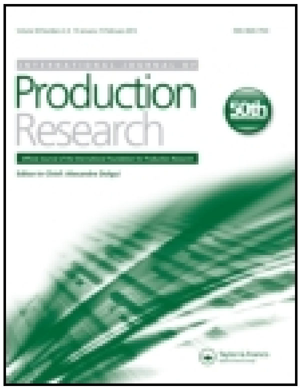

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The performance of Due Date setting rules in assembly and multi-stage job shops: an assessment by simulation

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The performance of Due Date setting rules in assembly and multi-stage job shops: an assessment by simulation

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Setting short yet reliable Due Dates (DDs) is an important early production planning and control task. The majority of job-shop research on DD setting assumes simple product structures without assembly operations. However, in practice, product structures are often complex, and multiple final assembly operations may be required. This paper evaluates the performance of DD setting rules in the context of complex product structures, considering two scenarios: two-level assembly job shops, where orders converge on one final assembly operation; and two-level multi-stage job shops, where a series of assembly operations are undertaken. New rules are proposed which are substantially simpler and more suitable for practical use than those in the literature. These rules are only outperformed by a more sophisticated rule from the wider literature, newly introduced into the context of assembly and multi-stage job shops. Which rule to apply in practice depends on whether a manager considers the improvement in performance more important than the loss of simplicity. Future research should investigate how jobs can be planned and controlled effectively when some or all DDs are set externally by customers rather than internally using a DD setting rule.

Keywords: Due Date setting; assembly job shop; multi-stage job shop; simulation

1. Introduction

This study assesses the performance of Due Date (DD) setting rules suitable for two-level assembly and multi-stage job shops. In these contexts, final products or assembly orders consist of multiple sub-assemblies, known as work orders. Work orders progress through the 'Level 1' job shop independently before converging on the 'Level 2' final assembly operation(s). In an assembly job shop, there is only one assembly operation; in a multi-stage job shop, a series of assembly operations have to be completed for each final assembled product. In both cases, assembly is fed with orders from the preceding job shop. Thus, DD adherence in assembly and multi-stage job shops is dependent on the timely progress through the job shop of all work orders that make up the final product. This is a more complex problem than the well-studied single-level or standard job shop problem, where operations are serial, and DD adherence is dependent on the progress of only one order (Adam *et al.* 1987).

In Make-To-Order (MTO) companies, DD setting is a complex task of strategic importance (Kingsman *et al.* 1989, Hopp and Sturgis 2000, Stevenson *et al.* 2005) which must be undertaken for each order individually, as order specifications can vary greatly from one job to the next. In such a context, the ability to quote DDs that are both competitive and realistic is a key priority (Bertrand 1983b, Spearman and Zhang 1999). However, although a broad literature concerned with DD setting in job shops exists (e.g. Weeks 1979, Baker 1984, Ragatz and Mabert 1984, Cheng and Gupta 1989, Wein 1991, Hopp and Sturgis 2000), only limited attention has been paid to assembly or multi-stage job shops (e.g. Fry *et al.* 1989b, Adam *et al.* 1993). This is a significant research gap, as many job shops encountered in practice have one or more final assembly operations (Portioli-Staudacher 2000, Silva *et al.* 2006, Stevenson *et al.* 2011).

Research concerned with assembly or multi-stage job shops has focused on scheduling and dispatching, generally neglecting DD setting (e.g. Fry *et al.* 1989a, Philipoom *et al.* 1991, Pongcharoen *et al.* 2002, Thiagarajan and Rajendran 2005, Natarajan *et al.* 2007). While these contributions are valuable, improving our understanding of

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how DDs should be set in assembly and multi-stage job shops is critical: it is argued that DD setting is a crucial first stage of production planning and control that should not be neglected. If DDs are set appropriately, lead times reflect the current load on the shop floor, and simple dispatching rules can be applied; there is also then no need for complex scheduling heuristics for 'fire-fighting' or expediting (e.g. Kingsman *et al.* 1989). The limited research concerned with DD setting is scattered and disparate; a clear body of literature is missing and available contributions have not been consolidated. For example, although Fry *et al.* (1989b) showed that the Total Work Content of the Critical Path (TWKCP) DD setting rule is inappropriate for assembly shops, many subsequent research contributions have applied this rule regardless (e.g. Thiagarajan and Rajendran 2005, Choi and You 2006, Lu *et al.* 2011).

This study consolidates the available literature on DD setting in assembly and multi-stage job shops and presents – for the first time since Fry *et al.* (1989b) – a performance evaluation of the alternative rules using simulation. New rules are developed and – owing to its outstanding performance in standard job shops (Bertrand 1983a, b) – a DD setting rule that considers detailed workload information over time is introduced. Based on the results, guidance is provided for practitioners regarding which rule to apply in two-level assembly and multi-stage job shops.

The remainder of the paper is organised as follows. Section 2 reviews the literature on DD setting rules before the simulation model is presented in Section 3. Results are analysed and discussed in Section 4 followed by final conclusions in Section 5.

2. Literature review

This section reviews the literature related to DD setting in the context of assembly and multi-stage job shops. The first studies that considered the estimation of lead times and DDs in assembly job shops were presented by Maxwell and Mehra (1968) and Goodwin and Goodwin (1982). These authors presented simple rules to estimate lead times: the CONstant (CON); the Total Work Content (TWK); and the TWKCP rules. TWK and TWKCP were later compared by Fry *et al.* (1989b) along with five other rules. Equations (1)–(7) summarise the lead-time estimates, t_{lead}, of the resulting seven rules. These rules were simple (Equations (1)–(3)), linear (Equations (4) and (5)) and multiplicative (Equations (6) and (7)) forms of three elements of basic job and shop information: TWK – job information; TWKCP – job information; and WINS (Work-IN-Shop) – shop information. The coefficients (C_1 to C_9) were determined by regression analysis.

$$t_{\text{lead}} = C_1 \cdot \text{TWK} \tag{1}$$

$$t_{\text{lead}} = C_2 \cdot \text{TWKCP} \tag{2}$$

$$t_{\text{lead}} = C_3 \cdot \text{WINS} \tag{3}$$

$$t_{\text{lead}} = C_4 \cdot \text{TWK} + C_5 \cdot \text{WINS} \tag{4}$$

$$t_{\text{lead}} = C_6 \cdot \text{TWKCP} + C_7 \cdot \text{WINS} \tag{5}$$

$$t_{\text{lead}} = C_8 \cdot (\text{TWK} \cdot \text{WINS}) \tag{6}$$

$$t_{\text{lead}} = C_9 \cdot (\text{TWKCP} \cdot \text{WINS}). \tag{7}$$

Fry *et al.* (1989b) found that linear rules, i.e. Equations (4) and (5), perform best. Despite their popularity (e.g. Sculli 1980, Goodwin and Goodwin 1982, Fry *et al.* 1989a), Fry *et al.* (1989b) also concluded that TWK and TWKCP, i.e. Equations (1) and (2), are an inaccurate means of estimating lead times. This finding was in line with previous studies from the wider job-shop literature, underlining the superior performance of DD setting rules that consider some kind of shop-load information (e.g. Weeks 1979, Ragatz and Mabert 1984).

Adam *et al.* (1993) then questioned the use of regression analysis, as used by Fry *et al.* (1989b) to derive coefficients C_1 to C_9, as this technique does not respond dynamically to changes on the shop floor. Adam *et al.* (1993) argued that this means coefficients are based on historical data and not on the current state of the shop. In response, Adam *et al.* (1993) presented dynamic extensions to the basic static TWK, TWKCP, and CON rules. The coefficients in the dynamic rules were based on current shop-load information instead of regression analysis, and each of the new rules was shown to outperform their static counterpart. However, all were outperformed by another new rule: the Critical Path Flow Time (CPFT) rule. CPFT considers waiting time estimates at work centres based on shop load information. Thus, the lead time is given by the sum of the estimated operation throughput times (waiting and processing time) on the critical path. This rule can be regarded as being similar to TWKCP + WINS (Equation (5)); however, CPFT estimates the waiting time. According to the CPFT rule, the estimated waiting time at a work centre is given by the quotient of the current number of jobs queuing and an estimate of the job arrival rate at the work centre. As a result, it does not require an additional parameter to be set, whereas TWKCP + WINS uses regression to link the work content and the current load on the shop floor to the lead time.

To ensure zero lateness, Adam *et al.* (1993) introduced a correction, multiplying t_{lead} by an adjustment factor that reflects current lateness. Thus, Adam *et al.* (1993) re-introduced an additional, albeit dynamic, parameter. Moreover, despite criticising Fry *et al.* (1989b), the authors did not compare the performance of their new rule against the best-performing rules from Fry *et al.* (1989b): TWK + WINS and TWKCP + WINS (Equations (4) and (5), respectively). Therefore, which of the rules performs the best – and should therefore be applied in practice – remained unknown.

Smith *et al.* (1995) then tested a rule similar to TWKCP + WINS (Equation (5)) from Fry *et al.* (1989b). As in Fry *et al.* (1989b), regression analysis was used to determine coefficients. The authors also proposed a dynamic version of their rule (based on Gee and Smith 1993), which repeats regression analysis and updates the coefficients after every 200 jobs. Like TWKCP + WINS (from Fry *et al.* 1989b), the rule outperformed the TWKCP rule (Equation (2) above), but it was not compared against any other rules from the literature (e.g. CPFT, as presented by Adam *et al.* 1993). Moreover, both Fry *et al.* (1989b) and Smith *et al.* (1995) considered only aggregated shop-load information, despite the fact that Ragatz and Mabert (1984) had earlier demonstrated that considering the load (or number of jobs) queuing in front of each work centre (and thus the expected load in the routing of a job) improves the accuracy of lead-time estimates in the context of the standard job shop.

Roman and del Valle (1996) then presented a simulation-based rule that estimates the required lead time for a new job by conducting a simulation, considering all unfinished jobs (assuming no new jobs arrive on the shop floor). The rule outperformed both TWK and TWKCP. Interestingly, the authors' results contradicted Fry *et al.* (1989b) and Adam *et al.* (1993), who had both previously found no significant difference in performance between TWK and TWKCP. Roman and del Valle's (1996) results suggested that the performance of TWK is far superior to that of TWKCP, but, again, a new rule was introduced without comparing it against the best-performing rules from previous research (i.e. TWKCP + WINS and CPFT).

The final contribution to the set of available DD setting rules for assembly and multi-stage job shops was provided by Bertrand and Van de Wakker (2002), who applied a rule based on Forward Infinite Loading (FIL); this can be considered a static version of the CPFT rule presented by Adam *et al.* (1993). The rule does not use continuous shop-load information; instead, the waiting time is estimated by a constant factor (a so-called flow-time allowance factor). The best performance of the rule was achieved with the flow-time allowance set equal to the average operation waiting time in the shop. No comparison with the best-performing rules from prior research was provided.

To conclude this brief review, the most important DD setting rules from the literature on assembly and multi-stage job shops are summarised in Table 1. The rules are taken from a range of different studies, and – with the exception of TWK and TWKCP (which both performed poorly) – their performance has not been adequately compared. Furthermore, none of the rules consider detailed workload information over time; this is a significant shortcoming given the outstanding performance of such rules, as reported in the wider job-shop literature (e.g. Bertrand 1983a, b).

The majority of the available literature on assembly and multi-stage job shops has focused on scheduling and dispatching (e.g. Philipoom *et al.* 1991, Thiagarajan and Rajendran 2005, Choi and You 2006). The limited contributions on DD setting are fragmented, with different rules being favoured by different authors; an overall performance evaluation is missing. Moreover, DD setting rules, which use detailed workload information over time, have been neglected. It therefore follows that there is a need to establish the current state of the art in DD setting in the context of assembly and multi-stage job shops, and to extend the available set of DD setting rules. This is an important research gap given that most job shops found in practice have some assembly operations (Adam *et al.* 1987, Portioli-Staudacher 2000, Stevenson *et al.* 2011).

Table 1. Summary of Due Date setting rules from the literature.

Name	Information	Applied by	Advantages	Disadvantages
Total Work Content (TWK – Equation 1) and Total Work Content Critical Path (TWKCP – Equation (2))	Job information	Fry *et al.* (1989), Adam *et al.* (1993), Smith *et al.* (1995), Roman and del Valle (1996)	Simple	Poor performance – outperformed by all alternative rules
Total Work Content Critical Path + Work In Shop (TWKCP + WINS – Equation (5))	Job and aggregate shop load information	Fry *et al.* (1989), Smith *et al.* (1995)	Simple; outperformed TWK and TWKCP	Regression analysis to determine coefficients
Critical Path Flow Time (CPFT)	Job and aggregate shop load information	Adam *et al.* (1993)	Simple, outperformed TWK and TWKCP	Adjustment heuristic necessary to ensure zero lateness
Total Work Based on Simulation	Job and detailed shop load information – current system status	Roman and del Valle (1996)	Outperformed TWK and TWKCP	Complex; system status needs to be known; simulation model necessary
Forward Infinite Loading (FIL)	Job information	Bertrand and van de Wakker (2002)	Simple	Performance relative to alternatives is unknown

3. Simulation

The main research question identified from the literature review is as follows: 'Which DD setting rule should be implemented in assembly and multi-stage job shops in practice?' To answer this research question, we compare the performance of eight rules under four different utilisation levels (75, 80, 85, and 90%). Based on the results, the best-performing DD setting rules are identified, and managerial implications are provided. Most of the eight rules explicitly consider feedback information, which restricts the analytical tractability of the studied problem. Therefore, discrete event simulation is used, which allows the gap between practice and analytical research to be bridged (Bertrand and Fransoo 2002).

3.1 *Overview of shop characteristics*

Two different models have been developed using the SimPy © module of Python ©: (1) a two-level assembly job shop; and (2) a two-level multi-stage job shop. These models have been chosen as generalisations of two shop structures commonly found in practice (e.g. Portioli-Staudacher 2000, Silva *et al.* 2006, Stevenson *et al.* 2011). The two shop structures are discussed in Sections 3.1.1 and 3.1.2.

3.1.1 *Assembly job-shop model*

This model extends the pure job-shop model used by Melnyk and Ragatz (1989). It is similar to that applied by Bertrand and Van de Wakker (2002), Natarajan *et al.* (2007) and Lu *et al.* (2011). The job shop contains six work centres, where each is a single and unique capacity resource. The number of operations per work order (or sub-assembly) is equally distributed between one and six. All work centres have an equal probability of being visited, and a particular work centre is required at most once in the routing of a work order. Work orders leaving the job shop go to an assembly work centre, where they await other work orders that make up a particular final assembly order. When all work orders have arrived, the order is complete, and the work orders leave the shop together as an assembled product. As in Lu *et al.* (2011), the assembly time is negligible to avoid distracting the focus of the study away from assembly orders to bottlenecks. The number of work orders per assembly order is uniformly distributed between one and six. The resulting job-shop model is summarised in Figure 1. The probability that a job enters the shop floor, leaves the shop floor, or moves to a certain work centre is indicated by the strength (or thickness) of an arrow in the figure. All work orders leaving the level 1 job shop move to the level 2 assembly shop.

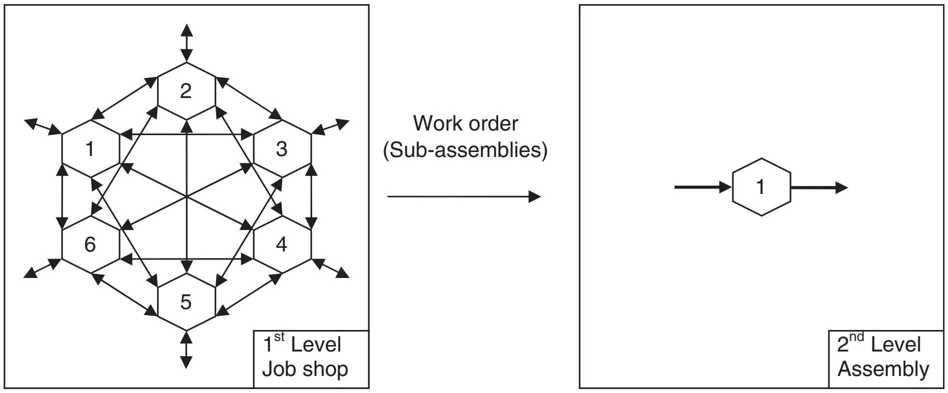

Figure 1. Assembly job shop.

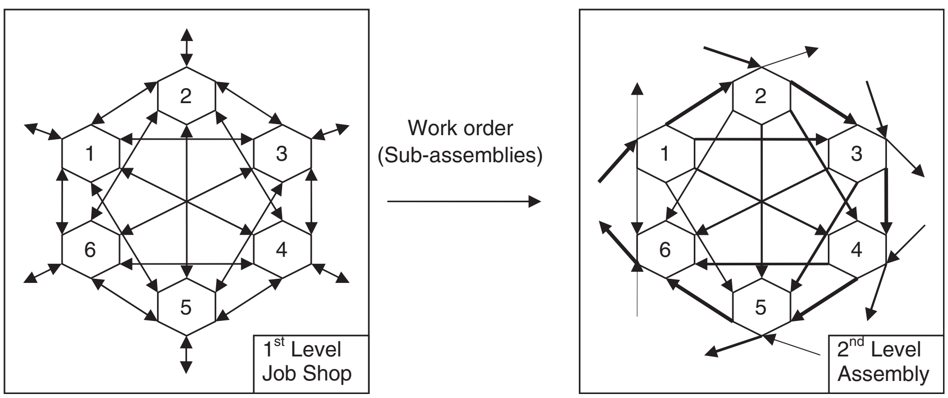

Figure 2. Two-level multi-stage job shop.

To illustrate the assembly job shop, consider the following example. An assembly order consists of three work orders. The sequence and number of operations necessary to complete each work order are random, and all work centres have an equal probability of being visited (i.e. a pure job shop). When an order first enters the system, all three of its work orders start progressing through the level 1 job shop. Once a work order is finished, it progresses to the level 2 assembly shop where it awaits the remaining work orders. Once all of the work orders that comprise an assembly order are finished, the order is complete, and the fully assembled final product leaves the system.

3.1.2 *Multi-stage job-shop model*

This model extends the assembly job-shop model outlined above; it is similar to the model discussed by Portioli-Staudacher (2000). Work orders leaving the job shop go to an assembly shop, where they are assembled into a final product (the assembly order) according to a predetermined sequence. The assembly shop represents a general flow shop (Oosterman *et al*. 2000), i.e. the flow is random but fully directed. Assembly operations at upstream work centres always precede assembly operations at downstream work centres. The shop consists of six assembly work centres, where each is a single and unique capacity resource. All assembly work centres have an equal probability of being the assembly work centre where a certain work order is assembled into an assembly order. A particular work centre is required at most once in the routing of an assembly order, meaning each assembly work centre undertakes only one assembly operation per assembly order. The number of work orders per assembly order is uniformly distributed between one and six. The resulting job-shop model is summarised in Figure 2. As for the assembly job shop, the probability that a job enters the shop floor, leaves the shop floor or moves to a certain work centre is indicated by the strength (or thickness) of an arrow. All work orders leaving the level 1 job shop move to the level 2 assembly shop.

To illustrate the multi-stage job shop, consider the following example. An assembly order is made up of three work orders; it therefore requires three assembly operations (two plus a further one – the first – which is considered preparatory work, i.e. setting up the assembly), which take place at three different work centres. The sequence in which assembly work centres are visited is predetermined and directed, i.e. there are typical upstream and typical downstream work centres. When an order first enters the system, all three of its work orders start progressing through the job shop. Once the first work order in the routing of the assembly order is finished, the assembly order starts progressing in the assembly shop. The precedence of work orders must be considered, i.e. a certain assembly operation in the assembly shop cannot take place if the corresponding work order is not yet finished in the preceding job shop – it has to wait until the completion of the work order. When all assembly operations have been undertaken, the order is complete, and the fully assembled final product leaves the system.

3.2 *Due Date setting rules*

The eight rules applied are the: adjusted Critical Path Flow Time (CPFT); Regression based Work-In-Queue (RWIQ); SIMulation based (SIM); FIL; Simple Work-In-Queue (SWIQ); Direct Work-In-Queue (DWIQ); Forward Finite Loading (FFL); and, Total Work Content Critical Path (TWKCP) rule. CPFT was the best-performing rule in Adam *et al.* (1993), outperforming the simple rules presented by Fry *et al.* (1989b). RWIQ represents rules based on TWKCP + WINS, a class of rules identified as best-performing in Fry *et al.* (1989b) and Smith *et al.* (1995). Instead of focusing on workload information for the whole shop, RWIQ focuses on the workload queuing in front of each work centre in the routing of an order. This has been found to improve performance over rules that focus on the load of the whole shop floor (Ragatz and Mabert 1984). SIM and FIL have been chosen as the best-performing rules from Roman and del Valle (1996) and Bertrand and Van de Wakker (2002), respectively. SWIQ and DWIQ are newly developed for this study: the former, SWIQ, is a single-parameter simplification of RWIQ; the latter, DWIQ, is a further simplification that does not need any parameters to be specified. FFL has been chosen from the wider job-shop literature, as it performed extremely well in previous research (Bertrand 1983a, b); it considers detailed workload information over time. Finally, TWKCP is included as a basis for comparison.

These eight rules are used to determine the work order DDs and, in the multi-stage job shop (where multiple assembly operations also have to be scheduled), the assembly DD. The rules are outlined in Sections 3.2.1 to 3.2.8, respectively, before the setting of assembly DDs is discussed in Section 3.2.9.

3.2.1 *Total Work Content Critical Path (TWKCP)*

The DD of an order is determined using Equation (8):

$$\mathrm{DD} = \mathrm{RD} + C_1 \cdot \sum_k p_k, \tag{8}$$

where RD = release date, i.e. the date when materials are assumed to be available, and the order is released onto the shop floor; $k = 1, 2 \ldots$ operations in the routing of an order; and p_k = processing time of operation k

3.2.2 *Forward Infinite Loading (FIL)*

The DD of an order is determined using Equation (9):

$$\mathrm{DD} = \mathrm{RD} + \sum_k (p_k + a), \tag{9}$$

where a = estimated waiting time (or flow time allowance factor).

3.2.3 *Critical Path Flow Time (CPFT)*

The DD of an order is determined using Equation (10):

$$\mathrm{DD} = \mathrm{RD} + \left(\sum_k p_k + \sum_j \frac{NJQ_{t,j}}{\lambda_{t,j}}\right) \cdot (1 + ADJ_t), \tag{10}$$

where $j = 1, 2. \dots$ work centre in the routing of an order; $\lambda_{t,j}$ = estimated arrival rate at current time t at work centre j; $NJQ_{t,j}$ = number of jobs at current time t in the queue at work centre j; ADJ_t = adjustment factor.

The adjustment factor at a certain time t (ADJ_t) is set following Equations (11), (12), and (13). $ADJ_{t'}$ represents ADJ when the previous DD was determined; the starting $ADJ_{t'}$ is set to zero.

$$ADJ_t = \max\left(\frac{L_t}{LT_t - L_t}, ADJ_{t'}\right) \quad \text{if} \frac{L_t}{LT_t - L_t} > 0 \tag{11}$$

$$ADJ_t = \min\left(\frac{L_t}{LT_t - L_t}, ADJ_{t'}\right) \quad \text{if} \frac{L_t}{LT_t - L_t} < 0 \tag{12}$$

$$ADJ_t = 0 \quad \text{if} \frac{L_t}{LT_t - L_t} = 0, \tag{13}$$

where L_t = average lateness of the last 400 time units; LT_t = average lead time of the last 400 time units.

A time period of 400 time units is used to determine the average lateness and lead time. This was determined through preliminary simulation experiments as the time period that results in the best performance; note that Adam *et al.* (1993) did not specify the time period used in their study.

3.2.4 *Regression-based Work-In-Queue (RWIQ)*

The DD of an order is determined using Equation (14):

$$\text{DD} = \text{RD} + C_1 \cdot \sum_k p_k + C_2 \cdot \sum_j WIQ_{t,j}, \tag{14}$$

where $WIQ_{t,j}$ = total workload at time t of all jobs in the queue or in process at work centre j

As in Fry *et al.* (1989b) and Smith *et al.* (1995), coefficients C_1 and C_2 are determined via regression analysis for each experimental setting. An iterative regression analysis, as proposed in Gee and Smith (1993) and Smith *et al.* (1995), is applied. As a hypothetical model is applied, no historical data are available for the regression analysis. Therefore, a simulation run of 10,000 time units is conducted, and the lead time (dependent variable) and p_k and $WIQ_{t,i}$ (independent variables) are recorded for each order. The warm-up period is set to 3000 time units to avoid start-up effects. The coefficients are then determined from these data. The simulation run is then repeated (i.e. with the same random number stream) using the coefficients determined in the previous step; this results in a new set of data and coefficients. This procedure continues to be repeated until no further performance improvements can be achieved. As in Smith *et al.* (1995), the DD is initially set (i.e. in the first run) according to a simple alternative rule – in this study, FIL is applied. The flow-time allowance factor a for FIL is set such that the mean lateness approximates to zero.

3.2.5 *Simulation-based (SIM)*

The DD of an order is determined using Equation (15) below.

$$\text{DD} = \text{RD} + C_1 \cdot \text{LTSIM}, \tag{15}$$

where LTSIM = lead time estimate based on simulation.

When an order arrives, a simulation is conducted that includes all orders currently on the shop floor plus the new order. LTSIM is given by the resulting lead time for the order. It is assumed that no new orders arrive in the system during this simulation; therefore, order progress interference by newly arriving orders is avoided, and the resulting lead time estimate is likely to be too short. LTSIM is multiplied by a coefficient to compensate for this underestimation.

3.2.6 *Simple Work-In-Queue (SWIQ)*

RWIQ (see Section 3.2.4 above) differs from the other rules tested in that it uses two parameters. To provide a fair comparison with the alternative (single-parameter) rules, and to assess the impact that the use of a further parameter has on performance, SWIQ is introduced. Like the other rules, SWIQ only needs one parameter to be specified. The DD of an order is determined using Equation (16):

$$\mathrm{DD} = \mathrm{RD} + \sum_k p_k + C_1 \cdot \sum_j WIQ_{t,j}. \tag{16}$$

Rather than linking job information, shop load information, and lead times by regression, SWIQ estimates the waiting time by considering the WIQ. It is similar to CPFT, but the dynamic adjustment factor used in CPFT is replaced by a constant coefficient.

3.2.7 *Direct Work-In-Queue (DWIQ)*

This rule is a further development of SWIQ, which does not require any parameters to be specified whatsoever. The DD of an order is determined using Equation (17):

$$\mathrm{DD} = \mathrm{RD} + \sum_k p_k + \sum_j DWIQ_{t,j}, \tag{17}$$

where $DWIQ_{t,j}$ = direct workload (i.e. the workload to be processed at work centre *j*) at time *t* of all jobs in the queue or in process at work centre *j*.

The workload of an order can be divided into the upstream load (which is already processed) and the downstream load (which is yet to be processed). Following Land and Gaalman (1998), the downstream load can be further subdivided into the direct and indirect load. The direct load refers to the workload, which will be processed at a given work centre, while the indirect load is the workload, which will be processed at work centres further downstream in the routing of an order. The direct load of all the orders in the queue at a given work centre represents the waiting time for a new order arriving at this work centre at current time *t,* assuming first-come-first-served dispatching is applied. It is argued here that, even if an alternative dispatching rule is applied, the direct load would still provide a useful estimate of the anticipated waiting time at a work centre. This further simplifies the rule compared with RWIQ and SWIQ.

3.2.8 *Forward Finite Loading (FFL)*

The forward finite loading method applied in this study is based on that presented by Bertrand (1983a, 1983b). Starting from the release date, the Operation Due Date (ODD) of a certain operation *k* at work centre *j* in the routing of an order is determined using Equation (18) below. The ODD of the last operation is the DD. The workload scheduled ($W_{t,j}$) and capacity available ($C_{t,j}$) at a certain time *t* at a work centre is reflected in the flow-time allowance factor $F(W_{t,j},C_{t,j})$; *b* represents the minimum flow time allowance.

$$ODD_k = ODD_{k-1} + p_k + b + F\left(W_{t,j}, C_{t,j}\right). \tag{18}$$

The way in which the DD and the $F(W_{t,j},C_{t,j})$ for each operation are determined is illustrated in Figure 3. First, the planning horizon is broken down into time buckets. Second, starting at the release date (ODD_0), the cumulative

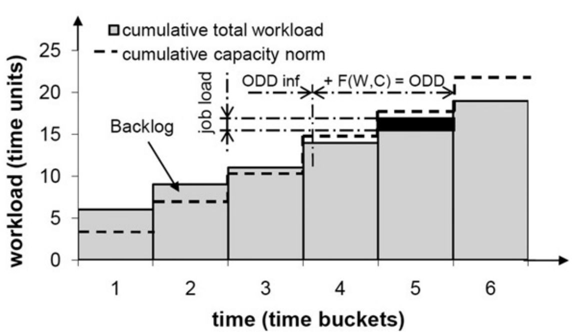

Figure 3. Methodology of the Bertrand approach (Bertrand 1983a, b).

workload is fit to the cumulative capacity in each time bucket as follows:

(i) If the time bucket into which the ODD_{inf} (which is equal to $ODD_{k-1} + b + p_k$) falls has sufficient capacity available to accommodate the order (i.e. without violating a pre-specified workload level), the job is loaded into the time bucket.
(ii) If no or insufficient capacity is available, the next time bucket is considered until the workload of the operation has been successfully loaded.
(iii) $F(W_{t,j},C_{t,j})$ is given by the resulting ODD (i.e. the end of the time bucket in which the operation has been loaded) minus the ODD_{inf}.
(iv) This procedure is repeated until all ODDs have been determined.

Finally, to account for the backlog (i.e. work either ahead or behind schedule), the load of an operation is subtracted from the cumulative load once an operation has been completed. The time buckets are set to one time unit; the available capacity per time bucket is set to 0.9 time units.

3.2.9 *Setting assembly due dates*

In the assembly job shop, there is only one final assembly operation; and, the assembly order is considered complete once its last work order has been processed. Therefore, the DD of the assembly order is set equal to the latest DD among its work orders (critical path). In the multi-stage job shop, there are several assembly operations, and the DD of the assembly order is determined by applying the same DD setting rule as in the preceding job shop. In addition, owing to the precedence of assembly operations, the time when the work order required for a particular assembly operation is expected to have been completed in the job shop (i.e. the work order DD) also has to be considered. The resulting DD setting policies can be summarised as follows:

- *Assembly Job Shop*: The assembly DD is given by the latest DD among all the work orders of an assembly order (the critical path).
- *Multi-stage Job Shop*: First, DDs are determined for each work order. Then, starting from the DD of the work order required at the first assembly operation (ODD_0), the assembly DD is determined by forward scheduling. For each assembly operation k, an ODD_k is determined by applying a DD setting rule step-by-step rather than in its aggregated form. The Earliest Operation Start Date (EOSD) of operation k ($EOSD_k$), from which the next operation is scheduled, is given by the maximum of the ODD of the preceding operation (ODD_{k-1}) and the DD of the work order required for operation k at the work centre ($WODD_k$); see Equation (19).

$$EOSD_k = \max(ODD_{k-1},\ WODD_k). \tag{19}$$

These DD setting policies apply for all rules except SIM. DDs are estimated for SIM based on the assembly lead time, which is obtained by simulation. Finally, the parameters for the DD setting rules have been set to values that minimise the mean absolute lateness (i.e. mean lateness approximates to zero). These parameters have been determined through preliminarily simulation experiments. The resulting parameters for the four different utilisation levels considered in this study are summarised in Tables 2 and 3 for the assembly and multi-stage job shop, respectively. The preceding job shop is the same in both simulation models – i.e. in the assembly and multi-stage job

Table 2. Parameters for the assembly job shop.

Due Date setting rule	75% utilisation	80% utilisation	85% utilisation	90% utilisation
TWKCP	$C_1 = 4.2$	$C_1 = 5.4$	$C_1 = 6.8$	$C_1 = 9.8$
FIL	$a = 3.7$	$a = 4.9$	$a = 6.5$	$a = 9.7$
CPFT	None	None	None	None
RWIQ	$C_1 = 2.3,\ C_2 = 0.18$	$C_1 = 2.3,\ C_2 = 0.19$	$C_1 = 2.7,\ C_2 = 0.19$	$C_1 = 3.3,\ C_2 = 0.19$
SIM	$C_1 = 1.55$	$C_1 = 1.7$	$C_1 = 1.9$	$C_1 = 2.3$
SWIQ	$C_1 = 0.275$	$C_1 = 0.27$	$C_1 = 0.265$	$C_1 = 0.257$
DWIQ	None	None	None	None
FFL	$b = 2$	$b = 2$	$b = 2$	$b = 3$

Table 3. Parameters for level 2 in the multi-stage job shop.

Due Date setting rule	75% utilisation	80% utilisation	85% utilisation	90% utilisation
TWKCP	$C_1 = 2.2$	$C_1 = 2.4$	$C_1 = 2.9$	$C_1 = 4$
FIL	$a = 4.1$	$a = 5.3$	$a = 8$	$a = 12.5$
CPFT	None	None	None	None
RWIQ	$C_1 = 1.3,\ C_2 = 0.22$	$C_1 = 1.3,\ C_2 = 0.23$	$C_1 = 1.3,\ C_2 = 0.23$	$C_1 = 1.2,\ C_2 = 0.23$
SIM	$C_1 = 1.6$	$C_1 = 1.7$	$C_1 = 2$	$C_1 = 2.4$
SWIQ	$C_1 = 0.27$	$C_1 = 0.267$	$C_1 = 0.259$	$C_1 = 0.24$
DWIQ	None	None	None	None
FFL	$b = 2$	$b = 2$	$b = 2$	$b = 2$

shop – and independent from subsequent assembly operation(s). Thus, for the multi-stage job shop, the parameters for the preceding job shop are the same as those given in Table 2; as a result, only the parameters for the level 2 assembly shop are given in Table 3.

3.3 *Dispatching rules*

Three dispatching rules are applied: the EJDD (Earliest Job Due Date) rule, which selects the job with the earliest DD; the Operation Due Date rule, which selects the job with the earliest ODD; and the First in System First Served (FSFS) rule, which selects the job that arrived first on the shop floor. Each DD setting rule is linked to a particular dispatching rule. For example, Roman and del Valle (1996) underlined the necessary link between SIM and FSFS dispatching; Bertrand (1983a, 1983b) emphasised the need for ODD dispatching when FFL is applied; and EJDD performed well with the WIQ, CPFT, and TWKCP rules in Fry *et al.* (1989b), Adam *et al.* (1993), and Smith *et al.* (1993). Table 4 summarises the DD setting and dispatching rules before Table 5 summarises the combinations of DD setting and dispatching rules applied in the experiments.

3.4 *Job characteristics*

Operation processing times in the job shop (i.e. level 1) follow a truncated 2-Erlang distribution with a mean of 1 time unit and a maximum of 4 time units. In a given experiment, the utilisation level is the same in the job shop (level 1) as in the assembly shop (level 2). Therefore, a constant of 2.5 time units is added to the truncated 2-Erlang distribution (mean of 1 and a maximum of 4 time units) for assembly times in the multi-stage job shop. The performance of the DD setting rules is assessed under four utilisation levels: 75%, 80%, 85%, and 90%. The inter-arrival time of assembly orders follows an exponential distribution with a mean of 2.72, 2.55, 2.4, and 2.27 time units, respectively. Tables 6 and 7 summarise the simulated shop and job characteristics, respectively.

3.5 *Experimental design and performance measures*

Experiments are full factorial for the eight different sets of DD setting and dispatching rules, the two assembly shop types, and the four utilisation levels. Each simulation experiment consists of 100 runs, and each run consists of 10,000 time units. The warm-up period is set to 3000 time units to avoid start-up effects. These simulation parameters are consistent with previous studies that applied similar job-shop models (e.g. Oosterman *et al.* 2000) and allow us to obtain stable results while keeping the simulation run time at a reasonable level.

The main performance measure considered in our experiments is the 95% reliable lead time (95% RLT) measure presented by Bertrand and Van de Wakker (2002). The 95% RLT is the lead time that would have to be quoted to the customer in order to achieve 95% delivery reliability; it therefore reflects a DD setting rule's ability to quote short and reliable DDs. Assuming the standard deviation of lateness approximates to a normal distribution function (Enns 1995, Hopp and Sturgis 2000, Bertrand and Van de Wakker 2002), the 95% RLT is equal to the average assembly lead time plus 1.645 multiplied by the standard deviation (σ) of the assembly order lateness (Figure 4). In addition to this measure, the average assembly lead time (i.e. assembly order completion date minus assembly order entry date) is also considered.

Table 4. Summary of Due Date (DD) setting and dispatching rules applied in this study.

Abbreviation	Full name	Classification	Brief description
TWKCP	Total Work Content Critical Path	Due Date Setting Rule	The DD is determined considering only the processing time of the order
FIL	Forward Infinite Loading	Due Date Setting Rule	The DD is determined by considering the processing time of the order and a constant estimation of the operation waiting time
RWIQ	Regression Based Work In Queue	Due Date Setting Rule	The DD is determined by regression considering the processing time and the total workload currently queuing and processing at a work centre in the routing of the order
CPFT	Critical Path Flow Time (adjusted)	Due Date Setting Rule	The DD is determined considering the processing time and an estimation of the operation waiting time. This estimate is given by the quotient of the number of jobs in the queue and the estimated arrival time to the work centres in the routing of the order.
SIM	Simulation Based	Due Date Setting Rule	A lead time estimate is obtained by a simulation considering all jobs currently on the shop floor
SWIQ	Simple Work In Queue	Due Date Setting Rule	The DD is determined considering the processing time and the total workload currently queuing and processing at a work centre in the routing of the order
DWIQ	Direct Work In Queue	Due Date Setting Rule	The DD is determined considering the processing time and the direct workload currently queuing and processing at a work centre in the routing of the order. Direct workload refers to this part of the total workload of the jobs in the queue that will be processed at the work centre.
FFL	Forward Finite Loading (Bertrand Approach)	Due Date Setting Rule	First, the planning horizon is broken down into time buckets. Then, the cumulative workload of each time bucket is fitted into the cumulative capacity for each time bucket to determine the Operation Due Date (ODD) of each operation. The ODD of the last operation is the DD.
EJDD	Earliest Job Due Date	Dispatching Rule	The job with the earliest DD is chosen from the queue
ODD	Operation Due Date	Dispatching Rule	The job with the earliest ODD is chosen from the queue
FSFS	First at System First Served	Dispatching Rule	The job with the earliest shop-floor entry time is chosen from the queue

Table 5. Experimental design.

	TWKCP	FIL	CPFT	RWIQ	SIM	SWIQ	DWIQ	FFL
EJDD	X		X	X		X	X	
ODD		X						X
FSFS					X			

Table 6. Summary of simulated shop characteristics.

Shop type	Assembly job shop; multi-stage job shop
Routing variability	Random routing, no re-entrant flows
No. of work centres (job shop)	6
No. of work centres (assembly shop)	Assembly job shop (1); multi-stage job shop (6)
Interchangeability of work centres	No interchangeability
Work centre capacities	All equal

Finally, the significance of the differences between the outcomes of individual experiments has been verified by paired *t*-tests that comply with the use of common random number streams to reduce variation across experiments. Whenever we discuss a difference in outcomes between two experiments, the significance can be proven by a paired t-test at a level of 97.5%.

Table 7. Summary of simulated job characteristics.

No. of work orders per assembly order	Discrete uniform[1, 6]
No. of operations per work order	Discrete uniform[1, 6]
Operation processing times	Truncated 2–Erlang, $\mu = 1$, max = 4
Assembly times (multi-stage job shop)	2.5 + a; a truncated 2–Erlang, $\mu = 1$, max = 4
Inter-arrival times	Exp. distribution, mean = 2.27; 2.4; 2.55; and 2.72
Set-up times	Not considered
Due Date determination	Special policy (see Section 3.2)
Complexity of product structures	Simple dependent product structures

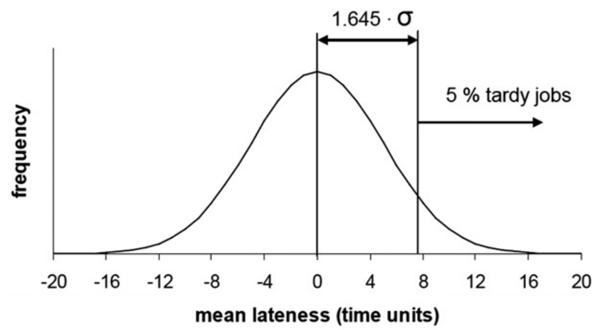

Figure 4. Standard deviation of lateness.

4. Results

This section outlines our results towards identifying the best-performing DD setting rules for assembly and multi-stage job shops. Results for the eight different rules (TWKCP, FIL, CPFT, RWIQ, SIM, SWIQ, DWIQ, and FFL) are presented in Section 4.1 for the assembly job shop before Section 4.2 presents results for the multi-stage job shop. As, in practice, managers may not wish to determine new parameters each time the shop situation changes, the sensitivity of results to uncertainty in parameters is discussed in Section 4.3. A final discussion is presented in Section 4.4 to conclude the presentation of results.

4.1 *Performance of DD setting rules in the assembly job shop*

The performance results for the assembly job shop are summarised in Table 8. In addition to the 95% RLT, the average lead time is given in parentheses.

The results confirm the superior performance of RWIQ, CPFT, and SIM over TWKCP. In fact, TWKCP is outperformed by all sets of rules in terms of 95% RLT, regardless of the utilisation level. This means that a shorter lead time can be quoted to a prospective customer while maintaining the same level of reliability or DD adherence. This supports prior criticisms of TWKCP, such as by Fry *et al.* (1989b). More specifically, the following can be observed:

- *TWKCP and FIL:* The results for these two rules are similar, as they have comparable structures. Both apply one parameter and only consider job information. The waiting time is accounted for by the coefficient in TWKCP and the additive term in FIL. The main difference in performance is due to the dispatching rule applied. EJDD favours small jobs, whereas ODD focuses on achieving a constant flow of small and large work orders on the shop floor. Assembly order performance in the assembly job shop depends on the progress of the critical path work order; therefore, EJDD leads to worse performance compared with ODD.
- *RWIQ, CPFT, SWIQ and DWIQ:* There is no significant difference between the performance of RWIQ, CPFT and DWIQ while SWIQ performs slightly better. As stated earlier (see, e.g., Section 3.2.6), there are differences in terms of the structure of these rules. CPFT, SWIQ, and DWIQ estimate the waiting time by applying one (or none) parameter, whereas RWIQ applies two parameters and gives a higher weighting to the processing time ($C_1 > 1$). The superior performance of DD setting rules that consider shop load information is due to the explicit consideration of this information, rather than the increase in flexibility that results from employing a second parameter. This is confirmed by the fact that SWIQ outperforms not only FIL and TWKCP, but also RWIQ.
- *SIM:* This rule performs better in terms of 95% RLT than TWKCP and FIL but is outperformed by all other rules. Determining DDs by SIM results in a high standard deviation of lateness. There are two reasons for this: (1) the FSFS dispatching rule, which does not consider the urgency or DDs of orders (compared with ODD or EJDD); and (2) the simulations tend to underestimate lead times owing to the

Table 8. Performance results for the assembly job shop.

DD setting and dispatching rule	75% utilisation	80% utilisation	85% utilisation	90% utilisation
TWKCP + EJDD	42.0[a] (23.7)[b]	51.7 (29.2)	66.5 (37.6)	94.9 (54.0)
FIL + ODD	39.6 (22.6)	49.4 (28.0)	63.1 (36.1)	92.5 (52.5)
CPFT + EJDD	31.7 (23.7)	37.7 (28.8)	48.5 (37.1)	65.7 (52.6)
RWIQ + EJDD	32.2 (23.7)	37.9 (28.8)	47.6 (37.1)	65.8 (52.7)
SIM + FSFS	32.7 (21.3)	40.2 (25.6)	54.0 (33.0)	76.4 (45.9)
SWIQ + EJDD	31.3 (23.7)	37.1 (29.1)	46.8 (37.3)	64.1 (52.9)
DWIQ + EJDD	31.5 (24.0)	37.3 (29.2)	48.2 (37.4)	66.2 (52.7)
FFL + ODD	25.5 (21.1)	29.6 (25.3)	36.2 (32.0)	49.9 (45.8)

Notes: [a]95% reliable lead time; [b]lead time.

Table 9. Performance results for the multi-stage job shop.

DD setting and dispatching rule	75% utilisation	80% utilisation	85% utilisation	90% utilisation
TWKCP + EJDD	67.1[a] (43.2)[b]	81.2 (51.6)	103.5 (64.9)	146.3 (90.7)
FIL + ODD	69.2 (45.1)	84.0 (54.3)	106.1 (68.4)	149.7 (95.9)
CPFT + EJDD	56.2 (43.3)	66.0 (51.6)	82.7 (65.0)	111.6 (90.10
RWIQ + EJDD	56.6 (43.5)	66.1 (51.8)	81.5 (65.3)	112.0 (91.6)
SIM + FSFS	77.7 (42.9)	93.6 (50.6)	121.2 (65.2)	174.8 (93.2)
SWIQ + EJDD	56.1 (43.7)	66.2 (52.2)	82.2 (66.1)	110.8 (92.4)
DWIQ + EJDD	56.2 (43.7)	65.9 (52.0)	81.4 (65.3)	110.7 (90.4)
FFL + ODD	48.8 (40.4)	56.6 (47.6)	68.8 (59.4)	94.1 (83.5)

Notes: [a]95% reliable lead time; [b]lead time.

assumption that no new job arrives on the simulated shop floor – this underestimation is stronger when there is a high workload on the shop floor and weaker when the workload is low.

- *FFL:* The best performance in terms of 95% RLT across the eight DD setting rules is achieved by FFL. The methodology underlying FFL is similar to SWIQ, DWIQ, and CPFT. The difference is that SWIQ, DWIQ, and CPFT assign DDs while considering current congestion on the shop floor, whereas FFL estimates the future shop-floor congestion. FFL considers the load distribution over time (i.e. it explicitly considers the indirect load), estimating the future direct load to a work centre. If only the current load situation on the shop floor is considered, the problem is that the load situation might have changed dramatically by the time an order actually arrives at a work centre. As an example: the queue in front of a work centre is empty when a DD is assigned, but there is a high workload for the work centre still upstream (i.e. the work centre has a high indirect load). The estimated waiting time assigned is therefore zero, but when the work order eventually arrives at the work centre, the load previously upstream has also arrived, and the work order has to wait. A further advantage of FFL is that it levels or smoothes the workload over time by explicitly considering capacity constraints; this results in the shorter lead time observed for this rule.

4.2 *Performance of DD setting rules in the multi-stage job shop*

The results obtained for the multi-stage job shop are summarised in Table 9.

As for the assembly job shop, TWKCP is outperformed by CPFT, RWIQ, SWIQ, DWIQ, and FFL; however, in contrast to the assembly job shop, TWKCP performs better in terms of 95% RLT than FIL and SIM. More specifically, the following can be observed:

- *TWKCP and FIL:* TWKCP outperforms FIL in terms of the lead time in the level 2 assembly shop. This leads to better performance in terms of 95% RLT. As stated for the assembly job shop, EJDD favours small jobs, but here – and in contrast to the assembly job shop – this actually leads to a performance improvement because the progress of the assembly order is not entirely dependent on the critical path work order.

- *RWIQ, CPFT, SWIQ, and DWIQ:* There is no significant difference between the performance of these four rules. This finding further questions both the use of more than one parameter and the use of regression. It further underlines the suggestion that performance improvement compared with alternative rules is due to the explicit consideration of shop-load information rather than the increased flexibility obtained by introducing additional parameters.
- *SIM:* The performance of SIM clearly deteriorates compared with the assembly job shop; its performance in terms of 95% RLT is the poorest of all the rules applied in this study. This is due to the extremely high standard deviation of lateness. The lead time is similar to that achieved by the other rules, but variance increases. As the simulation time lengthens (i.e. as the lead time to be determined becomes longer), the simulated shop-floor environment becomes gradually less realistic – if the simulation time is too long, an order may even encounter a completely empty or idle shop floor. The reason for this is that jobs proceed faster through the shop floor than in reality, as it is assumed that no new jobs arrive on the shop floor. The resulting error is small for a short simulation runtime but increases exponentially the longer the simulation run continues.
- *FFL:* As in the assembly job shop, the best performance in terms of 95% RLT among all rules is achieved by FFL. FFL gains an advantage over alternative rules in two respects: (1) by effectively estimating the future direct load; and (2) by load balancing. Both result in shorter lead times, a lower standard deviation of lateness and a shorter 95% RLT.

Results for the multi-stage job shop generally support the results presented earlier for the assembly job shop. FFL performs the best in terms of 95% RLT, followed by RWIQ, CPFT, SWIQ, and DWIQ. As the preceding job shop and assembly shop are independent, the assembly shop does not influence work order performance. Therefore, the main difference in assembly order performance between the assembly and multi-stage job shops is due to the progress of the assembly order in the assembly shop.

4.3 *Sensitivity analysis of results*

The results presented in Sections 4.1 and 4.2 assumed that there are no changes in the average utilisation level. Thus, a unique and stable set of parameters can be determined for each shop situation. In practice, however, changes in the utilisation level are commonplace, but a manager may not wish to determine new parameters each time the situation changes. To address this issue, additional simulation experiments have been conducted in which the parameters are not adjusted for each utilisation level. This demonstrates the sensitivity of the results to the use of inaccurate parameters. As an example, Table 10 summarises the results for the DD setting rules obtained for the 80% and 90% utilisation levels by applying the parameters for 85% utilisation; hence, it shows the effects of a 5% shift in utilisation in both directions and a zero change in parameters. In addition to the 95% RLT, the mean lateness is given in parentheses to allow the impact on the accuracy of lead time estimates to be assessed.

Table 10. Sensitivity analysis – parameter setting.

DD setting and dispatching rule	Assembly job shop		Multi-stage job shop	
	80% utilisation	90% utilisation	80% utilisation	90% utilisation
TWKCP + EJDD	53.4[a] (–7.8)[b]	92.7 (14.3)	82.5 (–12.5)	145.2 (24.6)
FIL + ODD	51.8 (–7.6)	87.6 (12.4)	87.3 (–13.4)	146.3 (22.7)
RWIQ + EJDD	38.2 (–1.6)	65.6 (2.8)	66.3 (–1.6)	110.9 (2.3)
SIM + FSFS	41.4 (–2.8)	74.7 (7.3)	100.5 (–8.2)	165.5 (14.3)
SWIQ + EJDD	37.3 (1.3)	64.7 (–1.1)	66.0 (1.6)	112.5 (–3.4)
FFL + ODD	29.6 (0.0)	49.1 (0.6)	56.6 (0.0)	94.1 (0.0)

Notes: [a]95% reliable lead time; [b]mean lateness.

The following can be observed from the results:

- *Assembly Job Shop:* Compared with the results from Sections 4.1 and 4.2, a significant difference in 95% RLT can be observed for TWKCP and FIL. As expected, both rules show the highest mean lateness. The estimated lead time is equivalent to that estimated under 85% utilisation, as these rules do not reflect the increase in the workload on the shop floor. If the utilisation level increases, the (lower) parameter leads to an underestimation of the lead time. This results in a slightly better performance in terms of 95% RLT, but this is offset by the inaccuracy of the lead-time estimates. RWIQ, SWIQ, and FFL show the lowest mean lateness, and performance is robust to changes in the utilisation level.
- *Multi-Stage Job Shop:* The results obtained are similar to those for the assembly job shop. Compared with the results from Sections 4.1 and 4.2, a significant difference in 95% RLT can be observed for FIL and SIM. TWKCP, FIL, and SIM are the most inaccurate – they show the highest mean lateness. RWIQ, SWIQ, and FFL show the lowest mean lateness, and performance is robust to changes in the utilisation level.

From the above, it can be concluded that the setting of accurate parameters that reflect the shop situation is an important issue for TWKCP, FIL, and SIM. RWIQ, SWIQ, and FFL are able to accommodate changes in the utilisation level, as they reflect the current workload situation on the shop floor. A concluding discussion of results now follows in Section 4.4, before final conclusions are drawn in Section 5.

4.4 *Discussion of results*

As in previous research (e.g. Fry *et al.* 1989b, Adam *et al.* 1993, Smith *et al.* 1995), RWIQ and CPFT improved performance compared with TWKCP. Fry *et al.* (1989b) and Smith *et al.* (1995) identified RWIQ as the best-performing DD setting rule, while CPFT was considered the best by Adam *et al.* (1993). In this study, two new rules were introduced: (1) SWIQ, a single-parameter TWKCP + WINS based rule to allow comparison with CPFT; and (2) DWIQ, a 'zero-parameter' rule (i.e. a rule that requires no parameters to be set whatsoever). Our results show that there is almost no difference between these rules in terms of feedback requirements or performance. All four require information on the current workload in the queue of a work centre. The main difference is the number of parameters that need to be set or specified. Adam *et al.* (1993) questioned Fry *et al.*'s (1989b) use of regression analysis with historical data (for the RWIQ rule), but the rule proposed by Adam *et al.* (1993) – CPFT – is also heavily dependent on the accuracy of historical data. For CPFT, it is important to keep track of lead times and the lateness of orders to adjust the estimated lead time. Moreover, the performance of RWIQ was not sensitive to changes in the utilisation level. Here, it is argued that the dynamic nature of the shop floor is already represented by the feedback loop for the shop-floor workload, and this questions the need for a further dynamic parameter, e.g. the adjustment factor in the CPFT rule. But this study questions the need of all three: for multiple factors, regression analysis and adjustment. A simple single-parameter rule based on TWKCP + WINS performs similar to, or even better than, rules based on multiple factors. This significantly simplifies the setting of parameters and avoids the need for regression. Meanwhile, the newly introduced DWIQ rule does not require any parameters to be specified at all, making it simple to apply in practice.

SIM and FIL did not 'live up' to their good results from previous studies: both were outperformed in terms of 95% RLT by the above rules under all tested conditions. FIL (Bertrand and Van de Wakker 2002) performed slightly better than TWKCP in terms of 95% RLT in the assembly job shop but was outperformed by TWKCP in the multi-stage job shop. This difference in performance is mainly due to the influence of the accompanying dispatching rule. SIM (Roman and del Valle 1996) has the potential to outperform TWKCP, but performance depends heavily on the simulation (and thus assembly) time.

The best performance was achieved by Forward Finite Loading (FFL – as presented by Bertrand 1983a, b), supporting our argument for the need to introduce rules that consider detailed workload information over time to the assembly and multi-stage job shops found in practice. FFL requires operation completion information to be fed back from the shop floor, but this is also required by CPFT, RWIQ, SWIQ, and DWIQ. The main difference between FFL and these other rules is twofold: (1) FFL uses this information to estimate the future direct load to a work centre, considering the indirect load, and (2) FFL takes capacity constraints into consideration, thereby balancing the load. Compared with TWKCP, performance improvements approaching 50% in terms of 95% RLT are evident in the assembly job shop and approaching 30% in the multi stage job shop.

Finally, the following important managerial implications can be derived:

- The study has re-emphasised the argument that information on the current shop-floor workload should be considered when determining DDs (Weeks 1979, Ragatz and Mabert 1984, Fry *et al*. 1989b). This is likely to require technology for feeding back information from the shop floor to a central planning function in a timely manner and may mean that significant investment is first required. However, here it is argued that any costs would be offset by the benefits of improved performance.
- The DD setting rule applied in practice should be either DWIQ or FFL. DWIQ excels in its simplicity, with a performance equalling that of most alternative rules presented in the literature without requiring any parameter to be specified or historical data to be collected. FFL is more complex and requires one parameter to be specified, but this is offset by its outstanding performance in terms of 95% RLT, which allows the DD quoted to be short and reliable.

5. Conclusion

DD setting is a critical early planning and control task. While there is a broad literature on DD setting for standard job shops and simple product structures, literature on DD setting in the context of assembly and multi-stage job shops is scarce. The limited available literature provides no clear message regarding which rules should be applied in the assembly and multi-stage job shops found in practice. This is an important research gap given that infeasible DDs negatively affect the performance of subsequent control levels (e.g. order release, scheduling and dispatching) and can lead to either poor overall performance or constant 'fire-fighting' on the shop floor. This paper provides an update to the contribution by Fry *et al*. (1989b), assessing the performance of DD setting rules from the literature in assembly and multi-stage job shops. New rules (SWIQ and DWIQ) have been introduced that simplify existing rules (RWIQ and CPFT); for example, DWIQ does not require any parameters to be specified whatsoever, improving applicability in practice. In addition, a rule from the wider job-shop literature has been introduced into the context of assembly shops (FFL). Of the eight DD setting rules tested in this paper, FFL performs the best followed by DWIQ, SWIQ, RWIQ, and CPFT. It is concluded that FFL should be used in assembly and multi-stage job shops if quoting short and reliable lead times is the main objective. Performance improvements in terms of shorter and more reliable lead times should translate into financial benefits (e.g. more repeat orders, less late delivery penalties, etc), and this should compensate for the greater complexity and, where necessary, any investment required prior to implementation (e.g. in technology). But DWIQ represents a viable alternative owing to its simplicity and should be the first choice for companies looking for a simple means of improving performance. It does not require any more than keeping track of the current direct load in front of a work centre.

The main limitation of this study is that all DDs are assumed to be set internally by the company using a DD setting rule. In practice, however, a certain percentage of DDs are likely to be set externally, i.e. specified by customers, and not determined internally by the DD setting rule. Therefore, future research should consider how these orders can be handled at the higher planning levels. Another important issue is to assess whether performance improvements achieved in previous scheduling research also hold if more effective rules than TWKCP are applied for DD setting. This should provide guidance for practitioners as to which control level plays the key role and how DD setting and scheduling can be combined effectively.

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