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Takt Time Grouping: A Method to Implement Kanban-Flow Manufacturing in an Unbalanced Process with Moving Constraints

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Comparison to One Piece Flow and Drum Buffer Rope: Which is Better, When and Why

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Abstract

One-piece flow and kanban/pull methods have been used to reduce WIP and speed flowtime in manufacturing flow processes; however, these methods have limitations. For example, one-piece flow does not work well when there are relatively large set-up times required between different components. One-piece flow also requires operations to be well-balanced. Unfortunately, these conditions often do not exist. The Theory of Constraints drum-buffer-rope (DBR) method is designed for unbalanced processes, and it has been shown to be effective for products with large operation time variation. However, DBR does not generally optimize flowtime and cannot handle a process with moving constraints (bottlenecks). Recognizing that there are manufacturing applications that have these limitations, we have developed a method called Takt Time Grouping (TTG) for implementing kanban-flow manufacturing when one-piece flow or DBR do not perform well. TTG combines one-piece flow, transfer-batch sizing and DBR concepts through the use of a grouping algorithm. Using a discrete event simulation model, the application of TTG, one-piece flow, DBR and a dynamic version of DBR, that moves the time-buffer and drum when it is known that constraints move (DynDBR), was investigated under varying conditions and production processes. Generalized findings of TTG's advantages over competing methods are presented.

Section 1: Introduction

This research was motivated by a manufacturing company that wanted to implement cellular flow manufacturing. However, their application did not fit any of the well-known flow manufacturing methods. The authors, in the role of a consultant, conceptualized a new method called Takt Time Grouping (TTG) to enable cellular flow manufacturing when existing methods do not provide good solutions.

Section 1.1: Flow Cell Methods

Manufacturing flow cells are a series of spatially adjacent or connected machines/operations through which tangible parts or components flow and are processed in a fixed sequence. The cells provide the efficiency of a flow process while allowing some degree of component variety and processing flexibility. When the component characteristics, mix, and volumes are such that the operations within the cell are very well-balanced with little randomness or time variation, one-piece flow with simple sequencing of the component types works well. However, one-piece flow does not work well when: 1) the cell must produce substantially different components with relatively large set-up times from one part number to the next, making batch processing an economic necessity; 2) processing/cycle times for operations vary considerably from component to component and operation to operation, which causes constraints/bottlenecks, 3) the bottleneck(s) "move" depending on the component being produced; 4) individual processing times exhibit significant randomness; or 5) when move-time to transport product between operations must be done manually and is a significant percentage of operation cycle time. If there is a constraint operation in the cell, work-in-process (WIP) inventory can become large while many other operations may have low utilization unless the dispatching of products through the cell is well-controlled. The drum-buffer-rope (DBR) method, based on the Theory of Constraints (Goldratt and Cox, 1986; Schragenheim and Ronen,1990), has been shown to be an effective mechanism for controlling the flow of product through unbalanced cells. DBR uses the constraint operation to set the tempo (the "drum") and limits entry of material into the cell. The term drum-buffer-rope can be explained as follows. The operation cycle time of the constraint sets the pace for the entire process and therefore acts as the drum. An inventory buffer is situated immediately upstream of the constraint. The "rope" is a signal from the constraint's buffer to the beginning of the production system, which controls the release of materials. If WIP builds above a limit at the constraint's time-buffer, the "rope" signals the beginning of the flow cell to stop releasing new orders into the flow cell. The effectiveness of the DBR approach decreases though if there is not a stationary constraint operation (i.e., if the bottleneck "moves"). In addition, production systems can lose efficiency when there is variation in processing times from component to component and operation to operation due to differences in components or general process randomness. One-piece flow is especially sensitive to randomness and variation in processing times, and efficiency decreases rapidly as randomness and variation increase (Yavuz and Satir, 1995).

Section 1.2: Research Motivation

The manufacturing company that motivated this research, suffered from long production flowtime (and therefore long lead-times quoted to customers), unacceptable throughput rate, poor on-time delivery to customers and excessive work-in-process inventory of machined components. [We define the four performance measures below.

Flowtime = time from when an entity begins processing at the first operation until it completes the last operation. (1)

Throughput quantity = number of entities completed by the process (2)

Throughput rate = throughput quantity per unit time (hour, shift, week) (3)

Work-in-process inventory = the total number of units that have completed the first process but have not completed the last process (4)

Makespan = the total time to complete a fixed quantity of units (5)]

The company used material requirements planning to schedule production of components through multiple work-centers and processed in batches equal to order quantities. Order quantities could be in the thousands for the machined components they produced. The components produced were of the company's own design, which it used in downstream assembly operations.

Company managers thought that one-piece flow or DBR might be the solutions to their problems. However, for the initial application (a product requiring light machining processes), problems with each were identified. One-piece flow relies on 1) well-balanced operations with approximately equal work content at each operation, 2) minimal operation cycle time variation, 3) very fast set-ups to change from one product to another, and 4) minimal times to hand off products from one operation to the next. These four requirements enable even flow within the cell, resulting in very fast throughput times and low WIP inventory levels. The production characteristics of the application did not match these requirements. The product required primarily machining operations, with only some assembly operations. We could not break up machining steps into equal duration time-buckets. Therefore, the process could never be balanced. The machining and assembly steps in the process exhibited significant random operation cycle time variation. As stated earlier, variation can disrupt the even flow of product through a one-piece flow cell. Set-up times varied from 15 to 45 minutes, which was large enough to idle operations and operators. The long set-up times also eliminated the possibility of using mixed-model sequencing of products through the cell (Boysen et. al. 2009).

DBR seemed more appropriate; however, it also had significant problems. First, DBR relies on the process having one constraint that signals the beginning of the flow cell to release the next order. In their product lines, different product families had their constraining cycle time at different operations. The literature calls this "moving constraints" (Ronen and Starr, 1990; Plenert, 1993). When a process has moving constraints, the drum-buffer-rope signal concept breaks down. This might be solved by designing a DBR method that reacts to deterministically known moving constraints. This possibility was investigated as part of this research study. The method we developed, Dynamic DBR (DynDBR), locates the time-buffer based on the constraint operation of the part number entering the flow cell. However, even by reacting to moving constraints, DBR does not generally minimize WIP inventory or flowtime. WIP inventory is controlled primarily at the constraint, which can allow greater WIP inventory build-up than the one-piece flow method. This also translates into longer flowtime. (Customers wanted reduced lead times and improved responsiveness to emergencies.) This motivated the author to develop a new method for implementing flow manufacturing in this environment.

Section 1.3: Takt Time Grouping Concept

This paper presents a solution to producing components with large operation cycle time variation in an unbalanced process, where set-up time is a consideration; move-times are long, and constraints move. The proposed method, Takt Time Grouping (TTG), calculates a transfer-batch size for each product (called Takt Time Group size below). (Takt is a German word for tempo. It is used by one-piece flow cell designers to designate the tempo of the cell or how often one unit of production leaves the process (Costanza, 1996). Takt time is measured as time per unit.) The Takt Time Group size may be different for each product because the operation cycle time at the constraint can be different for every product. However, the average processing times for transfer-batches at each product's constraint operation is approximately the same, across all product lines. Kanbans are then used to control the movement of the Takt Time Groups through the production cell using a pull mechanism. The result is essentially one-piece flow, where the "piece" is a transfer-batch. TTG accommodates imbalances among operations with no loss of performance, just as DBR accommodates unbalanced production processes. A lot size or customer order is broken up into equal Takt Time Groups (of the same product), but the groups are processed consecutively until the order quantity or lot size is completed. Therefore, the entire order of the product is processed with one set-up, but material is released among operations in smaller transfer-batches.

Takt Time Grouping solves a number of problems. No additional set-up time is required because orders are completed in their entirety without breaking into the set-up to produce other products. The group quantities (transfer batch sizes) are large enough so that the operation cycle time variation of transfer-batches at operations is very small, relative to the mean time to process the batch (due to the law of large numbers). This allows the process to function at high throughput rates with minimal WIP inventory, even in a high operation cycle time variation environment. TTG cells enjoy consistent flow, producing products according to an exogenously determined tempo time. This is accomplished because the grouping formula converts products with greatly differing operation cycle times to transfer-batches with equal time "buckets" at their constraint. The following research shows that in the flow cell environments studied, TTG generally produces significantly larger throughput rates and shorter makespan times than one-piece flow. In addition, while DBR creates high utilization at a stationary constraint operation, unlike DBR, TTG creates high utilization even when there are multiple constraining operations (moving bottlenecks). This results in TTG generally having higher throughput rates and shorter makespan times with less work-in-process inventory than DBR.

Section 1.4: Manuscript Sections

This manuscript is laid out as follows. Section 2 reviews all relevant literature. Section 3 describes the TTG model, including how the grouping tempo time is determined. Section 4 lays out the research questions we seek to answer in this study. These are noted as eight hypotheses. Section 5 explains the data used in this study and the various experimental settings. Section 6 describes the details of the simulation model used in this study. Section 7 studies the four production methods (one-piece flow, DBR, DynDBR and TTG) using a light machining data set. Results are explained including which method performed best, based on three performance measures (throughput rate, flowtime and WIP), under various conditions. Section 8 studies the four production methods using a heavy machining data set. Section 9 studies the four production methods using an assembly data set. Section 10 analyzes when the amount of labor available is varied. In Section 11 we compare the performance of the four production methods using makespan instead of throughput rate. We conclude in Section 12 by identifying what results can be generalized and discussing areas for future research.

Section 2: Literature Review

The research that informed the development of Takt Time Grouping includes the following subject areas:

- Cellular production
- Kanban and one piece flow
- Theory of Constraints and DBR
- Problems with DBR
- Combining one-piece flow and DBR
- Comparing one-piece flow and DBR
- Transfer-batch sizing

Section 2.1: Cellular Manufacturing

Cellular manufacturing consists of grouping together dissimilar equipment types dedicated to the production of a specific set of parts with similar processing requirements called part families. Manufacturing products in a production cell has been shown to improve response time, quality and efficiency with a minimum capital investment (Marsh et al. 1999). A number of research studies have sought to improve upon the general concept by creating cell design models (Suresh, 1991; Murthy and Srinvansan, 1995; Kannan, 1998; Shambu and Suresh, 2000; Venkataramanaiah and Krishnaiah, 2002; Viguier and Pierreval, 2004; Gravel, 2007). Most companies operating production cells initially used material requirements planning (MRP) and manufacturing resource planning (MRP2) to schedule orders (Gupta and Snyder, 2009). In the 1980's and 1990's, two methods were widely adopted in industry to improve performance of a production cell by controlling WIP and signaling the release of production: one-piece flow and the theory of constraints' drum-buffer-rope.

Section 2.2: Kanban and One-Piece Flow

One-piece flow, which is associated with the Toyota Production System, also known as lean production, was popularized, and to some extent introduced to western (European and American) manufacturing companies, by two books, *Lean Thinking* (Womack and Jones, 1996) and *Demand Flow Technology* (Costanza, 1996). A one-piece flow production cell utilizes the concept of pull. Before one-piece flow, manufacturers used manufacturing resource planning (MRP2) computer systems to schedule production cells. MRP2 system processes batches through operations based on planned scheduling. MRP2 systems use "push" scheduling because they in effect, schedule batches at the first operation and "push" the batches to subsequent operations regardless of whether there are other products queued up in front of the operations (Chakavorty and Atwater, 1996; Benton and Shih, 1998; Gupta and Snyder, 2009). In comparison, "pull" production uses kanbans (kanban translates to a "signal" in Japanese) to signal upstream operations that downstream operations are ready for the next product. Pull creates synchronization of all operations in a production cell (Womack and Jones, 1996; Costanza, 1996; Liker, 2004; Black, 2007; Sataglu et al. 2010). One-piece flow was a further enhancement of kanban manufacturing (or just-in-time manufacturing) by processing only one unit at a time, instead of a batch. This has the effect of minimizing flowtime, WIP and lead time, which developed as an important strategic differentiator in the 1990s (Constanza, 1996).

One approach that enabled the application of one-piece flow in medium volume, high mix manufacturing was Conwip, or constant WIP (Spearman et al. 1990). These researchers replaced the kanban card system, where each card had a specific part number, with a more general method, where the kanban bins or cards are not identified with specific parts, but instead control WIP inventory as it moves through a flow cell. The number of kanbans "allowed" in the process controls WIP inventory. The Conwip method is used in one-piece flow cells. One-piece flow, however, has limitations identified by proponents (Constanza, 1996; Monden, 1998; Black, 2007) that were discussed in the Introduction (operations must be well balanced with approximately equal work-content at each operation, set-ups to change from one product to another must be fast, and operations must be physically close to minimize time required to hand-off products from one operation to the next). If the operations in a cellular production system do not adhere to these requirements, the applicability of one-piece flow is limited and/or performance (in terms of throughput rate, WIP and flowtime) suffers. Another significant limitation of one-piece flow cells was discovered by Yavuz and Satir (1995). They studied the effect of operation cycle time variation on one-piece flow cell performance. These researchers, using simulation models, found that operation cycle time variation disturbs cell performance by preventing consistent flow of material. This research and additional studies comparing one-piece flow to other cellular production methods provided manufacturing companies with useful boundaries, as to when they could apply one-piece flow as an inventory control and scheduling method.

Section 2.3: Theory of Constraints and DBR

At the same time that one-piece flow was being popularized in the 1980s, a separate manufacturing process called theory of constraints was gaining attention from industry and researchers due to the success of the book, *The Goal* (Goldratt and Cox, 1986). The implementation of Theory of Constraints (TOC) in manufacturing utilizes a production control method called drum-buffer-rope (DBR). In a DBR production process, a buffer at the constraining resource controls flow by signaling the first operation to release material (Schragenheim and Ronen, 1990). Numerous researchers have studied DBR, contributing to the general understanding of this method and its applications in different production environments (Raban and Nagel, 1991; Schragenheim, Cox and Ronen, 1994; Martin, 1997; Ruelle, 1997; Rippenhagen and Krishnaswamy, 1998; Rahman, 1998; Mabin and Balderstone, 2003; Pegels and Watrous, 2005; Umble et al. 2006a, Umble et al. 2006b).

DBR research has improved on buffer sizing, scheduling, transfer-batch sizing as compared to the original concept. Radovilsky (1998) and Louw and Page (2004) use queuing theory to optimize the time-buffer with the objective of maximizing profit generated by the DBR production cell. Georgiadis and Politou (2013) create a method of altering the time-buffer daily, to consider demand, due-dates and mean production time. A number of studies have been conducted to improve performance of a DBR production cell through scheduling and enable the use of DBR under special conditions. Wu and Yeh (2006) develop a model to schedule batches through a bottleneck when the batch traverses the bottleneck multiple times. Sirikrai and Yenradee (2006) modify the DBR rope scheduling method to handle the special case when the bottleneck has two non-identical parallel machines. Chen and Chen (2009) develop a heuristic for handling the more complicated case when there are non-identical parallel machines at multiple stages of production.

Transfer-batch sizing (or lot-splitting) is an important aspect to the successful operation of a DBR process (Jacobs and Bragg, 1988; Russel and Fry, 1997). Hilmola (2004) and Russel and Fry (1997) study the effect of transfer-batches in DBR production processes. Hilmola (2004) used an iterative approach, comparing inventory costs to operational performance, to size transfer-batch sizes based on a constraints perspective. They constrain the transfer-batch sizing decision to ensure that set-up time on machines does not create bottlenecks.

Like one-piece flow, researchers have found problems with DBR. The most widely documented is when multiple constraints exist in the process. In this situation, the DBR method is not feasible as the drum concept breaks down (Ronen and Starr, 1990; Plenert, 1993). Hadas et al (2009) dealt with implementing DBR when the bottleneck appears to wander. Their proposed solution, however, requires materials requirement planning software.

Section 2.4: Combining DBR and One-Piece Flow

There has been limited research combining DBR with one-piece flow manufacturing. A hierarchical control algorithm using DBR was developed to improve production output of flow cells (Raban and Nagel, 1991). Gung and Steudel (1999) demonstrated how to calculate production lot sizes to ensure that no operation becomes a bottleneck on a one-piece flow line operation due to set-up (or product-to-product changeover) time. The bottleneck is mathematically represented as an operation with the largest utilization % in the process. When production lots are too small, in combination with long set-up times, the operation can spend so much time on set-up that it becomes a bottleneck, even if this operation does not have the greatest cycle time. The authors showed how to calculate minimum production lot sizes to avoid creating a bottleneck due to set-up. Lambrecht and Decaluwe (1988) recognized that one-piece flow cells can have bottlenecks. They applied DBR methods, increasing the WIP buffer (by increasing the allowable number of kanbans) upstream and downstream of the bottleneck to improve performance of a one-piece flow cell. In DBR terminology this is called "elevating the constraint." Schonberger (2001) demonstrated that kanbans can be an effective approach for managing over-production of inventory at non-bottleneck processes in a DBR production cell. Boysen et al. (2009) develop a scheduling method for a one-piece flow cell based on limited space to store WIP between operations (which the authors call material storage constraints).

Section 2.5: Comparing DBR and One-Piece Flow

There are numerous studies comparing one-piece flow versus DBR. Gupta and Snyder (2009) conducted a literature review of comparisons of these two methods. Many of the papers used discrete event simulation to make the comparisons. In some simulations one-piece flow performed best while for others DBR performed best. The greatest controversy concerns the supremacy of one-piece flow or DBR. There seems to be a bias by authors as to which system is better, and the arguments reflect their bias. DBR with constraint buffering is better than a one-piece flow system with equal buffers and trigger levels at each station (Lambrecht and Segaert, 1990). Simulation has been used to determine that the DBR system performed better when station variability was high, while one-piece flow performed best when station variability was low (Chakravorty and Atwater, 1996). This can be explained by the law of large numbers and kanban control of work-in-process inventory. One-piece flow processes one unit at a time at an operation. Therefore, the full variability of the process will impact these parts. This can create gaps (of no product) in the flow cell. Gaps will reduce utilization of machines and people, and therefore will reduce throughput rate. In a DBR system, variation is reduced because orders are processed in batches. According to the law of large numbers, operation cycle time variation of a large batch will be reduced relative to the mean cycle time of the batch. Simulation was also used to compare tradeoffs in capacity and inventory between DBR and one-piece flow approaches (Hurley and Whybark, 1999). Output and utilization are higher using DBR. Ronen and Starr (1990) differentiate DBR's goals and methods to one-piece flow's goals and methods. First, DBR accepts unbalanced operations, recognizing that often one operation is the constraint. One-piece flow balances the work-content and capacity of all operations. Second, DBR utilizes the constraint's "drum" to set the pace of the production process. One-piece flow maintains a pace based on balancing work-content at all operations to meet a customer-demand rate, defined as the Takt Time. DBR buffers only the constraint. One-piece flow utilizes kanban work-in-process inventory control at all operations. DBR seeks only to reduce set-up at the constraint. One-piece reduces set-up at all operations. A numerical model was used to compare how one-piece flow works in an unbalanced, bottlenecked, production line to a DBR production system (Takahashi et al, 2007). It is concluded that one-piece flow reduces total cost when inventory value is high, but DBR was lower cost when inventory value is low.

Section 2.6: Transfer-Batch Sizing

The grouping algorithm that forms the key contribution of TTG (discussed in Section 3) is a form of transfer-batch sizing. The first reference to transfer-batching (also known as lot streaming and lot splitting) was by Reiter (1966) who defined it as overlapping processing of one job on successive machines. The reason to consider transfer-batching is that transfer-batches reduce flow time as compared to lot quantity batch production (Jacobs and Bragg, 1988). Additional applications of transfer-batch sizing have been developed. Kropp and Smunt (1990) evaluate lot splitting in a flow shop. They develop mixed integer linear math programs for calculating optimal split-lot sizes, which allows a lot to be split in different quantities after each operation. As important as the methodology is, they point out that while optimal in theory, lot-splitting in different quantities after each operation is not easy to implement. Recent papers have presented math programming models to improve performance (Biskup and Feldmann, 2006). Transfer-batching has been referred to in DBR studies (Jacobs and Bragg, 1988). However, only Himola (2004) provides guidance on determining a transfer-batch size within a DBR operation. This method used an iterative approach, comparing inventory costs to operational performance, to size transfer-batch sizes based on a constraints perspective.

Section 2.7: Gaps in the Research

Despite the extensive literature, we find three significant gaps in the research.

- First, although Chakravorty and Atwater (1996) suggest that the combination of DBR and one-piece flow is essential, we find few models that combine these methods to solve the problems with each. The focus of research involving both DBR and one-piece flow is often on comparing the two methods, with researchers choosing one method over the other (Gupta and Snyder, 2009).
- Second, researchers have not tried to combine transfer-batching with kanban as a method of controlling work-in-process inventory and reducing flowtime.
- Third, researchers have compared one-piece flow and DBR by 1) altering the coefficient of variation of processes and 2) changing the value of WIP inventory to determine which method is optimal under varying values of these two factors. However, researchers have not considered practical issues such as the time to move WIP from one operation to the next or set-up time. In addition, there is a lack of research on interaction effects from multiple factors.
- Fourth, researchers have not provided easy-to-use methods for practitioners to utilize DBR when there are moving constraints. The one method developed (Hadas et al. 2009) requires an MRP system to manage two time-buffers.
- Fifth, researchers have not studied the effect of constrained or slack labor on the performance of one-piece flow and DBR.
- Finally, the research has compared one-piece flow and using throughput rate or makespan. However, no study compares these methods using both metrics, to determine if evaluation using different metrics will provide different answers to the question of, “which is better.”

Section 3: The Takt Time Grouping Method

Takt Time Grouping (TTG) can produce many different components in a flow cell. Each component may require set-up and possibly have different constraints. To implement TTG we borrow the concept of Takt (a German word for tempo) used by one-piece flow cell designers to designate the tempo time of the cell or how often one unit of production leaves the process (Costanza, 1996). Takt time is measured as time per unit. In TTG, we use this term, but change its meaning to be the tempo time that the "group of component i" spends being processed at its' constraint. This group quantity, also known as transfer batch size, is a subset of the total customer order quantity, or lot size, for each component. In the transfer-batch, parts travel as a group and do not wait for the rest of the lot quantity to be completed at any operation.

The Takt Time Group Quantity is calculated as follows.

$TTGQ_i = T / CTc_i$ for all $i = 1 \ldots n$ (6)

n = number of different components produced by the flow cell

Where:

$TTGQ_i$ = Group Quantity of Component i

T = Exogenously chosen grouping tempo time of the flow cell (see Figure 1 or explanation of how the tempo time is determined)

CT_{ij} = Mean operation cycle time for component i at operation j ($j = 1 \ldots m$)

CTc_i= Maximum CT_{ij} w.r.t. $j = 1 \ldots m$ for all $i = 1 \ldots n$ (7)

m = number of operations in the flow cell

This algorithm, and the one-piece flow manufacturing method of controlling WIP using kanbans, allows components of very different operation cycle times to be produced by the same set of machines in a flow manufacturing cell. Products with longer operation cycle times will have smaller TTG quantities. Products with shorter operation cycle times will have larger TTG quantities. This is designed so that processing time of each group at its constraint, regardless of group size, is approximately equal to the tempo time (T). As a simple example, suppose we are producing three components in a TTG flow cell with the following operation cycle time at the constraint:

CTc_1 = 60 seconds

CTc_2 = 30 seconds

CTc_3 = 15 seconds

If T (tempo time) = 15 minutes, then:

$TTGQ_1$ = 900 seconds / 60 seconds = 15

$TTGQ_2$ = 900 seconds / 30 seconds = 30

$TTGQ_3$ = 900 seconds / 15 seconds = 60

Customer orders are broken up into Takt Time Groups that flow sequentially through the flow cell until the entire customer order quantity has entered the flow cell. The last group of one component part number is followed by the next component part number on the schedule. An entire order is run sequentially, with no extra set-ups required. The number of Takt Time Groups per customer order of a component is the customer order quantity divided by the Takt Time Group quantity.

# of groups per customer order for component i = Customer order quantity / $TTGQ_i$

(8)

Customer orders can be rounded up to multiples of the Takt Time Group quantity to ensure integer values of Takt Time Groups are produced at the end of the customer order. Alternatively, the last group can be a fraction of the group quantity. If the number of groups per customer order is large, this will have a minimal effect on flow cell performance. In general, TTG assumes that the customer order size is much larger than the Takt Time Group size for all products produced in a TTG flow cell.

If the customer order quantity for each of the three hypothetical products shown above is equal to 300 units, then the number of groups per order is equal to:

of $TTGQ_1$ = 300 / 15 = 20 groups

of $TTGQ_2$ = 300 / 30 = 10 groups

of $TTGQ_3$ = 300 / 60 = 5 groups

For operations that are not the constraint, the Takt Time Group will spend less time than the pre-determined grouping tempo time at these operations. Using the principles of DBR, however, we know that the constraining resource controls the tempo time of production. Therefore, we focus on the constraining operation for that component and use the TTG algorithm to ensure that component i, in its group quantity, spends on average "T" (the grouping tempo time or Takt time) amount of time at the constraint. All components, no matter their operation cycle time at the constraint, will spend this same amount of time, "T" (the grouping tempo time or Takt time), at their constraint. Like the DBR method, we do not try to create a perfectly balanced production line (Cook, 1994), and instead focus on the tempo time at the constraining resource.

Another beneficial property of the TTG quantity algorithm is that the constraint does not have to be the same machine for every component. Theory of Constraints assumes that the constraint in a process is the same for every product (Goldratt and Cox, 1986). This is often not the case as noted by Ronen and Starr (1990) and Plenert (1993). A TTG flow cell doesn't require this limitation. Each component i will spend, on average, time "T" at its constraining operation. Therefore, each Takt Time Group of all components will exit the production flow cell, on average, at the grouping tempo time "T". Moving constraints may actually be beneficial as they can even-out machine utilization, allowing greater throughput.

The Takt Time, or grouping tempo time, is chosen exogenously. There are additional research opportunities, which will be discussed in the Conclusion, to optimize the grouping tempo time using math models. However, in this paper we will present a simple decision flow chart for exogenously choosing the grouping tempo time. Choosing the grouping tempo time "T" involves tradeoffs of throughput rate, flowtime and WIP levels. A larger tempo time will result in larger transfer-batch sizes. Large transfer-batch sizes reduce operation cycle time variation of the batch relative to the mean operation cycle time. Higher operation cycle time variation was shown by Yavuz and Satir (1995) to reduce throughput rate. Therefore, large transfer-batch sizes can increase throughput rate. However, large transfer-batches can also increase flowtime, which is a measure of responsiveness of the flow cell. Spearman et al. (1990) proved, using Little's law, that flowtime is controlled by the amount of WIP in the process. Greater WIP results in a longer flowtime, or a less responsive production process. In addition, larger transfer-batch sizes increase WIP (Hilmola, 2004). Greater WIP levels negatively affect the financial performance of a production process by increasing inventory holding costs of the firm. The decision flowchart to choose the grouping tempo time "T" is shown in Figure 1. This decision flow chart balances intrinsic choices practitioners must make when choosing the grouping tempo time. Table 1 shows different transfer-batch sizes and the expected variation reduction, WIP level and calculated flowtime based on the choice of the grouping tempo time.

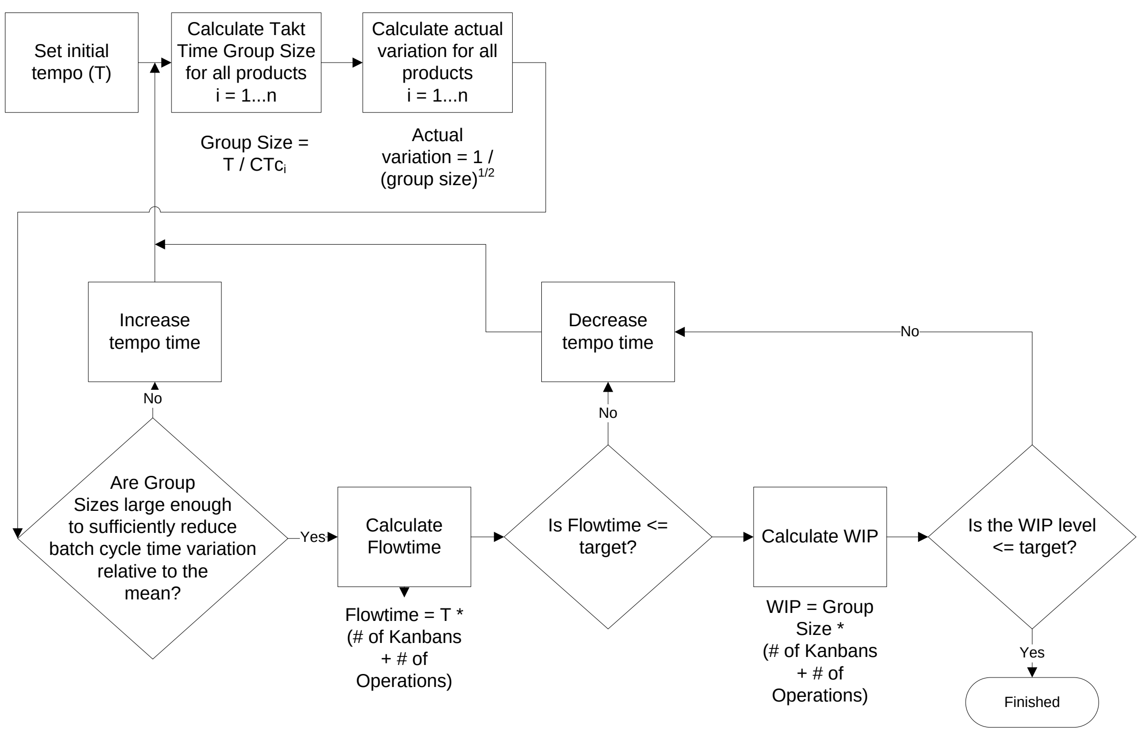


Figure 1: Logic Flow for Determining Tempo time (T)

Measure	Tempo time = 5 minutes (units)	Tempo time = 15 minutes (units)	Tempo time = 30 minutes (units)	Tempo time = 60 minutes (units)
Group Quantity*	10	30	60	120
Variation Reduction	68.38%	81.74%	87.09%	90.87%
WIP Level+ (units)	180	540	1080	2160
Calculated Flowtime ^ (min)	90	270	540	1080

Table 1: Data for Choosing the Takt Time Grouping Tempo time

*Based on CTc_i = 30 seconds

+Based on 2 kanbans per operation and 6 operations (see Figure 1 for calculation)

^Based on 2 kanbans per operation and 6 operations (see Figure 1 for calculation)

Section 4: Key Research Questions

The purpose of this research is to provide practitioners with limits of TTG's application. This will help companies choose when they should use TTG, or alternatively one-piece flow or DBR. In addition, we created a flexible version of DBR, DynDBR, which moves the time-buffer and drum based on deterministically-known moving constraints. The general theme of the research study is to understand which of the four WIP control methods is better, for what applications and why. To accomplish this purpose, three factors that can practically affect performance of manufacturing production cells were chosen. These factors are time to move work-in-process product from one operation to the next (move-time), the coefficient of variation (COV) of operation cycle time and the duration of changeover time on machinery to produce different products (set-up time). A priori understanding of manufacturing processes has allowed for development of hypotheses with regards to these three factors that will be investigated during this research study. As will be discussed in more detail in Section 5, these three factors are used in a full factorial ANOVA experiment applied to three different manufacturing data sets. The only commonality of the data sets is that each has moving constraint operations.

Some manufacturing processes produce small products using large machinery. Therefore, move-time can be a significant percentage of the operation cycle time. Automated conveyors are often used to move parts between machines; however, it is not always practical to utilize conveyors. When manually moving a single unit in a one-piece flow cell, this move-time is added to an operation's cycle time, increasing the time required for production. However, when moving a transfer-batch, such as used by DBR, DynDBR and TTG, the move-time is allocated over a larger quantity. This diminishes the impact of move-time for a large transfer-batch. Therefore, we propose hypothesis H1.

- H1: Throughput rate performance of one-piece flow is more negatively affected by large move-times than DBR, DynDBR and TTG.

Coefficient of variation (COV) was shown by Yavuz and Satir (1995) to negatively affect the throughput rate performance of a one-piece flow cell. However, DBR, DynDBR and TTG, which use transfer-batches take advantage of the law of large numbers, which states that the variation of large quantities is reduced relative to the mean of the batch. Therefore we propose hypothesis H2.

- H2: Throughput rate performance of one-piece flow is more negatively affected by high operation cycle time variation than DBR, DynDBR and TTG.

One-piece flow is designed for the least WIP. This is due to the combination of kanbans that limit WIP at every operation and the fact that there is only one unit-of-production in each kanban. Less WIP, while often desirable, can negatively affect throughput rate performance by not providing enough buffer to overcome the duration of a set-up or operation cycle time variation. The result may be that, at certain times, the one-piece flow cell is "starved" of WIP, idling operations. DBR, DynDBR and TTG are designed for larger levels of WIP, because they use transfer-batches versus one-piece. Therefore, we propose hypothesis H3.

- H3: Throughput rate performance of one-piece flow is more negatively affected by large set-up times than DBR, DynDBR and TTG.

As stated in the Literature Review, researchers have not studied the interaction effects of multiple factors on DBR and one-piece flow. We believe interaction effects amongst the three factors exist, which affects throughput rate performance of the four methods tested in this research study. Therefore, we propose hypothesis H4.

- H4: Interaction effects exist between move-time, operation cycle time variation and set-up time which affect throughput rate of all four methods.

There are additional expected differences between the four methods, under all conditions, that will be confirmed or rejected. As stated above, one-piece flow cells are designed to minimize WIP and flowtime. Therefore, we propose hypothesis H5.

- H5: One-piece flow will have the lowest WIP and fastest flowtime for all applications.

The DBR method has been shown to reduce WIP and flowtime when compared to traditional batch production methods. However, DBR is not intended to minimize WIP, but rather to maximize throughput rate. DBR controls WIP only at the constraint operation, via a time-buffer. The WIP at non-constraint operations is usually much smaller than the time buffer because these operations are faster. However, low WIP is not the objective of the DBR method. TTG controls WIP at every operation using kanbans. Kanban control at every operation will provide for improved WIP control throughout the entire flow cell. Therefore we believe that TTG will maintain lower WIP levels than DBR. In addition, lower WIP can result in faster flowtime (Spearman et al. 1990). Therefore, we propose hypothesis H6.

- H6: TTG will always have lower WIP and faster flowtime than DBR and DynDBR.

This research study uses three different types of production processes to test the four competing methods. These are described in greater detail in Section 5. However, as a summary they are 1) a light machining process with unbalanced operation cycle times, unbalanced and moderate set-up times, 2) a heavy machining process with unbalanced operation cycle times, very unbalanced and large set-up times, and 3) an assembly process with relatively balanced operation cycle times, smaller and balanced set-up times. One-piece flow requires balanced production and low set-up times. TTG, DBR and DynDBR are intended for unbalanced operation cycle times with moderate to large set-up times. Therefore, we propose hypothesis H7 and H8.

- H7: One-piece flow will out-perform DBR, DynDBR and TTG, as measured by throughput rate, for the assembly process.
- H8: One-piece flow will perform worse than DBR, DynDBR and TTG, as measured by throughput rate, for the light and heavy machining processes.

The specific questions studied in this dissertation are:

- What are the effects of: 1) move-time, 2) operation cycle time variation and 3) set-up time on the throughput rate performance of one-piece flow, DBR, DynDBR and TTG?
- Are there interaction effects amongst these three factors? Do changes in these three factors affect one method more than another? Are interaction effects, if they exist, more pronounced in one method? (Note, while one-piece flow and DBR have been heavily researched, no one has published an ANOVA study of factors that affect performance.)

- How does TTG compare to one-piece flow, DBR and DynDBR when applied to three very different production processes (light machining, heavy machining, and assembly)?
- How does move-time, operation cycle time variation and set-up time affect the throughput rate performance of all four methods in each of the three different production applications?

By answering "why" the specific outcomes occur, we seek to generalize the application of TTG beyond the three data sets and full factorial settings used in this study.

As this research was conducted, we realized that to generalize the results, we needed to extend the analysis beyond the factors and performance measures discussed above. We therefore analyzed the performance of each method, for all three data sets, using makespan as a performance measure. As will be discussed in Section 11, makespan may be a more appropriate performance measure for certain manufacturers. In addition, by evaluating the four methods using makespan as the performance measure of interest, we also increase the general understanding of which method is better, when and why.

The last factor analyzed is the amount of labor resources available to staff the flow cell. This was evaluated for only one application (light machining) and for one treatment (the normal settings of the actual process). The light machining application required only three labor resources to achieve an 80%, or greater labor utilization. However, the number of workstations is six. Therefore the "operators" in the simulation model move to different workstations to keep WIP moving through the process. While most firms seek to maximize labor utilization, this constrained labor resource case may not be the most profitable way to run the flow cell. If adding labor increases marginal profit, then having slack labor resources may be more profitable. We therefore created an unconstrained labor case, with six operators (one per workstation) to compare to the constrained (three operator) case for all four WIP control methods. Analysis of throughput rate and WIP is conducted, and marginal profit is calculated for each method.

Section 5: Details of the Research Methodology

Previously it was unknown under what conditions TTG is superior to one-piece flow or DBR as measured by throughput rate, WIP inventory and flowtime. This research used data sets from three manufacturing processes. These processes can be categorized as 1) light machining (producing a product referred to as piston discs), 2) heavy machining (producing a product referred to as slide-valves) and 3) assembly (producing a product referred to as solenoids).

We ran multiple experiments using these three data sets. Details of each experiment's design are explained in the following sub-sections. Section 5.1 will review the full factorial ANOVA experimental design to test the effect of the move-time, operation cycle time variation and set-up time factors on throughput rate, WIP and flowtime performance of each WIP control method. Section 5.2 will review the details of the experiment to test the effect of unconstrained labor. Section 5.3 will review the details of the experiments using makespan as the performance measure on interest.

Section 5.1: Full Factorial ANOVA Experimental Design

The data was used in full factorial experiments evaluating the three factors (move-time, operation cycle time variation and set-up) under high and low settings. Specific experimental settings are shown in Table 2. The output data was analyzed using ANOVA. Output of ANOVA showed the performance of each of the four methods (one-piece flow, DBR, DynDBR and TTG) and the interaction effects of the three factors (move-time, operation cycle time variation and set-up) under the various operating conditions of the three production processes (light machining, heavy machining and assembly). The full factorial experiments were run separately for the one-piece flow, DBR, DynDBR and TTG production methods.

	Move-time	COV	Set-Up Time*
Experiment 1	High (10 seconds)	High (50%)	High
Experiment 2	High (10 seconds)	Low (10%)	High
Experiment 3	High (10 seconds)	High (50%)	Low
Experiment 4	High (10 seconds)	Low (10%)	Low
Experiment 5	Low (1 second)	High (50%)	High
Experiment 6	Low (1 second)	Low (10%)	High
Experiment 7	Low (1 second)	High (50%)	Low
Experiment 8	Low (1 second)	Low (10%)	Low

Table 2: Full Factorial Experimental Design
*Set up time high and low settings vary by the application and are described below

The three factors were altered in the full factorial experimental design as follows:

- Move-time is the time to transport parts from one operation to the next.
    - Move-time is either set at high (10 seconds) or low (1 second) setting.
    - The high move-time represents a process where distances between operations are large and operators have to walk to move parts to the next process.
    - The low move-time represents an assembly process where workstations are close, requiring minimal move-time.

    - Move-time is <u>not</u> subject to stochastic conditions. The reasoning is discussed in Section 6.
- Operation cycle time variation is modeled by modifying the standard deviation used in the simulation model.
    - The standard deviation for each operation was set to represent low variation (standard deviation = 10% of the average operation cycle time) or high variation (standard deviation = 50% of the average operation cycle time).
    - The standard deviation is used within a normal probability distribution function by the simulation model (See Appendix).
- Set-up time is the time to changeover from one product to the next in the schedule.
    - Set-up time is based on actual set-up times shown in Tables 3, 4 and 5.
    - The high set-up time settings represent machining processes with significant set-up time, such as the light and heavy machining processes used to produce the piston-disc (Figure 2) and slide-valve (Figure 3). These times vary from ten minutes to four hours depending on the operation and application.
    - The low set-up times represent an assembly process with minimal set-up, such as used to assemble the solenoid shown in Figure 4.
    - Set-up is subject to stochastic conditions as described in the Appendix.

Specific information about the three production processes is documented below.

- Light machining of piston discs
    - These processes are mostly done using machines with some assembly operations. They exhibit significant differences in operation cycle time from one family to

another (unbalanced production) and require set-up time that many manufacturers would consider moderate. Due to the small size of the piston disc and the large machinery used in the production process, move-time is significant relative to operation cycle time. The piston disc is shown in Figure 2. Each disc pictured below is approximately ½ inch in diameter. There are nine families of piston-discs based on size. Manufacturing operation cycle time data of the piston disc is shown in Table 3.

Figure 2: Piston-Disc in a Takt Time Group Kanban Tray

		Cut from stock				Deburr				Drill				Sub Assemble				Face				Test				
Part #	Move Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	CTc
D1	10	**20**	**20**	10	2700	0	5	2.5	100	12	12	6	900	0	7	3.5	100	19	19	9.5	1800	12	12	6	600	**20**
D2	10	**20**	**20**	10	2700	0	7	3.5	100	17	17	8.5	900	0	5	2.5	100	19	19	9.5	1800	12	12	6	600	**20**
D3	10	**20**	**20**	10	2700	0	12	6	100	15	15	7.5	900	0	7	3.5	100	19	19	9.5	1800	12	12	6	600	**20**
D4	10	27	27	14	2700	0	7	3.5	100	**30**	**30**	15	900	0	10	5	100	19	19	9.5	1800	12	12	6	600	**30**
D5	10	27	27	14	2700	0	9	4.5	100	**30**	**30**	15	900	0	8	4	100	19	19	9.5	1800	12	12	6	600	**30**
D6	10	27	27	14	2700	0	21	11	100	**30**	**30**	15	900	0	9	4.5	100	25	25	13	1800	12	12	6	600	**30**
D7	10	34	34	17	2700	0	5	2.5	100	12	12	6	900	0	7	3.5	100	**60**	**60**	30	1800	12	12	6	600	**60**
D8	10	34	34	17	2700	0	8	4	100	21	21	11	900	0	5	2.5	100	**60**	**60**	30	1800	12	12	6	600	**60**
D9	10	34	34	17	2700	0	12	6	100	15	15	7.5	900	0	7	3.5	100	**60**	**60**	30	1800	12	12	6	600	**60**
	Avg. =	27	27			0	9.6			20	20			0	7.2			33	33			12	12			

Table 3: Piston Disc Operation Cycle Time Data in Seconds

Constraining operation for each product is highlighted in yellow

- Heavy machining of slide-valves
    - These processes include a combination of machining operations, manual assembly and semi-automated testing. The machining operations require set-up times that would be considered very long, with one set-up requiring four hours. Due to the large machinery used in the production process, move-time is significant relative to operation cycle time. One of these valves is shown in Figure 3. The valve pictured below is approximately two feet tall. Manufacturing operation cycle time data of the slide-valve is shown in Table 4.

Figure 3: Slide-Valve

		Assemble & Machine Stem-Seat				Brazing				Machine Body				Pre-Assemble				Assemble & Test				Paint				
Part #	Move Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	**CTc**
S8	10	88	88	44	5400	157	157	79	3600	187	187	93.5	3600	0	**240**	120	100	219	219	110	100	0	213	107	600	**240**
S10	10	88	88	44	5400	208	208	104	3600	205	205	103	7200	0	**300**	150	100	144	144	72	100	0	213	107	600	**300**
S12	10	88	88	44	5400	**326**	**326**	163	3600	298	298	149	7200	0	236	118	100	268	268	134	100	0	213	107	600	**326**
S16	10	88	88	44	5400	330	330	165	3600	**448**	**448**	224	14400	0	236	118	100	382	382	191	100	0	304	152	1050	**448**
Avg. =		88	88			255	255			285	285			0	253			253	253			0	236			

Table 4: Slide-Valve Operation Cycle Time Data in Seconds

Constraining operation for each product is highlighted in yellow

- Assembly of small (solenoid) valves
  - Assembly is done using labor to manually assemble products from machined components (including the piston-discs), then test and packaged these products. There is almost no set-up time incurred in producing these products. The operations are very close together. These are the types of processes that one would typically use one-piece flow. One of these solenoid valves, produced in a one-piece flow cell, is shown in Figure 4. The valve pictured below is approximately three inches tall. Manufacturing operation cycle time data of the solenoid is shown in Table 5.

Figure 4: Small Solenoid Valve

		Assemble				Internal Test				Noise Test				Pre-Pack				Package				Box				
Part #	Move Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	Machine	Labor	STDEV	Set-Up Time	**CTc**
E1	1	0	26	2.6	100	0	24	2.4	100	0	28	2.8	100	0	30	3.0	100	0	45	4.5	100	0	42	4.2	100	**45**
E2	1	0	26	2.6	100	0	25	2.5	100	0	28	2.8	100	0	27	2.7	100	0	45	4.5	100	0	42	4.2	100	**45**
E3	1	0	22	2.2	100	0	24	2.4	100	0	50	5.0	100	0	31	3.1	100	0	44	4.4	100	0	41	4.1	100	**50**
E4	1	0	31	3.1	100	0	23	2.3	100	0	27	2.7	100	0	30	3.0	100	0	44	4.4	100	0	41	4.1	100	**44**
E5	1	0	41	4.1	100	0	27	2.7	100	0	28	2.8	100	0	31	3.1	100	0	45	4.5	100	0	42	4.2	100	**45**
E6	1	0	45	4.5	100	0	23	2.3	100	0	27	2.7	100	0	30	3.0	100	0	44	4.4	100	0	41	4.1	100	**44**
E7	1	0	34	3.4	100	0	24	2.4	100	0	27	2.7	100	0	30	3.0	100	0	44	4.4	100	0	41	4.1	100	**44**
E8	1	0	23	2.3	100	0	26	2.6	100	0	28	2.8	100	0	31	3.1	100	0	45	4.5	100	0	42	4.2	100	**45**
E9	1	0	28	2.8	100	0	25	2.5	100	0	50	5.0	100	0	30	3.0	100	0	44	4.4	100	0	42	4.2	100	**50**
	Avg. =	0	31			0	25			0	33			0	30			0	44			0	42			

Table 5: Small Solenoid Valve Operation Cycle Time Data in Seconds

Constraining operation for each product is highlighted in yellow

In all experiments, comparisons are be made between one-piece flow, DBR, DynDBR and TTG. Performance measures under evaluation are throughput rate (quantity completed during a fixed time period of 120 hours (simulating a five day, three shift operation)), average WIP inventory in the flow cell and average flowtime of all entities. An entity can be one unit, a Takt Time Group or a DBR transfer-batch. In addition, WIP will be measured and, if needed, reported at one hour intervals. This clarity of WIP levels should provide additional understanding of the throughput rate results. Throughput rate only measures entities (single units) complete after 120 hours. (Note, there is no warm-up period used in this experiment. The reason for no warm-up period is described in Section 6.) Entities that have gone through operation 1 but are not complete are WIP. Finding how many hours pass before WIP achieves a steady-state condition will provide insight into each methods' ability to control WIP, which may affect throughput rate.

Section 5.2: Labor Resource Experimental Design

A factor that we did not alter in the full factorial experiments is labor. The number of labor resources used in all simulation models was calculated to achieve greater than 80% utilization. This follows general practices in most companies which try to have minimal idle labor. The number of labor resources used in our simulation models was always less than the number of operations. In an unbalanced flow cell (a mix of fast and slower operations) there will often be fewer people than workstations. This occurs because, if labor-time is similar to operation cycle time, then there is less labor needed at the faster operations and more labor needed at the slower operations. If a firm wants to minimize idle labor they would require their labor resources to move to operations within the flow cell, as needed, based on the location of WIP. If there was no WIP to process then the labor resource would move to an operation that had WIP in its incoming queue. We could therefore consider these experiments as having constrained labor resources.

The application that was the most interesting to use for the unconstrained-labor experiment was the light machining process. The light machining process required three operators to achieve labor utilization greater than 80%. (It should be noted that the need for three labor resources was not determined experimentally; it was calculated external to the simulation model.) In the simulation, these three labor resources go wherever they are seized and stay at that process until released. We investigate the results of relaxing the labor constraint by placing six labor resources in the system. This gives each workstation its own labor resource. Production, in the unconstrained case, was therefore never delayed due to a shortage of labor.

The reason we used the light machining applications for this experiment was because the heavy machining and assembly applications already used five labor resources, and six was the maximum that could be used in these six operation flow cells. As explained above, the need for five labor resources was based on a calculation to achieve 80% or greater labor utilization. Experimenting with increasing the labor resources from five to six is generally less interesting and has limits for conducting future research, which could involve creating throughput rate versus labor resource curves. Therefore, we chose the light machining application for this experiment.

We did not alter any of the factors discussed in Section 5.1 in the labor experiment. A single treatment (high Move, high COV, high Set-up) was used because it represents the most realistic factor settings of the actual light machining process.

Section 5.3: Makespan Experimental Design

In all of the experiments described above we were primarily concerned with measuring the throughput rate of each method. When measuring throughput rate, time is fixed and the quantity completed varies. An alternative method of measuring the performance of a production cell is makespan. The definition of makespan (see equation 5 in the Introduction) is the total time to complete a fixed set of products. While the literature often uses throughput rate to determine a production method's performance, one could make the case that makespan is a better performance measure. In a throughput rate scenario a firm would set-up the production cell, run it for a fixed duration (in our case 120 hours) and then be left with WIP. The literature does not address what happens with the remaining WIP. In reality, this WIP has to either be completed through the production process or stocked for the next time this product is run. If the remaining WIP is stocked, this often requires multiple sub-part numbers to keep track of which operations have been completed and which remain. The WIP would then be brought back into the production cell the next time the product is run, and stocked in front of the appropriate operation (based on the sub-part number). In addition, while flowtime measures the speed of an item being completed in the flow process, we do not know if this translates into the speed of completing an entire order. An analysis of makespan should help us understand how long it takes each of the four methods to complete a fixed set of orders. In this makespan scenario the firm would have enough customer or stocking orders to justify running the production cell. The firm would take the total quantity of parts needed to be produced in the flow cell and run the cell long enough to complete the entire quantity.

In these experiments we ran the simulations for the light machining, heavy machining and assembly applications, using a single treatment for each. The light and heavy machining applications used the high Move, high COV and high Set-up settings. The assembly application used the low Move, low COV and low Set-up time setting.

Section 6: Discrete Event Simulation Model

This research was largely carried out using discrete event simulation modeling. Discrete event simulation has a number of advantages for use evaluating manufacturing scheduling systems. These include:

- Evaluating uncertainty in cycle and set-up times
- Altering probability distribution factors
- Modeling complex interdependencies between operation queues via kanban control
- Providing information about transient states in the production process in addition to production completed
- Development of statistics and confidence intervals of performance measures

An important aspect of the simulation model is the ability to create kanban control of WIP inventory flow and machine set-up time when changing products. Additional details of the how the discrete event simulation model created kanban control and allowed for set-up are discussed in Appendix A.

A discrete event simulation model was developed to compare performance of a TTG flow cell to a one-piece flow, DBR and DynDBR production cell. This simulation model is based on the characteristics of a functioning TTG flow cell at an actual manufacturing facility described in the Introduction. It should be noted that the simulation model in this paper was validated using the actual performing TTG flow cell. The model performs similarly to the real TTG flow cells described in Section 5.

The simulation model allowed us to empirically compare the performance of TTG to one-piece flow, DBR and DynDBR. Set-up and operation cycle times were randomized by the model. Every simulation run is replicated 100 times. Performance was measured by three metrics; throughput rate, work-in-process inventory level and flowtime. Throughput rate is measured as the number of individual units of finished goods completed in 120 hours; a five day, three shift operation. The use of a fixed duration simulation is common in production simulation literature (Chu and Shih, 1992). All simulations "start" with an empty flow cell (no WIP). We decided <u>not</u> to use a warm-up period. Some of the applications did not reach steady-state conditions even after the 120 hour duration of the simulation. As will be discussed in Section 7, one of the applications, DBR, when applied to an unbalanced production process with moving constraints, will never reach steady state. In addition, the one-piece flow method has an advantage in speed (flowtime) and very quickly was producing completed components. Using a warm-up period, to allow the flow cell to fill up with WIP, penalizes one-piece flow as compared to DBR and TTG. Finally, in many companies flow cells can be turned-on and off. They do not have to be run continuously. This is best represented with a replicating simulation. Therefore, the analysis below is based on a "cold-start" production process and how many units each application can complete in 120 hours.

Work in process inventory is measured as units of production that have completed operation 1 but have not completed the final operation, at the end of the week. WIP is reported as a average over the duration of the simulation. Flowtime is measured as the average time each entity (Takt Time Group, one piece or transfer-batch) spent in the flow cell; from the time it exited the first operation until it exited the last operation.

Operation cycle time and set-up time were subject to stochastic conditions, and chosen probability distributions, based on observations of the actual production processes used in this study. Move-time per transfer batch, however, is constant in the simulation. It is not subject to stochastic conditions. While move-time is certainly subject to stochasticity in real-life applications, and these stochastic conditions could impact the performance metrics, the author decided to not include randomness of move-time in the experiment.

Labor (resource) allocation was modelled using Arena's default setting. This setting gives the entity that has waited the longest, across all process queues, the highest priority for seizing a labor resource that has been released. Other, possibly more effective, methods for modelling where labor resources go when they are released will be discussed in Section 10 and the Conclusion.

Four models were created to test one piece flow, DBR and DynDBR and TTG. The TTG and one piece flow scheduling / WIP control methods were run through similar models. The only difference is the TTG model processed items individually, but moved them as a transfer-batch based on the Takt Time Group quantity. One-piece flow moved items as a transfer-batch of one unit. The DBR and DynDBR methods were run through a model that used a time-buffer versus kanban. The TTG and one piece flow model utilizes two kanbans at each operation. For one-piece flow each kanban holds a single item transfer-batch. For TTG each kanban holds a Takt Time Group transfer-batch. The kanbans prevent any new transfer-batch from entering a process if there are currently two transfer-batches (either one item for one-piece flow, or a Takt Time Group quantity) in queue in front of that process. Effectively this limits the number of transfer-batches in the entire process to 18, or two transfer batches in queue in front of each of the six processes and one transfer-batch in each of the six processes.

The DBR simulation model has important differences. The DBR model utilizes a hold step, but it holds entities at the beginning of the flow cell based on a time-buffer in front of a single operation. The single constraint is chosen because it is the highest overall utilization operation, and is therefore the drum. The rope from this operation releases entities into the flow cell. Using the formula from Radovilsky (1998) we calculated an optimal time-buffer for each of the three production processes. The number of components in the buffered operation's queue, times the cycle time of these components at this operation determines the actual "time" in front of the "constraint" operation. When this time is greater than the time-buffer, the process stops releasing new entities into the flow cell. The entity of the DBR simulation model is a single unit, but like the TTG model it is batched and moved as a transfer-batch. Using the range of Takt Time Group sizes as a guide, we follow the advice of Hilmola (2004) and iteratively determine the optimal transfer-batch size.

The moving constraints in these applications, from a deterministic perspective, are known (See Table 3, 4 and 5). We therefore created the DynDBR model because a practitioner may ask, "if the moving constraints are known, couldn't we move the time buffer and drum?" The DynDBR simulation model will help us understand how a DBR system that reacts to moving constraints will perform. We need to note, however, that the practical ability to implement DynDBR may be limited. Every part number in the sequence could have a different constraint operation than the part that was run prior in the sequence, requiring a continuous change in the location of the time-buffer and drum signaling operation.

The DynDBR simulation was identical to the DBR model, except it allowed the time buffer and drum to move to the operation that was the constraint operation for entities entering the cell. The constraint operation of the part numbers was read into the simulation from the data file. The model placed the time-buffer and drum at that operation when the entity is released into the system. This allowed the time-buffer and drum to move with the known constraint operation for a specific part. Note, other methods could be used to relocate the time-buffer and drum, such as changing the time-buffer location after the part leaves the constraint. However, given the short transfer time intervals, "drum-shifting" methods more complicated than the one used would probably be very difficult to implement in practice.

The transfer-batch size varied for each method and production process (light machining, heavy machining and assembly). The transfer-batch sizes are shown in Table 6 below. One-piece flow always had a transfer-batch size of one unit. TTG's transfer batch size varied based on the tempo time chosen for each production process (15 minutes for light machining, 30 minutes for heavy machining and 15 minutes for assembly). DBR and DynDBR was always set at the minimum transfer-batch size of the TTG process.

Process	One-Piece Flow (units)	DBR (units)	DynDBR (units)	TTG * (units)
Light Machining	1	15	15	15, 30, 45
Heavy Machining	1	8	8	8, 11, 12, 15
Assembly	1	18	18	18, 20

Table 6: Transfer-Batch Sizes

* Transfer batch size varies per Takt Time Group sizing formula

The production quantities used in the simulation models is important. The light machining process has nine products (D1, D2, D3, D4, D5, D6, D7, D8, D9) which differ slightly based on size. The light machining data set read into the simulation model produces 900 of each part number, sequentially. The assembly process also has nine products (E1 – E9). (The solenoids produced in the assembly process use the piston discs produced in the light machining process.) The assembly data set read into the simulation model produces 900 of each part number sequentially. The heavy machining process produces a different quantity of each of the four part numbers (S8, S10, S12, S16). Specifically we are simulating the production of 480 S8 slide-valves, 72 S10 slide-valves, 220 S12 slide-valves and 200 S16 slide valves. These quantities may seem odd, but they match the average demand per week per part number of the slide-valve product line.

Section 7: Performance of One-Piece Flow, DBR, DynDBR and TTG Under Varying Conditions – Light Machining Flow Cell Process

The discussion of the experimental results for the application of one-piece flow, DBR, DynDBR and TTG under varying conditions for a light machining process is divided into seven sections. Section 7.1 presents the results of the experiments, comparing the performance of the four methods (one-piece flow, DBR, DynDBR and TTG) for all treatments (all combinations of high and low move-time, coefficient of variation and set-up time), considering all three performance measures (throughput rate flowtime and WIP). While all three performance measures are important, the primary concern of this study is increasing throughput rate. Therefore, much of the analysis will be on understanding the four methods' throughput rate performance. This analysis includes the comparisons of the four methods and the effects of the three factors (move-time, operation cycle time variation and set-up time) on throughput rate. The other two performance measures, WIP and flowtime, will support the analysis of how each method performed as measured by throughput rate. Section 7.2 will discuss the effect, on each of the four methods, of high and low move-time. This will include statistical significance and discussion of the practical importance of high move-time on the throughput rate performance of each method. Section 7.3 will discuss the effect, on each of the four methods, of high and low operation cycle time variation (also presented as the coefficient of variation or COV). Section 7.4 will discuss the effect, on each of the four methods, of high and low set-up time. Section 7.5 will analyze the interaction effects of the three factors on each production method and whether the interactions are statistically significant. The analyses in Sections 7.2, 7.3, 7.4 and 7.5 will enable a deeper understanding of **why** certain performance results were achieved. Section 7.6 will discuss the comparison of the four methods for the light machining application, considering all three performance metrics. Section 7.7 will summarize the advantages of TTG for the light machining process.

Section 7.1: Overall Results for the Light Machining Process

The results for the full factorial experiment are shown in Table 7. In terms of throughput rate, TTG outperformed one-piece flow and DBR for all treatments, and outperformed DynDBR for five the eight treatments. DynDBR outperformed TTG by 1% for two treatments and was statistically equal to TTG for one treatment. These three treatments all had low Set-up time factor settings. When evaluating the throughput rate results, based on the average of all treatments, TTG performed best, DynDBR second, DBR third and one-piece flow was last.

In terms of mean flowtime and average WIP in the production process, one-piece flow, not surprisingly, was the clear winner with a mean flowtime of 10 minutes and an average of only 11 units in WIP. TTG was second best in terms of flowtime and WIP. DBR was the next best and DynDBR was the worst when measuring WIP and flowtime. DynDBR had more WIP and a longer average flowtime than the other three methods.

Section 7.6 will discuss the specific reasons why TTG outperformed one-piece flow, DBR and DynDBR on average throughput rate, and why TTG outperformed DBR and DynDBR on WIP and flowtime.

				One Piece			Drum Buffer Rope			Dyn-DBR			Takt Time Grouping		
				Through-put Rate	Flow-Time	WIP	Through-put Rate	Flow-Time	WIP	Through-put Rate	Flow-Time	WIP	Through-put Rate	Flow-Time	WIP
Treat-ment	Move	COV	Set-up	Average (units)	Average (min)	Average (units)	Average (units)	Average (min)	Average (units)	Average (units)	Average (min)	Average (units)	Average (units)	Average (min)	Average (units)
1	1	1	1	6602	13	12	8466	542	918	8649	672	1156	9203	222	326
2	1	0	1	6770	13	13	8495	532	904	8630	657	1143	9241	220	322
3	1	1	0	7735	12	13	9470	379	628	9787	471	804	9826	190	295
4	1	0	0	7885	12	14	9455	376	629	9857	465	791	9854	188	292
5	0	1	1	8350	8	9	8759	483	803	8948	593	1006	9296	212	310
6	0	0	1	8388	8	9	8761	471	783	8933	587	998	9315	212	311
7	0	1	0	9402	7	10	9622	338	554	9998	431	728	9899	182	281
8	0	0	0	9432	7	10	9656	334	547	10041	424	717	9940	178	276
		Average =		**8071**	**10**	**11**	**9085**	**432**	**721**	**9355**	**538**	**918**	**9572**	**200**	**301**

Table 7: Results for Light Machining Flow Cell Process

Note: 1 = high setting, 0 = low setting

Section 7.2: Effect of Move-Time on Throughput Rate – Light Machining Process

The effect of the "Move" factor setting on throughput rate performance of all four production methods is shown in Table 8. This factor represents the time to move a transfer batch from one operation to the next. The high setting of move-time per transfer batch is 10 seconds. The low setting is 1 second.

	One-Piece	DBR	DynDBR	TTG
Average Move = 1 (10 seconds)	7248	8971	9231	9531
Average Move = 0 (1 second)	8893	9200	9480	9612
Difference 0 vs. 1 Setting	1645	229	249	81
% Difference	18.5%	2.48%	2.63%	0.85%
p-value	<0.0001	<0.0001	<0.0001	<0.0001

Table 8: Average Throughput Rate Results for Move-Time Factor Settings – Light Machining Process

For the one-piece flow method, "Move" (move-time per transfer batch quantity of 1 unit) at the high versus low setting was statistically significant and practically important. The p-value was very low (< 0.0001) and the delta from high to low was 1645 units, or an 18.5% reduction in throughput rate. One-piece flow's throughput rate performance was very sensitive to move-time in this light machining process. The degradation of throughput rate when move-time is high was expected in one-piece flow. In this light machining, one-piece flow, process, the move-time was "allocated" over a quantity of only one unit. (In one-piece flow, the transfer-batch size is one unit.) Therefore, the high setting for the move-time delayed every unit from reaching the next operation for 10 seconds. In one-piece flow, each operation was only buffered by one unit (by the one kanban allowed between two operations). When there was a 10 second delay in getting a unit to the next operation, the minimal buffer of one unit could not prevent a WIP "outage", and therefore, significantly reduced utilization on all operations. This was especially true for the constraining operation of each product. The 10 second delay is an unrecoverable amount of time when considering throughput rate. The overall results will be summarized in Section 7.6, however, it is easy to see that when a production process has any significant level of move-time between operations, one-piece flow would not be the best choice of a scheduling / WIP control method.

For the DBR and DynDBR applications, "Move" (move-time per transfer-batch) at the high versus low setting was statistically significant and somewhat less practically important than one-piece flow. For DBR, the p-value was very low (< 0.0001), but the delta from high to low was 228 units, or a 2.48% reduction in throughput rate. For DynDBR the degradation was also statistically significant (p value < 0.0001) and slightly worse at 249 units or a 2.63% reduction in throughput rate. The degradation of throughput rate when move-time was high for both DBR processes (traditional DBR and DynDBR), as compared to TTG was not surprising. In the light machining DBR and DynDBR process, the move-time was "allocated" over a quantity of only 15 units in the light machining process. (The transfer-batch size of the DBR and DynDBR application was fixed at 15 units, based on iterative experiments (Hilmola, 2004) discussed below.) This was half the average transfer-batch size of the TTG process. Therefore, the 10 second move-time for a transfer-batch was effectively 2/3^{rds} of a second per unit. For a number of operations, when compared to the operation cycle times in the light machining process, this was a meaningful percentage of non-value added time. This effect could be negated by increasing the transfer-batch size used in the DBR and DynDBR models. However, larger transfer-batch sizes were tested in the simulation model. We iteratively reduced the transfer-batch size within the range of Takt Time Group sizes (from 45 down to 15), using the method from Hilmola (2004). The smallest transfer-batch size tested, 15 units, was the best overall throughput rate performer in the DBR and DynDBR production methods.

For the TTG process, “Move” (move-time per transfer-batch) at the high versus low setting was statistically significant, but had the lowest degradation in throughput rate. The p-value was very low (< 0.0001). The delta from high to low was only 81, or a 0.85% reduction in throughput rate. The reduced degradation in throughput rate was due to the use of relatively larger (than DBR) transfer-batches in the TTG method. Move-time was “allocated” over a quantity of, on average, 30 units in the TTG light machining process. (The transfer-batch sizes were 45, 30 and 15 units.) Therefore, even the 10 second move-time for a transfer-batch was effectively only 1/3rd of a second per unit. We can conclude that when a production process has high move-time (where operations are far apart) TTG would be the preferential scheduling / WIP control method. The use of relatively large transfer-batch sizes by the TTG method negates the effect of move-time on throughput rate.

Section 7.3: Effect of Operation Cycle Time Variation on Throughput Rate – Light Machining Process

The effect of the "COV" (coefficient of variation of the operation cycle time) factor setting on throughput rate performance of all four production methods is shown in Table 9. The high setting of COV was 50% (the standard deviation is 50% of the average operation cycle time). The low setting was 10%.

	One-Piece	DBR	DynDBR	TTG
Average COV = 1 (50%)	8022	9079	9345	9556
Average COV = 0 (10%)	8119	9092	9365	9587
Difference 0 vs. 1 Setting	97	13	20	31
% Difference	1.19%	0.14%	.21%	0.33%
p-value	<0.0001	0.596	0.512	0.032

Table 9: Average Throughput Rate Results for Operation Cycle Time Variation Factor Settings – Light Machining Process

Of the four methods, high operation cycle time variation had the largest (throughput rate degradation) effect when using the one-piece flow method. The delta from the high COV setting (standard deviation = 50% of each operations' cycle time) to the low setting (standard deviation = 10% of each operations' cycle time) was 97 units, or 1.19%. This was statistically significant (p-value < 0.0001); and was also expected. The one-piece flow method had the least WIP in the production cell (average of 11 units) and the smallest transfer-batch size (one unit). Both WIP and large transfer-batches dampen the effect of variation. The reasoning is as follows. Operation cycle time variation can create gaps of "no-WIP" at certain operations. If a cycle of an operation was on the faster end of the probability distribution, followed by a cycle on the slower end of the probability distribution, the downstream operation may "empty-out" of anything to process. When there was ample WIP between operations this negates the effect of variation, as there are usually items to process. Minimal WIP, therefore, can create gaps of "no WIP" in the process. Additional support for this hypothesis, and for one-piece flow's underperformance under high operation cycle time variation, can be seen more clearly in Figure 5 (below), which shows the average WIP level in the one-piece flow cell reported out once each hour. Whenever WIP was below six units, at least one of the flow cell operations was idle. Note, not shown on this graph is that for some replications, at several time-periods, the one-piece flow cell had zero WIP, which implies that all operations are idle, resulting in zero throughput. Essentially, the one-piece flow cell, by design, did not provide enough WIP to overcome the gaps of "no WIP" that result from variation in operation cycle time. These gaps created "lost utilization" on constraint operations, resulting in lost throughput. As opposed to DBR and TTG, which allow larger amounts of WIP in the flow cell (discussed later), one-piece flow "starved" itself at various points in time.

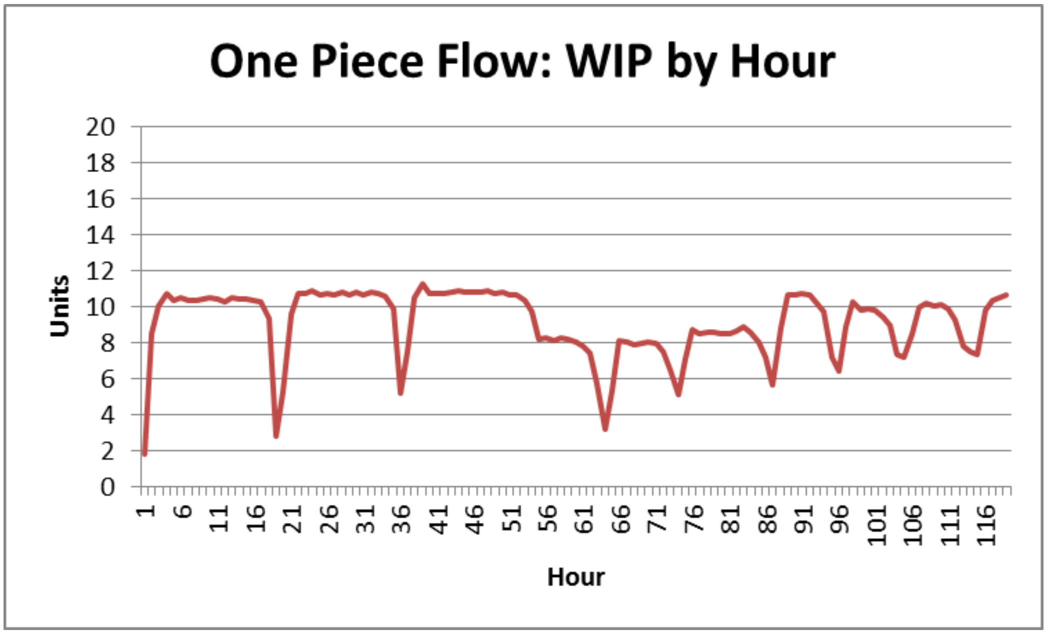


Figure 5: One-Piece Flow WIP by Hour – Light Machining Process

The one unit transfer-batch size used in one-piece flow also hurt throughput rate performance under conditions of high operation cycle time variation. One piece flow's transfer-batch size of one unit resulted in each operation realizing the full operation cycle time variation. According to the Law of large numbers, processing time variation of a large batch will be reduced relative to the mean of the batch (realized variation = 1 / transfer-batch$^{1/2}$). With one unit in the transfer-batch, the Law of large numbers has no effect. This confirms the findings of Yavuz and Satir (1995). It should be noted that Yavuz and Satir (1995) evaluated many more levels of COV; from 10% up to 90%. Their study showed greater degradation in throughput rate as COV increased beyond 50%. (Note a COV setting of 50% was used in this study, as this was the highest observed operation cycle time variation provided by the case study company. We wanted to use a high, but realistic, level of variation in this experiment.)

However, despite the reasons that high operation cycle time variation affected throughput rate performance of a one-piece flow cell more than DBR or TTG, it is interesting that high operation cycle time variation only degraded throughput rate by 1.19%. This may, or may not be important to practitioners. This was the least "impactful" of the three factors for one-piece flow. Therefore, for this light machining process, with a high operation cycle time variation, even one piece flow may be a reasonable choice of production method. This would depend, of course, on the value of 1% improvement in throughput rate to the firm.

The effect of high operation cycle time variation, for the DBR and DynDBR methods, was not significant. When operation cycle time variation was high versus low, the impact was negligible. The delta from high to low for DBR was only 13 units, and for DynDBR it was only 20 units. This was not statistically significant (p-value = 0.596 and 0.512). The DBR and DynDBR methods had similarly large quantities of WIP in the production cell. In addition, they had the largest amount of WIP at every operation (see Figure 6 below). As mentioned above, WIP dampens the effect of variation. Therefore, it was no surprise that the methods with the most WIP would be least affected by high operation cycle time variation. In addition, transfer-batches used in the DBR and DynDBR methods reduce variation of the batch, as supported by the Law of large numbers. With a transfer-batch size of 15 units, the variation, relative to an individual unit, realized in any transfer-batch was reduced by 74% ($1 - 1/15^{1/2}$). DBR and DynDBR's combination of high WIP levels and the use of transfer-batches negate the impact of operation cycle time variation on this light machining process; even with unbalanced cycle times and moving constraints. Therefore, processes with high operation cycle time variation may lend themselves to the use of DBR or DynDBR as the choice of scheduling / WIP control method.

For the TTG process, the difference of operation cycle time variation at the high versus low setting was statistically significant. However, the degradation can be considered practically unimportant. While the p-value was 0.032, the delta from high to low was only 31 units, or a 0.33% reduction in throughput rate. TTG was robust with regards to operation cycle time variation for the same reasons as DBR (discussed above). With an average transfer-batch size of 30 units, the variation realized by the batch was reduced by 82% ($1 - 1/30^{1/2}$). The fact that it was impacted more (a reduction in throughput rate of 13 for DBR and 20 for DynDBR versus 31for TTG) is due to the lower level of WIP in the TTG process (see Figure 6). However, this difference in the reduction for the TTG versus the DBR method (18 units over an entire week) and DynDBR method (11 units over an entire week) may not be something that would be important to practitioners.

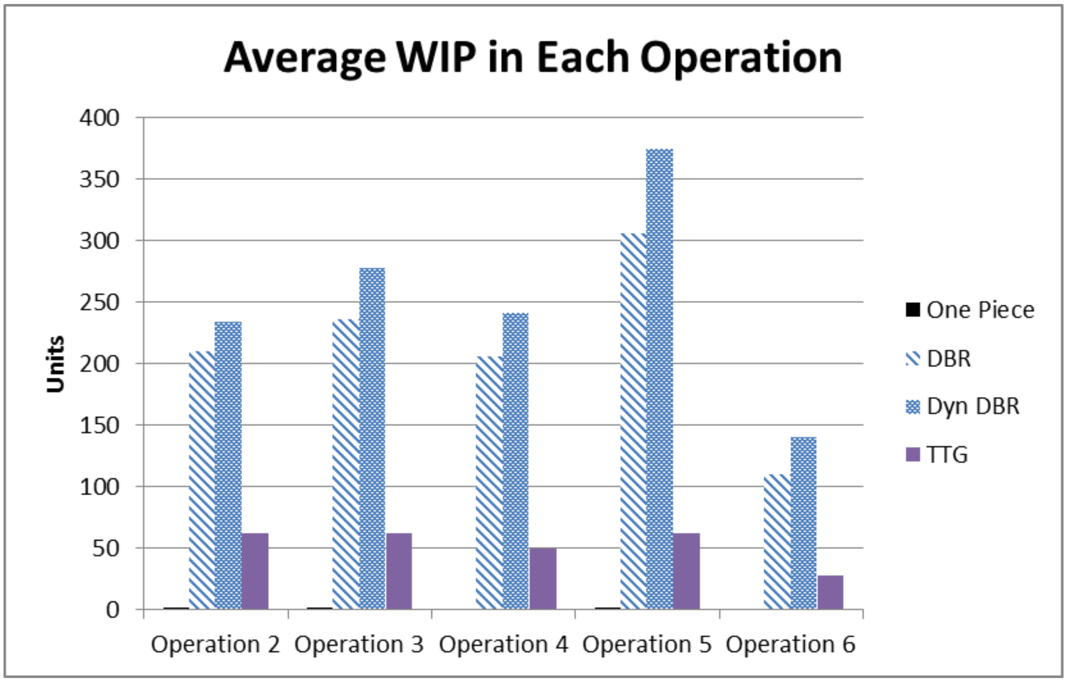


Figure 6: WIP in Each Operation – Light Machining Process
Graph is for the high Move, high COV, high Set-Up treatment

Section 7.4: Effect of Set-Up Time on Throughput Rate – Light Machining Process

The effect of the "Set-Up" factor setting on throughput rate performance of all four production methods is shown in Table 10. The high setting of set-up is the normal set-up time for this light machining process (shown in Table 3, Section 5). The low setting is 10% of the actual set-up time. It should be noted that the sequence used for all four methods was identical. Products must be completed in their order quantity before a set-up occurs. Therefore, the number of set-ups for all four methods will be nearly identical. (A method will only have additional set-ups if it produces more units and reaches the next part number in the sequence.)

	One-Piece	DBR	DynDBR	TTG
Average Set-Up = 1 (actual times)	7528	8620	8790	9264
Average Set-Up = 0 (10% of actual)	8613	9551	9921	9880
Difference 0 vs. 1 Setting	1085	931	1311	616
% Difference	12.61%	9.74%	11.4%	6.24%
p-value	<0.0001	<0.0001	<0.0001	<0.0001

Table 10: Average Throughput Rate Results for Set-Up Factor Settings – Light Machining Process

See Table 3 (Section 5) for actual set-up times of the light machining process

For one-piece flow, "Set-Up" at the high versus low setting was statistically significant and practically important. The p-value was very low (< 0.0001) and the delta from high to low was 1085 units, or a 12.61% reduction in throughput rate. The degradation of throughput rate, when set-up time was high, was expected in a one-piece flow application. Referencing Figure 5 and 6 above, we can see that there was not enough WIP in the one-piece flow cell to overcome the effects of when set-up occurs.

When the one-piece flow cell changes over from one product to the next, the very low WIP level virtually guarantees that the flow cell empties of all WIP. In addition to Figure 5 and 6 we reported the percent of the simulation duration where an operation had zero-WIP on Figure 7. The percentage of time there was zero-WIP in an operation was much higher for one-piece flow than DBR, DynDBR or TTG. From Table 3 (Section 5) we see that the mean set-up duration is 10 to 45 minutes, depending on the specific operation. Given that the operation cycle times varied from 20 to 60 seconds, even a set-up that requires 10 minutes will empty out the one-piece flow cell. This was no surprise, as one of the most important tools within the Toyota Lean Production System is quick-changeover (Shingo, 1985). Quick-changeover is an important enabler of one-piece flow. When a manufacturer does not have the resources to make large reductions in set-up time, one-piece flow is often not feasible (Monden, 1998).

For DBR, “Set-Up” at the high versus low setting was statistically significant and practically important. The p-value was very low (< 0.0001) and the delta from high to low was 931 units, or a 9.74% reduction in throughput rate. Higher set-up time logically reduces throughput rate as machines undergoing set-up cannot produce, even when there was ample WIP in the production cell. For TTG, “Set-Up” at the high versus low setting was also statistically significant and practically important. The p-value was very low (< 0.0001) and the delta from high to low was 623 units, or a 6.31% reduction in throughput rate. It is perhaps most interesting, however, that TTG outperformed DBR from the perspective of degradation of throughput rate when set-up was at the high versus low setting, even though DBR had an average level of WIP much higher than that of TTG.

(WIP levels can be seen on Table 7 and Figure 6.) One use of WIP in production cells is to buffer against set-up. WIP can help operations that are not undergoing set-up to continue to process. One possibility that we evaluated was that TTG outperformed DBR when set-up was high because it had less "zero-WIP" occurrences. We believed that the more uneven flow of the DBR process could have created these zero-WIP occurrences, where there was no inventory to process. However, Figure 7 shows that DBR and TTG had similar amounts of time that there was zero-WIP at an operation. In fact, DBR was slightly better, having zero-WIP, on average, 1.2% of the simulation duration. TTG had zero-WIP, on average, 1.7% of the simulation duration. DBR, therefore, should have performed similarly to TTG, or slightly better.

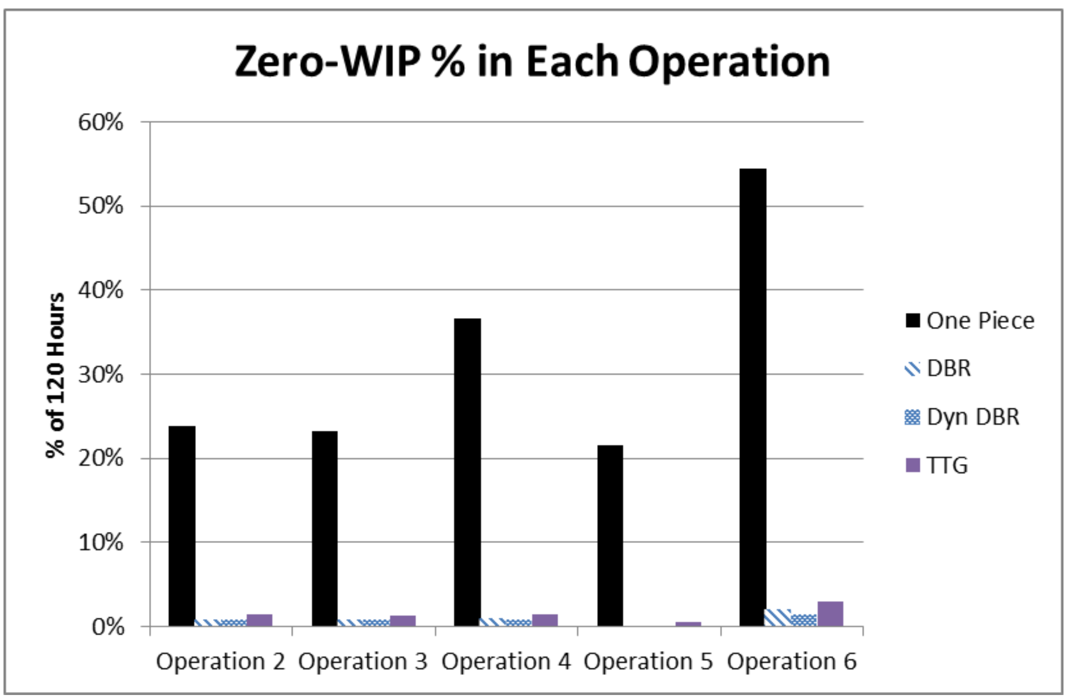


Figure 7: Zero WIP % of Time in Each Operation – Light Machining Process
Graph is for the high Move, high COV, high Set-Up treatment

The next investigation is whether the high WIP levels in DBR are actually causing the higher (than TTG) degradation of throughput rate when set-up time was high. Figure 8 shows the graph of WIP levels of the DBR process, over time. It is apparent that DBR never achieved steady-state conditions (entities "in" = entities "out"). This could lead one to believe that the simulation was not run long enough. However, 120 hours is a long time for a discrete production operation, such as our light machining application, to not achieve steady-state. The ever-increasing levels of WIP, however, makes sense when one looks at the reason DBR is not recommended for production applications have moving constraints. As noted in the Literature Review, researchers state that the DBR concept breaks down when constraints move. However, they do not discuss why. We can see why in Figure 8. DBR releases material (entities in this simulation) into the production cell based on the status of a time-buffer in front of one operation. In the light machining application the time-buffer was placed in front of Operation 5. However, other operations could be the constraint depending on the products currently going through the cell. Therefore, the DBR process would release additional items into the production cell at a pace **faster** than the constraint could process them, resulting in infinitely increasing WIP. TTG does not have this limitation. It allows for moving constraints because it uses kanban control at all operations and varying transfer-batch sizes.

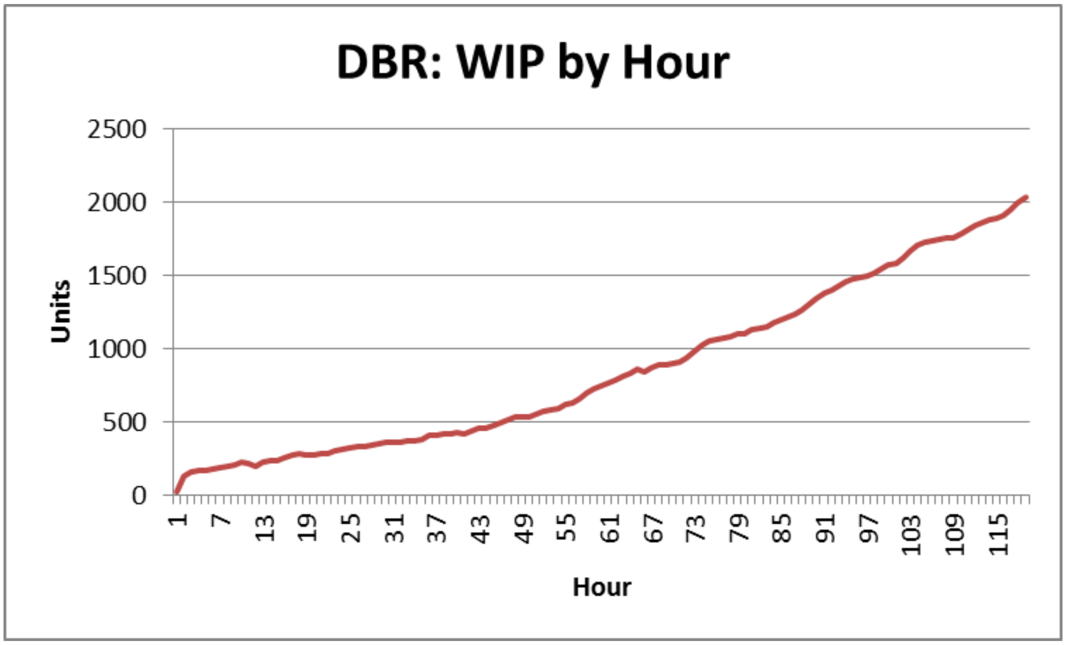


Figure 8: DBR WIP by Hour – Light Machining Process
Graph is for the high Move, high COV, high Set-Up treatment

The results for DBR, in fact, led us to develop the DynDBR simulation model. It was hoped that by moving the time-buffer and drum these unplanned queues, and the ever-increasing WIP, would not occur. Given that the moving constraints are known, from a deterministic perspective, this could be seen as a more "fair" comparison of the DBR concept versus TTG.

The DynDBR method performed differently than DBR. As mentioned in Section 7.1, it outperformed DBR for all treatments, as measured by throughput rate. However, DynDBR required more WIP and had a slower flowtime than DBR. DynDBR had a higher throughput rate than TTG when the set-up time was low (9921 average throughput rate for DynDBR, 9880 average throughput rate for TTG). Conversely, DynDBR had the worst degradation in throughput rate from low to high set-up time of all four methods. DynDBR produced 1311 fewer units, on average, when set-up time was high versus low.

The expected benefit of the DynDBR method over DBR is conceptually logical. The ability to move the time-buffer and drum based on the product entering the production cell would intuitively improve the performance of a production application with known moving constraints. Referencing Figure 7 above, DynDBR had the lowest zero-WIP % (0.93%). However, we can also see that DynDBR had much more WIP, and a slower flowtime, than DBR (Table 7 and Figure 6). While the DynDBR method would seem to be able to keep WIP lower than DBR, a few key issues increase WIP. First, as discussed in Section 6, the simulation sets the drum-operation based on the constraint operation of the parts entering the production cell. With multiple part numbers flowing through the process, the drum was not accurate for many of the parts currently in WIP; and there was a lot of WIP in the DynDBR production cell. This potentially creates a type of system confusion, which results in the unplanned queues in DynDBR. These unplanned queues are the result of a control mechanism that was receiving poorly timed feedback. DynDBR built up new queues, based on the new drum, but it did a poor job in draining these queues to the very low levels expected from a DBR system; where most of the WIP was only at the time-buffer.

The unplanned queues of the DynDBR method were, in fact, better at reducing zero-WIP occurrences, but still created a lot of inventory that was "stuck" in the production cell. Observing the data in Table 7 we can see that the WIP level in the DynDBR process, when set-up was high, was significantly greater than when set- up was low. The average WIP in the DynDBR production cell at the high set-up time setting was 1076 units, while the low set-up time setting had, on average, 760 units in WIP. This was a 42% increase in WIP. TTG, on the other hand, was much more balanced. The average WIP in the TTG flow cell at the high set-up setting was 317 units, while the low set-up setting had on average 286 units. TTG had only 11% more WIP when set-up was at the high versus low setting. As discussed above, WIP is often used to buffer set-ups. However, when the WIP is located upstream of the operating undergoing set-up it doesn't help the production cell because operations downstream of a long set-up will still be starved of WIP to process.

Once again we look at the method of signaling the release of new items into the process as a possible cause of poor performance of DynDBR; even if this signal moves with the constraint. The drum signals the beginning of the production cell to release new items if it has less WIP than the time-buffer target, which was 2.5 hours for the light machining process (Radovilsky, 1998). However, if an operation upstream of the time-buffer was undergoing a set-up then this WIP will be held up in front of that operation until the set-up was complete. This "starves" the time- buffer in front of the drum operations, which would cause the drum to signal for the release of more items into the production cell. The signal for more items caused operations upstream of the time-buffer to receive WIP even when they were undergoing set-up. Since operations cannot process parts until the set-up was complete, this WIP built up in their queue. We now see that for processes with long set-up times the DynDBR process does not function in a logical manner. It may seem to the reader that there should be a "stop" mechanism for releasing items into the process during set-up. However, this could be detrimental if this prevents WIP from getting quickly to the constraint. In addition, the logic would have to determine which set-up would create this stop mechanism and how long the stop should last. These improvements are possible, but are not within the scope of this study.

In general, we can see the advantage of kanban control and the constant tempo time of TTG, when the system was subject to interruptions, such as set-up. TTG maintains two transfer-batches in front of all operations. When two transfer-batches are in any operation it stops the prior operation from sending any more transfer-batches downstream. This creates the even level of WIP shown in Figure 6. TTG reacts faster than DBR or DynDBR, preventing unplanned queues, and keeping the WIP moving through the system. DynDBR, with its greater WIP level, did a better job in reducing zero-WIP occurrences when interruptions were not part of the production process, but did not improve throughput rate. In addition, DynDBR had the most WIP and the longest flowtime of all four methods.

This negative aspect of DBR and DynDBR, when the process has moving constraints, is reinforced with the data in Table 11. This table shows the average WIP by operation and the WIP at the end of the simulation (120 hours). We can see that all four methods had higher WIP at the end of the 120 hour simulation, relative to the average. DBR's increase, however, was greater than the other two methods, with Operation 5 more than doubling the WIP at shutdown versus the average.

WIP is generally seen, in the production literature, as a negative performance measure. However, it does have value as these units have completed at least one process. Given that there are conflicting objectives, we report the amount of WIP in each operation at the end of the 120 hour simulation duration. It should be noted that the production literature does not seem to address the issue of reporting WIP at the end of a fixed duration simulation, nor what "happens" to this WIP. In real-world applications it is often put into inventory storage as a semi-finished product (with a unique part number) and then put back into production the next time these products are run in the production cell.

	One Piece		DBR		Dyn DBR		TTG	
	Average	Shutdown	Average	Shutdown	Average	Shutdown	Average	Shutdown
Op 2	1.3	1.8	211	402	234	433	62	76
Op 3	1.3	1.7	237	355	278	463	62	86
Op 4	1.0	1.1	206	359	241	538	50	67
Op 5	1.4	1.3	306	769	375	734	63	80
Op 6	0.6	1.0	111	273	141	303	28	34

Table 11: WIP by Operation: Average and at Shutdown – Light Machining Process
Table is for the high Move, high COV, high Set-Up treatment

The literature favors fixed simulation duration (Chu and Shih, 1992), which was reason for our original choice of using 120 hour fixed duration, and measuring throughput rate. However, based the difference between the WIP on average and WIP at the end of the 120 hour simulation, we identified the need to understand each method from a makespan perspective. Makespan (as discussed in the Introduction) is measured as the time to complete a fixed quantity of items. Instead of limiting time and measuring quantity, we are fixing quantity and measuring time. We need to note that the two ways of running these experiments, measuring throughput rate based on fixed time duration, and measuring makespan are both viable based on practice in industry. Some companies will wait to run their production cell when they have a fixed quantity to run. Others will run their production cells for a fixed duration, putting the excess WIP into inventory storage until these products are scheduled to run again. The makespan analysis is discussed in Section 10.

Section 7.5: Factor Interaction Effects on Throughput Rate – Light Machining Process

As stated above in Hypothesis 4, it is believed that interactions of the three factors may affect throughput rate. Interaction effects are shown below on Figure 9. (Note, the scale of the graphs is held constant for the one-piece flow, DBR, DynDBR and TTG analyses.) The p-values of the interaction effects are shown below on Table 12. The Move-COV and Move-Setup interactions are statistically significant for one-piece flow. The Move-Setup interaction was statistically significant for the DBR process. No factor interactions are significant for DynDBR or TTG.

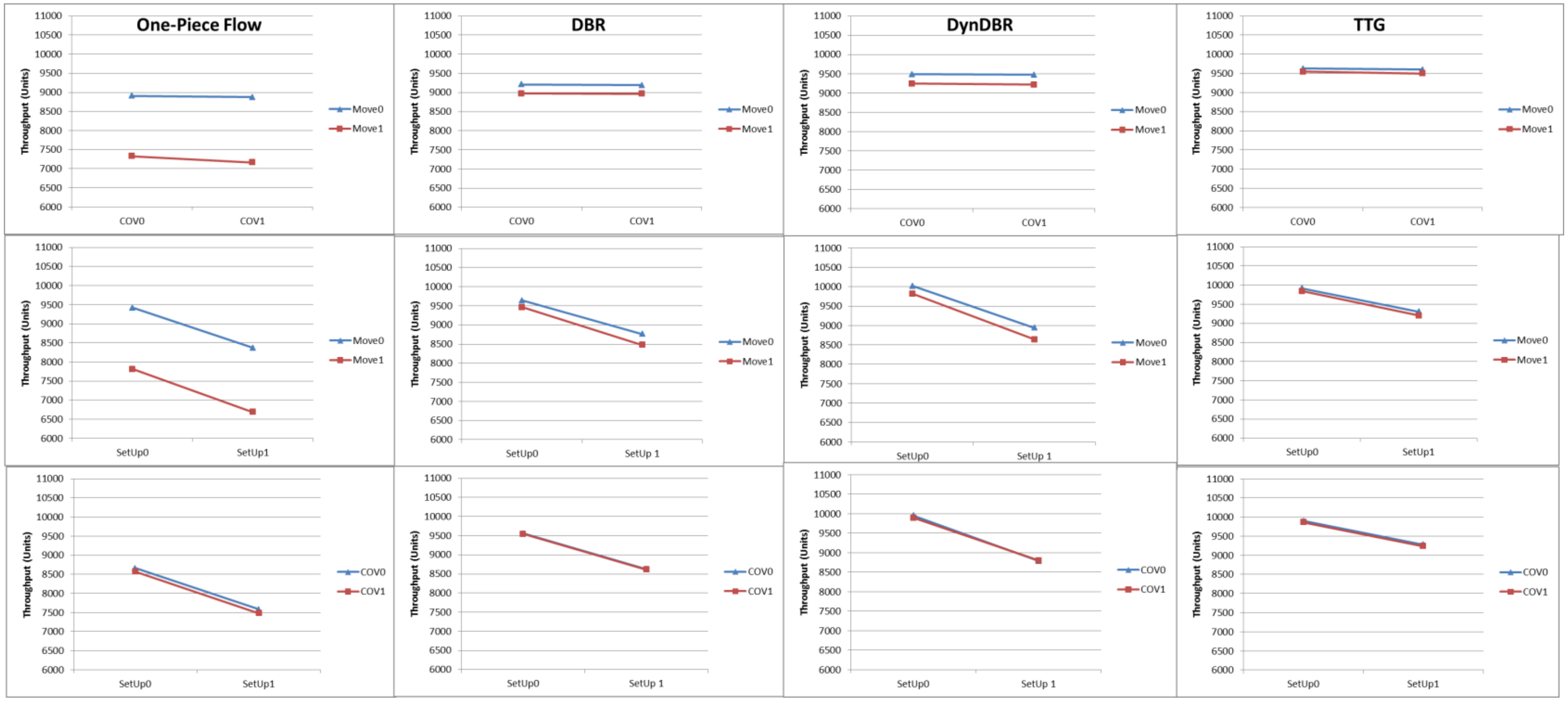


Figure 9: Factor Interaction Effects for One-Piece Flow, DBR, DynDBR, TTG – Light Machining Process

	One-Piece	DBR	DynDBR	TTG
Move COV	<0.0001	0.822	0.855	0.642
Move Setup	<0.0001	0.027	0.091	0.601
COV Setup	0.073	0.898	0.234	0.815

Table 12: p-values of Interaction Effects – Light Machining Process

The high Move and high COV combination interacted and degraded one-piece flow's throughput rate by 124.5 units (159 minus 34 or 1583 minus 1707). The combination of high Move and high Set-up interacted and degraded throughput rate of the one-piece flow cell by 76 units (1124 minus 1048 or 1683 minus 1607). This data is shown in Table 13.

	COV0	COV1	Delta =
Move0	8910	8876	34
Move1	7327	7169	159
Delta =	1583	1707	**-124.5**
	SetUp0	SetUp1	Delta =
Move0	9417	8369	1048
Move1	7810	6686	1124
Delta =	1607	1683	**-76.0**

Table 13: One-Piece Flow Interaction Effect Table – Light Machining Process

The combination of high Move and high Set-up interacted and degraded throughput rate of DBR by 103 units (982 minus 879 or 280 minus 176). This data is shown in Table 14.

	SetUp0	SetUp1	Delta =
Move0	9639	8760	879
Move1	9463	8480	982
Delta =	176	280	**-103.3**

Table 14: DBR Interaction Effect Table – Light Machining Process

The interaction effects that were statistically significant were also the factors that were most significant and practically important for each production method. Move and Set-up were the two factors that had the greatest impact on the throughput rate of one-piece flow. Operation cycle time variation, while statistically significant, was less important. DBR's interaction effects can be explained similarly. The two statistically significant factors, Move and Set-up, interacted to create a greater than expected degradation of throughput rate. However, the interaction effects were small relative to the main effects. What we can learn from this analysis is primarily that TTG did not have interaction effects. TTG proved to be more robust, not only to the main effects, but also to interaction effects.

Section 7.6: Comparison of the Four Methods – Light Machining Process

As discussed in Section 7.1, the results show that for this light machining production process, TTG produces the highest throughput rate when averaging all treatments. One-piece flow "allows" only a minimum amount of WIP inventory in the flow cell, so it was not surprising that in terms of WIP inventory level and flowtime, one-piece flow performed best. One-piece flow completed the light machined products, on average, in 7 to 13 minutes, depending on the treatment, with only an average of 9 to 14 units of WIP in the entire flow cell. (See Table 7 for all data and Table 15 below for a more granular analysis of throughput rate data.) Our light machining one-piece flow cell could have, at most, 18 units in process. (This design was discussed in Section 6.) In addition, with one-piece flow, completed items do not have to wait at a given operation for other units in a transfer-batch to be completed at that operation. They move to the next operation with almost no time in queue. However, low WIP comes at the expense of lower throughput rate because it causes substantial idle time in operations. DBR, DynDBR and TTG had slower flowtimes and greater WIP inventory levels. In DBR, DynDBR and TTG flow cells, however, items are processed and transferred in batches, so each unit must wait until an entire transfer-batch has been processed, before moving to the next operation.

Although we evaluate the four methods based on three performance metrics, throughput rate was our primary concern. The results in Table 7 show that although one-piece flow had the advantage in flowtime and WIP, one-piece flow was the worst performer for throughput rate (see Table 15 below). One-piece flow's underperformance can be attributed to the low amount of WIP "allowed" in the flow cell and the fact that each unit travels through the process as a one-unit transfer batch. Both of these features make one-piece flow unable to adapt well to set-up times and operation cycle time variation. However, one-piece flow's under-performance cannot be due to only high move-time, variation and set-up because one-piece flow underperformed DBR, DynDBR and TTG on throughput rate regardless of the levels of the three factors. One-piece flow was the worst throughput rate method due to the unbalanced nature of this light machining production process. As stated in the Introduction, one-piece flow is intended for balanced production processes. The operation cycle times of the six operations in this light machining process are not balanced (see Table 3 in Section 5). In general, it is often impossible to balance machining processes in a flow cell, because machine times cannot be "broken-up" like manual labor times. Therefore, even when Move, COV and Set-Up were at the low setting, one-piece flow underperformed DBR, DynDBR and TTG on throughput rate. This confirms the work of Takahashi et al. (2007) that in unbalanced systems, with low WIP values, DBR (with greater allowable WIP) will outperform one-piece flow. In summary, although individual items passed through the flow cell quickly with one-piece flow, and WIP was kept low, the unbalanced nature of this light machining process leaves individual operations, or even the entire cell, idle for periods of time.

Treat-ment	Move	COV	Set-up	One Piece Through-put Rate Average (units)	DBR Through-put Rate Average (units)	DynDBR Through-put Rate Average (units)	TTG Through-put Rate Average (units)		Throughput Rate TTG > OnePiece	TTG > DBR	TTG > Dyn DBR
1	1	1	1	6602	8466	8649	9203		39.4%	8.7%	6.4%
2	1	0	1	6770	8495	8630	9241		36.5%	8.8%	7.1%
3	1	1	0	7735	9470	9787	9826		27.0%	3.8%	0.4%
4	1	0	0	7885	9455	9857	9854		25.0%	4.2%	0.0%
5	0	1	1	8350	8759	8948	9296		11.3%	6.1%	3.9%
6	0	0	1	8388	8761	8933	9315		11.1%	6.3%	4.3%
7	0	1	0	9402	9622	9998	9899		5.3%	2.9%	-1.0%
8	0	0	0	9432	9656	10041	9940		5.4%	2.9%	-1.0%
		Average =		**8071**	**9085**	**9355**	**9572**		**18.6%**	**5.4%**	**2.3%**

Table 15: Throughput Rate Comparison – Light Machining Process

DBR, DynDBR and TTG perform somewhat similarly because both use transfer-batches, have greater WIP inventory than one-piece flow, and are constraints-focused. However, in the light machining application TTG outperformed DBR on all three performance metrics and for all treatments. TTG outperformed DynDBR on all three performance metrics when set-up time was high. TTG also had lower WIP and faster flowtime than DynDBR for all treatments. TTG's performance in the light machining process is due to the nature of the TTG transfer-batch sizing and kanban control when there are moving constraints.

The convention when using DBR is to fix the transfer-batch. In this study the transfer-batch was fixed at 15 units. (The reason for 15 units was discussed in Section 6.) Therefore each part number's transfer-batch spent either 5, 10 or 15 minutes at its constraint. (In this experiment, not only are the flow cell operation cycle times unbalanced, but the constraint operation varies depending on the part number.) In contrast, Takt Time Group sizes for this application were either 15, 30 or 45 units depending on the part number. (The average Takt Time Group size, or transfer-batch size was therefore 30 units.) These group sizes were based on a tempo time of 15 minutes and the operation cycle times at the constraint for each part number shown in Table 3 (Section 5). Therefore, each part numbers' group spent approximately 15 minutes at its constraint.

Intuitively it would seem that DBR and DynDBR, with smaller transfer-batch sizes (15 units versus an average Takt Time Group size of 30 units for the TTG flow cell), would process items through the flow cell faster. However, as Table 7 shows, TTG was almost 54% faster (200 versus 432 minutes) with 58% less WIP (301 versus 721 units) than DBR; and 63% faster (200 versus 538 minutes) with 67% less WIP (301 versus 918 units) than DynDBR. Previous research has shown that DBR can operate with relatively low WIP, and techniques have been applied to minimize flowtime. However, that research assumed a stationary constraint. The light machining production process has three constraints depending on the product in the flow cell (See Table 3). Because the DBR transfer-batch quantity was fixed at 15 units, but the operation cycle times at the constraints vary from 20 to 60 seconds, the transfer-batches spend substantially different amounts of time (5, 10 or 15 minutes) at their constraint. If a "fast" product follows a "slow" product, the slow product can back-up the fast product, creating queues that are not intended, and at operations that are not time-buffered. The time-buffer was placed in front of operation 5, which was overall the highest utilization operation. Operation 5, therefore, controls the signal to release more transfer-batches. However, depending on the product in the DBR production cell, the constraint may be operation 1 or 3. The unplanned queues in DBR create the greater level of WIP inventory and longer flowtime as compared to TTG. This is seen clearly in Figure 6 (WIP in each operation) and Figure 8 (WIP by hour for the DBR method). In the DBR method, there should be very little WIP at any operation except Operation 5. However, every operation using the DBR method had a higher WIP level than TTG. A single time-buffer works well with a stationary constraint, but not when the constraint moves. When unplanned queues are created, inventory does not flow evenly. Uneven flow can create back-ups of WIP that do not move quickly to the next operation, and therefore negatively affect throughput rate. As discussed above, DBR, with moving constraints will continually build up WIP.

A stationary constraint process will (almost) always have WIP in front of the constraint because of the calculated time-buffer and the drum release mechanism. However, when constraints move to different operations, back-ups of WIP at non-constraining operations can occur. This is the primary reason that DBR underperformed TTG, when higher WIP levels would seem to support improved throughput rate performance (to offset high set-up times and high operation cycle time variation). When constraints move, the WIP in a DBR process can back-up at multiple operations and build up on the production cell. Unlike TTG, there is no pull mechanism at every operation to ensure that the WIP keeps moving through the process. DBR doesn't use a pull mechanism at all operations because all non-constraint operations are faster than the constraint. In these "normal" DBR processes, WIP moves through non-constraint operations quickly and relatively evenly, with the only large queue located in front of the constraint operation. However, moving constraints pushed WIP to the next operation even if there was a large queue in front of that operation. "Push" processes often build up large WIP levels (Spearman et al, 1990) at multiple operations, which is what occurred with the DBR process.

Finally, DBR, using a fixed transfer-batch size, also results in varying time spent at the constraints. This exacerbates the uneven flow. The fact that transfer-batches in the DBR process are spending 5, 10 or 15 minutes at their constraint will create WIP backups (unplanned queues) when the constraints move.

We created the DynDBR model to understand how a DBR system that reacts to moving constraints would perform. DynDBR was better than DBR on throughput rate but was worse, on average, than TTG. DynDBR's improvement in throughput rate over DBR is logical as a system that can move the time-buffer and drum should improve throughput. DynDBR performed worse than TTG, specifically when set-up times are high. DynDBR did reduce zero-WIP occurrences (0.93%) relative to DBR (1.08%) and TTG (1.56%). However, it still built up unplanned queues. In fact, we can see on Table 11 that once a queue was created, it was hard for it to "drain down" to the very low levels expected in DBR at non-constraint operations. In Table 11, the end-of-simulation WIP level for DynDBR was very high. The end-of-simulation measure was taken at a point-in-time. If the time-buffers were working as planned, the queue at all but one operation (whichever operation was the constraint operation at that moment) would be low. The fact that queues were large at multiple operations demonstrates that queues in a moving constraint process, with interruptions, such as set-up, are difficult to "drain down" to designed (low) levels. In general this shows the weakness of the single-operation signaling method, such as DynDBR, when constraints move. The signal was not sensitive to interruptions or unplanned build-up of WIP. Additional signals may be needed to "moderate" the release of new items when there is an interruption. In general, unintended negative results can occur when a control method is receiving badly timed feedback.

TTG, in contrast, uses varying transfer-batch sizes (Takt Time Group sizes) to create a constant tempo time. Each Takt Time Group spends approximately 15 minutes (based on our chosen tempo time) at its constraint. TTG also controls WIP at every operation with kanbans. The kanbans ensure that there are no unplanned queues. Each queue was set at two kanbans, regardless of where the constraint was located. Each kanban holds a single Takt Time Group or transfer-batch. TTG uses kanbans at every operation because of the realization that with moving constraints, we don't know which operation may be the constraint at any point in time. In addition, stochasticity further exacerbates the problem of moving constraints, as the actual constraint may not be as planned. The combination of a constant tempo time and kanban WIP control at every operation improves the evenness of product flow and keeps WIP moving through the process. This is seen clearly in Figure 6, where TTG had a relatively even amount of WIP at each operation. The result was a 5.5% average greater throughput rate achieved by TTG (average 9572 units) versus DBR (average 9085 units) and 2.5% average greater throughput rate than DynDBR (average 9355 units), as seen on Table 15 above.

Section 7.7: TTG's Robustness – Light Machining Process

As discussed in the Introduction, TTG was conceptualized to implement flow manufacturing when processes are unbalanced, constraints move and set-up times cause interruptions in the flow. In these situations neither one-piece flow nor DBR are reasonable choices as a WIP control and scheduling method. As demonstrated in this study, one-piece flow had the lowest throughput rate performance due to the unbalanced nature of this light machining process. Even when the three factors (move-time, operation cycle time variation and set-up) that could negatively affect throughput rate performance of a one-piece flow cell were low, it still had the worst throughput rate performance. DBR performed worse than TTG, based on all three measures. DynDBR performed worse than TTG, based on all three measures, when set-up times were high. DynDBR also always had more WIP and a slower flowtime than TTG for all treatments. Even though for some low set-up applications DynDBR slightly outperformed TTG (producing about 1% more piston-discs), it required a greater investment in WIP inventory and was much slower than TTG. Overall, TTG balanced high throughput rate with relatively low levels of WIP and moderately fast flowtime.

TTG also proved the most robust of the four methods, when applied to the light machining process. It had the smallest degradation of throughput rate when both move-time and set-up time were at the high setting (and was only slightly higher than DBR for high operation cycle time variation). It was the only method that had no factor interaction effects. For all conditions in this experiment, it was the best performer and the most impervious to changes in conditions.

There are three aspects of TTG that resulted in its superior performance for this unbalanced production process with moving constraints, and robustness to changes in move-time, operation cycle time variation and set-up time. The first is the nature of the TTG algorithm. TTG's transfer-batch sizes vary in quantity, but hold the operation cycle time for batches at the constraint constant (or as constant as possible, given the stochastic nature of operation cycle times). This effectively balances the work-cell, creating more even flow through the process and minimizing unplanned queues. Unplanned queues back-up flow, preventing WIP from moving to the next operation and completing the process. Second, TTG uses relatively large transfer-batch sizes, without suffering long flowtimes or high WIP levels. The large transfer-batch sizes reduce the impact of high move-time (which gets allocated over a large quantity) and high operation cycle time variation due to the Law of large numbers. Third, TTG controls WIP at every operation using kanbans, which reduces the effects of workstation imbalances and keeps WIP relatively low, while also minimizing zero-WIP occurrences. These results demonstrate the benefit to industry of the TTG method for light machining processes that are unbalanced, have moving constraints and experience interruptions to the production flow from activities such as set-up.

Section 8: Performance of One-Piece Flow, DBR, DynDBR and TTG Under Varying Conditions – Heavy Machining Flow Cell Process

The subsections in Section 8 are similar to those in Section 7. While a complete analysis will be performed, we will attempt to not be repetitive in the explanations of outcomes. A brief discussion of the overall results will be covered in Section 8.1. Each factor's impact on performance will be analyzed in Sections 8.2, 8.3 and 8.4. Factor interactions will be analyzed in Section 8.5. Results will be summarized in Section 8.6.

Section 8.1: Overall Results for the Heavy Machining Process

The results for the full factorial experiment are shown in Table 16. TTG and DBR's average throughput rate, over all treatments, differed by three units, or 0.18%. This difference was not statistically significant (p-value = 0.191). DynDBR's throughput rate was five units less than TTG. One-piece flow performed worst, based on throughput rate. In terms of mean flowtime and average WIP in the production process, however, one-piece flow was again the clear winner with a mean flowtime of 43 minutes and an average of only 8 units of WIP. TTG was second best in terms of WIP and flowtime. TTG flow cells had, on average, 57% faster flowtime (560 minutes) than DBR (1294 minutes) and 53% faster flowtime than DynDBR (1184 minutes). TTG also had 52% less WIP (142 units) than DBR (297 units) and DynDBR (296 units).

Throughout Section 8, the results from the light machining application will be compared to the results from the heavy machining application. Therefore, we created Table 17, which gives the percentage different in throughput rate between TTG and the other three production methods for the light and heavy machining applications.

				One Piece			Drum Buffer Rope			DynDBR			Takt Time Grouping		
Treat-ment	Move	COV	Set-up	Through-put Rate Average (units)	Flow-Time Average (min)	WIP Average (units)	Through-put Rate Average (units)	Flow-Time Average (min)	WIP Average (units)	Through-put Rate Average (units)	Flow-Time Average (min)	WIP Average (units)	Through-put Rate Average (units)	Flow-Time Average (min)	WIP Average (units)
1	1	1	1	1025	48	8	1178	1460	324	1166	1440	355	1185	642	155
2	1	0	1	1099	43	7	1189	1439	359	1171	1413	348	1194	620	153
3	1	1	0	1272	44	9	1369	965	247	1370	964	246	1363	500	131
4	1	0	0	1372	39	8	1383	937	240	1383	936	240	1374	483	128
5	0	1	1	1033	47	8	1178	1463	365	1161	1435	354	1188	636	154
6	0	0	1	1103	42	7	1194	1430	357	1174	1402	346	1195	622	151
7	0	1	0	1283	43	8	1377	956	245	1375	954	243	1363	497	131
8	0	0	0	1379	38	8	1386	1705	238	1388	930	238	1374	482	128
		Average =		**1196**	**43**	**8**	**1282**	**1294**	**297**	**1274**	**1184**	**296**	**1279**	**560**	**142**

Table 16: Results for Heavy Machining Flow Cell Process

				TTG v. One Piece		TTG v. DBR		TTG v. DynDBR	
Treat-ment	Move	COV	Set-up	Light Machine	Heavy Machine	Light Machine	Heavy Machine	Light Machine	Heavy Machine
1	1	1	1	39.4%	15.6%	8.7%	0.6%	6.4%	1.7%
2	1	0	1	36.5%	8.7%	8.8%	0.4%	7.1%	1.9%
3	1	1	0	27.0%	7.2%	3.8%	-0.5%	0.4%	-0.6%
4	1	0	0	25.0%	0.1%	4.2%	-0.7%	0.0%	-0.7%
5	0	1	1	11.3%	15.0%	6.1%	0.9%	3.9%	2.3%
6	0	0	1	11.1%	8.4%	6.3%	0.1%	4.3%	1.8%
7	0	1	0	5.3%	6.3%	2.9%	-1.0%	-1.0%	-0.9%
8	0	0	0	5.4%	-0.4%	2.9%	-0.9%	-1.0%	-1.0%
		Average =		**18.6%**	**7.6%**	**5.4%**	**-0.1%**	**2.3%**	**0.6%**

Table 17: % Difference of TTG Throughput Rate versus all Methods, Light Machining and Heavy Machining

Section 8.2: Effect of Move-Time on Throughput Rate – Heavy Machining Process

The effect of the "Move" factor setting on throughput rate performance of all four production methods is shown in Table 18. This factor represents the time to move a transfer batch from one operation to the next. The high setting of move-time per transfer batch was 10 seconds. The low setting was 1 second.

	One-Piece	DBR	DynDBR	TTG
Average Move = 1 (10 seconds)	1192	1280	1273	1279
Average Move = 0 (1 second)	1199	1284	1275	1280
Difference 0 vs. 1 Setting	7	4	2	1
% Difference	0.63%	0.30%	.15%	0.10%
p-value	0.054	0.308	.651	0.777

Table 18: Average Throughput Rate Results for Move-Time Factor Settings – Heavy Machining Process

Move-time did not have a significant effect (at the 95% confidence level) for any of the four production methods. At first this seems surprising, given the impact of move-time on the light machining process. However, observing Table 19 (average set-up and cycle time data for the light and heavy machining processes), we see that the heavy machining process has cycle times that are five to ten times greater than the light machining process. Even when the ten second move-time was allocated over a single unit, for one-piece flow, this time was small compared to the very long operation cycle time. Therefore, unlike the light machining process, within reasonable limits, move-time was not a significant consideration when choosing a production method for heavy machining. This finding is important as heavy machining processes often have long distances between operations, requiring meaningful move time to transport WIP. (As a reminder, the ten second move-time was based on actual observation of the heavy and light machining production processes.)

	Operation 1			Operation 2			Operation 3			Operation 4			Operation 5			Operation 6		
Move Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time
Light Machining	27	27	2700	0	9.6	100	20	20	900	0	7.2	100	33	33	1800	12	12	600
Heavy Machining	88	88	5400	255	255	3600	285	285	8100	0	253	100	253	253	100	0	236	713

Table 19: Light Machining and Heavy Machining – Average Operation Cycle and Average Set-up Times (in Seconds)

Section 8.3: Effect of Operation Cycle Time Variation on Throughput Rate – Heavy Machining Process

The effect of the "COV" (coefficient of variation of the operation cycle time) factor setting on throughput rate performance of all four production methods is shown in Table 20. The high setting of COV was 50% (the standard deviation is 50% of the average operation cycle time). The low setting was 10%.

	One-Piece	DBR	DynDBR	TTG
Average COV = 1 (50%)	1153	1275	1268	1275
Average COV = 0 (10%)	1238	1288	1279	1284
Difference 0 vs. 1 Setting	85	13	11	9
% Difference	6.87%	1.01%	0.87%	0.75%
p-value	<0.0001	<0.0001	0.009	0.027

Table 20: Average Throughput Rate Results for Operation Cycle Time Variation Factor Settings – Heavy Machining Process

The operation cycle time variation factor had the largest throughput rate degradation impact on the one-piece flow method. The delta from the high operation cycle time variation setting to the low setting was 85 units, or 6.87%, which was statistically significant (p-value < 0.0001). The one-piece flow method suffered much greater degradation than DBR (13 unit degradation between the low and high setting), DynDBR (11 units) and TTG (9 units). As explained previously in Section 7.3, one-piece flow will be more susceptible to operation cycle time variation because of the single unit transfer-batch size and the minimal WIP "allowed" in the process.

The effect of high operation cycle time variation, for the DBR, DynDBR and TTG methods was also statistically significant. (In the light machining application operation cycle time variation was **not** statistically significant for DBR, DynDBR and TTG.) The greater impact of high operation cycle time variation on DBR, DynDBR and TTG within the heavy machining application, as compared to the light machining application, can largely be explained by the smaller transfer-batch sizes used in the heavy machining process. Table 6 in Section 6 shows the transfer-batch sizes used in the heavy machining process. DBR and DynDBR used an 8 unit transfer-batch size for the heavy machining application versus 15 units for the light machining application. TTG used transfer-batch sizes of 15, 12, 11 and 8 units for the heavy machining application versus 15, 30 and 45 for the light machining application. The smaller transfer-batch sizes used in the heavy machining process by DBR, DynDBR and TTG reduced the effect of the Law of large numbers to minimize operation cycle time variation relative to the mean of the batch (as compared to the light machining process). While the reduction in throughput rate was not considerable (less than 1%), it was enough to make operation cycle time variation for DBR, DynDBR and TTG statistically significant.

Section 8.4: Effect of Set-Up Time on Throughput Rate – Heavy Machining Process

The effect of "Set-Up" time on throughput rate performance of all four production methods is shown in Table 21. The high setting of set-up was the normal set-up time for this heavy machining process (part number specific set-up times are shown in Table 4 of Section 5 and average set-up times by operation are shown in Table 19). We used this data set specifically because the set-up times would be considered long for a production process. The low setting was 10% of the actual set-up time. We chose the low setting of 10% based on assumptions of what may be possible with the use of quick-changeover techniques and capital to purchase quick-changeover tooling. With enough investment in time to implement quick-changeover and capital to purchase tooling, these reductions in set-up time have been achieved (Shingo, 1985). Therefore, analysis of results at this level is potentially useful in practice.

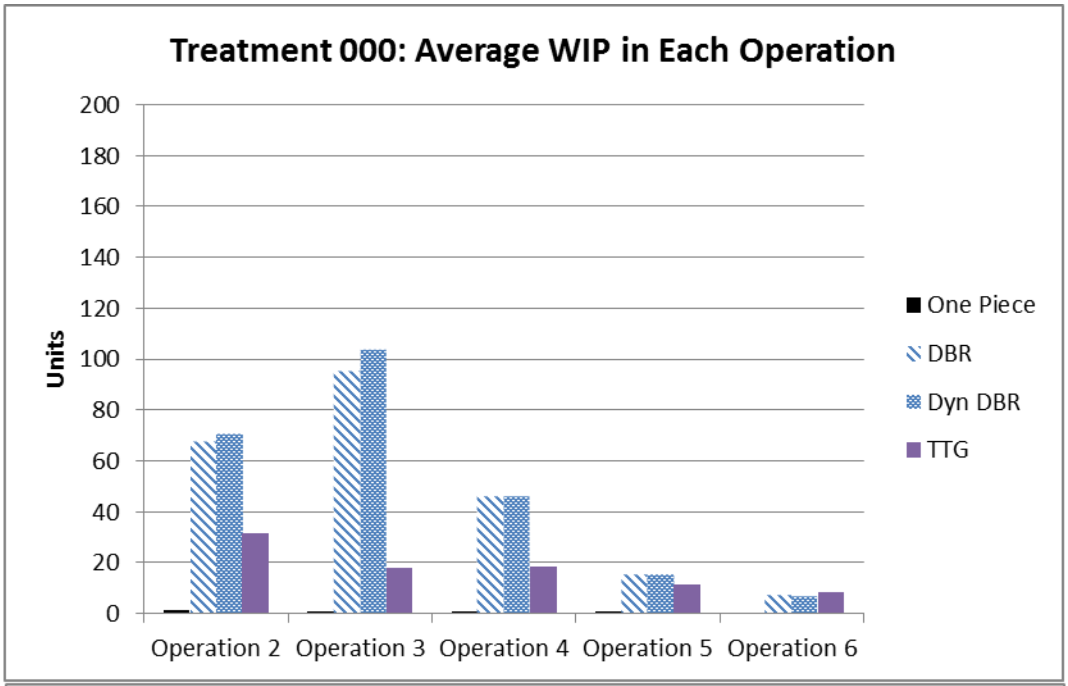
	One-Piece	DBR	DynDBR	TTG
Average Set-Up = 1 (actual times)	1065	1185	1168	1190
Average Set-Up = 0 (10% of actual)	1326	1379	1379	1368
Difference 0 vs. 1 Setting	261	194	211	178
% Difference	19.74%	14.08%	15.3%	13.01%
p-value	<0.0001	<0.0001	<0.0001	<0.0001

Table 21: Average Throughput Rate Results for Set-Up Factor Settings – Heavy Machining Process

If we look at the individual treatment results in Table 16, we see that one-piece flow performed similarly to TTG for two treatments with low set-up. (Both of these treatments are also low operation cycle time variation. As discussed above, high operation cycle time variation had a large negative effect on one-piece flow's throughput rate performance. Low operation cycle time variation, therefore, reduces the advantage of TTG's relatively larger transfer-batches over one-piece flow's single unit transfer-batch size.) This was, initially an unexpected result. However, by observing Table 19 we see that the heavy machining process is actually, on average, <u>a well-balanced process</u>. Except for Operation 1 (average operation cycle time = 88 seconds per unit), the average operation cycle times of all operations are similar (236 to 285 seconds per unit). The heavy machining process has a fast operation at the front (Operation 1, whose average operation cycle time is 88 seconds per unit) followed by a well-balanced process. This process, therefore, moves items quickly through Operation 1, onto a series of relatively well-balanced operations. Light machining is comparatively more unbalanced. The two fastest light machining operations require an average of 7.2 and 9.6 seconds per unit, while the two slowest operations require an average of 27 and 33 seconds per unit. In addition, by carefully observing Table 19, we see that the light machining operations actually alternate between slow, fast, back to slow and so on. This is extreme imbalance in a flow process. (As a reminder to the reader, all data sets are based on actual production systems and have not been altered.) These results verify prior research, that one-piece flow is most suitable for balanced processes with low set-up times and low operation cycle time variation. It also shows that in a well-balanced process, where the only imbalance is a fast operation at the very beginning, DBR, DynDBR and TTG perform similarly.

The difference between the throughput rate of DBR, DynDBR and TTG, for fast versus long set-ups was minimal. All three methods saw a 13 – 15% reduction in throughput rate when set-up times were high. It appears that if there is sufficient WIP, the heavy machining process will perform within a narrow throughput rate range.

While the throughput rate results were similar, the way DBR and DynDBR distributed WIP was very different than TTG; particularly when set-up times were high. This difference is worth studying more closely. This analysis demonstrated a weakness in the DBR and DynDBR methods, which could be improved in a future research study. To analyze the distribution of WIP we created Figure 10, Tables 22a and 22b. Figure 10 shows the average WIP-by-operation for all four production methods. Tables 22a and 22b show the data of the WIP-by-operation, on average, and at shutdown. These figures and tables have the low Move, low COV and low Set-up treatment on the top and the high Move, high COV and high Set-up treatment on the bottom for comparison purposes.



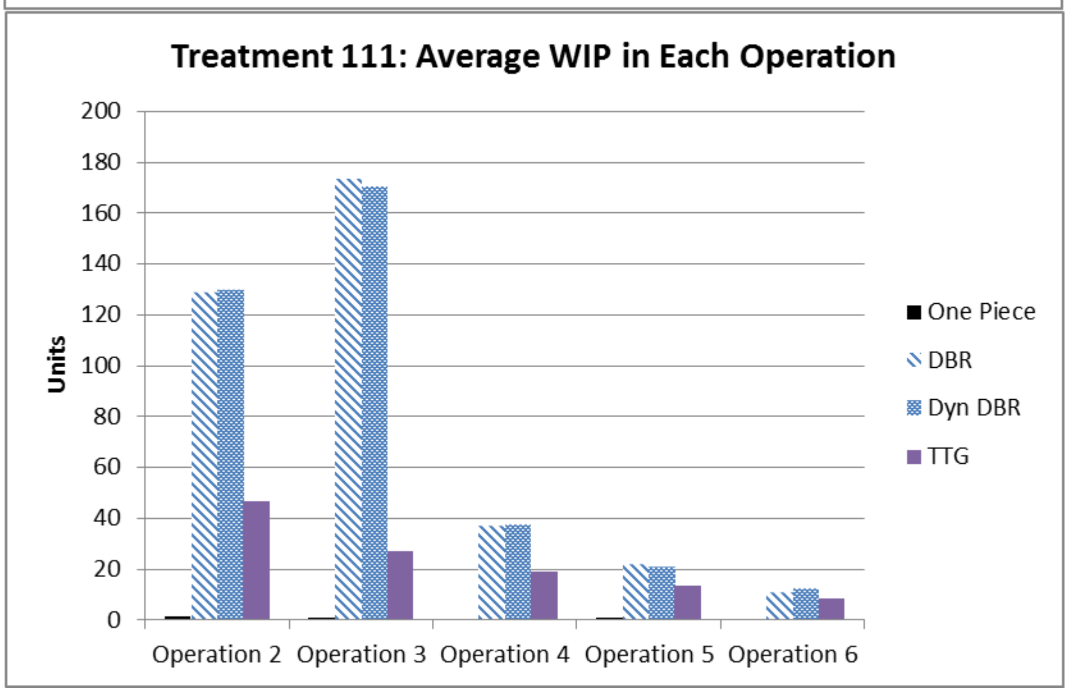


Figure 10: Average WIP in Each Operation – Heavy Machining Process
Top Graph is for the low Move, low COV, low Set-Up treatment (000)
Bottom Graph is for the high Move, high COV, high Set-Up treatment (111)

	One Piece		DBR		Dyn DBR		TTG	
	Average	Shutdown	Average	Shutdown	Average	Shutdown	Average	Shutdown
Op 2	1.4	1.4	68	114	71	97	32	65
Op 3	0.9	0.9	95	108	104	185	18	27
Op 4	0.6	0.5	46	67	46	68	18	20
Op 5	0.6	0.6	15	36	15	36	11	14
Op 6	0.2	0.2	7	15	7	14	8	8

Table 22a: Treatment 000, WIP by Operation: Average and at Shutdown – Heavy Machining Process
Table is for the low Move, low COV, low Set-Up treatment

	One Piece		DBR		Dyn DBR		TTG	
	Average	Shutdown	Average	Shutdown	Average	Shutdown	Average	Shutdown
Op 2	1.3	1.3	129	183	130	216	47	78
Op 3	0.9	0.9	173	307	170	279	27	31
Op 4	0.7	0.7	36	43	37	50	19	18
Op 5	0.9	0.9	22	31	20	36	13	14
Op 6	0.6	0.6	10	16	12	19	8	9

Table 22b: Treatment 111, WIP by Operation: Average and at Shutdown – Heavy Machining Process
Table is for the high Move, high COV, high Set-Up treatment

Figure 10 shows the very large build-up of WIP for DBR and DynDBR in front of Operations 2 and 3. Observing the top versus bottom graph we see that this build-up gets worse when set-up times are high. The DBR and DynDBR processes were designed to release new items into the system when the time-buffer in front of the drum operation was less than the 12 hour target calculated from the formula by Radovilsky (1998). If an operation upstream of the time-buffer (moving or stationary) is undergoing a set-up, then any WIP flowing to that operation will be held up in its queue during the set-up. This "starves" a drum operation located downstream of WIP, which would cause it to signal for the release of more items into the production cell. This will occur even though there is likely substantial WIP at operations upstream of the time-buffer.

In the heavy machining process, the reason the WIP build-up was greater during high set-up times is as follows. The constraint operation for the heavy machining process could be Operations 2, 3 or 4, depending on the specific product (see Table 4 for part number specific operation cycle time data). Operation 1, 2 and 3 had mean set-up times of 90, 60 and 135 minutes. (Operations 4, 5 and 6 had much shorter mean set-up times of approximately 2, 2 and 12 minutes.) During the long set-up times at Operations 1, 2 or 3, if the time-buffered operation was downstream of the set-up operation, the WIP in the time-buffer would drop below the target. (Operations that are not undergoing set-up will always process any WIP in their queue.) When a very long set-up is occurring at an operation upstream of the time-buffer, the drum operation will continue to signal the first operation to send more items into the production cell because it is starved of WIP. The drum "ignores" WIP that is further upstream, even if it is a substantial quantity. This increased the WIP in the DBR and DynDBR production cell, as compared to the low set-up time treatments, and created the greater imbalance in the WIP queues.

This analysis indicates that further refinements to the DBR and DynDBR are required to ameliorate this condition. The drum could, perhaps, be turned off if a very long set-up is occurring upstream of the time-buffer. This should not be done, however, for set-ups downstream of the time-buffer as this would potentially starve the time-buffer. Given that the heavy machining data set was based on a real application, we did not attempt to preemptively customize the drum mechanism. These results were discovered during experimentation and are therefore reported without additional changes to the DBR or DynDBR item-release mechanism. Additional upgrades to DBR and DynDBR could potentially be done in a future research study.

TTG, in contrast didn't change the WIP distribution very much when set-up time was high versus low (See Figure 10). TTG maintains two kanbans (each with one transfer-batch) in front of all operations. When more than two transfer-batches are in any operation, it stops the prior operation from sending more transfer-batches downstream to the next operation. TTG therefore maintained a more even WIP level even when the process was interrupted by a long set-up.

Section 8.5: Factor Interaction Effects on Throughput Rate – Heavy Machining Process

As stated above in Hypothesis 4, it is believed that interactions of the three factors may affect throughput rate. Interaction effects are shown below on Figure 11. (Note, the scale of the graphs is held constant for the one-piece flow, DBR, DynDBR and TTG analyses.) The p-values of the interaction effects are shown below on Table 23. The only factor interaction that was statistically significant was COV-Setup; for one-piece flow. There are no factor interactions that are significant for DBR, DynDBR or TTG. This result was different than the light machining process, where only the TTG method had no interaction effects. The fact that one-piece flow had a significant factor interaction was expected. One piece flow is very sensitive to variability and disruptions (such as set-up). Therefore, the combination of high operation cycle time variation and high set-up time had additional effects on the one-piece flow, beyond those explained by the main effects.

	One-Piece	DBR	DynDBR	TTG
Move COV	0.642	0.963	0.653	0.949
Move Setup	0.665	0.712	0.485	0.849
COV Setup	0.001	0.752	0.679	0.747

Table 23: p-values of Interaction Effects – Heavy Machining Process

The most important aspect of the factor interaction effect analysis is the continued similarity of DBR, DynDBR and TTG, as measured by throughput rate, for the heavy machining process. In all aspects of this experiment the factors affected each of these three methods similarly.

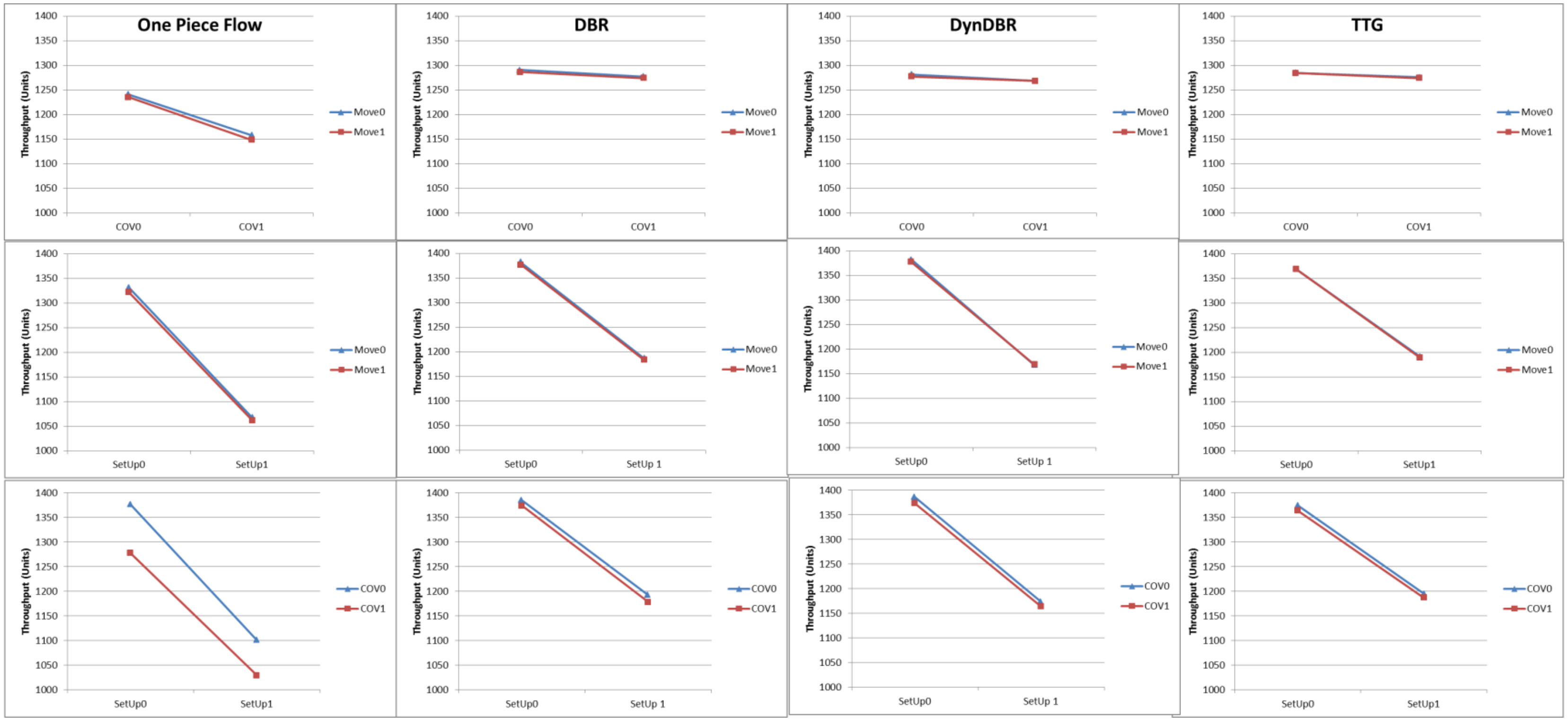


Figure 11: Factor Interaction Effects for One-Piece Flow, DBR, TTG – Heavy Machining Process

Section 8.6: Comparison of the Four Methods – Heavy Machining Process

When considering flowtime and WIP, one-piece flow was the best performer (fastest flowtime and least WIP) and TTG was second best. DBR and DynDBR required more than twice the time to complete a single item, and required about twice the WIP, as compared to TTG. When measuring throughput rate, however, DBR, DynDBR and TTG were virtually tied; and were far superior to one-piece flow.

The heavy machining process was, in fact, a relatively well-balanced process. As seen in Table 19, the operation cycle times, with the exception of Operation 1, are similar. There is a relatively minor difference between the slowest and fastest operation (except for Operation 1). In addition, Operation 1 has very fast operation cycle times and therefore moves items to the rest of the well-balanced operations very quickly. When there was little variation and short set-up times, one-piece flow worked very well in this type of production process. (This contrasts with how poorly one-piece flow performed in all cases in the light machining process.) The DBR, DynDBR and TTG methods worked well, in terms of throughput rate, for all treatment combinations of the heavy machining process.

In this application, somewhat surprisingly, being able to move the time-buffer and drum held no advantage over traditional DBR, with a stationary time-buffer and drum. In fact, DynDBR performed slightly, but statistically, worse than DBR. DynDBR, by design, creates time-buffers at different operations. When the process is well balanced, these queues are almost impossible to drain down. Therefore, there is no reason to use

DynDBR, even if constraints move, when the process is relatively well balanced. DBR performed slightly better, and is less complicated to manage.

TTG's overall (balanced) superior performance of moderate WIP, relatively fast flowtime and high throughput rate are the result of the combination of transfer-batches <u>with</u> kanban WIP control. Transfer-batches have a number of positive benefits. First, they reduce the effect of high move time by allocating this time over larger quantities. Second, they reduce the effect of operational cycle time variation (due to the Law of large numbers). Finally, transfer-batches "allowed" the build-up of a moderate level of WIP in the production cell, which further dampened the effect of operation cycle time variation. Transfer batches primarily provided TTG's advantage over one-piece flow. (DBR and DynDBR also used transfer-batches.) Controlling WIP, by using kanbans between all operations, maintained an even flow of material through the production cell, even when there were interruptions from long set-up times. The kanbans used in TTG reacted to the interruption of the process flow from a set-up by turning off the flow of items that are allowed to move to the next operation. This is a classic pull process (Womack and Jones, 1996). In contrast, DBR and DynDBR, which are intended to be hybrid push/pull systems (pulling items into the cell from the constraint, then pushing them within the cell), acted more like just a push system when set-up times were high. DBR and DynDBR pushed items to operations that already had very large queues of WIP, but weren't the drum operation. TTG acted like a pure pull system, which only sends material into the production cell if Operation 2 signals Operation 1 that it needs more material to process. Operation 2 was signaled to send more items downstream by

Operation 3; this continues for all operations. When WIP backed up in the TTG flow cell, because a set-up was occurring, the kanbans signaled the upstream operation to stop sending more items downstream. This quickly reached the beginning of the production process, shutting off the release of new items until the set-up was completed and WIP began flowing.

These results may require choices by practitioners; they do not point to a clear winner, as with the light-machining process. If in this heavy machining process we could: 1) minimize move-time by conveying parts from one operation to the next with minimal labor, 2) minimize operation cycle time variation through statistical process improvement methods such as Six Sigma (Klefsjö, et al. 2001), and 3) reduce set-up time through Lean tools such as quick-changeover, then one-piece flow may be the preferred method. As we state this, however, it must be recognized that in any stochastic process deviations from these conditions are possible. If there are any deviations from the low COV or Set-up conditions, TTG becomes substantially better in terms of throughput rate, as compared to one-piece flow. Therefore, even in a low Move, low COV and low Set-up process it may be "safer" for practitioners to use TTG.

Overall, when set-up times were low, DBR and DynDBR had the highest throughput rate. However, they also had more than twice as much WIP, and required more than twice the time to complete items, as compared to TTG. TTG provides the most balanced performance when considering all three performance metrics, across all treatments.

Section 9: Performance of One-Piece Flow, DBR, DynDBR and TTG Under Varying Conditions – Assembly Process

The assembly process is quite different than the light machining and heavy machining applications discussed in Sections 7 and 8. Move time was minor as the workstations in the actual assembly flow cell are so close that production-operators can hand off items or kanbans to the next operation in about 1 second. Set-up time was also almost non-existent, as there is no tooling required in this production process. We therefore estimated the low setting for set-up time at 100 seconds and the high setting at 10 times this low level, or 1000 seconds. All experimental settings are discussed in greater detail below in Sections 9.2, 9.3 and 9.4.

The results of the assembly process were also quite different than light machining and heavy machining. This application required additional experimentation beyond those conducted in Sections 7 and 8. The focus of the analysis will be conducted in Section 9.6 which reviews why DynDBR initially was the best throughput rate performer, and the results from our additional experimentation which made changes to TTG's kanban distribution. This analysis will also help explain why TTG performed so well in the light machining application.

Section 9.1: Overall Results for the Assembly Process

The results for the full factorial experiment are shown in Table 24. In addition, we present the percentage difference of each method as compared to TTG for each treatment in Table 25. We see that for this application DynDBR performed best in terms of throughput rate. It produced, on average, 1% more solenoids than TTG (9167 for DynDBR versus 9074 for TTG), which was statistically significant ($p < 0.0001$). In addition, unlike previous applications, DynDBR was only slightly slower than TTG (136 minute flowtime for DynDBR versus 113 minute flowtime for TTG) and had only slightly more WIP than TTG (151 items for DynDBR versus 125 for TTG). Overall, DBR was the third best throughput rate performer and one-piece flow was the worst. (The only exception was the low-low-low treatment, where one-piece flow had a higher throughput rate than DBR.)

				One Piece			Drum Buffer Rope			DynDBR			Takt Time Grouping		
				Through-put Rate	Flow-Time	WIP	Through-put Rate	Flow-Time	WIP	Through-put Rate	Flow-Time	WIP	Through-put Rate	Flow-Time	WIP
Treat-ment	Move	COV	Set-up	Average (units)	Average (min)	Average (units)	Average (units)	Average (min)	Average (units)	Average (units)	Average (min)	Average (units)	Average (units)	Average (min)	Average (units)
1	1	1	1	6943	9.9	10.0	8275	250	308	9009	208	250	8849	149	176
2	1	0	1	7160	9.7	10.1	8310	240	295	9095	190	222	8905	146	171
3	1	1	0	7994	9.0	10.4	8754	135	157	9266	80	76	9249	85	84
4	1	0	0	8280	8.9	10.6	8862	114	128	9277	71	65	9269	75	71
5	0	1	1	7470	8.8	9.7	8311	240	292	9049	202	240	8866	148	175
6	0	0	1	7824	7.9	9.0	8353	230	279	9100	187	218	8932	145	170
7	0	1	0	8688	8.0	10.0	8802	125	143	9265	79	75	9251	85	85
8	0	0	0	9167	7.1	9.4	8902	105	115	9277	70	64	9270	75	70
		Average =		**7941**	**8.7**	**9.9**	**8571**	**180**	**214**	**9167**	**136**	**151**	**9074**	**113**	**125**

Table 24: Results for Assembly Flow Cell Process

				One Piece Throughput Rate	DBR Throughput Rate	DynDBR Throughput Rate	TTG Throughput Rate		Throughput Rate		
Treat-ment	Move	COV	Set-up	Average (units)	Average (units)	Average (units)	Average (units)		TTG > OnePiece	TTG > DBR	TTG > DynDBR
1	1	1	1	6943	8275	9009	8849		27.4%	6.9%	-1.8%
2	1	0	1	7160	8310	9095	8905		24.4%	7.2%	-2.1%
3	1	1	0	7994	8754	9266	9249		15.7%	5.7%	-0.2%
4	1	0	0	8280	8862	9277	9269		12.0%	4.6%	-0.1%
5	0	1	1	7470	8311	9049	8866		18.7%	6.7%	-2.0%
6	0	0	1	7824	8353	9100	8932		14.2%	6.9%	-1.8%
7	0	1	0	8688	8802	9265	9251		6.5%	5.1%	-0.2%
8	0	0	0	9167	8902	9277	9270		1.1%	4.1%	-0.1%
		Average =		**7941**	**8571**	**9167**	**9074**		**14.3%**	**5.9%**	**-1.0%**

Table 25: % Difference of TTG Throughput Rate versus all Methods – Assembly

Section 9.2: Effect of Move-Time on Throughput Rate – Assembly Process

The effect of the "Move" factor setting on throughput rate performance of all four production methods is shown in Table 26. This factor represents the time to move a transfer batch from one operation to the next.

	One-Piece	DBR	DynDBR	TTG
Average Move = 1 (10 seconds)	7594	8550	9162	9068
Average Move = 0 (1 second)	8287	8592	9173	9080
Difference 0 vs. 1 Setting	693	42	11	12
% Difference	8.36%	0.49%	.12%	0.13%
p-value	<0.0001	<0.0001	0.094	0.0002

Table 26: Average Throughput Rate Results for Move-Time Factor Settings – Assembly Process

Only DynDBR was <u>not</u> statistically affected by move-time in this assembly process (using p-value of 5% as a guide). One can see, however, that the actual reductions in throughput rate for DynDBR (11 units) and TTG (12 units) are almost identical. The transfer-batch size for DBR and DynDBR was 18 units; the transfer batch size for TTG was either 18 or 20 units, based on the part number. (This small difference in the transfer-batch sizes between the DBR methods and TTG will be discussed further in Section 9.6.) The difference in statistical significance of DynDBR versus TTG, given the small difference in throughput rate, appears illogical. To understand why, we have to dig deeper into the ANOVA calculations. The sum of squares of the move factor in DynDBR and TTG are also similar. However, the total explained variation in the TTG model was much higher, meaning the sum of squares of the error was much lower (almost 1/3rd the SSE of DynDBR). Therefore, the F value of the TTG Move factor was larger, resulting in the statistical significance. This data can be provided upon request.

The throughput rate degradation of DBR was worse than expected, as compared to DynDBR, when move-time was high. Logically, DBR should have been affected similarly to DynDBR. The transfer-batch sizes used in DBR and DynDBR were identical (18 units). Overall, DBR underperformed DynDBR, as measured by throughput rate, by approximately 7% (8571 units versus DynDBR's 9174 units). In the assembly process, DBR both underperformed DynDBR overall and was more susceptible to all factor level changes, including move-time. This phenomenon will be explained in greater detail in Section 9.6, which will review the specific reasons for DynDBR's superior performance and robustness in this assembly process.

Section 9.3: Effect of Operation Cycle Time Variation on Throughput Rate – Assembly Process

The effect of the "COV" (coefficient of variation of the operation cycle time) factor setting on throughput rate performance of all four production methods is shown in Table 27. The high setting of COV was 50% (the standard deviation is 50% of the average operation cycle time). The low setting was 10%. In the actual solenoid assembly process the operation cycle times could be consistent (low) or inconsistent (high). While it usually is a very consistent process, certain changes, such as incoming quality of components could vary the time it takes to perform the operations in this application. Therefore, the experimental settings represent the range of variation that could be expected.

	One-Piece	DBR	DynDBR	TTG
Average COV = 1 (50%)	7774	8536	9147	9054
Average COV = 0 (10%)	8108	8607	9187	9094
Difference 0 vs. 1 Setting	334	71	40	40
% Difference	4.12%	0.83%	0.43%	0.44%
p-value	<0.0001	<0.0001	<0.0001	<0.0001

Table 27: Average Throughput Rate Results for Operation Cycle Time Variation Factor Settings – Assembly Process

The effect of high operation cycle time variation was significant for all four production methods. This differs from the light machining process, where only one-piece flow was statistically affected by high operation cycle time variation. The reason DBR, DynDBR and TTG experienced significant degradation in throughput rate when operation cycle time variation was high is the relatively lower level of WIP in the assembly process versus light machining. The average WIP levels of DBR, DynDBR and TTG in the light machining process were 721, 918 and 301 units (see Table 7 in Section 7). The average WIP levels of DBR, DynDBR and TTG were 214, 151 and 125 units. As discussed previously, more WIP in a process helps to dampen the impact of variation. The lower WIP levels achieved by the assembly process (which is generally viewed as positive) worsened the negative impact of high operation cycle time variation. One-piece flow, with its single unit transfer batch size, was affected even more than the other production methods.

We also want to point out, as discussed in Section 9.2, that once again, DBR had greater throughput rate degradation than DynDBR. This occurred despite the fact that the transfer-batch size was identical, and DBR had a greater level of WIP. This phenomenon points to the robustness of DynDBR to factor level changes in this assembly application (and the specific data set used in the simulation model). Additional details of why DynDBR performed so well, and better than DBR, are contained in Section 9.6.

Section 9.4: Effect of Set-Up Time on Throughput Rate – Assembly Process

The effect of "Set-Up" time on throughput rate performance of all four production methods is shown in Table 28. As discussed above, the low setting of set-up was the actual mean set-up time for this assembly process (100 seconds). This assembly process does not have significant tooling. It requires only changes in work-instructions, purchased components and tools to change-over to the next product. However, it is possible that there may be a problem in locating work-instructions, purchased components or tools. Additionally, it may take longer for new employees to perform the simple change-over. Therefore, the high setting of all operations' set-up times, at 1000 seconds (or 16.7 minutes) is feasible in practice.

	One-Piece	DBR	DynDBR	TTG
Average Set-Up = 1 (1000 seconds)	7350	8312	9063	8888
Average Set-Up = 0 (100 seconds)	8532	8830	9271	9260
Difference 0 vs. 1 Setting	1182	518	208	372
% Difference	13.86%	5.86%	2.24%	4.05%
p-value	<0.0001	<0.0001	<0.0001	<0.0001

Table 28: Average Throughput Rate Results for Set-Up Factor Settings – Assembly Process

As expected, all four production methods were significantly impacted by high set-up times. The results are similar to those from the two other applications (light machining and heavy machining), with the exception of DynDBR. The DynDBR method experienced the least degradation in throughput rate when set-up times were high. Once again, as seen in Sections 9.2 and 9.3, DynDBR had less degradation in throughput rate, at the high factor level, than the other three methods. DynDBR not only was the best throughput rate method when producing items in this light machining application, but also was the most robust to factor level changes. DynDBR, like TTG in the light machining application, was able to maintain an even flow and create WIP queues in better locations to maximize throughput rate. The reasons for the performance of DynDBR, and its robustness to factor level changes will be explained in Section 9.6.

Section 9.5: Factor Interaction Effects on Throughput Rate – Assembly Process

The p-values of the interaction effects are shown below on Table 29. The COV-Setup interaction was statistically significant for all four methods. One-piece flow had statistically significant interactions for Move-Setup and Move-COV. In addition, TTG had a statistically significant interaction effect for Move-Setup. We did not include the interaction effect graphs in this section. Like Sections 7 and 8 the interaction effects that were significant were also very small compared to the main effects.

	One-Piece	DBR	DynDBR	TTG
Move COV	<0.0001	0.962	0.198	0.544
Move Setup	<0.0001	0.714	0.09	0.005
COV Setup	<0.0001	<0.0001	<0.0001	<0.0001

Table 29: p-values of Interaction Effects – Assembly Process

What is most interesting from this analysis is the fact that TTG was not among the most robust methods when considering factor interaction effects. In the other production applications, TTG and DynDBR were the most unaffected by factor interactions. Specifically, in the light machining application only DynDBR and TTG had no statistically significant interaction effects. In the heavy machining application DBR, DynDBR and TTG had no statistically significant factor interaction effects. In this assembly production application TTG was significantly affected by Move-Setup and COV-Setup. DBR and DynDBR are only significantly affected by COV-Setup. As discussed throughout Section 9, DynDBR was the one method that demonstrates robustness to factor level changes and factor interactions in the assembly process.

Section 9.6: Comparison of the Four Methods – Assembly Process

The best throughput rate performer in this assembly process (and the associated data set of operation cycle times and set-up times) was DynDBR. It had a 1% higher throughput rate than the second best method, TTG. However, DynDBR had 16% greater flowtime and 17% more WIP than TTG. The remaining two methods performed as follows. DBR had lower throughput rate than DynDBR and TTG, with more WIP and longer flowtime. One-piece flow was once again the fastest method (smallest flowtime) and had the least WIP, but it was the worst throughput rate performer for all but one treatment.

This analysis will include comparisons of the assembly data set to the data sets associated with the light machining and heavy machining experiments. Therefore we provide Table 30, the average operation cycle time and set-up time for all three production applications. (This is similar to Table 19 in Section 8.) However, the average operation cycle times do not provide the answers to why DynDBR outperformed the other methods, and particularly TTG. For these answers we need the part-number specific operation cycle time data. This is shown in Table 31. Table 31 is a compilation of the operation cycle times and set-up times from Tables 3, 4 and 5 in Section 4. For the reader we point out that the part numbers are referenced down the left side of the table. For example, D1 through D9 are piston disc part numbers and E1 through E9 are solenoid part numbers. The part number references the size of the product. S8, S10, S12 and S16 are different size slide-valves. In Table 31 we highlight the operation cycle time at the constraint (CTc) for all part-numbers. For example, in the light machining application, D1 – D3's CTc is 20 seconds at Operation 1, D4 – D6's CTc is 30 seconds at Operation 3 and D7 – D9's CTc is 60 seconds at Operation 5.

	Operation 1			Operation 2			Operation 3			Operation 4			Operation 5			Operation 6		
Move Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time
Light Machining	27	27	2700	0	9.6	100	20	20	900	0	7.2	100	33	33	1800	12	12	600
Heavy Machining	88	88	5400	255	255	3600	285	285	8100	0	253	100	253	253	100	0	236	713
Light Assembly	0	31	100	0	25	100	0	33	100	0	30	100	0	44	100	0	42	100

Table 30: Average Operation Cycle and Average Set-up Times (in Seconds) – All Applications

		Operation 1			Operation 2			Operation 3			Operation 4			Operation 5			Operation 6			
Part #	Move Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	Machine	Labor	Set-Up Time	CTc
Piston Discs - Light Machining																				
D1	10	**20**	**20**	2700	0	5	100	12	12	900	0	7	100	19	19	1800	12	12	600	**20**
D2	10	**20**	**20**	2700	0	7	100	17	17	900	0	5	100	19	19	1800	12	12	600	**20**
D3	10	**20**	**20**	2700	0	12	100	15	15	900	0	7	100	19	19	1800	12	12	600	**20**
D4	10	27	27	2700	0	7	100	**30**	**30**	900	0	10	100	19	19	1800	12	12	600	**30**
D5	10	27	27	2700	0	9	100	**30**	**30**	900	0	8	100	19	19	1800	12	12	600	**30**
D6	10	27	27	2700	0	21	100	**30**	**30**	900	0	9	100	25	25	1800	12	12	600	**30**
D7	10	34	34	2700	0	5	100	12	12	900	0	7	100	**60**	**60**	1800	12	12	600	**60**
D8	10	34	34	2700	0	8	100	21	21	900	0	5	100	**60**	**60**	1800	12	12	600	**60**
D9	10	34	34	2700	0	12	100	15	15	900	0	7	100	**60**	**60**	1800	12	12	600	**60**
Slide Valve - Heavy Machining																				
S8	10	88	88	5400	157	157	3600	187	187	3600	0	**240**	100	219	219	100	0	213	600	**240**
S10	10	88	88	5400	208	208	3600	205	205	7200	0	**300**	100	144	144	100	0	213	600	**300**
S12	10	88	88	5400	**326**	**326**	3600	298	298	7200	0	236	100	268	268	100	0	213	600	**326**
S16	10	88	88	5400	330	330	3600	**448**	**448**	14400	0	236	100	382	382	100	0	304	1050	**448**
Soleniod - Light Assembly																				
E1	1	0	26	100	0	24	100	0	28	100	0	30	100	0	**45**	100	0	42	100	**45**
E2	1	0	26	100	0	25	100	0	28	100	0	27	100	0	**45**	100	0	42	100	**45**
E3	1	0	22	100	0	24	100	0	**50**	100	0	31	100	0	44	100	0	41	100	**50**
E4	1	0	31	100	0	23	100	0	27	100	0	30	100	0	**44**	100	0	41	100	**44**
E5	1	0	41	100	0	27	100	0	28	100	0	31	100	0	**45**	100	0	42	100	**45**
E6	1	0	45	100	0	23	100	0	27	100	0	30	100	0	**44**	100	0	41	100	**44**
E7	1	0	34	100	0	24	100	0	27	100	0	30	100	0	**44**	100	0	41	100	**44**
E8	1	0	23	100	0	26	100	0	28	100	0	31	100	0	**45**	100	0	42	100	**45**
E9	1	0	28	100	0	25	100	0	**50**	100	0	30	100	0	44	100	0	42	100	**50**

Table 31: Actual Operation Cycle and Average Set-up Times (in Seconds) – All Applications

As we evaluate the differences in results of the three applications (light machining, heavy machining and assembly), we must evaluate how balanced or unbalanced each production process is on average (see Table 30). Heavy machining appears relatively balanced, except for Operation 1, which is much faster than the other operations. Assembly appears relatively balanced from Operations 1 through 4, with two slower operations at the end of the process (Operations 5 and 6). In addition, assembly's set-up times were identical across all operations, which can be in important factor with respect to balance. Light machining was the most unbalanced process with alternating slow then fast operations. This data, however, does not explain why, in the assembly application, DynDBR was the most robust method and the best overall performer. Instead we must observe the differences in the operation cycle time at the constraint (CTc). A well balanced process, from both a flow and constraints perspective considers not only average cycle times across the processes, but the difference in the CTc of all products. The difference in CTc for all part numbers within a production process can be seen in Table 31.

In the light machining application the CTc can be as fast as 20 seconds or as slow as 60 seconds; a 1:3 ratio. In the heavy machining application the CTc can be as fast as 240 seconds or as slow as 448 seconds, an approximately 1:2 ratio. In the assembly application, however, the CTc times are very similar (fastest = 44 seconds, slowest = 50 seconds). As a reminder for the reader, a key aspect of the TTG method is its ability to vary the transfer-batch size to maintain a constant tempo through the flow process. When the ratio of the fastest to slowest CTc is large, such as for the light machining application, this benefit becomes most pronounced. In a production process, such as the light machining data set used in this study, fixed-size transfer-batches move through the light machining application at very different tempos, creating unevenness of low. In contrast, varying transfer-batch sizes, as TTG does, creates more even flow. In a process such as assembly, with similar CTc's, there is little to no advantage for TTG over a fixed-size transfer-batch, because the varying transfer-batch size does not actually vary much. (The transfer-batch sizes for TTG in the assembly process were either 18 or 20 units, while the transfer- batch sizes for DynDBR and DBR were 18 units.) Therefore, in the assembly application the tempo, or the time spent at the constraint operation, of transfer-batches moving through the flow cell using the DynDBR method was basically identical to TTG. However, based on the superior performance of TTG in the light machining and heavy machining applications we would not have expected DynDBR to outperform TTG. This required additional investigation, which will be explained later in this section.

The reason DynDBR performed so well is explained by how WIP was distributed. In Figure 12 (below) we see the distribution of WIP across all operations. (This graph is for the low Move, low COV, low Setup treatment. However, all treatments showed a similar distribution.) Unlike the light machining and heavy machining applications, the DynDBR's distribution of WIP in the assembly application was close to ideal. Operation 5 was the constraint operation for seven of nine part numbers. In the DynDBR simulation, Operation 5 was the operation with the most WIP. Operation 3 was the only other constraint operation (for two of the nine part numbers). Operation 3 had the second most amount of WIP. All of the other operations in the DynDBR simulation had very low WIP; lower than any other production method, including TTG. TTG, because it controls WIP with two kanbans at each operation (each kanban can contain one transfer-batch), maintains a more even level of WIP at each operation. Therefore at Operations 5 and 3 TTG had less WIP than DynDBR, but at the non-constraint operations (2, 4 and 6) it had more WIP. DynDBR, by creating and moving an optimized time-buffer (3.5 hours for the assembly application) in front of Operations 3 and 5, puts the WIP where it belongs; in front of the “current” constraint operation. For this relatively well-balanced and low set-up time assembly process, this difference in WIP distribution improved throughput, maintained a reasonably low level of WIP and fast flowtime as compared to the other three production methods.

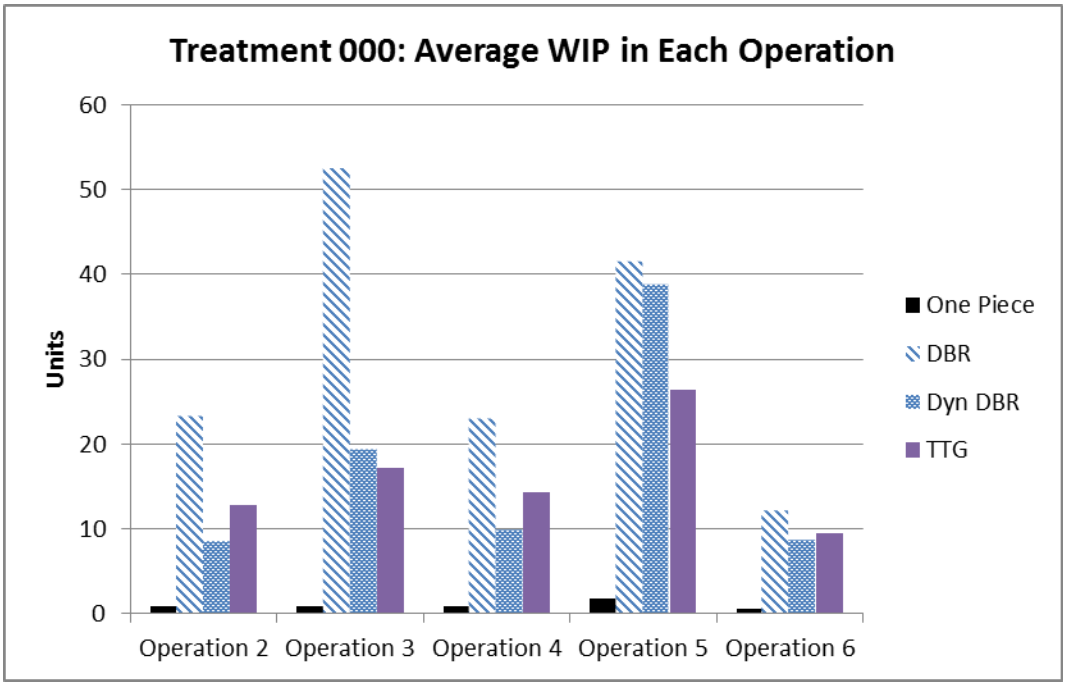


Figure 12: Average WIP in Each Operation – Assembly Process
Graph is for the low Move, low COV, low Set-Up treatment (000)

Traditional DBR, with a fixed time-buffer, performed relatively poorly in the assembly application because it did not appear to place the WIP in the best locations and created unplanned WIP queues. Specifically, we notice the large WIP queue in DBR’s Operation 3 (see Figure 12). In this application, the fixed time-buffer for DBR was located in front of Operation 5, which was the overall highest utilization operation. DBR therefore signaled the system to send more items into the flow cell based on the status of Operation 5’s time-buffer. When Operation 3 was the “current” constraint, however, it processed items more slowly than Operation 5. This results in the uncontrolled WIP queue that built up in front of Operation 3. As we have seen previously, when an uncontrolled WIP queue is created, it is hard to drain down. This dramatically increased the WIP in the DBR process, slowed flowtime and reduced throughput rate.

The results of the DynDBR simulations suggest an opportunity to improve the operation of TTG. Using the WIP distribution difference shown in Figure 12 we made adjustments to TTG's kanban placement. As stated in Section 6, in all of these experiments we used 2 kanbans at each operation. However, the results from DynDBR show that there was some advantage to placing more WIP in front of Operations 3 and 5. Therefore we adjusted the kanbans in TTG to be more similar to how DynDBR distributed WIP, but held the total number of kanbans as twelve. The altered kanban placement for TTG was:

- Operation 1 = 2 kanbans,
- Operation 2 = 1 kanban,
- Operation 3 = 3 kanbans,
- Operation 4 = 1 kanban,
- Operation 5 = 4 kanbans
- Operation 6 = 1 kanban

We reran this kanban placement using the high Move, high COV, high Setup treatment. This treatment was used because it resulted in a large difference between DynDBR and TTG's throughput rate (9009 for DynDBR, 8849 for TTG, a 1.8%

difference). The results of this experiment, which are given in Table 32, show the throughput rate and average WIP for DynDBR and TTG with the original "uniform" kanban distribution and with the unbalanced kanban distribution.

	Dynamic DBR	TTG Uniform Kanbans	TTG Unbalanced Kanbans
Throughput Rate	9009	8849	9021
WIP	250	176	198

Table 32: Experimental Results of Non-Uniform Kanban Placement in TTG – Assembly Process
Table is for the high Move, high COV, high Set-Up treatment

By using the results of our original experiment and improving the placement of kanbans in TTG we increased throughput rate by 172 units. In fact, "unbalanced" TTG had both greater throughput rate and less WIP than DynDBR.

DynDBR originally outperformed TTG because the benefits of TTG, including varying the transfer-batch size to maintain an even tempo at the constraint and controlling WIP evenly at each operation with kanbans, were not benefits for this application. The tempo of DynDBR and TTG were similar because the transfer-batch sizes were very similar. TTG's control of WIP at each operation, based a uniform distribution of two kanbans at each operation, was actually sub-optimal in this assembly application because it stores WIP at levels that are too high at some operations and too low at others. However, by placing more kanbans where they provide a buffer specifically for constraint operations, and less at non-constraint operations, TTG slightly outperformed DynDBR.

Conversely the assembly analysis shows why TTG performed so well within the light machining application. That process, with its operation cycle time imbalances across the process, and within each products' operation cycle time at the constraint (CTc), is what TTG was designed to optimize. The imbalances were evened-out by the constant tempo (due to varying transfer-batch sizes) and by controlling, and maintaining, a small amount of WIP at each operation.

Finally, DynDBR outperformed traditional DBR because it was able to move the time-buffer dynamically, as needed. This moved the control of the WIP in the system to the proper operation, which works well in the relatively well balanced assembly process with comparatively low set-up times. In the assembly application the DynDBR method performed as Goldratt intended when he conceptualized the drum-buffer-rope; even with moving constraints. DynDBR maintained a reasonable amount of WIP at the constraint operation and very low WIP at all other operations.

Section 10: Relieving the Labor Constraint in the Light Machining Process

As discussed in Section 5.2, in the full factorial experiments we purposely constrained labor to achieve a high utilization. The number of labor resources in these flow cells is always less than the number of workstations; requiring the "operators" to move to different workstations to keep the WIP moving to completion. In the light machining application the number of labor resources used in the full factorial experiment is three. We therefore chose to create a completely unconstrained case, with six operators responsible for six workstations. Since the light machining application is unbalanced, this would ensure that the lack of labor would never delay production.

In Table 33 below, we show the throughput rate and WIP results for the constrained and unconstrained levels of labor resources in the system. In addition, we show the labor utilization so the reader will be aware of the idleness of labor in the two scenarios. Note, this analysis was done only for the high Move, high COV and high Set-up time treatment of the light machining process. This treatment "stresses" the process the most and requires the labor resources to perform multiple functions (move, operation, set-up).

First we notice that with labor based on the level calculated to maintain high utilization, the labor resources are, in fact, highly utilized (87.5% or higher). However, it is also apparent that this significantly constrained the throughput rate. TTG had the smallest increase when labor was doubled; a 10.58% increase (10176 vs 9203). While TTG improved the least, this would conversely mean that TTG does the best job utilizing labor resources when they are constrained to achieve high utilization. Because TTG tries to balance WIP at all operations, and maintains a reasonable level of WIP (more than one-piece flow, but less than DBR of DynDBR), it ensures the labor is working on items in such a way that they move through the system.

DBR and DynDBR had similar 21% increases in throughput rate when labor resources were doubled. They also saw a similar reduction in labor utilization of 45%. Both methods surpassed TTG in throughput rate performance. Therefore, DBR and DynDBR with slack labor resources move more WIP towards completion. This is logical; with lots of WIP and excess labor there is no reason, except for set-up, that production should ever be delayed at the constraints. Most notably, however, is that DynDBR, with unconstrained labor, was the best throughput rate performer. This supports the statement above, that more WIP and excess labor is a recipe for greater throughput rate in this unbalanced production cell application. DynDBR had the highest WIP level in the constrained (3 labor resource) case.

The method that had the greatest increase in throughput rate, and the least degradation in utilization, was one-piece flow. While it started from a lower throughput rate, one-piece flow utilized the additional labor best (61.4% utilization) and completed 44% more piston-discs. One-piece flow did not, however, produce as many piston-discs as DBR, DynDBR or TTG. While it benefited the most, even if additional labor was profitable (discussed below), we would still not use one-piece flow in this application.

	One Piece			Drum Buffer Rope			Dyn-DBR			Takt Time Grouping		
# of Labor Resources	Through-put Rate	WIP	Labor Utilization	Through-put Rate	WIP	Labor Utilization	Through-put Rate	WIP	Labor Utilization	Through-put Rate	WIP	Labor Utilization
3	6602	13	89.9%	8466	542	90.2%	8649	672	94.9%	9203	222	87.5%
6	9475	8	61.4%	10285	187	49.1%	10474	383	51.7%	10176	189	48.0%
% Difference	**44%**	**-36%**	**-32%**	**21%**	**-66%**	**-46%**	**21%**	**-43%**	**-46%**	**11%**	**-15%**	**-45%**

Table 33: Throughput Rate and WIP When Labor is Unconstrained – Light Machining Process

Data is for the high Move, high COV, high Set-up treatment

	Dyn-DBR (same as Table 33)			Takt Time Grouping 2 Kanbans per Operation			Takt Time Grouping 4 Kanbans per Operation			Takt Time Grouping 6 Kanbans per Operation		
# of Labor Resources	Through-put Rate	WIP	Labor Utilization	Through-put Rate	WIP	Labor Utilization	Through-put Rate	WIP	Labor Utilization	Through-put Rate	WIP	Labor Utilization
3	8649	672	94.9%	9203	222	87.5%	9315	510	89.8%	9442	704	92.4%
6	10474	383	51.7%	10176	189	48.0%	10385	285	49.2%	10529	429	50.2%
% Difference	**21%**	**-43%**	**-46%**	**11%**	**-15%**	**-45%**	**11%**	**-44%**	**-45%**	**12%**	**-39%**	**-46%**

Table 34: TTG with Additional Kanbans – Throughput Rate and WIP When Labor is Unconstrained – Light Machining Process

Data is for the high Move, high COV, high Set-up treatment

The results from the initial experiment led to the conclusion that a higher WIP level in the cell, coupled with more labor, can increase throughput rate. Therefore, we sought to know if TTG could benefit from greater WIP levels, if labor was unconstrained. In Table 34 we show the results of increasing the number of kanbans from two per operation to four and six. We left the DynDBR results from the initial experiment in this table to compare TTG against the best throughput rate performer from the initial experiment discussed in this Section. What we find provides support for additional research on WIP levels and labor in TTG flow cells. Increasing the allowable level of WIP, by increasing the number of kanbans between each operation, increases throughput rate. However, this comes at a cost of additional WIP, and likely slower flowtime. (We do not show the flowtime results, but prior research proved, using Little's Law, that flowtime correlates with WIP levels (Spearman et al. 1990).) TTG out-performs DynDBR with unconstrained labor, when TTG uses 6 kanbans per operation; but then the WIP level was slightly higher than DynDBR (429 units for TTG, 383 units for DynDBR).

However, while the analysis above is interesting, what we don't know from this specific experiment is whether having slack labor resources available in the production cell is economical. This would depend on the cost of labor and the value of the items being produced. We must determine whether the marginal profit earned from the additional labor is positive. To help practitioners make this decision, a simple gross profit versus labor cost analysis is shown below in Table 35. We are assuming that each piston-disc earns the firm on average $1 of gross profit (sale price minus material cost) and the variable wage rate for an operator working in the light machining flow cell is $20 per hour. We can see that increasing the number of people from three to six is not a wise financial decision for any of the production methods.

Profit of running cell with 3 Operators

	One-Piece	DBR	DynDBR	TTG
Units Produced	6602	8466	8649	9203
Gross Profit $	$6,602	$8,466	$8,649	$9,203
Labor Hours	360	360	360	360
Labor Cost	$7,200	$7,200	$7,200	$7,200
Profit / Loss	-$598	$1,266	$1,449	$2,003

Profit of running cell with 6 Operators

	One-Piece	DBR	DynDBR	TTG
Units	9475	10285	10474	10176
Gross Profit $	$9,475	$10,285	$10,474	$10,176
Labor Hours	720	720	720	720
Labor Cost	$14,400	$14,400	$14,400	$14,400
Profit / Loss	-$4,925	-$4,115	-$3,926	-$4,224

Profit Delta	-$4,327	-$5,381	-$5,374	-$6,226

Table 35: Weekly Profit or Loss from Additional Labor – Light Machining Process
Data is for the high Move, high COV, high Set-up treatment

We have learned three important lessons from the unconstrained labor experiments. First, TTG does the best job in utilizing constrained labor resources to move WIP through the production process towards completion. If labor resources are constrained (perhaps because of availability of skilled operators) or labor is expensive relative to the value of the product being manufactured, TTG is the preferred method. This is important as this light-machining process, in reality, requires skilled operators who can set-up and run machinery that creates a product requiring fine tolerances. Second, we can improve the performance of the TTG flow cell by increasing the allowable WIP level. This was true when labor was constrained (3 operators) or unconstrained (6 operators). Finally, it is clear from this experiment that labor has a large and significant effect on the throughput rate of these four production processes. The magnitude of the effect is second only to the set-up time factor. In Section 6 we noted that labor was allocated to entities based on Arena's default setting (the entity that was in any process queue the longest gets the highest priority for seizing labor resources). Additional options are available to prioritize the entities that seize labor resources that are released. Two options that could be realistically implemented, and may provide benefits to firms under constrained resource scenarios, are 1) labor resources preferentially go, when released, to "current" constraint operations, if this operation does not have a labor resource, and 2) labor resources go, when released, to the process that has the largest queue and does not have a labor resource. It is possible that the four methods under investigation in this study may react differently when different labor prioritization schemes are used. Therefore, additional comparison analysis is needed to understand how TTG performs against one-piece flow, DBR and DynDBR when these labor resource schemes are applied.

We also see that additional analysis is needed to understand if and when firms can profitably add slack labor to produce more units. While firms do not often size their labor force to achieve lower labor-utilization, that may be a profitable decision. Future studies could develop general tradeoff curves to determine if having idle production operators, so that they could be available when needed, would actually increase a firm's profit. Additionally, application-specific simulation analysis could be used to optimize the decision of how much labor to use in any of the methods investigated in this study.

Finally, the results show that increasing the number of kanbans improves throughput rate for both constrained and unconstrained labor. More experiments are needed to determine optimal buffering and understand the tradeoff of throughput rate versus more WIP and slower flowtime.

Section 11: Makespan Performance of One-Piece Flow, DBR, DynDBR and TTG

This analysis is divided into four sections. In Sections 11.1, 11.2 and 11.3 we compare the makespan and average WIP performance for each method on each of the three production applications (light machining, heavy machining and assembly). In Section 11.4 we will discuss the overall findings of measuring makespan and average WIP.

Section 11.1: Makespan Performance in the Light Machining Process

In the light machining makespan experiment we produced 450 of each part number (D1 through D9), for a total quantity produced of 4050. The high Move, high COV, high Setup treatment was used for this experiment. This treatment most closely matches the actual parameters of this operating production cell. The performance measures include the makespan and average WIP in the production cell from initiation until each replication had completed 4050 units (for 100 replications). The results are shown in Table 36a and the percent difference of TTG versus the other production methods is shown in Table 36b. In addition to the data, Figure 13 shows the level of WIP by hour, averaged over all replications. (The reason why there was WIP in the process after the average makespan times in Table 36a was due to the randomness of makespan in the 100 replications.)

	One Piece	DBR	DynDBR	TTG
Avg. Makespan (hours)	78.2	59.4	57.3	56.3
Average WIP (units)	12.6	555	673	261

Table 36a: Makespan and Average WIP – Light Machining Process
Data is for the high Move, high COV, high Set-up treatment

	TTG vs. OnePiece	TTG vs. DBR	TTG vs. DynDBR
Avg. Makespan (hours)	-28.0%	-5.3%	-1.8%
Average WIP (units)	1968.9%	-53.0%	-61.3%

Table 36b: Percent Difference TTG versus Other Methods, Makespan and Average WIP – Light Machining Process

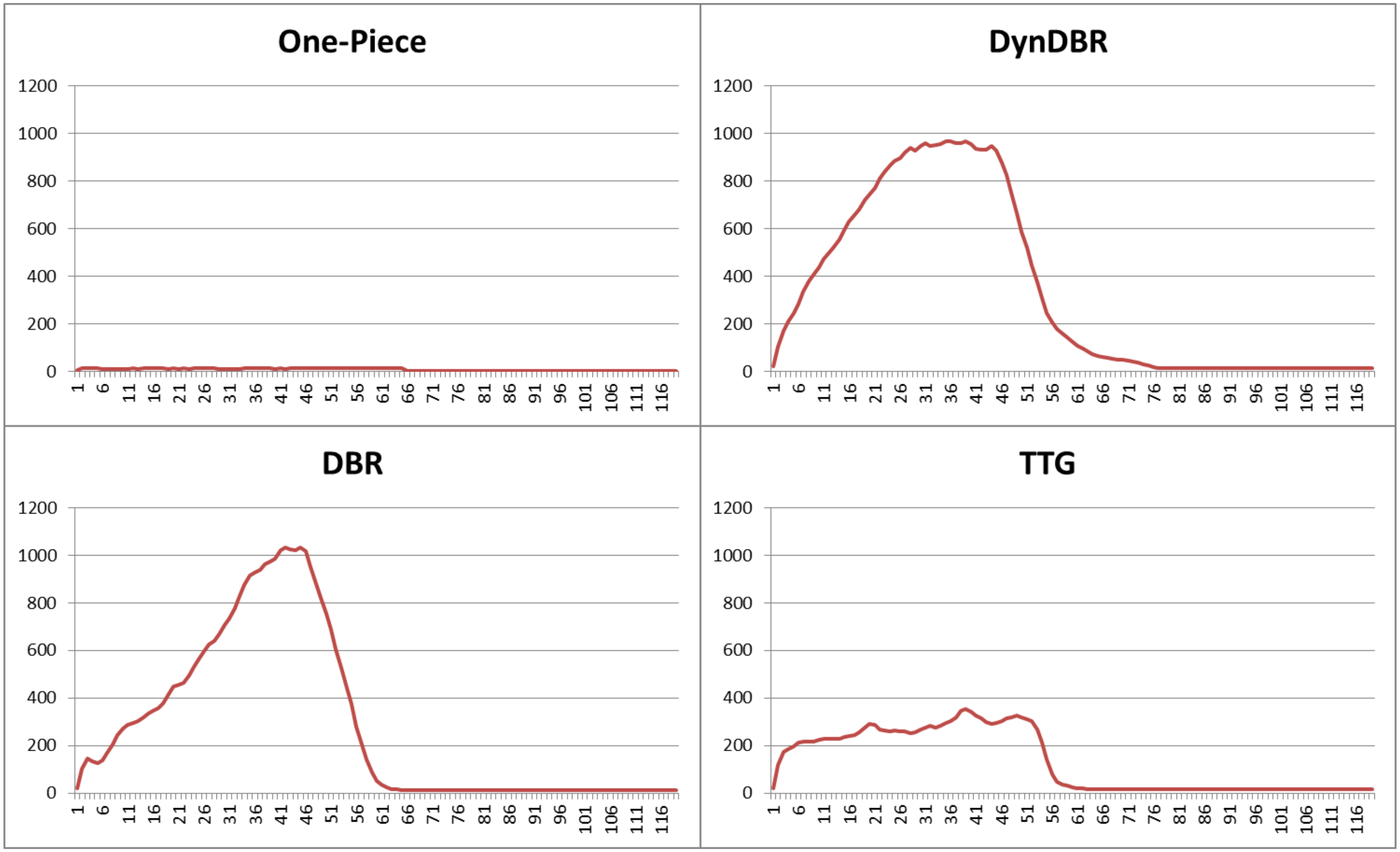


Figure 13: WIP by Hour – Makespan Experiment – Light Machining Process

The results of measuring makespan and average WIP are similar to the throughput rate experiments in Section 7. On average, TTG completed the total order quantity the fastest at 56.3 hours. It was 1.8% faster than DynDBR (57.3 hours) and 5.3% faster than DBR (59.4 hours). One-piece flow was the worst performer, requiring 78.2 hours to complete 4050 piston discs. While the difference in makespan between TTG and DynDBR was only one hour, this was statistically significant ($p = 0.0165$). TTG also completed the total order quantity using less than half the average WIP of DynDBR and DBR.

When considering a makespan scenario, the average amount of WIP could be considered to be unimportant, as it all will be turned into finished goods. However, if floor-space is limited, a firm would still want to use a method that minimizes, and closely controls, WIP. We also measured WIP to evaluate the change in WIP levels over time. Figure 13 provides additional insight into how WIP flows through the flow cell using each method. One-piece flow maintains a very low level of WIP throughout the simulation and drops off to zero very quickly. DBR and DynDBR both climb to very high WIP levels, then go down somewhat slowly as new items stop entering the system. TTG reacts similarly to one-piece flow but with a moderately higher WIP level. Unlike DBR and DynDBR, TTG does not have a spike in WIP level. It maintains a level amount of WIP, and then quickly depletes all WIP in the process.

The analysis in Section 7 explained the positive benefit of a moderate WIP level for reducing the effect of operation cycle time variation and set-up. This analysis applies when using makespan as the performance measure. From both the throughput rate and makespan analyses, we see that TTG allows a reasonable amount of WIP in the system, maintains that level, and uses varying transfer-batch sizes to create even flow in the light machining process. This results in high throughput rate and short makespan time.

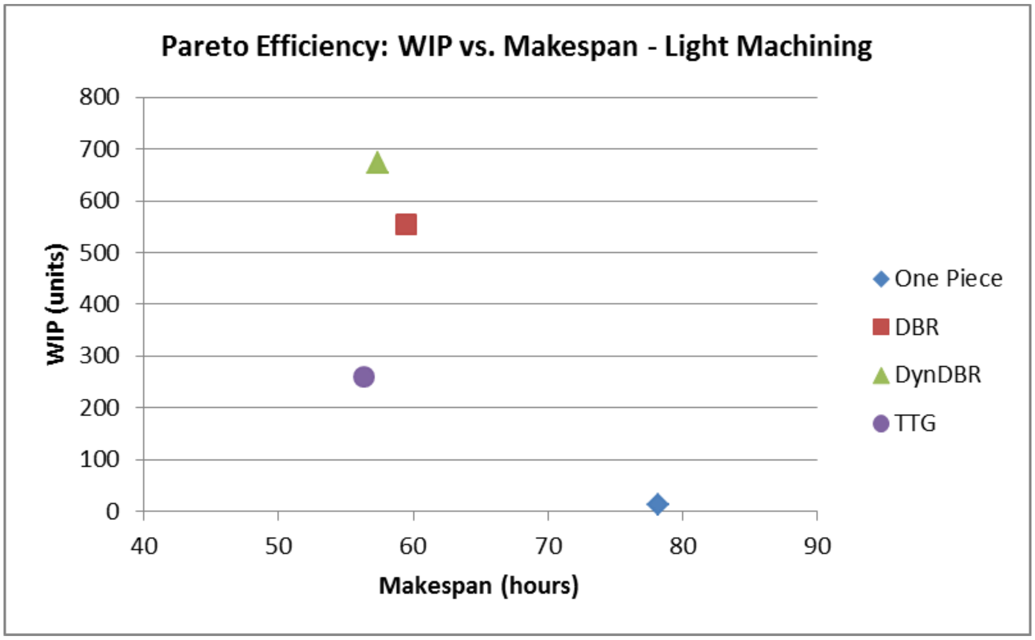


Figure 14: Pareto Efficiency: WIP versus Makespan – Light Machining Process

An alternate analysis for evaluating the results of the light machining application is to graph WIP versus makespan. This is shown in Figure 14. This graph clearly demonstrates that TTG, with a faster makespan time and much less WIP, is more Pareto efficient than DBR or DynDBR. The choice between TTG and one-piece flow, from this perspective is not as clear. TTG and one-piece flow create a Pareto frontier (Fang et al. 2011). If less WIP is the preference of the firm, then one-piece flow would be the chosen method, whereas if faster makespan is the preference of the firm (which is likely), then TTG is superior. DBR and DynDBR would never be the preferred methods as they have much more WIP than either TTG or one-piece flow, and have a longer makespan than

TTG. A logical next step in this research is to apply a value to makespan, which would enable practitioners to determine the most profitable method, based on the tradeoff of the cost of WIP versus the value of faster makespan.

Section 11.2: Makespan Performance in the Heavy Machining Process

In the heavy machining makespan experiment we produced a total quantity of 532 slide-valves, or approximately half of a week's worth of demand. Specifically we produced the following quantities of each of the four part numbers in the slide-valve product family; 240 S8 slide-valves, 72 S10 slide-valves, 110 S12 slide-valves and 100 S16 slide valves. (As a reference, the quantity per part number used in all of the throughput rate simulation models was discussed at the end of Section 6.) The high Move, high COV, high Setup treatment was used for this experiment. This treatment most closely matches the actual parameters of this operating production cell. We measure the average time and the average WIP in the production cell from initiation until each replication had completed 532 units (over all 100 replications). The results are shown in Table 37a. Table 37b has the percentage improvement of TTG versus the other three methods.

	One Piece	DBR	DynDBR	TTG
Makespan (Hours)	72.2	65.1	65.2	64.8
Average WIP (units)	7.1	165	162	113

Table 37a: Makespan and Average WIP – Heavy Machining Process
Data is for the high Move, high COV, high Set-up treatment

	TTG vs. OnePiece	TTG vs. DBR	TTG vs. DynDBR
Makespan (Hours)	-10.4%	-0.6%	-0.7%
Average WIP (units)	1493.3%	-31.3%	-30.3%

Table 37b: Percent Difference TTG versus Other Methods, Makespan and Average WIP – Heavy Machining Process

Figure 15 shows the WIP by hour for each method. It should be noted, that while DBR and DynDBR look identical, there are small differences in these graphs. In addition, the reason why there was WIP in the process after the makespan times shown in Table 37a was due to the randomness of makespan in the 100 replications.

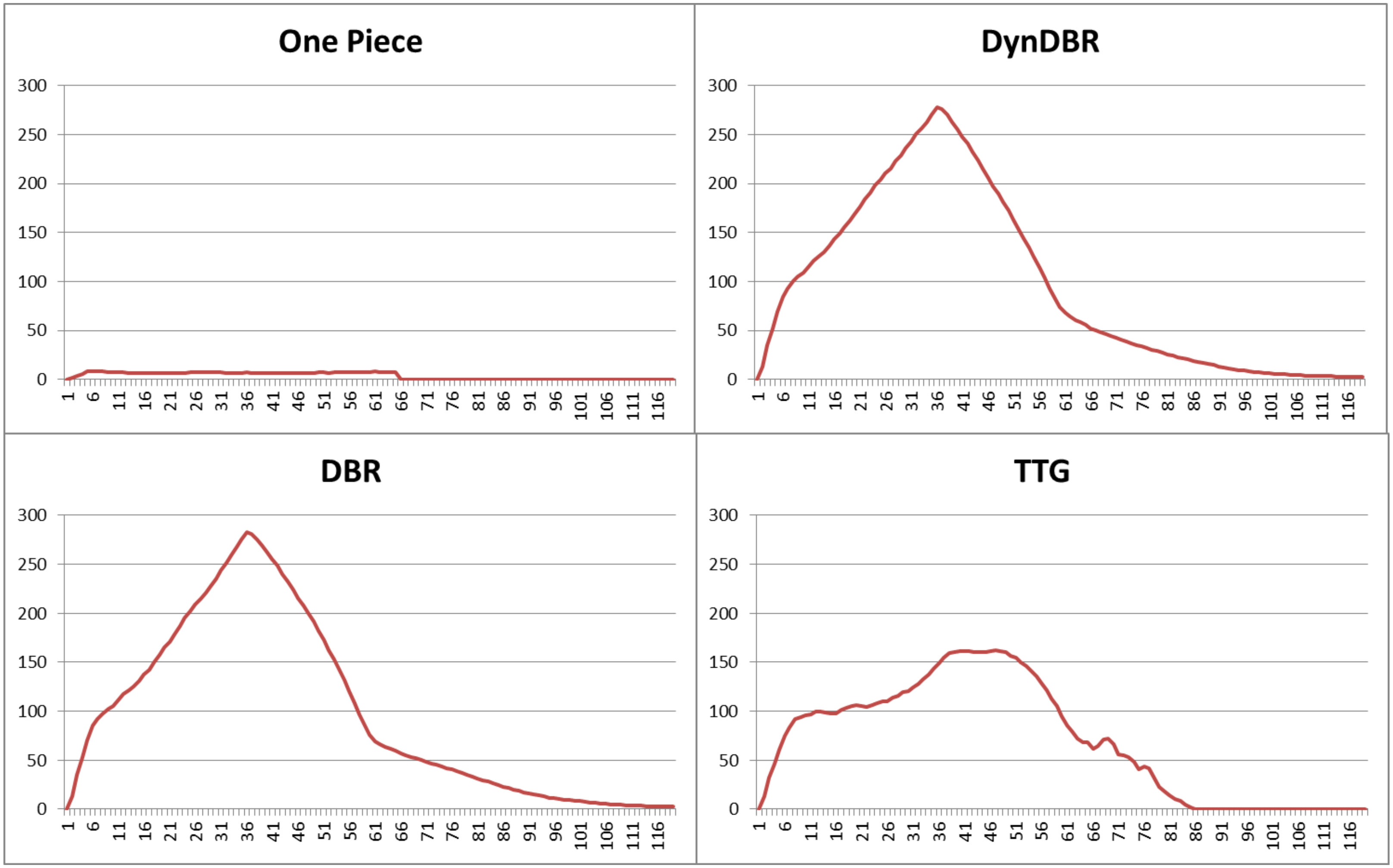


Figure 15: WIP by Hour – Makespan Experiment – Heavy Machining Process

Once again TTG completed the total order quantity the fastest, with an average makespan of 64.8 hours. However, the difference from the next fastest, DBR at 65.1 hours, or DynDBR at 65.2 hours was not statistically significant (p-value = 0.386). One-piece flow was the worst performer, requiring 72.2 hours to complete 532 slide-valves. Therefore, the results, based on makespan, are similar to those in Section 8. TTG, DBR and DynDBR were all very close in performance as measured by throughput rate. (In the fixed duration experiments discussed in Section 8, TTG and DBR were not statistically different and DynDBR was only slightly worse.) As stated in Section 8, in this heavy machining application, sufficient WIP helps to overcome the disruptions due to operation cycle time variation and very long set-up times.

The TTG graph in Figure 15, however, provides further insight into why TTG did not substantially outperform DBR or DynDBR in the heavy machining application. Unlike the light-machining application, TTG did not demonstrate an even flow of WIP. If one compares the TTG graph from Figure 13 to Figure 15, we see that TTG had increasing levels of WIP in the heavy machining process versus even levels of WIP in the light machining process. Increasing levels of WIP could have been logical if the sequence of items being produced in the heavy machining process had successively larger transfer-batch sizes. WIP would increase because the same number of transfer-batches with larger transfer-batch sizes equates to more WIP. However, the opposite was true. The sequence started with S8, then S10, S12 and finally S16 slide-valves. The transfer-batch sizes of these part-numbers got smaller, further into the sequence, as seen in Table

38. Even though the transfer-batch sizes were getting smaller, WIP in the TTG flow cell increased.

Part Number	**Transfer-Batch Size (units)**
S8	15
S10	12
S12	11
S16	8

Table 38: Takt Time Group (Transfer-Batch) Sizes – Heavy Machining Process
Based on 60 minute Tempo-Time (T)

The reason WIP increased in the TTG flow cell was the increasingly large set-up times further into the sequence. As seen in Table 4 of Section 5 and Table 31 of Section 9, the set-up times at Operations 3 and 6 increased dramatically further into the sequence. The set-up time of the S16 slide-valve, at Operations 3 and 6, approximately double the set-up time of the prior part number in the sequence, the S12 slide-valve. These very long set-up times cause all of the kanbans to be filled with transfer-batches, creating the peak of WIP towards the end of the production run.

These results suggest that TTG's variable transfer-batch sizes (which create a relatively constant tempo of all transfer batches at their constraint operation) did not provide the same benefit in the heavy machining process as it did in the light machining process. Instead it was TTG's kanban WIP control at each operation, in combination with the use of transfer-batches, that provided the minimum, but sufficient, level of WIP to overcome disruptions in the heavy-machining application. This production process, has large cycle times, very long and uneven set-up times, and process variation. These attributes created disruptions in the flow of product through the operations. The TTG method was able to overcome these disruptions, with much less WIP than DBR and DynDBR. The kanbans between each operation essentially maintained the minimum WIP level needed to overcome the disruptions. A process with less WIP, if disruptions and variation are ameliorated, will have faster makespan time due to Little's Law.

This experiment demonstrates the robustness of the TTG method. Because it combines multiple features from other WIP control methods (kanbans, transfer-batches, and constraints-based transfer-batch sizing), it can perform well in many different applications.

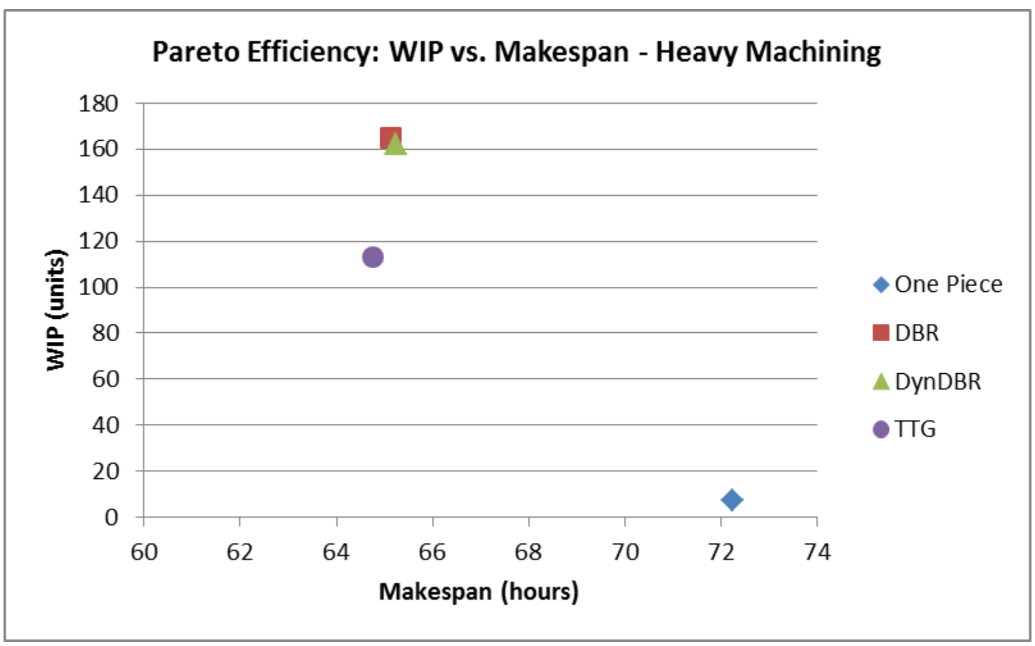


Figure 16: Pareto Efficiency: WIP versus Makespan – Heavy Machining Process

Figure 16 shows the Pareto efficiency of each method for the heavy machining application. Similar to the light machining application, this graph demonstrates that

TTG, with a faster makespan time and less WIP, is more Pareto efficient than DBR or DynDBR. The choice between TTG and one-piece flow, from this perspective is not as clear because TTG and one-piece flow create a Pareto frontier. If less WIP is the preference of the firm, then one-piece flow would be the chosen method, whereas if faster makespan in the preference of the firm (which is likely), then TTG is superior. DBR and DynDBR would never be the preferred methods as they have much more WIP than either TTG or one-piece flow, and have a longer makespan than TTG.

Section 11.3: Makespan Performance in the Assembly Process

In the assembly makespan experiment we produced a total quantity of 4050 solenoids, or approximately half of a week's worth of demand. The low Move, low COV, low Setup treatment was used for this experiment. The results are shown in Table 39a. Table 39b has the percentage improvement of TTG versus the other three methods. Figure 17 shows the WIP by hour for each method.

	One Piece	DBR	DynDBR	TTG
Makespan (Hours)	53.35	55.90	53.14	53.20
Average WIP (units)	9.4	120	89	94

Table 39a: Makespan and Average WIP – Assembly Process
Data is for the high Move, high COV, high Set-up treatment

	TTG vs. OnePiece	TTG vs. DBR	TTG vs. DynDBR
Makespan (Hours)	-0.3%	-4.8%	0.1%
Average WIP (units)	897.7%	-21.8%	5.6%

Table 39b: Percent Difference TTG versus Other Methods, Makespan and Average WIP – Assembly Process

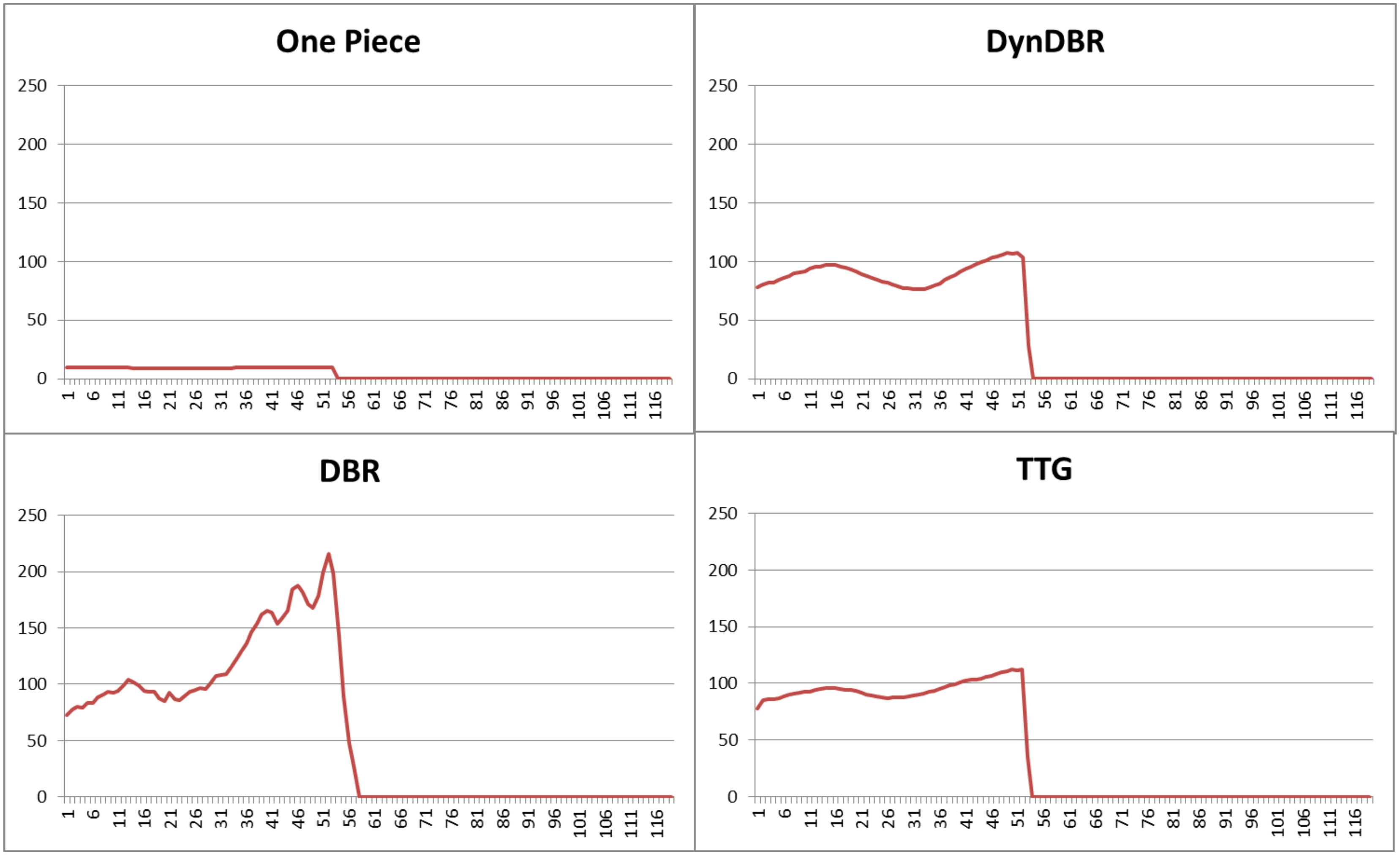


Figure 17: WIP by Hour – Makespan Experiment – Assembly Process

Unlike the light machining and heavy machining applications, in this experiment we used the low Move, low COV, low Setup treatment. As discussed in Section 9, the assembly application can experience a range of factor levels. However, most often this process has low operation cycle time variation and low set-up time. In this application one-piece flow, DynDBR and TTG are virtually equal in makespan. The difference in DynDBR's makespan (53.14 hours) versus one-piece flow's makespan (53.35 hours) was approximately 13 minutes. The difference in DynDBR's makespan (53.14 hours) and TTG's makespan (53.20 hours) was approximately 4 minutes. These differences, while very small, are actually statistically significant (p-value < 0.0001) because makespan was extremely consistent over the 100 replications. The standard deviation of makespan was 0.105 hours for one-piece flow, 0.103 hours for DynDBR and 0.097 hours for TTG. This consistency can also be seen in Figure 17's one-piece flow, DynDBR and TTG graphs. Unlike Figure 13 (light machining) and Figure 15 (heavy machining) the WIP in Figure 17 drops off quickly for one-piece flow, DynDBR and TTG.

In the comparatively balanced assembly process we see a practical three-way tie in makespan. To understand the similarities in one-piece flow, DynDBR and TTG we added to this analysis the WIP by hour graph for the one-piece flow method with its natural scale (See Figure 18 below). Comparing this graph with the pattern of WIP by hour in Figure 17's DynDBR and TTG graphs, we can see that they all look similar, with the slight edge in makespan performance going to DynDBR. However, these are essentially the same makespan times, even if there is a statistically significant difference.

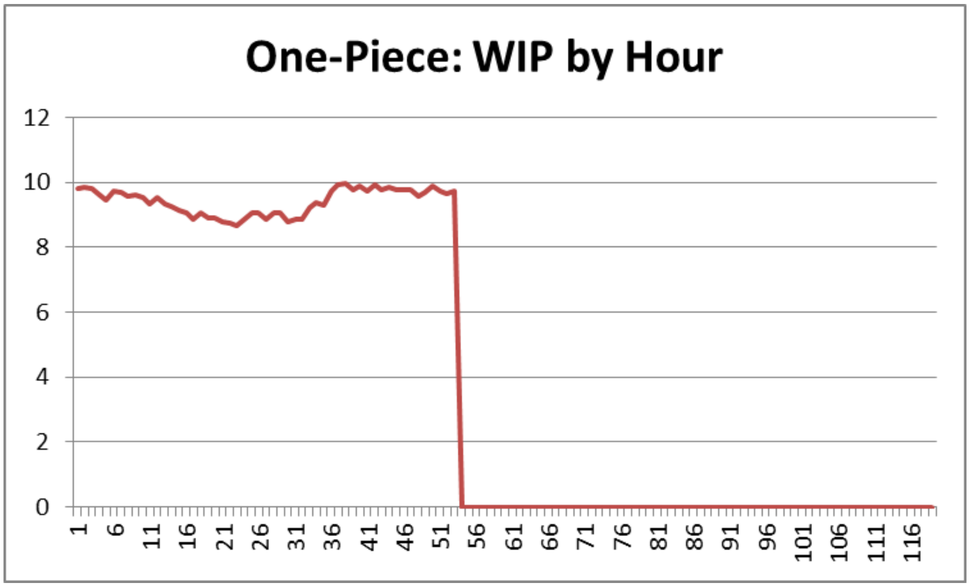


Figure 18: One-Piece Flow WIP by Hour – Makespan Experiment – Assembly Process

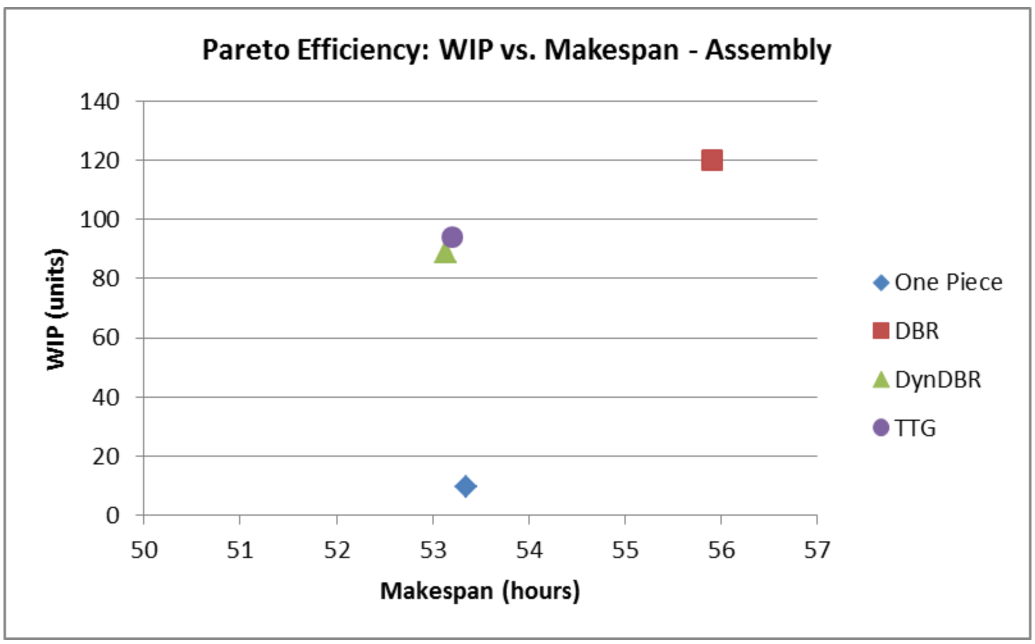


Figure 19: Pareto Efficiency: WIP versus Makespan – Assembly Process

Figure 19 shows the WIP by makespan graph of the four methods for the assembly process. As a reminder to the reader, the treatment used in this application was the low Move, low COV, low Setup. From this graph we see the advantages that one-piece flow demonstrates in a balanced process with minimal disruptions. It had almost as fast a makespan time as DynDBR and TTG, but with much less WIP. As stated previously in this study, these results are not surprising. One-piece flow was intended for balanced processes with minimal disruptions due to operation cycle time variation (Yavuz and Satir, 1995) or set-up time (Monden, 1998). These were exactly the conditions that existed for the assembly application in this makespan experiment, and as expected, one-piece flow was the best choice when considering both WIP and makespan.

Practitioners would, therefore, appear to have a choice of methods in this relatively well balanced case. Although this assembly application is especially suitable for one-piece flow, TTG has shown itself to be more robust than one-piece flow over a range of conditions. In addition, TTG is probably easier to apply than DynDBR.

Section 11.4: Summary Makespan Experiments

The results from the makespan experiment generally match and reinforce those from the throughput rate experiments. However, these results provide clarification. TTG was either the best performer (for the light machining and heavy machining application) or, in the assembly application, matched one-piece flow and DynDBR in terms of makespan. In the assembly application, one-piece flow, DynDBR and TTG had similar performance due to the very similar patterns of WIP flow over time.

The makespan experiments also provided clarification of why TTG does not substantially outperform DBR or DynDBR in the heavy machining application, when using throughput rate as the primary performance measure. This application had very long and unbalanced set-up times. In this production environment there was no significant advantage to TTG's varying transfer-batch size and constant tempo. The set-up times were too disruptive, and order quantities too small, to make an even flow of WIP possible. Instead, it was TTG's moderate level of WIP from the use of transfer-batches and kanban control of WIP at each operation that allowed it to perform slightly better than DBR and DynDBR in terms of throughput rate (See Section 8), with smaller levels of WIP.

The most important conclusion of these experiments is that TTG was always the best or among the best performers. No other method achieved this level of makespan (and throughput rate) performance across all three manufacturing applications.

Section 12: Conclusion

The conclusion is divided into three sections. Section 12.1 will review the generalized findings from this research study. Section 12.2 will summarize why TTG achieved superior performance in these applications. Section 12.3 will discuss areas for additional research of the TTG method, including extensions and improvements.

Section 12.1: Generalized Findings about Takt Time Grouping

Takt Time Grouping (TTG) was developed to utilize flow manufacturing in an unbalanced production process with moving constraints. Neither one-piece flow nor DBR have been shown to be effective in these production environments. In this study we compared TTG to one-piece flow, DBR, and a modified DBR designed for processes with moving constraint operations that we call Dynamic DBR (DynDBR). These four methods were tested under various operating conditions while measuring multiple performance metrics. The operating conditions we altered include: 1) balanced and unbalanced flow processes, 2) low, medium and high set-up times, 3) high and low move time between operations, 4) high and low operation cycle time variation, and 5) constrained and unconstrained labor availability. The results demonstrate that TTG is the most robust method across these varied operating conditions. In every case TTG had the best, or very close to the best performance, as measured by throughput rate and makespan; with consideration given to secondary performance measures, flowtime and WIP. One-piece flow consistently had the fastest flowtime and least WIP, but was always the worst, or almost the worst, in throughput rate and makespan performance. TTG always outperformed DBR and DynDBR when measuring flowtime and WIP. We can therefore conclude that when a firm faces a large range of possible operating conditions in its flow cells, either from the deterministic nature of the process or due to process randomness, TTG is likely the best choice to optimize throughput rate and makespan performance.

In addition to these general findings, we can accept or reject most of the hypotheses from Section 4. These conclusions are shown in Table 40.

#	Hypothesis Description	Accept	Reject	In-conclusive
H1	Throughput rate performance of one-piece flow is more negatively affected by large move-times than DBR, DynDBR and TTG	X		
H2	Throughput rate performance of one-piece flow is more negatively affected by high operation cycle time variation than DBR, DynDBR and TTG	X		
H3	Throughput rate performance of one-piece flow is more negatively affected by large set-up times than DBR, DynDBR and TTG	X		
H4	Interaction effects exist between move-time, operation cycle time variation and set-up time which affect throughput rate of all four methods			X
H5	One-piece flow will have the lowest WIP and fastest flowtime for all applications	X		
H6	TTG will always have lower WIP and faster flowtime than DBR and DynDBR	X		
H7	One-piece flow will out-perform DBR, DynDBR and TTG, as measured by throughput rate, for the assembly process		X	
H8	One-piece flow will perform worse than DBR, DynDBR and TTG, as measured by throughput rate, for the light and heavy machining processes	X		

Table 40: Conclusions to Hypotheses

Section 12.2: Why TTG Achieved Superior Performance

The superior performance of TTG is due to three elements: 1) the use of transfer-batches, 2) varying the transfer-batch size to attain a near-constant tempo at constraint operations and 3) kanban control of WIP at every operation. Transfer-batching has multiple benefits. When comparing the use of transfer-batches to a one-piece flow cell design, transfer-batches reduce the effect of move-time between operations by allocating the move time over a larger quantity. Transfer-batches also create a moderate level of WIP, which reduces the impact of set-up time disruptions and dampens operation cycle time variation. Finally, transfer-batches reduce the impact of operation cycle time variation because of the Law of large numbers.

Varying transfer-batch sizes across the items produced in a flow cell, to maintain a near-constant tempo at constraint operations, keeps a relatively even flow of WIP moving through the process. This near-constant tempo enables TTG to maintain an even flow of WIP (transfer-batches) when constraints move and the operation cycle times at the constraints are very different. These outcomes are best seen in the light machining experiments. This application has very different cycle times at the constraint operations and three different constraint operations. In this application TTG produced greater throughput rate and shorter makespan times than any of the other three methods.

Kanban control of WIP at each operation distributes WIP relatively evenly at all operations. When combined with transfer-batches, kanbans create a moderate level of WIP, evenly distributed in the flow cell. Although greater than the one-piece flow method, WIP levels for TTG are less than DBR or DynDBR. This evenly distributed, moderate level of WIP, buffers set-ups and dampens operation cycle time variation. In addition, because the WIP level is significantly smaller than DBR and DynDBR the TTG flow cells generally operated faster than these two methods, as measured by flowtime. This was shown experimentally in this study and supported using Little's Law by Spearman et al. (1990). TTG's kanban buffers can also be designed to accommodate balanced and unbalanced processes. This was demonstrated in the assembly application experiments. With evenly distributed kanbans, TTG very slightly underperformed DynDBR, in terms of throughput rate, in the balanced assembly application. However, when the kanbans are distributed to place more WIP at the constraint operations, TTG outperformed DynDBR as measured by throughput rate, and achieved these results with less WIP. In the very unbalanced light machining application, it is the even distribution of WIP in the TTG flow cell that improved flow and achieved a demonstrably higher throughput rate than DBR and DynDBR. Finally, kanban control of WIP results in the most effective use of constrained labor resources. Because there is a moderate level of WIP at all operations in a TTG flow cell, constrained labor resources will move to different operations and therefore keep the product moving to completion.

Section 12.3: Future Research Opportunities – Extending and Improving TTG

The experiments and analysis in this study are only the beginning of the research into TTG. The additional research questions under consideration fall into four categories: 1) understanding the effect of labor on TTG and its competing methods, 2) modifications and refinements to TTG to enhance its performance, 3) extensions to processes beyond discrete manufacturing, and 4) extensions to supply chains.

Understanding the Effect of Labor

The experiments from Section 10 highlighted multiple opportunities to understand how TTG, and the competing methods, perform when labor resources are the experimental factor that is changed. The experiment described in Section 10 altered the number of labor resources from highly constrained (achieving greater than 80% utilization) to completely unconstrained. We saw that this changed the results and had a large impact on throughput rate of all four WIP control methods. Using these results we have conceived additional experiments. First, we can increase the number of labor resources from three to six, by single labor resource increments, and understand shape of the throughput rate versus labor resource graph. In addition, we can use the financial metrics from Section 10 (labor costs, gross profit per unit) to graph marginal profit versus the number of labor resources.

Other experiments would alter the way labor resources are prioritized when released at a process. Two possible methods discussed in Section 10 are 1) prioritizing the current constraint operation and 2) prioritizing operations with the largest WIP queue.

The purpose of all experiments would be to understand how TTG and its competing methods react to changing labor allocation schemes. This will further the understanding of when TTG is better and why. It may be that TTG is most effective in labor constrained environments. We expect to use these results to provide industry with recommendations for how to design and operate their TTG flow cells.

Improving TTG's Performance

Perhaps the most interesting research area for TTG is improving its intrinsic performance. We have mentioned earlier three implementation decisions that need further refinement; 1) determining the grouping tempo-time, 2) how to sequence different part numbers when part numbers have different constraints, and 3) determining the best number and location of kanbans. We will seek to create analytical models to provide optimal solutions. However, if optimal solutions are not attainable, developing heuristics or decision flow charts to improve TTG's performance would still be beneficial.

The decision flow chart in Figure 1 shows how the author has worked with industry partners to determine the tempo-time. An optimal, or near-optimal solution, would depend on variables such as move-time between operations, set-up time, probability distributions of operation cycle times, the cost of labor and the value of the products. The solution would attempt to maximize profit by balancing the costs of inventory (WIP) and labor, with the value of additional throughput. It is likely that a closed-form equation is not achievable due to the non-linear effect of a stochastic variable (operation cycle time variation). Therefore, we may decide to omit operation cycle time variation from the analytical expression or develop nomographs to determine near optimal solutions.

Another "optimal decision" opportunity is the development of an analytical expression to choose the best WIP control method when choosing between faster makespan and less WIP. As discussed in Section 11, we can evaluate the four methods from the perspective of which is Pareto efficient when considering WIP and makespan performance. However, in this study we did not create analytical expressions to decide which method, along the Pareto frontier, provides the firm optimal profits. To do this we will need to determine the value of faster makespan. Once this determination is made, we should be able to create an analytical expression to optimize the tradeoff decision of faster makespan versus the cost of additional WIP.

An obvious opportunity for improvement lies in developing heuristics for sequencing different part numbers. Some (undocumented) experiments made during this study indicate that the part number sequence influences throughput rate. This is an area where manufacturing scheduling literature can provide some insight. Numerous heuristics exist such as shortest processing time first, longest processing time first and critical ratio. Initial experiments indicate there may be an advantage in sequencing products according to the location of their constraint; the earlier in the flow cell a products' constraint operation occurs, the earlier in the sequence the product should be run.

Another area that can benefit from existing literature is improving buffering the flow cell. In the DBR literature, two prominent studies (Radovilsky, 1998; Louw, et al. 2004) determined optimal time-buffers for DBR processes, and for one-piece flow. Price et al. (1994) summarized different optimization models for determining the number of kanbans to use in a production system. We can build on this literature for TTG, which uses kanbans that contain transfer-batches. In addition, in Section 9 we saw that unevenly distributing the kanbans improved performance of TTG in the assembly application. We plan to use the literature, and these initial findings, to determine the optimal number and placement of kanbans in a TTG flow cell.

Extensions Beyond Discrete Manufacturing

Rahman (1998) reviewed applications of TOC and DBR in industry. The DBR method, which started in discrete manufacturing, has been extended into process industries (Schragenheim et al. 1994), healthcare (Umble et al. 2006b) and others mentioned in the Literature Review. We believe TTG can also be extended beyond discrete manufacturing to process industries, healthcare and financial services (processing tax returns, loan applications, etc.). This research would combine the actual implementation of TTG, in coordination with our industry partners, and simulation modelling to perform deeper analysis.

Extensions to Supply Chains

The ultimate application of TTG would take it beyond a single factory or company to a supply chain. The data used in this study was from a single company that both manufactures components and assembles valves. However, we can utilize these data to consider a three-echelon supply chain. The piston disc produced in the light machining application is actually used in the solenoid produced in the assembly application. If one observes Figures 3 and 4 we can see that the solenoid is a component of the slide-valve. (The solenoid actuates the mechanism that moves the slide-valve into the open-shut position.) When one considers the optimization studies proposed above, decisions could change if the parts produced in a single flow cell all go on a truck and get stocked as components in a different factory which then are assembled and shipped to a third factory. Perhaps in this case the WIP value in the cell is immaterial as it will be stocked in much larger quantities on the truck and as components used in a downstream flow cell. We would like to also study if the entire supply chain could operate on a single Takt time used for the transfer-batch sizing formula. Currently many auto assembly plants, and their suppliers, operate on a single Takt time used to balance one-piece flow processes. When one-piece flow is sub-optimal it may be beneficial to use TTG throughout the supply chain, creating a single tempo for all echelons. In addition to buffering the flow cell, we would like to determine how to size the buffer in between echelons. The problem of buffering echelons between supply chains has been studied previously by many supply chain researchers, but not for a supply chain using TTG. Finally, we discussed the potential benefit of sequencing different part numbers to improve throughput rate and makespan. We may be able to determine the potential for sequencing this three-echelon supply chain and understand if sub-optimizing one echelon can improve results for the overall supply chain.

Appendix A: Discrete Event Simulation Model Design

The discrete event simulation model was created using Arena® software. The simulation model was originally designed to mimic an actual functioning TTG flow cell producing components used in shut-off (solenoid) valves. Important aspects of the model's design will be discussed in detail. The first is how to model an entity being held at an operation waiting for a kanban signal from a downstream operation to pull it into the operation. This code models the "pull" of a kanban-flow production system. The second important aspect is how to model a new part number going through a set-up on any operation that requires set-up.

The entities within the model represent different part numbers. Figure 2 shows a picture of the parts produced by a Takt Time Grouping flow cell. The tray represents a kanban in the flow cell. The kanbans shown are based on the Conwip concept by Spearman et al. (1990) in that it is generic and will hold all parts, in their transfer-batch quantity, flowing through the cell. The kanban is not part number specific. The example kanban tray is a 10x10 grid that can hold a group quantity up to 100 on small pins that stick out of the tray.

One of the first actions of the model after creation of the entities is to read in entity attributes from a data file. A sample of the data file (with titles added) is shown below in Table 41. Group quantity is used within the process blocks (or operations) to ensure the entity delays the resource (labor and machine) for the correct time. The customer order quantity is 900 for all parts i = 1..9. We used 900 as it is close to actual customer order quantities, and as a convenience to ensure an integer value of the total number of groups for all part numbers. The cycle time of a part number in an operation is multiplied by the group quantity to represent how long the entity will spend being processed (delayed) within the operation. The first group of every part number was also processed (delayed) for the duration of the set-up time. Set-up code is described in greater detail below.

The operation cycle time and set-up time expressions used in the model were based on observations of the actual operations and created data. The realized variation in operation cycle time is also based on observed and experimental settings, as well as adherence to the Law of large numbers for large quantities of parts within an entity. Set-up times used a non-symmetric triangular distribution with the following settings:

Minimum = set-up time / 2

Most Likely = set-up time

Maximum = set-up time *2

Stochastic operation cycle times used a normal distribution. We varied the standard deviation as an experimental setting. The operation cycle times shown in Table 41 represent the mean cycle time of each operation.

Sequent #	Part #	Group Quantity	Op 1 Cycle Time	Op 1 Set-up Time	Op 2 Cycle Time	Op 3 Cycle Time	Op 3 Set-up Time	Op 4 Cycle Time	Op 5 Machine Time	Op 5 Labor Time	Op 5 Set-up Time	Op 6 Cycle Time	Op 6 Set-up Time
1	1	45	20	2700	5	12	900	7	19	19	1800	12	600
2	1	45	20	2700	5	12	900	7	19	19	1800	12	600
3	1	45	20	2700	5	12	900	7	19	19	1800	12	600
4	1	45	20	2700	5	12	900	7	19	19	1800	12	600
5	1	45	20	2700	5	12	900	7	19	19	1800	12	600
6	1	45	20	2700	5	12	900	7	19	19	1800	12	600
7	1	45	20	2700	5	12	900	7	19	19	1800	12	600
8	1	45	20	2700	5	12	900	7	19	19	1800	12	600
9	1	45	20	2700	5	12	900	7	19	19	1800	12	600
10	1	45	20	2700	5	12	900	7	19	19	1800	12	600
11	1	45	20	2700	5	12	900	7	19	19	1800	12	600
12	1	45	20	2700	5	12	900	7	19	19	1800	12	600
13	1	45	20	2700	5	12	900	7	19	19	1800	12	600
14	1	45	20	2700	5	12	900	7	19	19	1800	12	600
15	1	45	20	2700	5	12	900	7	19	19	1800	12	600
16	1	45	20	2700	5	12	900	7	19	19	1800	12	600
17	1	45	20	2700	5	12	900	7	19	19	1800	12	600
18	1	45	20	2700	5	12	900	7	19	19	1800	12	600
19	1	45	20	2700	5	12	900	7	19	19	1800	12	600
20	1	45	20	2700	5	12	900	7	19	19	1800	12	600
21	2	45	20	2700	7	17	900	5	19	19	1800	12	600
22	2	45	20	2700	7	17	900	5	19	19	1800	12	600

Table 41: Sample of Entity Operation cycle time Attributes

This model simulates a kanban pull process by holding entities in an operation until the downstream operation can accept an additional entity based on the number of kanbans between the two operations. As an entity is entering an operation, an “assign block” updates a global variable EntitiesInProcessX by 1 (X denotes the operation number). This is shown below in Figure 20. The entity then seizes and delays the resource in the “process block” based on the entity’s group quantity and operation cycle time attributes. The “hold block”, shown in Figure 21, holds the entity until the number of entities in the downstream operation is less than a preset variable ProcessXKanban (X denotes the operation number). If the number of entities in the operation is less than ProcessXKanban, the “release block” releases the entity from the resource and the entity moves to the next operation. The “assign block” then subtracts one from the global variable EntitiesInProcessX. Entities are moved to the next operation by a separate move block that uses only labor resources to move the entity based on inputted move-times, which are set at a constant of either one or ten seconds based on the experimental run.

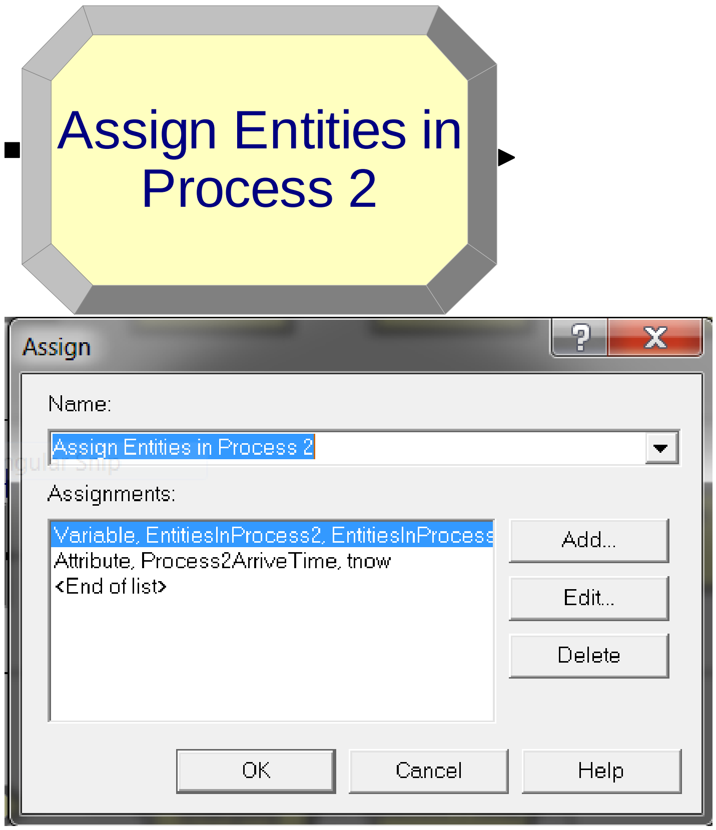


Figure 20: Assigning Entity Count in an Operation

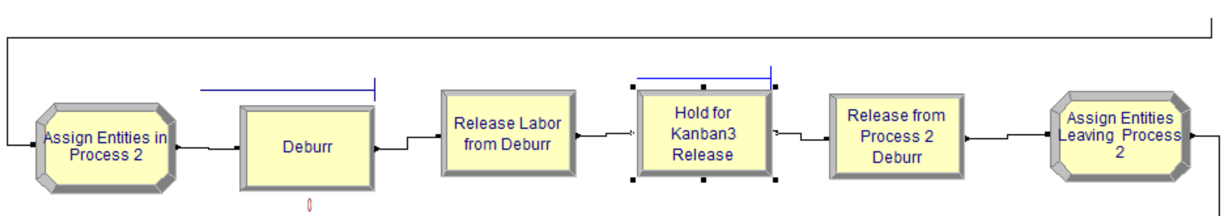


Figure 21: Kanban Hold and Release Logic

The TTG methodology is intended for machine-based production. Most machinery has some set-up time associated with changing over from one part number to another. Therefore, set-up logic had to be included in the simulation model. The block logic is shown below in Figure 22. When data is read into the model, the second column of data is PartNumber, an entity attribute. At each operation that requires set-up a global variable is assigned with the current part number of the entity going through the operation. Note, we assigned the entity part number to the global variable at the "assign block" Machine-X-undergoing-changeover (X denotes the operation number). These assignments are shown in Figure 22. Because we are assigning a global variable it holds the current entity part number entering the operation whether that entity goes through the set-up seize-delay-release or if it skips this step.

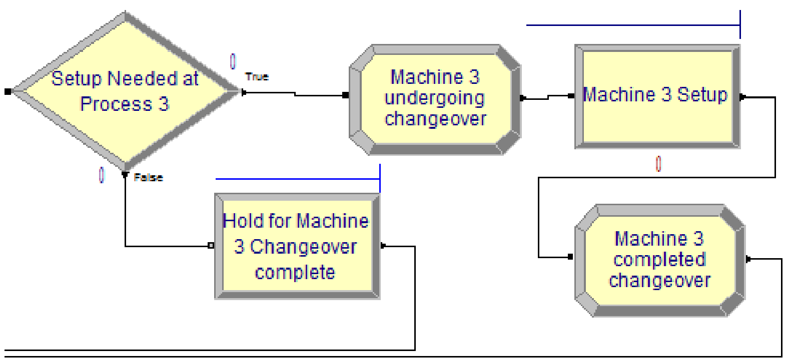


Figure 22: Set-up Logic

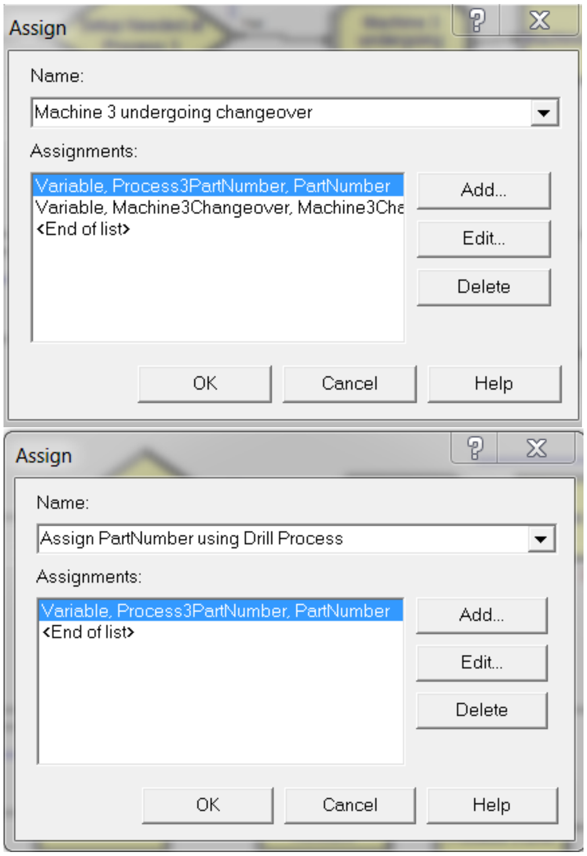


Figure 23: Assigning the Current Part Number going through the Process

At the "decide block", the program logic compares the entity at the "decide block" with the last part number that entered the operation. If these part numbers are not the same, it satisfies the "true" condition and sends that entity through the set-up "process block". Finally, we had to account for the fact that while the machine resource is seized during the entire set-up process, all other entities of that same part number had to wait until the set-up is complete. Therefore, we added a "hold block" that looks for the condition that there is no entity in the set-up process. We did this by creating a global variable, MachineXChangeover (X denotes the operation number). As an entity enters the changeover "process block" we add one to this variable. When an entity leaves the changeover “process block” we subtract one from this variable. The “hold block” holds entities, preventing them from entering the operation, if MachineXChangeover is >= 1.

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