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"PULL" REPLENISHMENT PERFORMANCE AS A FUNCTION OF DEMAND RATES AND SETUP TIMES UNDER OPTIMAL SETTINGS

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ABSTRACT

The problem of optimizing decision variables in a single-stage replenishment loop with capacity-constrained batch processing is examined. Simulation and response surface methods are used to model total inventory and delivery performance for a continuous-review reorder point system and a single-card Kanban system. Performance tradeoff curves based on optimal settings are created using non-linear optimization. The area under these curves is used as a single response for comparison. If tradeoff curves are experimentally replicated, main and interaction effects can also be statistically analyzed. Results show that under time-varying demand the reorder point system performs slightly better. Improvements in performance with setup time reduction are similar for both systems.

1 INTRODUCTION

Kanban and reorder point systems are both commonly used in supply chain replenishment. However, the differences with respect to the decision-making logic and performance are not always well understood. This paper seeks to provide insight into the behavior of these types of "pull" replenishment. Performance under capacity-constrained batch processing with significant setup times is of particular interest. The issue of optimally setting the decision variables, such as lot sizes, the number of Kanban cards or the reorder point, is addressed. A methodology that allows comparison of replenishment systems when each is run under optimal settings is presented. Along with differences due to replenishment logic, the effects of demand rates and lot setup times are also investigated.

Kanban systems have become well accepted, in part due to their simplicity and transparency. Specifically, some of the advantages can be identified as follows. First, Kanban systems do not require a separate inventory information system. Second, they are more robust with respect to information accuracy. For example, since replenishment is not based on a current count, unaccounted for loss of inventory will not affect future replenishment in the same way as within a reorder point system. Third, Kanban systems are better at supporting continuous improvement. The status of orders is visible on the shop floor and adjustments can be made without interfacing with the information system. Finally, Kanban systems naturally limit the maximum inventory in the replenishment loop. This is important in the event of a failure within the replenishment loop, such as a machine breakdown.

However, it can be argued that continuous-review reorder point systems also have unique strengths. The setting of the reorder point is more flexible. Since it is not associated with the status of Kanban cards the order point need not be a multiple of the lot size. As well, reorder point systems are more likely to use the information system to transmit orders upstream electronically. This could mean that orders are communicated more quickly and responsiveness is improved. Finally, reorder point systems consider backorder information whereas Kanban systems do not. This may be an advantage when demand is highly variable or seasonal.

Figure 1 illustrates the inventory positions over time for a single-card Kanban system with three cards in the replenishment loop. The order size associated with each Kanban is the lot size, *LS*. It can be observed that when demand increases and the inventory position becomes negative, the next order cannot be placed earlier than the next replenishment arrival, no matter how high backorders become. Figure 2 illustrates a similar scenario using a continuous-review reorder point system. In this case order placements are independent of delivery times even when the inventory position is negative. The final order illustrated is placed as soon as the inventory position falls one lot size below the reorder point.

Krajewski et. al (1987) concluded that there was not much difference between Kanban and reorder point performance. Other factors, like scrap rates, were found to have a greater impact on performance than the choice of replenishment system. Yang (1998) concluded a Kanban system was superior. However, the Kanban logic was modified to essentially allow lot sizes of one and dispatching facilitated by setup time reduction. Since the lot sizing and dispatching policies were not consistently applied, it cannot be stated that the replenishment logic was responsible for the inferior performance of the reorder point system. Enns (2006a) explored the effects of sequentially processing lots of the same part type to reduce setups. This study concluded reorder points systems outperformed Kanban systems with or without reduced-setup dispatching. Suwanruji and Enns (2006) concluded that reorder point systems are generally superior unless demand patterns are level, in which case it is possible for a Kanban system to perform slightly better due to decreased lot interarrival time variability.

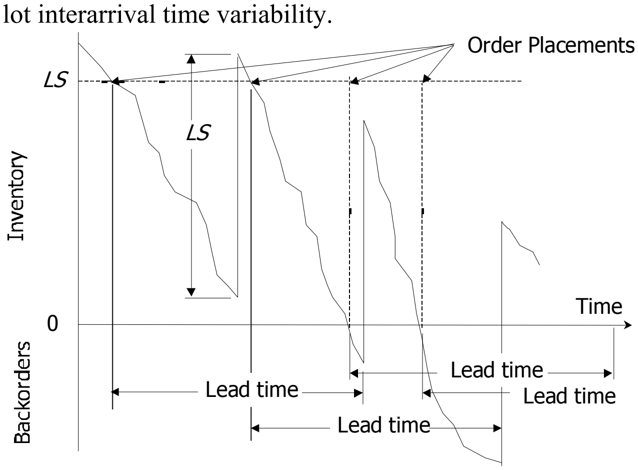

Figure 1: Replenishment with kanban system

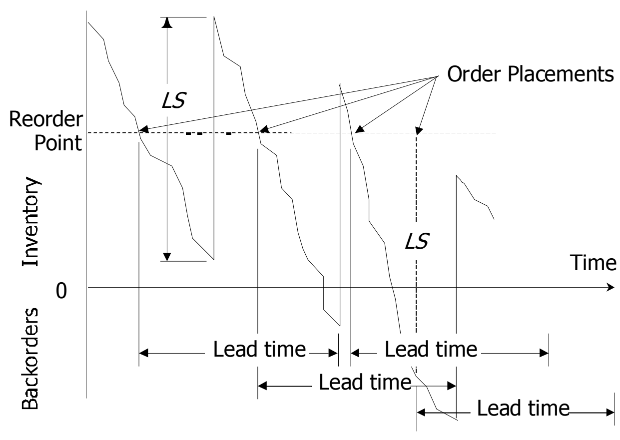

Figure 2: Replenishment with reorder point system

Comparing replenishment strategies, such as reorder point or Kanban systems, raises the issue of performance measurement. In many cases some measure of delivery performance, such as mean tardiness or proportion of deliveries from stock, is of interest. However, delivery performance is dependent on the inventory levels carried within the system. A tradeoff exists between delivery performance and inventory levels. Therefore, most comparison studies take both types of measures into account.

The problem then becomes one of dealing with two performance measures simultaneously. One approach is to set the performance level for one measure the same across all replenishment systems and then make comparisons on the basis of the other measure. For example, inventory levels could be set the same across all replenishment systems and comparisons made on the basis of delivery performance. The main challenge is to determine decision variable settings, such as lot sizes, Kanban cards or reorder points, that will result in equal inventory levels. This generally requires extensive experimentation. As well, conclusions are limited to results obtained at one particular inventory level. Jacobs and Whybark (1992) provided a study comparing material requirements planning (MRP) and reorder point systems using this approach.

Another approach is to develop tradeoff curves. This requires obtaining inventory and delivery performance results over a range of relevant values. If the curve for one replenishment system dominates another, it can be concluded that this replenishment system is superior. An advantage of this approach is that conclusions are based on a range of inventory or delivery service levels, not one particular point. Whybark and Williams (1976) illustrated this approach in an early study on safety leadtimes and safety stocks in MRP systems.

However even with the use of tradeoff curves there is the problem of which decision variables to change in generating the tradeoff curves and what settings to use for the decision variables that remain fixed. For example, in Kanban systems the decision may be to select a particular lot size and vary the number of Kanban cards to experimentally generate the tradeoff curves. Reorder point experiments could then be run by using the same lot size and varying the reorder point. Other decision variables that could be considered include the number of transporters (or frequency of delivery) and, if the system is capacity constrained, the dispatch rule. The approach of varying only the number of Kanban cards or the reorder point while holding all other decision variables constant was used by Suwanruji and Enns (2006).

Conclusions based on the tradeoff curve approach will be valid for the conditions tested but may not be generalizable, especially given that the fixed decision variables may not be optimally set. For example, it may be that the lot sizes are not set near optimal and this may affect the relative performance of the Kanban and reorder point systems. Furthermore, there is no reason to believe that optimal lot sizes for the Kanban system will necessarily be the same as those for the reorder point system. Ideally comparisons should be made when all the decision variables for each replenishment system are optimally set. Comparisons under these conditions would allow more robust conclusions to be drawn.

The problem of finding optimal decision variables is not trivial. Even for simple problems, this is difficult because the decision variables interact and must be considered simultaneously. Enns (2006b) illustrated a methodology for comparing Kanban and continuous-review reorder point replenishment using optimal settings. The current study extends this research by considering multiple experimental factors, such as demand rates and setup times, simultaneously. As well, select factors are run at three levels so that the linearity of behavior can be investigated.

The next section describes the methodology developed. A single-stage, capacity-constrained scenario to facilitate experimentation is then described. Experimental designs, results, analysis and conclusions follow.

2 METHODOLOGY

In the case of single-card Kanban systems the two decision variables most often considered are the lot size and the number of Kanban cards, or containers, in the replenishment loop. For continuous-review reorder point replenishment systems it is the lot size and the reorder point. These decision variables interact in determining performance and cannot be treated independently. Furthermore, there are commonly at least two types of performance measure of interest, one related to the inventory level and the other to delivery performance. A tradeoff between these two types of measure exists. Therefore the problem is one of obtaining the desired performance across multiple performance measures through the selection of multiple interacting decision variables. Since relationships to analytically deal with such problems are non-existent, an experimental approach is required. Response surface methods (RSM) can be used for analysis and optimization if appropriate data can be collected.

In this research simulations are first run based on an experimental design where both lot sizes and the number of Kanban cards or reorder points are changed over a range of values. The results from these runs can then be used to create a response surface model for the inventory levels. Another response surface model can be developed for the delivery performance. Equation 1 shows an example of a cubic model for a Kanban system with only two decision variables, appropriate for a single product scenario. The decision variables are *KC*, the number of Kanban cards, and *LS*, the lot size. The two separate responses are *TI*, a measure of the inventory, and *SL*, a measure of the delivery service level. In this research *TI* is defined to be the total system inventory count, all inventory in transit. *SL* is defined as the proportion of deliveries from stock (i.e. not backordered).

$$
\begin{aligned}
TI, SL = {} & b_0 + b_1 LS + b_2 KC + b_3 LS(KC) + b_4 LS^2 + \\
& b_5 KC^2 + b_6 LS^2 KC + b_7 LS(KC)^2 + b_8 LS^3 + b_9 KC^3
\end{aligned}
\tag{1}
$$

One approach to find good combinations of decision variables is to set a target delivery service level, *SL*, and use nonlinear optimization to find the decision variables that will minimize the inventory, *TI*. Since the decision variables must be integer, this requires the use of integer programming. Equation 2 illustrates an example optimization model where the proportion of deliveries from stock is targeted to be 0.85.

$$
\begin{aligned}
& Min: TI \\
& s.t.\ SL \geq 0.85 \\
& KC, LS\ Integer
\end{aligned}
\tag{2}
$$

The inequality in the constraint is necessary since integer values for the decision variables make it impossible to obtain a service level of exactly 0.85. Since *TI* is being minimized, the solution procedure will try to obtain an *SL* value that is as small as possible without violating the constraints.

By plugging in various targeted service levels and solving Equation 2 each time, a performance tradeoff curve can be generated. This approach can be used for both the Kanban and the reorder point system. It is then possible to visually determine if one curve dominates the other.

This type of approach is based on tradeoff curves created using fitted models. A better approach is to take the decision variable combinations along the optimal tradeoff curves and run them in the actual simulation model. This not only allows the fitted model errors to be eliminated but also allows the tradeoff curves to be experimentally replicated. A single response, namely the area under the curve, can then be used for statistical evaluation. Figure 3 illustrates two sets of tradeoff curves, each replicated three times, along with the user-selected service level bounds (dashed lines) on which basis areas are to be compared. In this illustration the reorder point system (*ROP)* dominates the Kanban system (*Kbn)* since it results in less area under (or to the left of) the curve.

Statistical differences between the areas for the two sets of response curves can be evaluated using analysis of variance (ANOVA) techniques. This approach allows both main and interaction effects to be evaluated when there are multiple experimental factors, resulting in numerous sets of tradeoff curves.

This methodology is summarized in Figure 4. Reference will be made to the specific steps in this flow chart when discussing the simulation experiments in Section 4.

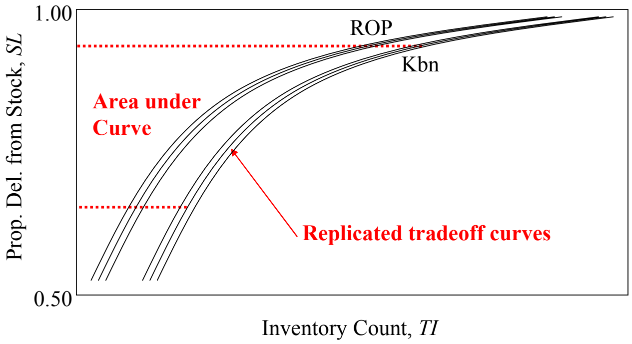

Figure 3: Tradeoff curves for area calculations

1. **Experimental Factor**
   Two levels of replenishment systems (*Kbn* or *ROP*)

2. **Run designed simulation experiments**
   Factors: Lot sizes (*LS*)
   Kanbans (*KC*), reorder points (*OP*)
   Measures: Total Inventory (*TI*), Service Level (*SL*)

3. **Build response surface models**
   ***TI* as response**
   ***SL* as response**

4. **Optimize *LS* and *KC* or *OP* settings**
   Min *TI*
   s.t. *SL* constraints (50% to 95%)
   ***LS*, *KC* and *OP* integers**

5. **Generate trade-off curves using simulation**
   TI* versus *SL
   Replicate tradeoff curves

6. **Calculate area under trade-off curves**

7. **Perform statistical comparison**
   ***Area* as response**

Figure 4: Methodology flow chart

3 EXPERIMENTAL SCENARIO

A basic illustration of the scenario used in this research is shown in Figure 5. There are two part types that come from suppliers and are then processed on the same capacity-constrained machine. The completed lots of processed parts become finished goods that are consumed by individual customers taking single items. The customer demand for each part type is Poisson but the rate is adjusted every time unit according to a seasonal demand pattern. The expected demand for both part types follows a sinusoidal pattern. The mean demand is treated as an experimental factor. The demand pattern amplitude is assumed to equal 0.2 times the mean and the cycle length is 250 time units. However, the demand patterns for the two part types are offset by 125 time units. Therefore the aggregate workload requirement at the machine is fairly constant through time. The actual demand rate during each time unit is based on sampling from a Normal distribution centered around the expected demand rate indicated by the sinusoidal demand curves. The standard deviation of this distribution is specified to be 0.1 times the expected demand rate. Figure 6 illustrates an example of the demand patterns for the two part types, *P1* and *P2*, through one demand cycle. In this diagram a time unit is assumed to equal one day.

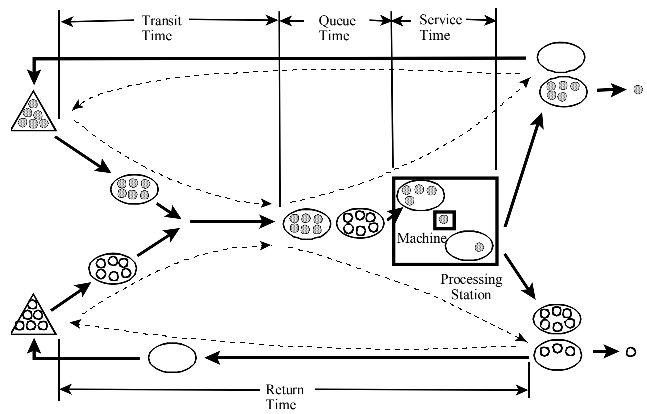

Figure 5: Configuration of single-stage system

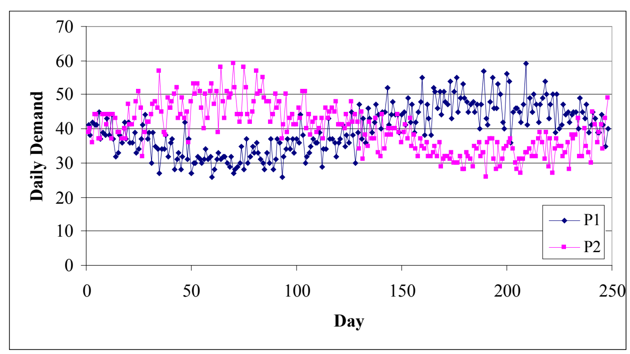

Figure 6: Demand pattern

Replenishment is controlled by a single-card Kanban (*Kbn*) or a continuous-review reorder point (*ROP*) system. Performance is measured in terms of total inventory counts, *TI*, and the proportion of customer demand filled from stock, *SL*. If the desired part type is not in stock, a customer backorder is placed and then filled as soon as finished goods inventory is replenished.

The two part types are assumed to be identical in terms of processing and replenishment time requirements. However a unique setup is required for each part type and they are not interchangeable with respect to the supply source or customer demand. This assumption simplifies the number of decision variables that must be dealt with since the lot sizes and the number of Kanban cards or reorder points for both part types are assumed to be equal. The lot setup time for both part types is an experimental factor. Each part in the lot requires a processing time of 0.008 time units. There is no uncertainty associated with these times. When a lot has been completed, it is immediately made available as finished goods to meet customer demand.

The logic for placing a replenishment order for the single-card Kanban system (*Kbn*) is given by Equation 3, where $Q_{i,t}$ is the order quantity for part type *i* at time *t*. This equation assumes the Kanban card is released upstream for recirculation when a container is completely depleted.

$$Q_{i,t} = \max\left(0, \left\lceil \frac{(KC_i - 1)LS_i - (FG_{i,t} + OR_{i,t} + OT_{i,t} + OQ_{i,t}) + 1}{LS_i} \right\rceil LS_i\right) \quad (3)$$

where:

- KC_i - Number of Kanban cards for part type *i*
- $FG_{i,t}$ - Qty of part type *i* finished goods in stock
- $OR_{i,t}$ - Qty of part type *i* orders released to supplier but not yet filled
- $OT_{i,t}$ - Qty of part type *i* in transit
- $OQ_{i,t}$ - Qty of part type *i* in queue or on machine

When a lot of parts is depleted by customer demand, the Kanban card associated with this lot, or container, is made available for return to the supplier. There are 24 transporters in continuous circulation in each of the replenishment loops. The circuit for these is shown as dashed lines in Figure 5. It is assumed these transporters also carry other parts from the suppliers to the plant and therefore circulate even if there are no Kanban orders to fill for the given part types. Once a transporter makes a delivery from the supplier it immediately picks up any waiting Kanban cards for the same part type and then begins the return trip to the supplier. The number of cards picked up may be zero or any integer value. The expected travel time to the supplier is described by a Gamma distribution with a mean of 8 and a standard deviation of 0.8 time units.

The supplier is assumed to always have parts in stock so there is no delay in filling any Kanban order. The travel time to the workstation follows the same distribution as the travel time to the supplier. The lots arriving at the capacity-constrained machine join a queue if the machine is busy. Lots are processed in first-come-first-served (FCFS) order, with each lot incurring a setup. The assumptions are such that the Kanban cards and containers in circulation could be considered equivalent. A further assumption is that the decision variables remain constant through time despite the seasonality of demand.

The logic for the continuous-review reorder point (*ROP*) system is given by Equation 4.

$$Q_{i,t} = \max\left(0, \left\lceil \frac{OP_i - (FG_{i,t} + OR_{i,t} + OT_{i,t} + OQ_{i,t} - BO_{i,t}) + 1}{LS_i} \right\rceil LS_i\right) \quad (4)$$

where:

- OP_i - Order point for part type *i*
- $BO_{i,t}$ - Quantity of part type *i* backordered

The implementation for reorder point replenishment is different in that customer backorders are considered in the replenishment decision. In this research, all other assumptions for the reorder point system were consistent with those for the Kanban system, including the delays in order transmission to the suppliers.

4 EXPERIMENTAL DESIGN

This section describes the experimental design, the experiments and the process to obtain the optimal decision variables along each of the tradeoff curves dictated by the experimental design. Discrete-event simulations were performed using Arena® 5.0 (Kelton, Sadowski, and Sturrock 2004) and response surfaces were created using Design-Expert® 7.0 software (Montgomery 2001).

4.1 Factorial Design

Three experimental factors were used in this research, as indicated by Step 1 in Figure 4. The first factor was the replenishment system (*Sys*). This was run at 2 levels; namely the Kanban system (*Kbn*) and the reorder point system (*ROP*). The second factor was the demand rate (*DR*). This was run at three levels. The third factor was the lot setup time (*ST*) and this was also run at 3 levels. Table 1 summarizes the settings used for each of the factors. A full factorial design meant that the total number of tradeoff curves along which optimal settings had to be determined was 18.

Table 1: Factor settings

Factors	Levels
Sys	Kbn, ROP
DR	30, 40, 50
ST	0.1, 0.2, 0.3

4.2 Simulations for Response Surfaces

As shown in Step 2 of Figure 4, combinations of lot sizes (*LS*) and Kanban cards (*KC*) or order points (*OP*) were run to obtain tradeoff curves in the region of optimal decision variable combinations for each factor setting combination. Three replications of each tradeoff curve were run. A typical set of curves, averaged across the three replications, is shown in Figure 7 as dashed lines. This figure is for curves obtained with *Sys* set as *Kbn*, *DR* as 40 per unit time and *ST* as 0.2 time units. Each curve represents use of a different number of Kanban cards and the points along each curve moving toward the right represent increasing lot sizes.

Typically at least seven Kanban or reorder point settings were used along with each of at least 6 lot size settings. This means at least 42 combinations were used in generating the data from which to create each of the 18 response surfaces. Since each curve was replicated 3 times, the total number of simulation runs was at least 2268 (42*3*18). Each simulation run was 2750 time units in length, with the first 250 time units used for initialization.

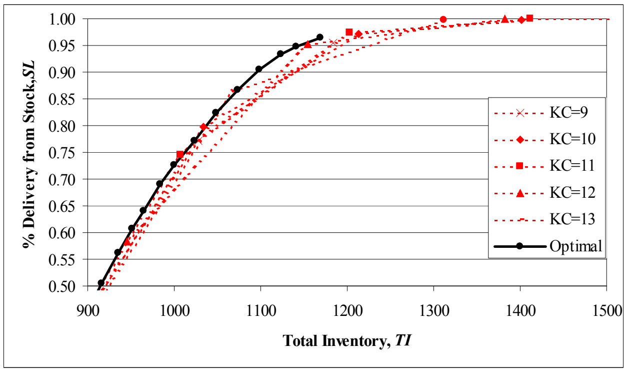

Figure 7: Tradeoff curves for response surfaces

4.3 Response Surface Models

Using sets of tradeoff curves similar to those illustrated in Figure 7 it was possible to generate separate response surface models for both the inventory, *TI*, and delivery service level, *SL*, measures. This conforms to Step 3 in Figure 4.

Observations with service levels below 50% and above 99% were eliminated. It was then found that a cubic model, similar to the one shown in Equation 1 fit both the *TI* and *SL* responses very well. As examples, Equations 5 and 6 illustrate the response surfaces obtained for *Kbn* with *DR*=40 and *ST*=0.2. These equations were generated using Design-Expert®.

$$
\begin{aligned}
TI = &+7208.51896 \\
&-158.95079 && *\,LS \\
&-777.20402 && *\,KC \\
&+11.78467 && *\,LS * KC \\
&+1.12471 && *\,LS^2 \\
&+26.82223 && *\,KC^2 \\
&-0.034387 && *\,LS^2 * KC \\
&-0.15455 && *\,LS * KC^2 \\
&-2.72865\text{E-}003 && *\,LS^3 \\
&-0.32885 && *\,KC^3
\end{aligned} \tag{5}
$$

$$
\begin{aligned}
SL = &-50.42506 \\
&+0.99890 && *\,LS \\
&+3.55111 && *\,KC \\
&-0.033513 && *\,LS * KC \\
&-7.69164\text{E-}003 && *\,LS^2 \\
&-0.092943 && *\,KC^2 \\
&+1.16369\text{E-}004 && *\,LS^2 * KC \\
&+1.72967\text{E-}004 && *\,LS * KC^2 \\
&+2.12824\text{E-}005 && *\,LS^3 \\
&+1.05648\text{E-}003 && *\,KC^3
\end{aligned} \tag{6}
$$

4.4 Optimal Tradeoff Curves

Optimal combinations of lot sizes and Kanban cards or reorder points along each of the tradeoff curves were next determined, as indicated in Step 4 of Figure 4. The response surface models were solved to minimize total inventory, *TI*, while target service levels, *SL*, were incremented by 2.5% over the range of 50% to 95%. This was done using the Excel Solver® add-in.

Table 2 illustrates an example of the optimal decision variables obtained for one tradeoff curve. These results are for *Kbn* with *DR*=40 and *ST*=0.2.

Table 2: Optimal tradeoff curve settings

LS	KC	TI	SL	Util
82	10	898	0.537	0.835
75	11	913	0.550	0.853
76	11	931	0.597	0.851
77	11	950	0.641	0.848
71	12	964	0.651	0.865
72	12	984	0.699	0.862
67	13	1002	0.713	0.879
63	14	1025	0.741	0.894
64	14	1050	0.792	0.890
65	14	1074	0.839	0.886
66	14	1099	0.883	0.882
67	14	1124	0.922	0.879
63	15	1142	0.930	0.894
64	15	1169	0.967	0.890

5 EXPERIMENTAL RESULTS

This section presents the results obtained when the optimal decision variable combinations are run experimentally and then analyzed using *Area* as a response.

5.1 Optimal Experimental Tradeoff Curves

Each of the 18 optimal tradeoff curves was replicated 3 times using the same simulation model and run lengths as previous. This is indicated as Step 5 in Figure 4.

A sample set of curves, averaged across three replications, with *DR*=40 is shown in Figure 8. From this graph it is obvious that the *ROP* system outperforms the *Kbn* system at each setup time, especially at lower service levels.

The optimal experimental curve for the Kanban system with *DR*=40 and *ST*=0.20 is also shown plotted as a solid line on Figure 7. The fact that this line is above the tradeoff curves used to generate the response surface confirms it is closer to optimal.

5.2 Tradeoff Curves Areas

The areas under each replication of all the "optimal" tradeoff curves was next calculated, as indicated in Step 6 of

Figure 4. For convenience, calculations were constrained to be for the region with service levels between 75% and 90%.

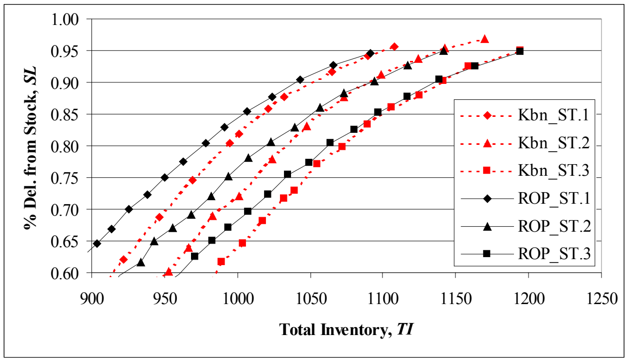

Figure 8: Optimal experimental tradeoff curves

The areas were calculated using an algorithm that assumed straight line segments between the points along the tradeoff curves. Computations were made using a Visual Basic for Applications (VBA) macro in an Excel workbook. For example, the areas calculated for the three replicated tradeoff curves using the settings shown in Table 2 were 158.540, 157.266 and 157.005.

5.3 Statistical Analysis

Finally, as illustrated by Step 7 of Figure 4, the *Area* response was analyzed using Analysis of Variance (ANOVA). The least-squares reduced model based on all optimal tradeoff curves is shown as Equation 7. The system variable (*Sys*) was treated as –1 for *Kbn* and +1 for *ROP*.

$$Area = 96.68 - 0.8053\ Sys - 1.752\ DR - 147.7\ ST + 5.700\ DR*ST + 0.07104\ DR*DR \qquad (7)$$

This model had an R^2-*value* of 99.8%. Residual analysis also confirmed a good fit. The sums of squares and *p-values* for this model are shown as Table 3.

Table 3: ANOVA results

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	96335.66	5	19267.13	6577.47	< 0.0001
Sys	35.02	1	35.02	11.96	0.0012
DR	92591.39	1	92591.39	31609.1	< 0.0001
ST	2323.74	1	2323.74	793.28	< 0.0001
DR*ST	779.92	1	779.92	266.25	< 0.0001
DR*DR	605.59	1	605.59	206.74	< 0.0001
Residual	140.6	48	2.93		
Lack of Fit	55.83	12	4.65	1.98	0.0571
Pure Error	84.78	36	2.35		
Cor Total	96476.27	53			

Figure 9 shows a surface plot for the *Area* response using *Kbn*. The surface plot for *ROP* was very similar.

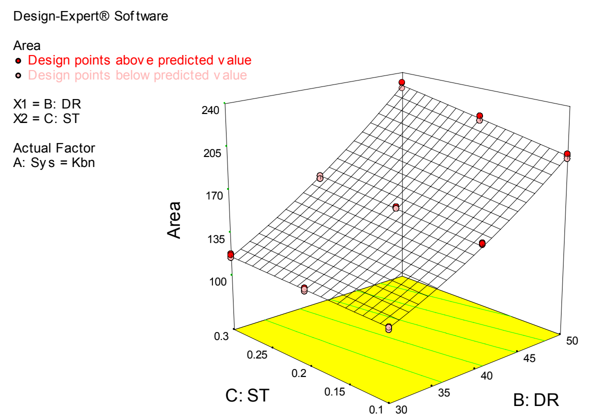

Figure 9: Surface plot of *Area*

6 DISCUSSION OF RESULTS

This section examines the behavior of the replenishment systems in greater detail.

6.1 Main and Interaction Effects

The ANOVA results show that the difference between the *Kbn* and *ROP* performance is statistically significant. However, differences are relatively small and it is likely practical considerations would dominate the choice of which replenishment system to implement.

The demand rate (*DR*) and lot setup time (*ST*) both have a significant impact on performance. As well, there is an interaction effect between these. Figures 10 and 11 show interaction plots generated using Design-Expert®. Figure 10 shows that *Area* decreases linearly with setup times (*ST*) at each demand rate (*DR*). However, the rate of improvement with setup time reduction is greatest at high demand rates, as indicated by an increasing slope as the demand rate increases.

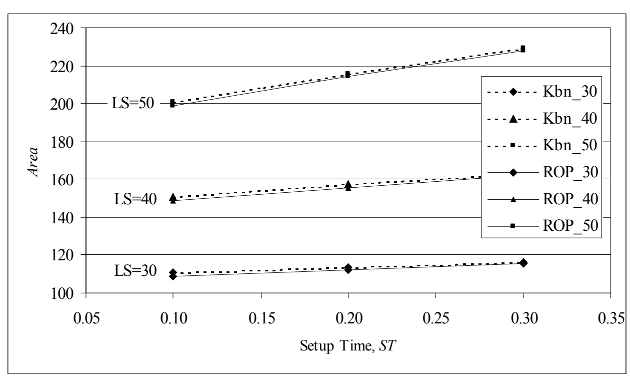

Figure 10: Plot of *Area* versus *ST*

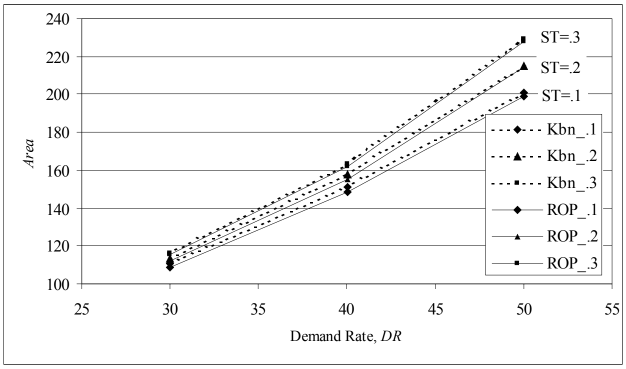

Figure 11: Plot of *Area* versus *DR*

6.2 Adjustment of Service Levels

Several observations were also made on the decision variable settings required to obtain targeted service levels, *SL*. First, the Kanban system is very granular in that increasing or decreasing the number of cards by one can result in a big change in delivery performance. In this research the lot size was also allowed to change when targeting a specific service level. However, in practice it is likely that fixed lot sizes would be used. For this reason practitioners like Toyota sometimes change the frequency of lot deliveries when adjustments to service levels are desired, such as when demand changes temporarily. In this research the frequency of lot deliveries was not a decision variable. The delivery pattern provided by the transporters was assumed fixed.

It was also observed that in the case of the reorder point system lot sizes affect delivery performance very little even if it is acceptable to change them. The reason is due to the use of backorder information. As lot sizes are decreased, more orders are simply released into the replenishment loop. In other words, there is no limit to the orders that are released at any given time, unlike with Kanban systems. This behavior is illustrated in Figure 12. Each curve segment represents increasing lot sizes at a given order point (*OP*) level. If the lot sizes become too small, there are too many setups and machine utilization becomes too large. Service levels then fall off sharply, as illustrated by some of the tails on the segments. Fortunately, reorder point systems allow order points to be changed by as little as a single unit. This makes adjustment much less granular than for Kanban systems, where changing the number of cards is equivalent to adjusting by a complete lot size.

7 CONCLUSIONS

A methodology for finding optimal decision variable settings for replenishment systems has been demonstrated in this research. This allows comparisons to be made on a more equitable basis. As well, use of the area under trade-off curves as a response has been illustrated. This helps overcome the problem of dealing with multiple interdependent responses. It also facilitates performing statistical analysis of main and interaction effects, as illustrated in Section 5.3, to improve theoretical understanding of replenishment behavior. However, this methodology is likely too cumbersome to be used in practice, especially as the number of decision variables increases.

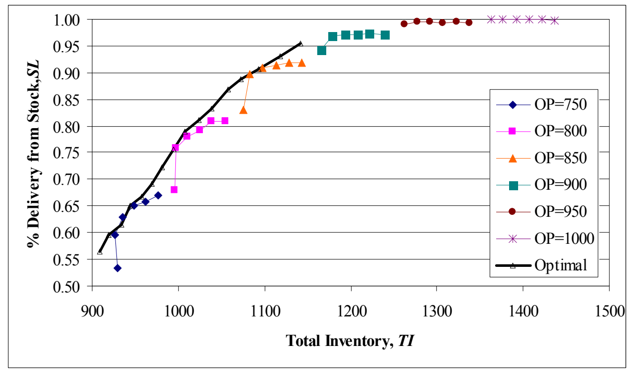

Figure 12: *ROP* performance as a function of lot sizes

This research has also contributed to understanding the behavior of replenishment systems by looking at three levels of factor settings. The linearity of behavior can therefore be examined. Results show that performance changes linearly with setup times under optimal settings. As well, at high demand levels the rate of improvement due to setup time reduction is greater. It is also interesting to note that the behavior of the two replenishment systems examined is very similar. The ability to use one model to fit the *Area* response for both the Kanban and reorder point experimental data confirms this.

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