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LETTER FROM THE EDITOR

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TESTING THE VALIDITY OF MILES AND SNOW'S TYPOLOGY

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ABSTRACT

Within the context of the strategic alignment of information technology, Miles and Snow's (1978) typology was used to measure the business strategy construct, as operationalized with an instrument developed by Segev (1987). A survey of 301 firms indicates that this typology, after some modifications to the original measure, is still appropriate to evaluate business strategy. A confirmatory factor analysis approach was adopted, using structural equation modeling. This paper addresses methodological aspects of this investigation.

INTRODUCTION

Since the early 1990s, improving the information system planning process has been one of the top ten concerns of senior information systems executives (e.g., Janz, Brancheau & Wetherbe, 1996). Gartner Group's 1999 annual survey reports that aligning information technology with business goals is still CIOs' critical technology management issues (Raphaelian & Broadbent, 1999). In order to carry out this planning process successfully, it is deemed important to align the information systems plan with the organization's business plan. A few recent studies have successfully observed the effect of the alignment of information technology with organizational variables on organizational performance. Specifically, information systems management and business strategy gain to be mutually planned to improve organizational growth and profitability (Bergeron & Raymond, 1995; Raymond, Paré & Bergeron, 1995; Chan, Huff, Barclay & Copeland, 1997).

From a methodological point of view, various instruments have been used to explore the relationship between business strategy and performance; for instance, Venkatraman's (1989) instrument on strategic orientation has been frequently used. However, the best known approach to characterize business strategy originates from Miles and Snow (1978), which has been quoted more than 650 times in the last years (Social Sciences Quotation Index, 1989-1998). The principal strength of this typology is the simultaneous consideration of the structure and processes necessary for the realization of a given type of business strategy. Miles and Snow's

(1978) typology reflects a complex view of organizational and environmental processes, as well as the attributes of product, market, technology, organizational structure and management characteristics (Smith, Guthrie & Chen, 1989).

Within the context of strategic alignment of information technology, the purpose of this research is to validate Miles and Snow's typology as operationalized by Segev (I 987).

MILES AND SNOW'S TYPOLOGY

Business strategy is the outcome of decisions made to guide an organization with respect to the environment, structure and processes that influence its organizational performance. Approaches to identifying a business strategy can be textual, multivariate or typological (Hambrick, 1980). The typological approach is recognized as creating a better understanding of the strategic reality of an organization, since all types of business strategy are viewed as having particular characteristics but a common strategic orientation. While several typologies have been proposed (see Ansoff & Stewart, 1967; Freeman, 1974; Porter, 1980; Miles & Snow, 1978), the most frequently used in empirical research is Miles and Snow's (Zahra & Pearce, 1990, Smith, Guthrie & Chen, 1989).

Miles and Snow's typology consists of four ideal types of business strategy defined as prospector, analyzer, defender, and reactor. Firms choose one type rather than another according, to the perception they have of their environment. The first three types can be considered along a continuum, expected to enhance organizational performance. The prospector strategy is at one end of the continuum, and the defender one at the other. The analyzer strategy is a combination of the two. The reactor strategy is excluded from the continuum since it represents an organization having, no specific strategy identified. This last type is expected to impede organizational performance.

Organizations opting for the prospector strategy wish to have access to the largest possible market. They are characterized by their repeated efforts to innovate and bring about possible changes in their industry. Organizations selecting the defender strategy have a restricted market and stress production efficiency. They emphasize the excellence of their products, the quality of their services, and their lower prices. Organizations choosing the analyzer strategy do all of the above, but in moderation. Finally, organizations having a reactor strategy ignore new opportunities, nor can they maintain markets already acquired or take true risks.

Several empirical studies have used Miles and Snow's typology (1978) (Snow & Hrebiniak, 1980; Hambrick, 1983; Conant, Moksa & Burnett, 1989; Namiki, 1989; Smith, Guthrie & Chen, 1989; Tavakolian, 1989; Shortell & Zajac, 1990; Thomas, Litschert & Ramaswamy, 1991; Parry & Parry, 1992; Abernethy & Guthrie, 1994; Julien *et al.*, 1996, Karimi *et al*, 1996). The presence of the four strategic types vary depending upon the industry, the sample size or the other constructs linked to business strategy. Among those studies, some have used an item-based approach (Segev, 1987; Conant *et al.*, 1989; Namiki, 1989; Smith *et al.*, 1989; Thomas *et al*, 1991), whereas others have used the self-typing approach (Snow &

Hrebiniak, 1980; Tavakolian, 1989; Shortell & Zajac, 1990; Parry & Parry, 1992; Julien *et al.*, 1996; Karimi *et al.,* 1996).

METHODOLOGY

The instrument used to measure Miles and Snow's typology in this study was taken from Segev (1987) which uses 25 items on a Likert-type scale varying from I to 7 (highly disagree to highly agree). This instrument was chosen among others because of its content validity, characterizing all four types of business strategy, and was the only one readily made available to researchers through its publication. Following in-depth interviews used to pre-test the research instrument, questionnaires were sent to a sample 1,949 Canadian firms. These companies were listed in Dun & Bradstreet's directory. The selection criteria were to have more than 250 employees and to come from various branches of industry. A total of 301 companies returned the questionnaire addressed to the CEO for a final response rate of 15.4%.

RESULTS

Given the research objectives, a confirmatory factor analysis approach was adopted, using, Wold's (1982) PLS ("partial least squares") implementation of structural equation modeling. Such an approach is based on *a priori'* information about the structure of the business strategy construct. The structural model estimation and results provide assessments of unidimensionality and convergent validity, reliability, discriminant validity, and predictive validity of this construct.

The structural model to be solved for unidimensionality and convergent validity can be defined as $x = \Lambda\xi + \delta$ where x is a vector of the 25 observed variables (indicators or items), ξ is a vector of the 4 latent variables (traits or factors), δ is a vector of random (measurement) errors, and Λ is a 25 by 4 matrix of factor loadings (λ) relating the observed variables to the latent variables. The initial PLS estimates obtained for Λ are presented in Table 1. Six items (D4, D5, D7, AN2, AN3, PR5) were dropped because of their weak loadings on their hypothesized factors. A seventh one (ANI: "The firm adopts quickly promising innovations in the industry") was transferred from the analyzer to the prospector dimension as it loaded more strongly on the latter and could plausibly be attributed to it on a theoretical basis. The results obtained from estimating the modified model, based on the 19 remaining items, are presented in Table 2. Based on the new values obtained, it can be concluded that the four types of business strategy achieve unidimensionality and convergent validity.

Within the structural equation modeling framework, construct reliability (ρ) is conceptualized as the proportion of measured variance in the observed variables attributed to their underlying latent variable, and is calculated as the ratio of factor variance to the sum of factor and error variance. Thus, a ρ value greater than the recommended 0.7 value indicates that the factor captured at least 70% of the measurement variance. Returning to Table 2, one sees this to be the case for all four dimensions in the modified model.

Discriminant validity refers to the extent to which the measures of the four types of business strategy are unique from each other. This is verified when the square root of the average variance extracted by a factor from its associated items (i.e., $[\Sigma_{i=1,q}\lambda_{i,j}^2/q]^{1/2}$) is inferior to the correlation (i.e., $[\text{shared variance}]^{1/2}$) between this factor and any other factor. Looking at Table 3, this is shown to be the case for all four dimensions, thus confirming their distinctive characteristics.

When looking at the predictive validity of a construct, one ascertains if its measures relate to an antecedent or consequent construct in accordance to the theoretical framework from which it emanates. In this study, given Miles and Snow's (1978) arguments on the links between their typology and business performance and the use of this typology in subsequent empirical studies, the four types of business strategy were related to two fundamental dimensions of performance, namely growth and profitability, using Venkatraman's (1989) perceptual measure (3 and 5 items respectively). The results of correlating the business strategy and performance constructs are presented in Table 4 and discussed below.

DISCUSSION

Overall, the data analyzed seem to adequately support the notion that the four types of business strategy are unidimensional, and that the operational indicators used here show reliability and construct validity. One can further discuss the behavior of these indicators in terms of statistical and theoretical criteria by examining the relationships among the types, as well as between each type and performance. Looking at the intercorrelations of the four dimensions estimated by PLS (Table 3), one finds as expected that the more firms exhibit reactive behaviors, the less they act in both a prospective and an analytical manner. Whereas firms that exhibit more prospective behaviors also tend to be more analytical and less defensive. This empirical pattern of interrelationships among the four types of strategic activities thus appears to be coherent with Miles and Snow's underlying assumptions on strategic types.

Results presented in Table 4 show how each type of business strategy relates to business growth in terms of sales and market share increases, and to profitability in terms of financial position relative to the competition. As predicted by the theory, reactor and prospector business strategies are respectively associated here with inferior and superior performance. However, the relationship of both defender and analyzer business strategies with performance was not significant. One could tentatively argue here from a contingency theory point of view. Being less extreme, more "middle-of-the-road", defender and analyzer business strategies would need to match other fundamental aspects of the organization to be effective, and thus cannot be shown to increase performance without taking into account other dimensions such as the firm's environment, structure and information technology.

CONCLUSION

It can be concluded from this study that Miles and Snow's typology of business strategy, as operationalized by Segev, is a valid instrument once modified through statistical analysis. The modifications consist in removing inconsistent items and assigning one item to a different strategic type. These changes may be due to the fact that Segev's instrument had been tested with students, and thus possibly lacked external validity. An evolution in the concept of business strategy, between the time the measure was designed (1987) and its present testing (1999) might be another reason. Overall, the redesigned instrument is now considered appropriate to pursue research on the strategic alignment of information technology.

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Table 1 : Unidimensionality, convergent validity, and reliability of initial model

factor item	reactor	defender	analyzer	prospector
R1	.75[a]	-	-	-
R2	.73	-	-	-
R3	.67	-	-	-
R1	-	.69	-	-
D2	-	.68	-	-
D3	-	.62	-	-
D4	-	.07	-	-
D5	-	.18	-	-
D6	-	.61	-	-
D7	-	.25	-	-
D8	-	.65	-	-
D9	-	.59	-	-
AN1	-	-	.61	.67
AN2	-	-	-	-
AN3	-	-	-	-
AN4	-	-	.68	-
AN5	-	-	.34	-
AN6	-	-	.75	-
PR1	-	-	-	.67
PR2	-	-	-	.52
PR3	-	-	-	.59
PR4	-	-	-	..68
PR5	-	-	-	.13
PR6		-	-	.66
PR7		-	-	.71
ρ	.76	.74	.69	.78

[a]loading of observed variable on latent variable (a dash indicates a loading inferior to 0.40)

Table 2 : Unidimensionality, convergent validity, and reliability of modified model

factor item	reactor	defender	analyzer	prospector
R1	.75	-	-	-
R2	.73	-	-	-
R3	.67	-	-	-
D1	-	.70	-	-
D2	-	.71	-	-
D3	-	.59	-	-
D4	-	(removed)	-	-
D5	-	(removed)	-	-
D6	-	.61	-	-
D7	-	(removed)	-	-
D8	-	.64	-	-
D9	-	.57	-	-
AN1	-	-	(removed)	.69
AN2	-	-	(removed)	-
AN3	-	-	(removed)	-
AN4	-	-	.82	-
AN5	-	-	.43	-
AN6	-	-	.70	-
PR1	-	-	-	.47
PR2	-	-	-	.53
PR3	-	-	-	.64
PR4	-	-	-	.69
PR5	-	-	-	(removed)
PR6	-	-	-	.71
PR7	-	-	-	.81
ρ^b	.76	.80	.70	.84

[b]reliability coefficient = $(\Sigma\lambda)^2 / (\Sigma\lambda)^2+\Sigma(1-\lambda^2)$

Table 3 : Assessment of discriminant validity

Strategy	reactor	defend	analyzer	prospect
reactor	.72[a]			
defender	.08[b]	.64		
analyzer	-.32***	.10	.67	
prospect	-.52***	-.21**	.30***	.66

*: $p<.05$ **: $p<.01$ ***: $p<.001$

Table 4 : Assessment of predictive validity

Strategy	reactor	defend	analyzer	prospect
With Perform[c]				
Growth	-.30***	-.01	-.02	.36***
Profit	-.15*	-.01	-.02	.24***

[a]diagonal : (average variance extracted from the observed variables by the latent variable)$^{1/2}$ = $(\Sigma\lambda^2/q)^{1/2}$
[b]subdiagonals : correlation between latent variables = (shared variance)$^{1/2}$
[c]correlation with the two Performance dimensions (whose measurement was assessed similarly to the Strategy dimensions, satisfying criteria of reliability, unidimensionality, convergent and discriminant validity)

GENDER DIFFERENCES IN PERCEPTION OF EFFECTIVENESS OF USING STATISTICAL SOFTWARE IN LEARNING STATISTICS

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ABSTRACT

The primary focus of this research was to investigate if there were gender differences in the perception of effectiveness of various methodologies of teaching advanced business statistics. A questionnaire was administered to students enrolled in advanced statistics in the fall semester of 1998 and the spring semester of 1999. Statistical analysis of results indicates that there are significant differences in gender acceptance and opinion regarding the understanding of statistics when using statistical software (MINITAB). Females tend to see MINITAB as being less helpful in their understanding of both parametric tests and non-parametric tests than do the males. However, as the tests get more complex, both genders tend to disagree less with the statement that MINITAB aids understanding.

INTRODUCTION

In 1973, Lucy W. Sells identified mathematics as the “critical filter” that prohibits many women from entering the ranks of higher paying, prestigious occupations, and since the publication of that seminal work there has been a great emphasis upon gender differences in mathematical performance.

Studies of gender differences in mathematics performance indicate that females "showed a slight superiority in computation in elementary school and middle school. There were no gender differences in problem solving in elementary or middle school; differences favoring men emerge in high school and college" (Hyde, Fennama & Lamon, 1990). Leo (1999) states that females lag behind males in math and science test scores. Enzensberger (1999) goes so far as to state "…[mathematical ability] is established genetically in the human brain." These conflicting data are rather typical of the disagreement in literature regarding the evidence for a male advantage in math performance (Casey, Nuttall & Pezaris, 1997). They do state that there is a gender difference favoring males among high-ability students at measured by the Mathematics Scholastic Aptitude Test (SAT-M), and this has major implications for women's entrance into math-science fields.

There have been fewer studies concerning gender difference in the use and acceptance of computers. Dambrot, et al (1985) states that "there is every reason to believe that people in general and women in particular who have had problems with mathematics will find working with computers even more difficult and threatening". A study by Igbaria and Parasuraman (1989) indicates that there is a moderate connection between math anxiety and computer anxiety with managers

OVERVIEW OF CURRICULUM CONSIDERATIONS

Virtually all universities and colleges require students to take one or more statistics courses in many different majors, e.g., education, psychology, business, etc., for the non-specialist, and most Schools of Business require one or more courses in computer literacy. This paper focuses on whether there are gender differences in the perception of how helpful a statistical software package (MINITAB) is in learning statistical procedures for those non-specialists who are majoring in a field within business. The traditional method currently used in teaching statistics is widely viewed as being ineffective (Cobb, 1993; Mosteller, 1988).

The recommendations of the American Statistical Association and the Mathematical Association of America (ASA/MAA, 1996) Committee on Undergraduate Statistics should be integrated into the methodology utilized for teaching statistical courses. These recommendations are to teach statistical thinking; to emphasize more data and concepts, less theory and fewer recipes; and, to foster active learning. There are several approaches for teaching statistics to the non-specialists: (1) the use of manual calculations by using a hand-held calculator, (2) the use of a computer software package, and (3) a combination using both the manual and computer software package. A computer software package, such as MINITAB, could be selected which would enhance the student's ability to visualize and explore basic statistical concepts. MINITAB provides the means to generate the output and then allows the student to become statistical thinkers.

Many students who enroll in the statistics courses do so without sufficient computer literacy skills, and, therefore, spend their time attempting to master those requisite computer skills, ultimately neglecting the in-dept understanding of the statistics which was the objective of the course. Students appear to be more interested in acquiring computer skills than mathematical skills, probably because it is much more fashionable to discuss computers than statistics, and, very importantly, students are aware that computer literacy skills are advertised as a prerequisite for most jobs whereas they seldom find mathematical competencies advertised as a prerequisite for jobs.

A study of undergraduates by Dambrot, et al (1985) indicates that computer aptitude was strongly related to mathematics ability and experience. The results show that females held more negative attitudes toward computers, scored lower in computer aptitude, and had less prerequisite mathematics ability and course work.

OVERVIEW OF PRESENT STUDY

Middle Tennessee State University (MTSU) students must take advanced business statistics (Statistical Methods II) which covers topics in hypothesis testing and regression analysis after taking the introductory statistics course. While each faculty member teaching these courses must cover specific core topics, the method of presentation is an individual decision. Teaching techniques range from those faculty members who make minimal use of a statistical software package (MINITAB) to those who make minimal use of manual calculations (hand-held calculators).

The MTSU statistics faculty have had considerable discussions on teaching methodologies and outcomes, particularly with regard to the emphasis placed upon statistical software in teaching statistical procedures. In an attempt to satisfy faculty at both ends of the continuum, many statistics faculty members introduce new topics to students with manual methods (hand-held calculators) then reinforce the topic with the use of a computer statistical package (MINITAB).

The College of Business at MTSU is AACSB accredited and has a state-of-the-art new building with computer labs and networked telecommunication facilities. Each classroom has multimedia, a projector, and is networked so that computer software is immediately available to the instructor and students alike. MINITAB for Windows is used in the classrooms and in the computer laboratory, making MINITAB available both in class and for out-of class assignments. In addition to the computer lab, there is a separate business statistics lab in the same locale as the offices of the faculty members who teach the statistical courses. The business statistics lab is staffed by graduate assistants whose job it is to assist students who require additional information, as well as help them utilize computer statistical packages.

RESEARCH METHODOLOGY

A questionnaire was created and administered to seven sections of the advanced statistics course (Statistical Methods II) during the last scheduled class day in the fall semester of 1998, and another seven sections during the last class day in the spring semester of 1999. The students were asked to relate their views on the effectiveness of the dual method of presentation, i.e., utilizing both the manual (hand-held calculators) and a computer software package, as well as their evaluation of the effectiveness of more or less presentation with either of the methods.

Various demographic data were also collected, including gender (See Appendix for Questionnaire). A Likert-type scale from 1 (strongly disagree) to 7 (strongly agree) was utilized in an effort to determine the student's perceptions of the benefits of one teaching methodology over the others, and whether these results would differ by gender.

DATA ANALYSIS

All statements in which the male and female responses differed significantly were identified (_ = 0.05). The responses of both genders to each of the twenty-six statements were tested using an Anderson-Darling test for normality, and all twenty-six statements were found to have responses that were not normally distributed at the 0.000 level of significance. Even the robustness of the normality assumption in ANOVA tests was not expected to compensate for that lack of normality, so the Mann-Whitney-Wilcoxon test was used to check for gender differences. The results for the nine statements showing significant (_ = 0.05) gender differences are presented in Table 1.

To rank these nine statements by the degree of gender difference (with 1 being the rank of the statement having the largest degree of gender difference) Z-values for the normal approximation to the Mann-Whitney-Wilcoxon test were calculated. For the Mann-Whitney-Wilcoxon test, the normal approximation formula used was:

$$Z = [M - (n_1)(n_T + 1)/2]/\text{sqrt}[(n_1)(n_2)(n_T + 1)/12],$$

where M was the computed value of the Mann-Whitney-Wilcoxon test;
n_1 was the number of female responses;
n_2 was the number of male responses; and
n_T was the sum of n_1 and n_2.

These Z-values and their ranks are shown in Table 1. Note that all the Z-values are negative. A negative Z-value indicates that the typical female response to each of these nine statements was lower than the typical male response.

TABLE 1
Mann-Whitney-Wilcoxon Test
Test of median of females = median of males versus median of females not = median of males

Statement	N Missing	N for Females	N for Males	Mann-Whitney-Wilcoxon Statistic	P	Female Median	Male Median	Z for Mann-Whitney-Wilcoxon	Z Ranks
C17	1	130	105	14274.5	0.0398	3.000	4.000	2.05647	9
C18	0	130	106	14331.0	0.0396	3.000	3.500	2.05871	8
C19	0	130	106	13859.0	0.0031	3.000	4.000	2.96348	3
C20	0	130	106	13929.0	0.0047	3.000	4.000	2.82929	5

C21	0	130	106	13900.5	0.0039	3.000	4.000	2.88393	4
C22	1	130	105	13767.5	0.0024	3.000	4.000	3.03500	2
C23	0	130	106	13794.0	0.0020	3.000	4.000	3.08807	1
C24	0	130	106	14002.5	0.0072	4.000	4.000	2.68841	6
C25	0	130	106	14183.0	0.0192	4.000	5.000	2.34241	7

Of the nine statements in Table 1, eight (18 – 25) dealt with the helpfulness of MINITAB with respect to a particular subset of statistical procedures. The other statement, (17), " It is easier to learn how to use MINITAB to perform a hypothesis test than it is to learn how to perform the hypothesis test manually" while more general, showed the least amount of gender difference in the group.

With regard to statements 18 – 25, two observations deserve special mention. The two statements that show the highest degree of gender difference are {23 and 22}. These two state that MINITAB was particularly helpful in understanding multiple-sample parametric and multiple-sample non-parametric tests. The four statements showing the highest degree of gender difference are {23, 22, 19 and 21}. This set of four statements includes all the types of non-parametric tests covered in the QM 362 course.

The results shown in Table 1 illustrate which statements in the survey have the largest amount of gender difference, but does not illustrate the type of gender difference. The negative Z-values show that the typical female response to a statement is significantly less than the typical male response for each of the nine statements in Table 1. However, it cannot be determined if both genders agreed, both genders disagreed, or the males agreed and the females disagreed. Quantification requires the use of additional hypothesis tests. The information provided by these tests allows the determination of the types of the nine gender differences shown in the responses to the statements in Table 1.

The Likert-type scale used to measure the degree of agreement (disagreement) had a midpoint of 4, so a null hypothesis that the midpoint of responses = 4 for the female responses and the male responses was tested for each of these nine statements. What test statistic should be used for these tests?

Since the Anderson-Darling tests indicated that the statement responses for each gender were not normally distributed, a t-test was not appropriate. The nagging question that remained was whether the responses constituted at least an interval level of measurement and justified the use of the Wilcoxon Signed-Rank test. The use of the Sign test for such responses is clearly justified, but is it the best test? It was decided to perform both the Wilcoxon Signed-Rank test and the Sign test on the female and male responses to each of these nine statements and be conservative in the interpretation of the results. Both tests had to show a significant effect or it would not be reported as significant. See Table 2.

TABLE 2

Nine Statements With The Most Significant Gender Differences										
	Females					Males				
Statement	N for Test	Wilcoxon Signed-Rank Statistic	P	Above	P	N for Test	Wilcoxon Signed- Rank Statistic	P	Above	P
C23	92	490.5	0.000	18	0.0000	68	814.0	0.028	29	0.2751
C22	97	950.5	0.000	25	0.0000	73	1259.5	0.619	35	0.8149
C19	91	350.0	0.000	11	0.0000	77	904.5	0.002	30	0.0682
C21	93	394.0	0.000	15	0.0000	70	758.5	0.005	25	0.0232
C20	93	372.0	0.000	15	0.0000	75	851.0	0.002	29	0.0647
C24	99	1412.0	0.000	39	0.0444	85	1871.5	0.849	49	0.1931
C25	104	2215.5	0.096	52	1.0000	84	2069.5	0.205	54	0.0121
C18	95	399.0	0.000	14	0.0000	74	670.5	0.000	21	0.0003
C17	107	1721.5	0.000	37	0.0020	89	1848.0	0.529	44	1.0000

Since two-tailed hypothesis tests were being used, the p-values of the tests show evidence of significant agreement or disagreement, but the p-value by itself does not indicate which one. It could mean significant agreement in one case and significant disagreement in another case. Again we used the Z approximations to the two test statistics to tell if there was agreement (positive Z-value) or disagreement (negative Z-value) and to make it easy to rank the degree of the agreement or the degree of disagreement.

For the Wilcoxon Signed-Rank test, the normal approximation formula is:

Z = [W - (n')(n' + 1)/4]/sqrt[(n')(n' + 1)(2n' + 1)/24],
where n' is the number of responses that differ from the hypothesized median.
These Z-values and their ranks and are shown in Table 3.

For the Sign test, the normal approximation formula is:

Z = [Above - (n')/2]/sqrt[(n')/4],
where n' is the number of responses that differ from the hypothesized median.
These Z-values and their ranks and are shown in Table 3.

The ranks in Table 3 represent the level of disagreement with the corresponding statement. The statement disagreed with at the highest level (most negative Z-value) received a rank of 1 and so on. Positive Z-values indicated agreement. Using the p-values in Table 2 and the sign of the Z-values in Table 3, Table 4 was constructed. It shows the types of the gender differences for the nine statements that showed a significant gender difference.

TABLE 3 Nine Statements with the Most Significant Gender Differences										
	Females					Males				
Statement	N for Females	Z for W	Rank	Z for Above	Rank	N for Males	Z for W	Rank	Z for Above	Rank
C23	92	-6.41909	5	-5.83840	5	68	-2.19362	5	-1.21268	5
C22	97	-5.13108	6	-4.77213	6	73	-0.50028	7	-0.35112	6
C19	91	-6.89863	3	-7.23317	1	77	-3.03125	2	-1.93733	4
C21	93	-6.86430	4	-6.53280	3.5	70	-2.83246	4	-2.39046	2
C20	93	-6.94859	2	-6.53280	3.5	75	-3.03104	3	-1.96299	3
C24	99	-3.71018	7	-2.11058	8	85	0.19280	8	1.41005	8
C25	104	-1.66842	9	0.00000	9	84	1.26881	9	2.61861	9
C18	95	-6.98201	1	-6.87405	2	74	-3.86265	1	-3.71992	1
C17	107	-3.62860	8	-3.19023	7	89	-0.63211	6	-0.10600	7

In seven out of the nine statements showing significant gender differences (17 - 23), both genders disagreed with the statements with the females disagreeing more strongly. In statement 24, the females significantly disagreed, while the males insignificantly agreed. In statement 25 the females insignificantly disagreed, while the males insignificantly agreed. In all nine statements showing significant gender differences, the female responses showed more disagreement that the male responses did.

TABLE 4 Nine Statements with the Most Significant Gender Differences				
	Females		Males	
Statement	A = Agree D = Disagree	_ = 0.05 S = significant I = insignificant	A = Agree D = Disagree	_ = 0.05 S = significant I = insignificant
C23	D	S	D	I
C22	D	S	D	I
C19	D	S	D	I
C21	D	S	D	S
C20	D	S	D	I

C24	D	S	A	I
C25	D	I	A	I
C18	D	S	D	S
C17	D	S	D	I

Eight of the nine statements showing significant gender differences (18 - 25) dealt with the helpfulness of MINITAB with respect to a particular subset of statistical procedures. The statistical procedures mentioned in these eight statements were broken down into two groups: the parametric statistical procedures {18, 20, 22, 24 and 25} and the non-parametric statistical procedures {19, 21 and 23}. The list {18, 20, 22, 24 and 25} orders the parametric statistical procedures by increasing complexity. Likewise, the list {19, 21 and 23} orders the non-parametric statistical procedures by increasing complexity. Table 5 was created to show each of the two groups of statistical procedures with the corresponding survey statements ordered by increasing complexity of the tests. The level-of-disagreement ranks from Table 3 were inserted in the same row with the corresponding statement. The purpose was to see how the level of difficulty of the test correlated with the level of disagreement with the statement shown by each gender. Regardless of the test used to obtain the level-of-disagreement ranks or the gender, the ranks were perfectly correlated with the level of difficulty in the parametric statistical procedures. As the level of difficulty of the parametric statistical procedure increased, the level of disagreement with the associated survey statement decreased. Regardless of the test used to obtain the level-of-disagreement ranks for the female responses, the ranks were perfectly correlated with the level of difficulty in the non-parametric statistical procedures. Using the Wilcoxon Signed-Rank test to obtain the level-of-disagreement ranks for the male responses, the ranks were perfectly correlated with the level of difficulty in the non-parametric statistical procedures. The only case where the correlation was not perfect ($R = 0.5$ if least complex gets a rank of 1) was when the Sign Test was used to obtain the level-of-disagreement ranks for the male responses.

TABLE 5
Level-of-disagreement Ranks Catagorized

	Parametric Statistical Procedures				Non-Parametric Statistical Procedures				
	Females		Males			Females		Males	
Statement	Wilcoxon Ranks	Sign Ranks	Wilcoxon Ranks	Sign Ranks	Statement	WilcoxonRanks	Sign Ranks	WilcoxonRanks	Sign Ranks
C18	1	2	1	1	C19	3	1	2	4
C20	2	3.5	3	3	C21	4	3.5	4	2
C22	6	6	7	6	C23	5	5	5	5
C24	7	8	8	8					
C25	9	9	9	9					

DISCUSSION OF RESULTS

Only nine statements showed a significant difference at the .05 level of significance. In all statements where there was a clear gender difference in the responses, the females had a higher level of disagreement with the statement than the males. If these nine statements are ordered by the degree of significance with the statements having the most significant gender differences being listed first, the order of the statements is: {23, 22, 19, 21, 20, 24, 25, 18 and 17}. In statements 23 and 22 both genders tended to disagree with these two statements, but the level of the female disagreement was significant (_ = 0.05). This result suggests the conclusion that females find MINITAB to be of less help than males in understanding multiple-sample statistical tests.

All three of the survey statements that mention non-parametric tests {19, 21 and 23} are in the "top four" of the nine statements with significant gender differences. Both genders tended to disagree with these three statements, but the level of the female disagreement was significantly more than that of the males. This result suggests the conclusion that females find MINITAB to be of less help than males in understanding non-parametric statistical tests.

In seven out of the nine statements showing significant gender differences (17 - 23), both genders were disagreeing with the statements with the females disagreeing more strongly. Of these seven statements, 19, 21, and 23 were addressed as a group above. A similar group is the group of the only three survey statements that specifically refer to parametric tests. Both genders tended to disagree with these three statements, but the level of the female disagreement was significantly more than that of the males. This result suggests the conclusion that females find MINITAB to be of less help than males in understanding one-sample, two-sample and multiple-sample parametric tests.

The other two statements dealt with regression. In statement 24, the females significantly disagreed, while the males insignificantly agreed. This result suggests the conclusion that males see some benefit in using MINITAB to help them understand simple linear correlation and regression, but the females do not. In statement 25 the females insignificantly disagreed, while the males insignificantly agreed. This result suggests the conclusion that the females do not see as much benefit in using MINITAB to help them understand multiple regression analysis as the males do.

In both parametric tests and non-parametric tests, the females tend to see MINITAB of being less helpful in their understanding of those statistical procedures than the males do. However, as the tests get more complex, both genders tend to disagree less with the statement that MINITAB aids understanding.

The females continue to disagree that MINITAB aids their understanding even up to the complexity of regression analysis, while the males start to agree that MINITAB is helpful when the complexity of regression analysis is reached.

SUMMARY AND CONCLUSIONS

A questionnaire was administered to students at MTSU who were enrolled in advanced statistics in the fall of 1998 and the spring of 1999 in an effort to investigate if there were gender differences in the perception of effectiveness of various methodologies of teaching advanced business statistics. Statistical analysis of the results indicates that there are differences in gender acceptance and opinion regarding the understanding of statistics when using statistical software (MINITAB).

In both parametric tests and non-parametric tests, the females tend to see MINITAB as being less helpful in their understanding of those statistical procedures than do the males. However, as the tests get more complex, both genders tend to disagree less with the statement that MINITAB aids understanding. The females continue to disagree that MINITAB aids their understanding even up to the complexity of regression analysis, while the males start to agree that MINITAB is helpful when the complexity of regression analysis is reached.

Further research is suggested to investigate the relationship between student's perception and actual performance using different teaching methodologies. Outcome assessment studies could be undertaken in order to analyze this relationship.

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APPENDIX

Q.M. 362 CLASSES

Student Perception of Learning: Comparing Manual Procedures with MINITAB

In many Q.M. 362 classes a statistical topic is introduced using manual techniques with hand-held calculators. Once the basic principles and procedures of the technique are presented MINITAB is then used to work the same or similar problems. In an effort to ascertain the benefits students obtain from the two approaches the following questionnaire has been devised.

Please circle your response to each of the following questions on a scale from 1 (strongly disagree) to 7 (strongly agree)

		Strongly Disagree — Strongly Agree
1.	I learn more from manual calculations than from problems solved with MINITAB	1 2 3 4 5 6 7
2.	I retain more knowledge of statistical techniques from problems worked with MINITAB than problems worked manually	1 2 3 4 5 6 7
3.	Introduction of statistical topics using manual procedures provide a good understanding of the rationale and techniques of the topics	1 2 3 4 5 6 7
4.	Reinforcement of statistical topics using MINITAB after manual techniques have been covered strengthens and enhances my understanding of the topics	1 2 3 4 5 6 7
5.	Manual exercises increased my knowledge of each statistical procedure	1 2 3 4 5 6 7
6.	MINITAB exercises increased my knowledge of each statistical procedure	1 2 3 4 5 6 7
7.	Manual computations distracted me in understanding and mastering concepts of statistical methodology	1 2 3 4 5 6 7
8.	MINITAB procedures distracted me in understanding and mastering concepts of statistical methodology	1 2 3 4 5 6 7
9.	I would prefer greater emphasis on manual calculations in the course	1 2 3 4 5 6 7
10.	MINITAB procedures were clear and understandable	1 2 3 4 5 6 7
11.	Manual procedures were clear and understandable	1 2 3 4 5 6 7
12.	MINITAB procedures challenge and encourage independent thought	1 2 3 4 5 6 7
13.	In the classroom MINITAB allows for better structure of content	1 2 3 4 5 6 7
14.	In the classroom MINITAB allows for standardized delivery of content	1 2 3 4 5 6 7
15.	In the classroom MINITAB allows for more interesting instruction	1 2 3 4 5 6 7
16.	In the classroom MINITAB allows for longer retention of course material	1 2 3 4 5 6 7
17.	It is easier to learn how to use MINITAB to perform a hypothesis than it is to learn how to perform the hypothesis test manually	1 2 3 4 5 6 7
18.	MINITAB was particularly helpful in understanding one-sample parametric tests	1 2 3 4 5 6 7
19.	MINITAB was particularly helpful in understanding one-sample non-parametric tests such as the Wilcoxon Signed Ranks test	1 2 3 4 5 6 7
20.	MINITAB was particularly helpful in understanding two-sample parametric tests such as two-sample t test with pooled variance	1 2 3 4 5 6 7
21.	MINITAB was particularly helpful in understanding two-sample non-parametric tests such as the Mann-Whitney test	1 2 3 4 5 6 7
22.	MINITAB was particularly helpful in understanding multiple-sample parametric tests such as ANOVA	1 2 3 4 5 6 7
23.	MINITAB was particularly helpful in understanding multiple-sample non-parametric tests such as the Kruskal-Wallis test	1 2 3 4 5 6 7
24.	MINITAB was particularly helpful in understanding simple linear correlation and regression	1 2 3 4 5 6 7
25.	MINITAB was particularly helpful in understanding multiple regression analysis	1 2 3 4 5 6 7
26.	At the beginning of this course I was already familiar with some computer software	1 2 3 4 5 6 7

DATA WAREHOUSE: EMPHASIS IN DECISION SUPPORT

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ABSTRACT

Historical information and technology trends have allowed many companies to expand and maximize profits in the past two to three decades. Information and the strategic use thereof has created a need for proactive information specialists who are able to perform multiple tasks and utilize information across functional boundaries. In a competitive and global marketplace it is essential that key managers have a grasp on the strategic use of information. Information can make or break an organization. The development of information warehouses has allowed management to harness the technological processes and put the strategic results to work as soon as possible.

INTRODUCTION

A data warehouse is the main essential element to the development of strategic information for the majority of corporations. A data warehouse is a read only analytical database that is used as the foundation of a decision support system (Baum, 1997). A decision support system supplies information to assist employees in making decisions and to enhance job performance. Decision support systems can be used for short term tactical decision making or for long term strategic decision making (Davis, 1996). Many support systems provide for operational systems which run the day-to-day business of the company.

Analytical databases provide information which is used to analyze a problem or situation. Analytical processing is primarily done through comparisons, or by examining patterns or trends. Analytical databases provide a snapshot of data (generally time specific) and are often quite large because they track huge volumes of historical data (Baum, 1997). A data warehouse is an analytical database that is used as the foundation of a decision support system.

Data warehouses exist to facilitate strategic and tactical decision making. A data warehouse is updated periodically, on a predefined basis; an operational system is updated in real time. Management Information System (MIS) reporting systems deliver standardized reports that are limited to a small number templates and the data warehouse must support users performing iterative, ad hoc analysis (Baum, 1997). The data warehouse provides users an analytical foundation for making decisions. The historical information contained in data warehouse is used to develop applications, algorithms, and models for business decisions. An integrated data warehouse gives an organization consistent quantitative figures, so that decision makers can all use the same numbers. The data warehouse has a much higher success rate if it is separate from the operational database, in a hardware environment distinct from operational systems, so that end users can use the warehouse with out effecting the day-to-day operations of the business (Griffin, 1996).

SUCCESSFUL WAREHOUSES

In successful warehouses, historical data is used to develop applications with clear business benefits that directly impact the bottom line. Applications that maximize core business benefits include (Poe, et al., 1998):

- Fraud detection systems detect and prevent fraud before losses are incurred
- Target marketing systems give the business an understanding of customer behaviors and product needs so marketing campaigns can be directed towards those individuals
- Profitability analysis shows which individual customers are profitable and which are not, allowing them to develop appropriate customer management programs
- Customer retention applications help companies identify and keep their profitable customers, which is much more cost-effective than acquiring new customers.
- Inventory management allows retailers and manufacturers to have the right products in the right place at the right time, rather than incurring heavy losses from out-of-stock items
- Credit risk analysis enables companies to avoid bad debt by identifying the best risks among prospects with mixed credit histories.
- Long-term value assessment enables companies to predict which customers will be profitable in the future and which will not.
- Competitive pricing enables companies to develop fundamental new pricing structures by understanding product demand, competitive positioning in the marketplace, and profit margins.

The critical success factors involved with a data warehouse include: designing the data warehouse with a focus on the business and not the technology, use of an iterative development methodology with short cycles and frequent deliveries, and including end users on the implementation team (Poe, et al., 1998). The data warehouse provides the necessary information to key level decision makers in an organization so they can make strategic (long run) or operational (short run) decisions about their organizations (Hackathorn, 1995).

WAREHOUSE ARCHITECTURE

An architecture is a set of rules or structures providing a framework for the overall design of a system or product. The data architecture provides the framework by identifying and understanding how the data will move throughout the system and how it will be used within the corporation.

The data architecture for a data warehouse has the following characteristics (Poe, et al., 1998):

- Data is extracted from source systems, databases, and files
- The data from the source systems is integrated before being loaded into the data warehouse
- The data warehouse is a separate, read only database designed specifically for decision support processing of large volumes of data
- Users access the data warehouse via some front-end tool or application

A primary component of data architecture for a data warehouse is a read-only database used for decision support. Source fields for a data warehouse may come from different databases, platforms, and a variety of data types and formats. The architecture should help resolve the technical solutions needs of the decision support system and create a solid data warehouse architecture within the parameters you have to work with (Griffin, 1996).

Technical infrastructures are the technologies, platforms, databases, gateways, and other components necessary to make the architecture functional within the corporation. Infrastructures provides the means through which independent users operate and manipulate information resources within the data warehouse (Singh, 1996). The typical levels of users for many organizations are (Poe, et al., 1998):

- Novice - this is the causal user

- Business Analyst - makes decisions from provided information
- Power User- Person that has interaction with different functional areas
- Application developer- designer of the system

Identifying data warehouse architecture and infrastructures should be a separate project from the actual development of the data warehouse. Figure 3 presents the relationship between architecture and infrastructures.

DECISION SUPPORT SYSTEM

A DSS (Decision Support System) application is collection of one or more predefined reports, analyses, or data navigation paths which are developed in advance by an application developer or a power user (Hackathorne, 1995). A specific predefined report can generate many unique variations simply by changing the constraints. The data warehouse stores two types of data: source data (run day-to-day business) and target data (data the is inserted into fields within the data warehouse database). The classes of tools users have available to them to manipulate the information include (Poe, et al., 1998):

- Data access/query tools provide a graphical user database to the data warehouse.
- Report writers may also provide a layer of abstraction that allows the assigning of business names to the different columns and tables.
- Multidimensional Database Management Systems (MDBMSs) provide advanced metric support with extensive cut and paste capabilities
- Advanced decision support tools provide advanced multidimensional analysis directly against the relational database management system.
- Executive Information Systems (EISs) provide a structured, big button interface to predefined reports that provide highly summarized top-line information about the business.

The Decision Support Life Cycle flows through ten general phases (Poe, et al., 1998):

- Planning
- Gathering data requirements and modeling
- Physical database design and development
- Data souring, integration, and mapping
- Populating the data warehouse
- Automating the data management process
- Creating the starter set of reports
- Data validation and testing
- Training
- Rollout

PLANNING

Planning involves creating a project plan and defining realistic time estimates which may be difficult because there are altogether new tasks within the decision support life cycle. It is imperative that the data warehouse data architecture and technical infrastructures be thought through before the project development begins. If the data architecture and technical infrastructures have not been established then all of the architecture and infrastructure analysis will need to be added to the project plan. Planning , is basically concerned with the following: defining and/ or clarifying the project scope, creating the project plan, defining the necessary technical resources, both internal and external, defining the business participants and responsibilities, defining the tasks and deliverables, defining the time lines, and defining the final project deliverables.

DATA MODELING AND DESIGN

Gathering data requirements and modeling is concerned with the understanding of the business needs and data requirements of the users of the system. Gathering data requirements includes understanding the following (Poe, et al., 1998):

- How the user does business
- What the business drivers are
- What attributes the user needs
- Which attributes are absolutely required and which attributes are a "wish list"
- What are the business hierarchies
- What data users have now and what would they like to have
- What levels of detail or summary the users need
- What type of front-end data access tools will be used
- How the user expects to see the results of their queries

To minimize these dilemmas, tasks, deliverables, and schedules should be defined that will assist analysts in moving through this phase quickly. The process of building a data warehouse is iterative in nature. Once the first round of data is loaded into the data warehouse and users have a chance to see what data is available to them, there will be changes and additions requested (Darling, 1997). Information collected during this phase will directly feed the data modeling phase.

The central focus of data modeling is to provide a logical data model covering the scope of the development project including relationships, cardinality, attributes, definitions and candidate keys (Greenfield, 1996). The dimensional business model that diagrams the facts, dimensions, hierarchies, relationships, and candidate keys for the scope of the development project. These issues can affect the timing of the data warehouse development and should be addressed before development begins if they were not resolved as technical infrastructures.

The physical database design and development phase covers database design and denormalization. The design and development phase focuses on:

- Designing the database, including fact tables, relationship tables, and description (lookup) tables
- Denormalizing the data
- Identifying keys
- Creating indexing strategies
- Creating appropriate database objects

For this phase, it is imperative that the user have an understanding of and training in the following: decision support concepts, the concepts of hierarchical dimensions and facts, and star schema database design concepts(type of database design used to support analytical processing). This phase of development should also be concerned with (Poe, et al., 1998): development of aggregation strategies, development of partitioning strategies, and refining capacity planning estimates.

The data souring, integration, and mapping phase is done in conjunction with the database design phase, because of the need to target data warehouse database design for the source of target mapping. Figure 4 displays data integration in a data warehouse

This phase will accomplish the following (Baum, 1997):

- Defining the possible source systems
- Defining file layouts
- Performing data analysis to determine the best (and cleanest) source of data
- Performing data analysis to integrate the data
- Developing written data conversion specifications for each field and refining the integration strategy
- Mapping source to target data

The data that is actually possible to source, which is often quite different from the data requested by end users, may modify your requirements, dimensional business model, and database design.

Populating the data warehouse is concerned with the full process of extracting, converting, and loading data into the target database. This process is often done with the assistance of data conversion technology. Using a data conversion tool will affect the timing of the life-cycle phases and may consolidate tasks and deliverables. This phase focuses on (Poe, et al., 1998):

- Developing programs or using tools to extract and move the data
- Developing load strategies
- Developing the procedures to load the data into the warehouse
- Developing programs or using data conversion tools to integrate data
- Developing update/ refresh strategies
- Testing extract, integration, and load programs and procedures

Technical infrastructures should be in place to assist with the crucial steps of data mapping, conversion, extraction, and loading. These infrastructures may include (Baum, 1997): DBA expertise, data conversion tool programming expertise, source programming expertise, quality assurance procedures, capacity planning expertise, and system/ platform expertise. Figure 5 is an example of technical infrastructures in a data warehouse architecture.

Automating the data load process is primarily concerned with automating the extraction, integration, and load of the data warehouse. This phase includes five steps (Poe et al., 1998):

- Automating and scheduling the data extraction process
- Automating and scheduling the data conversion process
- Automating and scheduling the data load process
- Creating backup and recovery procedures
- Conducting a full test of all the automated procedures

The development of a starter set of reports can begin as soon as the user loads a test subset of data. DSS application development is generally done through the use of data access tools to pre-build several reports. This phase is primarily concerned with (Poe, et al., 1998):

- Creating the starter set of predefined reports
- Testing reports
- Documenting applications
- Developing navigation paths

Data validation and testing processes should be included throughout the data extract, integration, and load development phases. Basically data validation can occur by three means: using the set of starter reports, using standard processes, and repeatedly changing the data. The new data modifications will be located, extracted, mapped, integrated, and loaded into the data warehouse (Varney, 1996). The training phase of the decision support life cycle is focused on creating training programs for the user community. To gain real business value from the warehouse development, users of all levels will need to be trained in (Poe, et al., 1998):

- The scope of the data in the warehouse
- The front-end access tool and how it works
- How to access and navigate metadata to get information on the data in the warehouse
- The DSS application or starter set of reports- the capabilities and navigation paths
- Ongoing training/user assistance as the system evolves

The rollout phase of the life cycle includes the necessary tasks for the deployment of the data warehouse to the user community. The rollout phase includes (Poe, et al., 1998):

- Installing the physical infrastructures for all users. The components that must be in place for the end user are the LAN/WAN, database connectivity, configured workstations, data access software, and managed metadata
- Deploying the DSS application
- Creating end-user support structures
- Creating procedures for adding new reports and expanding the DSS application
- Setting up procedures to back up the DSS application, not just the data warehouse
- Creating procedures for investing and resolving data integrity and related issues.
- Setting up procedures for metadata management
- Creating change management procedures

Ad hoc feedback from system users should be obtained to modify these steps accordingly as this phase develops.

The overall steps involved in developing the decision support system should match the requirements of the company. The benefits realized from an efficient DSS are (Baum, 1997): gaining a competitive advantage, increased revenues, reduced costs, improved profit, and creating new opportunities. The DSS life cycle is a tedious task and should include horizontal decision making across functional areas in the organization in order to include all constraints. Before moving into the creation of a full blown data warehouse, the company should first develop a pilot conversion project. The pilot project allows users to gain experience with the system, show users the value of decision support information, and clarifies the purpose of the pilot project. There are two main pilot implementation programs available: proof of concept pilot and the architecture and infrastructure. The architecture and infrastructure pilot is concerned with: understanding the complexities involved in developing a data warehouse for decision support, gaining experience with new tools and technologies, getting a sense of realistic time lines and learning curves for tasks, and providing a data warehouse for the purpose of supplying decision support information to users. The proof of the pilot conversion is a short run process and involves the use and conversion of existing technologies and equipment. Doing a pilot of either kind will result in the following advantages (Poe, et al. 111-112):

- A first cut of a dimensional business model
- Ideas on how to design your physical database
- An understanding on the cleanliness of your data
- A working prototype of a data warehouse
- Concrete analytical examples to serve as thought starters for end users
- An understanding of how the data access tools work

The pilot should be treated as a development process separate from the main conversion project. The main technical infrastructures should be in place in order to insure that the conversion process can be accomplished (Baum, 1997). The main understanding involved should clarify several key areas such as: owner of project, scope of project, data access software, training of personnel, finding the best source of data, choosing platforms, creating starter set of reports, and establishing securities. The pilot is a conversion stage that is just preliminary to the design of databases for the warehouse. The entire process is the components that derive the Decision Support Database (DSD). Decision Support Databases are designed to allow users to access information quickly and easily. The data analysis is historical in nature: daily, weekly, or monthly even yearly reports. Decision support systems have the following characteristics:

- Understandable: Data structures must be readily understood by users
- Mostly static: Most changes to the database occur in a controlled manner when data is loaded according to a predefined schedule
- Unpredictable and complex SQL queries: SQL query statements vary considerably from query to query.
- Advanced business measurements often require multiple SQL statements
- Multiple/large/iterative result sets should be supported
- Recoverable: Regular backups, or snapshots, of the static database ensure against data loss

A typical decision support database goals are achieved through the use of a star schema design. A star schema is a simple structure with few tables and well-defined join paths. This database design provides fast query response time and a simple schema that is readily understood by analysts and end users. The star is often used for data warehouse design because it provides faster response times, a simple database design allows users to yield better execution plans, simplifies the understanding and use of metadata for developers, and broadens the choices of front-end data access tools (Poe, et al., 1998).

METADATA

Metadata is data about data and is an important concept development of efficient warehouses. Figure 6 shows how Metadata interfaces with the data warehouse and end user.

A star schema provides two types of tables, fact tables and dimensional tables. Fact tables contain quantitative or factual data about a business and the information being queried. Dimensional tables hold descriptive data that reflects the dimensions and scopes of the business. A star design contains multiple fact tables and the primary key for the fact table is comprised of foreign keys from the dimensional tables. In schemas where the foreign keys from the dimensional tables do not provide a unique identifier, a multi-star schema can be used. In a multi-star schema, the fact table has both a set of foreign keys referencing the dimensions, and a primary key to provide a unique identifier to each row. Dimensions often contain business hierarchies to allow users to drill up and down to the level of detail necessary to provide answers. Aggregation is accumulating fact data along predefined attributes. Aggregation data that is requested by users on a daily basis will often be pre-calculated and loaded into the data warehouse to improve end-user query performance and reduce the number of CPU cycles needed (Zweig, 1996). The determination of which aggregates should be pre-stored will be based upon the frequency of end-user access, as well as the reduction in the total number of rows returned from a query. Data access is a major issue in developing a Decision Support System (DSS). The most common ways people receive information from the data warehouse include (Poe, et al., 1998):

- Parameter based ad-hoc report- Fixed report formats where the user can change the parameters.

- Electronic access to predefined reports- locations must be easily accessible locations for users to pull up for viewing as needed.
- Full ad hoc analysis- The user interacts directly with the tool to create a brand new analysis from scratch.
- Hard copy reports- predefined fixed format reports are generated, printed, and delivered to the user.
- Executive information system- provides navigation along predefined paths to access predefined analysis.
- Structured decision supports- provides navigation along predefined paths to access predefined and ad hoc reports.
- Unstructured decision support- provides access to all predefined and ad hoc reports.

Not all business users across functional areas have the same data and analytical requirements. An environment for data access includes the data access software, training, support, and a starter set of applications to enable users to access information from the data warehouse. A DSS application is a "starter set" of predefined reports created in the front-end tool to accommodate the need for different levels of users to have pre-built reports to begin their analysis (Baum, 1997). Different classes of tools may be used: report writers, data access/query tools, advanced decision support tools, and multidimensional database management systems (Zweig, 1996). Generally data access have the following characteristics: visualization of the data warehouse, formulation of the request, processing the request, and presentation of the results (Griffin, 1996).

IMPLEMENTATION AND INSTALLATION

The implementation and installation of a decision support data warehouse can not be accomplished effectively without the proper training, support, and rollout. Training should be comprehensive and focus on the following (Poe, et al., 1998):

- Introduction of data warehouse concepts
- Introduction to data, location in the warehouse, and how it relates to already installed reports and systems
- The mechanics of using the tool (Navigation)
- Type of analysis that can be preformed
- Using the tool against the data.

The best instruction is usually customized classes which utilize the particular tools of the required data. Proper support provided either through third party vendors of the installer of the system should be in place. The major support issues involved include (Poe, et al., 1998):

- Validity of the data
- Data use
- Pick reports
- Changes in the front-end application
- Building applications
- Navigation through metadata
- Adding new subject areas (data) to the existing warehouse

The best possible approach to supporting uses is to anticipate problems. Proactive decision thinking will allow system developers to anticipate problems and establish predefined solution models (Greenfield, 1996).

In planning a rollout of the DSS, a company should focus on the user requirements and establish effective strategies in order to effectively meet their needs. A phased rollout will allow management and users of the system to convert key systems first and allow debugging to occur before implementing other areas (Poe, et al., 1998). A rollout plan should have an established time line in order for managers and implementations to judge how effective their efforts at conversion are (Greenfield, 1996).

CONCLUSION

Overall, a database warehouse system is a strong development tool for providing information to key managers for decision support. The process is ad hoc in nature and no predefined established rules govern particular companies. The data warehouse is not an operational system and in many cases users are not required to use it. If the system is too difficult to use and appropriate levels of support and training are not provided then personnel may not use them. From the development of personal computers and the use of strategic information many companies have realized the importance of decision support information and the advances that it can bring to their organizations. The strategic use of information is an important component of successful businesses and will continue to be very important in the future. Managers should develop the skills necessary to manage this technology into the next millennium.

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DESIGN OF GROUP DECISION SUPPORT SYSTEMS FOR MANAGEMENT OF HOLONIC NETWORKS

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ABSTRACT

This paper will address the issues of management of a functional holonic network utilising a Group Decision Support System (GDSS). It is assumed that this network is formed from a group of manufacturing companies, producing a real world product, and having a profit motive. The management issues surrounding formation, planning, control, communications, and decision making for this network and its resident nodes are numerous, and will determine its ability to become a viable enterprise. Discussion of the fundaments of Decision Support Systems (DSS), Executive Information Systems (EIS), and the design criteria for Group DSS is provided.

INTRODUCTION

The holonic network dates its origins to the Hungarian author and philosopher Arthur Koestler. Approximately 25 years ago Koestler proposed the word "holon" to describe a basic organisational unit in the context of biological and social systems. *Holon* is a combination of the Greek work *holos,* meaning *whole*, and the suffix *on* meaning particle or part. When deriving this term, Koestler observed that in living organisms, and social organisations and systems, there was a total absence of autonomous, non-interacting entities. All units of identifiable organisations, such as individual cells in living organisms or a family unit in the social structure, are comprised of other basic units while at the same time forming a part of a larger unit of organisation. A holon, as Koestler derived the term, is an identifiable part of a system that has a unique individuality, yet is made up of sub-ordinate parts, while also forming a part of a larger whole.

The strength of holonic organisations is that they enable the construction of very complex systems. These systems are nonetheless efficient in the use of both internal and external available resources, adaptable to change, and resilient when dealing with disturbances in their environment. When Koestlers' term is applied to a manufacturing system, the concept takes on a more applied focus. A holonic network would be composed of a group of totally autonomous companies, each having a range of unique skills and capacities needed to allow delivery of the product. Each of these organisations is an independent business, having in place its own management structure, systems and procedures. When functioning within the network, the combination of skills and capacities allows the production of finished goods that individual holons could not individually manufacture. An example might be a network that produces specialised electronic equipment. One member company of the network could be a printed circuit board manufacturer, another a distributor of electronic components, a third company could produce the sheet metal cabinets or enclosures, a fourth produce the required wiring harnesses, with a fifth being the final assembly and test facility. The holonic network association may not account for the entire customer base, or production output of each holon. Equally important is the ability of the network to dynamically configure itself to meet the specific requirements for each order. Only those holons with the skills and capacity required will be summoned for each individual order placed with the network.

Management of an operational holonic network will be a complex task. Depending on the network structure and communications systems, management may take on several varying forms and formats. What appears to be clear from an analysis of the potential structures, is that management will be faced with multifaceted decision making requirements. It is also reasonable that the decision making process will be more widely spread throughout the network in a highly decentralised organisation. The need for rapid decision making in complex circumstances, which is both accurate and consistent will be a critical success factor in this type of organisation. The ability of a computer generated Decision Support System (DSS) can be an aid to this requirement.

DECISION SUPPORT SYSTEM (DSS) BASICS

Early work in defining a DSS, which aids the management of a business organisation, was provided by Michael S. Scott Morton in the 1970's, utilising the term "management decision systems." (Scott Morton, 1971) The DSS can be loosely defined as an *aid* to management decision making. Help with solutions to unstructured problems, utilising data input and models, is provided by the DSS in its elementary form.

Characteristics of DSS are vague, and defy succinct definition. Keen has shown that examples are an excellent way to visualise desired performance, and has generated about 30 examples and compared their characteristics. (Keen, 1978) "Observed characteristics, taken from the work of Alter, Keen and others are that:

- ♦ They tend to be aimed at the less well structured, under-specified problems that upper level managers typically face
- ♦ They attempt to combine the use of models or analytic techniques with traditional data access and retrieval functions
- ♦ They specifically focus on features which make them easy to use by non-computer people in an interactive mode
- ♦ They emphasize flexibility and adaptability to accommodate changes in the environment and the decision making approach of the user" (Sprague, 1993)

The necessity for flexibility and adaptability, and ability to accommodate changes in the existing business climate, coupled with variety of approach of the user will be necessary attributes for a DSS used with holonic networks.

Sprague and Watson suggest that the design of a DSS differ from that of a more standard Management Information System (MIS) (Sprague, 1993) They suggest that an iterative design process be used, rather than the systems approach of analysis, design, construction, and implementation. In this approach, the designer and user agree on a small, well-defined sub-problem that is then coded. The DSS is then used for a period of time, modified and incrementally expanded, until agreement about acceptable performance is reached.

What constitutes acceptable performance has some degree of personal preference. In general:

- A DSS must provide support for loosely structured or unstructured decisions. This type of business decision generally has little support from the Operations Research, or MIS systems. These kinds of problems largely fall in to the "too hard" basket by both systematic and cognitive style decision makers.
- Management at all levels within the organisation must be able to utilise the DSS. It is important that the DSS does not isolate any management layer, but provides a degree of integration across the organisation. The DSS must also integrate the decision process of several managers working on different parts of a complex problem.
- A DSS needs to provide a framework for decisions that are interdependent as well as decisions that are independent. Especially true for the holonic organisation, in which independent holons will be making *interdependent* decisions *independently* (Sprague, 1993).

Keen and Hackathorn explore three decision types as:

- **Independent:** the decision maker has full responsibility and authority to make and implement a full decision
- **Sequential Interdependent:** the decision maker makes part of the decision which gets passed on to someone else
- **Pooled Interdependent:** the decision must result from negotiation and interaction among decision makers (Sprague, 1993).

Additionally:

- A DSS will require the ability to support the decision making process in its entirety.
- A DSS must support a variety of decision-making processes, while primarily maintaining independence from the application of any single process. The tool must be broad enough in scope to support the style and cognitive abilities of a variety of users while remaining process independent.
- A DSS must be easy to use. It is vital that the tool be capable, but that it is user controlled and "friendly" (Sprague, 1993).

GROUP DECISION SUPPORT SYSTEMS (GDSS)

Decisions made by the functional holonic network will, by definition, be interdependent. Many higher level decisions, such as product choice, design decisions, adapting new technology, capital expenditure or investment commonly made management will need agreement from each of the nodes if the network is to be viable in the long term. Group Decision Support Systems (GDSS) lend themselves to this requirement. GDSS can be defined in different ways, but definitions have some common parameters. As shown by Turban (Turban, 1995) the GDSS consists of "software, hardware, language components, and procedures that support a group of people engaged in a decision related meeting."

The GDSS is a technology which provides support for idea generation, issue prioritisation, problem analysis, and strategy selection as part of the decision making process. The use of the tool also helps reduction of interpersonal issues that lower group effectiveness. A properly implemented GDSS will provide the additional benefit of documenting the team decision making process, and outcomes.

The goal of the GDSS is to provide a structure and methodology for improving the decision making process-taking place at a meeting. This is enabled in three levels:

1. Process Support
2. Decision Making Support
3. Rules of order

Level 1, the process support level, provides:

a. Electronic messaging between group members
b. Networks linking each members computer to other group members and common databases
c. A common screen that can be viewed by all members assembled at a central place
d. Anonymous input of votes and ideas allowing group members to maintain anonymity if they so choose
e. Active solicitation of ideas and votes from each group member, intending to encourage participation, remove intimidation, and enhance creativity
f. Summarise and display ideas and opinions, including statistical summaries when appropriate, and displays on the public screen of a tabulation of voting outcome

Level 2, the decision-making support level provides:

1. Short term and strategic planning, and financial models
2. Decision trees
3. Probability assessment models
4. Allocation and commitment of resource models

5.	Ethical and social judgement model

Level 3, the Rules of Order level, is most important and appropriate in multicultural settings. In this case the GDSS can aid avoidance of cultural faux pas, and aid the smooth functionality of the decision making process. These rules, for example, might include sequence of speaking, or voting rules. (Turban, 1995)

The holonic network offers a dynamic alternative to the manufacturing sector. Perhaps more so with a networked organisation than with a more formally structured one, management of the business can tend to be knife-edged. Decision-making must be exceptionally quick, consistent, accurate, and not burden the network with excessive management costs. Additionally, these decisions must be made across distance, national, and cultural boundaries. A DSS has the potential to aid with each of these requirements, and could potentially be the common thread that makes the promise of the holonic network become the manufacturing system of choice in the next century.

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CUSTOMER ORDER ACCEPTANCE DECISION MODELS FOR A PROCESS-FOCUSED PRODUCTION SYSTEM

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ABSTRACT

This paper attempts to improve and evaluate a model for the customer order acceptance decision in a process-focused production environment. The MANOVA was used as the primary statistical procedure for analyzing the results from the factorial experimental design of the research. The experimental factors include the customer order acceptance decision model and the utilization level. Tukey's test was used to isolate the performance of the specific customer order decision models. The statistical analysis indicates that the integer linear programming model described in this paper is in the superior performance category under all utilization levels tested compared to other order acceptance models.

INTRODUCTION

The ability to attract customer orders has long been recognized as one of the key success factors for process-focused production or job shops. Scant attention however has been devoted in the literature to the customer order acceptance decision. That is, the decision as to whether a customer order should in fact be accepted once it is received. This decision is part of the firm's demand management function.

Guerrero and Kern (1988) point out the importance of the customer order acceptance decision: "Under any circumstances, accepting orders without considering their possibly costly impact on capacity can lead to paying for the privilege of accepting an order" (p. 59). The need for order acceptance decision rules is also addressed by Matsui (1982, 1985) and others.

Guerrero and Kern (1988) suggest a framework for demand management. From a day-to-
day perspective, a simple demand management system, as shown in Figure 1, includes order entry, order accumulation, establishment of order priority, precapacity allocation, and order acceptance decision. A well developed demand management system offers at least two advantages for the firm. First, shop capacity can be more effectively planned and controlled. Second, realistic customer order due date commitments can be made. Traditionally, managers

have a tendency toward accepting all incoming orders. However, some customer orders may in fact not be a good match with current shop capacity. Two specific questions arise:

(a) What is the relationship between system performance and the customer order acceptance decision process?

(b) What types of decision rules might be adopted to assist managers in accepting customer orders in a process-focused production system?

Despite the importance of order control and acceptance in practice, researchers have published very little on the development of effective answers to these questions.

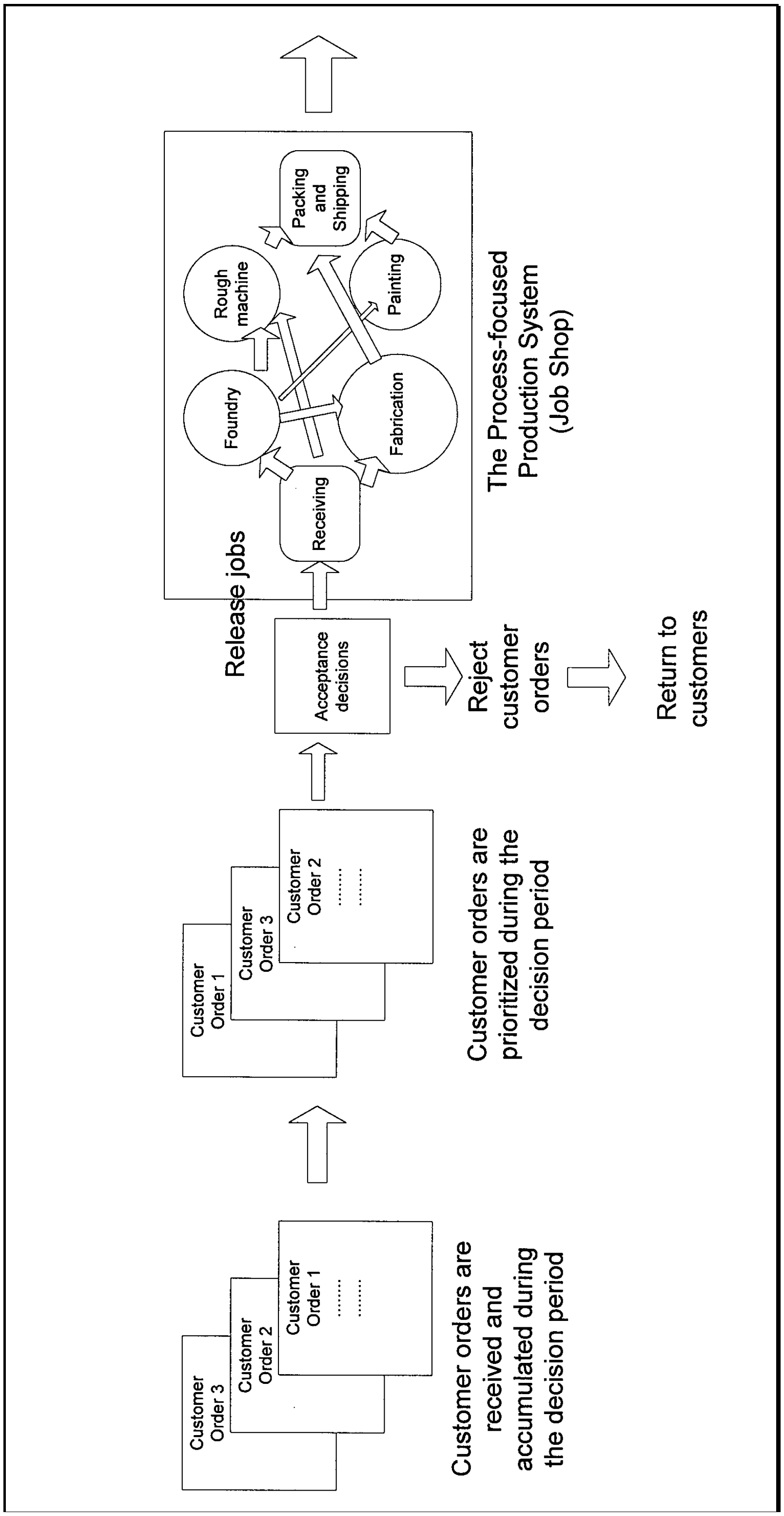
There are several important factors that impact customer order acceptance decisions. These factors include the decision period (the period of time over which orders may be collected before order acceptance decisions must be made), size of the order, due date requirements, current capacity constraints, and order preference (e.g. profit margin, customer credit, etc.).

The production system considered in this research is a make-to-order, non-MRP, process-focused production shop. Process-focused production systems are commonly referred to as job shops or intermittent production because products move from department to department in jobs that are normally determined by customer orders. An order acceptance decision is considered on a "micro" level for each individual order. Fixed capacity is assumed in the shop and due dates are the function of estimated processing time and set-up time. The primary purpose of this research is to test an order acceptance algorithm, the JOA model, for the customer order acceptance decision in a process-focused production system.

REVIEW OF LITERATURE

Little attention and effort has been directly devoted to demand management in the literature. Prior research has addressed demand management primarily in broad terms, for example, as demand forecasting, order entry, due date promising, customer order service, and other customer contact-related terms (Vollmann, Berry, & Whybark, 1988). Most research efforts related to demand management have been directed toward aggregate level decisions in an MRP environment, such as demand forecasting and the interaction between demand management and master production scheduling (MPS). McClelland (1988), for example, provides guidelines for the selection of an appropriate master scheduling method for a make-to-order firm to improve order promising.

Although job shop scheduling has an interactive relationship with demand management, including the individual order acceptance policy, job shop studies do not normally consider demand management decisions. That is, the demand management process is considered as external to most job shop research. Specifically, the literature dealing with order management in the job shop level is sparse and was practically nonexistent before 1970. Melnyk (1988) discussed "order review/releasing" (ORR), in which the process of order management changes from the planned system to the shop floor system. Although order review/releasing and order acceptance control have similar purposes, they are different functions. Order review/releasing concerns the job releasing mechanism, and is based on the assumption of accepting all the incoming jobs.



Customer Order 3
Customer Order 2
Customer Order 1
Customer orders are received and accumulated during the decision period
Customer Order 1
Customer Order 3
Customer Order 2
Customer orders are prioritized during the decision period
Acceptance decisions
Reject customer orders
Return to customers
Release jobs
Receiving
Foundry
Rough machine
Fabrication
Painting
Packing and Shipping
The Process-focused Production System (Job Shop)

Since 1970, there have been a few articles in the Japanese literature concerning aggregate order decision mechanisms (Nomura, 1974; Ikuta, 1975; Ichimura, 1977; Matsui, 1980, 1981, 1982; Nishimura, 1982). This research has been summarized by Matsui (1982, 1985) in an English language article. A number of papers have discussed the effective decision rules in customer order acceptance. Miller (1969), Lippman and Ross (1971), and Balachandran and Schaefer (1981) discussed the aggregate (i.e. not the individual) customer order acceptance decision. Guerrero and Kern (1988) discussed the use of the forward loading and backward finite loading methods in the process of order acceptance decision. Lee and Deane (1991a) devised a mathematical linear programming method for order acceptance decisions in a make-to-order job shop environment. Lee and Deane (1991b) compared two relatively simple order acceptance decision rules, the Workload Rank (WR) heuristic and the Input/Output (I/O) heuristic in a similar environment. Philipoom and Fry (1992) compared three different order review/release strategies to improve manufacturing performance. While the first two different strategies used by Philipoom and Fry are in fact similar to Lee and Deane's WR and I/O heuristics, the third strategy is not to use any decision rule in job order review/releases. Wang, Yang, and Lee (1994) used a neural network solution for multi-criteria order acceptance decision in a over-demand job shop.

A MATHEMATICAL PROGRAMMING MODEL

The primary objective of this study is to improve and evaluate a mathematical programming model, the Job Order Acceptance (JOA) model, for a process-focused production system. A custom order, after entering a production shop, is also referred to as a job. The model described in this paper is based on the early framework of JOA devised by Lee and Deane (1991a). The first section describes this mathematical programming model and its associated implementation issues. The objective function, constraints and model parameters are also discussed.

A mathematical programming approach is used to model the important decision variables and parameters in the customer order acceptance decision. The JOA model employs an integer programming algorithm executed at the end of each decision period. The purpose of the JOA model is to achieve both work-in-process related performance (e.g., minimize work-in-process inventory level, or mean and variance of shop flow time) and due-date related performance (e.g., minimize average tardiness).

With respect to work-in-process related performance, the JOA model seeks to minimize the difference between the current workload and the target workload at each machine. Within a capacity constraint, the JOA model not only maximizes the utilization level of each machine but also controls the work flow to the machines, thereby helping to reduce the average WIP. For due-date related performance, the JOA model seeks to maximize the slack time of accepted customer orders. As such, customer orders with tight due dates are afforded less priority since they increase the possibility of job tardiness. Although order release policy and sequencing rules at each station have an impact on WIP and due-date performance, they are not final solutions for long shop flow time and poor due-date performance in a high congestion shop. Research also indicated that dispatching rule has little impact on shop performance while the I/O control method is used (Ragatz & Mabert, 1988; Philipoom & Fry, 1992).

The JOA model makes an integrated decision as to which customer orders in a decision period should be accepted. The decision is "dis-aggregated" in that the workload of each machine is separately considered. The primary focus of the mathematical programming model is thus to select customer orders that best "fit" the available capacity in the shop, and have the best chance of being completed by their required due date.

Formulation of the JOA Model

The basic variables and parameters in the JOA model are:

k = total number of incoming customer orders during a decision period
i = customer order number (1 .. k)
M = total machine number
j = machine number (1 .. M)
d_i = job due date for customer order i
TNOW = time now
P_{ij} = estimated processing (run) time of customer order i on machine j
S_{ij} = estimated set-up time for customer order i on machine j
T = the number of planning periods
t = t-th planning period
TW_{tj} = target workload for machine j for t-th planning period
AW_{tj} = actual workload for machine j for t-th planning period

To formulate the JOA model, the current shop capacity should be expressed for M machines in a process-focused production system. A Forward Finite Loading (FFL) algorithm is used to compute the unfilled capacity (C_j) in the JOA model. Under the forward finite loading algorithm, time is divided into T planning periods and a target workload, TW_{tj}, in t-th period is assigned for j-th machine.

The target workload, TW_{tj}, is the value used to control utilization level. When the value of TW_{tj} is high, more customer orders are accepted to shop and the shop utilization is high. When the value of TW_{tj} is low, fewer customer orders are accepted to the shop and the shop utilization level is low. OW_{tj} denotes actual current workload which is greater than target workload for the machine j during planning period t:

$$OW_{0j} = 0$$
$$OW_{tj} = \max [0, (OW_{(t-1)j} + AW_{tj} - TW_{tj})] \quad \text{for } t \geq 1 \qquad (1)$$

Unfilled capacity available for machine j (C_j) during the planning period 1 to t is defined as:

$$C_j = \sum_t [\max (0, TW_{tj} - AW_{tj} - OW_{tj})]$$

The second factor for this formula involves assigning a priority to each incoming customer order. For due-date related performance, the JOA model seeks to maximize the slack time of accepted customer orders. As such, customer orders with tight due dates have lower chances since they increase the possibility of job tardiness. The estimate slack time for customer order i (SL_i) is computed as:

$$SL_i = d_i - TNOW - \sum_j P_{ij} - \sum_j S_{ij} \qquad (3)$$

Based on this slack calculation, customer orders with negative slack times cannot be selected by the algorithm. A "revised" slack time is therefore used to ensure that customer orders with negative slack times are properly considered by the algorithm:

$$RSL_i = SL_i + R \qquad (4)$$

The revised slack time, RSL_i, for customer order i is computed by adding an adjusting factor, R, to the slack time. The use of the revised slack calculation allows customer orders with negative slack time to be selected. The adjusting constant, R, is added to the slack value to force all the job slack values to be positive:

$$R = 1 - [\min (0, SL_i, \ .. \ Sl_k)] \qquad (5)$$

The value of R is computed as: 1 - [min (0, Estimated slack time for customer order 1 (SL_1), Estimated slack time for customer order 2 (SL_2), .., Estimated slack time for customer order k (SL_k))] + 1. For example, consider six customer orders with the estimated slack times, $SL_1 = 3$, $SL_2 = -4$, $SL_3 = -2$, $SL_4 = 5$, $SL_5 = 7$, $SL_6 = 0$. Based on these six customer orders, the adjusting constant, R, is 1 - (-4) = 5. The revised slack times are $SL_1 = 8$, $SL_2 = 1$, $SL_3 = 3$, $SL_4 = 10$, $SL_5 = 12$, $SL_6 = 5$.

The first constraint, is expressed in the following:

$$X_i = 0 \text{ or } 1 \qquad \text{for all } i \qquad (6)$$

This constraint prohibits a "partial" acceptance of an incoming customer order. Each customer order is accepted or rejected in its entirety. X_i is the decision variable for customer order i. When $X_i = 1$, customer order i is accepted. When $X_i = 0$, customer order i is rejected. The second constraint, representing the major constraint in the JOA model, is expressed in the following:

$$\sum_i [X_i * (P_{ij} + S_{ij})] \leq C_j \qquad \text{for all } i,j \qquad (7)$$

This constraint requires that the total assigned processing time for each machine not be greater than the available machine capacity. This constraint should be examined with the job with revised slack time. A customer order has higher priority in revised slack time will be rejected if it cannot meet this constraint. This constraint shows that the JOA model is based not only on maximizing total revised slack time but also meeting capacity capability.

The final formulation of the JOA model is given as follows:

Maximize:

$$\sum_i (X_i*RSL_i) \qquad (8)$$

subject to:

$X_i = 0$ or 1	for all i	(6)
$\sum_i [X_i * (P_{ij} + S_{ij})] \leq C_j$	for all i,j	(7)

Maximizing the objective function, Σ_i (X_i*RSL_i), guarantees that customer orders will be selected and furthermore directs that a preference be given to jobs with larger slack values. Since the objective function is to be maximized, the algorithm favors jobs with large slack time values. A full picture of the object function, constraints and variables of the JOA model is enclosed in Appendix. The decision model described above is appropriate for solution through integer program (IP) since constraint 2 in the formulation of the decision model requires discrete integer values. The decision variables X_i must be either 0 (reject job i) or 1 (accept job i). The solution time is dependent primarily upon the number of incoming jobs, not the number of machines in the shop. A test shows that the time required to solve a JOA integer programming problem is less than 15 seconds on a Pentium 200 computer with 14 incoming jobs in a an eight machine shop.

RESEARCH METHODOLOGY

The purpose of this research is to:

1. improve and evaluate the JOA order acceptance decision model in a make-to-order, process-focused production system, and
2. investigate the impact of target shop utilization levels on different order acceptance decision models.

It is hypothesized that several different decision models exhibit different performance while the JOA model should yield the best performance. It further hypothesized that the JOA model should perform much better than other models in a process-focused production environment under high utilization levels.

A computer simulation experimentation methodology was undertaken to imitate the job shop environment. Primary performance criteria for the study include mean job flow time and the degree to which order due date are met. Independent variables are order acceptance decision model and utilization level. Since the experimental design include two dependent metric variables and two non-metric independent variables, a full factorial fixed effect MANOVA model was used as the primary statistical procedure for analyzing different performance among decision models and utilization levels. There are three different decision models and three different utilization levels which yield 9 different experimental sets (3 * 3). Tables and graphics are used to summarize the experimental results.

A discrete event simulation model for an eight-machine process-focused production environment was developed using the SIMAN simulation language with a FORTRAN subroutine. The following sections describe details of alternative decision models, the performance criteria, experimental conditions, and data collection method.

Alternative Decision Models

The JOA algorithm is compared with three specific customer order acceptance decision models:

1. Backward Finite Loading (BFL) Approach. The BFL is based on the division of the planning horizon into "planning periods". Incoming customer orders are placed in a "selection pool" and ranked by due date. The BFL approach attempts to fit each operation of each job in the selection pool backward into a planning period from the job's assigned due date, starting with the last operation in the job and working toward the first. If adequate capacity is not available in a time period, the BFL attempts to schedule the operation in the next earliest period that adequate capacity is available. If adequate capacity is available for all operations of an order, the customer order should be accepted and moved from the selection pool to the releasing pool. The workload profile is also updated based on the accepted job order. In contrast, if adequate capacity is not available for a customer order, the customer order is temporarily placed into a holding pool. After a "first pass" attempt is made to fit all the orders in the selection pool into the schedule, a "shop unfilled capacity ratio" (SUCR) is computed by dividing unfilled capacity by target workload. If the shop unfilled ratio is higher than a critical percentage (for example, 15%). An additional customer order from the holding pool will be accepted. The order selected from the holding pool will be the one that creates the least total "overload" for machines in the shop. Additional orders are selected until the shop unfilled capacity ratio falls below the target percentage.

2. Workload Rank (WR) Heuristic. In the WR heuristic algorithm, a priority index is assigned to each customer order based on the projected workload of the machines required in processing the customer order. The WR algorithm computes the unfilled capacity at each machine center and uses it as a base to compute order priority. A job priority is computed based on the estimated unfilled capacity at each machine center on the job's routing. Based on the computed job priorities, orders are accepted by the shop. As each customer order is accepted, the workload of the customer order is added to the "committed workload" for each machine.

The addition of the customer order alters the unfilled capacity of one or more machines, and a recalculation of unfilled capacity (C_j) for each machine is made (Lee & Deane, 1991b).

3. I/O Heuristic. The I/O acceptance heuristic is based on the concept that work is accepted to the system when total shop workload falls below a pre-specified level. That is, the input to the system is guided by what is leaving the system as output. A version of this rule for job order releasing was tested by Baker (1984) and suggested earlier by Wright (1979). The I/O acceptance heuristic allows a customer order to be accepted only when the total aggregate workload in the shop is below a pre-specified level.

Performance Criteria

Primary performance criteria include average job flow time and root mean square of tardiness. Average shop flow time (F_{av}) is used as a primary measure of how well jobs move through the shop. Shop flow time is defined as the time between the release of the job to the shop floor and the time when the job completes its last operation. Average shop flow time (F_{av}) is computed as:

$$F_{av} = \frac{\sum_i (f_i - RE_i)}{n}$$

where

f_i: completion time of job i

RE_i: releasing time of job i

As an alternative measure of shop congestion, average system flow time is computed as follows:

$$S_{av} = \frac{\sum_i (f_i - A_i)}{n}$$

where

A_i: arrival date of customer order i

Although S_{av} and F_{av} are highly correlated, both have different objectives. General system congestion and customer lead time is measured by S_{av}, while work-in-process (WIP) inventory on the shop floor is measured by F_{av}. When utilization level is high, both average system flow time and average shop flow time are high.

Root Mean Square of Tardiness (T_{RMS}) is employed as the measure for due date performance since it is a somewhat "combined" measure of average tardiness and variance of tardiness. T_{RMS} is computed as:

$$T_{RMS} = \sqrt{\sum_i [\max(0, f_i - d_i)]^2 / n}$$

where

f_i: complete time of job i

d_i: due date of job i

n: number of jobs finished

Absolute deviation from due date (| D |) is also reported as a secondary measure of due date performance. Absolute deviation from due date is computed as follows:

$$| D | = (\Sigma \ | f_i - d_i |) / n$$

Mean and standard deviations (square root of variance) of system flow time, tardiness, lateness, absolute lateness, and earliness are also reported as secondary performance criteria. The percentages of customer orders accepted are also reported for all order acceptance decision models in tabular forms.

Experimental Conditions

The primary experimental factor is the job order acceptance model. Shop utilization level serves as a secondary experimental factor to compare the different order acceptance decision models.

Shop utilization level is the average "working time" of machines in the shop divided by total machine capacity. The concept of shop utilization levels in this study is not necessarily directly related to customer order arrival rate. Customer order arrival rate is an input, external factor to the job shop model while the actual utilization level is an internal, output level controlled in the shop (through the customer order acceptance process). For example, the utilization level can be controlled by varying the target workload (TW_{tj}) in the JOA model.

Shop utilization level certainly has an impact on the performance of the different decision models. For example, assume that two decision models are evaluated using an incoming job stream that would result in a 100% shop utilization level if all customer orders are accepted. If model A rejects 25% of incoming customer orders and model B rejects 10% of incoming customer orders, then obviously model A would yield better shop flow time and order due date performance. However, model B would result in more total work through the shop (and perhaps higher profits). In order to provide a "fair" comparison of alternative acceptance decision models, each model was evaluated at the same shop utilization level. In this paper, three levels of target shop utilization levels are used to compare decision models: 65%, 75%, and 85%.

In this simulation, arriving orders are accumulated during a "decision period" in order for the manager to make a customer order acceptance decision. That is, the decision period is the period of time over which orders are collected before order acceptance decisions must be made. The decision period may be as short as a few minutes or as long as a few days. The decision period can be an important factor influencing order acceptance performance. A longer decision period normally provides greater flexibility for the demand manager in making order acceptance decisions. Under a longer decision period, the decision process becomes more complex since more customer orders are considered during a decision period. The decision period in this simulation experiment was 6 time units, during which an average of 8 customer orders arrival and were accumulated. Average processing time or job size has a moderate relationship with shop utilization level. Long average processing time requires less setup time such that its utilization level is higher than that of short average processing time. Average total processing time, including setup time, is 6.01 time unit in this experiment.

In the eight-machine simulated shop, customer orders arrive and wait for the acceptance or rejection decision. When a customer order is accepted, it is moved directly to the first machine on its routing. Customer orders are "lost" to the system if rejected. Once in the shop, all jobs are dispatched via the EDD dispatching rule.

The process-focused production system simulated in this study is consistent with those used in previous research and with shops found in industry (Han, 1989; Kim, 1989). The job shop simulation model was validated through the input/output transformation analysis, a set of "snapshot" outputs and graphical animation analysis.

A summary description of the eight-machine shop is provided below:

1. relatively balanced shop (no bottleneck machines),
2. exponential customer order arrivals to the job shop ($\mu = 0.786$),
3. deterministic run and setup time (average total processing time, including setup time, is 6.01),
4. batch size is a random variable (following a discrete probability function),
5. operation overlapping and preemption are not allowed,
6. negligible wait time and move time between machines,
7. predetermined job routing through the shop,
8. machine break downs are not considered,
9. alternative job routings are not allowed (average number of job operations = 6),
10. unlimited queues allowed at each machine,
11. the shop is machine constrained, not labor constrained,
12. lot splitting is not allowed.

Data Collection

In order to eliminate initial bias, data from the initial transient period was discarded with the length of the transient period determined by plotting and examining the values of key variables as suggested by Conway (1967). A length of 500 simulation time units of transient period was found to be adequate to yield steady state by observing the plotted output from a pilot run. On average, there are 2486 jobs processed through the shop during each observation period after steady state was achieved.

The "batch means" approach was used for collecting observations in one long simulation run to avoid a run-in period for each observation. One long simulation run was broken down into "batches" (or subruns) so that the end of a simulation batch serves as the starting point for the next batch. Each batch yields one observation for each performance measure. For each experimental setting, twenty "observations" of approximately 2500 jobs, were collected to obtain a sufficient sample to test for differences in performance. The procedure used to determine this batch length was suggested by Fishman (1978). By Fishman's method, a subrun length of 2100 simulation time units was found to be adequate to yield independent observations. In addition, common random number seeds are used as a variance reduction technique to reduce the variances of the performance measures. Each model is therefore tested using exactly the same customer order arrival stream.

RESULTS

The MANOVA technique was used as the primary statistical procedure for analyzing the results from the factorial experimental design of the research because more than one performance criterion is employed in this research. The experimental factors include the customer order acceptance decision model and the utilization level. The full factorial MANOVA, rather than a series of ANOVA, was used to analyze simultaneously the impact of the factors on the multiple criteria. Tukey’s test was used to isolate the performance of the specific customer order decision models.

The MANOVA results for total shop performance are provided in Table 1. The results of the ANOVA for each performance criterion are shown in Tables 2 and 3. From these statistical analysis, both experimental factors have significant main effects and there is a significant interaction effect. The main effects of order acceptance models and shop utilization levels must therefore be interpreted jointly considering the interaction effect. From Tables 4 through 6, the results of Tukey's test show that the JOA model is in the best performance category under all utilization levels compared to other order acceptance decision models in terms of both flow time and due date performance. Table 7 and Table 8 summarize the performance of the order acceptance models at various utilization levels in a tabular form.

Table 1: Multivariate Analysis of Variance Table

Dependent Variables: Average Shop Flow Time (f_{av}) and Root Mean Square of Tardiness (TRMS)

Root Mean Square of Tardiness (T_{RMS})

			DF	

Source of Variance	Wilks' Criterion	F value	N*	D**	PR > F
Decision Model (DM) ***	0.01478003	546.73	6	454	0
Utilization Level	0.00055338	4711.37	4	454	0
DM x UL	0.02118589	222.09	12	454	0

* Numerator's degree of freedom for critical F value

** Denominator's degrees of freedom for critical F value

*** Decision model refers to order acceptance decision models: JOA, BFL, WR, and I/O

Table 2. Analysis of Variance Table – Average Shop Flow Time (F_{av})

Dependent Variable: F_{AV}

Source of Variance	DF	Sum of Squares	Mean Square	F Value	PR > F
MODEL	11	15263.01	1387.54	1266.38	0.0001
Decision Model (DM)	3	441.63		134.54	0
Utilization Level (UL)	2	14638.46		6690.62	0.0001
DM x UL	6	182.91		27.87	0.0001
RESIDUAL	228	249.42	1.09		
TOTAL	239	15512.43			

R-squared = 0.983921

Table 3. Analysis of Variance Table – Root Mean Square of Tardiness (T_{RMS})

Dependent Variable: T_{RMS}

Source of Variance	DF	Sum of Squares	Mean Square	F Value	PR > F
MODEL	11	4920175.5	447288.7	10874.4	0
Decision Model (DM)	3	285252.6		2311.7	0
Utilization Level (UL)	2	4312100.9		52417.4	0
DM x UL	6	322822.9		1308.1	0
RESIDUAL	228	9378.2	41.1		
TOTAL	239	4929553.7			

R-squared = 0.998098

Table 4. Turkey's Range Test for Decision Model Under 65% Utilization Level

$\alpha = 0.01$

	Turkey Grouping	Mean Value	Decision Model
F_{av}	A	14.34	I/O
	B	13.99	BFL
	B	13.95	WR
	B	12.91	JOA
	Turkey Grouping	Mean Value	Decision Model
T_{RMS}	A	16.29	I/O
	B	8.42	BFL
	B	7.31	WR
	B	7.25	JOA
Note: Means with the same letter are not significantly different			

Table 5. Turkey's Range Test for Decision Model Under 75% Utilization Level

$\alpha = 0.01$

	Turkey Grouping	Mean Value	Decision Model
F_{av}	A	22.09	I/O
	A	21.21	BFL
	B	19.77	WR
	C	17.90	JOA
	Turkey Grouping	Mean Value	Decision Model
T_{RMS}	A	60.92	I/O
	A	42.39	BFL
	B	32.40	WR
	B	31.30	JOA
Note: Means with the same letter are not significantly different			

Table 6. Turkey's Range Test for Decision Model Under 85% Utilization Level

$\alpha = 0.01$

	Turkey Grouping	Mean Value	Decision Model
F_{av}	A	35.58	I/O
	B	33.91	BFL
	C	31.50	WR
	D	29.12	JOA
	Turkey Grouping	Mean Value	Decision Model
T_{RMS}	A	452.80	I/O
	B	281.66	BFL
	C	251.43	WR
	C	247.56	JOA

Note: Means with the same letter are not significantly different

Table 7. Average Shop Flow Time*

	Decision Model			
Utilization Level	JOA	BFL	WR	I/O
65%	12.91	13.99	13.95	14.34
75%	17.90	21.21	19.77	22.09
85%	29.12	33.91	31.50	35.58

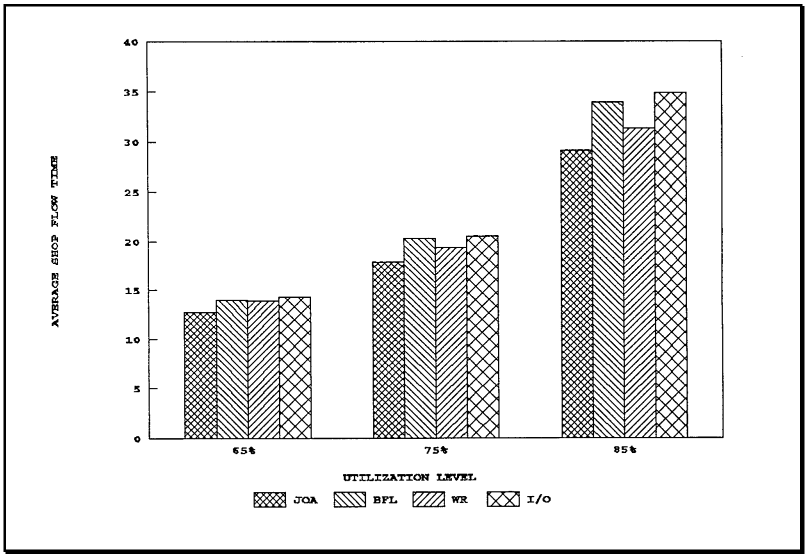
* Decision period = 6 time units; Job order arrival rate = exponential distribution with a mean of 0.786

Table 8. Root Mean Square of Tardiness*

	Decision Model			
Utilization Level	JOA	BFL	WR	I/O
65%	7.25	7.31	8.42	16.29
75%	31.30	32.40	42.39	60.92
85%	247.56	251.43	281.66	452.80

* Decision period = 6 time units; Job order arrival rate = exponential distribution with a mean of 0.786

Figures 2 and 3 depict performance of the order acceptance decision models in a graphical format. From these tables, graphs and Tukey's test, it is clear that the superiority of the JOA model varies with shop utilization level. Under low utilization levels, the differences among the order acceptance decision models may not be practically significant. At higher shop utilization levels, the JOA model is vastly superior to the other decision models in terms of average shop flow time and root mean square of tardiness.



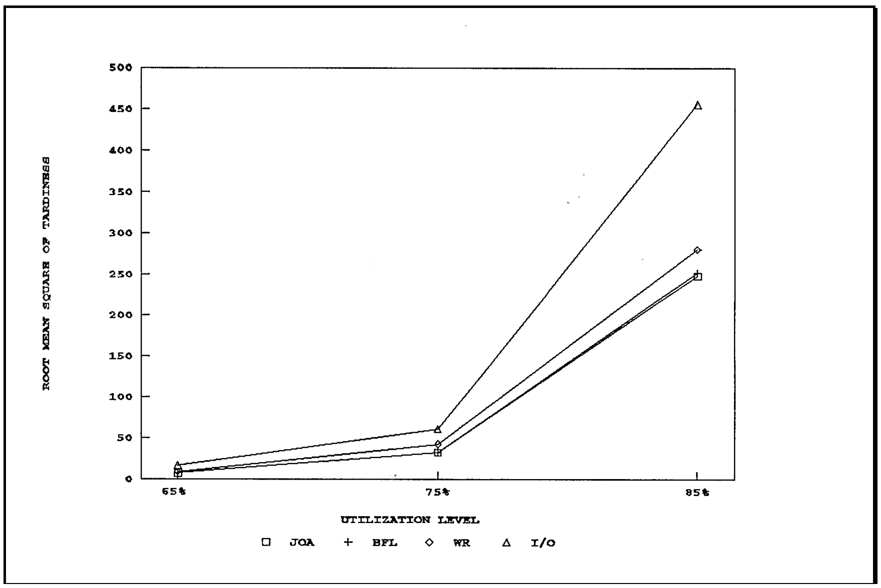


Table 9 shows secondary performance measures including means and standard deviations for system flow time, tardiness, lateness, absolute lateness, and earliness. The JOA model yields good performance for system flow time, earliness, absolute lateness, and lateness. The BFL model performs well for due date related performance criteria because it uses a structured approach that schedules backward from job due date. Unfortunately the BFL model often requires that jobs remain in the shop for longer time periods so that system flow time is excessive compared to the JOA model.

The general superiority of the JOA model arises from the fact that it jointly and simultaneously considers all incoming customer orders. The other models consider customer order acceptance decisions on a sequential basis. At lower utilization levels, excess capacity is available and work-in-process is small so that order acceptance decision models make relatively little difference in performance. However, higher levels of shop utilization are correlated directly with increased machine/work center loads, queues, and queue waiting time. Under such conditions, the JOA model is effective in considering the dis-aggregated workload on each machine, the available unfilled capacity, and job slack time. As such, the JOA model is able to show much better performance compared with other acceptance decision models. At higher utilization levels, the shop cannot afford to accept any order that does not exactly "fit" existing shop capacity.

Table 10 shows the percentage of incoming customer orders accepted under each model tested. Interestingly, the I/O model tends to accept a greater number of orders but essentially the same workload hours as the other models (i.e., all models yield the same utilization levels). In a decision period when only a relatively small amount of shop capacity is available, the JOA, BFL, and WR models, using a dis-aggregated approach, tend to accept very few orders. These sophisticated models reject more orders since machine capacity must be available for each individual job operation. During a subsequent decision period, additional capacity will likely become available so that larger orders can be accepted by the sophisticated models. However, in situations where available shop capacity is small, the I/O model tends to be able to accept one or more small orders because the acceptance decision is based only on comparing total available shop capacity with the aggregate workload of a job. That is, the I/O model does not match individual operations for arriving orders to individual machine capacities. The use of the I/O customer order acceptance model therefore increases the chances that smaller jobs can be accepted up to the limit of the total available shop capacity. Accepting more small job orders may of course not necessarily the best interest of the shop. The results of this research would seen to support such a generalization.

Table 9. Secondary Performance Measurements

	Utilization Level	JOA		BFL		WR		I/O	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
System Flow Time	65%	15.87	6.18	16.09	6.16	16.01	6.12	16.16	6.13
	75%	20.01	7.83	21.84	8.73	21.35	8.56	22.05	8.75
	85%	31.64	12.88	35.21	14.56	32.08	12.98	36.31	15.09
Tardiness	65%	1.11	2.44	1.15	2.51	1.22	2.63	1.93	3.49
	75%	3.09	4.66	3.19	4.79	3.88	5.22	4.84	6.12
	85%	11.07	11.53	11.98	11.32	12.37	10.45	16.88	12.94
Lateness	65%	-4.39	7.23	-4.37	7.24	-4.39	7.75	-1.63	6.85
	75%	-2.20	8.22	-1.13	8.25	0.9	8.58	2.73	8.55
	85%	11.07	11.53	11.09	10.72	12.35	10.45	16.39	13.72
Absolute Lateness	65%	6.19	5.28	6.22	5.08	8.89	4.73	9.99	5.24
	75%	6.40	5.16	6.27	5.19	6.86	5.21	6.96	5.68
	85%	12.79	9.58	12.88	9.64	13.24	9.74	17.37	12.46
Earliness	65%	5.48	5.84	5.5	6.01	5.61	6.29	3.56	4.58
	75%	3.3	5.04	3.1	4.98	2.98	4.8	2.11	3.91

	85%	0.86	2.67	0.87	2.75	0.9	2.82	0.49	2.01

Table 10. The Percentage of Number of Job Orders Accepted

Utilization Level	JOA	BFL	WR	I/O
65%	74%	73%	73%	82%
75%	82%	82%	82%	89%
85%	92%	92%	92%	95%

CONCLUSIONS

This paper attempts to improve and evaluate a model for the order acceptance decision in the process-focused production environment. The statistical analysis indicates that the JOA model is in the superior performance category under all utilization levels tested compared to other order acceptance models. The results also show that there are relatively small differences in performance at lower levels of utilization for the models examined. The implication is that JOA is particularly useful when management elects (and is able to) operate the shop at a higher utilization level. That is, the advantages of the JOA model are more pronounced at higher utilization levels.

A basic implication of this research is that a structured customer order acceptance control mechanism is vastly superior to a random or "naive" control mechanism. That is, the I/O heuristic model (most similar to the situation of naive control), is consistently inferior to other complex order acceptance decision models. Specifically, the research demonstrates that effective customer order acceptance can make a performance difference in terms of job flow time and job tardiness. In practice, managers tend to adopt decision heuristics based on ease of use, simplicity or perhaps because of a lack of knowledge about structured models. However, once a structured model, such as the JOA model, is implemented properly within a computerized information system, difficulty of usage, simplicity or lack of understanding becomes of less concern.

Future sensitivity testing of the JOA model is necessary. The impact of other factors, such as the length of decision period, due date tightness, or customer order arrival rate on the customer order acceptance process, should be investigated.

One possible drawback of the JOA model is its computation complexity in practice. The development of a more sophisticated heuristic based on the JOA principle may be possible. This paper was based on the assumption of a relatively balanced job shop with all job orders generating the same profit. An unbalanced job shop should be considered in future research.

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Appendix B. Formulation of the JOA Model

The specific formulation of the JOA model is given as follows:

Maximize:

$$\sum_i (X_i * RSL_i) \tag{8}$$

subject to:

$X_i = 0$ or 1 for all i (6)

$$\sum_i [X_i * (P_{ij} + S_{ij})] \leq C_j \quad \text{for all } i,j \tag{7}$$

where:

k = total number of incoming customer orders during a decision period

i = customer order number (1 .. k)

M = total machine number

j = machine number (1 .. M)

X_i: decision variable for customer order i

$X_i = 1$, accept customer order i

$X_i = 0$, do not accept customer order i,

$$SL_i = d_i - TNOW - \sum_j P_{ij} - \sum_j S_{ij} \tag{3}$$

d_i = job due date for customer order i

$RSL_i = SL_i + R$ (4)

R = the value for adjusting the slack time value in a decision period

$R = 1 - [\min (0, SL_i, \ldots Sl_k)]$ (5)

TNOW = time now

P_{ij} = estimated processing (run) time of customer order i on machine j

S_{ij} = estimated set-up time for customer order i on machine j

T = the number of planning periods

t = t-th planning period

TW_{tj} = target workload for machine j for t-th planning period

AW_{tj} = actual workload for machine j for t-th planning period

OW_{tj} = actual current workload which is greater than target workload for the machine j during planning period t

$OW_{0j} = 0$

$$OW_{tj} = \max [0, (OW_{(t-1)j} + AW_{tj} - TW_{tj})] \quad \text{for } t \geq 1 \tag{1}$$

C_j = unfilled capacity available for machine j during the planning period 1 to t

$$C_j = \sum_t [\max (0, TW_{tj} - AW_{tj} - Ow_{tj})] \tag{2}$$

INTEGRATION OF MATHEMATICAL AND SIMULATION MODELS FOR OPERATIONAL PLANNING OF FMS

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ABSTRACT

This paper presents an integrated procedure for operational level planning of FMS. The procedure hierarchically combines a mathematical planning model and a simulation model. The mathematical models alone cannot incorporate all the details of operational level planning of FMS. However, these details can be included by combining mathematical model with a simulation model. The main objective of the procedure is to generate more realistic results at the operational planning level.

In this paper, the procedure is illustrated for part assignment and tool allocation problem in FMS with the help of two numerical examples. Several aspects of the implementation of the procedure are also discussed.

INTRODUCTION

Flexible Manufacturing Systems (FMSs) are automated small-batch manufacturing systems consisting of a number of numerical and computerized numerical controlled metal cutting machine-tools linked together via an automated material handling system (MHS), Real-time control of machines and MHS is accomplished by computers and data transmitting links. The main objective of these integrated systems is to achieve the efficiency of automated high-volume mass production while retaining the flexibility of low-volume job-shop production. The flexibility in FMS is introduced via several factors which may include versatile machine - tools, small set-up and tool changing time, relatively large tool carrying capacity and the ability to automatically transfer tools between the machines. These factors allow a part to take alternate route while under process in the system. The possibility of the alternate routings adds an important element to the overall flexibility of these manufacturing systems.

An FMS possesses enormous potential for increasing overall productivity of manufacturing systems due to its flexibility. However, the task of operational level planning of FMS is more complex compared to traditional systems. During the operational planning of an FMS, small batches of parts are selected for simultaneous production in a manufacturing cycle. Several planning decisions such as, part production ratio, tool loading, machine grouping, and resource allocation (Stecke, 1983) are considered at the operational stage.

Numerous research studies are available in literature related to these operational planning problems (for review see: Buzacott & Yao, 1986; O'Grady & Menon, 1986). In general, the research studies in FMS production planning utilize the mathematical modeling approach to solve the problem. However, these mathematical models do not capture dynamic aspects (scheduling and other time-based factors) of the system. To address the dynamic aspects, discrete event simulation is widely employed (for review see: Gupta, Gupta & Bector, 1989). In typical FMS environment, the operational plamiing and scheduling problems are addressed at two different levels.

Since at the operational planning level, scheduling aspects are not considered, the results from the mathematical planning models are generally not realistic for FMS (Leung, Maheshwari & Miller, 1993). For example, the machine workload at the planning model results may be highly balanced, but due to scheduling constraints it may not be achievable during the actual operation of the FMS. This variance in the outcome of two models may result in the poor utilization of resources, longer makespan, etc.

In this paper, the part assignment and tool allocation problem in FMS is considered. The solution procedure utilized to solve the problems combines mathematical model with a discrete event si-tnulafion model. This procedure provides both optimal and realistic solution to mathematical model by integrating it with a simulation model. The remainder of the paper is organized as follows. The next section, briefly, reviews the literature on operational planning in FMS. Section 3 provides an overview of the problem and solution procedure. Section 4 provides proof of convergence of the procedure. This is followed by presentation of the example problems and the results obtained from these problems. Section 7 provides guidelines for parameter modificafion based on the example problems.

LITERATURE REVIEW

The operational planning problem in FMS has been extensively examined in the research literature. Mostly, operational planning problem is formulated as a mathematical model. The scheduling and control issues are not considered at this stage. Stecke (1983) formulated the machine loading problem as a non-linear programming model. Several different loading objectives were considered. These objectives included balancing the assigned machine processing times, maximizing the number of consecutive operations of a part on each machine, maximizing the sum of operation priorities, and maximizing the tool density of each magazine. Shanker and Tzen (1985) modified Stecke's (1983) model to include due dates. The modified objective function tries to balance the workload on each machine and to reduce the nwnber of late jobs simultaneously. Kusiak (1985) formulated FMS loading problem as a 0-1 linear integer model with the objective of minimizing total processing cost. However, he considered identical processing time for operations. Sarin and Chen (1987) formulated the machine loading and tool allocation as a 0-1 linear program. Part assignments and tool allocations were determined concurrently incorporating considerations such as tool life, tool slot capacity, and machine capacity. Leung, et al. (1993) formulated part assignment and tool allocation problem with material handling considerations.

Avonts and Van Wassenhove (1988) combined mathematical planning model with queuing network model to solve part mix and routing mix problems. They proposed a solution procedure where a linear programming model results were evaluated using CAN-Q. The results from the queuing model were fed into to the linear programming model. It was shown that combining a static linear programming model with a dynamic queuing model helped in achieving more realistic results for the part mix and routing mix problems.

The scheduling and control has been studied extensively in FMS. Gupta, et al. (1989) reviewed some aspects of FMS scheduling literature. Generally simulation is employed as the evaluation tool at this stage. A selective review of some of these studies is provided here.

Nof, Barash, and Solberg (1979) have studied the control problem in FMS. They have considered three rules for part releasing into the empty system and two rules for part releasing into the loaded system. The releasing sequence is either random or a function of the production requirement of part types. Their research shows that these rules have significant influence on system utilization and production rate. Stecke and Solberg (1981) carried out a simulation study of an FMS to show the impact of the several machine sequencing rules on the performance of the FMS under different loading objectives. They concluded that scheduling rules have significant influence on performance of the FMS. Similar conclusions have been made in a recent study by Montazeri and Van Wassenhove (1990). Carrie and Petsopoulos (1985) conducted simulation experiments to examine the part releasing rules, and part sequencing rules. However, their investigation of an existing FMS shows that neither the part releasing nor the part sequencing rules have significant impact on performance of that FMS.

Egbelu and Tanchoco (1984) explored the system from a different perspective. They tested the effect of vehicle dispatch and vehicle selection rules on the system performance. Their results show that vehicle dispatching rules have significant influence on the system performance. Due to high utilization of the material handling system, the vehicle selection rules did not show significant impact.

Most research studies at the operational level of FMS focus independently either on planning or scheduling problem. Some researchers (Stecke & Solberg, 1981; Shanker & Tzen, 1987; Maheshwari & Khator, 1993; etc.) have considered both problems simultaneously. These studies show that the performance of the system at the operational level is greatly influenced by dynamic factors such as part and vehicle scheduling rides. Avonts and Van Wassenhove (1988) have shown that the results from operational planning model for FMS can be more realistic if dynamic system factors are given some considerations. Hence at the operational stage, planning and scheduling model should be considered together, not separately.

PROBLEM STATEMENT AND SOLUTION STRATEGY

Two operational planning decisions, part assignment and tool allocation, are considered in this research. Part assignment is defined as the assignment of operations of part types to machines. Tool allocation refers to the loading of tools onto machine magazines. We utilized the mathematical model developed earlier by Leung et al. (1993).

The main objective of this research is to present an integrated solution procedure for part assignment and tool allocation problem in FMS. The integrated procedure combines the mathematical planning model with a simulation model in a hierarchical fashion.

The mathematical model determines part assignment and tool allocation based upon static system constraints such as resource capacity, tool life, operation times, etc. The consideration of detailed real-time factors (such as scheduling rules) makes mathematical model rather difficult to solve, if not impossible, However during actual operation of the system, there are several dynamic factors (part scheduling rules, vehicle scheduling rules, etc.) which influences the system performance. The overall system performance is a function of both mathematical planning model results as well as scheduling and control rules (Stecke & Solberg, 1979; Maheshwari & Khator, 1993). For example, a part may experience delays in actual operation of an FMS due to blocking of machines, blocking of the pathways of transporters, starving of machines, etc. However, these effects cannot be directly accounted at the mathematical model level. Consequently, the mathematical model results may become unattainable during actual operation, especially in terms of resources capacities, workload balancing, and makespan.

The procedure described here aims at achieving more realistic results from the mathematical model. The results from mathematical model are evaluated at simulation model. The necessary mathematical model parameters, such as machine utilization factors, vehicle utilization factor, length of the manufacturing cycle, are modified after the evaluation of mathematical model results. Another set of mathematical model results is obtained using these modified set of parameters. The procedure continues till a viable set of mathematical model results is obtained.

Part Assignment and Tool Allocation

The part assignment and tool allocation model is an integer linear programming model. The model is included in the Appendix. Readers are referred to Leung, et al.(1993) for the detailed mathematical formulation. For brevity, we describe the characteristics of the model in principle.

Decision Variables

There are two set of decision variables. The first set of decision variables represents the quantity of each part type whose specific operation is to be processed on a machine using a particular tool type after visiting a given machine for a preceding operation. Second set of decision variables depicts the number of tools of a given type allocated to a machine.

Constraints

The constraint sets include tool life constraint tool availability constraint, magazine size constraint, machine capacity constraint material handling capacity constraint, etc. These constraints are briefly addressed below.

- *Machines Features*. The operational characteristics of the machines such as operation capacity and tool compatibility are included in this constraint set (3). Tool magazine size is also considered (2).

- *Operational Requirements*. These constraints ensure, that all operations are processed and all output requirements are satisfied (5, 6). This constraint set also ensures that tool-life requirements are met at each machine (3).
- *Resource Constraints*. The assigned time for any resource is formulated to be less than the available time. The resources considered in this formulation are machines, and material handling system (7, 8). Cutting tools availability is also formulated as a constraint set (4).

Objective Function

The objective function incorporates the operation and travel times of parts (1). The travel times are a function of the distance between the machines and the velocity of material handling device. The travel times are multiplied by a factor to represent the empty travel time associated with the material handling device.

Scheduling Rules

A discrete event simulation model is used to incorporate the system details so that mathematical model results can be evaluated. Part releasing, part sequencing and vehicle dispatching rules are considered in this model. Two system parameters, number of buffer spaces and number of pallets, are also taken into consideration. Maheshwari and Khator (1993) have evaluated several different scheduling rules for a similar FMS. Only the rules which were found significant are used in this research.

Part Releasing Rule

This rule assigns priority to the parts awaiting release into the system. There is a finite number of parts circulating concurrently into the system. A part remains on a pallet while in the system. A pallet becomes available when a circulating part finishes all of its operations. A new part can be released into the system on an available pallet according to a priority rule. A releasing rule may depend upon the part characteristics such as processing time requirements, arrival time and number of operations, or upon the global system characteristics such as the up or down state of the machine a part needs to visit and instantaneous production ratio (Carrie & Petsopoulos, 1985). The following rule was utilized in this research.

Least Production Ratio (LPR). The production ratio is calculated as the number of parts released into the system divided by the production requirement for the given part type.

This rule tries to maintain the desired production ratio throughout the manufacturing cycle.

Part Sequencing Rules

The part sequencing rules deal with sequencing of parts waiting at a machine for processing. An operation processing priority is assigned to a part waiting to be processed at a machine. These priority rules are applicable only if more than one part is waiting at that machine. Several part sequencing rules have been examined in an FMS environment by Stecke and Solberg (1982) and Montazeri and Van Wassenhove (1990). The rules used here are:

Shortest Processing Time (SPT). SPT selects the part for processing for which operation can be completed in the least time. SPT is found to be generally efficient in the FMS environment (Stecke & Solberg, 1981).
Smallest ratio of imminent Processing Time/Total Processing Time (SPT/TPT). This sequencing rule arranges the parts for processing with a ratio of the processing time for the current operation to the total processing time. SPT/TPT has been reported to be a very efficient rule in terms of throughput rate (Stecke & Solberg, 1982; Montazeri &Van Wassenbove, 1990).

Vehicle Dispatching Rules

The vehicle dispatching rules are required when a part is to be transported from one machine to another machine or to the load/unload station. Priority is assigned for selecting the part if more than one part is waiting to be transported when a vehicle becomes idle. These priority schemes are called vehicle initiated rules (Egbelu & Tanchoco, 1984). Two different vehicle initiated rules--minimum work in input queue and minimum remaining outgoing queue space--are considered here. In the situations when a part has to select a vehicle, work-center initiated rule, from several idle vehicles, the shortest distance rule is always utilized.

Minimum Work in Input Queue (MWIQ). MWIQ determines transportation priority according to the work content in the destination queue of the part. Work content of a queue is defined as the sum of processing times of all the parts in that queue.
Minimum Remaining outgoing Queue Space (MRQS). MRQS assigns transportation priority to the parts according to the state of the buffer in the outgoing queue. A common input-output buffer is considered in this research. This rule attempts to reduce the transportation delay for incoming parts which may occur due to the non-availability of the buffer space at the machine.

System Parameters

The size of buffers and the number of pallets have direct impact on performance of the system (Schriber & Stecke, 1988). It is assumed that the same buffer area is used for both input and output of the parts at a machine. Two different buffer capacities, 5 and 6, are considered in this research. It is assumed that each machine has equal number of buffer spaces. Two different capacities of pallets, 10 and 12, are considered. These are 2.5 and 3 times of the number of machines, respectively.

Iterative Procedure: Integration of Mathematical and Simulation Models

The iterative procedure was first proposed by Leung, et al. (1993). This procedure links mathematical model to a simulation model to solve the part assignment and tool allocation problem in FMS. The steps of the procedure are as follow.

Step 1. Initialize parameters for mathematical model (machine utilization, vehicle utilization, number of vehicles, length of manufacturing cycle, etc.).

Step 2. Solve the mathematical model for part assignment and tool allocation. Obtain machine utilization and vehicle utilization.
Step 3. Input mathematical model results into the simulation model.
Step 4. Collect statistics on system utilization, makespan and vehicle utilization.
Step 5. Compare mathematical results with simulation results.
Step 6. Stop if, simulation outcomes comply with the results from the mathematical model; otherwise go to Step 7.
Step 7. Modify parameters of the mathematical model based on simulation results and go to Step 2.

CONVERGENCE OF THE ITERATIVE PROCEDURE

The utility of the above iterative procedure would be very limited in practice, if it fails to converge. A mathematical proof, that the procedure would converge to an overall optimum value, is rather difficult and will be function of a large number of operational level variables. However, it can be easily shown that if an optimal solutions exist, the iterative procedure will converge, provided some conditions are satisfied.

Lemma 1

There exists a lower bound and an upper bound to the solution of the iterative procedure, if some of the system parameters are predetermined, and if arbitrary slack time is not added to the length of manufacturing cycle.

Proof of Lemma 1

Let's assume that the part-mix ratio and production quantity to be produced are known, however, length of the planning cycle is variable. There are alternative machine and cutting-tools combinations for each operation of the given parts. Then, a lower bound on the makespan can be obtained by assigning parts using machine workload balancing objective.

An upper bound can be determined by simulating the mathematical model results obtained by maximizing the sum of processing and traveling time. The parts will be assigned to the least efficient machining center within the given constraints. All the dynamic delays (scheduling delays) can be accounted by the simulation model, The optimum solution to the procedure will lie between this lower and upper bound, if it exists. If arbitrary delays are introduced between the operations then there can be infmite solutions to the problem. The set of feasible schedules can be limited to a finite set only if no-delay schedules are considered.

Lemma 2

The iterative procedure will attain an optimum solution, if the optimum solution to the iterative procedure exists, and if some of the system parameters are predetermined.

Proof of Lemma 2

The procedure is non-monotonic in nature. However, according to lemma 1, if the production quantities are fixed, a lower (L_b) and upper (U_b) bound to the solution can be determined.

If an optimum solution exists, it will lie between L_b and U_b. Let's assume that value of the planning parameters (resource utilization factors and length of planning cycle) are modified randomly. Furthermore, the solution follows an arbitrary probability density function f(s). Mathematically, it can be defined as:

Probability Density Function	=	f(s),
where s	=	A solution to the mathematical model, and
s	$\geq$	L_b,
s	$\leq$	U_b,
L_b	=	Lower bound on s, and
L_b	$\geq$	0.
U_b	=	Upper bound on s, and
U_b	$\geq$	L_b.

Let I_s, be a small interval between L_b and U_b such that it contains the optimum solution to the iterative procedure. In other words, probability that a solution lies somewhere on I_s, is greater than zero ($P(I_s) > 0$). If a large number of random samples are drawn (random modification of the parameters at the end of each iteration will provide a random sample on solution space) then there is a finite probability that the solution to one of the sample will lie on the interval I_s. The length of the interval I_s can be made small to reach closer to the solution. In fact length I_s could be fixed on the basis of an acceptable variation between mathematical and simulation models results. Therefore, in general the process will converge to an optimum solution of the iterative procedure.

The above lemma, does not determine the speed convergence of the procedure. However, during the implementation process both upper and lower bounds can be updated at every iteration. Therefore, the spread of the solution range can be reduced at each step. The reduction of the solution space would assist in improving the rate. A mathematical bound on the rate of convergence cannot be obtained due to non-monotonicity of the procedure. Nevertheless, the practical utility of the procedure can be tested, especially if large number of problems are solved using this procedure. In this paper, two numerical problems were utilized to show the implementation of the procedure.

EXAMPLE PROBLEMS

A flexible manufacturing system may consists a large number of machining centers, however a typical number of machining centers in an FMS is usually between 3 and 6. An FMS with four machining centers is considered in this research. Each machining center has a fixed size tool (40 tools) magazine. It is assumed that tools are allocated at the beginning a manufacturing cycle only. No automated tool transfer is available during the manufacturing cycle.

Tables 1 and 2 show the range of parts to be manufactured in two independent test problems, henceforth referred as Problem I and Problem 2. In this research, only part assignment and tool allocation problem is considered. Therefore, it is assumed that part selection problem has been already been solved. Consequently, for each manufacturing cycle number and type of parts are known. But the part assignment and tool allocation are yet to be determined.

Table 1: Part Types and Operation Times (Min) for Problem 1

Part	Operation	Machine			
		1	2	3	4
1	1	3	*	*	4
	2	8	*	*	10
	3	14	*	8	19
	4	*	9	12	*
2	1	*	18	24	*
	2	*	*	13	17

	3	*	7	10	*
	4	*	*	3	4
	5	*	13	16	*
	6	5	*	*	6
3	1	*	1*	16	*
	2	6	*	*	7
	3	*	11	16	*
	4	*	12	16	*
4	1	*	7	9	*
	2	10	*	*	14
	3	*	17	23	*
	4	*	14	22	*

Table 2
Part Types and Operation Times (Min) for Problem 2

Part	Operation	Machine			
		1	2	3	4
5	1	6	*	*	9
	2	14	19	*	*
	3	11	*	*	16
	4	7	*	*	11
	5	11	*	*	18
6	1	6	*	*	8
	2	*	11	14	*
	3	*	15	23	*
	4	8	*	*	12
	5	*	4	7	*
7	1	*	3	4	*
	2	3	5	*	*
	3	*	*	15	20
	4	*	5	7	*
	5	15	*	*	22
8	1	18	*	*	27
	2	*	4	7	*

	3	*	4	6	*
	4	*	6	8	*
	5	*	8	13	*
	6	12	*	*	19
9	1	*	*	6	8
	2	*	13	18	*
	3	8	*	*	11
	4	7	*	*	12
	5	*	12	17	*
	6	*	16	24	*

Tables 1 and 2 also indicate operation times, in minutes, to perform each operation of every part type. Operations can be performed at an alternate machining center as well. Table 3 shows the number of parts to be processed, demand of each part type, in the given manufacturing cycle. The length of manufacturing cycle is assumed to be 2400 minutes.

Table 3: Demand Type for Each Part type in Problems 1 and 2

Part Type Requirement	Problem 1				
	1	2	3	4	
	20	40	32	20	
Part Type Requirement	Problem 2				
	5	6	7	8	9
	24	18	12	24	30

The procedure requires to solve two different models-- mathematical and simulation--at each iteration of the procedure. ne mathematical model is linear-integer model. It was solved using MPSX/370 version 2.0. The second model, used in the procedure, is a discrete event simulation model. This model was built using SIMAN IV simulation language and Microsoft C.

RESULTS

Mathematical Model Results

The mathematical model was solved with the utilization factors (machines utilization and MHS utilizations as 100% in the first iteration of the procedure for both Problems I and 2. This was necessary due to the lack of historical data. A common utilization factor was employed for all four machines in the system. Part assignments and tool allocations were obtained. In subsequent iterations, these parameters were modified according to the simulation results. Each time a parameter was modified, new mathematical model results were obtained. Tables 4 and 5 show the parameters and aggregate results for all iterations for Problem 1 and Problem 2, respectively. The parameter modification was based on makespan, mean waiting times, and vehicle utilization.

Table 4: Iterative Procedure: Mathematical Model Results for Problem 1

Iteration Number	Available Machine Capacity	Available Vehicle Capacity	Number of Vehicles	Length Planning Cycle	MHS Load	Total Machine Workload	Maximum Machine Workload
1	100%	80%	1	2400	1038	6225	2360
2	90%	50%	1	2400	1154	6693	2160
3	90%	35%	2	2400	1154	6693	2160

Table 5
Iterative Procedure: Mathematical Model Results for Problem 2

Iteration Number	Available Machine Capacity	Available Vehicle Capacity	Number of Vehicles	Length Planning Cycle	MHS Load	Total Machine Workload	Maximum Machine Workload
1	100%	80%	1	2400	1107	6182	2400
2	90%	50%	1	2400	1194	6563	2160
3	90%	35%	2	2400	1194	6563	2160
4	80%	35%	2	2400	1244	6780	1920

Simulation Model Results

The mathematical model results were used as the input to simulation model. At this stage, five different operational factors were considered. Only one part releasing rule was used. Whereas, two part sequencing rules, two vehicle dispatching rules, and two levels of buffer size and pallets were utilized to test the results at the simulation model. In all for each run there were 16 combinations (2 x 2 x 2 x 2) for a full factorial experiment. A fractional factorial design (1/2 x 2 x 2 x 2 x 2) was used to reduce the number of simulation runs. The results from the simulation model are displayed in Tables 6 and 7 for Problems 1 and 2, respectively.

Table 6

Iterative Procedure: Simulation Model Results for Problem 1

Scheduling Rules/System Parameters					Iteration 1			Iteration 2			Iteration 3		
PRR	VDR	PSZ	PAL	BUF	MS	VU	WT	MS	VU	WT	MS	VU	WT
1	2	2	10	5	2847	0.95	109	2809	0.94	93	2443	0.60	67
1	2	3	10	5	2826	0.94	147	2650	0.97	127	2482	0.59	104
1	2	2	12	6	2841	0.94	191	2725	0.96	162	2501	0.59	141
1	**2**	**3**	**12**	**6**	**2767**	**0.99**	**223**	**2666**	**0.99**	**190**	**2395**	**0.66**	**146**
1	3	2	12	5	2930	0.92	221	2601	0.99	194	2474	0.59	159
1	3	3	12	5	2758	0.98	165	2696	0.94	157	2494	0359	139
1	3	2	10	6	2753	0.99	121	2504	0.98	108	2405	0.62	91
1	3	3	10	6	2898	0.93	135	2733	0.96	121	2484	0.58	99
Iteration 4 is not needed													

PRR: Part Releasing Rules 1 - LPR; VDR: Vehicle Dispatching Rules; 2 - MRQS, 3 - MWIQ.
PSQ: Part Sequencing Rules 2 - SPT; 3 - SPT/TPT. PAL: Number of Pallets. BUF: Buffer Spaces
MS: Makespan in Minutes. VU: Mean Vehicle Utilization. WT: Mean Waiting and Traveling Time for a Part.

Table 7
Iterative Procedure: Simulation Model Results for Problem 2

Scheduling Rules/System Parameters					Iteration 1			Iteration 2			Iteration 3			Iteration 4		
PRR	VDR	PSZ	PAL	BUF	MS	VU	WT	MS	VU	WT	MS	VU	WT	MS	VU	WT
1	2	3	10	5	3140	0.74	89	2983	0.72	82	2785	0.41	73	2585	0.49	61
1	2	2	10	5	2883	0.85	102	2842	0.78	91	2688	0.43	82	2438	0.52	67
1	2	3	12	6	3144	0.77	181	3054	0.70	176	2917	0.39	169	2683	0.47	151
1	2	2	12	6	3156	0.76	151	3094	0.72	145	2934	0.39	133	2697	0.46	104
1	3	3	12	5	3203	0.75	178	3004	0.73	156	2894	0.40	131	2702	0.46	122
1	**3**	**2**	**12**	**5**	**2869**	**0.84**	**145**	**2800**	**0.78**	**140**	**2679**	**0.43**	**123**	**2429**	**0.53**	**106**
1	3	3	10	6	3240	0.73	98	3140	0.68	89	2974	0.38	80	2752	0.45	71
1	3	2	10	6	2972	0.78	100	2898	0.80	93	2801	0.39	90	2578	0.48	88

PRR: Part Releasing Rules 1 - LPR; VDR: Vehicle Dispatching Rules 2 - MRQS, 3 - MWIQ.
PSQ: Part Sequencing Rules 2 - SPT; 3 - SPT/TPT PAL: Number of Pallets BUF: Buffer Spaces
MS: Makespan in Minutes VU: Mean Vehicle Utilization WT: Mean Waiting and Traveling Time for a Part.

Results of Iterative Procedure

Problem 1 required three iterations to reach to a solution, whereas, Problem 2 required four iterations. Here, the results at the each iterations for both problems are discussed. A subsequent iteration became necessary for a problem because the results from the mathematical model were not feasible at the simulation level. Thus, some mathematical model parameters were modified at each iteration to get new results.

Iteration 1: Initial iteration started with 100% utilization factor in both the problems. Mathematical model makespan was 2400 and 2360 minutes respectively. However, when the results of the Problems 1 and 2 were simulated, minimum makespan was 2826 and 2869 minutes, respectively. This was about 17% longer than planned period of 2400 minutes. Vehicle utilization was 97% and 78%. Higher vehicle utilization indicates that there was higher empty travel time (e.g., vehicle utilization was 95% and makespan was 2826 minutes. Then, total time vehicles were used would be 0.95*2826 = 2685 minutes. Whereas, the planned loaded travel time was 1038 minutes only). The available loaded travel time on the vehicle should be reduced. On the basis of these results, two planning parameters--vehicle and machine utilization were updated for the next iteration for both the problems.

Iteration 2: New sets of mathematical model results were obtained using 90% machine capacity and 50% vehicle capacity. The mathematical model results were still infeasible at the simulation level. Vehicle utilization was 97% in the case of the Problem 1 and 78% in the case of the Problem 2. However, the results were closer to the mathematical model results compared to the results at iteration 1. This shows that solution is moving in the right direction.

The higher utilization of the vehicle resulted in relatively longer mean waiting time as well. In other words the reduction in the waiting time was very small from iteration 1 to iteration 2. Therefore for the next iteration, number of vehicles was increased to 2 and available vehicle time was further reduced to 35%.

Iteration 3: This iteration didn't require any solution of mathematical model. At that stage only material handling capacity was increased on the basis of simulation model results. However, the material handling capacity was not a binding constraint at the mathematical model stage at iteration 2. Therefore, increase in the MHS capacity would not change the mathematical model results from iteration 2 to iteration 3. A new set of simulation runs were made with increased capacity of MHS. The results show that the mathematical model results became feasible at simulation model for Problem 1. The makespan achieved at the simulation stage was 2395 as compared to 2400 at mathematical model. The iterative process terminates here for the Problem 1.

However, results were still not viable for the Problem 2. There was approximately 10% difference in the length of manufacturing cycle. But vehicle utilization was low--about 43%. Hence, any further increase in the vehicle capacity would not reduce the length of manufacturing cycle. Consequently, machine utilization was reduced to 80% for mathematical model for Problem 2.

Iteration 4: A new set of the mathematical model results was obtained for the Problem 2. The simulation and mathematical models results were within ±1.2% of the each other. The iterative process was terminated.

The results show that the solutions from the mathematical model without considerations to the utilization factors are not viable at the simulation level. Therefore, resource capacities at the mathematical model must be adjusted by utilization factors so that its results are feasible at both the levels.

Despite the lower material handling requirement in the example problems 1 and 2, the vehicle utilization was relatively very high. This was due to the fact that large amount of the empty travel is involved in the system layout under consideration. This layout allows only unidirectional travel of vehicles. Consequently, every loaded travel is accompanied by a significant amount of unloaded travel. This reduces the available time for loaded travel on a vehicle to less than 50% of the total time.

GUIDELINES FOR PARAMETER MODIFICATION

A link between mathematical and simulation models is established using modification of the planning parameters. The rate of convergence of the procedure is dependent on the modification of parameters. Therefore, it is important to have certain guidelines to adjust the parameters at every iteration.

Selection of Initial Parameters

Initial starting point is very critical to the iterative procedure. If good start point is selected, a faster convergence of the procedure can be expected. The initial parameters can be selected on the basis of the historical data on the system and the parameters of the problem under consideration. Further investigation is necessary to establish guidelines for initial parameter selection. If no reliable historical data is available, then procedure could be initiated with 100% utilization of all the resources.

Modification of Parameters

- ♦ Increase in MHS capacity (more number of vehicles) can be effective if vehicle utilization is large at the simulation model.

- ♦ Machine utilization factors should be considered for adjustment if simulation model cycle length and planning period differ by more dm a predetermined fraction, e.g., 0.05.

- Machine utilization should be reduced, if part waiting time is large. This adjustment requires some judgement because part waiting is also dependent on the number of pallets. If number of pallets increases, overall waiting time also increases. Therefore, if longer waiting time is contributed due to the number of pallets, than adjustment of utilization factors may not be desirable.

- While adjusting machine utilization parameters, the available machine capacity should be maintained at a level so that all the parts can be assigned. In both the problems, overall machine workload is approximately 70% of the total available time on the machines. That is, 30% of the time machines is idle to adjust scheduling delays. Most of the unassigned machine time was on the alternate machines (less efficient machines).

- The length of the planning period can be adjusted if the utilization factors and vehicle capacity do not achieve a viable solution in a given number of iterations.

CONCLUSIONS

In this paper we provide a procedure for operational planning of FMS which combines a mathematical planning model with a simulation model. The procedure is developed to solve part assignment and tool allocation problem in FMS. The procedure has three main components--an integer programming model, simulation model and parameter modification. Main objective of the procedure is to obtain the planning model results which are viable at the operational level.

It was demonstrated that the procedure would converge to a solution of a problem. However, no limits on the rate of convergence was established. The implementation of the procedure was illustrate with help of two examples. The results of these problems showed that the procedure could converge faster, hence, could be useful in real world situations. The examples illustrated that resource utilization factors had considerable impact on the viability of mathematical model results. Thus, effective linking of mathematical and simulation model is necessary to obtain viable results. The values of the utilization factors depend upon several operational elements. Estimates of the utilization factors can be obtained from historical results. The planning procedure can be used for further adjustment of the value of the utilization factors and other planning parameters.

Further examination on the optimality and the rate of convergence of procedure is needed. The procedure does not consider whole feasible region, instead it utilizes a point search. Every iteration represents a point in this search procedure. Therefore, some overall optimality testing criteria should be developed or else the procedure may terminate at a local optimal solution. Similarly, limits on the rate of convergence must be established, The practical utility of the procedure will be very limited if convergence of the procedure is slow.

Nevertheless, two problems showed that a relatively faster convergence is plausible. The procedure in above two cases converges in 3 and 4 iterations respectively.

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Appendix

The time minimization model can be written as follows (Leung et al., 1993):
Minimize:

(1) $Z = \Sigma_i\Sigma_j\Sigma_k\Sigma_r\Sigma_s\,(t_{ijks} + d_{kr} * 1/V * 1/\beta) * X_{ijkrs} + \Sigma_k\Sigma_s\,\delta * Y_{sk}$

Subject to,

(2)	$\Sigma_s N_s * Y_{sk}$	$\leq$	S_k	$\forall k$
(3)	$\Sigma_i \Sigma_{j\in\delta ikj} \Sigma_r t_{ijks} * X_{ijkrs}$	$\leq$	$Y_{sk} * \rho_k$	$\forall \in \varphi_{ks*s}$
(4)	$\Sigma_k Y_{sk}$	$\leq$	A_s	$\forall_s$
(5)	$\Sigma_k \Sigma_r \Sigma_s X_{i1krs}$	=	Q_1	$\forall_i$
(6)	$\Sigma_r\Sigma_s X_{ijkrs}$	=	$\Sigma_p\Sigma_s X_{ij+1pks}$	$\forall_{ij} \in \delta_{ikj} *^{k\in\varphi ks}$
(7)	$\Sigma_i \Sigma_{j\varepsilon\delta ikj} \Sigma_r \Sigma_s X_{ijkrs} * t_{ijks}$	$\leq$	$M_k * \quad \alpha_k$	$\forall_k$
(8)	$\Sigma_i\Sigma_{j\varepsilon\delta ikj}\Sigma_k\Sigma_r\Sigma_s X_{ijkrs} * d_{kr}$	$\leq$	$\mu * \xi$	

where:

X_{ijkrs}	Quantity of part type i whose j^{th} operation is to be processed on machine k using tool type s, after visiting machine r (for its j- 1^{st} operation)
Y_{sk}	Number of tools of type s loaded on machine k
t_{ijks}	Processing time of the j^{th} operation of the i^{th} part type on the k^{th} machine using the s^{th} tool type
p_s	Tool life of the s^{th} tool type
d_{kr}	Travel distance between machine k and machine r
β	Fraction of unloaded travel
S_k	Magazine capacity of machine k
$\{\varphi_{ks}\}$	Set of machines k which can hold tool type s
A_s	Available tools of type s
N_s	Number of slots required by a tool of type s
Q_i	Production requirement of part type i for a given planning period
$\{\delta_{ikj}\}$	Set of operations of part type i, which can be performed on machine k
M_k	Available time on machine k
α_k	Maximum utilization of machine k
μ	Capacity of material handling system
ξ	Maximum utilization of material handling system
δ	A very small number