"Master Production Schedule Stability Under Conditions of Finite Capacity"

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ABSTRACT

The Master production schedule (MPS) is the main tool to control product availability, which is the core element of improving customer service in the consumer goods industry. Calculation of the MPS becomes much more complex in a multi-product environment where forecast errors and capacity constraints can add a great deal of uncertainty to the planning process. This circumstance leads to a problematical issue known as MPS stability. In this article, we propose a new way to improve MPS stability under conditions of finite capacity. The approach has its genesis in a real world, make-to-stock situation that frequently occurs in the food industry and other related types of manufacturing. Using a comprehensive MPS model, we conduct a simulation study with experimental design to identify factors having a significant influence on MPS stability. Then we perform sensitivity analysis on select factors that hold the greatest promise for improvement by employing a simple predictive equation. Finally, we test a different way to plan safety stocks and report the results. In conclusion, we find that elimination of forecast bias and choice of safety stock method both are particularly important for improving MPS stability and ultimately customer service.

Keywords: master production schedule; stability; finite capacity; consumer goods industry; forecast bias; safety stock

1.0 INTRODUCTION

Customer service plays a central role in achieving marketing objectives for firms in the consumer goods industry. The most important element of customer service is product availability (Coyle, Bardi, and Langley 1992, p. 81). Commonly measured as the fill rate for incoming orders, product availability depends on the amount of end-item inventory in situations where a make-to-stock policy exists. Manufacturing firms in the consumer goods industry adopt the make-to-stock policy because the manufacturing lead-time for end-items is often longer than the cycle time for taking and shipping an order.

The main tool to control product availability is the master production schedule (MPS). By using the beginning inventory and the sales forecast for a particular end item, a planner can calculate the amount of production needed per period to meet anticipated customer demand. This calculation becomes more complex in a multi-product environment where forecast errors and capacity constraints can add a great deal of uncertainty to the planning process. As firms continue to integrate the MPS into supply chain planning, it is becoming increasingly clear that MPS stability plays a major role in managing the trade-off between costs and product availability.

This study examines a practical solution that enhances MPS stability. Data used for analysis is from a real situation in the consumer goods industry.[1] Divided into three parts, the study begins with the use of experimental design to test the impact of selected factors on MPS stability. The second part involves application of an equation to predict

[1] All data for this study is from Welch Foods, Inc.

MPS stability given several inputs. The study concludes with discussion of a solution to improve stability using dynamic safety stocks. As a side note, some aspects of the analysis presented in this article appear as part of the Open System for Master Production Scheduling (OSMPS). This is a new information technology architecture designed to deliver various advanced planning models to end-users (see APPENDIX A).

Before investigating the quantitative aspects of MPS stability, the next two sections provide a literature review of the topic and a definition of the specific problem under consideration for this study.

2.0 LITERATURE REVIEW

Though no formal definition exists, MPS stability relates to the frequency of changes in timing and quantity over time for end-items appearing in the MPS. While there is little empirical research on the subject, a consensus has emerged that either a) carrying safety stock at the end item level or b) freezing the MPS in a rolling horizon environment can improve MPS stability. Both of these approaches have a significant impact on costs and product availability that are quantifiable through mathematical modeling.

Several researchers propose solutions to the MPS stability problem. For a single product environment under conditions of demand uncertainty, Sridharan and Berry (1990) show that increasing the length of the frozen interval improves schedule stability but also increases costs. Chung and Krajewski (1986) demonstrate that in a hierarchical production planning framework for a rolling horizon MPS, the product cost structure influences the optimal choice of frozen interval lengths. In a comparative study, Shridharan and LaForge (1989) find that freezing a portion of the MPS produces lower lot-size cost and more stable schedules than using safety stock at the MPS level. Campbell (1992), using three different methods for determining safety stock requirements, concludes that as the length of frozen interval increases there could be a greater need for safety stock. Lin and Krajewski (1992) identify three MPS factors, namely, the length of the frozen interval, the replanning interval, and the forecast window that could have a significant impact on the total system costs. Finally, Zhao and Lee (1993), using a simulation model, find that longer frozen intervals could lead to greater scheduling stability but at the expense of lower customer service level and higher total cost. In contrast, Sridharan and LaForge (1994), assuming a single product environment, state that increasing the freezing interval does not result in a major loss in customer service (as measured by product availability), but increased freezing does lead to higher end-item inventory.

In summary, although these researchers have addressed some issues of MPS stability and its impact on product availability, they often assume a single item production environment with no capacity constraints. Data used for these models is theoretical. While these studies are valuable in establishing a framework for quantitative analysis, most operations managers would consider the approaches and assumptions unrealistic for nearly all manufacturing environments. This creates a gap between solutions proposed from academic research and MPS instability encountered in the real world.

In a broader sense, several studies exist that extend stability analysis to the supply chain level. These stability studies focus on component commonality (Zhao and Lam, 1997), setup cost (Stadtler, 2000; Johansen, 1999), and capacity utilization for individual production facilities (Wu and Meixell, 2004). For instance, Meixell (2005) suggests that designing component commonality into products and providing surplus capacity have a stabilizing effect on rolling production schedules. In this study, the stability for rolling schedules is measured by calculating the coefficient of variation for changes to scheduled quantities given a specific production period. Although, this body of research gives important insights regarding effective strategies for managing the stability of a supply chain, the situations discussed are limited to broad level studies and exclude day-to-day decision-making.

Meanwhile, one study does deal with real world conditions involving a case study of MPS stability for paint manufacturing (Venkataraman 1996). The author finds that under conditions of minimum batch-sizes and demand certainty, freezing the MPS leads to considerably higher levels of inventory and higher costs during peak periods of demand. In addition, Zhoa, Xie, and Jiang (2001) provide a comprehensive analysis of lot-sizing choice and freezing of the MPS as related to stability. Both of these studies analyze MPS stability under conditions of finite capacity (FC), an important consideration in the real world of manufacturing. As noted, several previous studies of MPS stability under conditions of infinite capacity exist, however Zhoa, Xie, and Jiang (2001, p. 47) comment, "It is uncertain whether the results found under uncapacitated systems can be applied to capacitated systems."

Given this background, the need exists to establish a robust model for determining the importance of factors that influence MPS stability in addition to providing a quantitative framework for making complex tradeoffs between MPS stability, product availability, and cost within the consumer goods industry.

3.0 PROBLEM DEFINITION

The goal of this study is to analyze the factors that affect MPS stability and to propose a method for improvement involving dynamic safety stocks. The MPS is important to link the sales forecast with production and material plans. Practitioners find that sudden changes in demand often cause MPS instability, disruption to material planning, and disruption to relationships with suppliers and customers alike.

Complicating matters, the pattern of forecast errors is seldom normally distributed for firms manufacturing and distributing products in the consumer goods industry. Since most mathematical models for determining the amount of on-hand inventory required to meet product availability targets assume normality of forecast errors, the chance for miscalculating inventory increases as forecasts become more biased. Planning production to the wrong inventory levels further complicates efforts to improve stability of the MPS and often leads to poor product availability or excessive amounts of inventory.

Although forecast bias is rarely incorporated into inventory calculations, an example from industry does make mention of the importance of dealing with this issue. Kakouros, Kuettner, and Cargille (2002) provide a case study of the impact of forecast bias on a product line produced by HP. They state that eliminating bias from forecasts resulted in a 20 to 30 percent reduction in inventory while still maintaining high levels of product availability. Similar results can be extended to the consumer goods industry where forecast bias is prevalent.

The causes of forecast bias come from several different sources. First, forecasts often are a sales goal rather than a realistic appraisal of demand. This leads to positive forecast bias and higher inventory levels. Second, the aggregate forecasting method often used in the consumer goods industry depends on accurate data to allocate a high-level forecast to manufacturing plants. Mis-allocation of a high-level forecast results in bias. Finally, with dynamic demand characteristic of the consumer goods industry it is difficult to re-center forecasts over time. In contrast, it is easy to see and eliminate bias when demand is constant. However, this is seldom typical for the consumer goods industry where product promotions can drive demand to high levels during short time periods. Generally, lumpy demand forecasts contain a great deal of bias.

In the context of forecast bias, finite capacity, and the proposed use of dynamic safety stocks, this study examines the typical situation in consumer goods manufacturing where a number of end-items are produced on a common manufacturing line and have to be sequenced to meet forecasted demand. Rather that use the practice of freezing a portion of the MPS, the focus of this study is on employing a safety stock method that accounts for forecast bias, and testing this approach against traditional safety stock methods in achieving improved MPS stability. The thesis of this study is that the use of bias adjusted dynamic safety stock methods will improve MPS stability as compared to the use of traditional methods for planning safety stock.

4.0 EXPERIMENTAL DESIGN

For analysis of factors that affect stability, the Modified Dixon Silver (MODS) method is used to develop the MPS under a variety of operating conditions (Allen, Martin, and Schuster 1997). The MODS model is a heuristic that gives realistic schedules based on deterministic forecast demand. All planning includes FC for a multiple-item production environment characteristic of manufacturing lines for consumer goods. Parameters include capacity, setup time, holding and setup cost, non-zero forecast bias, forecast error, demand variability safety stock method, and target customer service levels (product availability). The test example includes 22 products with a scheduling time-span of 52 weeks. The interval for planning is the amount of weekly production needed to meet forecasted demand. This represents a real situation encountered at Welch Foods, Inc., Concord, MA. For the assumptions of MODS see APPENDIX B.

The study uses experimental design (Box, Hunter, and Hunter 1978), in conjunction with the MODS model for producing a schedule, to observe the impact of selected MPS factors (inputs) on the measure of stability (the response). APPENDIX C shows the formula for the stability measure. A higher value means greater MPS instability over the 52-week planning horizon. The stability measure is statistically weighted to amplify schedule changes (instability) early in the planning horizon (1 – 5 weeks). This assumes near-term schedule changes are the most disruptive. Figure 1 shows the weights assigned to the stability measure for the first 20 weeks of the 52-week planning horizon (see APPENDIX C).

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Insert [Figure 1] here.

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To obtain the response, MODS is run for two planning cycles. Planning cycle 1 represents initial conditions. Planning cycle 2, one-step forward in time, includes a new forecast plus adjustments to select MPS parameters. This simulates a rolling 52-week horizon. Beginning inventories are adjusted to account for simulated shipments before running planning cycle 2. Measurement of the response (stability) occurs after completion of planning cycle 2 using the procedure outlined in APPENDIX B.

5.0 FACTORS AFFECTING STABILITY

The experimental design contains five factors for analysis that have potential to affect MPS stability. Four factors are quantitative and one factor is qualitative. The factors include:

- *Forecast bias* – Figure 2 shows an actual example of positive bias for a consumer product. The forecast is higher than actual demand for an extended time. The current study deals exclusively with positive forecast bias. Within MODS, a range of forecast bias is simulated from low (5%) to high (60%). This can be visualized as shifting the actual demand (red in Figure 2) up and down relative to the forecast while maintaining the same pattern. It should be noted that bias is calculated based on historical forecast and shipments. If a strong pattern of bias emerges, it is assumed this underlying process is stationary and will extend into the future unless independent action is taken to re-center the forecast.

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Insert [Figure 2] here.

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- *Capacity* - This represents line time available for production. We vary capacity from a minimum of 90 hours/week to a maximum of 110 hours/week. Normal capacity is 100 hours per week.

- *Demand Variability* – Represents the amplitude of actual demand fluctuation in relation to the mean forecast. Again, within MODS we can simulate a range of alternatives from low variability (15%) to high variability (50%).

- *Customer service level* - The proportion of cycles for which inventory can meet all demands. We vary customer service from 75% (low) to 99.5% (high).

- *Safety stock method* - We evaluate two methods of safety stock planning (Krupp 1982). The traditional method for safety stock (TMSS) assumes forecast errors are independent and randomly distributed according to the normal distribution. At any instant in time, there is an equal probability of actual demand being above or below the forecast. In contrast, Krupp's method for safety stock (KMSS) has a mechanism to adjust safety stock based on forecast bias. If forecast bias exists, KMSS adjusts safety stock based on a formula to compensate for the non normal distribution of forecast errors. For more details on TMSS and KMSS, please refer to APPENDIX D.

6.0 RESULTS AND ANALYSIS

A 2^5 full factorial design is run with two center points to determine how the five factors and all two-factor interactions affect the MPS stability measure. Raw data for this design is enumerated in APPENDIX E. These runs use coded variables for high/low settings +1 (high), -1 (low) or 0 (intermediate levels, for runs 33 and 34).

The full 15 factor model is significant (p = 5.7E-07, F = 13.98). However, not all of the 15 factors contribute to the model. We find *forecast bias* (p = 3.57E-10), *capacity* (p = 3.2E-05) and *safety stock method* (p = .0076) the only main factors that are significant. A joint interaction factor, *forecast bias x safety stock*, also contributes at p = .015.

Focusing on these four factors, a reduced model is formulated (APPENDIX F). The reduced model is significant (p = 3.69E-12, F = 46.08) and upon performing a partial F test, it is determined that the full 15-factor model is not a significant improvement over the reduced model. The two intermediate level runs provide a test for curvature which has an observed significance of p = .017. Figure 3 and Figure 4 confirm the presence of curvature by showing that slope changes when passing through the zero point for each choice of safety stock method. Figure 3 shows some evidence of interaction between forecast bias and safety stock method while Figure 4 shows little interaction between capacity and safety stock method.

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Insert [Figure 3] and [Figure 4] here.

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7.0 PREDICTING MPS STABILITY

The reduced model is a simple tool to predict MPS Stability in advance based on different settings for the factors. Since forecast bias has the largest coefficient, it is a good candidate to see the pattern of MPS stability over a range of settings. Keeping in mind a coded model is used, the equation to predict stability becomes:

Stability = 17.29 + 7.44 (Bias) - 3.33 (Capacity) – 1.77 (SS Method) - 1.63 (Bias x SS Method)

To convert coded independent variables the following general expression is used:

$y = \frac{x - \bar{x}}{r/2}$, where y is the coded variable, x is the physical variable, and r is the range.

The results are graphed over a range of forecast bias from 5% to 60%, for a typical capacity of 90 hours per week and TMSS (Figure 5):

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Insert [Figure 5] here.

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From Figure 5 it is observed that MPS instability more than doubles when moving from 5% to 60% positive forecast bias. It is common to experience forecast bias of 35% or more in the consumer goods industry. Based on Figure 5 this implies a 74% increase in MPS instability as compared to a centered forecast. It can be concluded that reducing forecast bias prior to FC scheduling is a good way to alleviate MPS instability. This is the approach adopted by Kakouros, Kuettner, and Cargille (2002).

8.0 SAFETY STOCK METHOD AS A MEANS OF IMPROVING STABILITY

In APPENDIX E, it is observed that *forecast bias* and *safety stock method* show a joint interaction affect on MPS stability (p = .015). This suggests that choice of safety stock method could be a way to reduce MPS instability caused by forecast bias. Further, any method incorporating forecast bias as an independent variable in the calculation of safety stock should have a positive impact on MPS stability. Based on analysis of the two safety stock methods used for this study, and the typical non normal distribution of forecast errors encountered in practice, it can be theorized that KMSS should provide more MPS stability in situations with high forecast bias.

KMSS also provides another advantage. It incorporates demand forecasts into safety stock calculations so that safety stock levels are dynamic. This is a powerful method to deal with lumpy demand situations encountered in the consumer goods industry (Schuster and Finch 1990).

9.0 TESTING THE TWO SAFETY STOCK METHODS

Figure 3 shows that under low bias situations, performance of the two safety stock methods on MPS stability is very close. However, the choice of safety stock method is significant in the high bias situation. KMSS reduces MPS instability, offering a 32% improvement compared to TMSS. Since no penalty exists for the low bias situation, it seems reasonable to use KMSS for all safety stock calculations regardless of the level of forecast bias.

Figure 4 shows the performance of the two safety stock methods under different conditions of capacity. Again, KMSS outperforms TMSS in reducing MPS instability. From these tests, it is clear that KMSS provides a robust solution that reduces MPS instability under conditions of FC.

10.0 CONCLUSION

From the experimental results of this study, it is reasonable to conclude that forecast bias is an important factor influencing MPS stability under conditions of FC. Since forecast bias appears to be prevalent in the consumer goods industry, steps to re-center the forecast would be the best approach to improving MPS stability. However, since many consumer goods firms produce hundreds of different stock keeping units in many different manufacturing plants it might not be possible to review and re-center each forecast manually.

In cases where re-centering is not possible, using KMSS mitigates the negative affects of forecast bias and improves MPS stability without freezing a portion of the planning horizon. Even if the forecast is re-centered, KMSS offers no penalty in terms of MPS stability. For this reason, KMSS should be considered a general solution for make-to-stock situations. If bias does creep into the forecast, the KMSS will automatically adjust out front safety stock projections based on the amount of historical bias identified. The result is improved MPS stability and optimized inventory levels based on product availability targets. In this way, the KMSS approach approximates a form of control theory where the ongoing recalculation of bias obtained from rolling forward through a finite time horizon serves as feedback mechanism to control production and the level of end-item inventory.

As a concluding note, a survey by LaForge and Craighead (2000) reports that only 25% of those firms with computerized scheduling systems use FC in some form. Based on the results from our study, we conclude that forecast bias is a contributing factor limiting the effectiveness of FC scheduling in practice. Better understanding of forecast bias and its impact on safety stock calculations, MPS stability, and cost will give logistics managers the capability to deliver improved customer service levels. This represents a significant incremental step in understanding the complex logistical trade-offs that firms must perform on a day-to-day basis to remain competitive in the consumer goods industry.

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APPENDIX A – OPEN SYSTEM FOR MASTER PRODUCTION SCHEDULING

The finite capacity planning system used in this paper to test schedule stability is also part of an open system approach to deliver sophisticated mathematical modeling capabilities to end-users via the Internet. Specifically, the M Language (mlanguage.mit.edu) in conjunction with other web standards enables end-users direct access to the Modified Dixon Silver Heuristic (MODS) through an information technology called Software as a Service (SaaS). This approach allows anyone access to the MODS algorithm located on a remote server using only a Microsoft Excel spreadsheet.[2] There is no implementation of MODS on local computing systems and access is immediate. Essentially, the algorithm serves as a calculator and does not store any data from the spreadsheet on the server.

Separating the interface from the computer code offers several advantages in rapid delivery of complex mathematical models to end-users and the control of versioning. The central idea is to host the MPS model, written in a structured computer language like Java or C++, on a single server with an interface that can be downloaded onto any computer using the Internet. The interface then connects to the central server when running the model. Such a system allows users located anywhere in the world to use a particular MPS approach with little implementation and at no cost.

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[2] To download the spreadsheet and connect to MODS, click on the following link (it is best to save the file to disk, and then re-open to execute MODS):

http://web.mit.edu/lmp/news/news_03_07_08.html

or

www.ed-w.info/osmps6.xls

Please note that users of the spreadsheet must enable the macros to allow access to the MODS algorithm located on a remote server.

A Microsoft Excel spreadsheet serves as the end-user interface for OSMPS. Spreadsheets are easy to understand and many firms already do master production scheduling in Excel using custom approaches developed internally. Enhancements in Excel 2003 and 2007 allow for direct interaction with a remote server that contains computer code such as Java.

Creating an open system for modeling using Excel spreadsheets also requires a robust way to treat semantics. The OSMPS uses the M Dictionary to provide consistent semantics for words and noun phrases contained in the spreadsheet interface that are elements of MODS. In this way, Internet search becomes precise and there is no ambiguity regarding the definition of terms used to describe the data fields, and Internet connections between and Excel spreadsheet and the code for the MPS.

Overall, the SaaS approach, combined with the M Language, quickly puts state-of-the-art modeling in the hands of many users with no local computer implementation other than downloading an Excel spreadsheet.

APPENDIX B - ASSUMPTIONS FOR MODS

1) Assume planning horizon = 52 weeks.

2) Setup cost, setup time, beginning inventory and carrying cost are non-zero and are known and constant throughout the 52-week period.

3) Assume finite capacity

4) No sequence dependencies. We model 22 products during a time span of 52 weeks.

5) Scheduling instability during the period close to actual production is likely to have greater impact than instability during a period in the distant future.

6) Assume that demand forecasts are independent.

7) Use Modified Dixon-Silver (MODS) heuristic model as a scheduling model.

We choose MODS for producing the MPS because it gives quick and reliable answers to difficult FC scheduling problems. Though MODS is a heuristic, extensive testing using experimental design proves it gives consistent answers that are close, if not equal, to optimal (Allen, Martin and Schuster 1997). The testing provides assurance that MODS will not introduce measurable noise into the experimental design because of algorithmic factors.

APPENDIX C - STABILITY MEASUREMENT

Several authors provide stability measures (Enns 1995; Inman and Gonsalvez 1997; Sridharan, Berry, and Udayabhanu 1988). For this study, we use a version of the stability measurement model presented by Sridharan, Berry, and Udayabhanu (1988). The measure is:

$$\text{Stability} = k \times \sum_{i=1}^{n} \sum_{t=1}^{H} W_t \times \left| Q_{i,t}^{p2} - Q_{i,t}^{p1} \right| / B$$

where:

i = 1…n, Item number
t = 1…H, Time period, weeks

n = Total number of products, n = 22

H = Planning horizon length, H = 52
$Q_{i,t}^{p2}$ = Scheduled production for item i, period t, during planning cycle 2
$Q_{i,t}^{p1}$ = Scheduled production for item i, period t during planning cycle 1
B = Total production for planning cycle 2
k = Multiple factor used to amplify the result,
for calculations in this paper k = 100
W_t = Weighting factor, Exp(1/t-1)

We incorporate a weighting factor because we believe the impact of schedule instability is not necessarily linear through time. Scheduling instability that occurs close to actual production has a greater impact and causes more disruption than instability during distant future periods.

APPENDIX D

Traditionally, safety stock is determined by the formula:

Safety Stock of item (i) = $k\sigma_I$

Where:

k = service level factor

σ_i = Standard deviation of the difference between forecasted value of item (i) and actual value of item (i).

The traditional model for safety stock (TMSS) assumes forecast errors (forecast minus actual for a time period) are independent and randomly distributed according to a Normal distribution. At any instant in time there is an equal probability of actual demand being above or below the forecast. TMSS is simple to understand. However, it may cause an overstocked or under stocked situation when there is a significant forecast bias. In this case, forecast errors do not form a Normal distribution through time.

It is the authors' experience that nearly all forecasts in the consumer goods industry have some degree of bias, making TMSS a poor choice to determine appropriate safety stock levels. In addition, TMSS has no visibility into future forecasts, relying only on historical data to calculate safety stock. With TMSS, a set level of safety stock is used for the entire planning horizon. For lumpy demand situations common to the fast moving consumer goods industry, a static safety stock based only on historical data is not effective (Schuster and Finch 1990).

In order to deal with forecast bias and lumpy demand, we introduce a different safety stock technique. Krupp (1982) put forth a method that has a mechanism to adjust safety stock based on forecast bias (KMSS). If any level of forecast bias exists, KMSS adjusts safety stock based on a formula to compensate for the non Normal distribution of forecast errors associated with forecast bias. If there is no bias in the forecast, KMSS approaches values generated by TMSS. As well, KMSS also incorporates demand forecasts into safety stock calculations so that safety stock levels change with time. This is a powerful method to deal with lumpy demand situations often encountered in FC planning situations by allowing safety stock levels to change dynamically. The following summarizes KMSS in mathematical terms:

Safety Stock = (S) x (k) x (TICF) x (u) x (t)

Where:

u = future forecasted demand per week
t = lead time
k = service level multiplier
s = suppression factor (straight line) = 1 – FETS
TICF = Time Increment Contingency Factor, a measure of variability indexed to the forecast

$$TICF = \left[\sum_{i=1}^{n} \left| u(i) - x(i) \right| / u(i) \right] / n$$

FETS = Forecast Error Tracking signal, a measure of forecast bias

$$FETS = \left[\sum_{i=1}^{n} \left(u(i) - x(i) / u(i) \right) / TICF \right] / n$$

u(i) = past forecast
x(i) = past actual sales
n = number of periods

<u>Note</u>: if u(i) = x(i) then TICF is zero and FETS is unbounded.

KMSS deals with long-term forecast bias by adjusting the level of safety stock using (s). If negative bias occurs (forecast consistently less than actual demand), KMSS will increase safety stock. The amount of increase is in proportion to the probability of overselling the forecast. In contrast, for positive forecast bias (forecast consistently more than actual demand), KMSS will adjust safety stock lower. However, KMSS works only under a certain range of forecast bias. KMSS does not work well in situations where there is a very high negative or positive forecast bias. The main reason is that by definition FETS will never be lower than –1 or greater than 1, limiting the capability to adjust safety stock for the severity of the forecast bias. The value for (s) will never range beyond 0 to 2. The authors have observed situations where extreme positive forecast bias caused over production even when safety stock was adjusted to zero using KMSS.

APPENDIX E – EXPERIMENTAL DATA

The following is experimental data used to run a 2^5 full factorial design to determine how the factors affect the MPS stability measure:

Experiment Number	Bias	Capacity	Demand Variation	Service Level	SS Method	Instability Measure
1	.05	.90	.15	.75	1	11.81
2	.05	.90	.15	.995	-1	12.98
3	.05	.90	.50	.75	-1	14.37
4	.05	.90	.50	.995	1	14.58
5	.05	1.10	.15	.75	-1	5.79
6	.05	1.10	.15	.995	1	4.62
7	.05	1.10	.50	.75	1	8.73
8	.05	1.10	.50	.995	-1	8.95
9	.60	.90	.15	.75	-1	37.55
10	.60	.90	.15	.995	1	26.99
11	.60	.90	.50	.75	1	23.94
12	.60	.90	.50	.995	-1	37.98
13	.60	1.10	.15	.75	1	20.48
14	.60	1.10	.15	.995	-1	25.65
15	.60	1.10	.50	.75	-1	18.80
16	.60	1.10	.50	.995	1	17.85
17	.05	.90	.15	.75	-1	11.51
18	.05	.90	.15	.995	1	12.39
19	.05	.90	.50	.75	1	13.91
20	.05	.90	.50	.995	-1	15.35
21	.05	1.10	.15	.75	1	5.45
22	.05	1.10	.15	.995	-1	5.61
23	.05	1.10	.50	.75	-1	8.71
24	.05	1.10	.50	.995	1	8.51
25	.60	.90	.15	.75	1	21.82
26	.60	.90	.15	.995	-1	33.09
27	.60	.90	.50	.75	-1	23.22
28	.60	.90	.50	.995	1	24.11
29	.60	1.10	.15	.75	-1	21.30
30	.60	1.10	.15	.995	1	20.06
31	.60	1.10	.50	.75	1	17.67
32	.60	1.10	.50	.995	-1	30.72
33	.325	1.0	.325	.8725	-1	12.33
34	.325	1.0	.325	.8725	1	10.92

APPENDIX F – RESULTS OF THE REDUCED MODEL

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.92954
R Square	0.864044
Adjusted R Square	0.845291
Standard Error	3.545131
Observations	34

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	2316.328	579.082	46.07607	3.68E-12
Residual	29	364.4707	12.56795		
Total	33	2680.799			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	17.28676	0.607985	28.43288	9.91E-23
Bias	7.43625	0.626697	11.86579	1.19E-12
Capacity	-3.33438	0.626697	-5.32056	1.04E-05
SS Method	-1.76676	0.607985	-2.90593	0.006944
SSMethodxBias	-1.62875	0.626697	-2.59895	0.014551

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FIGURE CAPTIONS

Figures	Captions
Figure 1	Weights assigned to the stability measure versus time (see Appendix B for details)
Figure 2	An actual case of forecast bias experienced in the consumer goods industry
Figure 3	A visualization of bias vs. instability
Figure 4	A visualization of capacity vs. instability
Figure 5	A model relating stability to bias