NOTAS ECONÓMICAS 4

REVISTA DA FACULDADE DE ECONOMIA DA UNIVERSIDADE DE COIMBRA

NÚMERO 4/Novembro'94/PREÇO 1 500$00/ISSN 0872-4733

Identifying a Dominant Multilevel Lot Sizing Heuristic for Use in MRP Research

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resumo

No domínio da investigação de MRP, convém dispor de uma lei de loteamento dominante, simultaneamente eficaz e constantemente quase-óptima numa grande variedade de situações experimentais. Este trabalho destina-se a determinar qual das heurísticas de loteamento em vários níveis actualmente disponíveis responde a essas condições e é a mais aconselhável para outros casos de MRP. O trabalho limita-se a quatro métodos relativamente simples e muito eficazes que já demonstraram anteriormente poder fornecer soluções quase-óptimas muito superiores à maioria das leis de loteamento geralmente utilizadas. Os quatros métodos são comparados entre si — o que até aqui nunca tinha ocorrido — num vasto leque de situações experimentais. Os resultados sugerem uma nova heurística recentemente proposta como alternativa muito prometedora para outros trabalhos de investigação sobre MRP.

résumé / abstract

Dans le domaine de la recherche MRP il est nécessaire de disposer d'une loi de groupage dominante, qui puisse être à la fois très efficace et continuellement quasi-optimale dans une grande variété de conditions expérimentales. Cette recherche a pour but d'identifier laquelle des heuristiques de groupage à plusieurs niveaux actuellement disponibles répond à ces critères et dont l'utilisation serait donc des plus conseillées en ce qui concerne la MRP. Nous nous concentrerons sur quatre méthodes relativement simples qui ont montré au cours de recherches précédentes pouvoir générer des solutions quasi-optimales bien supérieures à la plupart des lois de groupage communément utilisées dans les études en MRP. Ces quatre méthodes, qui jamais auparavant n'avaient été évaluées directement l'une contre l'autre, sont comparées sur un large éventail de conditions expérimentales. Les résultats expérimentaux désignent une heuristique récemment proposée comme une alternative très attrayante pour d'autres recherches en MRP.

What is needed in much of the MRP research is one dominant lot sizing rule, which can be relied upon to be both very efficient and consistently near-optimal across a wide variety of experimental conditions.
The present research seeks to identify which, if any, of the presently available multilevel lot sizing heuristics meet these criteria, and would thus be most suitable for use in studies of other MRP issues. The focus is on four relatively simple and very efficient methods which have been shown in previous research to generate near-optimal solutions vastly superior to many of the lot sizing rules commonly used in MRP studies. The four methods, which had previously never been evaluated directly against each other, are compared over a large and comprehensive experimental design. The experimental results point to a recently offered heuristic as a very attractive alternative for use in other MRP research.

Introduction

A variety of recent research on issues within Material Requirements Planning (MRP) has involved the integral use of lot sizing algorithms to determine solutions and system costs. This would include research into the impact of freezing the master production schedule, the impact of rolling planning horizons, and the effects on system nervousness and instability caused by safety stock, demand uncertainty, supply uncertainty, and inventory record accuracy, among others (Harrison, 1991; Ho and Ireland, 1989; Ho and Lau, 1990; Lin and Krajewski, 1989; Lin et al., 1990; Sridharan et al., 1987, 1988; Sridharan and Berry, 1990; Sridharan and LaForge, 1989a, 1989b, 1990; Subhashish and Grasso, 1991; Zhao and Lee, 1991). Much of this research to date, particularly that associated with freezing the master production schedule, has focused on single item or single level MRP systems. In response, a budding stream of new research has begun to study whether conclusions drawn in the single level studies can be generalized to multilevel systems (Harrison, 1991; Ho and Ireland, 1989; Ho and Lau, 1990; Lin and Krajewski, 1989; Lin et al., 1990; Subhashish and Grasso, 1991; Zhao and Lee, 1991).

However, most of this new multilevel research has retained the practice of using single item lot sizing rules, such as Silver-Meal, Wagner-Whitin, EOQ, Part Period Balancing, and the like, as a means of determining solutions (Harrison, 1991; Ho and Ireland, 1989; Ho and Lau, 1990; Lin and Krajewski, 1989; Lin et al., 1990; Subhashish and Grasso, 1991). These methods are simply being applied sequentially, from the top to the bottom of the product structure, an approach which ignores the cost trade-offs associated with multiple levels. This is true despite the fact that a preponderance of sources have established the poor and/or inconsistent lot sizing performance of these types of lot sizing methods in a multilevel environment (Biggs et al., 1977, 1980; Blackburn and Millen, 1982a, 1985; Choi et al., 1984; Coleman and McKnew, 1991; Collier, 1980; Jacobs and Khumawala, 1982; Krajewski et al., 1980; Rehmani and Steinberg, 1982; Veral and LaForge, 1985; Yellen, 1979). Precious few of the recent multilevel analyses have employed any of the much more effective lot sizing methods (Blackburn and Millen, 1982a, 1985; Coleman and McKnew, 1991; McLaren, 1976; McLaren and Whybark, 1976; Rehmani and Steinberg, 1982) which have been specifically designed for MRP's multilevel environment (see Zhao and Lee, 1991, as an exception).

The problem with this type of approach is that the resulting absence of consistently near-optimal lot sizing solutions potentially biases cost results when other issues are being addressed. This potential bias is due to the fact that many of the simpler, sequentially applied lot sizing heuristics commonly used have been shown to be extremely situationally dependent in their performance (see the many citations above). Thus, whereas an MRP researcher may conclude that, for example, one freezing method is better than another under certain situations, the difference in costs may actually be greatly attributable to the effectiveness (or lack thereof) of the single level lot sizing method(s) being used in those conditions.

What is needed in much of the multilevel MRP research where lot sizing is not the focus, but must be performed to obtain solutions, is a very efficient lot sizing algorithm which can be relied upon to consistently generate near-optimal multilevel solutions. Such a method would virtually eliminate any bias derived as a result of using a poor lot sizing methodology. The efficiency issue is also quite important, given the large scale nature of many MRP simulation experiments. Also, the use of one very good algorithm, as opposed to a group of two or three single-item rules (as is commonly practiced), could reduce the size of the experimental designs necessary to test the effects of other MRP conditions and methods.

The present research seeks to identify which, if any, of the presently available multilevel lot sizing heuristics meet both the efficiency and consistency criteria, and would thus be most suitable for use in studies of other MRP issues. The focus of the study will be on four relatively simple and very efficient methods which have been shown in previous research to generate near-optimal solutions vastly superior to many of the sequential single item lot sizing rules commonly used in MRP studies. All four have specific features designed to reflect MRP's multilevel environment, yet all four retain the straightforward, "one pass from top-to-bottom" nature of the more widely used techniques. However, the four techniques had heretofore never been previously compared over a broad-based, comprehensive experimental design. Given this previous lack of direct and thorough comparison, the present purpose is to identify the dominant of these four highly efficient algorithms, achieved by comparative evaluation across a wide variety of problem environments.

The next section provides a brief outline of the four heuristics which are compared. This is followed by a discussion of the two-phase experimental design which was employed for evaluation. The results of the experimentation are then presented, and subjected to an in-depth analysis to determine if algorithm preference is a function of the environmental factors present. Finally, we draw some conclusions regarding the relative performances of each approach.

Algorithm Descriptions

The four algorithms evaluated include the following: the Wagner-Whitin k-continuous, constrained (WW-KCC) (Blackburn and Millen, 1982a, 1985); the McLaren-Whybark Wagner-Whitin (MW-WW) (McLaren, 1976; McLaren and Whybark, 1976); the Simple Average Least Total Cost (SALTC) (Rehmani and Steinberg, 1982); and the Sequential TOPS with Incremental Look-Down (STIL) (Coleman and McKnew, 1991). The first three methods augment the ordering (setup) and/or holding costs used at each level to better reflect the dependencies that lower level items have on decisions made for items higher up in the product structure. The fourth heuristic also uses modified costs, but also employs specific "look-down" features to aid in decision making for items higher up in the product structure. A brief overview of the characteristics of each algorithm is provided below; the reader is referred to the cited works for detailed discussion of how each method is used.

The WW-KCC approach (Blackburn and Millen, 1982a, 1985) is a modified sequential Wagner-Whitin (WW) (Wagner and Whitin, 1958) application presented by Blackburn and Millen in which both the order/setup and "echelon" (marginal) holding costs are modified. Information from all of a given item's components is included in the modified cost estimates for that item. Revised setup and echelon holding cost calculations are made from the lowest level items up the product structure to the end item. The modified setup and echelon holding costs are then used in conjunction with a sequential pass of WW to determine solutions. An advantage of this approach versus many others is its "structure-deep" consideration of an item's components when determining modified costs.

Like the Blackburn and Millen heuristic, the MW-WW method (McLaren, 1976; McLaren and Whybark, 1976) is another modified sequential WW method presented by McLaren and Whybark in which only the ordering (setup) costs are adjusted for each item. Each item's setup cost is adjusted by adding to it the "Time-Between-Orders ratio-adjusted" setup cost of each of its immediate components. Following these cost modifications, Wagner-Whitin is applied sequentially from the top to the bottom of the product structure using the adjusted setup costs and unadjusted full-value holding costs. MW-WW is not a "structure-deep" heuristic, as it only uses cost information from components at the very next level when making a given lot sizing decision.

The SALTC approach (Rehmani and Steinberg, 1982) combines a sequential application of the Least Total Cost (LTC, or Part Period Balancing without look ahead, look back) heuristic with a modified version of the well-known Economic Part Period (EPP) ratio to make order decisions. The novelty of SALTC is in the modification of the cost ratio rather than individual costs. The simple average (SA) of the EPP of each item and those of all its immediate components is employed. As with MW-WW, SALTC also considers information only from the next lower level when revising cost inputs. SALTC was shown to be superior to MW-WW in the somewhat limited experimentation in (Rehmani and Steinberg, 1982).

The STIL algorithm (Coleman and McKnew, 1991) is a one-pass heuristic founded upon the Technique for Order Placement and Sizing (TOPS) single-level routine (Coleman and McKnew, 1990), an approach which has been shown to closely emulate single item optimality. STIL is a modified sequential application of TOPS, in which the ramifications of a given lot sizing choice on component item costs are analyzed before an action is taken. This analysis is done by way of two "look-down" features. STIL is the only known single pass heuristic presented in the literature with specific features which attempt to account for lower level ramifications during its execution. All other methods, including the three just described, make adjustments to heuristic inputs (costs) *prior* to application, leaving the procedure itself unchanged.

Experimental Design

In an effort not to bias the analysis in favor of a particular method, the experimentation was divided into two phases. The first set of problems, which will be referred to as Phase I, was designed to replicate much of the design used by Blackburn and Millen when presenting WW-KCC (Blackburn and Millen, 1982a, 1982b, 1985). The parameters used in Phase I were also similar to those described by Graves in another multilevel lot sizing study (Graves, 1981). Table I outlines the Phase I experimentation. The second part, referred to as Phase II, utilized design factors consistent with those used by Coleman and McKnew in the presentation of the STIL heuristic, and to those used by LaForge and Veral and LaForge in their lot sizing analyses (Coleman and McKnew, 1991; LaForge, 1985; Veral and LaForge, 1985). Table II summarizes the Phase II experimentation. Phase I incorporated the product structures shown in Figure 1, and Phase II employed the 1:1 production ratio structures exhibited in Figure 2, and the mixed production ratio structure shown in Figure 3.

It should be noted that a significant portion of the original Blackburn and Millen design elements were very similar to those from Coleman and McKnew. In response, the Phase I examples reflected those Blackburn and Millen factor settings that were different. The combination of Phase I and Phase II experimental problems represented a comprehensive coverage, within which each method's strengths and weaknesses had an opportunity to be revealed.

Table I. Phase I Experimental Design Factors and Factor Levels (All Five-Item, 12-Period Problems with 1:1 Production Ratios).

Factor	Number of Levels	Level Descriptions
Product Structure Configurations	5•	2, Two 3, 4, and 5 Level Structures
Ordering (Setup) Costs	Randomized	Uniform [50, 300, 600, 1500](a)
Echelon Holding Costs	Randomized	Uniform [0.1, 0.5, 1.0, 2.0](a)
Demand Variation	3	U[0,200]; NID(μ=100,σ=20);
		NID(μ=125,σ=20) with probability
		of 0.8, 0 with probability of 0.2[b]

Notes: (a) Twenty-five combinations of ordering (setup) and holding costs were used. The echelon holding costs for all stage 5 items were set equal to 1.00.
(b) Three replications of each level of demand variability were used.

Table II. Phase II Experimental Design Factors and Factor Levels (All Nine-Item, 52-Period Problems).

Factor	Number of Levels	Level Descriptions
Product Structure Configurations	4	3, 4, 5, and 6 Level Structures
Ordering (Setup) Cost Factors	3	0.4, 0.6, and 0.8 (a)
Holding Cost (Value-Added) Factors	6	1.1, 1.2, 1.3, 1.4, 1.6, and 2.0 (b)
Production Ratio Arrangements	2	1:1 and Mixed
Coefficients of Demand Variation	3	0.31, 0.75, and 1.16 (c)

Notes: (a) An ordering cost of $50 was assumed for all items without a lower-level part. The ordering (setup) cost for each item along the longest branch in the given product structure was determined by multiplying the ordering (setup) cost of its immediate component by the ordering (setup) cost factor. Ordering (setup) costs for all other items in the structure were similarly calculated by multiplying the ordering (setup) cost of their immediate component by the order cost factor.
(b) Holding costs were computed by simply multiplying the total holding costs of an item's immediate components (accounting for production ratios) by the respective holding cost factor.
(c) To provide replication, three randomly generated demand streams were derived from a normal distribution with mean 92.0 for each of the variability parameters.

Figure 1. Product Strutures Used in Phase I Experimentation

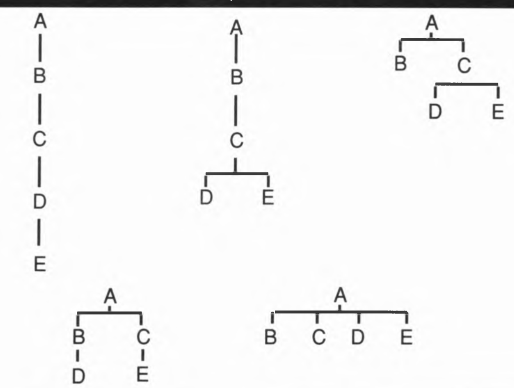


Figure 2. One-to-One Production Ratio Product Structures Used in Phase II Experimentation

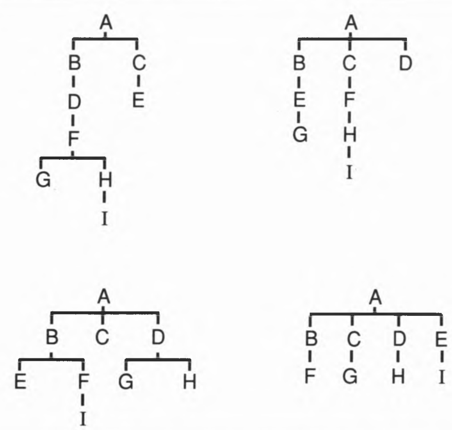
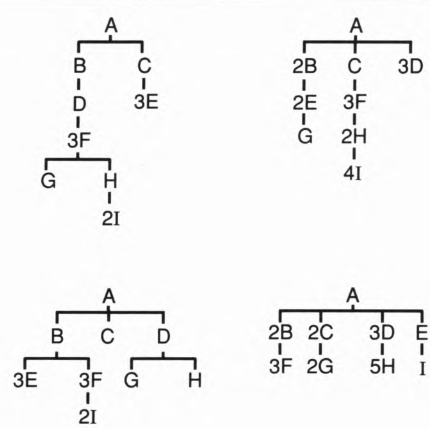


Figure 3. Mixed Production Ratio Product Structures Used in Phase II Experimentation



Solutions for all problems were derived according to the four heuristics discussed. The response variable of interest in both phases was total ordering (setup) and holding costs (based on ending inventory) of solutions yielded by each method. As in multiple other lot sizing studies, a cost index was calculated for each algorithm for each test case (Blackburn and Millen, 1982a, 1982b, 1985; Coleman and McKnew, 1991; Veral and LaForge, 1985). This was done by dividing a heuristic's total cost by the total cost of the algorithm chosen as the benchmark. The heuristic used as the benchmark was the one showing the overall lowest mean cost across all test cases. Besides mean cost, other aggregate total cost criteria used included maximum improvement over the benchmark algorithm, maximum penalty (deficit) versus the benchmark algorithm, and the frequency of test problems in which the algorithm performed better than the benchmark. Each of these were examined from an overall standpoint, with mean cost results also broken down by factor levels in each phase.

A secondary response variable of interest in the present study was computational time required to reach solutions. However, it should be noted that no practical differences in computational time were shown for the four algorithms. For the largest cases, average times for the WW-based algorithms were on the order of 1 second of real time when executed on an IBM PS/2 Model 50Z (80286 processor) equipped with a math coprocessor. STIL times averaged about one to two tenths of a second faster, with SALTC averaging about one-half second in duration. The most efficient WW code available in the literature was employed (Saydam and McKnew, 1987). Even using the relatively slow 80286 processor, all of the times met the efficiency criteria necessary for use in large scale MRP research experiments.

Experimentation Results

Phase I Overall Results

Table III summarizes the average total cost produced by each technique across all 1125 Phase I problems. Indexed solutions shown reflect the average deviation from a STIL basis of 1.0, as this method was shown to exhibit the overall lowest average cost. Indices were computed by simply dividing the cost solution yielded by the heuristic for each example by the STIL total cost, and subsequently averaging over all cases. Table IV summarizes the relative quality of solutions for each heuristic for all one-way factor levels, once again assuming a STIL base index of 1.0 in each instance.

Table III. Summary Statistics for 1125 Phase I Problems Using STIL as Basis (STIL Mean Cost = 14,937.78).

		HEURISTIC	
PERFORMANCE MEASURE	WW-KCC	MW-WW	SALTC
Mean Cost	15,278.38	15,165.49	17,631.15
Avg. Index (STIL=1.0)	1.024	1.018	1.188
Percent of Time Better Than STIL (a)	21.4% (n=241)	19.1% (n=215)	1.0% n=11)
Percent of Time Worse Than STIL (a)	48.7% n=548)	61.2% (n=689)	97.8% (n=1100)
Maximum Improvement Over STIL Algorithm (Index)	1199.80 (.928)	002.00 (.948)	668.00 (.958)
Worst Performance Versus STIL Algorithm (Index)	8645.00 (1.619)	1825.50 (1.191)	18,683.00 (1.982)
Average Improvement Over STIL Algorithm When Better (Average Index)	259.84 (.984)	255.41 (.985)	297.32 (.981)
Average Deviation From STIL When STIL Better (Average Index)	813.49 (1.056)	451.51 (1.033)	2757.56 (1.192)

Note: (a) STIL and WW-KCC generated identical costs on 336 occasions (29.9% of the time). STIL and MW-WW generated identical costs on 221 occasions (19.6%).STIL and SALTC generated identical costs on 14 occasions (1.2%).

Table IV. Mean Indexed Solutions by Factor Levels for 1125 Phase I Problems (All STIL Indices=1.0).

Factor	Level	STIL MeanCost	WW-KCC	MW-WW	SALTC
Product Structure Depth (n=225):	5(a)	15,445.66	1.078	1.038	1.127
	4	5,147.92	1.033	1.032	1.196
	3	14,661.01	.997	1.010	1.266
	3	14,882.51	1.003	1.010	1.131
	2	14,551.79	1.007	.998	1.220
Demand Variation (n=375):	1(b)	14,420.06	1.024	1.017	1.205
	2	15,977.81	1.019	1.014	1.166
	3	14,415.46	1.028	1.022	1.193

Notes: (a) Levels in product structure.
(b) Level 1=U[0,200]; 2=NID(μ=100,σ=20); 3=NID(μ=125,σ=20), zero with probability=.20.

Several items from Table III are of interest. Firstly, in terms of mean overall cost performance, there was virtually no difference between the top three algorithms, STIL, MW-WW, and WW-KCC, with each of these exhibiting overall mean costs far superior to (i.e., approximately 19% lower than) the SALTC heuristic. However, even though the overall average differences between the three best methods were negligible, the other aggregate measures were in favor of the STIL benchmark. Versus all three other algorithms, it exhibited a better cost solution far more often than it generated a worse solution. STIL at times drastically improved the WW-KCC by $8645 (approximately 62 percent), MW-WW by $1825.50 (about 19 percent), and SALTC by $18,683.00 (over 98 percent), while the largest improvement of all of the other algorithms over STIL was between four and seven percent. When STIL did generate a worse solution than another algorithm, its average cost was maintained well within two percent. The average relative performances of WW-KCC, MW-WW, and SALTC were much worse when STIL was superior.

Phase I Sensitivity Analysis

The Phase I experimentation, because of its many randomized elements, did not lend itself to extensive examination of the impact of various factors. Table IV lists the results for the two controlled factors that were present, allowing some additional insights regarding performance consistency. In all but two cases, STIL exhibited a mean index better than its three counterparts. In those instances, mean cost performance was within three-tenths of one percent of the other method. The table also allows for some analysis of the impact of various factors on algorithm performance. Most notably, the presence of deeper product structures appeared to enhance the relative performance of STIL versus all three other methods. Differences in demand variation did little to change relative results.

Phase II Overall Results

The overall results of Phase II were consistent with those of Phase I, although the magnitude of performance differences was not as pronounced. Table V summarizes the relative cost performance of all Phase II problems, using the same format as in Table III. Once again, no practical differences in overall mean cost were exhibited among the three best algorithms, with SALTC lagging far behind. In fact, SALTC's relative performance declined phenomenally in Phase II, with costs which at times were on the order of nearly *fifteen times* higher.

The advantage STIL claimed in Phase I in terms of the frequency of best performance was reversed in Phase II in favor of WW-KCC, but was maintained at similar levels versus MW-WW and SALTC. As in Phase I, STIL's maximum and average improvements over the other methods exceeded the maximum and average deficits it exhibited when beaten. STIL, on average, was well within 1% of the best algorithm when another method was better, while MW-WW and WW-KCC yielded respective average deficits of 1.4% and 3% when STIL was better. Perhaps the only criteria which clearly and significantly favored a particular algorithm was the maximum improvement gained. STIL was never surpassed by more than four and a half percent, but at times improved WW-KCC by more than 19% and MW-WW by over 11%.

Table V. Summary Statistics for 1,296 Phase II Problems Using STIL as Basis (STIL Mean Cost = 7639.54).

PERFORMANCE MEASURE	HEURISTIC WW-KCC	MW-WW	SALTC
Mean Cost	7729.02	682.47	15,281.21
Avg. Index (STIL=1.0)	.009	1.006	1.839
Percent of Time Better Than STIL (a)	4.6% (n=708)	38.2% (n=495)	00.0%
Percent of Time Worse Than STIL (a)	43.7% (n=566)	61.4% (n=796)	100.0%
Maximum Improvement Over STIL Algorithm (Index)	307.60 (.956)	265.60 (.956)	- -
Worst Performance Versus STIL Algorithm (Index)	1911.70 (1.190)	953.60 (1.112)	135,981.30 (15.083)
Average Improvement Over STIL Algorithm When Better (Average Index)	53.62 (.992)	48.06 (.993)	- -
Average Deviation From STIL When STIL Better (Average Index)	271.97 (1.030)	99.79 (1.014)	7641.67 (1.839)

Note: (a) STIL and WW-KCC generated identical costs on 22 occasions (1.7%). STIL and MW-WW generated identical costs on 5 occasions (0.39%).

Phase II Sensitivity Analysis

The more structured factor levels in Phase II allowed for a more thorough analysis of the impact of environmental factors on relative solutions. Table VI indicates that, as before, demand variability changed relative performance very little. The same can be said for the ordering (setup) cost factor, even though higher levels tended to favor WW-KCC and MW-WW to a small degree. Unlike as in Phase I, increased product structure depth did not play a major, consistent role in relative cost performances, save possibly for MW-WW.

What was important in determining relative quality of solutions was the holding cost (value-added) factor, and the presence of mixed versus 1:1 production ratios. Both WW-KCC and MW-WW were slightly improved over STIL for the highest holding cost factors, with relative performances which got monotonically worse as the factor approached 1.0. WW-KCC also showed stronger performance than STIL for 1:1 production ratio problems, while mixed ratios severely hampered what was at least a “reasonable” (although still a 23% higher cost) performance for SALTC for 1:1 ratios. When STIL was outperformed for any level of any factor, its average performance was within one-half of one-percent of the other algorithm. Contrastingly, the “unfavorable” levels for each of the two “delineating” factors for the other three methods yielded average costs which were at times more than 2% (MW-WW), 4% (WW-KCC), and 290% (SALTC) worse than STIL.

Further examination reveals the extent to which the production ratios and the holding cost factor affected results. The highest three holding cost factors were involved in almost 69% of the cases in which WW-KCC generated lower costs than STIL, and nearly 75% of the replications for which MW-WW was better than STIL. This was true even though these factor levels were present in only one half of the test cases. The impact of the production ratio factor was also pronounced, as production ratios of 1:1 were present approximately 64% of the time that WW-KCC performed better than STIL.

Table VI. Mean Indexed Solutions by Factor Levels for 1,296 Phase II Problems(All STIL Indices=1.0).

Factor	Level	STIL Mean Cost	WW-KCC	MW-WW	SALTC
Product Structure Depth (n=324):	6 (a)	6734.31	1.007	.012	1.308
	5	7570.95	1.014	1.010	3.115
	4	7736.10	.998	1.003	1.463
	3	8516.80	1.016	1.000b	1.470
Ordering (Setup) Cost Factor (n=432):	.4	6342.08	1.004	1.002	2.037
	.6	7519.47	1.010	1.005	1.828
	.8	9057.07	1.012	1.011	1.652
Holding Cost Factor (n=216):	1.1	6823.78	1.044	1.026	1.404
	1.2	7189.11	1.018	1.012	1.476
	1.3	7482.65	1.002	1.004	1.575
	1.4	7712.12	.998	1.001	1.668
	1.6	8074.98	.995	.998	1.981
	2.0	8554.61	.994	.996	2.931
Coefficient of Demand Variation (n=432):	.31	8196.43	1.006	1.004	1.605
	.75	7509.64	1.009	1.006	1.839
	1.16	7212.56	1.010	1.008	2.074
Production Ratio (n=648):	1:1	5803.22	.995	1.005	1.229
	Mixed	9475.86	1.022	1.007	2.449

Notes: (a) Levels in product structure.
(b) Rounded up at the fourth decimal place.

Table VII. Comparative Performance Measures of WW-KCC and MW-WW Indexed Solutions for Two-Way Interaction Between Holding Cost Factor and Production Ratio Arrangement (All STIL Indices=1.0, n=108 for each cell).

HOLDING COST FACTOR		PRODUCTION RATIOS 1:1		MIXED	
		WW-KCC	MW-WW	WW-KCC	MW-WW
1.1	Average	1.005	1.025	1.082	1.027
	Minimum	.976	.968	.991	.998
	Maximum	1.035	1.091	1.190	1.112
	STIL Best (%)	62.0%	83.3%	96.3%	98.1%
1.2	Average	.997	1.011	1.039	1.012
	Minimum	.956	.956	.990	.991
	Maximum	1.021	1.069	1.119	1.054
	STIL Best (%)	43.5%	74.1%	97.2%	93.5%
1.3	Average	.992	1.003	1.013	1.005
	Minimum	.961	.968	.983	.991
	Maximum	1.019	1.039	1.070	1.021
	STIL Best (%)	20.4%	56.5%	76.9%	77.8%
1.4	Average	.993	1.001	1.002	1.002
	Minimum	.973	.978	.987	.986
	Maximum	.023	1.032	1.024	1.014
	STIL Best (%)	25.0% (1 same)	50.0% (2 same)	53.7%	68.5%
1.6	Average	.993	.997	.997	.999
	Minimum	.975	.975	.988	.988
	Maximum	1.009	1.015	1.005	1.007
	STIL Best (%)	2.0% (1 same)	38.0% (1 same)	19.4% (5 same)	51.9% (1 same)
2.0	Average	.992	.994	.997	.997
	Minimum	.966	.969	.981	.981
	Maximum	1.005	1.015	1.001	1.003
	STIL Best (%)	9.3% (4 same)	24.1% (1 same)	8.3% (7 same)	21.3% (2 same)

Given that the production ratio and holding cost factors were the most important in defining differences between the leading algorithms in Phase II, the analysis was extended to more thoroughly evaluate their effects. Table VII summarizes the interaction between the two factors. Examination of all rows and columns shows consistent, monotonic improvement in the relative mean performance of STIL as the holding cost factor is lowered, and/or as production ratios move from 1:1 to mixed. The exact inverse is true for WW-KCC and MW-WW. The most dramatic differences in performance are shown when each factor is at the "favorable" level for each algorithm. With 1:1 production ratios and a holding cost factor of 2.0, both WW-KCC and MW-WW exhibit their best performances. Conversely, with mixed ratios and a 1.1 cost factor, STIL performs at its highest level. However, in comparing these two cases, as well as those throughout the table, the overall comparison favors STIL. For example, in WW-KCC's most favorable environment, STIL's average cost was well within 1% of WW-KCC, its maximum deficit was 3.4%, and it improved WW-KCC 10 of 108 times. In contrast, in STIL's most favorable situation, WW-KCC's average cost was over 8% worse on average, its maximum deficit was 19%, and it improved STIL four times. Very similar remarks can be made for MW-WW.

Summary and Conclusions

The relative cost performances of four algorithms efficient enough for lot sizing in multilevel MRP simulation studies were compared. These included two modified cost Wagner-Whitin methods (WW-KCC and MW-WW), a modified cost Least Total Cost method (SALTC), and a TOPS-based method which incorporates both modified costs and look-down features (STIL). The criteria used in the evaluation of the four heuristics reflected the preferred characteristics of strength and consistency of cost performance.

Given the extremely similar overall mean cost results of the top three methods, and to a large extent the similarity of mean costs for many of the factor levels, the maximum penalties (i.e., the measure of performance consistency across all experimental conditions) emerged as the predominant delineating factor in the present study. Given this as the determinative criteria, the experimentation favored STIL over WW-KCC, MW-WW, and SALTC, across both phases of the experimental design. Its maximum deviation from the best algorithm in any case, in either phase, was 7.2%. In contrast, WW-KCC was surpassed at times in Phase II by 19%, and MW-WW on occasion by over 11%. These figures were even more pronounced in Phase I, where WW-KCC and MW-WW experienced deficits of approximately 62% and 19%, respectively. Although changes in some factor conditions affected the magnitude of these results, STIL *never was a poor alternative.* The same could not be said of the remaining algorithms. This was not only true of WW-KCC and MW-WW, but especially so for the SALTC heuristic, for which it was particularly interesting to note the incredibly severe impact that mixed production ratios had on its performance. Consolidation of the results from both phases suggest that STIL's closest competition, WW-KCC and MW-WW, while very similar in overall mean costs, are much more volatile in their relative performances.

Therefore, the experimentation performed here points to STIL as the most effective and consistent alternative for use in research on other MRP issues, such as that now being performed in the area of master production schedule freezing. When viewed in conjunction with (Coleman and McKnew, 1991), the results here suggest that STIL can be relied upon to generate near-optimal lot sizing solutions in the types of experimental environments commonly found in other MRP research. Moreover, the differences between its computational requirements and that required of a sequentially applied single item method such as least total cost are inconsequential (e.g. averaging less than one half of a real-time second for the problems and hardware used here). As such, its employment is suggested as a means of minimizing any lot sizing bias that may result from the use of much more sub-optimal routines.

References

Biggs, J. R.; Goodman, S. H.; Hardy, S. T. (1977) Lot sizing rules in a hierarchical multistage inventory system, *Production and Inventory Management*, vol. 18, 1, 104-115.

Biggs, J. R.; Hahn, C. K.; Pinto, P. A. (1980) Performance of lot-sizing rules in an MRP system with different operating conditions, *Academy of Management Review*, vol. 5, 1, 89-96.

Blackburn, J. D.; Millen, R. A. (1982a) Improved heuristics for multi-stage requirements planning systems, *Management Science*, vol. 28, 1, 44-56.

Blackburn, J. D.; Millen, R. A. (1982b) The impact of a rolling schedule in a multi-level MRP system, *Journal of Operations Management*, vol. 2, 2, 125-134.

Blackburn, J. D.; Millen, R. A. (1985) An evaluation of heuristic performance in multi-stage lot-sizing systems, *International Journal of Production Research*, vol. 23, 5, 857-866.

Choi, H.; Malstrom, E. M.; Classen, R. J. (1984) Computer simulation of lot-sizing algorithms in three-stage multi-echelon inventory systems, *Journal of Operations Management*, vol. 4, 3, 259-277.

Coleman, B. J.; McKnew, M. A. (1990) A technique for order placement and sizing, *Journal of Purchasing and Materials Management*, vol. 26, 2, 32-40.

Coleman, B. J.; McKnew, M. A. (1991) An improved heuristic for multi-level lot-sizing in material requirements planning, *Decision Sciences*, vol.22, 1, 136-156.

Collier, D. A (1980) The interaction of single-stage lot size models in a material requirements planning system, *Production and Inventory Management*, vol. 20, 4, 11-20.

Graves, S. C. (1981) Multi-stage lot sizing: An iterative procedure, in Schwarz, L. B. (ed.) *Multi-Level Production/Inventory Control Systems: Theory and Practice*, New York, North-Holland, Chapter 4.

Harrison, B. (1991) An investigation of the performance of a material requirements planning system under inventory record uncertainty, *Proceedings of the Decision Sciences Institute*, vol. 3, 1453-1455.

Ho, C.; Ireland, T. C. (1989) A diagnostic analysis of the impact of forecast errors on production planning via MRP system nervousness, *Proceedings of the Decision Sciences Institute*, vol. 2, 996-998.

Ho, C.; Lau, H. (1990) Evaluating the impact of lead time uncertainty in material requirements planning systems, *Proceedings of the Decision Sciences Institute*, vol. 2, 1543-1545.

Jacobs, F. R.; Khumawala, B. M. (1982) Multi-level lot sizing in material requirements planning: An empirical investigation, *Computers and Operations Research*, vol. 9, 2, 139-144.

Krajewski, L. J.; Ritzman, L. P.; Wong, D. S. (1980) The relationship between product structure and multistage lot sizes: A preliminary analysis, *Proceedings of the American Institute of Decision Sciences*, 6-8.

LaForge, R. L. (1985) A decision rule for creating planned orders in MRP, *Production and Inventory Management*, vol. 26, 4, 115-126.

Lin, N. P.; Krajewski, L. (1989) Master production scheduling in uncertain environments, *Proceedings of the Decision Sciences Institute*, vol. 2, 999-1001.

Lin, N. P. et al. (1990) Strategies for master production scheduling in uncertain environments, *Proceedings of the Decision Sciences Institute*, vol. 2, 1734-1736.

McLaren, B. J (1976) *A Study of Multiple Level Lot Sizing Techniques for Material Requirements Planning Systems*, unpublished doctoral dissertation, Purdue University.

McLaren, B. J.; Whybark, D. C. (1976) *Multi-level lot sizing procedures in an MRP environment*, Discussion paper No. 64, Division of Research, School of Business, Indiana University

Rehmani, O.; Steinberg, E. (1982) Simple single pass, multiple level lot sizing heuristics, *Proceedings of the National American Institute of Decision Sciences*, 124-126.

Saydam, C. A.; McKnew, M. A. (1987) A fast microcomputer program for ordering using the Wagner-Whitin algorithm, *Production and Inventory Management Journal*, vol. 28, 4, 15-19.

Sridharan, S. V.; Berry, W. L.; Udayabjanu, V. (1987) Freezing the master production schedule under rolling planning horizons, *Management Science*, vol. 33, 9, 1137-1149.

Sridharan, S. V.; Berry, W. L.; Udayabjanu, V. (1988) Measuring master production schedule stability under rolling planning horizons, *Decision Sciences*, vol. 19, 1, 147-165.

Sridharan, V.; Berry, W. L. (1990) Freezing the master production schedule under demand uncertainty, *Decision Sciences*, vol. 21, 1, 97-120.

Sridharan, S. V.; LaForge, R. L. (1989) The effect of safety stock and freezing on schedule instability, *Proceedings of the Decision Sciences Institute*, vol. 2, 993-995.

Sridharan, S. V.; LaForge, R. L. (1989) The impact of safety stock on schedule instability, cost, and service, *Journal of Operations Management*, vol. 8, 4, 327-347.

Sridharan, S. V.; LaForge, R. L. (1990) An analysis of alternative policies to achieve schedule stability, *Journal of Manufacturing and Operations Management*, vol. 3, 1, 53-73.

Subhashish, S.; Grasso, E. T. (1991) Flexible loading and operations of MRP Based production systems: A simulation experiment, *Proceedings of the Decision Sciences Institute*, vol. 3, 1456-1458.

Veral, E. A.; LaForge, R. L. (1985) The performance of a simple incremental lot-sizing rule in a multilevel inventory environment, *Decision Sciences*, vol. 16, 1, 57-72.

Wagner, H. M.; Whitin, T. M. (1958) Dynamic version of the economic lot size model, *Management Science*, vol. 5, 1, 89-96.

Yelle, L. E. (1979) Materials requirements lot sizing: A multi-level approach, *International Journal of Production Research*, vol. 17, 3, 223-232.

Zhao, X.; Lee, T. S. (1991) Freezing master production schedule for material requirements planning systems under demand uncertainty, *Proceedings of the Decision Sciences Institute*, vol. 3, 1459-1461.