Dispatching rules for production scheduling in the capital goods industry

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Abstract

Research on dispatching rules has focused upon deterministic job shop situations or small assembly environments and ignored operational factors. This work uses data obtained from a capital goods company that produces complex products.

The paper first explores the influence of the data update period and the minimum setup, machining and transfer times under stochastic infinite capacity conditions. It then investigates the significance of these factors and the relative performance of eight dispatching rules with finite capacity and stochastic processing times. Dispatching rules and most operational parameters were statistically significant. With finite capacity, the ‘best’ dispatching rule was different at the component and product levels and varied according to the performance measure used. The shortest operation time first rule generally produced the best results, particularly at product level.

Keywords: ; ;

1. Introduction

A distinction is often made between sequencing, scheduling and production planning (Stoop and Wiers, 1996). Sequencing determines the order of tasks based upon operation and assembly precedence. It does not involve timing. Scheduling was defined by Baker (1974) as “the allocation of resources over time to perform a collection of tasks”. A schedule specifies sequence and timing, normally expressed in terms of a set of start and due times. Blackstone et al. (1982) made a distinction between job sequencing, which orders all items in the queue and job dispatching which just selects the next item from the queue depending upon some attributes of the job and/or the shop. Scheduling and sequencing are planning activities, whereas dispatching rules are used when a plan is executed.

There has been extensive research relating to the use of dispatching rules, most of which has focused upon deterministic shops producing independent items without subassembly and assembly processes (Fry et al., 1989). More recent research has investigated simple assembly systems (e.g. Reja and Rajendran, 2000; Mohanasundaram et al., 2003). A general limitation of previous work is that other significant factors such as minimum setup,
machining and transfer times have been neglected (King and Spackis, 1980; Pongcharoen, 2001).

The aim of this paper is to investigate the relative performance of dispatching rules for executing plans in capital goods companies that produce complex products in low volume under stochastic conditions.

The specific objectives of this paper are to:

1. explain the characteristics of capital goods companies,
2. describe the simulation model that was developed to represent the manufacture of complex products,
3. introduce a case study that was based upon an 18 months schedule of production obtained from a collaborating company,
4. explain a full factorial experiment that investigated the effect of four operational parameters (minimum set-up, processing and transfer times and the data update period) on manufacturing performance under infinite capacity conditions with stochastic processing times. This scenario represented the most favourable scenario that could be achieved through the extensive outsourcing of activities,
5. describe an experimental programme that investigated the performance of dispatching rules, as well as the four operational parameters, with finite capacity and stochastic processing times. The relative performance of the dispatching rules is considered in terms of mean tardiness (at both component and product levels) for each of the product families.

The paper first reviews the characteristic capital goods companies that produce complex products in low volume. Section 3 describes the large-scale simulation model that was developed to represent manufacturing facilities under the control of a Computer Aided Production Management system. Section 4 presents a case study from a collaborating company. Section 5 describes the experimental design and the results appear in Section 6.

2. Capital goods companies

The main business activities of capital goods companies are the design, manufacture and construction of large products such as turbine generators, cranes and boilers. These companies also produce spare parts that are similar to parts of the main product. During periods of low demand the companies perform subcontract machining, which involves the production items that are not related to the primary business activities. The main product, spares and subcontract items are all produced in low volume using common manufacturing facilities. It is common to find a small number of orders, each of which requires a large proportion of available capacity. The main products have deep and complex product structures, typically with ten levels of assembly. In contrast, the spares and subcontract businesses produce items with shallow product structure, typically with 1–3 levels of assembly. The process routings are often long and require many operations on multiple machines (Hicks, 1998). A typical product structure for a main assembly manufactured by a collaborating company is shown in Fig. 1. Each node represents a product (top level), assemblies or subassemblies (intermediate levels) and components (bottom level). The lines between the nodes represent the assembly precedence relationships within the product.

Scheduling the production of capital goods is difficult because the long and complex routings make the potential number of sequences very large. The stock turn ratio (turnover/inventory) for capital goods companies is low, typically between 2 and 3. This is due to high levels of work in progress, which makes manufacturing control and dispatching rules very important.

There has been only limited research on the use of various dispatching rules for executing a given plan in the capital goods industry. Hicks (1998) and Hicks and Braiden (2000) investigated the production of complex capital goods using eight different dispatching rules. This work used data from a capital goods company and assumed deterministic process times. A wide range of performance measures was used to evaluate the relative performance of the dispatching rules. This work found that the performance of dispatching rules was different at the component and product levels.
When the manufacturing facilities were treated as a job shop the shortest operation time first rule generally produced the best results. This result was in agreement with (Blackstone et al., 1982). At product level it was found that the least slack first and earliest due date first dispatching rules that maintained planning priorities performed best. The durations of component and assembly processes are uncertain in capital goods companies. The work of Hicks (1998) and Hicks and Braiden (2000) did not investigate the impact of dispatching rules or other factors in stochastic situations.

3. Manufacturing system simulation model (MSSM)

The MSSM (shown in Fig. 2) is based upon the discrete event paradigm (Kreutzer, 1986) and was developed by Hicks (1998). It represents a manufacturing facility interacting with a computer-aided production management system and has the capability to represent the manufacture of a range of product families with either shallow or deep product structure using jobbing, batch, flow and assembly processes. The model was developed without reference to any particular site and can be configured at run time to represent a specific company using a series of user-friendly forms.

The MSSM provides an environment in which changes can be made to the manufacturing facility, the manufacturing planning and control system, or to the demand in terms of volume or product mix. Resources are defined using a hierarchical structure that allows companies to be decomposed into a maximum of four levels. A typical model would include factory, department, cell and machine levels. Similar resources, that can share work, can be assigned to work centres. The characteristics of each resource, including shift patterns, stochastic behaviour, batching rules and dispatching rules can be specified individually, or global values can be used.

Individual products are defined in terms of a hierarchy that represents the product structure and allows multiple instances of like items at any level. A product structure code defines the position of each item within the product structure in terms of a series of part codes. This describes relationships between different types of part, which provides full traceability of parts and permits like parts in different products to be identified.

Products, assemblies and components may be assigned to different product families. This facilitates the modelling of the sharing of resources by different business activities. The usage of resources is broken down by product family, which enables the interactions between the different businesses to be identified and contention for resources to be detected.

The planning process takes place before the simulation of activities within the manufacturing facility. Aspects relating to the execution of plans, such as dispatching and batch splitting rules, determine the sequence of operations during simulation. Uncertainties may be represented by a wide range of statistical distributions (Berny, Beta, Normal, Exponential, Gamma, Lognormal, Multi-

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![Fig. 2. Manufacturing system simulation model.](image-url)
modal or Weibull) or by empirical distributions (Wall, 1994).

The experimental frame, which defines the initial state of the simulation, includes resource data, planning data, operational and control parameters and termination conditions for the simulation. Hicks and Braiden (2000) described the configuration, calibration and validation of the model in more detail.

4. Case study

An 18 month plan was obtained from a collaborating capital goods company (see Table 1). The factory produced: main products (which were complex with a deep product structure), spares and subcontract items. There was a mix of jobbing, batch, flow and assembly processes with final construction and commissioning of the main products taking place at customers’ sites. Planning and operational data were obtained from the Company’s CAPM system.

Modelling the whole Company was too ambitious due to the large volumes of data and the complexity of the manufacturing environment. An area was selected that represented the key characteristics of MTO/ETO capital goods manufacturing. The heavy machine shop was chosen as it produced the highest value, longest lead-time items. The data volumes were manageable and the data was likely to be more accurate than in the other manufacturing areas due to the relatively large operation times and the slow movement of material.

The main product and spares businesses were the largest in terms of work content. The main product components were components of complex assemblies with up to eight levels of product structure. The spares and subcontract machining businesses had relatively simple shallow product structures.

5. Experimental programme

The first experiments explored operational factors (data update period and minimum setup, machining and transfer times) under infinite capacity conditions with stochastic processing times. This scenario represented the most favourable scenario that could be achieved with extensive outsourcing. The aims were: (i) to identify the best possible manufacturing performance that could be achieved without capacity constraints, (ii) to find the relative significance of the operational parameters, and (iii) to identify the feasibility of the Company’s plans.

The second experiments considered finite capacity experiments with eight dispatching rules and stochastic processing times. The aims were to: (i) identify the relative significance of the dispatching rules and other operational parameters, (ii) identify the ‘best’ dispatching rules for each product family at component and product levels, and (iii) to evaluate the impact of the finite capacity constraint.

Experimental design has two related components: (i) the selection of the factors and levels, and (ii) statistical analysis. A full factorial design was used with 50 replications. Factorial designs are more efficient than ‘one factor at a time’ experiments. They are necessary when interactions may be present to avoid misleading conclusions. They also allow the effects of a factor to be estimated at several levels of the other factors, yielding conclusions that are valid over a range of experimental conditions (Montgomery 1997, p. 234).

A survey of capital goods companies identified the operational factors that were important (see Table 2).

Table 2
Experimental design

<table>
<thead>
<tr>
<th>Factors coded value</th>
<th>No. of levels</th>
<th>Levels</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Low (0)</td>
<td>High (1)</td>
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<tr>
<td>Minimum setup time</td>
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<tr>
<td>Minimum machining time</td>
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<td>0min</td>
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<tr>
<td>Minimum transfer time</td>
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<tr>
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<td>Infinite</td>
</tr>
<tr>
<td>Dispatching rules</td>
<td>8</td>
<td>See text</td>
</tr>
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</table>
Table 2) together with realistic lower and upper bounds (Hicks, 1998).

The first three factors specified the minimum duration of activities. The fourth factor, the data update period, represented the procedure used for data collection. Foremen often enter data into the system at the end of the shift (offline updating). Fig. 3 illustrates a data update period of 480 min (8 h).

Due date performance = completion time – due time.

Regression analysis: Regression analysis produces a model that describes the relationship between independent (predictor) variables (\(x\)) and a dependent (response) variable (\(y\)) (see Eq. (3)). This predictive model estimates the impact of main effects and interactions for numerical variables (Montgomery, 1997).

6. Experimental results

6.1. Stochastic simulation runs with infinite capacity

A full factorial experiment was replicated 50 times with the factors and levels shown in Table 2 (except dispatching rules). Mean tardiness was measured for the subcontract, main product and spares product families, at component and product level.

6.1.1. Mean tardiness at product level (infinite capacity)

Table 3 summarises the \(p\)-values for the main effects and the first level interactions, which established their statistical significance with respect to mean tardiness for each of the product families at product level. The \(p\)-values that were statistically significant are shown in italics (with either 95% or
was unrealistic. This is because many items were already late at the start of the simulation period.

6.1.2. Mean tardiness at component level (infinite capacity)

Table 4 shows the statistical significance of the main effects and interactions for all the product families at component level. All the main effects were statistically significant for all the product families with the exception of minimum machining time, which was not statistically significant for spares components. There were more interactions that were significant at component level than at the product level. The interaction TRT*DUP was significant for all the product families, whilst other interactions were only significant for some product families.

The regression models for mean tardiness (T) are shown in Eqs. (7)–(9). More factors and interactions were statistically significant compared to the results at product level. The predicted minimum mean tardiness for the subcontract, main product and spares components were 42.2, 125 and 11.9 days, respectively. The corresponding figures at product level were, 106, 27 and 6.73 days (from Eqs. (4)–(6)). Thus, the tardiness at product level was less than at component level for the main product and spares. This suggests that the component level plans for these product families included significant contingencies to take into account capacity constraints. However, Eqs. (7)–(9) still predict late delivery for components, which indicates that the Company was

Table 4

<table>
<thead>
<tr>
<th>Predictor</th>
<th>p-values at component level</th>
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<tr>
<td></td>
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<td><strong>Main factors</strong></td>
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<td>SUT*DUP</td>
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<tr>
<td>TRT*DUP</td>
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</table>
behind schedule at the start of the simulation period:

\[ T_{\text{sub}} = 42.2 + 0.03 \text{SUT} + 0.02 \text{MCT} + 3.49 \text{TRT} \\
+ 0.24 \text{DUP} - 0.01 \text{SUT} \times \text{MCT} \\
\times 0.03 \text{SUT} \times \text{DUP} + 0.05 \text{TRT} \times \text{DUP}, \] (7)

\[ T_{\text{mainp}} = 125 + 0.06 \text{SUT} + 0.01 \text{MCT} + 5.33 \text{TRT} \\
+ 0.39 \text{DUP} - 0.02 \text{SUT} \times \text{MCT} \\
+ 0.01 \text{MCT} \times \text{DUP} + 0.03 \text{TRT} \times \text{DUP}, \] (8)

\[ T_{\text{spares}} = 11.9 + 0.02 \text{SUT} + 2.26 \text{TRT} + 0.2 \text{DUP} \\
+ 0.003 \text{SUT} \times \text{TRT} + 0.1 \text{SUT} \times \text{DUP} \\
+ 0.01 \text{TRT} \times \text{DUP}. \] (9)

The following section investigates more realistic finite capacity situations.

6.2. Stochastic simulation runs with finite capacity

Table 2 identified the factors and levels that were used for this experiment. A full factorial experiment was replicated 50 times. The total number of runs was therefore \(2 \times 2 \times 2 \times 2 \times 8 \times 50 = 6400\). The results are summarised in Table 5, which shows the relative performance of the dispatching rules in terms of mean tardiness \(T\).

The best dispatching rule for each of the performance measures is single underlined, whilst the worst is double underlined. The minimum mean tardiness at product level was achieved with the SOF for the subcontract products, the LSF for the main products and the MRF for the spares products. At component level, the rules that produced minimum mean tardiness were: LOF for subcontract items, EDF for main product components and EDF for spare parts.

The best and the worst dispatching rules were considered further to evaluate the maximum impact that dispatching rules could have on manufacturing performance. Regression analysis requires numerical variables. The dispatching rules were therefore translated into coded values (worst rule = 0, best rule = 1). Six predictive regression models were produced (for the subcontract, main product and spares families at the product and component levels), which are outlined in the following sections.

6.2.1. Mean tardiness at product level (finite capacity)

Table 6 summarises the \(p\)-values for the main effects and the first level interactions for each of the product families at product level.

The minimum transfer time (TRT) and dispatching rule (DPR) were statistically significant for all product families. The remaining main factors were only significant for some of the product families. The SUT*DUP, SUT*DPR and DUP*DPR interactions were statistically significant for all of the product families. The other statistically significant interactions were: SUT*TRT, MCT*TRT TRT*DUP and TRT*DPR for subcontract products and MCT*DUP, TRT*DUP and TRT*DPR for main products.

Predictive regression models were produced for mean tardiness \(T\) for subcontract, main products and spares at product level (see Eqs. (10)–(12)). These models only included the factors and interactions that were statistically significant (see Table 6).
interactions had a large impact on the mean main products most of the main factors and the interactions had a relatively small impact. For subcontract products the magnitude of the impact followed by the TRT. The other factors and coefficients indicates that the DPR had the greatest impact on the SUT and TRT and high level of the DPR (i.e. the best rule) should be used.

6.2.2. Mean tardiness at component level (finite capacity)

Table 7 summarises the p-values for the main effects and the first level interactions for each of the product families at component level. All of the main factors are statistically significant for all product families, except the minimum machining time (MCT). The interactions that were statistically significant were: SUT*DPR, TRT*DPR and DUP*DPR for subcontract components; SUT*DPR, TRT*DUP and TRT*DPR for main product components and SUT*DUP, DUP*DPR, TRT*DUP, TRT*DPR and DUP*DPR for spares components.

The predictive regression models for mean tardiness (7) at component level are shown in Eqs. (13)–(15). The regression coefficient for the dispatching rule is the largest coefficient, indicating

6). The coefficients for the main factors are all positive, except the DPR. This is because the best dispatching rule was arbitrarily coded ‘1’ rather than ‘0’.

\[ T_{\text{sub}} = 217 + 0.45SUT + 6.56TRT + 0.54DUP \]
\[ - 32.8DPR - 0.39SUT \times TRT \]
\[ + 0.35SUT \times DUP + 1.15SUT \times DPR \]
\[ - 0.23MCT \times TRT + 0.86TRT \times DUP \]
\[ + 1.3TRT \times DPR - 0.9DUP \times DPR \]  

\[ T_{\text{main}} = 406 + 5.13MCT + 36.1TRT + 59DUP \]
\[ - 19.6DPR - 10.7SUT \times DUP \]
\[ + 9.36SUT \times DPR - 3.84MCT \times DUP \]
\[ - 5.12TRT \times DUP - 15.1TRT \times DPR \]
\[ - 47.2DUP \times DPR \]

\[ T_{\text{spares}} = 536 + 25.4SUT + 9.26TRT - 267DPR \]
\[ - 12.9SUT \times DUP + 75.2SUT \times DPR \]
\[ - 24.7DUP \times DPR. \]

For subcontract products the magnitude of the coefficients indicates that the DPR had the greatest impact followed by the TRT. The other factors and the interactions had a relatively small impact. For main products most of the main factors and the interactions had a large impact on the mean tardiness. The model predicts that the mean tardiness can be decreased by at least 196 days when the best dispatching rule (indicated in Table 5) is used. For the spares products, the DPR had the greatest impact. To minimise the mean tardiness of spares products (see Eq. (12)), the low level of the SUT and TRT and high level of the DPR (i.e. the best rule) should be used.

Table 7

<table>
<thead>
<tr>
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<tr>
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<td>DUP*DPR</td>
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</table>
that this factor has the greatest impact for all of the product families. The transfer time has the next largest impact for the subcontract and main products components. The other main factors and the interactions had a relatively small impact. The highest mean tardiness within product families was predicted for spare parts at both component (see Eq. (15)) and product levels (see Eq. (12)). This result was completely different with assuming infinite capacity:

$$T_{\text{sub}} = 140 + 0.77\text{SUT} + 4.31\text{TRT} - 0.81\text{DUP}$$
$$- 42.9\text{DPR} - 0.46\text{SUT} \ast \text{DPR}$$
$$- 2.28\text{TRT} \ast \text{DPR} + 0.95\text{DUP} \ast \text{DPR},$$ (13)

$$T_{\text{mainp}} = 287 + 1.47\text{SUT} + 7.05\text{TRT} + 0.65\text{DUP}$$
$$- 47.4\text{DPR} + 0.35\text{SUT} \ast \text{DPR}$$
$$+ 0.31\text{TRT} \ast \text{DUP} - 3.17\text{TRT} \ast \text{DPR},$$ (14)

$$T_{\text{spares}} = 447 + 1.84\text{SUT} + 1.27\text{TRT} + 0.69\text{DUP}$$
$$- 12.7\text{DPR} - 0.34\text{SUT} \ast \text{DUP}$$
$$- 0.685\text{SUT} \ast \text{DPR} + 0.26\text{TRT} \ast \text{DUP}$$
$$+ 0.58\text{TRT} \ast \text{DPR} - 0.57\text{DUP} \ast \text{DPR},$$ (15)

7. Conclusions

Most of the research on dispatching rules has focused upon job shop situations. The limited research that has investigated dispatching rules in assembly environments has neglected the impact of other operational factors such as minimum setup, machining and transfer times and data update period. Most of the work has investigated small theoretical situations with deterministic process times and single product families.

This research has investigated the use dispatching rules in stochastic situation using data obtained from a capital goods company that produce three families of complex products. Companies in this sector have low stock turn ratios (typically 2–3), which is due to high levels of work in progress (WIP). This may be attributed to poor planning and control, but in some circumstances WIP is used as a buffer to maintain resource utilisation during periods of fluctuating demand. High WIP leads to significant queues that make dispatching rules particularly important.

The work was based upon an 18 month schedule obtained from a collaborating company that included 56 products and 5539 operations processed on 36 resources. The relative significance of dispatching rules was compared to other operational factors. Component and assembly processing times were assumed to be normally distributed with a standard deviation of 0.1 times the mean. The scenarios presented are far more realistic than previous work. Full factorial experiments considered both infinite and finite capacity constraints. Manufacturing performance was measured in terms of mean tardiness for all the product families at both component and product levels.

The results for the infinite capacity experiments showed that the Company was well behind schedule at the start of the period simulated. With infinite capacity the mean tardiness (days) for products was 106 for subcontract items, 27 for main products and 6.73 for spares. The corresponding figures for components were 42.2, 125 and 11.9. When the tardiness at component level was greater than at product level it implies that the plans included contingencies. Similarly, when tardiness was greater for products it implies that the lower level plans were not sufficiently coordinated. Likewise tardiness at either product or component level is an indicator that high work in progress was due to planning and control difficulties rather than being an intentional buffer to mitigate the effects of work load variations.

The results from the infinite capacity experiments indicated that more factors and interactions were statistically significant at the component level than at product level. With infinite capacity, the minimum transfer time was the most significant factor. Minimum setup, machining and transfer times and the data update period should all be minimised to achieve the best manufacturing performance. The mean tardiness at product level was greatest for the subcontract products. At component level, the main product components were most tardy.

The finite capacity experiments included the use of dispatching rules. At product level the best rules were: SOF for subcontract products; LSF for main products; and MRF for spares products.

At component level the best rules were: LOF for subcontract components, EDF for the main products; and SOF for spare components. Thus, the ‘best’ dispatching rule was different at the compo-
nent and product levels and the product family. Furthermore, the results were different from those obtained by other research including Hicks and Braiden (2000) which used the same dataset, but assumed deterministic processing times.

The dispatching rule was the most important factor for all families at both component and product level. The correct selection of dispatching rule is therefore particularly important when producing complex products. Although the ‘best’ dispatching rule varies according circumstances, SOF generally produced the best results, particularly at product level. It is interesting to note that a survey by Blackstone (1982) also recommended the SOF rule.

The finite capacity results suggested that within the product families, spare parts at both component and product levels had the worst mean tardiness. This indicates that the due date setting for the spare parts was optimistic. The relative manufacturing performance for all of the product families was different in the infinite and finite capacity cases.

The case study considered was representative of a sample of nine capital goods companies (Hicks, 1998). The specific results were dependent upon the particular data set used. However, the production of multiple product families with common resources and backlog of work were representative characteristics of capital goods companies. It is on this basis that the results and conclusions are considered to be generally applicable to the sector.

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References