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A SIMULATION-BASED BACKWARD PLANNING APPROACH FOR ORDER-RELEASE

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ABSTRACT

The problem of order release planning for a make-to-order production facility is addressed. Traditionally, order-release planning in a multi-stage shop is performed with material requirements planning (MRP) logic. MRP assumes infinite resource capacity and component lead times that are estimated using historical data, past experience, and rules-of-thumb. These assumptions often result in infeasible plans that make the task of scheduling difficult. An approach to order release planning termed qRP (resource planning based on queuing simulation) is discussed. qRP generates order release plans via a backward bill of material explosion logic similar to MRP except that a queuing simulation model of the facility is used. The simulation model captures the appropriate level of detail to provide a more realistic picture for planning. Component lead times are time-based (dependent on the current state of the shop) and may change from period to period. Automatic factory and simulation model generators are developed to compare this dynamic lead time approach with the static approach offered by MRP. Generalizations are made for key manufacturing attributes.

1 INTRODUCTION

The traditional manufacturing planning process is divided into 7 planning modules: production planning and resource planning, master scheduling and rough-cut capacity planning (RCCP), material requirements planning (MRP) and capacity requirements planning (CRP), and detailed scheduling. This design, conceived of in the 60’s and 70’s, we based on the assumption that large inventories were necessary to support production (Orlicky 1975). Today’s planners must manage smaller inventories, promise shorter lead times, and react quicker to faster changing market demands. This environment demands new ways of controlling production and new ways of planning for production.

MRP-based planning systems are the most common procedure for order-release planning in a discrete parts environment. Despite its popularity, there are significant limitations inherent in the MRP approach (Maxwell, et al. 1983, St. John 1984). In particular, the following points characterize the major drawbacks with current MRP philosophy: 1) MRP has primitive modeling capabilities and cannot accurately represent finite resource capacities and shop constraints; 2) MRP uses planned lead times to determine offsets during the backward planning process. 3) The production planning framework which incorporates MRP, capacity requirements planning (CRP), and shop floor control is not integrated (Toye 1990). Independent shop floor control systems are required to execute the plan generated by the MRP system Production environments today require a more sensitive and responsive planning system, one that can generate realistic plans based on anticipated shop conditions.

Backward simulation models of discrete manufacturing systems have been developed for finite scheduling purposes (Gelders and Van Steelandt 1980, Pope et al. 1990, Yunk 1981). If a backward simulation model of a system is developed and due dates are provided then the simulation can generate ‘backward’ dispatch lists. How the information is used varies depending on the application.

Recent advances in computer hardware and software now allow simulation models to schedule and control the shop floor. A simulation model may also be used to generate order-release plans to accomplish the same basic functions as MRP. The difference is that the simulation model represents actual shop floor capacities, and component lead times are not predetermined but rather calculated based on the anticipated queuing in the system. To plan in this way, a backward explosion through bill-of-material (BOM) from the end-item due date is required to establish the appropriate order-release dates. This process may be referred to as *simulation based order release planning* to emphasize its main function, *simulation based backward planning* to emphasize the use of simulation for backward planning, and *simulation based resource planning* to emphasize the analogy with MRP.

In this paper, we present a simulation based resource planning approach that uses simulated lead times (based on queuing in the system) instead of predetermined lead times. In this paper we refer to this approach as qRP to emphasize its substitutive relationship with MRP. We assume a make-to-order (MTO) production environment where product is not made to stock but rather tied to a specific customer's (perhaps customized) order. qRP is applied at the macro level to generate order-release plans that are based on realistic shop conditions. qRP is compared with the MRP planning approach in a make-to-order production environment. Experiments are performed to generalize the performance of qRP relative to traditional MRP logic.

2 qRP PLANNING APPROACH

The qRP planning approach is considered to be a replacement for the MRP/CRP modules in the traditional planning hierarchy (see Figure 1). In fact, many commercial enterprise business software systems are making an effort to incorporate a more realistic representation of system constraints for planning purposes. But to our knowledge there are no commercial attempts, and there is little literature, to support the inclusion of discrete-event queue simulation into the planning process at this stage.

The qRP approach consists of two stages: a backward planning pass determines requirements for future planned orders (firm and forecast), and a forward planning pass incorporates open orders into the plan. The qRP process requires a master schedule of demand for all end items, a (backward and forward) simulation model of the production facility, and basic process information such as part routings, bill-of-materials, and work-in-process. In this paper, we use two independent simulation models to run the backward pass and the forward pass. Below we give a brief overview of the purpose of each planning pass but we refer the reader to other sources for a more detailed explanation (Watson, et al. 1995; (Watson 1993).

2.1 Backward Pass

The backward pass simulation model essentially starts each end-item at the master scheduled due date and passes them through the shop based on the reverse sequence of their part routing. Parts queue for the required resources and process based on deterministic time standards. After each part completes its last operation, it will either be disassembled or sent to raw material storage. Various forms of slack can be used when planning. Slack can be applied to every operation, to select operations, or based on time. In this paper, the slack assumed by qRP is equivalent to that used by the MRP system setup for comparison purposes.

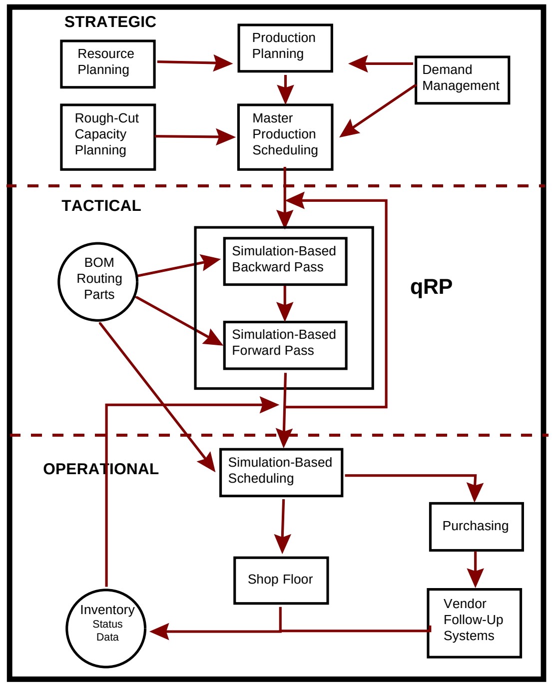

Figure 1: qRP Embedded in the Planning Hierarchy

The backward simulation planning pass consists of determining order-release dates from order due dates based on finite capacities and on simulated component and assembly lead times. Lead time may be influenced by a number of factors: shop load, shop capacity, order priority, resource schedules, part routings, end-item BOM, order lot size; as well as any shop rules or constraints built into the models. The backward planning pass performs a backward bill-of-material explosion similar to MRP. The release time for all primary components is established during the backward pass and is then provided as input into the forward planning model. Since open orders are not considered during the backward planning pass, a forward simulation pass is next made to construct a feasible plan.

2.2 Forward Pass

The forward pass simulation model integrates the open orders with the planned orders, constructed by the backward pass, to ensure that the component release plan is feasible. The integration of current work-in-process

(WIP) is important since WIP may place a high priority demand on the constrained resources. The backward planned release dates generated from the backward planning pass can be considered priorities for this forward pass.

The forward pass uses a component release strategy to determine the actual scheduled release time for every primary component. The component release strategy utilizes the detailed sequencing logic that takes place during the execution of the forward simulation pass. The actual scheduled release time of the primary component is based on when the component is planned for release and, if the release is executed, when the component actually begins processing at its first workstation. In this manner, a component release may be delayed if excessive congestion is anticipated.

Outside of resource utilization, there may be no desire to collect statistics or generate reports during the backward or forward planning passes. Dispatch lists are created from a finite scheduling module (e.g., a simulation based scheduler). In this paper, we use a stochastic simulation model to evaluate the plans.

2.3 qRP Mechanics and Assumptions

Although the simulation based backwards planning approach is intuitively appealing, a discussion of the mechanics of the implementation have left some people confused. Here we provide a brief overview of the mechanics, but we refer the reader to other sources for a more detailed explanation (Watson, et al. 1995; Watson 1993).

If we assume a production facility with three processes, a simple forward simulation model might include the following constructs: CREATE NEW ORDER ENTITY :: QUEUE AT PROCESS ONE :: EXECUTE PROCESS ONE :: QUEUE AT PROCESS TWO :: EXECUTE PROCESS TWO :: QUEUE AT PROCESS THREE :: EXECUTE PROCESS THREE :: TERMINATE COMPLETED ORDER ENTITY. Each order entity has a process routing associated with it. For instance, *xyz* orders follow the following routing: PROCESS ONE => PROCESS THREE => PROCESS TWO. In a backward planning mode, order *xyz* would assume the reverse sequence of the routing: PROCESS TWO => PROCESS THREE => PROCESS ONE. Furthermore, the backward pass simulation model would include the following constructs: CREATE COMPLETED ORDER ENTITY :: QUEUE AT PROCESS ONE :: EXECUTE PROCESS ONE :: QUEUE AT PROCESS TWO :: EXECUTE PROCESS TWO :: QUEUE AT PROCESS THREE :: EXECUTE PROCESS THREE :: TERMINATE NEW ORDER ENTITY. In this simple model, identical model components exist for both models, but the introduction and termination of order entities differ. One can view the backward pass and forward pass models as being very similar, yet distinctively different. As the model needed for planning becomes increasingly complex (e.g., multiple resource types, complex control logic, complex process rules), one would expect these differences to become more significant.

As inferred from Figure 1, planning at the tactical level assumes a more aggregate perspective than planning at the operational level. It would be apparent that one should assume that the simulation models used for the backward and forward pass of qRP would be more aggregate than a simulation model used for detailed scheduling. Various assumptions are made in this paper to keep the focus on the feasibility of a dynamic lead time approach to planning, as opposed to addressing model aggregation and backward model representation issues.

The impact that queuing will have at the planning (macro) level is not necessarily intuitive. The issue is whether qRP can accurately capture the finite capacity and shop constraints on the shop floor and be effective for planning purposes.

3 BASIS FOR COMPARISON

Since the qRP approach is of practical importance, it compared to an approach that is widely accepted in practice. It is the goal of this paper to convince the reader that, for the manufacturing systems assumed in the experiments, the qRP approach is clearly superior to the traditional MRP approach. The MRP approach is by far the most popular approach to order-release planning. Thus, the traditional MRP approach that assumes infinite capacity and planned lead times during the planning process is used as a base case for comparison. We refer to our implementation of MRP as *pMRP* (pseudo-MRP) since we do not use a commercial implementation of the software. Our objective is to have an experimental framework with great breadth (in representing different types of systems) and reasonable depth (to capture the appropriate level of detail for planning). We generalize the results so that a production planner can understand when this approach may be appropriate in practice.

To make the comparison fair, we use a forward simulation model to determine fixed component lead times for pMRP. The intent of using this method of MRP lead time determination is to give pMRP an advantage which ultimately minimizes the chances of an unfair bias during the experimentation effort. Every effort is made to make this comparison fair and reasonable. Additional details on the experimental assumptions is available elsewhere (Watson, 1993).

3.1 Comparative Procedure

The procedure to compare the qRP approach with the MRP approach is automated. We discuss the simulation models used for the comparison here. In the next section we discuss how these models are created. All of the models are implemented in the SIMAN V (Pegden, et al. 1990) discrete simulation language. The models created to support the experimental comparison are illustrated in Figure 2 and discussed below.

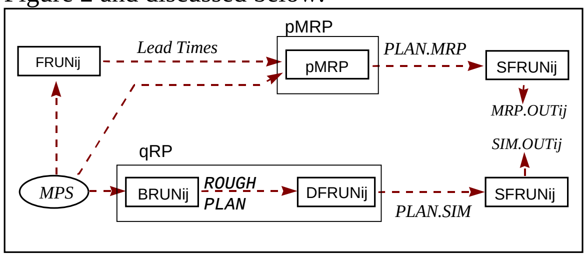

Figure 2: Models Used for Experiments

The MPS represents a string of end-item customer demand. The qRP approach consists of two models. BRUN is a deterministic backward pass simulation model that converts the end-item demand into the planned backward pass release dates. The release priorities from BRUN are provided as input to DFRUN. DFRUN is the deterministic forward pass simulation model that converts the backward pass release dates into the actual scheduled release dates that are equivalent to an MRP component release plan.

In order to evaluate how good the plan is, a stochastic (forward) simulation model (SFRUN) representing a real-world implementation is used. In this experiment, SFRUN is very similar to DFRUN with the key difference being its inclusion of uncertainty in process time, machine failures and repairs, and material handling.

Fixed lead times for pMRP are determined during a forward simulation run (FRUN). The pMRP model simply contains BOM information for each end-item and generates a component release plan. Similar to the evaluation procedure for qRP, SFRUN is used to execute the plan. After executing both plans with SFRUN, and generating the appropriate output, a direct comparison between the two planning approaches is made. For instance, if ‘measure’ represents the performance measure of interest, then the data point used for analysis is the mathematical difference (delta) as follows,

$$\delta_{\text{measure}} = \text{measure}_{\text{pMRP}} - \text{measure}_{\text{qRP}}$$

3.2 System Generator

The evaluation, or comparison, of two different planning approaches requires an experimental design that leads to the generalization of results. In order to generate numerous manufacturing systems for experimentation, an automated system/model generator is developed. For each system definition, multiple random instances of the system can be generated. Each instance serves as an independent ‘observation’ for experimental purposes. This generator functions in two steps as shown in Figure 3.

In the first step, a manufacturing system environment is defined by assigning values to a set of manufacturing variables: shop, job, environment, planning, and experiment. Because of the randomness built into the system generator, an unlimited number of instances (each inheriting the environment characteristics) for each manufacturing environment can be randomly generated.

The second step in this process is the SIMAN V model generator. Each manufacturing system that is generated is defined by a set of components: facility layout, end-items, BOMs, component routings, MPS, etc. These components are converted into the planning and scheduling models used by the experimentation procedure and shown in Figure 2. This generator is based on concepts developed by Harmonosky and Sadowski (1990). Details concerning the automated system generation procedure can be found elsewhere (Watson 1993).

The experimental production facility consists of 15 work centers: 12 basic processing work centers, 2 sub-assembly work centers, and 1 final assembly work center. A shop of this size is easily managed and is conducive to automated experimentation. This study emphasizes the multi-level assembly environment that is most often encountered in practice. Four different types of product structures can be created: string, single-level, multiple-level with many levels but only few components per assembly (tall), and multiple-level with many levels and many components per assembly (hybrid).

The operations routing for each part consists of a sequence of work center visitations that may be ordered either unidirectional or non-unidirectional. A primary component (i.e., one that is not assembled) will visit, on the average, fifteen percent (15%) of the basic process work centers. An assembled component (i.e., sub-assembly or final assembly) will visit, on the average, ten percent (10%) of the basic process work centers. These parameters are chosen arbitrarily.

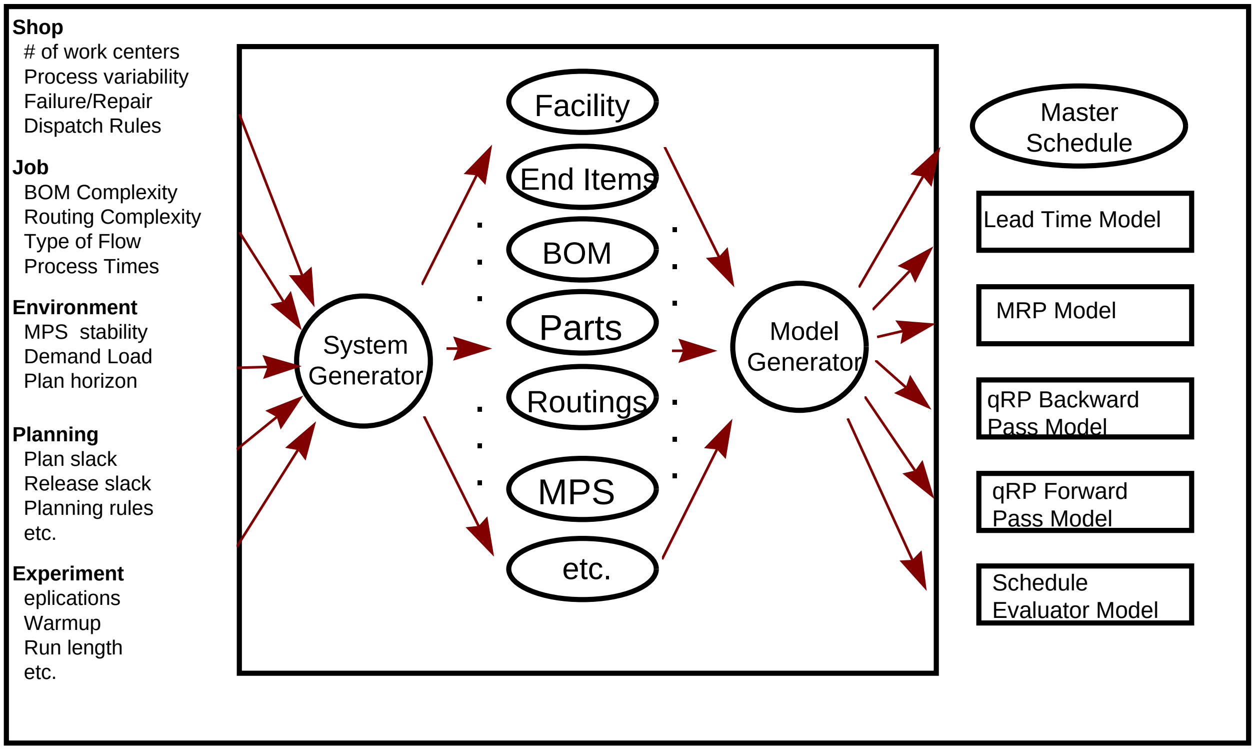

Figure 3 System and Model Generator

4 COMPARISON OF qRP AND MRP

Two distinct experiments are discussed below. In the first experiment we focus on 8 manufacturing environment factors to determine how qRP performs relative to pMRP. A detailed report of this experiment is provided by Watson, et al. (1995); here we only discuss key issues that have lead to the second experiment. The second experiment has not been reported elsewhere and is discussed below.

4.1 Preliminary Experimentation and Analysis

In the first experiment (Watson, et al. 1995) eight factors are used in a full factorial with replications experimental design: product structure (flat, tall, complex), shop flow (job shop, flow shop), master schedule demand pattern (stable, unstable), shop load (light, heavy), system variability (low, high), shop balance (single bottleneck, multiple bottlenecks), due date assignment (constant, based on work rule), and initial shop load (light, heavy).

Performance measures are used to capture customer satisfaction levels and inventory investment levels: mean tardiness of orders, percent tardy of orders, mean earliness of orders, mean work-in-process, mean stacked lead time (sum of component and assembly flow times), and mean order lead time. Following the first two-level factorial experiments, focus is placed on product structure and master schedule demand pattern and a three level factorial experiment is conducted.

The conclusions that can be drawn from this experiments are: 1) In a make-to-order environment the qRP approach will consistently result in better overall system performance levels relative to a traditional MRP implementation; 2) In general, as the product structure grows increasingly complex (i.e., more components per assembly, and more levels in the bill of material), the advantage of qRP over pMRP increases; 3) In general, as the master production schedule grows increasingly unstable, the advantage of qRP over pMRP increases; 4) Explicit representation of queues during the backward and forward qRP passes appears to be an effective tool for order release plan construction (at least at the macro level).

Following this experiment, various questions surfaced regarding, for instance, what happens in a volatile shop where order cancellations and emergency orders are the norm, and what happens if we assume a queue dispatching rule other than first in first out (as assumed above). The next experiment attempts to address this questions.

4.2 Additional Experimentation and Analysis

Four factors are defined in the second experiment as follows: Factor A denotes shop type (dynamic or static), Factor B denotes Product Structure, Factor C denotes queue rank rule, and Factor D denotes shop load. The shop type factor indicates whether order cancellations and new order introductions are allowed during the plan evaluation run mode (SFRUN). At the low level, actual demand is identical to planned demand. At the high level, twenty percent of the planned demand is canceled. As well, twenty percent of the actual demand is doubled to represent new orders. The total actual demand over the planning horizon is the same as the total planned demand, but the actual demand from period to period could vary significantly from the plan. In this experiment we assume that same performance measures as above with the exception of the stacked lead time measures since it was found to be highly correlated with the total component work-in-process measure.

A full factorial (2^4) experiment is conducted to determine the significance of the four factors and their two-way interactions on the mean difference between qRP and pMRP ($\delta_{measure}$). The MANOVA procedure is first used to determine the significance of the factors with respect to all five performance measures. MANOVA allows one to take advantage of the correlation between the measures to provide a significance test that has more power thus resulting in a more sensitive test. As illustrated in Table 1, we find that each of the four factors evaluated are significant. As well, all but two of the two way interactions are significant. Univariate ANOVA is then conducted to focus on specific performance measures.

Table 1: Results from MANOVA

MANOVA					
Effect	**Crit.**	**Stat.**	**F**	**DF**	**P**
A-DynShop	Wilk's	0.368	41.27	(6,144)	0.00
B-ProdStrc	Wilk's	0.370	40.92	(6,144)	0.00
C-QrankRul	Wilk's	0.256	69.72	(6,144)	0.00
D-Load	Wilk's	0.145	141.27	(6,144)	0.00
A*B	Wilk's	0.947	1.33	(6,144)	0.25
A*C	Wilk's	0.892	2.91	(6,144)	0.01
A*D	Wilk's	0.910	2.37	(6,144)	0.03
B*C	Wilk's	0.779	6.80	(6,144)	0.00
B*D	Wilk's	0.504	23.62	(6,144)	0.00
C*D	Wilk's	0.398	36.28	(6,144)	0.00

ANOVA is conducted for each performance measure. With some exception, the results are very similar across performance measures. The results for Mean Tardy are shown in Table 2. It is apparent that Factors B, C, and D are significant at the 5% level. For the most part, two-way interactions involving Factor A (Dynamic Shop) are not significant, with one exception being Percent Tardy shown in Table 4. This observation suggests that when a shop is truly chaotic, subject to substantial order cancellations and emergency orders, the qRP approach offers no clear advantage over the traditional MRP approach.

Table 2: ANOVA Results for Mean Tardy

ANOVA on Mean Tardy					
Source	**DF**	**SS**	**MS**	**F**	**P**
A: Dyn_Shop	1	0.09	0.09	3.53	0.06
B: ProdStrc	1	0.17	0.17	6.59	0.01
C: QrankRul	1	5.83	5.83	231.22	0.00
D: Load	1	3.11	3.11	123.19	0.00
A * B	1	0.03	0.03	1.14	0.29
A * C	1	0.05	0.05	1.83	0.18
A * D	1	0.01	0.01	0.28	0.60
B * C	1	0.09	0.09	3.63	0.06
B * D	1	0.04	0.04	1.65	0.20
C * D	1	4.00	4.00	158.42	0.00
Error	149	3.76	0.03		
Total	159				

Table 3: ANOVA Results for Percent Tardy

ANOVA on Percent Tardy					
Source	**DF**	**SS**	**MS**	**F**	**P**
A: Dyn_Shop	1	3520.1	3520.1	196.72	0.00
B: ProdStrc	1	347.9	347.9	19.44	0.00
C: QRankRul	1	820.5	820.5	45.85	0.00
D: Load	1	856.7	856.7	47.88	0.00
A * B	1	109.6	109.6	6.12	0.01
A * C	1	168.3	168.3	9.40	0.00
A * D	1	223.6	223.6	12.49	0.00
B * C	1	158.8	158.8	8.87	0.00
B * D	1	27.9	27.9	1.56	0.21
C * D	1	582.9	582.9	32.57	0.00
Error	149	2666.2	17.9		
Total	159				

The main effects plots for Mean Tardy illustrate three interesting points. As the planner is faced with an increasing number of order cancellations and new order introductions, the advantage of the qRP approach (relative to MRP) tends to diminish. This is expected, especially since neither planning system is designed to respond in real-time to alleviate problems associated with actual demands that are significantly different than those planned for.

Second, when the FIFO queue dispatching strategy is assumed during the plan evaluation mode (SFRUN), the qRP approach performs much better than the MRP approach, but this advantage is almost reversed if we change the dispatch strategy to Early Due Date, for instance. This is not so surprising considering that during the backward and forward passes (BRUN and DFRUN), the simulation model assumes a FIFO queue dispatching strategy.

Third, as observed during the preliminary analysis, increasing the load on the facility leads to an increase in the qRP advantage. The ANOVA for Mean Tardy indicates there is a significant interaction between Factor C (Queue Rank Rule) and D (Load). After investigating the interactions plot, it is observed that when the load is low (78%) there is almost no difference in performance between the two queue dispatching strategies observed (FIFO and EDD). Only when the load is high (90%) can we make the above observation that qRP performance is poor when a queue dispatch strategy other than FIFO is assumed.

The two-way interaction plots for Percent Tardy in Figure 4 illustrate that qRP performs better, relative to MRP, in a shop that does not experience significant order cancellations and introductions. As well, this advantage is slightly diminished as the product structure grows increasingly complex and the queue dispatch strategy is not FIFO. But qRP does improve, relative to MRP, when the load on the shop is high. Also, if the queue dispatch strategy is not FIFO, the effect of the product structure is the same regardless of which product structure is assumed..

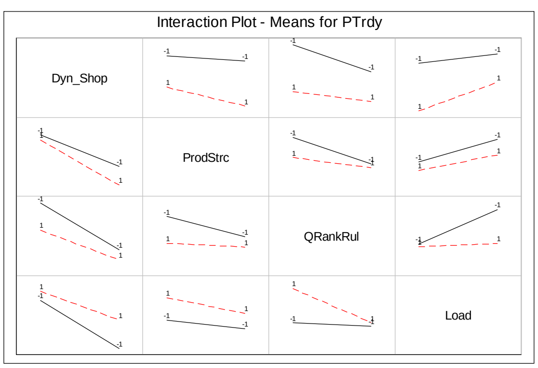

Figure 4: Two-way Interactions for Percent Tardy

An interesting observation is made when we look at a histogram of the difference in staging delays for all assemblies (each observation on the histogram represents the difference between the ready time for the first component ready for assembly and the last component ready for assembly). A comparison of MRP and qRP staging delay histograms for Experiment 1 where all Factors are set at their low levels is illustrated in Figure 5. The mean of the staging delays is 28.8% lower for qRP and the standard deviation is 5.4% lower. This indicates that qRP is better able to coordinate components for assembly under the conditions set forth in Experiment 1.

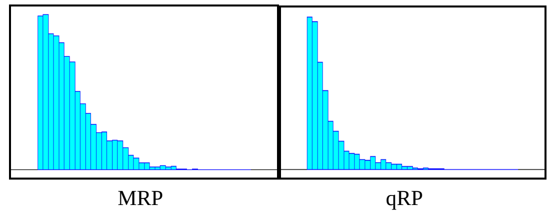

Figure 5: Experiment 1 Staging Delays

Figure 6 illustrates the same comparison for Experiment 16 where all the Factors are set at their high levels. The mean of the staging delays is actually 1.4% higher for qRP and the standard deviation is 7% higher. The difference of the means seems to be insignificant, but it does indicate that the qRP is less successful at coordinating components for assembly when the shop experiences significant order cancellations and introductions, as product structure becomes increasingly complex, and as we move away from a FIFO queue dispatching strategy. The same observations are made when we look at order completion time versus order due date (for Experiments 1 and 16).

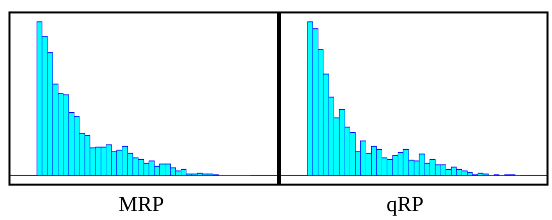

Figure 6: Experiment 16 Staging Delays

5 CONCLUSIONS

A new methodology for requirements planning (qRP) based on discrete simulation was discussed. qRP was fairly compared with a MRP-based approach using an automated system/model generator and an experimental framework that allows us to generalize our results. Through the additional experimentation efforts reported first in this paper, evidence was found to support the following conclusions: 1) The benefits of qRP tend to diminish as we a shop becomes more volatile (increase conditions where customers orders are often canceled and emergency orders injected into the system at the last moment); and 2) The benefits of qRP tend to diminish if the planner uses a queue dispatch strategy other than FIFO during the DFRUN pass, and the scheduler does the same in the SFRUN pass. This finding suggests that queue dispatching is a key factor, perhaps one that can be used to increase the benefits of qRP. As well, further studies to investigate the replanning effectiveness of qRP under volatile conditions may be justified.

From the results of the experiments conducted thus far, we suggest that qRP may be most beneficial in environments where demand can be forecasted fairly well at least one planning period in advance, where there are large variations in the utilization of various resources from period to period (roving bottlenecks), where shop load is relatively high at least some of the time, where product structures have many levels and many components per assembly, and where the shop is governed by complex control and flow logic.

In summary, this experimentation indicates that qRP may be a superior approach for MTO environment. In such environments, production managers are not capable of anticipating the affect of change since they have little experience on which to base it. qRP provides the insight required to make intelligent decisions.

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