# Why Is High Due-Date Performance So Difficult to Achieve?—An Experimental Study

**Jiun-Huei Lee**
*National Chiao Tung University, 1001 Tashu Road, Hsinchu, Taiwan 300, Taiwan, viviligood@gmail.com*

**Yunn Jin Hwang**
*National Chiao Tung University, 1001 Tashu Road, Hsinchu, Taiwan 300, Taiwan, t0403650@seed.net.tw*

**Mei-Ting Wang**
*National Chiao Tung University, 1001 Tashu Road, Hsinchu, Taiwan 300, Taiwan*

**Rong Kwei Li** *(Corresponding author)*
*National Chiao Tung University, 1001 Tashu Road, Hsinchu, Taiwan 300, Taiwan, rkli@cc.nctu.edu.tw*

## ABSTRACT

Due-date performance (DDP) is extremely important in a make-to-order environment (MTO), but despite numerous academic studies, as well as the development of practical methods by industrial practitioners, poor DDP persists. Understanding why high DDP is so difficult to achieve and identifying the major barriers to its realization are of high concern. This investigation identifies two main causes for the difficulties in improving DDP: excessive variability in MTO environments and mode of managing operations. While it is difficult to identify in reality which of the two main causes is the root cause (and should be improved first), it is possible to conduct virtual tests. This study develops an experiment using three scenarios to gather data regarding the root cause. Thirty-five teams containing a total of 245 participants from local companies participated in the experiment. The experimental results indicate that the mode of managing operations is the root cause of poor DDP and should be improved first. Accordingly, criteria of good solutions to high DDP can also be identified.

***Keywords:*** TOC, Due-Date Performance, Drum-Buffer-Rope

## INTRODUCTION

Clients constantly request higher levels of reliable due-date performance (DDP) in make-to-order (MTO) environments. Winning businesses are those with a strong ability to fulfill the DDP requirement. In fact, in an effort to improve DDP, numerous academic papers on improving DDP have been published. Some studies have focused on investigating how to determine the right dispatching rules (working priorities) for different production environments (Lu and Kumar 1991; Katcher et al. 1993; Grabot and Geneste 1994; Lin et al. 2001; Dabbas and Fowler 2003), others concentrate on rules for controlling order release (Graves and Milne 1997; Tsai et al. 1997; Breithaupt and Nyhuis 2002; Nandi and Rogers 2003; Chung et al. 2003) and dealing with bottleneck starvation issues (Lozinski and Glassey 1988; Glassey and Petrakian 1989; Rippenhagen and Krishnaswamy 1998; Chiang and Kuo 2000; Roser et al. 2002; Gorinsky and Jechlitschek 2007). Previous literature has demonstrated that DDP can be improved by effective management of order release, working priorities, and bottlenecks. Despite the academic research, business also employs numerous approaches developed by industrial practitioners to improve DDP. These approaches include Just-in-Time (JIT), advanced production scheduling system (APS), and theory of constraints (TOC) (Watson et al. 2007).

Drum-buffer-rope (DBR), developed by Goldratt (Goldratt 1986, 1990, 1992, 1996), is the most famous approach to improving DDP. Hundreds of accounts of successful DBR implementations (Mabin and Balderstone 2000; Lilly 2004; Umble et al. 2006) have been made, all claiming that it is possible to rapidly achieve highly reliable DDP. Traditional DBR employs a three-buffer system to protect both the due dates and the detailed finite-capacity schedule of the capacity constraint resources (CCR). DBR assumes an active CCR, but this is only rarely the case in reality. In most cases a company's constraint is in the market, which means sufficient protective capacity exists even on the CCR and it is unnecessary to protect the limited resource capacity within the shop. Schragenheim and Dettmer (2001) proposed a simplified DBR (SDBR) method that uses one buffer (production buffer) and has been shown to be effective even when an internal CCR is active. In SDBR, a planned-load concept and a method of setting order due date were developed (Schragenheim et al., 2006; Schragenheim 2006). Goldratt (2006) also developed a strategy and tactics tree to provide guidance in creating change.

Despite hundreds of accounts of successful DBR and SDBR implementations, our interviews with local managers revealed few who were confident of their ability to build a highly reliable DDP plant with SDBR. The interviews were conducted in our three-hour public workshops,* attended by more than 300 people. The majority of attendees were plant managers and supervisors, production planners and controllers, and material managers. Sixty percent of the attendees came from high-tech industries such as wafer fabrication, IC assembly/test, PCB/substrate, and LED/LCD and TFT panels. The other 40% were from traditional industries such as plastic injection, airplane engine components, machine tools, auto parts, textile, and bicycle manufacturing.

In answer to the question "Why is it difficult to manage production?" we ask respondents not just to write what they believe causes production difficulties, but also what they think others would say. Eighty-five percent of reasons given can be summarized as excessive variability (such as machine breakdowns), quality issues, changes in demand, material shortages, unreliable processes, and so on. These responses demonstrate why reducing variability has become the focus of improvement efforts, with programs such as lean and six sigma becoming the norm at many companies. Yet in response to the question "If you have adopted lean and six sigma programs, was DDP improved significantly?" 80% of respondents indicated that their DDP remains a major issue. The other 20% said their DDP levels have improved, but with lengthy effort.

Managing a plant to achieve highly reliable DDP is easy in theory. First, the plant manager determines a market-accepted quoted lead time (QLT) for the products. QLT varies between the low and peak seasons. It typically exceeds the plant's production lead time and should have a buffer large enough to handle variability.

In most cases, customers place their orders at least one QLT ahead while also providing a required delivery date. Sales personnel review the date with the production planner, and if it is achievable, the order is confirmed. If, due to capacity loading, the required date cannot be met, the customer is given a new delivery date. If the new date is accepted, the order is confirmed. If not, negotiation begins or the order is lost.

When the delivery date has been confirmed, the plant manager becomes responsible for producing and delivering the order on time. If variability occurs, the order may be delayed. If the plant manager does not inform sales personnel of the delay until the day of delivery, they have no time to notify the client, who may be dissatisfied. But if the plant manager informs sales personnel before the due date, they can notify the client, who can add a buffer and consequently may not be hurt by the delay.

If excessive variability is the main reason for low DDP, as claimed by the plant managers interviewed in this study, DDP should be significantly improved by programs that reduce variability. But in fact, such programs do not improve DDP, or do so slowly. According to our literature review (Goldratt 2006) and our study of SDBR implementation, excessive variability is just one of four major causes of poor DDP. The others stem from poor management of production planning and execution. They are

(1) over-promising (setting order due dates that do not consider the planned load of the CCR);

* *In 2007, five workshops titled "Production the TOC Way" (January, 27th, March 3rd, May 11th, July 13th and September 28th) were conducted on the campus of National Chiao Tung University, Hsinchu, Taiwan.*

(2) unrestricted order releasing (having too many orders on the shop floor due to excessively early release, which masks priorities, promotes local optima behavior, prolongs lead time, and significantly disrupts DDP); and
(3) lack of management priorities that leads to late delivery of some orders. These three causes are termed "mode of managing operations."

How do we know which of the above causes is to blame in a particular situation? Since it is impossible to pinpoint the correct cause in reality, we use a job shop game, with three experimental scenarios, to identify the root cause to be improved first.

## JOB SHOP GAME AND SCENARIO DESIGN

In a job shop, machines are arranged according to function, with equipment with similar processing characteristics grouped together in a work center. Each released order follows a specific routing, or processing sequence, through the work centers. With the high variety of routings and loads (setup and run times), a job shop is a complex environment in which scheduling is very difficult. Bottlenecks and CCRs seem to constantly shift, making it difficult to determine when orders will be completed.

The job shop game was developed by Holt (2000) and is modified slightly here to meet the needs of our research. The game involves four work centers (A–D), each with one machine. Each work center has a specialized processing capability, which means alternative routings are not possible. Moreover, each machine can complete only one operation per day. There are four product types (1–4). Each order card (Figure 1) represents a unique product within each product type. The process routing, or the sequence work center to work center, is stated on the order card. Orders must be processed by the work centers in the same sequence as the routing. With processing time of one day per operation per work center, the touch time, or theoretical processing time, for each order card is four days. Each work center can process only one order card a day. QLT is 12 days (or three times the touch time), and demand is unlimited. Because of

**FIGURE 1:** Product Order Cards

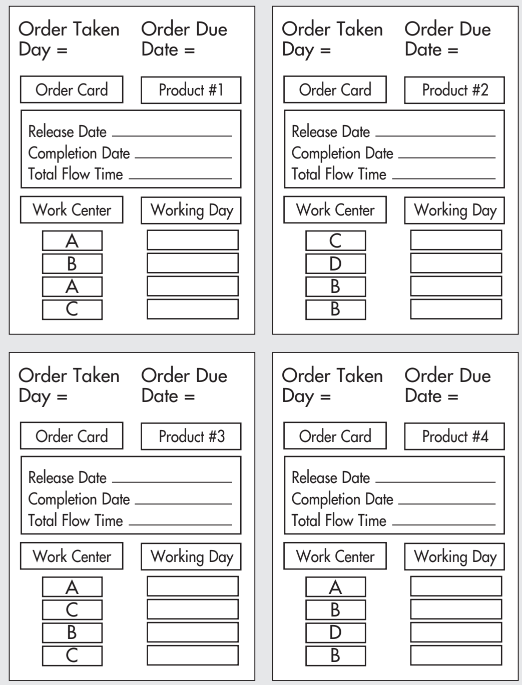
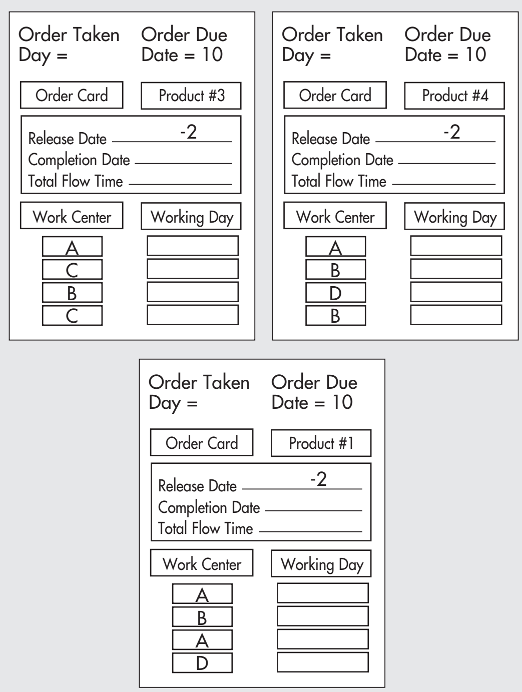



**FIGURE 2:** Initial WIPs in Front of Operators A and B



market constraints, at least four orders must be completed per product.

The job shop game aims to design a "perfect plant" free of variability and is used to design three scenarios that verify the claims made in this study. Scenario 1 tests whether or not variability is the root cause of poor DDP. Since the job shop in the game is a perfect plant, achieving high DDP should be easy. However, if DDP is poor in this scenario, then the root cause is not variability, but rather mode of managing operations. Scenarios 2 and 3 collect data supporting the hypothesis that mode of managing operations is the root cause and should be improved first.

### *Scenario 1*

Scenario 1 requires seven players on a team. The sales manager and production planner work together to take orders from the market (the market is not the constraint) and determine the due date for each taken order. They can take as many orders as they wish, provided the due date can be accepted by the market. The accepted due date for an order must be 12 or less days after the order is taken (QLT). For example, at day 4, if they want to take product 1, they must promise a due date of day 16 or earlier—a promise of a day later than day 16 will cause the client to go to their competitors. The plant manager leads four operators (A, B, C, and D) working in their own work centers. The plant manager determines when to release orders into the system and for ensuring that due dates are met. Work center operators process the work (one job per day per work center) according to the routing given on the work order card.

The game runs from day 0 to day 36 and the end day is hidden from players. Day 0 is the setup day, during which works in progress (WIPs) are set for operators A and B (Figure 2). Operator A has two WIPs, products 3 and 4. Both products were released to the shop two days ago and are due on day 10. Meanwhile, operator B has product 1 awaiting processing. Product 1 was released to the shop two days ago and is due on day 10. On each day, the instructor calls out, "Shop day," and executes two events sequentially. Event 1 is a sales and operations planning event. The sales manager and production planner determine how many order cards they are going to take and set the due date for each card. They can take no orders, one order, or as many orders as they believe they can deliver within 12 days. The production planner writes the shop day and due date on the order taken day and order due date lines.

Each order is passed to the plant manager for the second event, order execution. The plant manager decides whether to release no orders, one order, or all the orders awaiting release. When the instructor says, "Write," the plant manager writes the shop day on the release day line of the order card. When the instructor says, "Pass," the plant manager passes the order card to the queue of the initial work center (the first operation). When the instructor says, "Write," each work center operator takes one order card from his or her queue, if the queue contains any cards, and writes the shop day in the appropriate routing box. When the instructor says, "Pass," the operator passes the order card to the next work center queue on the routing or to the plant manager if the order card is completed. Each operator can process just one order per day.

### *Scenario 2*

In this scenario, the due date of each order is given. (Due dates are determined using the TOC SDBR planned-load concept and the method of setting order due date, addressed at the end of this section.) The sales manager and production planner have done a good job and have avoided over-promising. If the DDP of scenario 2 is significantly better than that of scenario 1, and the data from scenario 1 demonstrate that poor DDP is caused by over promising (which means the setting of the order due dates does not consider the planned load of the CCR), then over promising to cause poor DDP. If the DDP of scenario 2 is not significantly better than that in scenario one, further analysis is necessary.

There are five players on each team: the plant manager and four operators. Thirty-six orders (Table 1), with due dates predefined according to the loading of work center B, are given to the plant manager. Each order is associated with a due date but not with an order-release day. There is no "S&OP event"; otherwise, the game proceeds as

**TABLE 1:** Order Due Date and Release Date Determined with SDBR Method

| Order number | Date order taken | Customer promise date | Date plant can deliver | Order release date |
|---|---|---|---|---|
| P1 | -2 | 10 | 5 | -2 |
| P3 | -2 | 10 | 8 | -2 |
| P4 | -2 | 10 | 6 | -2 |
| P4 | 1 | 13 | 9 | 1 |
| P2 | 1 | 13 | 11 | 3 |
| P2 | 1 | 13 | 13 | 5 |
| P3 | 3 | 15 | 15 | 7 |
| P3 | 4 | 16 | 16 | 8 |
| P3 | 5 | 17 | 17 | 9 |
| P4 | 6 | 18 | 18 | 10 |
| P3 | 8 | 20 | 20 | 12 |
| P3 | 9 | 21 | 21 | 13 |
| P1 | 10 | 22 | 22 | 14 |
| P4 | 11 | 23 | 23 | 15 |
| P3 | 13 | 25 | 25 | 17 |
| P3 | 14 | 26 | 26 | 18 |
| P2 | 15 | 27 | 27 | 19 |
| P2 | 17 | 29 | 29 | 21 |
| P3 | 19 | 31 | 31 | 23 |
| P1 | 20 | 32 | 32 | 24 |
| P3 | 21 | 33 | 33 | 25 |
| P3 | 22 | 34 | 34 | 26 |
| P1 | 23 | 35 | 35 | 27 |
| P3 | 24 | 36 | 36 | 28 |
| P2 | 25 | 37 | 37 | 29 |
| P2 | 27 | 39 | 39 | 31 |
| P4 | 29 | 41 | 41 | 33 |
| P1 | 31 | 43 | 43 | 35 |
| P2 | 32 | 44 | 44 | 36 |
| P4 | 34 | 46 | 46 | 38 |
| P1 | 36 | 48 | 48 | 40 |
| P2 | 37 | 49 | 49 | 41 |
| P1 | 39 | 51 | 51 | 43 |
| P1 | 40 | 52 | 52 | 44 |
| P4 | 41 | 53 | 53 | 45 |
| P2 | 43 | 55 | 55 | 47 |

in scenario 1. The plant manager has to determine when to release the orders into the system and must expedite the orders to meet the due date. Work center operators process the work according to the routing on the work order card.

In both scenarios, each team uses their intuition and experience to attempt to achieve good DDP.

***Scenario 3***

In this scenario, the due date and the release date are given for each order. The game proceeds as in scenario 2, except the plant manager must release the order on the given release date. Because order release is controlled in scenario 3, if the production lead time is significantly shorter than in scenarios 1 and 2, we can demonstrate that no choking of the releasing behavior occurs in scenarios 1 and 2, and that such behavior prolongs production lead time. However, it is still impossible to prove whether this behavior will significantly disrupt DDP. For example, if the release is not choked in scenario 2, the lead time is considerably longer than in scenario 3 but the DDP is significantly better than in scenario 1 (which means long production lead time but good DDP).

To explain this situation, we perform another experiment involving only scenario 2. If the DDP of the scenario 2 in the new experiment does not differ from that of scenario 1 in the first experiment, then we can prove that not choking the releasing behavior will significantly disrupt DDP. Failure to choke the release behavior will significantly disrupt DDP because of a failure to manage priorities, which causes chaos on the floor and results in late orders. Another way to show that mismanaging priorities occurs is to check teams with late orders in scenario 2 of the first experiment.

Scenario 3 involves five players. Thirty-six orders (Table 1) with due dates and release dates predefined according to the loading of work center B are given to the plant manager. The plant manager releases the orders according to the predefined release dates. Operators are instructed to prioritize their orders according to the order due date; one exception is if machine B has limited capacity, in which case the operator should process the order that will feed machine B first.

This study adopts the planned-load concept of TOC SDBR and its method of setting order due date (Schragenheim et al. 2006; Schragenheim 2006) to set due dates and release dates for the 36 orders listed in Table 1. The planned load is the accumulation of the load derived on the CCR (or bottleneck machine) for the firm orders requiring delivery within a certain timeframe. For example, suppose three orders must be delivered within the standard 12-day timeframe. Order 1 requires one day of work on the CCR, order 3 requires two days, and order 4 requires one day. The planned load is simply the total of 1+2+1=4 days. Meanwhile, the front of the planned load indicates when, on average, the CCR will be able to work on the new order. As only one production buffer is assumed, SDBR decides to release the materials half the time-buffer prior to when the CCR is supposed to be working on it. This assumption is not critical, since the timing on the CCR is not especially concrete. SDBR also assumes that within half of the total production buffer, enough orders will arrive at the CCR to prevent unnecessary starvation. The question thus arises: When should orders be promised? Given the above, a safe delivery time could be realized by adding half a production buffer to the current front of the planned load. Figure 3 illustrates the method.

Now, take scenario 3 as an example. In this scenario the QLT is 12 days and the production

**FIGURE 3**: Planned-Load Concept and Order Due Date Setting Method

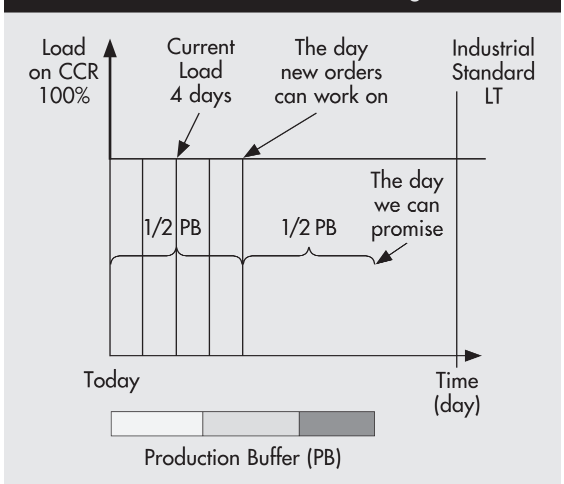


**TABLE 2:** Participants in the Experiment

| Companies | Business types | Experiment | No. of Teams Participate | Job Descriptions | Production Types |
|---|---|---|---|---|---|
| A | Wafer Fabrication (Foundry) | First | 2 | 2-S, 6-PC, 6-PM* | Make To Order |
| B | Wafer Fabrication (Foundry) | First | 2 | 2-S, 3-PC, 9-PM | Make To Order |
| C | Wafer Fabrication (IDM) | First | 2 | 2-S, 4-PC, 8-PM | Make To Order |
| D | Bicycle | First | 1 | 1-S, 2-PC, 4-PM | Make To Order |
| E | IC Assembly/Test | First | 2 | 2-S, 3-PC, 3-PM | Make To Order |
| F | IC Assembly/Test | First | 1 | 1-S, 3-PC, 3-PM | Make To Order |
| G | PCB | First | 2 | 2-S, 5-PC, 7-PM | Make To Order |
| H | IC Substrate | First | 1 | 1-S, 2-PC, 4-PM | Make To Order |
| I | Machine Tools (CNC Working Centers) | First | 1 | 1-S, 2-PC, 4-PM | Make To Order |
| J | Machine Tools (Punching Machines) | First | 2 | 2-S, 2-PC, 10-PM | Make To Order |
| K | Machine Tools (Plastic Injection Machines) | First | 1 | 1-S, 2-PC, 4-PM | Make To Order |
| L | Machine Tooling (Cutting Tools) | First | 2 | 2-S, 2-PC, 10-PM | Make To Order |
| M | Machine Tools (CNC Working Centers) | First | 1 | 1-S, 2-PC, 4-PM | Make To Order |
| N | Engine Components | First | 2 | 2-S, 4-PC, 8-PM | Make To Order |
| O | Metal Forging Components | First | 1 | 1-S, 3-PC, 3-PM | Make To Order |
| P | Plastic Injection Components | First | 1 | 1-S, 3-PC, 3-PM | Make To Order |
| Q | Plastic Injection Components | First | 1 | 1-S, 2-PC, 4-PM | Make To Order |
| R | TFT Panel | Second | 1 | 1-S, 2-PC, 4-PM | Make To Stock |
| S | LED Components | Second | 2 | 2-S, 6-PC, 6-PM | Make To Stock |
| T | Wafer Fabrication (DRAM) | Second | 2 | 2-S, 8-PC, 4-PM | Make To Stock |

*2-S: Two Sale Persons
*6-PC: Six Production planners/controllers
*6-PM: Six Production Managers/Supervisors

buffer is 8 days. Initially three orders (1, 3 and 4) are already on the floor. The accumulation of the load on the CCR for these three WIPs is 4 days (as shown in Figure 3). When can reliable delivery dates be offered for orders on day 1? Order 2 is taken as an example. The planned load is four days from now, and work on the new order can begin on machine B on day 5. The reliable due date is five plus half of the production buffer (plus four days). Therefore, the safe due date is nine days away and the order can be delivered on day 9. In this case, this study sticks to a QLT of 12 days from now—meaning delivery is promised for day 13. The order is released to the floor on day 1 according to the following formula: planned load minus half the production buffer (five days minus four days equals one day. Because order 2 requires two days on machine B, the planned load for the firm orders is six days. Continuing to apply the same approach, we can rapidly determine safe due dates and release dates for orders.

We invited local manufacturing companies to participate in the experiment. Thirty-five teams from 20 companies accepted our invitation. Thirty teams from 17 make-to-order-type companies took part in the first experiment. The remaining five teams from three make-to-stock (MTS) companies participated in the second experiment (Table 2). Participants had between 3 and 25 years experience, with an average of 7 years. Team members played salespeople, production planners/controllers, plant managers, or supervisors.

The experimental process was as follows: (1) Explanation of the purpose of the experiment. (2) Explanation of scenario 1 followed by a trial run. (3) Fifteen minutes of discussion of how to play scenario 1 to achieve high DDP. (4) Scenario 1. (5) Analysis and discussion of the results of scenario 1. (6) Explanation of scenario 2 followed by play. (7) Analysis and discussion of the results of scenario 2. (8) Explanation of scenario 3 followed by play. (9) Analysis and comparison of the results of the three scenarios.

The game starts on day 0 with three order cards on the shop floor (WIP). Each experiment takes approximately six hours.

## ANALYSIS OF THE RESULTS

Thirty teams participated in the first experiment. Table 3 lists the experimental results based on each team's three scenarios. Column 1 lists the total number of completed orders (both on-time and delayed). Column 2 contains the number of orders completed but delayed. Column three contains the number of orders due before day 36, but still incomplete and on the shop floor (WIP). Column 4 lists the number of orders whose due date is later than day 36, but which have already been completed. Column 5 lists the total number of orders that the plant promised to deliver within 36 days (column 1 + column 3 - column 4). Column 6 lists the DDP, which is equal to the total number of orders completed on time (column 5 - column 2 - column 3) divided by the total number of orders that the plant promised to deliver within 36 days (column 5). Column 7 is the average production lead time, and column 8 lists the production lead time, within which 90% of ultimately completed orders are finished. The production lead time for each completed order equals the order completion day minus the order release day.

### *Analysis of Over Promising*

We used a hypothesis test to see whether the DDP of scenario 1 is 95% or higher. The mean value is approximately 72%, and thus the null hypothesis is rejected (Figure 4a). Since the job shop game is intended to design a perfect plant free of variability, then provided such a plant is achieved, realizing high DDP (equal to or greater than 95%) should be easy. Unfortunately, the result is the opposite. The root cause can be claimed to be something other than variability, though mode of managing operations still cannot be said to be the root cause of the poor DDP result in scenario 1. We used a second hypothesis test to see whether the DDP of scenario two is equal to 95% or higher. The mean value is about 95%, and thus the null hypothesis is accepted (Figure 4b). Our third hypothesis test, looking at whether scenarios 1 and 2 differ significantly in DDP, demonstrates that scenario 2 differs significantly statistically from scenario 1 in DDP (Figure 4c).

This investigation further examines the evidence to demonstrate the occurrence of

**TABLE 3:** Results of First Experiment

| Scenarios / Results / Teams | Number of orders completed | | | Number of orders completed but delayed | | | Number of orders due before 36th day but still not completed yet | | | Number of orders whose due date is after 36th day but already completed | | | Total number of orders that the plant promised to deliver within 36th day | | | Due date performance (DDP) | | | Average production lead time | | | The production LT that 90% of completed orders finished before this time | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | S1 | S2 | S3 | S1 | S2 | S3 | S1 | S2 | S3 | S1 | S2 | S3 | S1 | S2 | S3 | S1 | S2 | S3 | S1 | S2 | S3 | S1 | S2 | S3 |
| **1** | 26 | 26 | 26 | 3 | 0 | 1 | 0 | 1 | 0 | 2 | 3 | 2 | 24 | 24 | 24 | 0.88 | 0.96 | 0.96 | 8.3 | 8.6 | 6.0 | 10 | 12 | 8 |
| **2** | 26 | 2 | 25 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 2 | 1 | 22 | 24 | 24 | 1.00 | 1.00 | 1.00 | 8.1 | 1.3 | 5.7 | 12 | 13 | 7 |
| **3** | 27 | 26 | 24 | 1 | 0 | 0 | 0 | 0 | 0 | 2 | 2 | 0 | 25 | 24 | 24 | 0.96 | 1.00 | 1.00 | 8.7 | 10.4 | 5.8 | 12 | 16 | 7 |
| **4** | 24 | 26 | 25 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 1 | 23 | 24 | 24 | 0.96 | 1.00 | 1.00 | 8.3 | 7.6 | 5.8 | 11 | 9 | 7 |
| **5** | 27 | 24 | 25 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 1 | 24 | 24 | 24 | 1.00 | 1.00 | 1.00 | 9.3 | 9.8 | 5.9 | 12 | 12 | 7 |
| **6** | 24 | 25 | 25 | 0 | 1 | 0 | 0 | 0 | 0 | 6 | 1 | 1 | 18 | 24 | 24 | 1.00 | 0.96 | 1.00 | 5.3 | 7.2 | 5.6 | 7 | 9 | 7 |
| **7** | 24 | 26 | 25 | 0 | 0 | 0 | 5 | 0 | 0 | 2 | 2 | 1 | 27 | 24 | 24 | 0.81 | 1.00 | 1.00 | 8.5 | 13.1 | 6.0 | 11 | 21 | 7 |
| **8** | 24 | 26 | 25 | 1 | 0 | 0 | 2 | 0 | 0 | 0 | 2 | 1 | 26 | 24 | 24 | 0.88 | 1.00 | 1.00 | 9.4 | 8.8 | 5.9 | 12 | 11 | 7 |
| **9** | 27 | 24 | 24 | 1 | 0 | 1 | 0 | 2 | 0 | 4 | 2 | 0 | 23 | 24 | 24 | 0.96 | 0.92 | 0.96 | 8.7 | 9.1 | 6.0 | 11 | 12 | 7 |
| **10** | 24 | 25 | 25 | 1 | 1 | 0 | 3 | 1 | 1 | 2 | 2 | 2 | 25 | 24 | 24 | 0.84 | 0.92 | 0.96 | 8.1 | 10.7 | 5.8 | 12 | 18 | 7 |
| **11** | 24 | 24 | 25 | 2 | 0 | 1 | 0 | 4 | 0 | 4 | 4 | 1 | 20 | 24 | 24 | 0.90 | 0.83 | 0.96 | 8.6 | 10.0 | 6.4 | 12 | 19 | 7 |
| **12** | 24 | 24 | 25 | 10 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 1 | 21 | 24 | 24 | 0.52 | 1.00 | 1.00 | 10.0 | 11.4 | 6.2 | 16 | 19 | 8 |
| **13** | 26 | 26 | 26 | 11 | 0 | 0 | 3 | 0 | 1 | 1 | 3 | 2 | 28 | 24 | 24 | 0.50 | 0.96 | 1.00 | 11.2 | 10.6 | 5.8 | 26 | 19 | 7 |
| **14** | 27 | 26 | 25 | 11 | 0 | 0 | 6 | 0 | 0 | 1 | 2 | 1 | 32 | 24 | 24 | 0.47 | 1.00 | 1.00 | 13.3 | 12.9 | 5.8 | 20 | 20 | 7 |
| **15** | 24 | 26 | 24 | 13 | 0 | 0 | 8 | 2 | 1 | 0 | 4 | 1 | 32 | 24 | 24 | 0.34 | 0.92 | 0.96 | 13.7 | 11.6 | 5.7 | 20 | 17 | 7 |
| **16** | 26 | 25 | 26 | 2 | 1 | 1 | 0 | 0 | 0 | 3 | 1 | 2 | 23 | 24 | 24 | 0.91 | 0.96 | 0.96 | 9.2 | 10.1 | 5.9 | 12 | 14 | 7 |
| **17** | 26 | 24 | 24 | 3 | 0 | 1 | 4 | 1 | 1 | 2 | 1 | 1 | 28 | 24 | 24 | 0.75 | 0.96 | 0.92 | 10.6 | 13.9 | 6.7 | 13 | 22 | 8 |
| **18** | 25 | 27 | 25 | 9 | 0 | 0 | 12 | 2 | 0 | 0 | 5 | 1 | 37 | 24 | 24 | 0.43 | 0.92 | 1.00 | 13.3 | 10.6 | 6.2 | 25 | 23 | 8 |
| **19** | 24 | 24 | 26 | 3 | 1 | 0 | 0 | 3 | 0 | 0 | 3 | 2 | 24 | 24 | 24 | 0.88 | 0.83 | 1.00 | 9.7 | 11.3 | 5.8 | 12 | 22 | 7 |
| **20** | 27 | 25 | 25 | 6 | 1 | 0 | 2 | 1 | 0 | 1 | 2 | 1 | 28 | 24 | 24 | 0.71 | 0.92 | 1.00 | 10.8 | 11.3 | 5.8 | 15 | 17 | 7 |
| **21** | 24 | 26 | 25 | 9 | 0 | 0 | 1 | 0 | 0 | 0 | 2 | 1 | 25 | 24 | 24 | 0.60 | 1.00 | 1.00 | 10.6 | 8.0 | 5.9 | 13 | 11 | 7 |
| **22** | 27 | 25 | 26 | 10 | 0 | 0 | 7 | 1 | 0 | 1 | 2 | 2 | 33 | 24 | 24 | 0.48 | 0.96 | 1.00 | 12.4 | 7.5 | 6.0 | 20 | 9 | 7 |
| **23** | 23 | 26 | 24 | 1 | 1 | 0 | 1 | 2 | 0 | 3 | 4 | 0 | 21 | 24 | 24 | 0.90 | 0.88 | 1.00 | 8.2 | 11.1 | 5.8 | 12 | 20 | 7 |
| **24** | 24 | 26 | 25 | 3 | 1 | 1 | 5 | 1 | 0 | 2 | 3 | 1 | 27 | 24 | 24 | 0.70 | 0.92 | 0.96 | 9.0 | 11.4 | 6.2 | 15 | 23 | 8 |
| **25** | 24 | 25 | 24 | 13 | 1 | 2 | 0 | 0 | 0 | 1 | 1 | 0 | 23 | 24 | 24 | 0.43 | 0.96 | 0.92 | 12.0 | 15.2 | 6.1 | 19 | 22 | 7 |
| **26** | 25 | 25 | 25 | 16 | 2 | 4 | 5 | 0 | 0 | 0 | 2 | 1 | 30 | 24 | 24 | 0.30 | 0.92 | 0.83 | 12.4 | 11.9 | 6.7 | 18 | 16 | 9 |
| **27** | 24 | 25 | 25 | 0 | 0 | 0 | 0 | 1 | 0 | 3 | 2 | 1 | 21 | 24 | 24 | 1.00 | 0.96 | 1.00 | 5.6 | 10.7 | 5.6 | 9 | 18 | 7 |
| **28** | 26 | 27 | 24 | 14 | 1 | 0 | 6 | 3 | 1 | 0 | 6 | 1 | 32 | 24 | 24 | 0.38 | 0.83 | 0.96 | 13.4 | 9.1 | 6.0 | 22 | 13 | 7 |
| **29** | 23 | 24 | 25 | 13 | 0 | 0 | 9 | 1 | 0 | 0 | 1 | 1 | 32 | 24 | 24 | 0.31 | 0.96 | 1.00 | 12.9 | 12.4 | 5.6 | 23 | 23 | 7 |
| **30** | 22 | 26 | 22 | 6 | 1 | 3 | 0 | 0 | 2 | 4 | 2 | 0 | 18 | 24 | 24 | 0.67 | 0.96 | 0.79 | 8.5 | 9.0 | 6.3 | 14 | 11 | 9 |
| **Average** | 25 | 25 | 25 | 5 | 0 | 1 | 3 | 1 | 0 | 2 | 2 | 1 | 26 | 24 | 24 | 0.72 | 0.95 | 0.97 | 10 | 11 | 6 | 15 | 16 | 7 |

**FIGURE 4:** Due-Date Performance Test

**(a) Scenario 1 Test**

$H_0 : P_1 \geq 95\%$
$H_1 : P_1 < 95\%$
$\alpha = 0.05$

| Variable | Test of means against reference constant (Value) (DDP) (Casewise deletion of missing data) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dv. | N | Std. Err. | Reference Constant | t-value | df | p |
| S1 | 0.716360 | 0.240393 | 30 | 0.043890 | 0.950000 | -5.32336 | 29 | 0.000010 |

**(b) Scenario 2 Test**

$H_0 : P_2 \geq 95\%$
$H_1 : P_2 < 95\%$
$\alpha = 0.05$

| Variable | Test of means against reference constant (Value) (DDP) (Casewise deletion of missing data) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dv. | N | Std. Err. | Reference Constant | t-value | df | p |
| S2 | 0.945833 | 0.051498 | 30 | 0.009402 | 0.950000 | -0.443157 | 29 | 0.660941 |

**(c) Scenarios 1 and 2 Test**

$H_0 : P_1 = P_2$
$H_1 : P_1 \neq P_2$
$\alpha = 0.05$

| Variable | T-test for Dependent Samples (DDP) Marked differences are significant at p< .05000 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dv. | N | Diff. | Std. Dv. Diff. | t | df | p |
| S1 | 0.716360 | 0.240393 | | | | | | |
| S2 | 0.945833 | 0.051498 | 30 | -0.229473 | 0.239299 | -5.25232 | 29 | 0.000013 |

over-promising in scenario 1. Because we examine only a 36 day period, counting the total number of orders that the plant promises to deliver within that period will indicate whether over-promising occurs. With SDBR, it is assumed that order safe due dates can be achieved if half of the production buffer time is still available after the day that machine B is available to process the order. To guarantee that the last order can be safely delivered on day 36, work on the order must begin on machine B no later than day 32. Consequently, for orders whose delivery is promised within 36 days, the planned load of machine B should not exceed 32 days. Because each order requires one to two days processing time on machine B, depending on the product mix, the plant can guarantee delivery of approximately 24 orders in 36 days. When it takes on more than 24 orders, the plant is over promising. In scenario 1, 16 of the 30 teams promised to deliver over 24 orders in 36 days. The highest promise was 37 orders.

Of the 14 teams that promised to deliver 24 orders or less, only 4 managed to achieve no order delays. For example, team 25 promised 23 orders, of which 13 were delayed. Analysis of the data revealed that over the 36-day period, they promised to deliver a reasonable number of orders. But for certain sub-periods, they still over promised. For example, 12 to 13 orders would be a reasonable number to promise between days 1 and 18, but team 25 promised more. The significant improvement in due date in scenario 2 compared to scenario 1 proves that over-promising is a major cause of the poor DDP in scenario 1.

Further analysis of scenario 1 revealed that teams with better DDP (less than 90%) displayed higher data values in column 4 compared to the other teams. The total number of orders that the plant promised to deliver within the 36 days (column 5) is lower than for the other teams, resulting in better DDP. Yet this outcome implies that the teams promised less than they were capable of delivering, a phenomenon known as under-promising. Both over-promising and under-promising result when the method for setting order due date does not consider the CCR planned load.

***Analysis of Order Release without Choking***

As we have claimed, if there is no restriction of the order release, local optimal behavior is promoted and lead time is prolonged. Using the data in columns 7 and 8, we conducted a hypothesis test demonstrating that scenarios 1 and 2 do not differ sufficiently in average production time and production lead time, as 90% of completed orders are completed before the due date (Figure 5a). However, the hypothesis testing across scenarios 3 and 1 (Figure 5b), and scenarios 3 and 2 (Figure 5c), demonstrates that scenario 3 differs significantly from scenarios 1 and 2. The major difference is the choking of order release. In scenario 3, the plant manager releases the order to the shop floor according to a predetermined release date (one production buffer time ahead). All but two teams achieved excellent performance in production lead time within eight days. (Teams 26 and 30 did so in nine days.) We compare this with scenarios 1 and 2, in which the average production lead times were approximately 10 days. Significant improvement in production lead time was achieved in scenario 3 primarily because of the choking of order release (lower WIP, shorter production lead time).

**FIGURE 5:** Production Lead Time Performance Test

**(a) Scenarios 1 and 2 Test**

$H_0: P_1 = P_2$
$H_1: P_1 \neq P_2$
$\alpha = 0.05$

T-test for Dependent Samples (LT)
Marked differences are significant at p< .05000

| Variable | Mean | Std. Dv. | N | Diff. | Std. Dv. Diff. | t | df | p |
|---|---|---|---|---|---|---|---|---|
| S1 | 9.94045 | 2.224630 | | | | | | |
| S2 | 10.51582 | 1.892637 | 30 | -0.575367 | 0.239299 | -1.34128 | 29 | 0.190241 |

**(b) Scenarios 1 and 3 Test**

$H_0: P_1 = P_3$
$H_1: P_1 \neq P_3$
$\alpha = 0.05$

T-test for Dependent Samples (LT)
Marked differences are significant at p< .05000

| Variable | Mean | Std. Dv. | N | Diff. | Std. Dv. Diff. | t | df | p |
|---|---|---|---|---|---|---|---|---|
| S1 | 9.940455 | 2.224630 | | | | | | |
| S3 | 5.969877 | 0.278190 | 30 | 3.970577 | 2.180413 | 9.974140 | 29 | 0.000000 |

**(c) Scenarios 2 and 3 Test**

$H_0: P_2 = P_3$
$H_1: P_2 \neq P_3$
$\alpha = 0.05$

T-test for Dependent Samples (LT)
Marked differences are significant at p< .05000

| Variable | Mean | Std. Dv. | N | Diff. | Std. Dv. Diff. | t | df | p |
|---|---|---|---|---|---|---|---|---|
| S2 | 10.51582 | 1.892637 | | | | | | |
| S3 | 5.96988 | 0.278190 | 30 | 4.545944 | 1.847570 | 13.47671 | 29 | 0.000000 |

Scenario 2 is free of over-promising, but the plant manager does not choke the order release, meaning the production lead time remains extremely high. We have claimed that lack of order release choking will significantly disrupt DDP, but the DDP in scenario 2 is considerably improved compared to scenario 1. Why? Based on observation and conversations with team members, it appears that in scenario 2 every player was focused on DDP and worked with the correct priority. The teams had learned from the poor results in scenario 1 and changed their behavior. These observations suggest that a plant focused on DDP can significantly improve DDP by working on the right priority. Although DDP is significantly improved in scenario 2, 11 teams have DDP of less than 95%. Most of these cases resulted from the team's failure to properly prioritize its work.

The production lead time result in scenario 3 and the DDP improvement in scenario 2 prove that not choking the release clearly prolongs production lead time, but also that if every player focuses on DDP and appropriately prioritizes the work, DDP will not suffer. In addition, failure to manage priorities can result in some orders still being late (meaning hectic priorities cause chaos on the floor). To further support the above claim, we conducted another experiment involving five teams. The experiment only involves scenario 2. Table 4 lists the results. Interestingly, the DDP and production lead time for scenario 2 resemble those for scenario 1, as in our first experiment. This outcome supports our claim that not choking the order release (meaning excessive numbers of orders on the shop floor) masks priorities, promotes local optimal behavior, prolongs lead-time, and significantly disrupts DDP. The outcome also supports the assumption that some orders will still be late without priority management.

### *Analysis of Failure to Manage the Priority*

As indicated above, we found that failure to manage priorities can lead to late orders. By analyzing (1) teams that promised to deliver less than 24 orders within 36 days in scenario 1 and still had poor DDP, and (2) teams with DDP below 95% in scenarios 2 and 3, we found that delayed orders are truly caused by failure to manage priorities. This finding highlights the importance of helping the shop floor prioritize orders correctly.

## CONCLUSION

Our experimental study examined why high DDP is difficult to achieve. Thirty teams participated in the first experiment and five teams in the second experiment (involving a total of 245 people). Our results support the notion that

**TABLE 4:** Results of Second Experiment

| Teams \ Scenarios \ Results | Number of orders completed | Number of orders completed but delayed | Number of orders due before 36th day but still not completed yet | Number of orders whose due date is after 36th day but already completed | Total number of orders that the plant promised to deliver within 36th day | Due Date Performance (DDP) | Average production lead time | The production LT that 90% of completed orders finished before this time |
|---|---|---|---|---|---|---|---|---|
| | S2 | S2 | S2 | S2 | S2 | S2 | S2 | S2 |
| 1 | 26 | 8 | 0 | 2 | 24 | 0.67 | 11.3 | 20 |
| 2 | 25 | 2 | 1 | 2 | 24 | 0.88 | 13.1 | 24 |
| 3 | 26 | 5 | 1 | 3 | 24 | 0.75 | 11.0 | 21 |
| 4 | 25 | 4 | 1 | 2 | 24 | 0.79 | 12.0 | 22 |
| 5 | 26 | 6 | 1 | 3 | 24 | 0.71 | 13.0 | 23 |
| Average | 26 | 5 | 0.8 | 2.4 | 24 | 0.76 | 12.1 | 22 |

in most cases, variability is not the root cause of poor DDP. Poor DDP is caused by the mode of managing operations, including the following phenomena: (1) over-promising, or setting order due dates that fail to consider the planned load of the CCR; (2) not choking the order release, which results in too many orders on the shop floor due to excessively early release, a situation that masks priorities, promotes local optimal behavior, prolongs lead time, and significantly disrupts DDP; (3) failure to manage priorities, resulting in hectic priorities that create chaos on the floor and lead to late orders.

Based on our findings, DDP improvement programs should first focus on improving the management of production planning and execution, instead of reducing variability. Although this investigation adopts the TOC SDBR planned-load concept and order due date setting method in scenario 3, TOC is not the only method of improving DDP. Whatever method is used to improve DDP must fulfill four fundamental concepts (Goldratt 2008): (1) Improving flow (or, equivalently, lead time) is a primary objective of operations. (2) This primary objective is translated into a practical mechanism that guides decisions regarding when not to produce (to prevent overproduction) (e.g. limiting space as in Henry Ford's system, limiting inventory as in the Toyota Production System (TPS) or Kanban system, or choking the releasing of materials, managing work priorities and setting due date according to the planned load of the key machine as in TOC or SDBR ). (3) Local efficiencies are abolished. The useful nature of the three methods is revealed when one realizes that the direct consequence of the methods when no space (Ford), no card (TPS), and no materials due to restrictions (TOC) are occurring, then the workers must stop producing. Therefore, in order to achieve flow, Ford, TPS and TOC had to abolish local efficiencies. Adhering to the flow concept mandates the abolishment of local efficiencies. (4) And finally, focusing the process on balanced flow (rather than capacity) should be the goal. For instance, Henry Ford used observation to gain understanding, TPS reduces setup and gradually reduces the number of containers and parts per container (the rock and water analogy), and TOC uses buffer management to remove bottlenecks and continually improve processes.

## REFERENCES

Breithaupt, J. W., M. Land, and P. Nyhuis. 2002. The workload control concept: Theory and practical extensions of load oriented order release. *Production Planning and Control* 13 (7): 625–638.

Chiang, S. Y., C. T. Kuo, and S. M. Meerkov. 2000. DT-bottlenecks in serial production lines: Theory and application. *IEEE Transactions on Robotics and Automation* 16 (5): 567–580.

Chung, S. H., W. L. Pearn, A. H. I. Lee, and W. T. Ke. 2003. Job order releasing and throughput planning for multi-priority orders in wafer fabs. *International Journal of Production Research* 41 (8): 1765–1784.

Dabbas, R. M., and J. W. Fowler. 2003. A new scheduling approach using combined dispatching criteria in wafer fabs. *IEEE Transactions on Semiconductor Manufacturing* 16 (3): 501–510.

Glassey, C. R., and R. G. Petrakian. 1989. The use of bottleneck starvation avoidance with queue predictions in shop floor control. *Proceedings of the 1989 Winter Simulation Conference* 908–917.

Goldratt, E. M. 1990. *The haystack syndrome: Sifting information out of the data ocean.* Croton-Hudson, New York: North River Press.

———. 1992. *The goal.* Croton-Hudson, New York: North River Press.

———. 1996. *Production the TOC way: A self-learning kit.* Croton-Hudson, New York: North River Press.

———. 2006. *Reliable rapid response strategy and tactics tree.* Goldratt Group.

———. 2008. Standing on the shoulders of giants: Production concepts versus production applications. *TOCICO International Conference*, Las Vegas, Nevada.

Goldratt, E. M., and R. E. Fox. 1986. *The Race.* Croton-Hudson, NY. North: River Press

Gorinsky, S. and C. Jechlitschek. 2007. Fair efficiency or low average delay without starvation. *Proceedings of 16th International Conference on Computer Communications and Networks*, 424–429.

Grabot, B., and L. Geneste. 1994. Dispatching rules in scheduling: A fuzzy approach. *International Journal of Production Research* 32 (4): 903–915.

Graves, R. J., and R. J. Milne. 1997. A new method for order release. *Production Planning and Control* 8 (4): 332–342.

Holt, J. R. 2000. *Job shop game.* Washington State University-Vancouver, Vancouver, Washington.

Katcher, D. I., H. Arakawa, and J. K. Strosnider. 1993. Engineering and analysis of fixed priority schedulers, *IEEE Transactions on Software Engineering* 19 (9): 920–934.

Lilly, M. 2004. Implementing simplified marketing pull. *TOCICO International Conference*, Miami, Florida.

Lin, J. T., F. K. Wang, and P. Y. Yen. 2001. Simulation analysis of dispatching rules for an automated inter bay material handling system in wafer fab. *International Journal of Production Research* 39 (6): 1221–1238.

Lozinski, C., and C. R. Glassey. 1988. Bottleneck starvation indicators for shop floor control in semiconductor manufacturing. *IEEE Transactions* 1 (4): 147–153.

Lu, S. H., and P. R. Kumar. 1991. Distributed scheduling based on due dates and buffer priorities. *IEEE Transactions on Automatic Control* 36 (12): 1406–1416.

Mabin, V. J., and S. J. Balderstone, 2000. The world of the theory of constraints: a review of the international literature. Boca Raton, Florida: St. Lucie Press.

Nandi, A. and P. Rogers, 2003. Behavior of an order release mechanism in a make-to-order manufacturing system with selected order acceptance. *Proceedings of the 2003 Winter Simulation Conference*. 1251–1259.

Rippenhage, C., and S. Krishnaswamy. 1998. Implementing the theory of constraints philosophy in highly reentrant systems. *1998 Winter Simulation Conference Proceedings* 993–996.

Roser, C., M. Nakano, and M. Tanaka. 2002. Shifting bottleneck detection. *Proceedings of the 2002 Winter Simulation Conference* 1079–1086

Schragenheim, E., and H. W. Dettmer. 2000. *Manufacturing at warp speed: optimizing supply chain financial performance.* Boca Raton, Florida: St. Lucie Press.

Schragenheim, E. 2006. *Using SDBR in Rapid Response Projects.* Goldratt group

Schragenheim, E., A. Weisenstern, and A. Schragenheim, 2006. What's really new in Simplified DBR. *TOCICO International Conference,* Las Vegas, Nevada.

Tsai, C. H., G. T. Chang, and R. K. Li. 1997. Integrating order release control with due-date assignment rules. *International Journal of Production Research* 35 (12): 3379–3392.

Umble, M., E. Umble, and S. Murakami, 2006. Implementing theory of constraints in a traditional Japanese manufacturing environment: The case of Hitachi Tool Engineering. *International Journal of Production Research* 44 (10): 1863–1880

Watson, K. V., J. H. Blackstone, and S. C. Gardiner. 2007. The evolution of a management philosophy: The theory of constraints. *Journal of Operations Management* 25: 387–402.