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EVALUATING THE PERFORMANCE OF SUPPLY CHAIN SIMULATIONS WITH TRADEOFFS BETWEEN MULITPLE OBJECTIVES

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ABSTRACT

Simulation is well suited to the development and analysis of supply chain models, since the problems of interest tend to be complex and encompass uncertainty. However, there are typically multiple performance objectives that tend to conflict. A major problem in supply chain studies is that assumptions need to be made about the performance tradeoffs involved. Therefore, the conclusions may not be general. In this paper we develop an approach that allows both delivery performance and inventory levels to be considered over a range of tradeoffs. By developing tradeoff curves and analyzing the area under each we are able to reach conclusions that are more general and can be shown to be statistically valid.

1 INTRODUCTION

The comparison of supply chain performance results obtained using simulation models is difficult for several reasons. First, the performance is dependent on many assumptions regarding both the supply chain environment and the replenishment control system. Second, there are numerous responses of potential interest. At a minimum, we are usually interested in some measure related to inventory investment and some measure related to customer delivery performance. However, there is a trade off between such measures, with one typically improving as the other deteriorates. One approach is to control the level of one or more output measure across experiments to be equal and then make comparisons on the basis of only one response measure. However, this approach is difficult to implement effectively. Furthermore, the resulting comparisons apply only under the restricted assumptions regarding the other fixed responses. Another approach is to weight the output measures and then aggregate them into a single response, usually an economic measure. This approach is also limited since conclusions may be contingent on the weights chosen.

The ability to effectively compare supply chain performance results is important. In particular, this is required to help understand the factors and interactions which affect the supply chain's performance. As well, it is becoming of increasing interest to compare different planning and control strategies used in supply chains. For example, it is not well understood under what conditions Distribution Requirements Planning (DRP), reorder point (ROP) or Kanban systems are preferable. A good approach for making comparisons is required to develop a better understanding of the relative strengths of these systems and provide guidelines for selection and implementation (Suwanruji and Enns 2002).

In this paper we present an analysis approach that has recently proved effective in comparing supply chain results generated using discrete-event simulation. This approach is well suited where metrics related to inventory and delivery performance are of interest. Tradeoffs are systematically evaluated within a given supply chain environment and then comparisons are made across different environments. The following sections describe and illustrate the steps in this analysis approach.

2 EVALUATION USING TRADEOFF CURVES

An experimental design must be developed for the supply chain scenarios to be tested before simulation results can be generated. This experimental design should include one factor that allows the tradeoff between inventory and delivery performance to be controlled. For example, if reorder points are being used as the replenishment strategy within the supply chain, the reorder point should be treated as one factor. This factor must take on a series of levels so that a tradeoff curve can be developed for each combination of the other factor settings. Figure 1 illustrates two tradeoff curves, indicating results when one additional factor is being run at two levels, A and B. In this illustration, mean tardiness is being used as the delivery performance measure and average inventory counts are being used as the inventory investment measure.

In Figure 1 it is clear that curve A dominates curve B. At any level of mean tardiness, curve A results in a lower inventory level. Likewise, at any inventory level, curve A

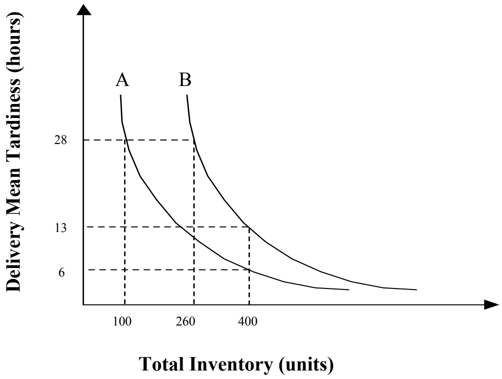

Figure 1: Tradeoff Curves

results in lower mean tardiness. Therefore, the scenario associated with curve A would be preferable to that of curve B. However, in many cases it is not clear if the differences in the resulting tradeoff curves are statistically significant. In some cases, there may even be a slight crossover in the curves. Furthermore, we are typically dealing with many comparisons in supply chain experiments. Therefore relying on tradeoff curves for analysis alone may be insufficient.

Calculating the area under each of the curves allows comparisons to be made across both delivery and inventory measures. If sufficient observations have been run along each of the curves, a simple algorithm based on straight line approximations between points along the curves will yield good estimates of the area. Figure 2 illustrates the computation of areas for each of two curves. The points X' and Y' illustrate bounds that can be used to restrict area computations to the region of relevance, based on acceptable performance limits.

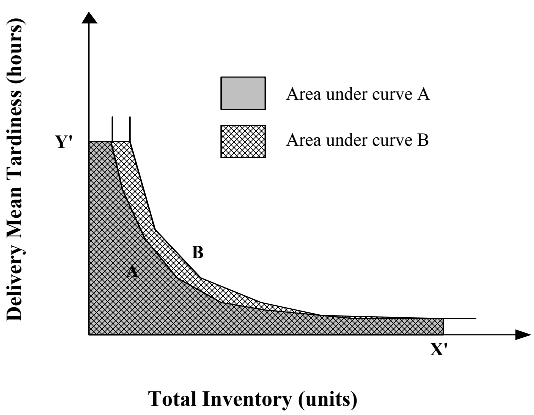

Figure 2: Tradeoff Curve Area Analysis

If each curve is replicated multiple times, it is readily possible to estimate the error associated with the area under each curve. Furthermore, we can apply Analysis of Variance (ANOVA) techniques to determine the statistical significance of differences between the mean results for curves across multiple scenarios. Therefore, the statistical significance of various main and interaction effects can be established. Furthermore, regression coefficients can be used to estimate the magnitude and direction of various effects. Montgomery (2001) is one good resource that provides details on experimental design and analysis.

3 EXAMPLE USING TRADEOFF CURVES

In this section we illustrate a simple example of the use of the analysis approach being presented.

3.1 Problem Scenario

Two supply chain scenarios are being compared, as illustrated in Figure 3. It is assumed that reorder points are being used for replenishment across the supply chain. The method of generating the tradeoff curves is illustrated by the following equation,

$$ROP_i = \lceil D_i (RT_i) SF_i \rceil. \tag{1}$$

where:

ROP_i - Reorder point for echelon i
D_i - Average demand per unit time at echelon i
RT_i - Expected replenishment time at echelon i
SF_i - Safety factor for echelon i

In this sample problem the average demand is 25 per hour at each of most downstream echelons. Expected replenishment times are 40 hours between each of the echelons. The tradeoff curves are generated by increasing the replenishment safety factor, SF, from 1.00 to 1.95 by increments of 0.05. Therefore, twenty points are generated to determine each tradeoff curve.

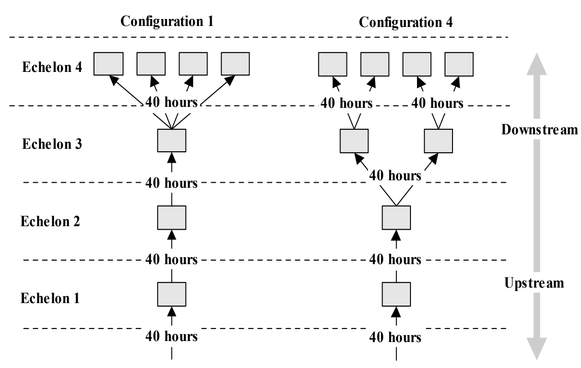

Figure 3: Supply Chain Configurations

3.2 Experimental Design

The experimental design involves five factors, in addition to the safety factor, SF, used to generate tradeoff curves for every combination of the other factors. These five factors are all run at two levels, resulting in a total of 32 combinations of experiments for the two-level factors. The model for this design, including only two-way interactions is,

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 + \hat{\beta}_4 x_4 + \hat{\beta}_5 x_5 + \sum_{g=1}^{5}\sum_{h=1}^{5} \hat{\beta}_{gh} x_g x_h . \quad (2)$$

Where:

$\hat{y}$ - Fitted area under trade off curve

$\hat{\beta}_0$ - Regression constant

$\hat{\beta}_1$ - Coefficient for A, configuration

x_1 - (-1) for Configuration 1, (+1) for Configuration 4

$\hat{\beta}_2$ - Coefficient for B, lot size

x_2 - (-1) for small lot size, (+1) for large lot size

$\hat{\beta}_3$ - Coefficient for C, demand pattern

x_3 - (-1) for level demand, (+1) for seasonal demand

$\hat{\beta}_4$ - Coefficient for D, demand uncertainty

x_4 - (-1) for low uncertainty, (+1) for high uncertainty

$\hat{\beta}_5$ - Coefficient for E, transit time uncertainty

x_5 - (-1) for low uncertainty, (+1) for high uncertainty

Note that the factor levels are shown only in terms of the coded values. The real values associated with each of the -1 and +1 levels are not of concern in this illustration.

3.3 Simulation Results

The experiments were run using the test bed described by Enns and Suwanruji (2003). The discrete-event simulation component in this test bed relies on the use of ARENA® 5.0 (Kelton, Sadowski, and Sadowski 2002).

The length of each simulation run was 10400 units of simulated time, with 2080 units of time being used for initialization to reach steady state. Three replications were used. In other words, three tradeoff curves were developed for each of the 32 combinations of two-level factor settings. Within group variance was quite low.

An example of one tradeoff curve is shown in Figure 4. This tradeoff curve compares the two configurations when lot sizes are small (-1), demand patterns are seasonal (+1), demand uncertainty is high (+1) and transit time uncertainty is low (-1). In this situation it would appear Configuration 1, represented by the lower curve, performs best.

3.4 Analysis of Results

Analysis of Variance (ANOVA) was performed using the area under each of the tradeoff curves as the response. Lower areas represent better performance. The ANOVA

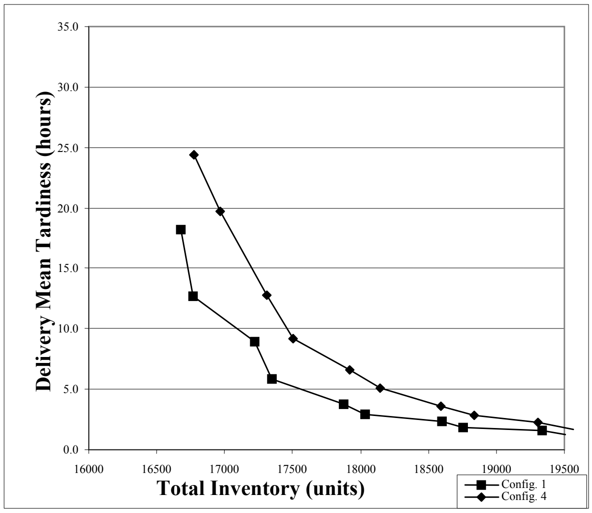

Figure 4: Sample Tradeoff Curve

results are shown in Table 1. Note that only the significant factors and interactions are shown. This analysis was generated using Design Expert® 6.0 (Montgomery, 2001).

Table 1: ANOVA Results

Analysis of variance table [Partial sum of squares]

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F
Model	5.86E+09	12	4.88E+08	701.0	< 0.0001
A	4.63E+08	1	4.63E+08	664.7	< 0.0001
B	1.11E+08	1	1.11E+08	159.2	< 0.0001
C	4.44E+09	1	4.44E+09	6373.3	< 0.0001
D	1.68E+08	1	1.68E+08	241.7	< 0.0001
E	1.80E+08	1	1.80E+08	257.7	< 0.0001
AC	3.49E+08	1	3.49E+08	501.5	< 0.0001
AD	5.27E+06	1	5.27E+06	7.6	0.0073
BC	1.30E+07	1	1.30E+07	18.6	< 0.0001
BE	1.51E+07	1	1.51E+07	21.7	< 0.0001
CD	7.88E+07	1	7.88E+07	113.2	< 0.0001
CE	2.73E+07	1	2.73E+07	39.2	< 0.0001
ACD	9.87E+06	1	9.87E+06	14.2	0.0003
Residual	5.78E+07	83	6.97E+05		
LackOfFit	9.78E+06	19	5.15E+05	0.7	0.8190
Pure Error	4.80E+07	64	7.51E+05		
Cor Total	5.92E+09	95			

The coefficients for the regression equation are illustrated in Table 2. These coefficients are particularly useful in this analysis since all the factors take on only two levels. Therefore it is very easy to determine the direction and point estimates for both the main and interaction effects.

The fit of this model was very good, with an R^2 value of 99.0%. Figure 5 shows that the plot of the residuals is normally distributed. Therefore, we can conclude that this model is suitable for evaluating the experimental design.

Table 2: Regression Coefficients

Area	=
20955	
2196	* A
1075	* B
6801	* C
1325	* D
1368	* E
1908	* A * C
-234	* A * D
-368	* B * C
397	* B * E
-906	* C * D
-534	* C * E
-321	* A * C * D

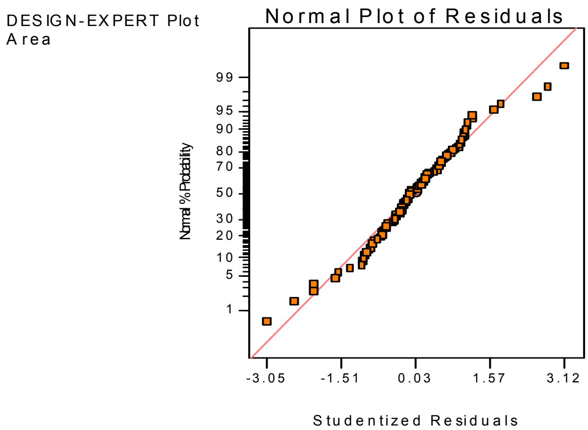

Figure 5: Normal Probability Plot of Residuals

Further analysis can provide insights into particular behavior that may be of interest. For example, Figure 6 provides one interaction plot that may be of interest. In this graph the configuration, Factor A, is plotted against the demand pattern, Factor C. When there is no demand seasonality (C=-1) there is little difference in the performance of the two configurations. When there is demand seasonality (C=1), the performance deteriorates under both configurations. However, Configuration 1 (A=1) does not deteriorate as much as Configuration 4 (A=4). From this we could conclude that, given the other factor settings, Configuration 1 is better than Configuration 4 if demand is seasonal.

4 CONCLUSIONS

This paper has illustrated an approach that has proved useful in understanding factors that affect supply chain performance and in comparing supply chain scenarios. Key strengths are that this approach allows multiple criteria to be used in evaluation and that results can be statistically validated. This approach is very practical to implement where structured experimentation can be performed, such as when simulation methodology is used. The approach can be especially useful when comparing different planning and control strategies, such as those using DRP, reorder point and Kanban systems. Although not illustrated in

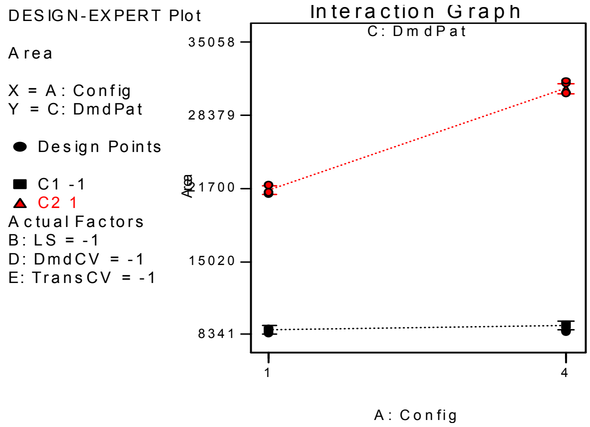

Figure 6: Sample Interaction Plot

the example given, this analysis approach is also applicable where factors take on more than two levels.

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