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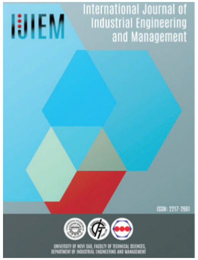

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Worker Assignment in Dual Resource Constrained Systems Subject to Machine Failures: A Simulation Study

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ABSTRACT

A production system constrained by workers and machines, where machines are not fully staffed and workers can be transferred between machines, is here considered. Previous simulation research on this type of dual resource constrained production systems assumes that machines are fully reliable. However, this is questionable in most practical situations. Discrete event simulation is used as research method to assess the impact of machine failures on where to transfer workers. Experimentation was carried out for different levels of machine availability, worker utilization and worker assignment rules. Results show that the modified operation due date rule for worker assignment improves tardiness related performance for all production situations considered. This rule shifts between a focus on completing jobs on time and a focus on speeding up jobs with short processing time. Results further show that ignoring the machine state at worker assignment may lead to significant performance deterioration. For a machine availability of 97% and a worker utilization of 90%, a deterioration between 101% and 416% on the percentage of tardy jobs was observed, compared to scenarios where machines are always available. However, if the machine state is considered, deterioration ranges only between 11% and 30% under the same conditions. This highlights the need to considered machine availability at worker assigment.

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1. Introduction

Production capacity is often constrained by the availability of different resources, such as workers, machines, tools, and equipment [1-4]. Dual Resource Constrained (DRC) systems refer to production systems where capacity is constrained by two of these resource types, typically workers and machines. In this paper, a DRC production system where machines are not fully staffed with workers is considered. Because jobs can only be processed if both a machine and a worker are available, there is a need to transfer workers between machines. How workers are assigned to machines consequently determines the performance of the system.

Worker assignment is usually managed through *when, where*, and *who* rules. *When* rules determine when the worker is transferred to a machine. Two

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commonly used approaches are: decentralized control, where a worker is eligible for transfer whenever the worker completes all the jobs queued at the current machine and the machine becomes idle; and centralized control, where a worker is eligible for transfer whenever the worker finishes a job at the machine. *Where* rules determine the machine to which the worker is transferred. Some commonly used *where* rules are first-come-first-served (FCFS), longest number in queue (LNQ), longest waiting time in queue (LWQ), shortest total processing time (STPT), earliest due date (EDD) and earliest operation due date (ODD). In circumstances where more than one skilled worker is available, a *who* rule is required to determine the worker that should be transferred.

While there exists a broad literature on worker assignment in DRC systems, all this literature assumes that resources are always available. For example, previous research assumes that machines are fully reliable. However, this assumption does not hold in many practical situations. This leads to the following research question: *How should workers be assigned to machines if these are subject to failures?*

To answer this question, a discrete even simulation model of a make-to-order flexible general flow shop with dual resource constraints is used. This study is focused on stochastic production environments. This excludes the use of scheduling, and rather greedy heuristics needs to be applied to assign workers. The focus is on *where* rules, in a shop where machines are not fully staffed and workers can operate more than one machine with equal proficiency. The objective is twofold. First, to assess the performance impact of different worker assignment rules for different levels of machine availability and workers utilization. Second, to provide guidance to managers on how to best manage dual resource constraints in real-life shops with unreliable machines.

2. Literature Review

Treleven [1] subdivided research on DRC shops into design issues, such as skill level of workers and associated training, and operating issues, such as worker assignment and production planning and control methods. There is little research that focuses on the former (e.g., [5-8]), mostly focused on layout decisions. As with most previous research, this study is focused on the latter, i.e., the operating level.

If the DRC shop is assumed to be deterministic, then different advanced scheduling techniques can be applied. For example, ElMaraghy et al. [9] use genetic algorithms to solve the production scheduling problem in DRC job shops; Araz & Salum [10] dynamically select worker assignment and dispatching rule employing artificial neural networks and a fuzzy inference system; Lei and Guo [11,12] use dynamic neighborhood search; Li et al. [13] use a branch population genetic algorithm; Zheng and Wang [14] use e knowledge-guided fruit fly optimization algorithm; Zhang et al. [15] use a hybrid discrete particle swarm optimization; Costa et al. [16] use tabu search; and Renna et al. [17] use a game theory model based on Gale-Shapley. Meanwhile, Jaber and Neumann [18] present a mixed-integer linear programming model to solve the problem of allocating one worker to n tasks (flexibility level) in m cycles considering fatigue and recovery. Recently, Berti et al. [19] assessed the impact of an aging workforce on DRC job shop scheduling.

Nelson [20], in one of the earliest investigations on worker assignment rules, concluded that in terms of *when* rule, central control decreases the mean and the variance of throughput times. Later, Bobrowski and Park [21] investigated several *when* and *where* rules, showing that a simple *where* the rule that moves a worker to the machine where the worker is most efficient dominates all other rules if labor is heterogeneous. Meanwhile, Kher [22] examined different *where* rules and concluded that rules incorporating information about the customer urgency outperform rules that do not include this information.

In general, the performance of the worker assignment rules is situational and depends on the operational conditions considered in a study. Some literature argues that *where* rules have less impact than *when* rules [23]. However, Kher and Fry [24] concluded that the choice of the *where* the rule is more important to shop performance than the choice of the *when* rule. Meanwhile, Malhotra and Kher [25], Bokhorst et al. [26], and Thürer et al. [27] showed that the *who* rule plays an important role in shops where task proficiency is different across workers. Another important research stream in the context of cross-trained workforces, where workers may possess different task proficiency levels, is learning (see e.g., [22, 28-31]).

The above review highlights that a broad literature on DRC shops exists. However, to the best of our knowledge, all the literature assumes that machines are always available. This study relaxes this rather impractical assumption and assesses the impact of machine failures on worker assignment.

3. Method

To answer the research question, discrete event simulation is used. Simulation is one of the most frequently used methods for evaluating system performance. It is particularly useful when studying complex systems subject to uncertainty and variability [32].

3.1 Simulation Model

A stochastic and steady-state simulation model of a *flexible general flow shop* has been developed using Arena® software. The shop has six production stages, each with a set of three parallel machines, resulting in a total of 18 machines. Parallel machine problems are among the most studied in the literature (see, e.g., [3, 33-36]). Meanwhile, the shop size was deliberately kept small to investigate the basic effects of the work assignment rules. There is a single workflow direction between production stages in the *general flow shop*, but jobs do not have to visit all production stages. In this study, jobs have a random number of operations, between one and six, with one operation per production stage.

As in previous DRC research (e.g., [27, 37-39]) and simulation research (e.g., [40]), machine capacity is considered constant over time. Worker availability constrains the production stage capacity because only if a worker is assigned to a machine the capacity of the machine is realized, and the job can be processed. At each production stage, there is one worker that operates all three machines with equal proficiency. Workers are assigned to a single production stage and may not move to other production stages. As in many practical circumstances, one worker is responsible for a small group of machines [26], which represents a dedicated assignment situation [41].

The inter-arrival time of jobs follows an exponential distribution. Three levels of worker utilization, 90%, 90.9%, and 92.8%, are considered. These levels were set in accordance with the levels of machine availability described below. They were realized by setting the mean inter-arrival time appropriately. Due dates are set exogenously by adding an allowance that is uniformly distributed between 45 and 60 hours to the job entry time. Operations processing times follow a 2-Erlang distribution with a mean of 1 hour. Table 1 summarizes the modelled shop and job characteristics.

Machine failures are modelled using an exponential distribution and considered as an experimental factor. Three levels of machine availability, 100%, 99%, and 97%, are considered. For a machine availability of 99%, the Mean Time to Repair (MTTR) is 1 hour, and the Mean Time Between Failures (MTBF) is 99 hours. For a machine availability of 97%, the MTTR is 3 hours, and the MTBF is 97 hours. The literature in the context of machine breakdowns is categorized by Glock [42] into three research streams: (i) production is no longer possible after a machine breakdown until the machine has been repaired (e.g., [43]); (ii) machines deteriorate over time thus ‘loosing’ capacity (e.g., [44]); (ii) the machine does not necessarily stop after failure or error, even if products may become defective (e.g., [45]). This study follows the first stream, but in addition, it is assumed that the current job on the machine can still be completed before the machine should be stopped and repaired. Finally, the following assumptions have been made in the simulation study: all materials and the information required for production are available at job arrival; distances and travel times of jobs and workers between machines

Table 1. Parametrization of the simulation model: job and shop characteristics

	Parameters	Values
Shop Characteristics	Number of production stages	6
	Number of machines per stage	3
	Number of workers per stage	1
	Workers’ utilization rate	90%, 90.9%, 92.8%
	Machines’ utilization rate	30%
Job Characteristics	Number of operations per job	Discrete Uniform (1, 6)
	Operations times	2-Erlang; *mean* = 1 hour
	Due date (hours)	Arrival time + Uniform (45, 60) hours
	Inter-arrival time	Exponential; *mean* = 0.648 hours

are considered negligible; and set-up times are sequence independent and considered part of the operation processing times.

3.2 Control Policies

Jobs that are arriving at a production stage are assigned to one of the three machines with equal probability. If the worker is busy or the machine is in a failed state, the job waits in a queue. Jobs in the queue are ranked according to the worker assignment rule. The priority dispatching decision is determined by the worker assignment decision and the job that determines worker assignment is processed first. Once the worker becomes available, the worker assignment decision is taken using a Visual Basic for Applications (VBA) routine. Then a signal is sent to the queue associated with the machine to which the worker was assigned to release a job for processing. Figure 1 illustrates the decision-making at a production stage using Arena blocks.

Based on results in previous research (e.g., [38]), only the centralized when the rule is considered in this study for worker assignment, and a worker is eligible for transfer after each job has been processed at a machine. At this decision moment, the where rule determines to which station the worker should be transferred. In this study, the following three where rules have been considered: (i) first-come-first-served (FCFS), i.e., the worker is transferred to the machine that contains the job with the earliest queue entry time; (ii) operation due date (ODD), i.e., the worker is transferred to the machine that contains the job with the earliest operation due date (i.e., the most urgent job); and (iii) modified ODD (MODD), i.e., the worker is transferred to the machine that has the most urgent job or the job with the shortest processing time. FCFS was included as a benchmark. The earliest ODD rule was included due to the good performance of due date-oriented rules in previous DRC studies (see e.g., [27, 46, 47]). MODD was included due to its good performance as a dispatching rule for shop floor control [48].

As in Thürer et al. [38], the operation due date τ_{ij} for the ith operation of a job j is determined by backwards scheduling following Equation (1).

$$\tau_{ij} = \delta_j - (n_j - i).c \qquad i = 1, \ldots, n_j \qquad (1)$$

δ_j= due date of job j

n_j = number of operations of job j.

c = estimated lead time for each operation of job j, which is based on the average cumulative flow times at production stages in this study.

The MODD rule gives priority to jobs with the lowest value of *max* (τ_{ij}, $t+p_{ij}$), where p_{ij} refers to the operation processing time, and t refers to the time when the worker assignment decision is taken. The MODD rule shifts between a focus on completing jobs on time and a focus on speeding up jobs with the shortest processing time during periods of high load, i.e., when multiple jobs exceed their ODD [48].

Finally, if machines are not reliable, then it may happen that at the decision moment some machines are in a failed state. Two types of strategies at worker assignment are therefore considered: (i) ignore the machine state, i.e., the worker may be assigned to a machine even if the machine is in a failed state; and (ii) integrating information about the machine state, i.e., the worker may not be assigned to machines that are in a failed state, unless all machines are in a failed state at the decision moment.

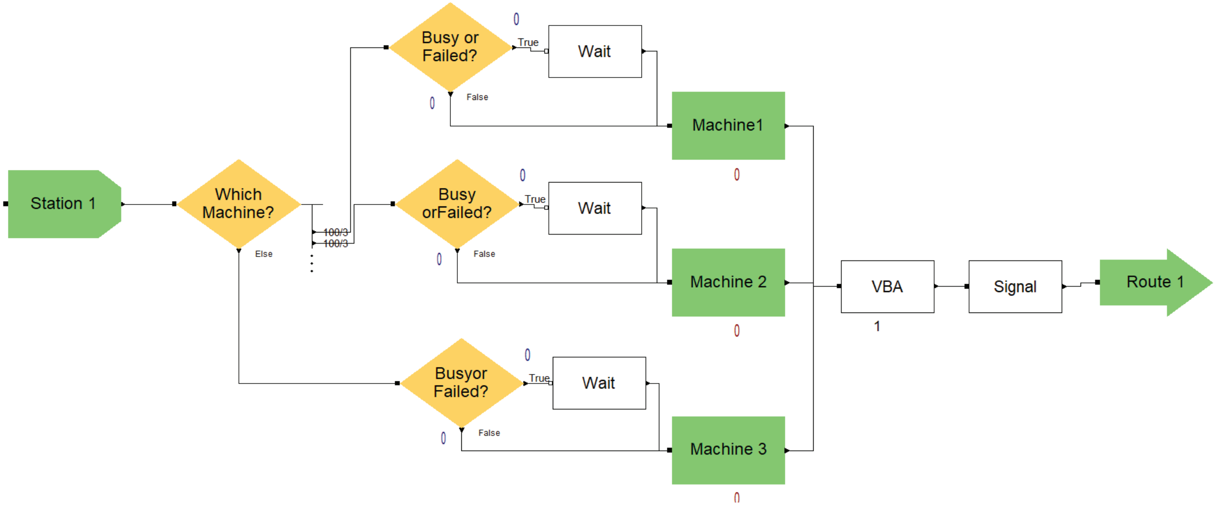

Figure 1. Arena model for worker assignment at a single production stage

3.3 Experimental Plan and Performance Measures

The experimental factors, and their levels, considered in this study are: (i) three *where* (or worker assignment) rules (FCFS, ODD and MODD); (ii) two types of worker assignment strategies (considering the machine state and ignoring the machine state); (iii) three levels of machine availability (100%, 99% and 97%); and (iv) three level of worker utilization (90%, 90.9% and 92.8%). A full factorial design with 54 (3x2x3x3) experimental scenarios was considered. Each experimental scenario was replicated 100 times. All results were collected over 12,000 time-units following a warm-up period of 2,000 time-units.

The main performance criterion is delivery performance. In this study delivery performance is measured by three performance measures as follows: (i) the percentage of tardy jobs, i.e., the percentage of jobs completed after the due date; (ii) the mean job throughput time, i.e., the mean difference between the arrival time and completion time of a job; and (iii) the mean tardiness of jobs. The percentage tardy provides the most general indication of delivery performance, while the throughput time measures the shop's ability to move work quickly to completion. It also indicates the mean lateness, and it can be used as an indicator of average work-in-process. Meanwhile, the mean tardiness measures the extent to which orders, on average, are completed after their due dates. It is used to indicate the dispersion of lateness across jobs.

4. Simulation Results and Analysis

In this section, the results from the simulation experiments are presented, analyzed, and discussed. Table 2 present the results for FCFS under both worker assignment strategies, i.e., considering and ignoring the machine state at worker assignment, together with the 95% confidence intervals on the mean. Tables 3 and 4 present the same results for ODD and MODD, respectively. The following can be observed from the results.

Concerning machine availability, as somewhat expected, the performance in terms of the percentage of tardy jobs, throughput time, and tardiness deteriorates for lower levels of machine availability. This performance deterioration depends on the worker assignment rules and on the worker assignment strategy. Meanwhile, when comparing the impact of machine failure (e.g., 97% available and 90% worker utilization) with a general increase in worker utilization (e.g., 100% available and 92.8% utilization), it can be observed that the former has less of an impact.

Concerning assignment rules, worker assignment based on the earliest ODD outperforms worker assignment based on FCFS, while worker assignment based on MODD performs the best. This is independent of the level of machine availability and worker utilization. Compared to FCFS, MODD allows for reducing the percentage of tardy jobs by about 82% if the machine state is ignored and by about 60% if the machine state is considered. These values are for a machine availability of 97% and a worker utilization of 90%.

Concerning worker assignment strategies, considering the machine state at worker assignment lessens the negative performance impact. If machine availability decreases slightly, i.e., to 99%, performance deterioration may not even occur. However, with an increase in machine unavailability, i.e., to 97%, the risk that all three machines are not available increases, in which case performance deteriorates. For 97% machine unavailability and 90% worker utilization, performance deterioration on the percentage of tardy jobs ranges from 101% to 416% if the machine state is ignored, depending on the worker assignment rule. If the machine state is considered, then the performance deterioration only ranges from 11% to 30%.

The literature on DRC shops ignores machine failures. But in real life shops, machine failures commonly occur. Using discrete event simulation, it is shown that ignoring the machine state leads to significant deterioration in performance. Considering the machine state at the decision moment, when the worker assignment decision is taken, allows for reducing this performance deterioration.

It can further be concluded that the performance of the ODD rule deteriorates more than the performance of the other two worker assignment rules considered, particularly when ignoring the machine state at worker assignment. For the highest level of machine failures and worker utilization considered in this study, FCFS approximates the performance of ODD in terms of the percentage of tardy jobs. MODD leads to best performance independently of the level of machine availability.

5. Conclusions

The performance of the worker assignment rule in the context of machine failures is assessed. The study is focused on *where* rules, which decide where to transfer a worker whenever a job operation is com-

Table 2. Results for the FCFS worker assignment rule

Worker Utilization (%)	Machine availability (%)	Considering Machine State at Worker Assignment		
		Tardy Jobs (%)	Tardiness (hours)	Throughput Time (hours)
90.0	100	8.62±0.78*	1.24±0.23	24.83±0.58
90.9		11.33±0.84	1.70±0.20	26.86±0.60
92.8		21.17±1.38	4.51±0.59	34.24±1.04
90.0	99	8.71±0.78	1.14±0.16	24.92±0.55
90.9		11.69±0.93	1.80±0.28	27.18±0.68
92.8		20.52±1.34	4.11±0.47	33.53±0.92
90.0	97	9.57±0.75	1.33±0.18	25.62±0.51
90.9		12.33±0.79	1.89±0.22	27.66±0.54
92.8		21.43±1.38	4.33±0.51	34.28±0.99
Worker Utilization (%)	Machine availability (%)	Ignoring Machine State at Worker Assignment		
		Tardy Jobs (%)	Tardiness (hours)	Throughput Time (hours)
90.0	100	8.62±0.78	1.24±0.23	24.83±0.58
90.9		11.33±0.84	1.70±0.20	26.86±0.60
92.8		21.17±1.38	4.51±0.59	34.24±1.04
90.0%	99	11.14 ±0.71	1.73±0.23	26.87±0.52
90.9		12.53±0.83	1.95±0.23	28.00±0.55
92.8		24.17±1.38	5.26±0.57	36.21±1.00
90.0	97	17.35 ±1.01	3.06±0.31	31.47±0.68
90.9		21.62 ±1.24	4.48±0.47	34.54±0.89
92.8		32.81 ±1.26	8.61±0.81	42.84±1.26

** Mean ± half with of the 95% confidence interval.*

Table 3. Results for the ODD worker assignment rule

Worker Utilization (%)	Machine availability (%)	Considering Machine State at Worker Assignment		
		Tardy Jobs (%)	Tardiness (hours)	Throughput Time (hours)
90.0	100	3.86±0.74*	0.39±0.17	24.78±0.55
90.9		4.85±0.71	0.43±0.10	26.34±0.50
92.8		14.88±1.81	2.01±0.37	33.29±0.96
90.0	99	3.69±0.69	0.35±0.10	24.86±0.50
90.9		5.90±0.94	0.62±0.18	26.94±0.62
92.8		13.73±1.62	1.76±0.31	32.99±0.88
90.0	97	4.58±0.79	0.41±0.10	25.60±0.54
90.9		6.50±0.87	0.66±0.16	27.71±0.58
92.8		15.76±1.98	2.17±0.45	34.13±1.02

Worker Utilization (%)	Machine availability (%)	Ignoring Machine State at Worker Assignment		
		Tardy Jobs (%)	Tardiness (hours)	Throughput Time (hours)
90.0	100	3.86±0.74	0.39±0.17	24.78±0.55
90.9		4.85±0.71	0.43±0.10	26.34±0.50
92.8		14.88±1.81	2.01±0.37	33.29±0.96
90.0	99	5.13±0.87	0.48±0.14	26.17±0.59
90.9		7.88±1.26	0.90±0.25	28.60±0.74
92.8		20.45±2.08	3.13±0.59	36.92±1.16
90.0	97	11.64±1.25	1.34±0.24	31.73±0.68
90.9		16.55±1.31	2.08±0.31	34.97±0.70
92.8		32.31±2.34	5.73±0.88	43.76±1.39

** Mean ± half with of the 95% confidence interval.*

Table 4. Results for the MODD worker assignment rule

Worker Utilization (%)	Machine availability (%)	Considering Machine State at Worker Assignment		
		Tardy Jobs (%)	Tardiness (hours)	Throughput Time (hours)
90.0	100	1.35±0.21*	0.19±0.06	24.07±0.40
90.9		2.42±0.34	0.41±0.09	26.32±0.46
92.8		5.21±0.54	1.22±0.21	31.28±0.67
90.0	99	1.46±0.22	0.22±0.04	24.12±0.41
90.9		2.07±0.31	0.31±0.06	25.92±0.47
92.8		5.03±0.52	1.07±0.16	30.92±0.55
90.0	97	1.75±0.28	0.24±0.06	24.80±0.41
90.9		2.42±0.34	0.41±0.09	26.32±0.46
92.8		6.59±1.76	1.31±0.18	32.15±0.59

Worker Utilization (%)	Machine availability (%)	Ignoring Machine State at Worker Assignment		
		Tardy Jobs (%)	Tardiness (hours)	Throughput Time (hours)
90.0	100	1.35±0.21	0.19±0.06	24.07±0.40
90.9		2.42±0.34	0.41±0.09	26.32±0.46
92.8		5.21±0.54	1.22±0.21	31.28±0.67
90.0	99	2.56±0.40	0.29±0.06	25.64±0.46
90.9		4.51±0.55	0.64±0.11	28.26±0.54
92.8		9.30±0.99	1.88±0.31	33.84±0.81
90.0	97	6.96±0.73	0.83±0.13	30.18±0.57
90.9		9.80±0.91	1.32±0.17	32.84±0.59
92.8		19.18±1.33	3.64±0.53	34.64±0.53

**Mean ± half with of the 95% confidence interval.*

pleted at a machine. Previous simulation studies on *where* rules assumed full machine availability. In response to the research question - how should workers be transferred to machines if these are subject to failures? – main findings from the discrete-event simulations highlight that in all instances: (i) considering machine failures at worker assignment significantly improves performance; (ii) assigning workers based on the *modified operation due date* rule provides superior percentage tardy and tardiness performance. For a machine availability of 97% and a worker utilization of 90%, considering machine failures at worker assignment allows to reduce deterioration on the percentage of tardy jobs from 101% - 416%, depending on the worker assignment rule, to 11% - 30%. For the same levels of machine availability and worker utilization, assigning workers based on the *modified operation due date* allows for reducing the percentage of tardy jobs by about 82%, when ignoring the machine state, and by about 60%, when considering the machine state, compared to first-come-first-served.

From a practical viewpoint, managers should therefore consider machine availability at worker assignments. However, it is important to note that experiments in this study assume the full availability of workers and instantaneous worker transfers. Both assumptions present the main limitations of the study, which provide important avenues for future research. The experimental setting could also be extended by incorporating further environmental factors such as variations in shop size, staffing levels, and job routings. Another limitation is the restricted set of worker assignment rules considered. However, much work is still needed to explore the performance effects of *where* rules in DRC systems are subject to machine failures, this work provides an important contribution.

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