Proceedings of the 2014 Winter Simulation Conference
A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, eds.

EVALUATING THE IMPACT OF BATCH DEGRADATION AND MAINTENANCE POLICIES ON THE PRODUCTION CAPACITY OF A BATCH PRODUCTION PROCESS

Bikram Sharda
Scott Bury
Process Optimization- Engineering Sciences,
The Dow Chemical Company
Freeport, TX- 77541, USA

ABSTRACT

This paper presents a case study that validated the production capacity of an industrial batch chemical process. A risk assessment review of the production system identified that different constraints and uncertainties could limit the actual production capacity of the plant to less than designed. To determine if production capacity was at risk, we developed a discrete event simulation to simulate a batch chemical production process with multiple parallel production units, interlocks in product loading steps, uncertainty in processing times caused by equipment failures, degradation of production process over time, and planned maintenance shutdowns. We evaluated the impact of variation in the degradation rate of the production process, and the impact of changes in renewal frequency on the total production capacity of the plant.

1 INTRODUCTION

Simulation modeling has been widely applied to address various type of manufacturing system problems. Negahban and Smith (2014) provide a comprehensive literature review and analysis of discrete event simulation related publications related to manufacturing applications between 2002 and 2013. The authors have noted a clear increase in relevant publications on use of simulation for manufacturing system design and operation. In more recent work, Ponsignon and Mönch (2014) used a simulation based approach for performance assessment of master planning approaches in semiconductor manufacturing. Melouk et al. (2013) developed a simulation optimization based decision support system for evaluating the work in process inventory levels and modifications in manufacturing process to reduce utilization costs. Zhang et al. (2014) investigated the impact of different operational variables (such as production speed, scrap rate and maintenance speed) on the manufacturing costs.

Discrete event simulation in the process industries is most commonly used in the context of reliability and maintainability (RAM) studies (Owens et al. 2010) along with traditional application areas in logistics and supply chain (Buss and Ivey 2001). In a series of Winter Simulation conference papers, and elsewhere, the authors and colleagues have shared what we believe are effective practices for maximizing the contribution of discrete event simulations to decision support systems as well (see Sharda and Bury (2008), Sharda and Bury (2011), Akiya *et al.* (2011), and Sharda and Akiya (2012)). In this paper, we present a case study validating the production capacity of a batch chemical production system that included discrete control logic as well as some time varying processes like equipment fouling. The simulation study was commissioned after an engineering-risk assessment review of a proposed capacity expansion of an existing batch plant. The subject matter experts (SME) identified three risk categories to achieving the targeted capacity expansion. These were operational constraints, specific component reliability and equipment degradation or fouling over time.

978-1-4799-7486-3/14/$31.00 ©2014 IEEE

We worked with the project team to define the decisions and the data required to make them, and negotiated a project charter to develop a DES to generate the required data. While incorporating more and more details in a simulation usually results in higher fidelity, there is the risk of out-modeling the available data (for input models) or creating models with intractable results. Understanding the client's decisions and data required to make the decisions as well as the consequences for making a right (wrong) decision helps guide the level of complexity and fidelity needed in a simulation.The primary decision was to confirm that proposed design would deliver the expected production capacity under the process constraints required for safe operation and environmental compliance. The second major decision was to determine if a change in maintenance polices would improve system productivity.

Our results showed that under the given constraints and uncertainties, the production system will be able to meet its desired production capacity. Sensitivity analysis of the variation in degradation rate and changes in planned maintenance policies reveals that higher production capacity can be attained by more frequent planned maintenance as compared to the existing policy.

This remainder of the paper is organized as follows. In Section 2, we provide a high level overview of the production process and the simulation development. Section 3 discusses the simulation results and finally Section 4 provides the summary of this work. The process has been simplified, and numbers discussed in the paper have been arbitrarily scaled for business confidentiality.

2 PROCESS OVERVIEW

Figure 1 shows an overview of the production process. The production system contains multiple parallel units producing a single product. The operational steps of different parallel units are constrained by interlocks that prevent simultaneous loading of raw material in the units. This is one of several layers of protection that ensures safe operation. The production capacity of each unit decreases over time due to degradation of a component within the unit, and unplanned failures are primarily due to mechanical reliability issues. Each of the production units goes through a scheduled sequence of short and long duration corrective maintenance. DES is well suited to model the uncertainties in the production rate caused by failures of various components, and facilitates the visualization of the complex system dynamics. The production process has 4 different trains, and each train consists of 2 parallel units (see Figure 1 for a more detailed overview of each train). Each production unit is a batch process. At the end of the batch operation, the product is transferred to the buffer storage and subsequently sent to downstream production units. At the beginning of each operation, the raw material is loaded into the production unit. To ensure safe operation, the product cannot be loaded simultaneously to other production units for the first X minutes of the loading process. Thus, all of the unit operations were modeled as two step operations , 1) product loading for x minutes and 2) remaining steps to simplify the modeling logic.

Based on the analysis of historical operating data and input from the project team, we assume that there are no upstream or downstream bottlenecks. This simplifying assumption accelerated the modeling timeline as it kept the focus of the modeling work on generating the data required to evaluate the production capacity and maintenance policies.

Although simplified to a two-step sequence, each of the steps was supported by the required safety and control logic as these represented the primary constraints on the process throughput. The performance of each production unit degrades over time due to degradation of a certain component within the unit. Based on SME feedback, it was assumed that each unit's performance degraded linearly from a "good" condition to a "bad" condition over a period of 30 days. Under a "good" unit condition, the unit can hold a batch size of 2000 Kg and the cycle time is 30 minutes. Under a "bad" case, the unit can hold a batch size of 1000 Kg and the cycle time is 60 minutes. Thus, over a period of time, the production unit runs a smaller batch size and takes higher cycle time to produce a batch. The batch size (in Kg) and cycle time (in minutes) can be computed using the following equations (1) and (2):

$$\text{Batch size }(t)= 2000+s_1\times t, \text{ where slope } s_1 = (1000-2000)/30= -33.33 \quad (1)$$

$$\text{Cycle time }(t)= 30+ s_2\times t, \text{ where slope } s_2 = (60-30)/30=1 \quad (2)$$

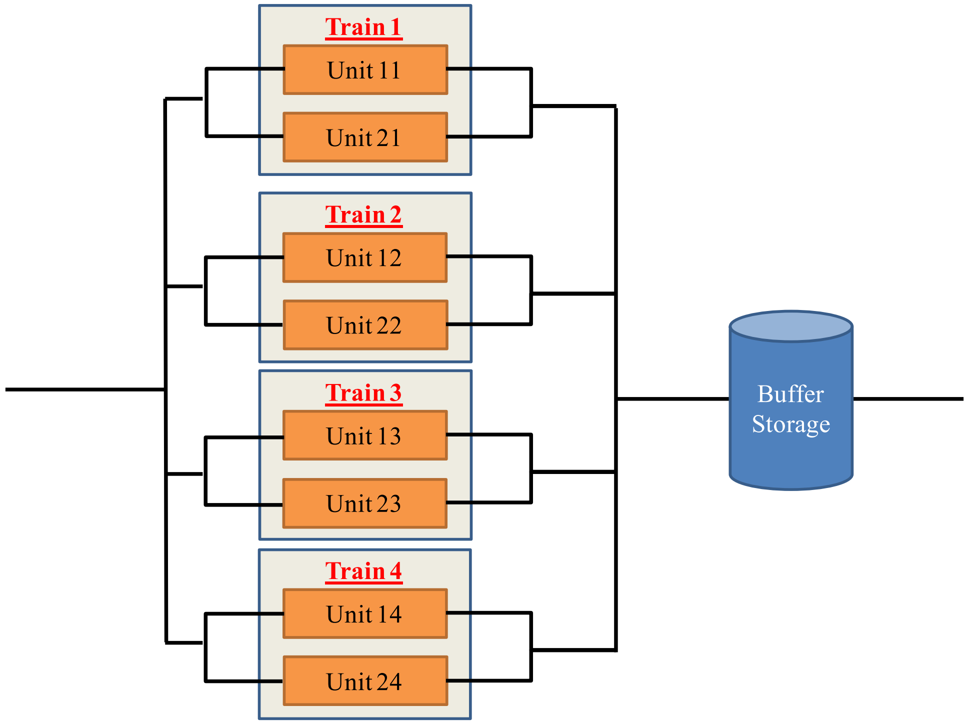

Figure 1: High level overview of the production process

Where t is the unit's working time (in days), excluding the downtimes. We assumed that during a downtime, the unit performance does not degrade. Therefore, only actual working time of the unit was used to compute the degradation rate.

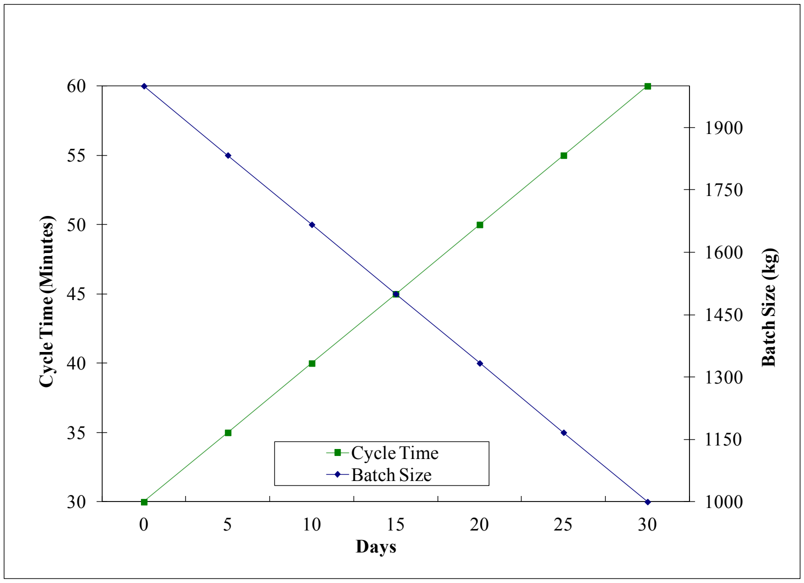

Figure 2: Changes in batch size and cycle time over a period of time

Each production unit is subject to periodic "short" and "long" duration maintenance (referred to as renewals). These renewals return the units to their optimal production capabilities (i.e. batch size= 2000 Kg, and cycle time=30 minutes). The "short" duration renewal requires a downtime of 8 hours (every 30 days) and "long" duration renewals requires a downtime of 48 hours (every 90 days). For each production unit, there are 12 renewals/year, including 8 "short" duration and 4 "long" duration renewals. In order to minimize the production variability due to the long and short term renewals, renewals for different production units were scheduled uniformly over a period of time. Within each month, the renewals were equally spaced in order to minimize production fluctuations. Similarly, the long duration renewals for different production units were equally spaced throughout a 12 month period to avoid significant production fluctuations.

We also conducted a sensitivity analysis of production rates against variation in the degradation rates (± 10% variation) and changes in the time between renewals (22.5 and 45 days instead of 30 days). Figure 3 and Figure 4 shows the effect of 10% variation in the degradation rate on batch size and cycle time. With a 10% decrease in degradation rate (better performance), the performance of production unit will degrade at a slower rate, and the unit will be able to produce a bigger batch size in a shorter cycle time as compared to the base case (at the end of 30^{th} day). We assumed a linear degradation change, so 10% decrease in degradation rate (better performance) implies that the new batch size will be 1000+0.10*1000=1100 kg, and the cycle time will be 60-0.10*60=54 minutes. Similar explanation follows for 10% increase in degradation rate (worse performance). For a 10% decrease in the degradation rate (better performance), the batch size and cycle time at any time (t) can be computed using equations (3) and (4):

Batch size (t)= 2000+$s_1 \times t$, where slope s_1 = (1100-2000)/30= -30 (3)

Cycle time (t)= 30+ $s_2 \times t$, where slope s_2 = (54-30)/30=0.8 (4)

For a 10% increase in the degradation rate (worse performance), the batch size and cycle time at any time (t) can be computed using equations (5) and (6):

Batch size (t)= 2000+$s_1 \times t$, where slope s_1 = (900-2000)/30= -36.67 (5)

Cycle time (t)= 30+ $s_2 \times t$, where slope s_2 = (66-30)/30=1.2 (6)

The resulting changes in the cycle time and batch size are plotted in the next two figures (3 &4).

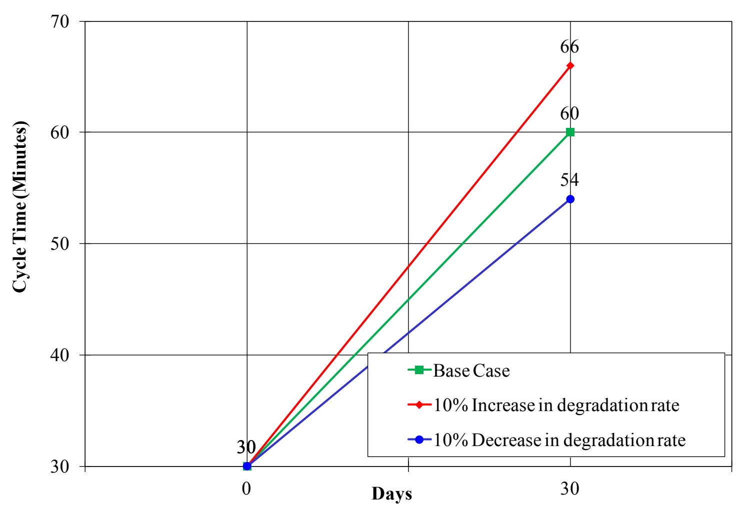

Figure 3: Sensitivity Curves for degradation rate on cycle time

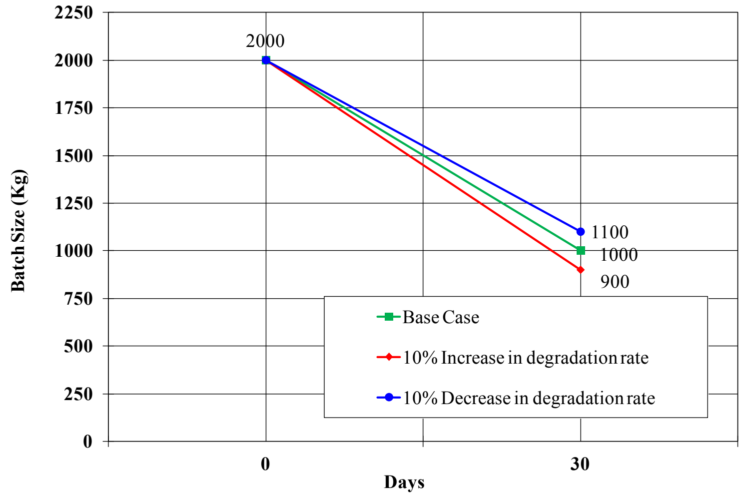

Figure 4: Sensitivity Curves for degradation rate on batch size

The discrete event simulation model for the in-scope process was developed using ExtendSim version 8.0.1 `<www.extendsim.com>` simulation software. We chose to model this system using discrete events without the use of the discrete rate library because of the focus on the interlocks and the states of the system to drive control decisions. Maintenance data was used to generate time to failure and time to repair distributions. The model was also designed to run in either the “pre-improvement” and “post-improvement” mode.

We used the following settings in the simulation model:

- Number of simulation replications: 20
- Simulation run length: 10 years
- Warm up period: 3 months.

3 RESULTS

We used the simulation model to first compute the predicted production rates in “pre-improvement mode” against the historical record. This provided the validation of the model results. The simulation model was then used to establish the expected “post-improvement” baseline. This confirmed that the improvements would deliver the required productivity. Next, we studied the variation in degradation rate (±10% variation) and time between renewals (22.5 and 45 days) on overall production.

Figure 5 and Figure 6 show the effect of using different time between renewals on cycle time and batch size of the production unit. We assumed that the long duration renewal (48 hour) would always be performed after 90 days. For example, under a 22.5 day time between renewals, there would be 3 “short” time duration renewals (8 hour) before a “long” time duration renewal. After the renewal, the production unit would be reset to its “good” working conditions. We note that while a shorter time duration renewal improves the average production rate (quantity produced/cycle time), it also increases the downtime of the unit.

Figure 7 shows the impact of renewal frequency and changes in the degradation rate of production units on the overall production. The red dotted line indicates the desired production capacity of the plant (54 Kilo Tons Per Annum (KTPA)). The 95% confidence interval from the simulation results were small, and were thus excluded from the figure.

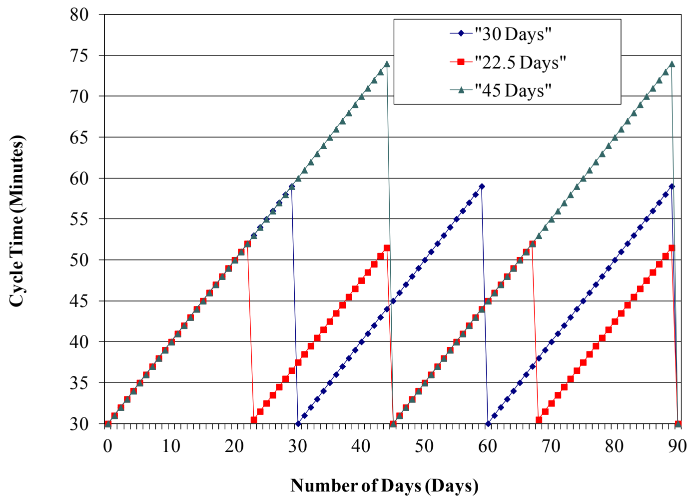

Figure 5: Effect of renewal frequency on cycle time

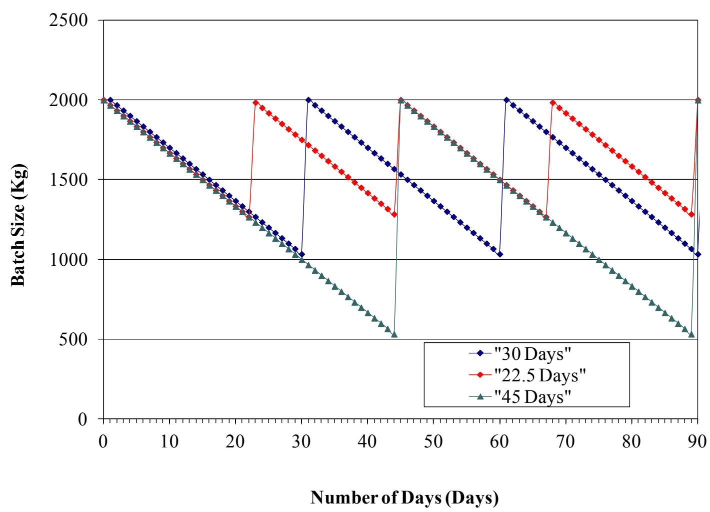

Figure 6: Effect of renewal frequency on batch size

The results indicate that without upstream and downstream bottlenecks, the production process would be able to meet the desired production rates (54 KTPA) for all the cases except with an increase in the degradation rate. As expected, the results indicate that the variation in the degradation rate of the production units can have a significant impact on the total production. The results also indicate that the variation in the renewal frequency can have a significant impact on improving the production capacity. For the Base Case, the results indicate that a change in renewal frequency from 30 to 45 days can lead to 0.71 KTPA improvement in production (~1% of the total annual production). Fewer renewals also decreases the yearly maintenance expenses thus improving the total plant margin.

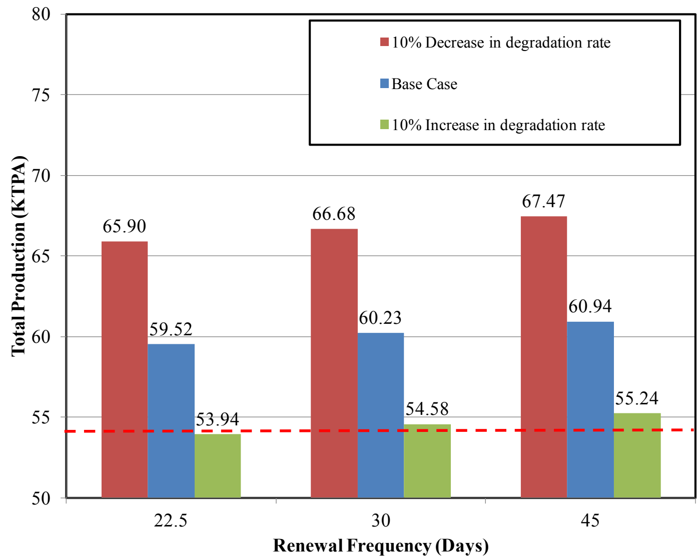

Figure 7: Impact of renewal frequency and degradation rate on total production. Dashed line is target production.

4 SUMMARY

This paper presents a case study to validate the production capacity of a batch chemical production system after a proposed expansion project. We developed a discrete event simulation to simulate the manufacturing with multiple parallel production units, interlocks in product loading steps, uncertainty in processing times due to equipment failures, degradation of production process over time, and planned maintenance shutdowns. We evaluated the impact of variation in the degradation rate of the production process, and the impact of changes in renewal frequency on the total production capacity of the plant. Our results indicate that the production process will be able to meet the designed production capacity under different constraints under the baseline conditions. However, the product process will not be able to attain the desired production capacity if the degradation rate of the production process increases significantly. Our results also indicate that higher production capacity and reduced costs can be attained by less frequent planned maintenance (45 days) as compared to the existing policy (30 days).

5 ACKNOWLEDGMENTS

We would like to thank the business for their support of new modeling approaches and express our appreciation of the team members for providing their expertise at different phases of the project. We would also like to thank our colleague Intan Hamdan for constructive feedback for improving the quality of the paper.

6 REFERENCES

Negahban, A. and J.S. Smith. 2014. "Simulation for manufacturign system design and operation: Literature review and analysis." *Journal of Manufacturing Systems* 33(2): 241-261.

Ponsignon, T. and L. Mönch. 2014. "Simulation based perofrmance assessment of master planning approaches in semiconductor manufacturing." *Omega* 46: 21-35.

Melouk, S.H., Freeman, N.K., Miller, D. and M. Dunning. 2013. "Simulation optimization based decision support for steel manufacturing." *International Journal of Production Economics* 141(1): 269-276.

Zhang, R., Chiang, W. and C. Wu. 2014. Investigating the impact of operational variables on manufacturing cost by simulation optimization. *International Journal of Production Economics* 147 147(c): 634-646.

Owens, J.W., Miller, A.S. and D.M. Deans. (2010). "Applying discrete event modeling in the real world." In *proceedings of 2010 Reliability and Maintainability Symposium (RAMS)*, 1(6): 25-28.

Buss, P. and N. Ivey. (2001). “Dow chemical design for six sigma rail delivery project.” *In Proceedings of the 2001 Winter Simulation Conference,* Edited by B.A. Peters, J.S. Smith, D.J. Medeiros, and M.W. Rohrer, 1248-1251.Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Akiya, N., S. J. Bury and J.M. Wassick. (2011). “Generic framework for simulating networks using rule-based queue and resource ask network.” In *Proceedings of the 2011 Winter Simulation Conference*, Edited by S. Jain, R.R. Creasey, J. Himmelspach, K.P. White, and M. Fu, 2194-2205. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Sharda, B. and N. Akiya. 2012. Selecting make-to-stock and postponement policies for different products in a chemical plant: A case study using discrete event simulation. *International Journal of Production Economics* 136(1): 161-171.

Sharda, B. and S.J. Bury. 2011. “Best Practices for Effective Application of Discrete Event Simulation in the Process Industries.” In *Proceedings of the 2011 Winter Simulation Conference*, Edited by S. Jain, R.R. Creasey, J. Himmelspach, K.P. White, and M. Fu, 2320-2329. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Sharda, B. and S. J. Bury. 2008. “A discrete event simulation model for reliability modeling of a chemical plant.” In *Proceedings of the 2008 Winter Simulation Conference*, edited by S. J. Mason, R. R. Hill, L. Mönch, O. Rose, T. Jefferson, J. W. Fowler, 1736-1740. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

AUTHOR BIOGRAPHIES

BIKRAM SHARDA is an Associate Scientist in the Process Optimization group of The Dow Chemical Company's Engineering Sciences organization within Core R&D. His research interests include simulation and mathematical modeling, risk analysis, data mining and pattern recognition. He is a member of IIE and a certified Green Belt Project Leader. His email address is <brsharda@dow.com>.

SCOTT J. BURY is a Principal Research Scientist in Core R&D at The Dow Chemical Company. His research interests include process simulation & optimization of chemical processes using both continuous and discrete event technology, and eliminating failure modes when implementing new process technology. He is a certified Six Sigma Black Belt. He often wonders about the various failure modes of his mountain bike as he hurtles downhill. His email address is <sjbury@dow.com>.