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バージョン：

Assessing the Effect of Setup Times and Shop Utilization Levels on Performance of ORR Policies in a Stochastic Dynamic Job Shop with Sequence-Dependent Setup Times: A Simulation Approach

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Abstract: Order review and release (ORR) controls making jobs from planning stage to execution stage. This article assesses the effect of setup times and shop utilization levels on ORR policies performance in stochastic dynamic job shop (SDJS) considering sequence-dependent setup time (SDST). The system performance indicators such as mean throughput time (MTT), mean lead time (MLT), number of tardy jobs (NOTJ), and total setups (TS) are used to assess system's performance. For conducting experiments, the simulation model is created using Promodel® simulation software. Results indicate that for a given ORR policy, at a given setup time and shop utilization level, as workload trigger level, increases MTT increases. In contrast, the other performance measures such as MLT, NOTJ, and TS decrease. Further, for a given ORR policy, as shop utilization decreases, MTT, MLT, and NOTJ decrease at all workload trigger levels for all setup time levels. In contrast, TS increase at all workload trigger levels for all setup time levels. Further, as setup time increases for a given ORR policy, MTT and MLT increase at all workload trigger levels for all shop utilization levels. In contrast, TS and NOTJ decrease.

Keywords: ORR policies, sequence-dependent setup times, setup time levels, shop utilization levels, stochastic dynamic job shop

1. Introduction

In today's market, due to increased competition and changing customer demands, there is a need to make the manufacturing system more effective. Thus, it is required to reduce manufacturing time so that products can be made on time to meet the due date [1)], which is possible with the help of improved production planning and control system [1)]. Make-to-order enterprises, generally job shops [2,3)], are best served by workload control (WLC) because it meets more of their planning and control requirements [4)]. Order release is one of the most crucial workload control points, which helps smooth jobs flow between machines by releasing the jobs at the right time [5)]. ORR makes a bridge between shop floor and planning system [6)]. This concept introduced three phases, i.e., entry, pre-shop pool (PSP), and ORR [6)]. The due date of jobs is determined at the entry phase. After that, PSP stores different jobs and arranges jobs according to PSP sequencing rule. Further, ORR decides release time of jobs as per requirement. In this way, ORR makes the manufacturing system more effective by controlling work-in-process (WIP) and making the smooth flow of jobs on the shop floor.

Three types of ORR policies are considered in the literature: periodic, continuous, and hybrid (periodic plus continuous). Jobs can be released at any time under a continuous release policy. On the other hand, the jobs are released at a set time interval with a periodic release policy. The third type (hybrid) of ORR policy releases jobs periodically, but the jobs are sent instantly when the workload at any machine becomes zero.

In a job shop, several jobs are processed on different machines which are capable of handling different types of jobs with specific operation sequences. In the past, SDJS with SDST is considered as one of the most challenging job shop problems [7)]. In SDJS, jobs arrive continuously in the system, and at least one job parameter is probabilistic [8)].

Setup time is needed to prepare the shop resources to perform the task, and is incurred when switching between job types. SDST is dependent on both the current and prior operation. SDST encounters in many industries such as printing, textile, plastic, and chemical [9)]. In some cases, less setup time is required, but it can also be equal or greater than the processing time in others [7]. Researchers classified setup time level with respect to operation processing time into three levels, i.e., setup time level 1, setup time level 2, and setup time level 3. Setup time level 1, 2, and 3 indicate that the ratio of setup time to operation processing time is less than one, equal to one, and greater than one respectively [7]. Further, Sharma & Jain [7] found that shop utilization affects system performance in SDJS when SDST is taken into consideration. Therefore, it is important to examine the effect of setup times levels and shop utilization levels on ORR policies performance in SDJS considering SDST.

The various sections of the paper discuss the following in detail. The literature review on ORR considering setup time is discussed in section 2. Section 3 defines the problem. Following that, in Section 4, the simulation model is designed. Section 5 contains information on how to run a simulation test. The last two sections, i.e., sections 6 and 7, present the simulation results and conclude observations and future directions.

2. Literature review

Kim and Bobrowski [10] were the first who extended earlier ORR job shop research by considering SDST. They considered four ORR policies: maximum shop load, immediate-release, backward infinite loading, and forward finite loading. The authors considered five performance measures: finished goods inventory, amount of finished work, number of jobs on the shop floor, WIP inventory, and standard deviation of lateness (SDL). They found that controlled-release improves system performance using the smallest critical ratio and shortest processing time dispatching rules. Fernandes & Carmo-Silva [11] examined the role of SDST in order release decision-making in a flow shop. They found that the time between release and shop load are crucial factors in determining which technique to employ, as they significantly impact system performance. Thürer et al. [12] extended their findings by examining the role of SDST in order release decision making in a job shop. According to the shortest slack rule, the jobs were released. The system's performance was evaluated in terms of the throughput time (TT), and percentage of tardy jobs (PTJ) performance measures. They concluded that WLC design best accommodated setup needs. Thürer et al. [13] worked on due date setting methods in a job shop using a simulation approach considering sequence-independent setup time (SIDST). The sequencing rule used by the authors was planned release time (PRT). Immediate-release rule was used for releasing jobs. The authors considered four system performance measures, viz., average lead time, average estimated lead times, and SDL. They concluded that due date based on finite loading gives better system performance. Thürer et al. [4] compared the ORR policies performance while considering SDST in a job shop. The authors considered four ORR policies: work centre planned release date, corrected aggregate load approach, superfluous load avoidance release, and Lancaster University Management School Corrected Order Release (LUMSCOR). The authors considered three performance measures, i.e., PTJ, lead time, and TT. They concluded that LUMSCOR is the most effective order release method. Fernandes et al. [14] examined the effect of ORR policies in unbalanced job shop SIDST. They considered three ORR policies, viz. periodic, periodic pull, continuous with PRT sequencing rule. The system's performance was evaluated in terms of PTJ, SDL, shop floor throughput time (SFTT), total throughput time (TTT), and bottleneck shiftiness index. They found that workload control could also be effective in unstable situations. Thürer, Stevenson, et al. [15] discussed a workload control concept combining customer inquiry management, due date, and ORR considering SIDST. They considered two order release policies, viz., immediate-release and LUMSCOR, along with PRT sequencing rule. The system performance measures considered by them were PTJ, MTT, and MLT. The results reveal that an integrated workload control approach may significantly improve PTJ. Fernandes et al. [5] compared the performance of various lot splitting policies for ORR and dispatching procedures considering SIDST. The order release policy used by them was periodic pull with PRT sequencing rule. The system performance measures considered by the authors were SFTT, TTT, PSP time, PTJ, SDL with planned operation start time dispatching rule. They demonstrated that the performance of systems is enhanced with appropriate combination of lot splitting strategy and dispatching rule. Grundstein et al. [16] integrated capacity control, sequencing, and ORR using autonomous production control (APC) technique considering SDST. The authors considered four ORR policies, i.e., constant WIP, decentralized WIP oriented ORR (DEWIP), plan-oriented ORR, and APC logic along with four queue processing rules, i.e., earliest due date, shortest processing time, priority-based approach, DEWIP, and APC. Results show the method's ability to meet the due date and emphasize the method's usefulness in real-world contexts. Fernandes et al. [17] attempted to improve workload control order release by introducing new continuous release methods considering SIDST using a simulation approach. They considered four ORR policies viz. continuous workload balancing starvation avoidance, continuous-release with starvation avoidance, continuous release, and LUMSCOR, along with two sequencing rules, i.e., modified capacity slack and planned release date (PRD). They concluded that the system's performance is improved for mean tardiness and SDL. Thürer et al. [18] integrated due date setting rules and ORR considering SIDST using simulation. They considered two ORR policies, i.e., periodic and LUMSCOR with PRT sequencing rule. The system's performance was evaluated in terms of lead time, PTJ, mean tardiness, and

SDL. The authors found that performance of the system is improved when ORR and due date is integrated. Vinod et al. [19] investigated the implications of ORR policies, dispatching rules, and setup times in an agile job shop considering SDST. They considered two ORR policies, i.e., immediate-release and WIP based release. The system performance measures considered by the authors were mean setup time, mean flow allowance, mean tardiness, PTJ, and mean flow time. As a result, they determined that the system's efficiency can be increased with a suitable mix-up of delivery date decisions and scheduling techniques under various shop floor conditions. Chen et al. [20] presented a refined ORR policy in a flow shop while considering SIDST. The authors considered two order release policies, i.e., LUMSCOR and LUMSCOR drum-buffer-rope with planned operation start time sequencing rule. The system's performance was evaluated in terms of mean TTT, PTJ, and SFTT. The results show that the refined ORR policy improves system performance with resource variability and higher protective capacity in a flow shop. Thürer et al. [21] used a simulation approach to control workload in additive manufacturing shop while considering SIDST. The authors considered two order release policies, i.e., continuous and additive manufacturing-based. They concluded that load limiting and sequencing should be used for upstream and downstream stations respectively. Mezzogori et al. [22] proposed a complementary method, i.e., production planning and control (PPC) methodology. SIDST was the setup time that was taken into account. The authors used two sequencing rules, i.e., operation due date and earliest due date. The system's performance was evaluated in terms of PTJ, percentage of negotiated due dates, and WIP levels. They concluded that the proposed methodology improves system performance when combined with a consistent forecasting system. Rani et al. [23] investigated the routing flexibility effect in a job shop while considering order release and SDST. The system's performance was evaluated in terms of MTT, MLT, TS, and mean tardiness performance measures. The authors concluded that combining ORR policies and routing flexibility improves system performance. Fernandes et al. [24] workload on direct workload control and simply continuous release method considering SIDST. They concluded that controlling direct workload control at each machine can improve the performance of both job shop and flow shop.

The literature review reveals that most authors considered six machines in their studies. Further, in most of the studies, the shop utilization considered is 90%, and number of operations per job varies from U [1-6]. Moreover, the authors considered only one type of setup time level, i.e., setup time is less than operation processing time. The literature review also reveals that most of the authors considered PRD sequencing rule, and all three types of ORR policies, i.e., periodic, continuous, and periodic plus continuous. It also reveals that researchers have made no attempt to evaluate the effect of setup times and shop utilization levels on ORR policies performance in SDJS considering SDST. The current research work is first attempt in this direction.

In the present research work, a job shop is considered with ‘m’ machines, and ‘n’ jobs and the jobs incur SDST. The job shop functions in stochastic dynamic environment, and an ORR policy is in place. The aim is to evaluate the effect of setup times and shop utilization levels on ORR policies performance as measured by MTT, MLT, TS, and NOTJ performance measures.

3. Job shop configuration

Based on previous research [4,11,12,20], the current study selects a job shop with six machines and an infinite input buffer.

3.1 Job data

In the present study, the arrival of jobs is considered stochastic and dynamic. The number of operations on a job varies between 4 to 6 with uniform distribution [4,12,23]. The processing time of jobs on different machines varies from U(6,7) to U(18,19). PRD sequencing rule is used to arrange the jobs in PSP [4,12,23]. To choose jobs from the machine queue, a dispatching rule is applied, i.e., similar setup plus shortest processing time [7]. Table 1, Table 2, and Table 3 shows setup time information for six job types at STL1, STL2, and STL3.

Table 1. Setup time data (STL1)

Preceding Job Type	Sequence and setup time of follower job type
JT1	JT1(0)), JT2(U(3,3.25)), JT3(U(3,3.75)), JT4(U((3,3.50)), JT5(U(3,3.50)), JT6(U(3,3.25))
JT2	JT1(U(3,3.50)), JT2(0), JT3(U(3,3.25)), JT4(U((3,3.75)), JT5(U(3,3.25)), JT6(U(3,3.50))
JT3	JT1(U(3,3.25)), JT2(U(3,3.50)), JT3(0), JT4(U((3,3.50)), JT5(U(3,3.75)), JT6(U(3,3.25))
JT4	JT1(U(3,3.75)), JT2(U(3,3.25)), JT3(U(3,3.50)), JT4(0), JT5(U(3,3.25)), JT6(U(3,3.50))
JT5	JT1(U(3,3.50)), JT2(U(3,3.75)), JT3(U(3,3.25)), JT4(U((3,3.50)), JT5(0), JT6(U(3,3.25))
JT6	JT1(U(3,3.25)), JT2(U(3,3.50)), JT3(U(3,3.75)), JT4(U((3,3.25)), JT5(U(3,3.50)), JT6(0)

Legends: JTi = Job type, U = Uniform distribution

3.2 Mean inter-arrival time

It is the average time between two job arrivals (λ). It is determined by the formula given below [8,23,25].

$$\lambda = \frac{\mu_g * \mu_p}{SU * NM} \quad (1)$$

Where μ_p = mean processing time per operation including setup time
SU= shop utilization
μ_g = mean number of operations per job
NM= number of machines

In this study, the values of μ_p are 14.08, 23.24, and 29.91 for STL1, STL2, and STL3, respectively. The value of μ_g is 4.83 for the given input data. This study considers six machines [4,12,23,26] with 80%, 85%, and 90% shop utilization. In addition, the predicted shop load is within a range of ±1.5% of the considered shop utilization level due to stochastic processing and setup time [8].

Table 2. Setup time data (STL2)

Preceding Job Type	Sequence and setup time of follower job type
JT1	JT1(0)), JT2(U(14,14.25)), JT3(U(14,14.75)), JT4(U((14,14.50)), JT5(U(14,14.50)), JT6(U(14,14.25))
JT2	JT1(U(14,14.50)), JT2(0), JT3(U(14,14.25)), JT4(U((14,14.75)), JT5(U(14,14.25)), JT6(U(14,14.50))
JT3	JT1(U(14,14.25)), JT2(U(14,14.50)), JT3(0), JT4(U((14,14.50)), JT5(U(14,14.75)), JT6(U(14,14.25))
JT4	JT1(U(14,14.75)), JT2(U(14,14.25)), JT3(U(14,14.50)), JT4(0), JT5(U(14,14.25)), JT6(U(14,14.50))
JT5	JT1(U(14,14.50)), JT2(U(14,14.75)), JT3(U(14,14.25)), JT4(U((14,14.50)), JT5(0), JT6(U(14,14.25))
JT6	JT1(U(14,14.25)), JT2(U(14,14.50)), JT3(U(14,14.75)), JT4(U((14,14.25)), JT5(U(14,14.50)), JT6(0)

Legends: JTi = Job type, U = Uniform distribution

3.3 Due date

It is the deadline by which a job order must be finished. Due date of jobs is determined either internally or externally. In case of internally determined due date, due date is based on the total work content (TWK) method. According to TWK method the due date is determined by taking sum of processing times and setup times of the job or number of operations to be performed on the job. The majority of researchers employ TWK approach to determine the due date of jobs as given by the equation [7,8,19,23,25,27].

$$due\_d_j = a_j + DTF\,(p_j + n_j\mu_s) \quad (2)$$

Where, due_d_j = due date of the job j
a_j = arrival time of the job j
DTF = due date tightness factor
p_j = mean total processing times of all the operations of job j,
n_j = number of operations of job j
μ_s = mean of mean setup time of all the changeover of job j

This study considers the due date tightness factor (DTF) three.

Table 3. Setup time data (STL3)

Preceding Job Type	Sequence and setup time of follower job type
JT1	JT1(0)), JT2(U(22,22.25)), JT3(U(22,22.75)), JT4(U((22,22.50)), JT5(U(22,22.50)), JT6(U(22,22.25))
JT2	JT1(U(22,22.50)), JT2(0), JT3(U(22,22.25)), JT4(U((22,22.75)), JT5(U(22,22.25)), JT6(U(22,22.50))
JT3	JT1(U(22,22.25)), JT2(U(22,22.50)), JT3(0), JT4(U((22,22.50)), JT5(U(22,22.75)), JT6(U(22,22.25))
JT4	JT1(U(22,22.75)), JT2(U(22,22.25)), JT3(U(22,22.50)), JT4(0), JT5(U(22,22.25)), JT6(U(22,22.50))
JT5	JT1(U(22,22.50)), JT2(U(22,22.75)), JT3(U(22,22.25)), JT4(U((22,22.50)), JT5(0), JT6(U(22,22.25))

JT6	JT1(U(22,22.25)), JT2(U(22,22.50)), JT3(U(22,22.75)), JT4(U((22,22.25)), JT5(U(22,22.50)), JT6(0)

Legends: JTi = Job type, U = Uniform distribution

3.4 ORR policies

In the current study, the term workload trigger is used for both periodic and continuous ORR policy. According to prior research [4,23,26], this study considers five ORR policies with three workload trigger (WLT) levels, i.e., CALA (60, 70, 80), CorrWLT (30, 35, 40), AGGWLT (330, 400, 470), WCWLT (1, 2, 3), and LUMSCOR (30, 35, 40). For direct load calculation, the processing time of the jobs currently in machine buffer and those being processed are added together. Furthermore, release frequency for LUMSCOR periodic part is fifteen-time units [23]. Table 4 summarises ORR policies. The release procedure of jobs for ORR policies is as similar as taken by [23].

4. Configuration of simulation model

Simulation modeling assists in analyzing the manufacturing system in a better way [28–32]. Using ProModel® software, the current study created a simulation model of ORR in a job shop with three setup times and shop utilization levels.

For the development of simulation model several assumptions such as pre-emption is not allowed, job can't process more than one machine simultaneously, one job processed on one machine while other on another machine simultaneously, jobs arrived dynamically on the shop floor and SDST is considered for each operation on a machine in-line with literature are taken in the present work [7,23,33]. The flow chart of ORR is shown in Figure 1. The present study considers four system performance measures, i.e., MTT, MLT, NOTJ, and TS [7,23].

5. Experimental design

Using simulation modeling, several experiments have been conducted on the developed simulation model using ProModel® software. The first stage identifies a steady state period using Welch's procedure [34]. For simulation experimentation, thirty replications are considered, and the information is collected for 25000 job completion. It is observed that after 5000 jobs completion, the system reaches a steady state.

Table 4. Summary of the ORR policies taken into consideration in this study

Abbreviations	Full Name	Classification	Description
CALA	Corrected Aggregate Load Approach	Periodic ORR policy	According to CALA ORR policy, jobs are released periodically when any machine's corrected aggregate load falls below preset value.
AGGWLT	Aggregate Workload Trigger	Continuous ORR policy	According to the AGGWLT ORR policy, jobs are released when the total shop load falls below preset value.
CorrWLT	Corrected Workload Trigger	Continuous ORR policy	According to CorrWLT ORR policy, the corrected aggregate load is taken into consideration, and it is calculated by dividing the direct load of the machine by the position of the machine.
WCWLT	Work Centre Workload Trigger	Continuous ORR policy	According to WCWLT ORR policy, jobs are released continuously when the direct load falls below preset value.
LUMSCOR	Lancaster University Management School Corrected Order Release	Periodic plus continuous ORR policy	In LUMSCOR ORR policy, the corrected aggregate load is considered for periodic release, and direct load is taken into consideration for continuous release.

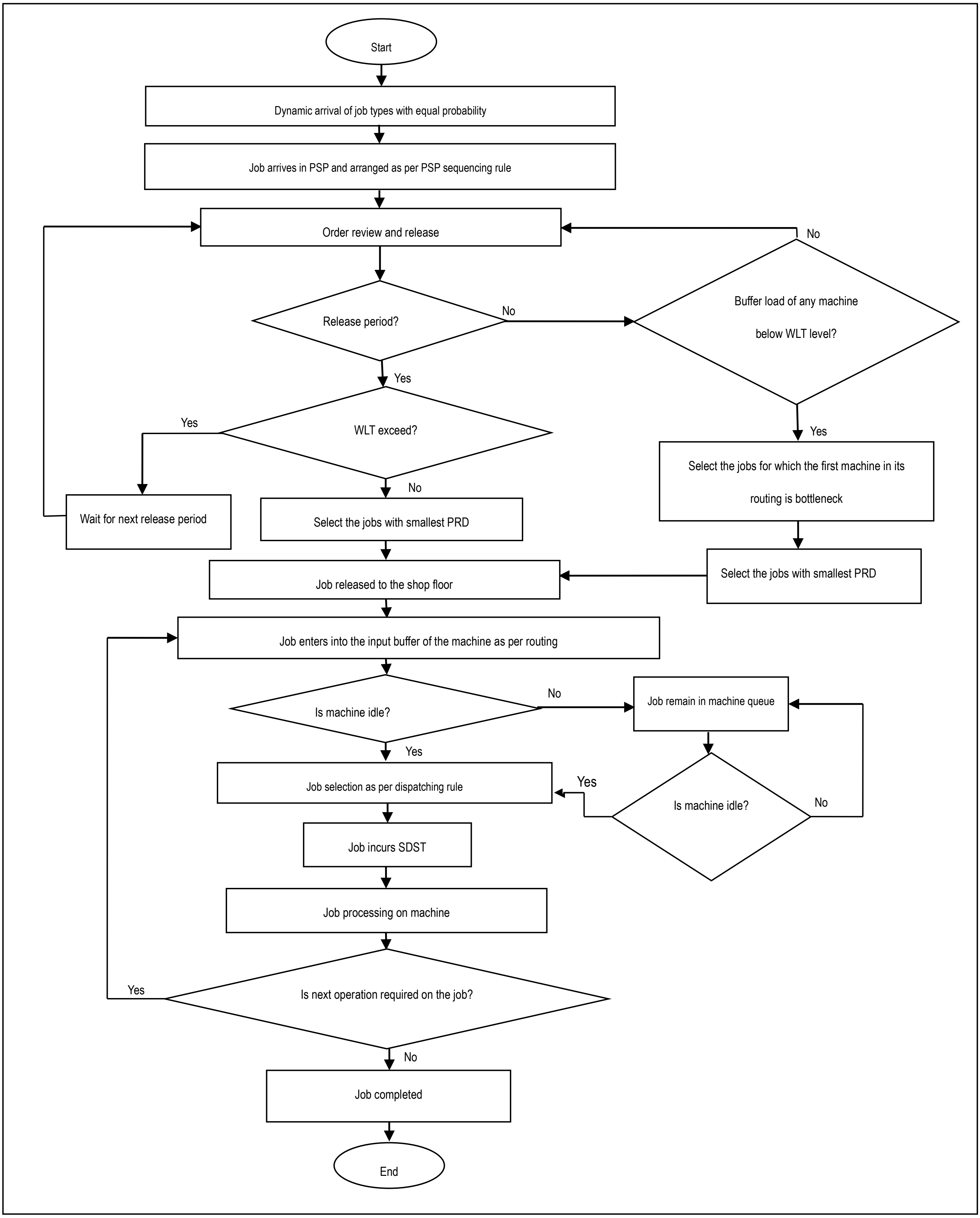

Figure 1. Flow chart of order review and release

6. Results and Discussions

Tables 5-8 show the results for MTT, MLT, TS, and NOTJ performance measures for the considered ORR policies at different shop utilization levels (90%, 85% and 80%) and setup time levels (STL1, STL2 and STL3).

Table 5 shows that for CALA ORR policy, as WLT level increases from 60 to 80, MTT increases at all shop utilization levels ((90%, 85%, 80%) and setup time levels (STL1, STL2, STL3). The reason is that as WLT level rises; PSP waiting time of jobs decreases which results in increase in number of jobs in the machine queue, and hence, MTT increases. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR. Table 5 also indicates that as shop utilization level decreases from 90% to 80% for CALA ORR policy, MTT decreases at all WLT levels (60,70, and 80) for all setup time levels (STL1, STL2, and STL3). The reason is that at low shop utilization levels, jobs wait for shorter period of time for processing at various machine queues, resulting in a drop in MTT. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR. Table 5 also shows that for CALA ORR policy as STL increases from STL1 to STL3, MTT increases at all WLT levels (60, 70, and 80) for all the shop utilization levels (90%, 85%, and 80%). The reason is that there is an increase in setup time as STL increases from STL1 to STL3, which increases MTT. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR.

Table 6 shows that for CALA ORR policy, as WLT level increases from 60 to 80, MLT decreases at all shop utilization levels (90%, 85%, 80%) and setup time levels (STL1, STL2, STL3). The reason is that as WLT level increases, jobs waiting time in PSP decreases, leading to a reduction in MLT. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR. Table 6 also indicates that for CALA ORR policy, as shop utilization level decreases from 90% to 80%, MLT decreases at all WLT levels (60,70, and 80) for all setup time levels (STL1, STL2, and STL3). The reason is that when shop utilization is low, jobs wait for a shorter duration in PSP, and hence, MLT decreases. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR. Table 6 also shows that as STL increases from STL1 to STL3 for CALA ORR policy, MLT increases at all WLT levels, i.e., 60, 70, and 80 for all shop utilization levels, i.e., 90%, 85%, and 80%. The reason is that as STL increases from STL1 to STL3, there is an increase in setup time, which increases MLT. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR.

Table 7 shows that as WLT level increases from 60 to 80 for CALA ORR policy, TS decrease at all shop utilization levels (90%, 85%, 80%) and setup time levels (STL1, STL2, STL3). The reason is that when WLT level increases, total jobs in the machine queue increase, which increases the chances of similar types of jobs in the machine queue, and hence TS decrease. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR. Table 7 also indicates that for CALA ORR policy, as shop utilization level decreases from 90% to 80%, TS increases at all WLT levels (60,70, and 80) for all setup time levels (STL1, STL2, and STL3). When shop utilization is low, the jobs arrival rate is low, and hence there are fewer identical types of jobs at any given time, which increases TS. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR. Table 7 also shows that as STL increases from STL1 to STL3 for CALA ORR policy, TS decrease at all WLT levels, i.e., 60, 70, and 80 for all shop utilization levels, i.e., 90%, 85%, and 80%. The reason is that as setup time increases, jobs wait longer in machine queue, which leads to an increase in the quantity of jobs of the similar type. Thus, the maximum number of jobs with the same setups are processed, and total setups decrease. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR.

Table 8 shows that as WLT level increases from 60 to 80 for CALA ORR policy, NOTJ decreases at all shop utilization levels (90%, 85%, 80%) and setup time levels (STL1, STL2, STL3). The reason is that when WLT level increases, number of jobs in the machine queue goes up. Because of this, number of similar jobs in the machine queue also goes up, as a result NOTJ decreases. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR. Table 8 also indicates that as shop utilization level decreases from 90% to 80% for CALA ORR policy, NOTJ decreases at all WLT levels for all setup time levels, i.e., STL1, STL2, and STL3. The reason is that when shop utilization levels are low, jobs arrive at shop at a slower rate, which means there are less jobs of the similar type available at any given time, which decreases NOTJ. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR. Table 8 also shows that as STL increases from STL1 to STL3 for CALA ORR policy, NOTJ decrease at all WLT levels, i.e., 60, 70, and 80 for all shop utilization levels, i.e., 90%, 85%, and 80%. The reason is that when setup time increases, the due date assigned to jobs using the TWK approach also increases as the TWK approach considers setup time. A similar trend is obtained for other ORR policies such as CorrWLT, AGGWLT, WCWLT, and LUMSCOR.

Table 9 shows the best performing ORR policies at different setup times levels and shop utilization levels for MTT, MLT, TS and NOTJ performance measure.

Table 5. Results for MTT performance measure for the considered ORR policies

ORR policies	**MTT**								
	STL1			**STL2**			**STL3**		
	90	**85**	**80**	**90**	**85**	**80**	**90**	**85**	**80**
CALA 60	**86.65**	**84.89**	**82.46**	**122.98**	**113.73**	**108.98**	**161.26**	**154.12**	**149.42**
CALA 70	87.39	86.05	83.08	125.96	115.47	109.30	161.46	155.94	149.79
CALA 80	87.73	86.06	83.83	130.15	115.73	110.39	169.90	156.26	150.22
AGGWLT 330	**84.19**	**81.31**	**78.42**	**124.4**	**115.14**	**113.92**	**159.81**	**148.74**	**145.27**
AGGWLT 400	85.07	81.55	78.76	126.30	117.12	114.10	159.82	152.46	149.51
AGGWLT 470	86.81	85.38	82.75	126.81	118.62	114.74	160.37	152.92	149.84
CorrWLT 30	**84.76**	**83.17**	**81.20**	**123.07**	**111.80**	**111.21**	**155.06**	**144.52**	**143.71**
CorrWLT 35	86.93	84.90	81.62	124.96	116.18	114.00	159.82	149.85	144.77
CorrWLT 40	87.31	86.85	82.04	125.20	118.65	115.14	162.22	152.59	147.99
LUMSCOR 30	**75.92**	**71.87**	**69.72**	**115.07**	**108.02**	**107.14**	**151.48**	**143.82**	**135.71**
LUMSCOR 35	77.00	74.45	71.92	116.96	109.32	108.18	153.86	145.86	136.77
LUMSCOR 40	78.05	76.06	73.22	117.20	109.34	108.98	155.06	146.22	141.59
WCWLT 1	**79.88**	**78.12**	**75.53**	**122.41**	**114.14**	**111.99**	**148.31**	**141.04**	**139.01**
WCWLT 2	81.13	79.79	76.95	124.13	115.18	112.02	149.06	147.68	142.60
WCWLT 3	82.87	81.21	79.68	124.70	117.65	112.84	156.70	153.83	149.59

Legends: MTT = Mean throughput time, STL = Setup time level, CALA = Corrected aggregate load approach, AGGWLT = Aggregate workload trigger, CorrWLT = Corrected workload trigger, WCWLT = Work centre workload trigger, LUMSCOR = Lancaster university management school corrected order release. The bold value represents the best value (minimum) of MTT performance measure for a given ORR policy, shop utilization, and setup time level.

Table 6. Results for MLT performance measure for the considered ORR policies

ORR policies	**MLT**								
	STL1			**STL2**			**STL3**		
	90	**85**	**80**	**90**	**85**	**80**	**90**	**85**	**80**
CALA 60	113.07	108.07	107.55	132.35	124.02	122.26	171.58	151.72	140.15
CALA 70	112.13	107.13	107.00	131.83	123.33	121.17	164.40	151.40	128.57
CALA 80	**111.73**	**106.73**	**106.61**	**130.80**	**121.96**	**120.46**	**162.90**	**147.94**	**133.22**
AGGWLT 330	117.42	112.42	95.89	129.68	121.34	113.44	163.20	152.08	147.15
AGGWLT 400	112.53	107.53	94.99	129.17	120.84	112.19	162.32	151.69	146.90
AGGWLT 470	**110.47**	**105.47**	**94.15**	**127.74**	**119.41**	**110.74**	**160.68**	**150.64**	**143.29**
CorrWLT 30	113.31	108.19	96.24	128.16	119.83	112.66	164.04	146.51	145.13
CorrWLT 35	112.59	107.09	95.57	127.92	119.59	111.65	163.53	146.04	140.85
CorrWLT 40	**110.67**	**106.65**	**94.18**	**126.08**	**117.74**	**110.72**	**161.68**	**145.67**	**139.14**
LUMSCOR 30	103.94	101.69	87.56	121.11	112.77	106.24	156.88	145.84	138.80
LUMSCOR 35	101.72	101.33	86.01	119.04	110.71	105.11	155.53	144.90	130.85
LUMSCOR 40	**100.03**	**98.42**	**84.77**	**118.30**	**109.97**	**103.87**	**153.35**	**143.90**	**130.14**
WCWLT 1	104.92	101.13	88.39	130.08	121.75	113.85	158.76	147.72	133.02
WCWLT 2	101.97	100.23	87.49	129.39	121.06	112.41	156.52	145.90	132.99
WCWLT 3	**100.87**	**98.97**	**86.31**	**124.76**	**119.42**	**109.72**	**149.75**	**134.96**	**130.74**

Legends: MLT = Mean lead time, STL = Setup time level, CALA = Corrected aggregate load approach, AGGWLT = Aggregate workload trigger, CorrWLT = Corrected workload trigger, WCWLT = Work centre workload trigger, LUMSCOR = Lancaster university management school corrected order release. The bold value represents the best value (minimum) of MLT performance measure for a given ORR policy, shop utilization, and setup time level

Table 7. Results for TS performance measure for the considered ORR policies

ORR policies	TS								
	STL1			STL2			STL3		
	90	**85**	**80**	**90**	**85**	**80**	**90**	**85**	**80**
CALA 60	77918	80545	80918	76565	77676	77722	75571	76724	77571
CALA 70	77457	80200	80545	75545	77088	77545	74848	76664	76035
CALA 80	**77406**	**78915**	**80200**	**75171**	**76186**	**76578**	**74083**	**75578**	**75626**
AGGWLT 330	81126	82704	83578	77983	79083	81441	77262	78663	79681
AGGWLT 400	80364	81981	82915	76436	77375	80359	76343	76792	78582
AGGWLT 470	**79234**	**80961**	**82014**	**75308**	**76275**	**80125**	**74746**	**76073**	**78544**
CorrWLT 30	81664	82045	82418	77602	80166	80516	76059	77772	78616
CorrWLT 35	80664	81700	82045	75926	79393	79897	75384	77249	78344
CorrWLT 40	**79645**	**80686**	**81900**	**75492**	**78098**	**79458**	**74146**	**77139**	**77868**
LUMSCOR 30	79489	79565	79676	76918	79065	79764	76113	77131	77772
LUMSCOR 35	79257	79268	79435	76457	78448	79393	75131	76674	77131
LUMSCOR 40	**79132**	**79137**	**79171**	**75206**	**76037**	**76516**	**74307**	**75564**	**76116**
WCWLT 1	80489	81755	81676	77857	78631	79741	76141	78131	79564
WCWLT 2	80257	80656	81035	77742	78005	78394	76104	77674	78193
WCWLT 3	**79134**	**79737**	**79871**	**76102**	**76834**	**76915**	**74932**	**76632**	**76734**

Legends: TS = Total setups, STL = Setup time level, CALA = Corrected aggregate load approach, AGGWLT = Aggregate workload trigger, CorrWLT = Corrected workload trigger, WCWLT = Work centre workload trigger, LUMSCOR = Lancaster university management school corrected order release. The bold value represents the best value (minimum) of the TS performance measure for a given ORR policy, shop utilization, and setup time level.

Table 8. Results for NOTJ performance measure for the considered ORR policies

ORR policies	NOTJ								
	STL1			STL2			STL3		
	90	**85**	**80**	**90**	**85**	**80**	**90**	**85**	**80**
CALA 60	3411	3066	2915	2870	2716	2653	2312	2022	1978
CALA 70	3355	2960	2846	2701	2684	2589	2298	2010	1890
CALA 80	**3327**	**2948**	**2823**	**2688**	**2574**	**2228**	**2255**	**1962**	**1817**
AGGWLT 330	4181	3930	3511	3643	3476	2743	3568	3337	2358
AGGWLT 400	4137	3800	3238	3583	3349	2711	3545	2947	2150
AGGWLT 470	**4047**	**3562**	**3030**	**3493**	**3079**	**2688**	**3330**	**2845**	**2012**
CorrWLT 30	4491	4320	3521	3773	3334	2822	3498	3196	2323
CorrWLT 35	4127	4048	3511	3683	3136	2603	3358	3054	2122
CorrWLT 40	**4057**	**3808**	**3327**	**3603**	**3053**	**2532**	**3343**	**3043**	**2018**
LUMSCOR 30	3482	3153	3050	3376	2994	2597	2141	2085	1859
LUMSCOR 35	3342	3006	2979	3191	2874	2342	1977	2007	1794
LUMSCOR 40	**3331**	**2993**	**2938**	**3160**	**2674**	**2504**	**1973**	**1960**	**1726**
WCWLT 1	5058	4516	3748	4872	4225	3429	3535	3043	2988
WCWLT 2	4854	4473	3485	4848	4182	2947	3516	2991	2702
WCWLT 3	**4838**	**4435**	**3425**	**4716**	**4144**	**2890**	**3479**	**2953**	**2689**

Legends: NOTJ= Number of tardy jobs, STL = Setup time level, CALA = Corrected aggregate load approach, AGGWLT = Aggregate workload trigger, CorrWLT = Corrected workload trigger, WCWLT = Work centre workload trigger, LUMSCOR = Lancaster university management school corrected order release. The bold value represents the best value (minimum) of the NOTJ performance measure for a given ORR policy, shop utilization, and setup time level

Table 9. Best performing ORR policies in decreasing order at different setup times levels and shop utilization levels for MTT, MLT, TS and NOTJ performance measure

Performance measures	**Shop utilization levels**	**Best performing ORR policies in decreasing order**		
		STL1	**STL2**	**STL3**
MTT	90%	LUMSCOR, WCWLT, AGGWLT, CorrWLT, CALA	LUMSCOR, WCWLT, CALA, CorrWLT, AGGWLT	WCWLT, LUMSCOR, CorrWLT, AGGWLT, CALA
	85%	LUMSCOR, WCWLT, AGGWLT, CorrWLT, CALA	LUMSCOR, CorrWLT, CALA, WCWLT, AGGWLT	WCWLT, LUMSCOR, CorrWLT, AGGWLT, CALA
	80%	LUMSCOR, WCWLT, AGGWLT, CorrWLT, CALA	LUMSCOR, CALA, CorrWLT, WCWLT, AGGWLT	LUMSCOR, WCWLT, CorrWLT, AGGWLT, CALA
MLT	90%	LUMSCOR, WCWLT, AGGWLT, CorrWLT, CALA	LUMSCOR, WCWLT, CorrWLT, AGGWLT, CALA	WCWLT, LUMSCOR, AGGWLT, CorrWLT, CALA
	85%	LUMSCOR, WCWLT, AGGWLT, CorrWLT, CALA	LUMSCOR, CorrWLT, AGGWLT, WCWLT, CALA	WCWLT, LUMSCOR, CorrWLT, CALA, AGGWLT
	80%	LUMSCOR, WCWLT, AGGWLT, CorrWLT, CALA	LUMSCOR, WCWLT, CorrWLT, AGGWLT, WCWLT, CALA	LUMSCOR, WCWLT, CALA, CorrWLT, AGGWLT
TS	90%	CALA, LUMSCOR, WCWLT, AGGWLT, CorrWLT	CALA, LUMSCOR, AGGWLT, CorrWLT, WCWLT	CALA, CorrWLT, LUMSCOR, AGGWLT, WCWLT
	85%	CALA, LUMSCOR, WCWLT, CorrWLT, AGGWLT	LUMSCOR, CALA, AGGWLT, WCWLT, CorrWLT	LUMSCOR, CALA, AGGWLT, WCWLT, CorrWLT
	80%	LUMSCOR, WCWLT, CALA, CorrWLT, AGGWLT	LUMSCOR, CALA, WCWLT, CorrWLT, AGGWLT	CALA, LUMSCOR, WCWLT, CorrWLT, AGGWLT
NOTJ	90%	CALA, LUMSCOR, AGGWLT, CorrWLT, WCWLT	CALA, LUMSCOR, AGGWLT, CorrWLT, WCWLT	LUMSCOR, CALA, AGGWLT, CorrWLT, WCWLT
	85%	CALA, LUMSCOR, AGGWLT, CorrWLT, WCWLT	CALA, LUMSCOR, CorrWLT, AGGWLT, WCWLT	LUMSCOR, CALA, AGGWLT, WCWLT, CorrWLT
	80%	CALA, LUMSCOR, AGGWLT, CorrWLT, WCWLT	CALA, LUMSCOR, CorrWLT, AGGWLT, WCWLT	LUMSCOR, CALA, AGGWLT, CorrWLT, WCWLT

Legends: MTT = Mean throughput time, MLT = Mean lead time, TS = Total setups, NOTJ= Number of tardy jobs, STL = Setup time level, CALA = Corrected aggregate load approach, AGGWLT = Aggregate workload trigger, CorrWLT = Corrected workload trigger, WCWLT = Work centre workload trigger, LUMSCOR = Lancaster university management school corrected order release

From the above discussion, it is concluded that both setup time level and shop utilization level have significant effect on the performance of ORR policies in SDJS considering SDST.

7. Conclusions

The present work investigates the effect of setup times and shop utilization levels on ORR policies performance within SDJS considering SDST. The system's performance is evaluated in terms of TS, MTT, MLT, and NOTJ performance measures. The following conclusions are drawn from the present work:

1) Results show that for a given ORR policy, at a given setup time level and shop utilization level, MTT increases as WLT level increases. In contrast, other performance measures, i.e., MLT, TS, and NOTJ decrease.
2) For a given ORR policy, as shop utilization decreases, MTT, MLT and NOTJ decrease at all WLT levels for all setup time levels. In contrast, TS increase at all WLT levels for all setup time levels.
3) As setup time increases for a given ORR policy, MTT and MLT increase at all WLT levels for all shop utilization levels. In contrast, TS and the NOTJ decrease.

This research work can be extended by taking into account new sequencing rules in PSP with varying setup times and shop utilization levels. Further, the impact of routing flexibility on ORR policies can be assessed in a job shop with varying setup times and shop utilization levels. Other alternative approaches, viz., LUMSCOR-drum-buffer-rope, Kanban, Drum-buffer-rope, and ConWIP can be considered.

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