



Analyzing the Impact of Workload Norms and Order Fill Rate on Job Shop Performance

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Abstract

The Garment manufacturing industry is facing several challenges in meeting its customer requirements due to uncertainties associated with production. Varieties of products that include many components to be produced on different machines having variations in terms of due dates and labour productivity which would make the job shop complicated for scheduling. Hence, an investigation is necessary to evaluate the influence of above underlying factors on the shop's performance. The conceptual model was initially developed, that represents the problem entity followed by the development of a simulation model on a discrete event simulation platform. The resource capacity, process timings and other related data required for feeding the model were collected through process observation techniques. The model was then validated by conducting sensitivity analysis for evaluating the model structure, logic, and causal relationships. Artificial scenarios were generated to experiment with the model performance that mimics real time situations in terms of varying the fill rate and workload norms at distinct levels. Effectiveness of order release policies and priority dispatching rules were monitored by conducting 90 experiments determined through design of experiments. Influence of the workload control methods were evaluated through Analysis of Variance techniques to understand the percentage contribution of each variable on performance. The influence of these variables on different output measures was evaluated through Tukey tests. The experimentation revealed that flowtime is influenced to the extent of 59.72 percent by workload norms and order release methods have 59.2 percent influence on throughput.

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1. Introduction

The Workload control (WLC) is intended to resolve problems associated with job shops which often suffer high flow time and increased work in process (Moreira & Alves, 2009), however, this could be regulated by stabilizing the waiting lines at bottleneck stations, preventing overload on machines, averting bottleneck shifting and, thereby, lowering flow time to meet the delivery requirements (Missbauer, 2002). The concept underlying the WLC is very simple and productive; however, its effectiveness would be realised when there are several backlog orders which are waiting to be processed, hence, released based on the criteria intended to fulfil the performance objectives (Land & Gaalman, 1996). The WLC tries to address the most significant issue of lead time syndrome in make-to-order manufacturing, which arise due to uncertainty, that hampers delivery date requirements (Mezzogori et al., 2022). The

implementation of the WLC system needs to have three decision control stages, like order generation, order release, and assignment of job processing sequence (Thürer et al., 2012a). Order release becomes a crucial stage as it determines when each order from the backlog must be fed to production to enforce WLC policies. The WLC focuses on the jobs that are being released into the shopfloor and waiting for processing by keeping a constant and controllable amount of work at every station. Several release policies have been developed, mostly focusing on resolving bottleneck issues by integrating input and output stages through capacity modifications. Vieira et al. (2022) developed a hybrid model for decision making in a stochastic dynamic environment having multiproduct demand which assisted in allocating humans and robots, refining lot sizing decisions, releasing production orders, and preparing schedule planning that minimized cost and delivery time with the most efficient task allocation feature. Research



conducted by Fernandes et al. (2016) designed different WLC synchronized lot splitting policies, especially for large jobs, to overcome the overlapping of operations to enhance the performance of a Job shop. Calle et al. (2025) observed a noteworthy influence of WLC integrated resource allocation policies in a dual resource-constrained flexible job shop. The policy assigns resources at the release stage, which surpasses the negative influence of the application of sequencing rules and worker re-assignment among workstations. WLC has proved its efficiency in handling disturbances in flexible shops that undergo machine breakdowns with uncertain repair times. A two-stage dynamic scheduling method could work effectively, which allows for modifying production plans without even having prior information about repair durations (Wang et al., 2022). Thürer et al., (2021) highlighted the relationship between blockage and the workload limiting feature of WLC and proved that load limitation in the form of a limited capacity buffer causes problems in a flow shop. Ngwu et al. (2025) highlighted the importance of adapting artificial intelligence (AI) driven scheduling and machine learning algorithms, such as integrating WLC with reinforcement learning in dynamic settings of modern manufacturing. Research by Lee et al. (2013) revealed the improvements in the garment industry by planning the resource allocation through the incorporation of radio frequency identification (RFID) that enables easy tracking of job progress and provides necessary information for workload management. Job shop characteristics of garment production present an uncertain environment due to high variability in process timings and operation sequences. Garment shops of this kind typically handle a specific product with multiple processes and are well-suited for WLC implementation. The WLC stabilizes the direct workload on the stations by reducing work-in-progress (WIP) inventory and improving resource utilization which would benefit the garment manufacturing by enhancing the delivery reliability. It is also evident that there is a lack of WLC research in the field of Garment manufacturing; thus, the present research tries to evaluate the benefits of WLC in such an uncertain environment. The study demonstrates the practical applications of WLC concepts by using discrete event simulation techniques to analyse the workload behaviour in a real garment manufacturing unit where various types of clothing compete for the shared resources.

2. Literature review

The WLC was developed to enhance the performance of job shops that struggle to attain delivery requirements due to unexpected changes in production. In WLC, the job shop is designed in such a way that due dates are assigned upon the arrival of an order. It gains control over the shop by tuning the decisions at three control points, such as job entry, job release, and job schedule of piled-up jobs. The research has incorporated customer enquiry management (CEM) in the job entry stage to determine the due dates for each order by tracking the current workload and the strike rates (Thürer et al., 2013). Saad et al. (2004) witnessed the performance improvement by the integration of a newly developed rule, “number of

operations” (NOP). Thürer et al. (2014a) integrated the CEM, which involves customers in due date setting even for the orders that are yet to be confirmed, by considering product details, current shop load, and capacity constraints, etc. Thürer et al. (2012b) noted that research on externally set due dates involving customer participation is extremely limited. They showed that simple work-in-queue and direct work-in-queue rules are effective in multilevel serial lines, reducing job tardiness by integrating planned release dates with due-date setting under processing time uncertainty. Thürer et al. (2017) highlighted that earlier experiments ignored key environmental factors such as rejection rates, machine failures, and sequence-dependent setup times. In make-to-order systems, where lead times are difficult to predict, capacity-based models can support feasible due-date decisions by matching required capacity with actual available capacity. Priority dispatching rules (PDR) help monitor jobs waiting at bottleneck machines, they would become unproductive when order release policies successfully control queue lengths. In such cases, the conservative first-come, first-served (FCFS) rule becomes more appropriate (Land et al., 1998). Thürer et al. (2015) showed that WLC performance improves when sequencing rules like modified capacity slack (MODCS) are applied at the pre-shop pool stage. Their results indicate that load-oriented sequencing rules outperform time-oriented rules under variable routings, processing time variations, and due-date fluctuations. Nahavandi (2009) found that WLC helps to balance the workloads throughout the stations by monitoring the input stage with a pre-shop pool. In addition, the job that was waiting in the pre-shop pool stage is selected based on the rules customised to improve delivery performance, especially by linking with due dates (Lu et al., 2011; Qi et al., 2009; Saad et al., 2004). Thürer et al. (2010) observed that superior performance is achieved by sequencing jobs based on routing length and mixing large with small jobs in the release mechanisms. Job shop performance further improves when sequencing considers job size, routing length, and rush orders, supported by an appropriate combination of setup time and dispatching rules. Missbauer, (2002) argues that the make-to-order shops face efficiency challenges due to high product variety, low volumes, and variable multi-operation processes that resemble Garment manufacturing. Sabuncuoglu & Karapinar (2000) highlight that these shops are most vulnerable to unstable flow time, high WIP, poor delivery performance due to inherent randomness and irregularity in the workflow. Missbauer (2002) demonstrates that lead time syndrome is a major issue in complex and stochastic job shops caused by new order releases, but WLC strategies are effective in mitigating these negative effects. Oosterman et al. (2000) investigated the performance by reducing the fluctuations at the input stage by keeping a sufficient buffer based on the difference between the workload norms set and the current workload. Lödding et al. (2003) established a concept named decentralised WIP that manages the workload locally and found it beneficial in dynamic job shops. Research has integrated two different concepts to yield mutual benefits of release methods, like the Drum-Buffer-Rope method (Riezebos et al., 2003) was combined with Push-Kanban (Müller et al., 2014;

Germes & Riezebos, 2010; Müller et al., 2014), that benefited in providing enhanced buffering along with improvements in job shop control. Continuous improvements have been witnessed by Silva et al. (2015) in WLC implementation in practical scenarios, which emphasise the focus on real world setting than on growing knowledge in the field. Furthermore, advanced tools like process diagrams were developed to overcome delivery reliability (Soepenbergh et al., 2008). Jung et al. (2022) developed a smart factory-based approach to capture real-time productivity data of garment workers, which was used as input for discrete event simulation. Ferro et al. (2021) proposed a discrete event simulation model for garment production analysis aimed at reducing production time and determining the optimal product mix using genetic algorithms. Bongomin et al. (2020) conducted a simulation-based line balancing study for a trouser assembly line to improve efficiency and to minimize the number of workstations without altering the process sequence, cycle time and resources. Rahman et al. (2023) demonstrated that productivity in garment manufacturing can be enhanced by using line balancing techniques so as to eliminate bottlenecks and to optimize workload distribution. Ünal & Bekiroğlu (2024) evaluated the benefits of simulation modeling with or without yarn clearing processes in a cloth production line. Although prior studies have extensively applied simulation modeling in garment manufacturing, the information relating to the WLC concept is rather scanty. Additionally, there is a lack of studies addressing scenarios in which a primary product is produced alongside multiple competing products sharing the same resources. Existing studies have largely overlooked the interaction among key performance measures such as flow time, tardiness, and throughput. Furthermore, limited attention has been given to modeling systems where a single product consists of multiple components requiring processing across multiple machines, including possible re-entrants. The discrete event simulation is a standard and appropriate tool to model, simulate and evaluate complex job shops. The model represents the unique features of the garment production like re-entrant flows, bottleneck issues, etc., and allows experimentation of different configurations (Nahavandi, 2009). Lu et al., (2011) and Moreira & Alves (2009) states that WLC methodology would permit to review the performance of input/output integration, and optimal combinations of workload norms and control policies significantly help optimize the job shop production, hence, based on the gaps found in the earlier research, an attempt has been made in the present research to determine the influence of WLC integrated strategies on garment manufacturing performance under uncertain situations.

3. Experimental

The research employed a simulation-based modelling, which has been a common choice in the field of study. The process starts by developing a conceptual model strengthened by information gathered from the Garment industry about the resource capacity and process timings through the observation of production methods. The subsequent action involves the development of a simulation model, followed by validation for

testing the operational accuracy. The experiments were designed to run under a distinct set of scenarios, followed by an analysis of results.

3.1. Job Shop Modelling

The job shop model employed in the research is shown in Figure 1 of Appendix A, which depicts the WLC integrated garment production line to produce a suit. The production process is designed to maximize efficiency through the simultaneous processing of subparts and the strategic allocation of resources. The jobs enter the shop on the acceptance of customer orders; however, released only if the condition of the order release strategy is satisfied. The unreleased jobs are made to wait in the pool. The jobs entering the system are again filtered based on the target fill rates and workload norms. This is employed to maintain a balanced WIP and prevent bottlenecks. Each suit is divided into sub-parts such as panel, placket, shoulder, neckline, sleeves, sides, bottom and the peak, which are made to pass through stations for simultaneous processing. However, waiting occurs if they need to process through the same station. The separation of these parts would reduce idle time of stations, thereby maximizing utilization of stations, improving throughput, and ensuring better quality. Data has been collected from the garment shop by observing and recording the process parameters for a duration of 11 h. The number of baby suits produced during this duration is approximately 30 units. The discrete process timings data for different machines is modelled to obtain probabilistic equations using the input modeling feature of Arena 16.2 Software. The recorded data has been used for modelling the process time, machine capacity, labour requirements, and production schedules. The shop is responsible for producing several products; however, research focuses on a single suit that has eight sub parts which compete for three machines, namely lockstitch, overlock and flatlock. The manufacturing of a baby suit begins with panel serging and pouch attachment using a lock stitch machine. This is followed by operations such as panel binding, attaching, top stitching, and inseam binding carried out by an overlock machine. Consequently, the overlock machine is also used for placket attachment, hemming, placket top stitching and closing operations, followed by a shoulder joining operation using a lock stitch machine. Subsequently, a flatlock machine is employed for neck binding followed by neck peak finishing using an overlock machine. Subsequently, a flat lock machine is used for sleeve arm hole binding; thereafter, side seams are stitched using a lock stitch machine. To finish, a flat lock machine is used for bottom binding, followed by arm hole peak finishing process carried out using an overlock machine. The process times of parts vary due to uncertainties in labour productivity and dependency on a single machine by multiple products. The probabilistic process times of various components of the suit under the required machines are shown in Table 1. Research generates the problem situation artificially by varying the shop characteristics, such as fill rate and workload norms and simulates the behaviour of the system under WLC strategies.

Table 1. Probabilistic process time

Machine	Components	Process Time (min)
Lockstitch	Panel	$4.15 + 3.85 * \text{BETA}(0.364, 0.615)$
	Placket	$4.15 + \text{LOGN}(1.75, 1.34)$
	Neckline	$0.999 + \text{GAMM}(0.72, 0.683)$
	Bottom	$\text{UNIF}(0.62, 2)$
	Peak	$\text{TRIA}(1.61, 2.63, 5)$
Overlock	Panel	$\text{NORM}(3.87, 0.537)$
	Shoulder	$1.01 + \text{LOGN}(0.472, 0.365)$
	Side	$\text{TRIA}(1, 3.13, 4)$
Flatlock	Neck	$\text{TRIA}(1.01, 1.31, 2)$
	Sleeve	$\text{NORM}(1.47, 0.293)$
	Bottom	$\text{TRIA}(0.75, 1.29, 2.55)$

3.2. Experimental Variables

The job shop model for the garment product line has been constructed using a discrete event simulation approach, rigorously incorporating both logical and quantitative factors to represent realistic production complexity. The experimental design utilizes a full factorial design to systematically explore the interactions between the four key experimental factors, such as order release methods (ORR), order fill rate, workload norms and PDR that result in unique experimental scenarios. The summary of shop and job characteristics of the experiment is shown in Table 2. The WLC mechanism is built on the integration of logical variables that determine control mechanisms for the shopfloor with the aim of balancing throughput and improving delivery performance (Land & Gaalman, 1996). Owing to the complexity of the garment shop due to variability in routing of distinct parts like the main body, collars, and sleeves of the product, the shop complex necessitates robust policies.

Table 2. Summary of the simulated shop and job characteristics

Characteristics	Details
Shop type	Job shop
Characteristics	Real
Routing variability	Yes
Number of machines	Three
Inter arrival time in min	Poisson distribution
Order release methods (ORR)	CR, PR
Priority dispatching rules (PDR)	FCFS, LCFS, EDD, PST, SPT
Order fill rate in percent	90, 95, 100
Workload norms	Tight, Medium, Loose
Due date equation in min	$\text{Processing time} + \text{uniform}(20, 30)$

ORR plays a significant role in controlling the performance of job shops by determining the release time of jobs and thereby streamlining the job flow and keeping WIP under limit. Two different ORR were employed in the study, namely Continuous release (CR) and Periodic release (PR) are found to be suitable for this production environment. The CR uses a Poisson distribution with a constant mean flow of jobs into the shop. To incorporate randomness at the input stage and maximum usage of resources, the job arrival rate is assumed to

follow a Poisson distribution with a mean time between arrivals of 1.4 min. In a high-volume, continuous manufacturing setup, this represents an independent arrival of new orders at a steady rate. The CR policy work is based on the research carried out by (Fernandes & Carmo-Silva, 2011), which states that jobs at the time of entry. In PR, jobs are released in batches of 25 units per h for 12 h of work per day. This approach allows an improved coordination between material handling and staffing (Land & Gaalman, 1996) by modelling production planning cycles in batches of orders that are released at the beginning of a production shift.

The PDRs are sequencing techniques deployed for the waiting jobs at each workstation to determine the subsequent job to be processed based on priority. They are crucial for managing queues and attaining specific performance goals, such as minimizing delays or improving utilization (Thürer, Stevenson, & Qu, 2016). Five prominent PDRs have been employed, such as First Come First Served (FCFS), Last Come First Served (LCFS), Earliest Due Date (EDD), Shortest Processing Time (SPT), and Remaining Processing Time Shortest (PST). In FCFS, the jobs are processed in the order of their arrival at a station. It is simple, proportional, and usually leads to little variance in the flow time. In LCFS, the most recently entered jobs are processed first. It reflects certain situations where new jobs take priority (Land et al., 1998). The EDD offers the job with the nearest due date priority. According to Baker (1965) this rule was found to be beneficial in reducing the total number of tardy jobs and their magnitude. The SPT gives priority to the job which has the minimum processing time of a particular station; however, the PST gives preference to jobs that need the minimum remaining process time in all the preceding stations. This method maximizes throughput and minimizes average flow time (Ebadian et al., 2009; Land et al., 2015).

The experimental variables are quantitative factors representing the randomness of garment manufacturing and introducing artificial uncertainty into process parameters. Accordingly, two key aspects of textile shops are order fill rates and workload norms. The order fill rates are the proportion of jobs that are filled from the semi-finished stock (Fernandes et al., 2015). In other words, it represents the number of orders considered for production based on the availability of semi-finished parts. In garment manufacturing, fluctuations in semi-finished parts are a common issue, which often hampers production. In the present study, three fill rate levels, ranging from 90 per cent to 100 per cent in increments of 5 per cent, have been considered, where lower fill rates indicate defects, missing parts, or process flaws that lead to production delays and congestion. The logic employed for order fill rates can be mathematically represented as

$$\text{Order fill rate in percentage} = \left(\frac{\text{Number of orders accepted}}{\text{Number of orders released}} \right) \times 100. \quad (1)$$

The workload norms reflect a desired level of work assigned to the stations; hence, they have a direct effect on the stations' load and their utilization. Three levels of workload norms were employed: loose, medium, and tight. The loose norms represent excess capacity in the system but reduced usage. Medium norms strike a balance between low lead time and

high throughput, thereby balancing the utilization. According to Thürrer, Stevenson, & Land (2016), tight norms reflect an extremely high and challenging utilization level, which might lead to machine idleness, lengthy queues, and stronger competition among the jobs. The research is based on norms of restricted usage of production resources with usage percentages approximating 100, 95 and 90, respectively, for loose, medium and tight norm conditions. The due date for each product is calculated by adding a uniform allowance of 20 to 30 min to its total processing time.

The experimentation considered two types of ORRs, five different PDRs under three levels of order fill rates and workload norms. Hence, $2 \times 5 \times 3 \times 3 = 90$ experiments with the full factorial design were chosen. The replication length was determined based on the assumption that the industry operates 6 days per week with 12 h of work per day, resulting in a replication length of 4320 min. A warm-up period equivalent to 30 per cent of the replication length was considered, based on the suggestion in research by Singh & Mathirajan (2019), who recommended that 30 per cent to 50 per cent is ideal for achieving the model steady state. The research considered 100 replications for each experiment.

3.3. Experimental Validation

The simulation model needs to be examined to ascertain whether it delivers the precise results and is sufficient to meet the purpose that was intended. Sensitivity analysis is a method that uses quantitative input parameters to check the influence of input variation on the model behaviour in terms of magnitude and direction of change (Sargent, 2011). The model was experimented with by generating randomness by increasing the percentage of job-1 type from 12.5 per cent to 30 per cent and the variation in output flow time that was observed is shown in Table 3. It indicates that the flow time increases with the increase in percentage of Job-1 and exhibits a positive correlation between the two variables with a Pearson correlation (r) of 0.919 and p-value of 0.0012.

Table 3. Regression test results

Percentage increase in Job-1	Flow time (min)
12.5	6.32
15	6.85
17.5	7.43
20	7.34
22.5	7.77
25	7.66
27.5	9.3
30	10.35

A simple linear model was plotted with a relation: Flow time = $3.6 + 0.198 \times (\text{percent increase in Job} - 1)$. The model presents a good fit with a R-square value of 0.846, revealing an 84.6 percent of variability in flow time due to increase in percentage of Job-1 type. The slope indicating each additional percentage point in Job-1 contributes 0.198 min to

the flow time which is depicted in Figure 2. These results confirm that flow time is consistently sensitive both in terms of direction and magnitude and thereby validating the expected qualitative and quantitative targets.

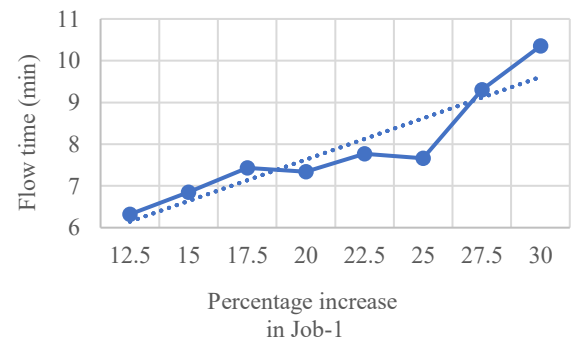


Fig. 2. Validity test results

Results of the research can be considered as authentic and valid when the simulation model is sensitive to changes prevailing in the real system. The research model incorporates changes in WIP levels of 5, 10 and 15 units and evaluates its effect on throughput. Each experiment is conducted with 5 replications, and the results of these trials are shown in Table 4.

Table 4. Throughput values under different levels of WIP

Replications	1	2	3	4	5
Throughput under WIP = 5 (Units)	179	180	178	178	178
Throughput under WIP = 10 (Units)	194	192	194	194	195
Throughput under WIP = 15 (Units)	194	193	194	194	195

The results indicate the influence of variations in WIP on throughput; however, a one-way ANOVA test has been conducted to confirm the significant difference, and the results of the same are shown in Table 5.

Table 5. One way ANOVA test for sensitivity analysis

Source	Sum of Squares	Degrees of freedom	Means Squares	F-value	p-value
Between Groups	788.16	2	394.08	692.79	0.0001
Within Groups	6.826	12	0.569		
Total	794.986	14			

It is evident from the results that there is a significant difference between WIP levels with F-value of 692.79 and p-value less than 0.0001. The outcomes demonstrate that WIP variations have a significant effect on throughput performance. Furthermore, a Kruskal-Wallis test was conducted to validate

these findings, and the same indicated a statistically significant difference with an H-value of 9.38 and a p-value of 0.009. The robustness of the model was validated by two tests, and the results were found to be consistent, which supports the behavioural validation of the model. The study is limited to internal and behavioral validation conducted using sensitivity analysis and controlled experimentation, since direct comparison of the simulation outputs with real garment manufacturing production data was not feasible. Yet, this level of validation is sufficient to meet the objectives of the study, as the primary aim is to investigate the influence of WLC techniques on garment manufacturing performance under varying process times.

4. Results and discussion

4.1. Graphical Analysis of ORR Performance

The research investigated the influence of a few key parameters that keep varying in a Garment shop. The output of the simulation experiments depicts the performance of the job shop in terms of flow time in min, throughput in units, and tardiness in per cent. These performance measures are depicted in Figures 3 to 9 of Appendix B. for different scenarios. The graphs illustrate different trends of variations in output due to the changes in the input parameters.

It is observed that flow time varies significantly with workload norms and order fill rates; however, its ill effect could be minimized through the application of suitable PDRs. The garment shop operates under lower levels of work pressure, with 90 per cent fill rates compared to higher fill rate objectives. The flow time is observed to be minimum, i.e., 6.5 min with SPT, but flow time escalates significantly as the norm level changes from medium to tight across all PDR rules. Flow time with FCFS under loose norms is 7.7 min, but rises to 17.1 min for FCFS under tight norms, which indicates that even with the maximum fill rate, the tightness of norms is a key factor in increasing the congestion of a system. A moderate increase in fill rate up to 95 per cent shows a marginal increase in flow time; however, a prominent performance gap among the PDRs is observed. The flow time under medium norms with SPT is 9 min, but with PST is 13.1 min. However, when workload norms are tight, the flow time with PST rises to 21.8 min, and the corresponding flow time under SPT is 13.2 min. The system experiences sensitivity under tighter norms, but appropriate PDR could dampen the negative effects of norms. When the fill rates are increased to 100 percent representing the times of high demand, several orders are released, resulting in increased flow times. When the tight norms are exercised, the system reaches an ultimate bottleneck situation with PST reaching a peak flow time of 27.8 min. However, SPT maintains a steady lower flow time of 14.8 min even under tight conditions, demonstrating approximately 47 per cent higher efficiency than PST.

When throughput values are considered at 90 per cent fill rate, the system was observed to be highly stable under the CR policy within a range of 194 to 198 units. A peak throughput of 198 units was achieved under the LCFS rule. It was observed to be decreasing consistently as the norms changed

from loose to tight; for instance, EDD dropped from 196 to 194 units. In contrast to that, the PR policy showed poor throughput with 175 units under tight conditions, signifying the merits of the CR policy over the PR policy. Similar findings were reported by Thürrer & Stevenson (2016), who concluded that the workload norms influence switching behavior concerning PDRs that become more prominent under lower workload norms while using the CR policy. Similarly, when the fill rate is raised to 95 per cent, there is an upward trend in throughput values, indicating that a high volume of production is necessary to achieve the target output. Throughput values were observed in a range of 205-208 units under the CR policy, with a noticeable downward shift in the throughput due to tighter norms. For instance, in the PR policy with EDD, throughput dropped from 187 to 182 units when the norm was changed from loose to tight. At higher fill rates, PR policy under tight norms can act as a bottleneck, whereas loose norms might better support the total output. The throughput reached a maximum output of 219 units under numerous rules like FCFS, PST and SPT under CR policy with loose norms. But CR with tight norms marginally weakens the system capacity by reducing the throughput in a range of 215-217 units. Conversely, in PR policy, a maximum throughput of 199 units was achieved under SPT with loose norms. It is noticed that the PR policy under tight norms shows poor performance with 187 units, which is comparatively lower than other policies; hence, this specific condition is not worthwhile for high-volume production.

The tardiness percentages are fluctuating under different simulated scenarios. When a 90 per cent fill rate is considered, it was observed that the shop achieved the lowest values among all other settings. SPT attained an extremely efficient tardiness rate of barely 2.3 per cent. When the job shop moves towards the tight norms, tardiness deteriorates significantly; for example, the CR policy in combination with the FCFS rule under tight norms reaches a peak value of 22.4 per cent. This is an indication that even under lower fill rates, the tighter workload norms could hamper due date performance if an FCFS rule is utilized. An increase in the fill rates up to 95 per cent would generate additional burden on the system, leading to a further increase in the number of late jobs. A CR policy under medium norms yields more reliable results with EDD and SPT rules maintaining tardiness below 8 per cent. But CR policy and PR policy performance under FCFS rule sharply decline under tight norms to 29.8 per cent and 28.8 per cent, respectively, proving that customer-oriented rule EDD or operations time-focused rule SPT becomes a prominent choice to avoid late deliveries. job shop congestion would increase at a 100 per cent fill rate, leading to higher tardiness issues. A more severe condition under tight norms was observed, i.e., the CR policy with FCFS rules resulted in a peak tardiness rate of 38.8 per cent, which is detrimental; however, SPT could limit the tardiness to 14 percent in which the system seems to be under control. Job shop appears to be manageable under loose norms, by keeping a lower tardiness in SPT, i.e., 3.5 per cent, highlighting that even at higher fill rates, the job shop could be managed to obtain minimal tardiness values, provided the system prevents tight workload norms and focuses

on effective sequencing. Similarly, Thüerer & Stevenson (2016) demonstrated that tighter order release norms lead to a significant increase in mean tardiness, particularly for large jobs; however, the use of appropriate PDRs can help in mitigating this impact. Experimental evidence suggests that the CR policy performs better than the PR policy, even under higher workload conditions, thereby compensating for possible negative effects. Similar results were reported by Thüerer et al. (2014b) in job shop environments with setup times. Furthermore, Fernandes et al. (2015) observed that the CR policy results in a lower percentage of tardy orders, even at higher fill rates. Although the CR policy may delay a small number of large jobs, it still achieves a comparatively lower overall tardiness rate. In contrast, the PR policy tends to produce lower average throughput (Fernandes et al., 2014). The limitations associated with both PR and CR policies can be effectively addressed by integrating them with appropriate sequencing rules, which significantly improve both throughput and tardiness performance (Thüerer et al., 2012a). Overall, these findings suggest that the benefits of ORRs can be maximized by combining them with suitable dispatching strategies, thereby supporting the outcomes of the present study.

4.2. Statistical Analysis

A statistical analysis has been carried out to understand the significant individual and combined effect of various factors on the performance which is shown in Table 6 of Appendix C. The present study incorporated a full factorial design by evaluating all experimental combinations of factors influencing suit production and each experiment was considered as an independent observation instead of using replicate mean values. Prior to ANOVA analysis, the assumptions were thoroughly reviewed. The Shapiro-Wilk test (Safavi & Blake, 2025) was employed to evaluate normality of residuals of the performance measures. These findings indicate slight variations from normality with a p-value of 0.0004 and a t-statistic of 0.9396, indicating data is not normally distributed. However, the homogeneity of variances among the experimental groups was confirmed by Levens test with a p-value of 0.5531 and Levens statistic of 0.3545. In addition, ANOVA analysis has revealed robust to moderate deviations from the normality. Each simulation replication was carried out independently by utilizing separate random number streams and the same experimental settings in order to satisfy the assumption of independence. In order to reduce the possibility of autocorrelation and dependence between observations, the output performance metrics were gathered once each replication is completed. The resulting observations were considered statistically independent and appropriate for an ANOVA-based comparison of experimental parameters because the replications were separately initiated and terminated. The ANOVA analysis was carried out to assess the main and interaction effect of four variables such as ORR, fill rate, norms, and PDR on the performance measures like flow time and throughput. The flow time results indicate that most of the variables influence either independently or in combination. When the main effects are considered based on p-values at 5 per cent significance level,

Norms, PDR, fill rate, and ORR have a direct impact with respective contributions of 59.72 per cent, 17.81 per cent, 10.29 per cent, and 3.56 per cent. It indicates that flow time is extremely sensitive to workload norms, and PDRs could dampen such negative effects. Based on interaction effects, (Norms*PDR) and (Fill Rate*PDR) have contributions of 8.14 per cent and 1.89 per cent, respectively. Hence, it can be noted that the Norms and PDR are extremely critical with respect to flow time performance. Based on throughput performance, results demonstrate that ORR and Fill rate are respectively responsible for 59.2 per cent and 39.26 per cent of variability. In addition, when the p-values with less than 0.05 are considered, norms indicate a significant relationship; however, the effect size is very minimal, i.e., 0.75 per cent. When the interaction effects are considered based on p-values (ORR*Fill Rate) and (ORR*Fill Rate*PDR) seems to have minimum influence, and the percentage of contribution may be negligible. Thus, ORR and Fill rate need to be more focused to optimise the throughput performance.

A Tukey's Honestly Significant Difference (HSD) analysis was conducted to assess which of the specific combinations of rules varied significantly. The ANOVA indicates the presence of differences but fails to determine the underlying causes for these differences. In addition, Tukey's test minimises the family-wise error while performing multiple pairwise comparisons. Tukey test confirms whether differences amongst the group's throughput, flow time and tardiness measure curves are statistically significant or not. These multiple comparisons statistically reinforced by the HSD are plotted on a spider web for four distinct factors, which are shown in Figures 6 to 9.

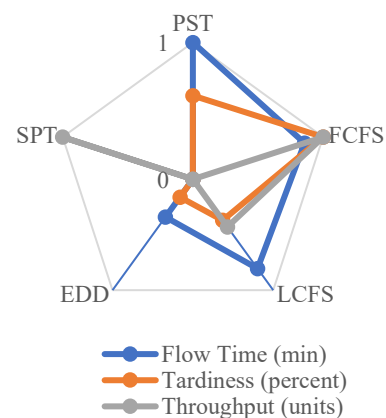


Fig. 6. PDR Performance

The HSD results of PDR are depicted in Figure 6, and it is evident that SPT overrides all other rules regarding minimum flow time, tardiness, and highest throughput. FCFS demonstrates the best throughput, but poor flow time and tardiness measures. Based on flow time measures, although EDD showed lower flow time and tardiness after SPT, it failed in terms of poor throughput. Based on the results, LCFS and PST witnessed deficient performance. When the ORR influence is considered, which is depicted in Figure 7, CR shows the highest throughput and lowest flow time and tardiness performance, whereas PR shows opposite results.

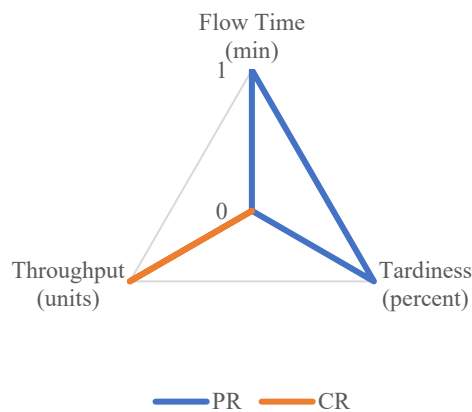


Fig. 7. ORR Performance

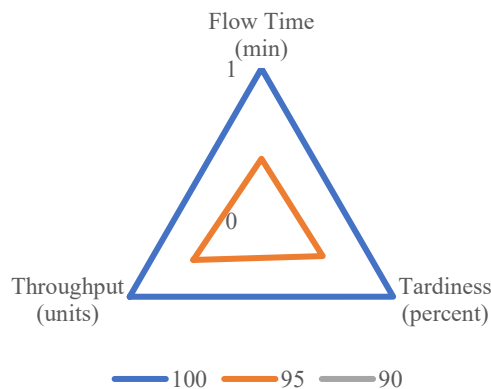


Fig. 8. Fill rate performance

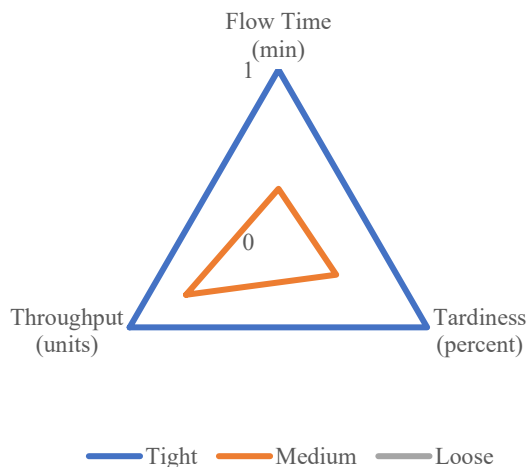


Fig. 9. Workload norms performance

Based on the order fill rate, the system generates the highest throughput when all the orders are executed, but flowtime and tardiness performance are affected, as shown in Figure 8. Similarly, at medium and lower levels of fill rate, throughput

reduces, which in turn lowers the tardiness, thereby reducing the flow time. The workload norms also witnessed similar patterns, such as under loose norms, a greater number of jobs are executed, hence throughput increases but gives rise to congestion on the shopfloor, leading to increased flowtime and tardiness, as shown in Figure 9. However, tightening the norms could moderately improve the throughput measures but hamper the tardiness.

5. Summary and conclusion

The investigations reveal that workload norms are the most critical factors in the garment shop's flow time performance, that attributes to 59.72 per cent of the variance. The study observes that flow time sharply degrades and tardiness values double as the norms transit from medium to tight with a critical non-linear association. The CR policy consistently outperformed the PR policy under full-load conditions with an increased mean throughput deviation of approximately 22 units. The ANOVA results indicate that ORRs have a minimal direct effect of 3.56 per cent on flow time; however, they significantly contribute about 59.2 per cent to throughput. These findings reveal that ORR could help in stabilizing the throughput performance under higher fill rates, showing its ability to manage high-demand scenarios. Based on the PDRs, the SPT rule showed to be the most resilient by influencing the flow time by 17.81 per cent. Conversely, FCFS and PST exhibited significantly weak delivery reliability under the uncertain situations. However, SPT has the ability to buffer against the tight norms, thereby preventing the snowball effect of tardy jobs. Although PDRs help in improving flow time, they do not have a significant influence on throughput. It is evident that across all key performance measures, the SPT rule and CR policy proved their significant advantages, and the outcomes were statistically validated by the Tukey test. These results endorse the research observations of (Fernandes et al., 2014; Thürrer et al., 2014b; Thürrer et al., 2012a), especially when CR policy is compared with PR policy at higher uncertainty levels. The findings of the research suggest that production managers may prioritize implementing CR policy over PR policy in order to protect the throughput, especially under high workload conditions in a Garment manufacturing unit with higher process time uncertainties. This recommendation is supported by the observed widening performance gap between these policies as the level of uncertainty increases. In addition, managers must pay attention while tightening the workload norms, since statistical analysis reveals that norms determine nearly 60 per cent of performance outcomes. Hence, it would be more beneficial to exercise loose to medium norms than aiming for maximum resource utilization, which often leads to bottlenecks. During uncertainties like process time variations, the SPT sequencing rule needs to be enforced as it is resilient in maintaining the stable mean flow time even under the highest fill rates. On the contrary, managers must avoid exercising sequencing rules like FCFS or PST, as they have significantly failed to perform under tight conditions. In conclusion, it is evident that strategically combining ORR, like CR, with PDR, like SPT would result in maximizing production efficiency

and ensuring on-time delivery. The present investigation simulated the performance of the job shop on a single product requiring three stations, and which involves multiple operations. The research has limitations in terms of incorporating factors such as multiple products, labor absenteeism, dual resources, maintenance breakdowns and sequence-dependent setup times in the model, which can be explored in future studies.

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Appendix

Appendix A

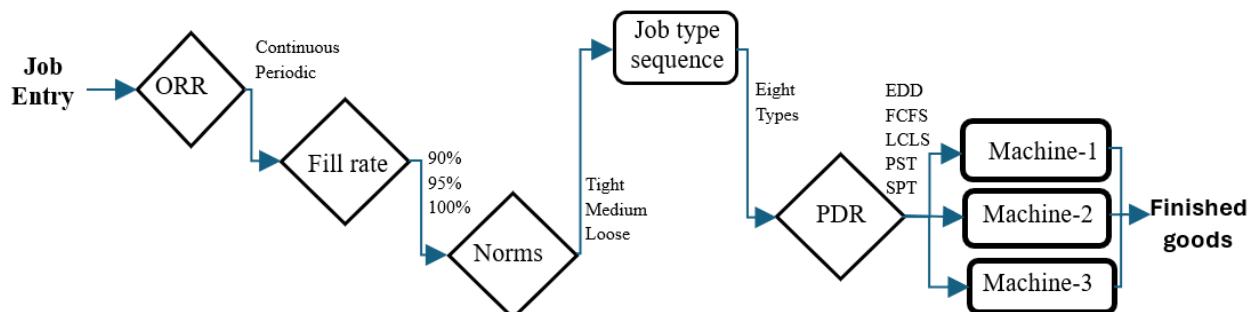


Fig. 1. Simulation model design

Appendix B

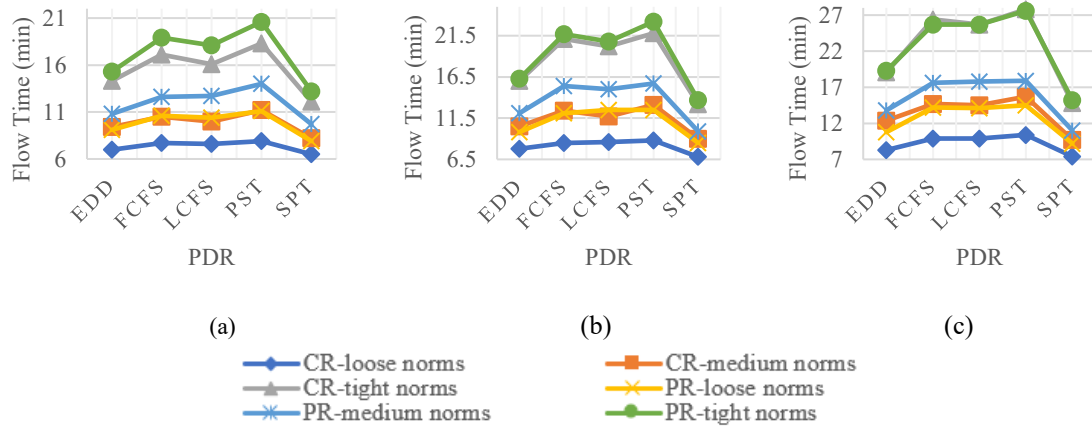


Fig. 3. Flow time results (a). 90 percent fill rate; (b). 95 percent fill rate; (c). 100 percent fill rate

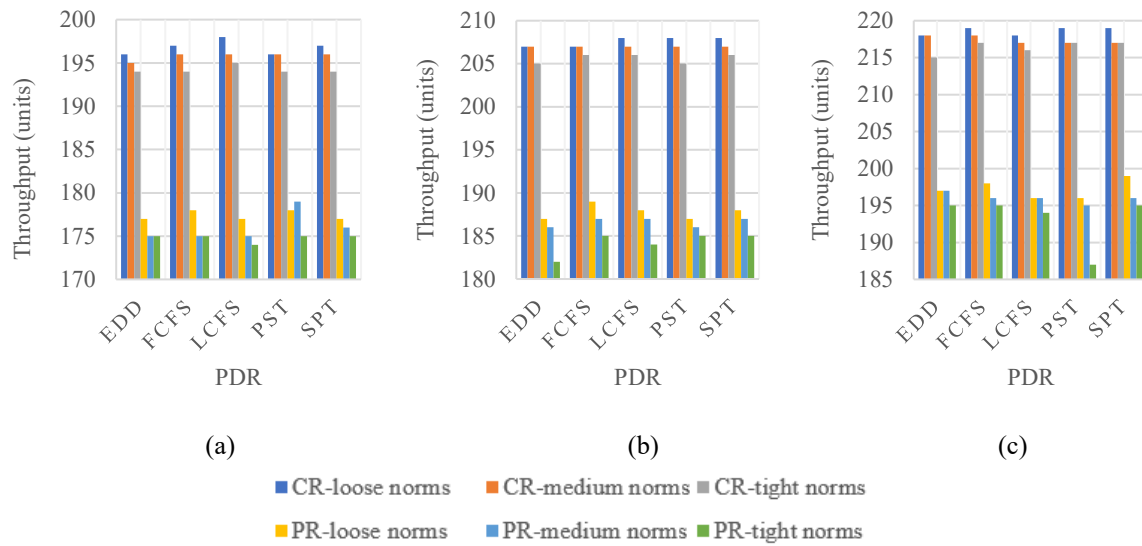


Fig. 4. Throughput results (a). 90 percent fill rate; (b). 95 percent fill rate; (c). 100 percent fill rate

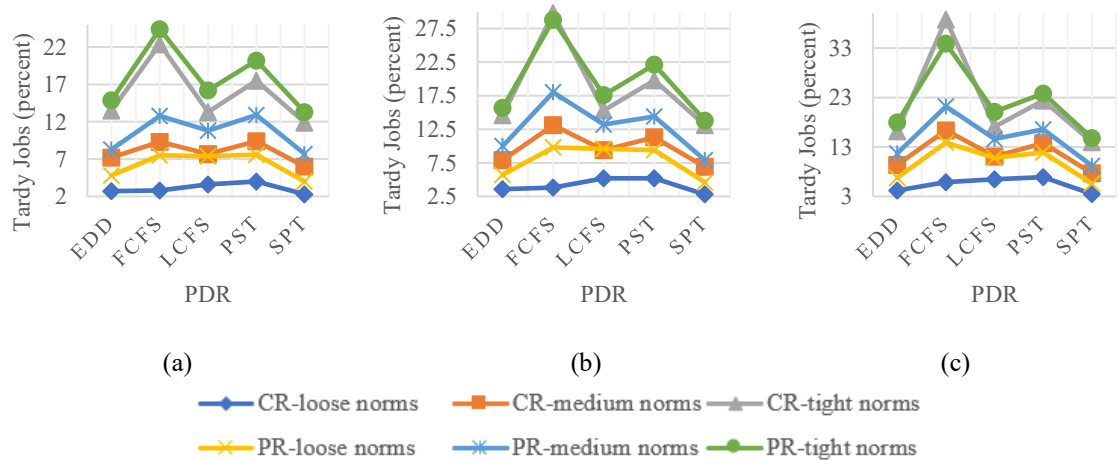


Fig. 5. Tardiness results (a) 90 percent fill rate; (b) 95 percent fill rate; (c) 100 percent fill rate

Appendix C

Table 6. ANOVA Table

Source	De- grees of free- dom	Flow time				Throughput			
		SS	F	p-va- lue	Percent	SS	F-value	p-va- lue	Percent
ORR	1	87.03	518.18	0.00	3.56	9630.68	10635.10	0.00	59.20
Fill Rate	2	251.72	749.41	0.00	10.29	6388.02	3527.13	0.00	39.26
Norms	2	1460.37	4347.78	0.00	59.72	122.42	67.60	0.00	0.75
PDR	4	435.49	648.27	0.00	17.81	8.73	2.41	0.08	0.05
ORR*Fill Rate	2	0.20	0.58	0.568	0.01	23.09	12.75	0.00	0.14
ORR*Norms	2	18.65	55.53	0.00	0.76	5.09	2.81	0.08	0.03
ORR*PDR	4	7.26	10.81	0.00	0.30	3.49	0.96	0.45	0.02
Fill Rate*Norms	4	44.02	65.53	0.00	1.80	1.18	0.33	0.86	0.01
Fill Rate*PDR	8	34.94	26.01	0.00	1.43	16.87	2.33	0.05	0.10
Norms*PDR	8	88.31	65.72	0.00	3.61	6.47	0.89	0.54	0.04
ORR*Fill Rate*Norms	4	4.50	6.69	0.001	0.18	3.84	1.06	0.40	0.02
ORR*Fill Rate*PDR	8	0.39	0.29	0.964	0.02	23.58	3.25	0.01	0.14
Fill Rate*Norms*PDR	16	8.48	3.15	0.005	0.35	13.93	0.96	0.52	0.09
Error	24	4.03			0.16	21.73			0.13