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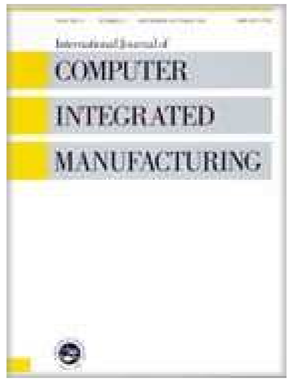

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A multi-objective comparison of dispatching rules in a Drum-Buffer-Rope production control system

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Abstract

The advantages of the TOC (Theory of Constraints) philosophy have been extensively documented in the literature since its introduction during the 80s. At the operational level, TOC is implemented by means of the well-known DBR (Drum-Buffer-Rope) production control system. In a multiproduct manufacturing environment, the performance of DBR is greatly affected by the dispatching rules employed in front of the bottleneck station. Furthermore, it has been proved that no single Dispatching Rule (DR) performs globally better than any others. Therefore, for systems usually influenced by variability conditions, the selection of a robust DR could help practitioners to reach a good system performance. In this paper we propose a methodology to obtain a robust DR (by means of Taguchi signal-to-noise ratio) from a set of previously selected rules according to the performance measures of the system pursued by the practicing managers. We study the performance of different dispatching rules for several conflicting objectives (namely average tardiness, maximum tardiness, and WIP) from a robustness viewpoint and for a range of manufacturing scenarios in a shop floor formed by five stations in line and three different products. Different variability sources, such as processing times, breakdowns and set-ups, are discussed. The results obtained are of special interest for practitioners.

Keywords: Production Control systems; Drum-Buffer-Rope; Theory Of Constraints; Taguchi; Multi-objective.

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1 Introduction

Manufacturing management switched during the 70s from mass production -and Just in Case (JIC)- to Just in Time (JIT). JIT is usually implemented at the shop floor level by means of the well-known Kanban production control system (Monden, 1983), initially developed for Toyota and successfully put into practice in a wide variety of manufacturing environments. After the JIT revolution, the Theory of Constraints (TOC) appeared in the 80s, focusing on identifying and exploiting system's constraints. Similarly to JIT, TOC is implemented at the operational level by means of the so-called DBR (Drum-Buffer-Rope) production control system (Goldratt and Fox 1986). Since its introduction, DBR has attracted a great deal of attention both from scientist and practitioners. Among the main contributions of theoretical nature, it is worth to mention Schragenheim and Ronen (1990, 1991), Daniel and Guide (1997), Simons *et al.* (1999), Kodipasaoglu *et al.* (2000), Sivassubramanian *et al.* (2000), Chakravorty (2001), Blackstone (2002), Gilland (2002), Riezebos *et al.* (2003), or Koh and Bulfin (2004), while the following works focus on practical implementations and applications of DBR: Guide (1996), Russel and Fry (1997), Kempf (1998), or Corbett and Csillag (2001).

In an extensive series of experiments, Duenyas (1994) shows that the most important feature affecting the performance of a production control system is the input control (i.e. when to release a job into the system), and that scheduling decisions (which type of job to be processed) are strongly dependent on input control and on the position of the bottleneck in the system. As in the DBR production control system there exist a strong relationship between the buffer in front of the bottleneck and the input control in the system, scheduling the jobs in front of the bottleneck seems to play an important role in the performance of this system. This aspect was previously stated by Baker (1984) when studying a simplified model, stressing the importance in the interconnection between the input control and the scheduling procedure.

Among the different approaches to schedule jobs in a system, dispatching rules (DRs) are widely used in practise, particularly in these scenarios where manufacturing is affected by different sources of variability, as global scheduling seems to be unsuitable in these cases. Indeed, Aytug *et al.* (2005) and Lawrence and Sewell (1997) remark that for systems with high uncertainty (as in the system under consideration in our work), completely reactive algorithms (i.e. dispatching rules) can be used with relative confidence and question the benefits of global scheduling procedures. In this line, the influence of priority rules on the performance of different production control systems has been studied by several authors (see e.g. Montarezi and Van Wassenhove (1990), Kayton *et al.* 1997, Lixing *et al.* (2000), or Lee *et al.* (2009).

The previous works compare the performance of a set of dispatching rules for a specific manufacturing scenario according to a single criterion. However, when selecting a suitable dispatching rule in practice, one should balance several (usually conflicting) criteria. This is a key issue, as previous simulation studies show that no single dispatching rule outperforms the other for every objective (see e.g. Montazeri and Van Wassenhove, 1990, or Pierreval and Mebarki, 1997). Focussing specifically on the DBR system, some contradictory results are found. Chakravorty (2001) stressed in his conclusions that more research regarding the influence of the DRs in DBR systems should prove to be useful for both researchers and practicing managers. The author only studied the SPT and FCFS rule, obtaining better results for the SPT rule. These results seem to be contrary to those obtained by Schragenheim and Ronen (1990) and Umble and Srikanth (1990) which obtained a poor performance of SPT. Furthermore, Kayton *et al.* (1996) and Kayton *et al.* (1997) studied the FCFS and the CR rule, showing that the best performance was obtained by the CR rule. Daniel and Guide (1997) focused their work in the influence of the DRs for non-bottleneck buffers, obtaining the better results for the FCFS and EDD rules. Other results have been obtained for different shop floor conditions, such as assembly and shared machines (Kayton *et al.* 1997), reprocessing (Daniel and Guide 1997), or job shop environments (Chakravorty 2001).

It is clear that DR performance is highly influenced by the production scenario, but it is also obvious that changes in the manufacturing environment due to the inherent variability of the shop floor can influence this performance as well. Therefore, it is not useful to select a dispatching rule if its performance quickly deteriorates when the initial conditions change due to breakdowns, unbalancing, set-ups, etc. In order to correctly select a DR, two possible approaches can be distinguished: (1) introducing a more or less sophisticated mechanism that dynamically switches in real-time the DR and select the best one, according to the environmental conditions, or (2) selecting a robust DR, i.e. using a DR which can stand different environmental changes. The former approach is known as Switch From Standard Rules (SFSR) heuristics (see Ramesh, 1990 for a survey of dynamic DRs). Some recent works used a Neuronal Network for a dynamic selection of DRs (see e.g Mouelhi-Chibani and Pierreval, 2009). Lee *et al.* (2009) based their approach on a model based on the extended object oriented Petri nets (EOPNs). To our best knowledge, the second approach (selecting a robust DR) is novel and constitutes the main contribution of this paper. Although the main advantage of the SFSR approach is its efficiency, these methods are too much sophisticated and require a real-time monitor in order to be implemented in practise. This aspect goes against the TOC philosophy and DBR, which advocate easy methods to be used in practise. Therefore, our work focuses on the second approach, analysing the influence of dispatching rules in the performance of a DBR system and trying to determine the most robust one under certain variability conditions.

In order to do that, we first conduct an experimental design based on several sources of variability taken from real manufacturing environments, i.e.: stochastically time process, unbalanced lines, machine breakdowns or set-up times. By using simulation, three locally performance measures widely used in manufacturing practice, i.e.: average tardiness, maximum tardiness, and average work in process (see e.g. Blackstone *et al.*, 1982, Baker, 1984, or Lalas *et al.*, 2006) are calculated. Finally, the global performance of each dispatching rule for different scenarios is computed according to its robustness, employing Taguchi's robustness concepts, which are widely used in selection problems (see Taguchi, 1996 and Moeeni *et al.*, 1997).

The remainder of this paper is organised as follows: In section 2, the DBR production control system is described. Section 3 is devoted to describe the conditions of the experiments, such as flow line parameters, simulation parameters, selected DRs, local and global performance measures, and scenarios. Section 4 shows the main results of the experiments, while the last section is devoted to obtain conclusions and remark future research work.

2 Drum-Buffer-Rope production control system

The DBR production control system is derived from the Theory of Constraints (TOC) introduced by Goldratt during the 80s (see e.g. Goldratt and Cox, 1984). It is known that a great number of companies have implemented TOC successfully (Mabin and Balderstone, 2000), while there is a certain interest in the mechanism among practicing managers (Erenguc *et al.* 1997). This methodology was a result of previous studies and the development of the production planning software known as OPT (Optimized Production Technology). TOC is based on the premise that the rate of goal achievement is limited by at least one constraining process. Only by increasing flow through the constraint can overall throughput be increased (see e.g. Goldratt and Cox, 1984). From the 90s up to now, TOC concepts were opened to the management field, being this extension known as Thinking Process, TP (see e.g. Goldratt, 1990, or Ye and Han, 2008).

The Five Focusing Steps of TOC are (Goldratt, 1990):

1. Identify the system constraint(s)
2. Exploit the constraint(s)
3. Subordinate all other decisions to step 2
4. Elevate the constraint
5. If constraint has moved, return to step 1. Don't let inertia become the constraint.

At the shop floor level, TOC is usually implemented by means of the DBR production control system. DBR is composed by three elements: Drum, Buffer and Rope. Goldratt and Cox (1984) show that the lower capacity station governs the throughput rate of the entire manufacturing line. This station is known as the 'drum', or CCR (Capacity Constraint Resource). The input control mechanism is the 'rope', and it is based on the utilization of the bottleneck. Finally, the 'buffer' represents the time period for an early arrival of jobs to the bottleneck from the entrance in the system. A detailed description DBR production control system can be found in Goldratt and Cox (1984), Goldratt and Fox (1986), Schragenheim and Ronen (1990) or Spencer and Cox (1995).

Two alternative input control mechanisms could be employed in the DBR system (Goldratt, 1990): In the first case ('time buffer'), an input rate is established, while the work in process (WIP) upstream the CCR fluctuates according to the stochastic behaviour of the system. Note that this rate should be periodically adjusted, otherwise it can result in infinite WIP. In the second case ('WIP buffer'), WIP upstream the CCR is established, while input rate fluctuates. Most authors (see e.g. Lambrecht and Segaert, 1990, Ramsay *et al.*, 1990,or Gilland, 2002) adopt the latter mechanism in their works, thus describing a DBR control system which limits the maximum WIP upstream the bottleneck by using cards to authorise the entrance of jobs in the system. This mechanism is similar to the Conwip production control system (Spearman *et al.*, 1990), although the latter limits the WIP in the whole system. In Figure 1 is shown a typical implementation of the WIP-buffer DBR system for a line formed by five stations in tandem, with a bottleneck station in the central position.

[Insert Figure 1 about here]

Figure 1. WIP-buffer DBR implementation

In Figure 1, the flow of material is shown in continuous line, while the flow of cards is represented in doted lines. The input control procedure is as follows: a job can enter the system if there is at least one card in the control panel. If so, the card is attached to the job until the job finishes it operation in the CCR. Once the job exits the CCR, the card is released and sent back to the control panel. Clearly, the maximum WIP is bounded by the number of cards in the system, being this number the main parameter governing its performance.

[Insert Figure 2 about here]

Figure 2. WIP-buffer DBR implementation for three type of products

As discussed before, the WIP upstream the CCR is limited by employing cards. As we consider a multi-product environment, individual cards counts can be set for each job (M-Closed input rule), or by establishing a single card count for all jobs (S-Closed input rule). Since Duenyas (1994) and Framinan *et al.* (2000) show that M-Closed is more effective than S-Closed, different card counts are employed for each product type (see Figure 2). In the system under consideration, the type of product that is allowed to enter the system is determined by the type of cards available in the control panel, and consequently there is no need to establish an input sequence for the jobs. Although in the long term time-buffer and WIP-buffer approaches are intertwined with Little's Law, in the sequel we adopt the latter, as it is the most often described and employed in practise.

3 Research Methodology

The research methodology is presented in five sections. First, we describe the model and hypotheses considered in the subsequent experiments. Next the selected DRs are introduced. Local performance measures for the system working under a certain DR are explained and the global performance measure to be computed for each DR over all scenarios is explained through the robustness concept, as well as the way to compute it. Finally, the scenarios to be conducted are presented. The proposed methodology can be summarized in the following steps:

1. System description. As mentioned earlier, DRs are very sensitive to the type on system (flow-shop, job-shop, assembly, etc,...). Detail all sources of variability in the system: set-up, breakdowns, re-entrant flows, etc,... They will be considered as noise factors in order to compute the robustness.
2. Selection of local performance measures. Take into account the performance measures for the environment as well as the management point of view: average tardiness, WIP, service level,... These local criteria will be used also as noise factors, in order to obtain robust DRs under different performance measures.

3. DRs selection, according to the local performance measures can be selected some DRs than shown in literature to perform well literature. We could also based on previous experiences.
4. Definition of the Scenarios, taking into account every source of variability and every performance measure. The system is modelled and a simulation design of experiments is conducted.
5. Definition of Global performance measures. Compute the robustness of the different DRs in order to obtain the most robust DR or a ranking of rules.

3.1 System description

Our study focuses on a flow-line formed by five stations in tandem using the DBR system shown in Figure 2. The problem under consideration is based on a real-life problem encountered at a gear-box factory, where three types of parts have to be produced in the same line, sharing the same machines, and later assembled in the gear box. In this line, the machines had breakdowns as well as set-up times were necessary in order to change the tools. These variables, based on a real-life problem are introduced in our model. We consider infinite raw material availability in the first station, i.e. jobs may enter the system if there are kanbans available for this job type in the control panel. The work in process (WIP) start counting once the job is entered the system. This is a common assumption in this type of simulation studies (see e.g. Bonvik *et al.*, 1997). Each station is composed of an input buffer and a machine. We consider three different types of products (I, II and III), sharing the same bottleneck under a make-to-order environment. The bottleneck is located in the central station of the line. Every buffer operates under a FCFS (First Come First Served) dispatching rule as suggested by Umble and Srikanth (1990), with the exception of the CCR buffer, which could follow different dispatching rules. For every type of job is defined a target level of jobs produced in the simulation period, defined as the 20%, 30% and 50% for jobs type I, II and III respectively.

The system variability was modelled through processing time variation, CCR downtime and set-up times inclusion, following the recommendations of Law and Kelton (1991) and trying to reproduce a hypothetical situation of a real environments. Processing times were generated from a log-normal distribution with means 15.0, 10.0 and 5.0 and a coefficient of variation (*cv*) equals to 0.2. The system performance is studied according two different levels of the CCR processing times, increased a 15% or 30% regarding to the processing times of the non-bottleneck stations. Additionally, we consider system downtime and set-up in the CCR for certain scenarios. These are only considered for the bottleneck station, as it has been shown that fluctuations in the bottleneck station influence the performance of the system more than similar fluctuations in other stations (see e.g. Fry *et al.*, 1992). Breakdowns were generated by exponential distributions with mean of 100 for the *MTBF* (Mean Time Between Failures) and 25 for the *MTTR* (Mean Time To Repair). This constitutes a system down time of 20%, or an availability of *MTBF*/(*MTBF*+*MTTR*) equals to 0.8. The CCR utilization rate was established to 95% for those scenarios without downtimes and 80% for those with breakdowns. For those scenarios with set-up times, a set-up time generated by a log-normal with mean a set-up time of 100 and a *cv* of 0.2, each time a new type of job is processed on the bottleneck. Finally, in order to set the due-dates of each job, we consider that at least a 10% of the jobs are considered as urgent, similar to Kayton *et al.* (1997). Thus for jobs released at time t, the due dates DD_i of job i are given by $DD_i = t + K \cdot \sum_j t_{ij}$, where:

t_{ij} is the mean processing time of job i in machine j at time t.

K is the allowance factor generated by a uniform distribution $U(1.5,2)$ for normal jobs, and $U(0.5,1.5)$ for urgent jobs.

By using this method we can obtain a certain guarantee about the independence of the DD_i, avoiding the correlation of due dates with certain rules. Additionally, has been taken into account some constrains regarding the throughput for every product type. Therefore, it was established that the percentage of finished jobs in the simulation horizon for every type of job should be greater than a target value less an allowance factor of 5%. Thus, the target throughput mix is 20%, 30% and 50% for products I, II and III respectively.

3.2 Local performance measures

The system's performance was measured locally for every scenario using three different criteria. Two criteria were used to asses the system's ability to deliver in time. One criterion was the mean tadiness. Previous research has shown that mean tardiness, $\overline{T}$, measured as the average amount of positives times by wich the completion time of a job exceeds its due date, are good measures to evalute the performance of scheduling systems (Blackstone *et al.*, 1982). The other criterion was the maximum tardiness, $T_{\max}$, (see e.g. Lalas *et al.*, 2006). The last studied criterion was the average work in process, $\overline{WIP}$, i.e. the average amount of jobs in the line (see e.g. Chang *et al.*, 1996). Usually, the mean flow time is measured, however, Baker (1984) has shown that there is a direct relationship between $\overline{WIP}$ and mean flow time.

3.3 Selected Dispatching rules

The selection of a set of candidate DRs is not an easy task, because of the contradictory results reported in literature and the vast research regarding the topic. There are several reviews: see e.g. Blackstone *et al.* (1982), Baker (1984), Montarezi and Van Wassenhove (1990), Ramesh (1990), Engell and Moser (1992), or Panwalkar and Iskander (1997) who classified 113 DRs. However, a universally accepted result of these studies is that no DR performs globally better than any others (Pierreval and Mebarki, 1997). Therefore, in our study it seems reasonable to use some DRs according to the environment and performance measures selected in the previous steps. According to that we have selected the following DRs: SPT, SRPT, LPT, SI, EDD, LS, CR, FCFS and SRO. DRs based on times (such SPT or SRPT) performs well on minimising the mean flowtime (or minimising the WIP), but obtain poor results for other criteria such minimising the maximum tardiness. The LPT is introduced as a benchmark for a comparison against other time-based rules. Rules based on due dates could work well in order to produce a delivery of jobs in time. This is the reason to include EDD, LS, CR, and the SI rules (in the appendix, the reasons to consider the SI rule as a due date based DR are explained). The NSUT rule could be interesting for this environment under set-up events. The FCFS rule is also included because it works well for a wide variety of conditions. Finally, the random selection rule, SRO, it is included in the study as a benchmark for all the DRs. Details of these DRs are included in the appendix section.

Note that the selection of these rules has been done taking into account also those focused on their influence in the performance of a DBR system (see e.g. Schragenheim and Ronen, 1990; Daniel and Guide, 1997; Chakravorty 2001). Finally, we also take into account the work of Fry *et al.* (1992), who discuss the influence of set-up times in the bottleneck.

3.4 Scenarios

In our analysis we consider two different scenarios depending on the absence or existence of set-up times (scenarios A and B, respectively). For each scenario, we consider two different situations depending on the values of two parameters: Δt_b, the increment of processing time in the bottleneck station (which can take the values +15% or +30% compared to those in other stations, as described in a previous section), and the existence or not of machine breakdowns (typed as YES or NOT), with the *MTBF* and *MTTR* values described in section 3.1. The combinations of the mentioned two variables –that is, a 2^2 or full factorial design– yields four different experiments for each scenario to test each dispatching rule. The full study implies a total amount of 228 experiments. For each mean value, a 99% confidence interval has been taken into account. For each scenario has been obtained the best set of kanbans that reach the best performance for the studied scenario using the ARENA 12.0 simulation software and the OptQuest optimization tool. Regarding the simulation horizon, some pilot experiments were conducted to appropriately set a single long run of 350 10^3 time units and a warm-up of 10^3 in order to obtain statistically reliable results.

3.5 Global performance measure: Robustness

As mentioned earlier, there is a vast body of research dealing with the DR, and a few works studying their influence in the DBR system under different criteria. However, to our best knowledge, there is not study trying to determine the DR under different variable conditions and taken into account all different criteria globally. Regarding to this concern, the robustness concept may play an important role in order to assess the practitioners for a DR – or a ranking of DRs – which may be applicable to some real life scenarios. The Taguchi's robustness concepts were traditionally used as tools to select among different products, process or services (see e.g. Moeeni *et al.*, 1997; Taguchi and Wu, 1980; Taguchi, 1986). Although Taguchi methods are not free of criticism, they have been successfully applied on a great variety of industrial environments. Taguchi methods are based on the concept of *off-line quality*, trying to identify the products, process or services which are robust in the sense that are less variable under changes in the environmental conditions, employing a signal-to-noise ratio to select the most robust product/process (see Taguchi and Wu, 1980; Taguchi, 1986).

Therefore, one could address the selection among the different dispatching rules, working under some variability conditions, as a Taguchi Robustness problem. To do so, the relative utilization of the bottleneck by using different increase (Δt_b) of processing time at bottleneck station, and breakdowns can be considered as environmental noise factors. Furthermore, the different performance measures are also computed as noise factors, because the global performance over all responses is also a robustness aspect of interest. The distance, *d*, measured as the percentage deviation of the obtained performance of a certain DR respect to the best result can be considered a quality characteristic to be computed. Hence, the main idea is to select the dispatching rule reaching the smallest distance to the efficient solution for every combination of environmental noise factors. This can be done by means of the following expression (Taguchi, 1986):

$$\eta = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} d_i^2\right) \tag{1}$$

where:

η is the signal-to-noise ratio (in decibels)

n is the number of experiments (12 in this case)

d_i is the response for a certain experiment

Signal-to-noise ratio is computed for different noise factors. Under Taguchi's point of view, one system is better if its signal-to-noise ratio is higher. Finally, note that the expression (1) is advised to be employed in quality responses under 'smaller the better criterion', which is the case in our study as the response is the d_i distance. In our case (minimization problem) the signal-to-noise ratio is a simple transformation of the squared difference across different scenarios. Nevertheless, for different optimisation criteria, alternative expressions should be employed (see e.g. Taguchi, 1986).

4 Results

Mean values for *d* on every local performance criterion are shown in order to obtain an idea of the distance from a particular DR to the DR which better performs. Values close to zero indicate that the system performs near to the best obtained DRs. Finally, we compute the signal-to-noise ratio, which takes into account the mean values and variance effects. The so-obtained results are presented for the different scenarios.

4.1 Scenario A (set-up times not included)

In this scenario, the NSUT rule is omitted in the comparisons, as it is only applicable in scenarios with set-up times. Tables 1 to 3 show the results for the distance, *d*, of the best solution found for each DR respect to the best. The distance has been divided in zones of preference from $z^{(1)}$, were results are promising to $z^{(4)}$, containing DR far to be the best. Each table contains the results for a different local performance measure.

For the criterion of minimising the average tardiness, it was expected that those DR based on due dates may obtain a better result than other rules. Thus, rules EDD, SI and CR are always in the best interval, $z^{(1)}$, respect to the best result found. However, the LS rule, also based on due dates, does not reach competitive results reaching 3 results in the zone $z^{(2)}$. This performance may be produced by the influence by the variability in cycle times, which are used to compute the priority. CR obtains better results in the more balanced scenarios, $\Delta t_b = 15\%$. FCFS obtains moderate results, since $11.9 \le d \le 26.2$. Regarding to the time based rules, it is important to note that SPRT always obtains better results than SPT. Furthermore, SPT yields the worst results in balanced scenarios ($\Delta t_b = 15\%$), even when compared with the random selection rule SRO. LPT rule is included in $z^{(1)}$ for 3 of the 4 experiments, reaching better results than other time based rules. As a summary, the best results are reached for this criterion by the SI, EDD, and CR rules.

Breakdowns	**NO**		**YES**	
Δt_b	**15%**	**30%**	**15%**	**30%**
$z^{(1)} : 0 \le d < 25$	EDD 0.0 SI 0.3 CR 0.4 LPT 5.6 FCFS 11.9	SI 0.0 EDD 1.1 CR 6.6 SPT 14.9 FCFS 20.5 SRPT 20.7	SI 0.0 EDD 0.8 CR 4.5 LPT 20.6	SI 0.0 EDD 1.0 FCFS 13.3 CR 15.4 LPT 18.7 SRPT 22.2
$z^{(2)} : 25 < d \le 50$	LS 47.1	LPT 27.9 LS 32.0	FCFS 26.2 SRPT 38.4 LS 39.7	SPT 30.9
$z^{(3)} : 50 < d \le 75$				
$z^{(4)} : 75 < d \le 100$	SRO 76.9 SRPT 78.8 SPT 100.0	SRO 100.0	SRO 80.5 SPT 100.0	SRO 83.2 LS 100.0

Table 1. Results for scenario A, $\min \overline{T}$

For the criterion of minimising the maximum tardiness, the results are still clearer that in the previous criterion, in the sense that due date based DR should obtain better results. The SI, EDD, FCFS and LS rules reached the best results always in $z^{(1)}$. Exceptionally, the FCFS rule is the only one that is not based on due dates. It is important to note that the LS rule, which obtained poor results under the criterion of minimizing the average tardiness, seems to work well under maximum tardiness minisation. The CR rule, although due date -based, obtains poor results – close to the SRO rule –, under this criterion. As expected, the time-based rules do not obtain good results, with the exception of the LPT rule, which works in acceptable manner for scenarios under breakdowns. As a summary, the best results are reached for this criterion by the SI, EDD and FCFS and LS rules.

Breakdowns	NO		YES	
Δt_b	15%	30%	15%	30%
$z^{(1)}: 0 \le d < 25$	SI 0.0 EDD 0.3 FCFS 0.7 LS 6.7	SI 0.0 EDD 0.1 FCFS 1.1 LS 4.6	SI 0.0 EDD 0.0 FCFS 0.1 LS 1.1 LPT 5.5	SI 0.0 EDD 0.1 FCFS 0.3 LS 1.3 SPT 10.4
$z^{(2)}: 25 < d \le 50$	LPT 33.4 CR 43.3		SPT 36.5 SRPT 38.4	CR 27.7 SRPT 34.3
$z^{(3)}: 50 < d \le 75$	SRO 74.0 SRPT 84.0	SPT 64.8 LPT 70.4	CR 53.7	
$z^{(4)}: 75 < d \le 100$	SPT 100.0	SRO 80.6 SRPT 84.7 CR 100.0	SRO 100.0	SRO 100.0

Table 2. Results for scenario A, $\min T_{\max}$

It should be expected that better results under the criterion of minimising the average work in process should be obtained by the (shortest) time based DR. However, the best performance was reached by the FCFS rule, especially for those scenarios with downtimes. Maybe it was influenced by the strong relationship between the input control and the dispatching rule in the card based DBR systems (see Duenyas, 1994, and Baker, 1984). The FCFS rule produces a stable flow of jobs and cards, obtaining the best way to optimally flow, maintaining low the inventory. The FCFS rule for the Conwip systems, which contains certain similarities with the card based DBR, is also recommended by Hopp and Roof (1998). Furthermore, the SI and EDD rules obtain good results. The implemented SI rule does not allow a job to spend more time than a certain amount of time in the queue (see Appendix sections for the definition of the DRs), being perhaps this aspect the reason for its good performance. Surprisingly, the EDD rule also works fine. In our opinion the behaviour of this rule is also strongly connected to the relation between the input control and the DR. Jobs sorted according to their due dates imply that urgent jobs are pushed to the completion of the process. When jobs finish their processing, a new job of the same type can enter the line. The results seem to indicate an efficient reduction of the WIP is reached with a suitable number of cards. The CR rule obtains a moderate performance, probably for the same reason. The performance for the SPT and SRPT rules are around those of the random selection for the case without downtimes and moderate for the case containing breakdowns. As a summary, the best results are reached for this criterion by the SI, EDD, and FCFS rules.

Breakdowns	NO				YES			
Δt_b	15%		30%		15%		30%	
$z^{(1)}: 0 \le d < 25$	EDD	0.0	SI	0.0	FCFS	0.0	FCFS	0.0
	SI	10.4	EDD	6.7	EDD	4.9	SI	9.0
	FCFS	10.7	FCFS	8.1	SI	7.5	EDD	9.1
	LPT	23.5	CR	14.8	CR	7.7	LPT	14.8
					LPT	13.7	LS	20.8
							SRPT	21.6
$z^{(2)}: 25 < d \le 50$	LS	25.6			SRPT	25.6	CR	31.5
	CR	26.7			SPT	39.6	SPT	48.1
$z^{(3)}: 50 < d \le 75$	SRO	53.4	SPT	61.3				
	SRPT	63.2	LS	72.4				
$z^{(4)}: 75 < d \le 100$	SPT	100.0	LPT	79.1	SRO	81.7	SRO	100.0
			SRPT	82.3	LS	100.0		
			SRO	100.0				

Table 3. Results for scenario A, $\min \overline{WIP}$

Regarding the robustness global criteria, results are summarized in Table 4 and in Figure 3. In order to obtain positive robustness values, results (distance *d*) are given as a fraction of unity.

	Criteria	Breakdows	Δt_b	SPT	SRPT	LPT	SI	EDD	LS	CR	FCFS	SRO
Noise Factors	$\min \overline{T}$	NO	15	1.000	0.788	0.056	0.003	0.000	0.471	0.004	0.119	0,769
		NO	50	0.149	0.207	0.279	0.000	0.011	0.320	0.066	0.205	1,000
		YES	15	1.000	0.384	0.206	0.000	0.008	0.397	0.045	0.262	0,805
		YES	50	0.309	0.222	0.187	0.000	0.010	1.000	0.154	0.133	0,832
	$\min T_{\max}$	NO	15	1.000	0.840	0.334	0.000	0.003	0.067	0.433	0.007	0,740
		NO	50	0.648	0.847	0.704	0.000	0.001	0.046	1.000	0.011	0,806
		YES	15	0.365	0.384	0.055	0.000	0.000	0.011	0.537	0.001	1,000
		YES	50	0.104	0.343	0.156	0.000	0.001	0.013	0.277	0.003	1,000
	$\min \overline{WIP}$	NO	15	1.000	0.632	0.235	0.104	0.000	0.256	0.267	0.107	0,534
		NO	50	0.613	0.823	0.791	0.000	0.067	0.724	0.148	0.081	1,000
		YES	15	0.396	0.256	0.137	0.075	0.049	1.000	0.077	0.000	0,817
		YES	50	0.481	0.216	0.148	0.090	0.091	0.208	0.315	0.000	1,000
		var		0,117	0.072	0.056	0.002	0.001	0.130	0.078	0.008	0.021
		η		3,432	5.065	8.988	26.909	**28.924**	5.848	8.287	18.739	1.210

Table 4. Robustness results for scenario A

[Insert Figure 3 about here]

Figure 3. Signal-to-noise ratio for Scenario A

In this scenario DRs can be clearly divided in two groups. One group is formed by the DRs which reach the highest values of the signal-to-noise ratio (i.e. the most robust DRs): EDD, SI and FCFS rules, while the other group is formed by the rest of rules. The worst results are obtained by SRPT, SPT, performing similarly to SRO. LPT, CR and LS perform similarly. In general, it can be observed that those DRs based on the estimation some average times (SPT, SRPT, LPT, LS, CR) have a higher variance in the results as compared to those DRs independent of that estimations. In our opinion these it could be influenced by the variability on processing times (exponentially distributed) and the other source of variability in the shop as well.

4.2 Scenario B (set-up times)

Tables 5 to 7 (for every local performance measure) show the results for the distance, *d*. The NSUT rule is included in the study.

Breakdowns	**NO**				**YES**			
Δt_b	**15%**		**30%**		**15%**		**30%**	
$z^{(1)}: 0 \le d < 25$	FCFS	0.0	FCFS	0.0	NSUT	0.0	SI	0.0
	NSUT	13.1	CR	3.3	LS	6.7	FCFS	6.5
	CR	16.0	SI	4.1	SI	12.9	SRPT	15.1
	SI	19.7	EDD	10.1	FCFS	13.3	EDD	15.3
			SRPT	23.2			CR	22.6
			SPT	23.5			NSUT	23.3
$z^{(2)}: 25 < d \le 50$	EDD	29.7	NSUT	25.5	SRPT	29.1	SRO	35.8
			LPT	27.7	SPT	32.3		
			SRO	35.6	EDD	41.6		
$z^{(3)}: 50 < d \le 75$	SRPT	65.7			CR	62.2	SPT	56.2
	LPT	71.1					LPT	60.0
	SPT	72.9						
$z^{(4)}: 75 < d \le 100$	LS	80.5	LS	100.0	SRO	98.9	LS	100.0
	SRO	100.0			LPT	100.0		

Table 5. Results for scenario B, $\min \overline{T}$

The inclusion of set-up times produces a strong increase of the variability in the system. For the first criterion studied, the DRs that are always contained in $z^{(1)}$ are SI and FCFS rules. It is also important to highlight the performance of the NSUT rule, obtaining results below 25.5%. The NSUT performance deteriorates for accurate bottlenecks ($\Delta t_b = 30\%$). The CR rule obtains good results for those scenarios without downtimes, and a poor performance for scenarios with downtimes. Time based rules obtained, in general, results far from the best positions. The SRPT rule obtains always better results than the SPT rule. Furthermore, increasing the variability in scenarios with set-ups produces worst results for the LS rule as compared with Scenario A. As a summary, the best results are reached for this criterion by the FCFS, NSUT, and SI rules.

Breakdowns	**NO**				**YES**			
Δt_b	**15%**		**30%**		**15%**		**30%**	
$z^{(1)}: 0 \le d < 25$	FCFS	0.00	FCFS	0.00	FCFS	0.00	FCFS	0.00
	NSUT	0.29	SI	0.32	SI	0.26	SI	0.43
	SI	0.38	EDD	0.39	EDD	0.63	EDD	0.75
	EDD	0.50	NSUT	0.85	NSUT	2.06	NSUT	2.61
	LS	3.84	LS	3.07	SRPT	2.60	LS	3.92
	SPT	5.22	SPT	24.34	SPT	2.70	SPT	4.58
	SRPT	8.49	SRPT	27.16	LS	3.10	SRPT	18.70
	CR	18.70			LPT	7.58		
	FCFS	0.00	FCFS	0.00	FCFS	0.00	FCFS	0.00
$z^{(2)}: 25 < d \le 50$	LPT	45.96	LPT	35.44				
			CR	38.71				
$z^{(3)}: 50 < d \le 75$							LPT	70.98
$z^{(4)}: 75 < d \le 100$	SRO	100.00	SRO	100.00	CR	80.21	CR	83.32
					SRO	100.00	SRO	100.00

Table 6. Results for scenario B, $\min T_{\max}$

For the minimisation of the maximum tardiness, the same effect than in Scenario A is observed, being FCFS, SI, and EDD the rules obtaining the best performance. As expected, the NSUT rule is also competitive. It is important to highlight that the use of DRs always obtain better results than a random selection. The CR rule obtains the worst results, compared to those obtained for the minimisation the average tardiness criterion. As a summary, best results are reached for this criterion by the FCFS, SI, NSUT, and EDD rules.

Breakdowns	NO				YES			
Δt_b	15%		30%		15%		30%	
$z^{(1)}: 0 \le d < 25$	SI	0.00	SI	0.00	FCFS	0.00	FCFS	0.00
	EDD	0.06	FCFS	0.23	SI	0.13	SI	6.23
	FCFS	0.13	EDD	0.27	EDD	0.16	EDD	9.91
	NSUT	0.95	NSUT	0.97	NSUT	3.98	SRPT	19.34
	SRPT	12.55	SRPT	8.06	SPT	18.03	NSUT	20.29
			SPT	16.12			LPT	20.51
			SRO	20.91				
			CR	24.48				
	SI	0.00	SI	0.00	FCFS	0.00	FCFS	0.00
$z^{(2)}: 25 < d \le 50$	SPT	29.44			SRPT	27.16	CR	26.12
	CR	30.89			SRO	29.11		
	SRO	47.61			LS	41.65		
$z^{(3)}: 50 < d \le 75$	LPT	68.79	LPT	69.40	CR	59.73	SPT	53.40
							LS	88.33
$z^{(4)}: 75 < d \le 100$	LS	100.00	LS	100.00	LPT	100.00	SRO	100.00

Table 7. Results for scenario B, $\min \overline{WIP}$

Under the criterion of minimising the average work in process, the same behaviour than in Scenario A is obtained, but now including the NSUT rule. It is also important to mention that the SRPT rule obtains always results lower than 27.16%. Results obtained by the SPT are moderate. The LS rule seems to be not competitive under the studied conditions. As a summary, best results are reached for this criterion by the SI, FCFS, ESS, and NSUT rules.

Regarding the robustness global criteria, results are summarized in Table 8 and in Figure 4.

	Criteria	Breakdows	Δt_b	SPT	SRPT	LPT	SI	EDD	LS	CR	FCFS	SRO	NSUT
Noise Factors	$\min \overline{T}$	NO	15	0.729	0.657	0.711	0.197	0.297	0.805	0.160	0.000	1.000	0.131
		NO	50	0.235	0.232	0.277	0.041	0.101	1.000	0.033	0.000	0.356	0.255
		YES	15	0.323	0.291	1.000	0.129	0.416	0.067	0.622	0.133	0.989	0.000
		YES	50	0.562	0.151	0.600	0.000	0.153	1.000	0.226	0.065	0.358	0.233
	$\min T_{\max}$	NO	15	0.052	0.085	0.460	0.004	0.005	0.038	0.187	0.000	1.000	0.003
		NO	50	0.243	0.272	0.354	0.003	0.004	0.031	0.387	0.000	1.000	0.009
		YES	15	0.027	0.026	0.076	0.003	0.006	0.031	0.802	0.000	1.000	0.021
		YES	50	0.046	0.187	0.710	0.004	0.007	0.039	0.833	0.000	1.000	0.026
	$\min \overline{WIP}$	NO	15	0.294	0.125	0.688	0.000	0.001	1.000	0.309	0.001	0.476	0.010
		NO	50	0.161	0.081	0.694	0.000	0.003	1.000	0.245	0.002	0.209	0.010
		YES	15	0.180	0.272	1.000	0.001	0.002	0.416	0.597	0.000	0.291	0.040
		YES	50	0.534	0.193	0.205	0.062	0.099	0.883	0.261	0.000	1.000	0.203
		var		0.050	0.027	0.087	0.004	0.019	0.208	0.069	0.002	0.119	0.010
		η		9.027	11.537	3.992	22.941	15.950	3.301	6.697	**27.401**	1.990	18.224

Table 8. Robustness results for scenario B

[Insert Figure 4 about here]

Figure 4. Signal-to-noise ratio for Scenario B

In this case, the gain (signal-to-noise ratio) is decreasing linearly from the best to the worst DR. The highest values of the signal-to-noise ratio (i.e. the most robust DRs) are obtained by FCFS, SI, NSUT and EDD, and the worst by LPT, LST, performing similarly to SRO. The results in this scenario show that the use of FCFS, SI, NSUT and EDD rules has important advantages with respect to not considering any rule (SRO). Regarding to variability, the same behaviour than Scenario A was found. According to the results, we recommend the use of FCFS or SI under set-up conditions, and EDD or SI if there is not set-up.

From a managerial point of view, it is important to remark that each DR implies a different sophistication level regarding its implementation. For example, the FIFO rule can be implemented easily either by exploiting the conveyors layout or visually in human manipulations. However, more sophisticated DR (e.g. EDD, or CR) require the support of an information system or a MES (Manufacturing Execution System) in order to be implemented. However, it is important to consider that for some local performance measures ($\min T_{\max}$, and $\min \overline{WIP}$) the FIFO rules obtain the best or similar results than EDD for those scenarios including set-up times and machine breakdowns (see Tables 2 and 3). Furthermore, in Table 4 it can be observed that the second and third robust DRs correspond to the SI and FIFO rules, which need less sophisticated controlling mechanisms in order to be implemented.

5 Conclusions

In this work it has been shown that DRs are dependent of the production nature (job-shop, flow-shop, assembly, etc,...) as well as of the stochastic variability conditions, produced by processing times, breakdowns, set-ups, etc... In order to correctly select a DR, two possible approaches can be distinguished: (1) introducing a dynamic procedure in order to switch in real-time to the most profitable DR, or (2) selecting a robust DR which can stand different environmental changes. TOC and particularly DBR advocate for simple procedures, avoiding complex procedures like (1). Thus, the selection of robust DRs can be a good option to be used in practise for DBR systems. Furthermore, this approach is related to nowadays market performance, since in the global era the markets are characterized for a more volatile demand, where from the design processes of new products, the production processes and later distribution to customers have to be adapted to its requirements. From a production point of view, these changes can produce a stressing behaviour in manufacturing, and therefore, mechanisms and policies trying to absorb these changes are welcome. In this sense, the proposed methodology can be used in order to provide the DBR production with the most profitable dispatching rules for a given scenario.

As stated previously, DRs are sensitive to the production environment under study. In order to correctly explain the proposed methodology for robust DR selection under DBR systems we focus on a simple, but widely common in practise, flow-line system. In our approach, we study different scenarios, including different relative utilization of the bottleneck, machine breakdowns, and set-up times. Local performance measures were computed and discussed for each scenario and every DR. Finally, the global performance of every DR is evaluated using Taguchi's robustness concept. Results shown that the most robust DRs are the EDD, SI and FCFS for environments without set-ups; and FCFS and SI for the case of set-ups. It is also worth noting that, for scenarios with set-up times, NSUT could be also a good alternative. Another interesting result is that some rules perform worst that the SRO rule. These results are consistent to the work of Chang *et al*. (1996), who observed the same phenomenon for different performance measures. The results are also consistent with those of Fry *et al.* (1992), who point out that the dispatching rules used in the OPT software were based on a trade of customer due-dates avoiding bottleneck set-ups times.

In our analysis we have consider only ten dispatching rules. Future research could extend the study to additional dispatching rules. Additionally, it could be interesting to extend the study to the effect of changes in the product mix, trying to identify those rules most robust under product mix variability conditions. Chakravorty and Atwater (2005) point out that DBR is very sensitive regarding the availability of raw material in front of the shop. This aspect could be included in a future research. Finally, it seems interesting address a hybrid combination of a global scheduling system and dispatching rules, such as pointed out by Roundy *et al*. (1991). Dynamic DRs selection in real-time by means of human-computer interactive systems for DBR can also be of interest (see e.g. Baek *et al.* 1999, or Kuo and Hwang, 1999).

Appendix: Definition of the dispatching rules

Despite the voluminous literature on the topic, there are no homogeneous definitions for some dispatching rules. Sometimes the same rule has different acronyms, or one acronym has different meanings. Therefore, in order to unambiguously describe the dispatching rules employed in our study, we briefly define them and indicate the reference from which each definition has been obtained. In order obtain practical results it was assumed that real processing times of job are unknown in advance. The following notation is used:

Z_{ij}, the priority of job i in station j at time t. Small values have greatest priority. Z_{ib} refers for the priority of job i in bottleneck station.

t, the current time.

t_{ij}, the mean processing time of job i in machine j. t_{ib} refers to the processing time at bottleneck station.

$CT_i(t)$, the average cycle time of job i at time t.

n, the number of stations in the line.

DD_i, the due-date of job i.

$AT_{i,j}$, the arrival time of job i at the queue of the station j.

The rules under comparison are the following:

a) Processing time based:

• SPT, Shortest Processing Time (Montarezi and Van Wassenhove, 1990). Select the job with the shortest processing time, i.e., selects the minimum Z_{ib}, where: $Z_{ib} = CT_i$.

• SRPT, Shortest Remaining Processing Time (Wu *et al*. 2008). Select the job with the shortest remaining processing time, i.e., selects the minimum Z_{ib}, where: $Z_{ib} = CT_i - (t - A_{i1}) + \sum_{j=b}^{n} t_{ij}$.

• LPT, Longest Processing Time (Montarezi and Van Wassenhove, 1990). Select the job with the longest processing time, i.e., select the minimum Z_{ib}, where: $Z_{ib} = -CT_i$.

b) Due-date based:

• EDD, Earliest Due Date (Panwalkar and Iskander, 1977). Select the job with the earliest due-date, that is, select the minimum Z_{ib}, where: $Z_{ib} = DD_i$.

• CR, Critical Ratio (Seagle and Fisk, 1982). Select the job with the minimum ratio, computed as the remaining time to the due-date divided by the remaining processing time, that is, select the minimum Z_{ib}, where: $Z_{ib}(t) = (DD_i - t)/(t - A_{i1})$.

• SI Truncated (see e.g. Blackstone *et al*., 1982 and Pierreval and Mebarki, 1997). A modified version of the SI^X was implemented because obtained better results. Two queues are formed. Randomly some α % of jobs go to first queue, while the rest go to the queue ordered by the due date.

• LS, Least Slack (Pierreval and Mebarki, 1997). Select the job the minimum slack time, that is, select the minimum Z_{ib}, where: $Z_{ib} = DD_i - CT_i - A_{i1}$.

c) Set-up time based:

• NSUT, No Set-Up Time (Panwalkar and Iskander, 1977). Select the job that requires no set-up time.

d) Arrival Times and Random based:

• FCFS, First Come First Served (Panwalkar and Iskander, 1977). Jobs are selected according to the arrival time. The priority is computed selecting the minimum Z_{ib}, where: $Z_{ib} = AT_{ib}$.

• SRO, Select in Random Order (Panwalkar and Iskander, 1977). Job is randomly selected. The priority is computed selecting Z_{ib}, where: $Z_{ib} = Random$.

Usually it is possible that priority of different jobs reach the same value. These tie situations are usually solved by the FCFS rule, which was also followed in this work.

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FIGURES

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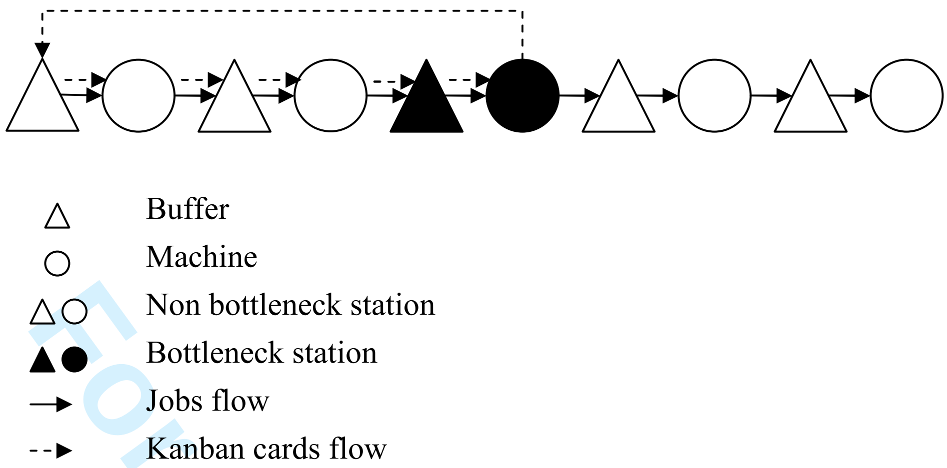

Figure 1. WIP-buffer DBR implementation

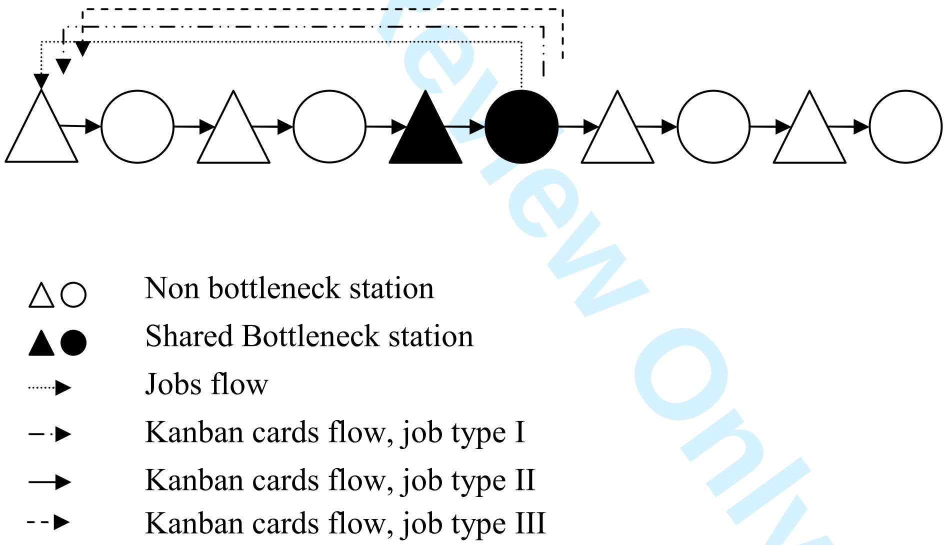

Figure 2. WIP-buffer DBR implementation for three type of products

FIGURES

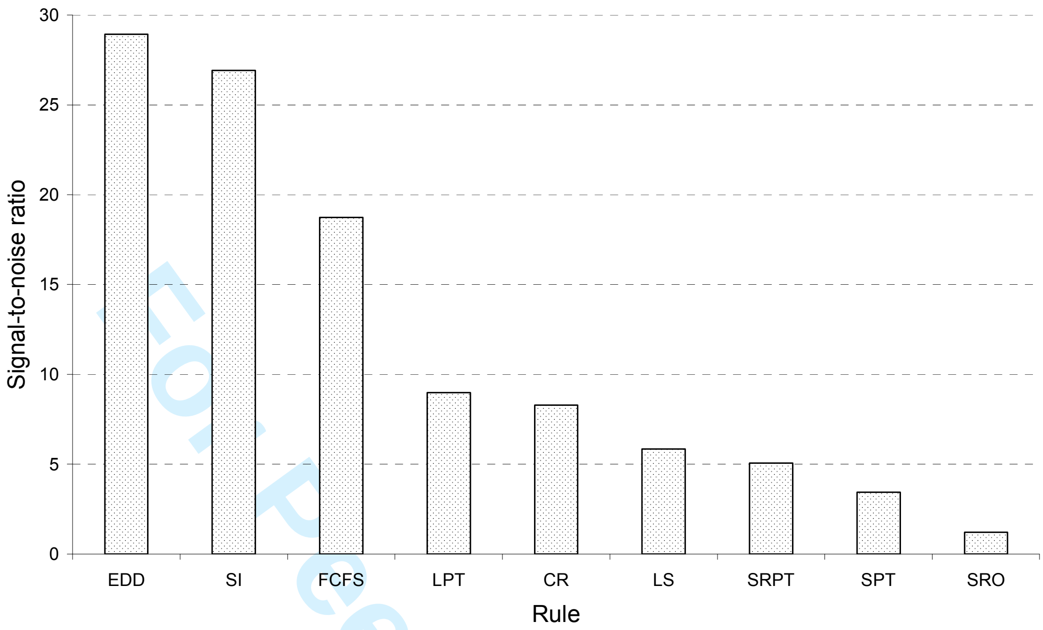

Figure 3. Signal-to-noise ratio for Scenario A

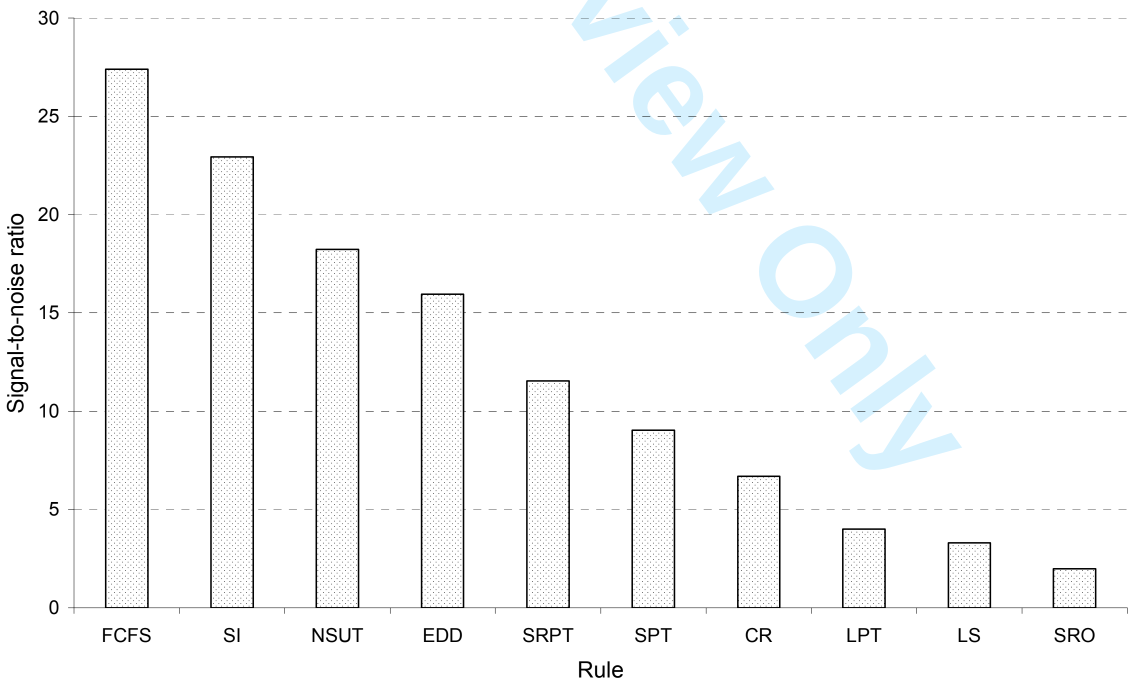

Figure 4. Signal-to-noise ratio for Scenario B