cambridge University Press.

Nair, V.N. 1992. Taguchi's parameter design: a panel discussion. *Technometrics* 34(2): 127-161.

Palle, H. 1994. Overview of problems of risk management of accidents with dangerous chemicals in Europe. *European Journal of Operational Research* 75(3): 488-498.

Pignatiello, J.J.Jr., and J.S. Ramberg. 1987. Discussion of performance measures independent of adjustment *Technometrics* 29: 274-277.

Sanchez, S.M., J.S. Ramberg, J. Fiero, and J.J.Jr. Pignatiello. 1993. Quality by design. In *Concurrent engineering: automation, tools, and techniques*, ed. Andrew Kusiak, 271-277. John Wiley & Sons, Inc.

Sanchez, S.M., P.J. Sanchez, J.S. Ramberg, and F. Moeeni. 1996. Effective engineering design through simulation. *International Transactions in Operational Research* 3(2): 169-185.

Schruben, L.W., and V.J. Cogliano. 1981. Simulation sensitivity analysis: a frequency domain approach. In *Proceedings of the 1981 Winter Simulation Conference*, 455-459. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

Spearman, M.L., D.L. Woodruff, and W.J. Hopp. 1990. Conwip: a pull alternative to Kanban, *International Journal of Production Research*, 28(5): 879-894.

Taguchi, G. 1959. Linear graphs for orthogonal arrays and their application to experimental design, with the aid of various techniques, *Reports of Statistical Application Research JUSE*, 6: 1-43.

Taguchi, G. 1986. *Introduction to quality engineering: designing quality into products and processes*, White Plains, New York: Kraus International Publications.

Taguchi, G., and M.S. Phadke. 1984. Quality engineering through design optimization. In *Conference record of the 1984 IEEE Globecom Conference*, Atlanta, Georgia, (3): 1106-1113. New York: Institute of Electrical and Electronics Engineers.

Wild, R.H. and J.J.Jr. Pignatiello. 1991. An experimental design strategy for designing robust systems using discrete-event simulation, *Simulation*, 57(6): 358-368.

Wolfstetter, E. 1996. Stochastic dominance: theory and applications, *series Sonderforschungsbereich 373*, Humboldt Universitaet Berlin. Available online from `http://econwpa.wustl.edu/WoPEc/data/Papers/wophumbsf960040.html` [accessed June 16, 1998].

AUTHOR BIOGRAPHIES

ERIC G.A. GAURY is a Ph.D. Student in Management Science at the Center for Economic Research (CentER), Tilburg University, Netherlands, and at the Laboratoire Inter-établissement d'Informatique, de Modélisation et d'Optimisation (LIMOS), University Blaise Pascal, Clermont-Ferrand, France. His research interest include pull production-control, optimization techniques, and robustness issues. He received a degree in Mechanical Engineering from the French Institute of Advanced Mechanical Engineering (IFMA), Clermont-Ferrand, and the equivalent of a M.Sc. in Computer Science and Engineering from University Blaise Pascal.

JACK P.C. KLEIJNEN is Professor of Simulation and Information Systems at Tilburg University, Netherlands. His research interests are in simulation, mathematical statistics, information systems, and logistics. He published six books and nearly 160 articles; one book was also translated into Russian. He consulted several organizations, and was on many editorial boards and scientific committees. He spent several years in the USA, at both universities and companies. He was awarded a number of international fellowships and awards.