Journal of Scientific & Industrial Research
Vol. 81, November 2022, pp. 1195-1203
DOI: 10.56042/jsir.v81i11.55732

Impact of Preventive Maintenance and Machine Breakdown on Performance of Stochastic Flexible Job Shop Scheduling with Setup Time

Shrajal Gupta* & Ajai Jain
Department of Mechanical Engineering, NIT Kurukshetra, Kurukshetra 136 119, Haryana, India

Received 02 October 2021; revised 27 October 2022; accepted 27 October 2022

Real-time scheduling problems increase the practical implementation of the manufacturing system. In this study, using a single objective performance measure i.e., Number of Tardy Jobs (NTJ), the influence of 5 input constraints, i.e., reliability level (R_L), percentage of machine failure (%McF), mean time to repair for random machine breakdown (MTR_RMcB), due date tightness factor (Ғ), and routing flexibility level (R_FL) were evaluated for considered stochastic Flexible Job Shop Scheduling Problem (FJSSP). The study integrated reliability-centered preventive maintenance (PM_{RC}) and random machine breakdown (RMcB) environment with sequence-dependent setup time in the considered problem. A statistical response surface methodology was used to assesses NTJ. A second-order regression model was obtained to compute correlation between input constraints and NOTJ at 95% confidence level. The results demonstrate that main effects of R_L, %McF, Ғ, and R_FL; the interaction effects of R_L and Ғ, %McF and R_FL, MTR_RMcB and R_FL, and Ғ and R_FL; and quadratic effects of Ғ and R_FL, have significant impact on NTJ performance measure. Ғ has emerged as the major factor affecting NTJ. The confirmatory data demonstrate that error is less than 5%, confirming model can be used for future computations. Further, the novelties of the work are shown by the fact that it takes into account the uncertainties in the scheduling issue, as well as the dynamic tasks arrival environment. The aforementioned findings will assist production managers in planning and scheduling flexible job shops in order to satisfy customer demand on time.

Keywords: Random machine failure, Reliability-based maintenance, Routing flexibility, Sequence-dependent setup time, Simulation-optimization approach

Introduction

Schedules are critical components of the manufacturing system that have an impact on the whole production process, both positively and negatively. Scheduling is a term used to describe activities that must be performed under various conditions in order to keep the production system under control and optimized. However, maintenance activities keep the production system running. So, practical maintenance may extend machine life. Most scheduling issues presume that machines are always available and that maintenance avoids unforeseen disruptions. Still, unexpected machine breakdown (McB) cause machine unavailability and reduced operating time. So, the manufacturing system must consider both preventive maintenance (PM) and RMcB.

PM is a set of checks and adjustments made to an apparatus before it develops a fault. Many strategies for PM are being measured by investigators. To get machine back to as-good-as-new state, several researchers have proposed seven different kinds of PM methods, according to Wang.[1] These approaches were specific time period, i.e., periodic, age-oriented, repair limit, reliability-oriented failure limit, number of repair based, sequential, and time bound reference PM. Numerous unforeseen issues may arise in an unplanned machine failure that reduces production efficiency and lengthens delivery times. Integrating PM_{RC} and RMcB in FJSSP will provide real-world scheduling circumstances. Therefore, integrating these characteristics is an important direction in scheduling problem.

An optimal reliability threshold of 0.82 was reported by Chen *et al*.[2] using reliability based maintenance under FJSSP with sequence-dependent setup time (*SdSt*). They discovered that the precise maintenance approach had a superior statistical record than the others. Rahmati *et al*.[3] considered condition-based maintenance (CBM) based on reliability to improve efficiency in an integrated FJSSP and maintenance strategy. They found that the suggested strategy was able to intelligently and independently

*Author for Correspondence
E-mail: shrajalgupta11@gmail.com

control the process. According to Liao *et al*.[4] age-T or periodic maintenance policy performs better than reliability-based PM strategy. It was determined that using this method will reduce both the frequency and expense of maintenance cycles. Gupta and Jain[5] studied the influence of reliability-centered periodic preventive maintenance (*rcppm*), and PM_{RC} approaches in job shop scheduling problem (JSSP). In *rcppm* method lower level of maintenance time provided the best results. They also found that for the PM_{RC} approach, 0.74, 0.78, and 0.82 were proposed for all response except NTJ and mean tardiness. However, if maintenance time was 15% or more PM_{RC}, and for maintenance time, 10% or less *rcppm* technique was recommended.

Holthus[6] studied the effect of dispatching rule dynamic JSSP with McB, and found varying the number of breakdown factors affect the performance of the dispatching rules. Simulation-based McB was investigated by Ahmadi *et al*.[7] under FJSSP. Their statistical findings suggest that for spacing, non-dominating sorting genetic algorithm-II (NSGA-II), and for diversity, non-dominated ranking genetic algorithm (NRGA) was the best method. Sajadi *et al*.[8] considered breakdown simulator for FJSSP with RMcB. Their results show that in all three used metrics NRGA presence was more robust and stable than NSGA-II. Goren and Sabuncuoglu[9] used simulation approach with variable processing time and McB in their studied. The study's findings demonstrated that a methodical approach yields superior results, regardless of issue size. Singh *et al*.[10] considered sequence-independent and *SdSt* in flow shop scheduling environment. They found that their hybrid GA method performed better and reduced the make span by five times. Shahzad *et al*.[11] studied a multi-objective single-machine scheduling problem using the branch and bound method. As a result, they reduce the search space by dominance rules in their study for a single machine. They also found that for a small-scale problem, the proposed method provides better results. Gupta and Jain[12] considered PM and RMcB aspect in FJSSP. They have done multi-objective optimization of system performance measure. Almahmoud *et al*.[13] studied the effect of reliability-based maintenance on Aluminum based manufacturing plant using dynamic programming approach. Their result indicates that the proposed method provides better results. They also found that higher reliability required larger number of shutdowns. They also concluded that implementing this model would be useful for the plants since it would help to maintain the machinery at safe reliability levels, hence lowering the probability of unexpected breakdowns. Pradhan and Satapathy[14] considered independent task scheduling problem with energy consideration. They energy-based performance measure, i.e., energy consumption is estimated based on minimum completion time. They found that their proposed method provides better results as compare to other.

The literature review reveals that most researchers considered Wei-bull distribution for McB with exponentially distributed elements. Researchers suggested considering simultaneously PM_{RC} and RMcB with *SdSt* and R_FL under stochastic and dynamic job scenario in JSSP. Most studies solely evaluated maintenance or machine failure in independent from scheduling issues, and only a minority of studies included both. This study aims to perform single-objective optimization using the desirability approach for considered stochastic FJSSP with simultaneous PM_{RC} and RMcB with *SdSt*.

Experimental Details

Job Shop Configuration

In this investigation, ten different machines are considered on the shop floor. Each machine characterised, distinct scale and shape parameter. Six distinct job types, i.e., Job Type^A to Job Type^F, were considered. Job arrived dynamically with equal likelihood on shop floor. Job type has distinct path and number of operations to perform (NOPP) as shown in Table 1. Job Type^B, Job Type^E and Job Type^C each have total 6 NOPP. Job Type^A and Job Type^F have total 5 NOPP and Job Type^D has total 4 NOPP. In this investigation, processing time (PT) and *SdSt* was utilised evenly distributed and stochastic. PT on substitute machines at different flexibility levels and *SdSt* on each job change are shown in Table 1 and Table 2, respectively. Further, routing flexibility levels (R_FL) are considered from R_FL0–R_FL6, and shortest processing time (SPT) sequencing rule was used for allocation of job.

Preventive Maintenance Data

In this research, PM_{RC} was employed, where if the machine's reliability drops below a certain threshold, the maintenance performed on it will bring it back to original specifications, i.e., as-good-as-new state. Two-parameter Wei-bull distribution was consider by various researchers to study machine failure.[2,4,5]

The Wei-bull distribution has a strong influence on determining the machine's operating duration, dependent on the failure probability. For machine at operation time T_k reliability $R_k(T_k)$ can be expressed by Eq. (1).[2,5]

$$R_k(T_k) = \exp\left[-\left(\frac{T_k}{\varnothing_k}\right)^{\beta_k}\right], T_k \geq 0 \qquad \dots (1)$$

The T_k can be calculated as given by Eq. (2).

$$T_k = (-1) \times \varnothing_k \times \left[\ln\left(R_k(T_k)\right)\right]^{\frac{1}{\beta_k}} \qquad \dots (2)$$

Normal-log distribution was suggested by researchers for computing the maintenance time (t) required for maintenance. The following interrelation ship is used to compute t as given by Eq. (3).[3,15]

Table 1— Processing time

Job Type[i]	Operation	Mc_1	Mc_2	Mc_3	Mc_4	Mc_5	Mc_6	Mc_7	Mc_8	Mc_9	Mc_{10}
A	1	NA	$U_n(6,7)$	NA	$U_n(10,11)$	$U_n(7,8)$	$U_n(11,12)$	$U_n(9,10)$	NA	$U_n(5,6)$	$U_n(8,9)$
	2	NA	$U_n(10,11)$	NA	$U_n(7,8)$	$U_n(11,12)$	$U_n(6,7)$	NA	$U_n(9,10)$	$U_n(12,13)$	$U_n(8,9)$
	3	$U_n(9,10)$	NA	$U_n(12,13)$	$U_n(11,12)$	NA	$U_n(10,11)$	$U_n(13,14)$	$U_n(8,9)$	NA	$U_n(7,8)$
	4	NA	$U_n(6,7)$	$U_n(9,10)$	$U_n(12,13)$	$U_n(7,8)$	NA	$U_n(8,9)$	NA	$U_n(11,12)$	$U_n(10,11)$
	5	$U_n(10,11)$	$U_n(14,15)$	$U_n(13,14)$	$U_n(8,9)$	NA	$U_n(12,13)$	NA	$U_n(11,12)$	NA	$U_n(9,10)$
B	1	$U_n(9,10)$	$U_n(13,14)$	NA	$U_n(10,11)$	$U_n(14,15)$	$U_n(11,12)$	NA	$U_n(8,9)$	NA	$U_n(12,13)$
	2	$U_n(9,10)$	NA	$U_n(5,6)$	NA	$U_n(8,9)$	NA	$U_n(6,7)$	$U_n(11,12)$	$U_n(10,11)$	$U_n(7,8)$
	3	$U_n(12,13)$	$U_n(7,8)$	$U_n(9,10)$	NA	$U_n(6,7)$	$U_n(11,12)$	$U_n(10,11)$	NA	$U_n(8,9)$	NA
	4	$U_n(11,12)$	NA	NA	$U_n(9,10)$	$U_n(13,14)$	$U_n(10,11)$	$U_n(8,9)$	$U_n(12,13)$	NA	$U_n(7,8)$
	5	$U_n(4,5)$	NA	$U_n(8,9)$	$U_n(7,8)$	NA	$U_n(6,7)$	NA	$U_n(9,10)$	$U_n(5,6)$	$U_n(10,11)$
	6	NA	$U_n(7,8)$	$U_n(10,11)$	NA	$U_n(12,13)$	$U_n(8,9)$	$U_n(13,14)$	$U_n(9,10)$	NA	$U_n(11,12)$
C	1	$U_n(10,11)$	NA	$U_n(12,13)$	$U_n(7,8)$	NA	$U_n(11,12)$	$U_n(6,7)$	NA	$U_n(9,10)$	$U_n(8,9)$
	2	$U_n(6,7)$	$U_n(4,5)$	NA	$U_n(8,9)$	$U_n(5,6)$	NA	$U_n(7,8)$	NA	$U_n(3,4)$	$U_n(9,10)$
	3	$U_n(11,12)$	NA	$U_n(6,7)$	$U_n(9,10)$	NA	$U_n(7,8)$	NA	$U_n(10,11)$	$U_n(12,13)$	$U_n(8,9)$
	4	$U_n(3, 4)$	NA	$U_n(6,7)$	$U_n(9,10)$	$U_n(5,6)$	NA	$U_n(8,9)$	$U_n(4,5)$	NA	$U_n(7,8)$
	5	$U_n(6,7)$	$U_n(9,10)$	NA	$U_n(4,5)$	NA	$U_n(7,8)$	$U_n(8,9)$	$U_n(10,11)$	NA	$U_n(5,6)$
	6	$U_n(11,12)$	NA	$U_n(12,13)$	$U_n(15,16)$	$U_n(16,17)$	$U_n(10,11)$	NA	$U_n(13,14)$	$U_n(14,15)$	NA
D	1	$U_n(9,10)$	NA	$U_n(5,6)$	NA	$U_n(4,5)$	$U_n(7,8)$	NA	$U_n(6,7)$	$U_n(10,11)$	$U_n(8,9)$
	2	$U_n(11,12)$	NA	$U_n(14,15)$	NA	$U_n(10,11)$	$U_n(15,16)$	$U_n(9,10)$	NA	$U_n(12,13)$	$U_n(13,14)$
	3	NA	$U_n(7,8)$	$U_n(12,13)$	$U_n(10,11)$	NA	$U_n(8,9)$	$U_n(9,10)$	NA	$U_n(6,7)$	$U_n(11,12)$
	4	$U_n(9,10)$	NA	$U_n(12,13)$	$U_n(8,9)$	$U_n(13,14)$	$U_n(10,11)$	NA	$U_n(7,8)$	NA	$U_n(11,12)$
E	1	NA	$U_n(7,8)$	NA	$U_n(10,11)$	$U_n(9,10)$	NA	$U_n(8,9)$	$U_n(13,14)$	$U_n(12,13)$	$U_n(11,12)$
	2	$U_n(5,6)$	$U_n(10,11)$	NA	$U_n(7,8)$	NA	$U_n(11,12)$	$U_n(9,10)$	NA	$U_n(6,7)$	$U_n(8,9)$
	3	$U_n(10,11)$	NA	$U_n(7,8)$	NA	$U_n(9,10)$	$U_n(8,9)$	NA	$U_n(6,7)$	$U_n(12,13)$	$U_n(11,12)$
	4	NA	$U_n(8,9)$	$U_n(12,13)$	$U_n(10,11)$	NA	$U_n(7,8)$	$U_n(11,12)$	$U_n(9,10)$	NA	$U_n(6,7)$
	5	$U_n(5, 6)$	NA	NA	$U_n(8,9)$	$U_n(10,11)$	$U_n(4,5)$	$U_n(9,10)$	NA	$U_n(7, 8)$	$U_n(6,7)$
	6	NA	$U_n(11,12)$	NA	$U_n(9,10)$	$U_n(12,13)$	NA	$U_n(13,14)$	$U_n(10,11)$	$U_n(15,16)$	$U_n(14,15)$
F	1	$U_n(10,11)$	$U_n(16,17)$	$U_n(13,14)$	NA	$U_n(11,12)$	NA	$U_n(15,16)$	$U_n(14,15)$	NA	$U_n(12,13)$
	2	NA	$U_n(6,7)$	$U_n(9,10)$	NA	$U_n(7,8)$	$U_n(10,11)$	$U_n(5,6)$	$U_n(11,12)$	$U_n(8,9)$	NA
	3	NA	$U_n(8,9)$	NA	$U_n(6,7)$	$U_n(11,12)$	$U_n(9,10)$	NA	$U_n(7,8)$	$U_n(5,6)$	$U_n(10,11)$
	4	$U_n(11,12)$	NA	$U_n(13,14)$	NA	$U_n(9,10)$	NA	$U_n(12,13)$	$U_n(14,15)$	$U_n(15,16)$	$U_n(10,11)$
	5	$U_n(12,13)$	NA	$U_n(9,10)$	$U_n(15,16)$	$U_n(11,12)$	NA	$U_n(10,11)$	NA	$U_n(14,15)$	$U_n(13,14)$

R_FL0	R_FL1	R_FL2	R_FL3	R_FL4	R_FL5	R_FL6

Legends: Mc_i = Machine number, U_n = Uniform distribution, R_FLi = Routing flexibility level

Table 2 — Setup time data

Preceding job type	Job Type^A	Job Type^B	Job Type^C	Job Type^D	Job Type^E	Job Type^F
Job Type^A	0	U_n(2.00, 2.25)	U_n(2.00, 2.50)	U_n(2.00, 2.75)	U_n(2.00, 2.50)	U_n(2.00, 2.25)
Job Type^B	U_n(2.00, 2.25)	0	U_n(2.00, 2.25)	U_n(2.00, 2.50)	U_n(2.00, 2.75)	U_n(2.00, 2.50)
Job Type^C	U_n(2.00, 2.50)	U_n(2.00, 2.25)	0	U_n(2.00, 2.75)	U_n(2.00, 2.50)	U_n(2.00, 2.25)
Job Type^D	U_n(2.00, 2.25)	U_n(2.00, 2.50)	U_n(2.00, 2.25)	0	U_n(2.00, 2.75)	U_n(2.00, 2.50)
Job Type^E	U_n(2.00, 2.25)	U_n(2.00, 2.50)	U_n(2.00, 2.25)	U_n(2.00, 2.75)	0	U_n(2.00, 2.50)
Job Type^F	U_n(2.00, 2.25)	U_n(2.00, 2.50)	U_n(2.00, 2.25)	U_n(2.00, 2.75)	U_n(2.00, 2.50)	0

Legends: Job Type^i = Job Type, U_n = Uniform distribution

Maintenance time (t) ~ log-normal (μ_{PM} ; σ_{PM}) … (3)

The values of β_k, $\varnothing_k$, μ_{PM}, and σ_{PM} are taken from the literature. Hence, t is distinct for each and every considered machine. Further, range of β_k, $\varnothing_k$, μ_{PM}, and σ_{PM} are varies between 1.5–1.96, 62–100, 3.61–7.11, and 0.09–0.179, respectively.[2–5] In this study, reliability level (R_L) was considered as input factor, which varies from 0.74 – 0.90.[(2–5)]

Symbols used in equations are:

T_k	- Operation time	t	- Maintenance time
β_k	- Shape parameter	$\varnothing_k$	- Scale parameter
$R_k(T_k)$	- Reliability machine	ofμ_{PM}	- Mean value
σ_{PM}	- Standard deviation	R_s	- Reliability threshold level

Random Machine Breakdown Data

Considering RMcB in FJSSP will paradigm the scheduling problem in real time manufacturing scenario, breakdown time and the duration between breakdowns are two measures used to describe machine failure. Which are exponentially distributed. Machine failure is expressed mathematically as %McF (percentage machine failure), and is calculated by Eq. (4).[(6,7)]

$$\%\text{McF} = \frac{\text{MTR\_RMcB}}{\text{MTR\_RMcB}+\text{MTBF\_RMcB}} \quad \ldots (4)$$

where, MTR_RMcB = mean time to repair for RMcB, and MTBF_RMcB = mean time between failure for RMcB. In this study, PMF and MTR_RMcB were varies from 0–10% and 1 × P − 10 × P, correspondingly. P is known average processing time.[6,7]

Mean Inter-Arrival Time (*miat*)

It is known as mean amount of time occupied throughout jobs arrival. As demonstrated by researchers, job arrival process obeys Poisson distribution. Therefore, interval between arrivals of jobs is exponentially. In present investigation, *miat* was kept in such a manner so as to maintain the shop at 90% utilization level. Moreover, as nature of considered problem is stochastic. Thus, shop load is assessed between 1.5% of the targeted shop load.[16,17]

Jobs Due Date

It is the time frame in which the order to complete the task must be fulfilled. In this study, we used the total work content (TWC) methodology. It is computed using Eq. (5).[(16,17)]

$$\text{due\_d}_j = a_j + F(p_j + n_j\mu_s) \quad \ldots (5)$$

where, due_d_j = jobs due date, a_j = job arrival time, p_j = mean processing time, n_j = number of operations, and μ_s= average of average setup time. In present investigation, F varies from 1–4.

Simulation Model Configuration

Simulation modelling is approach to find a solution of intricate issue. This study uses Pro-Model® simulation software to develop a discrete-event simulation model for stochastic JSSP under simultaneous RMcB and PM_{RC} with routing flexibility and *SdSt*. The work flow of the issue under consideration is demonstrated in Fig. 1. The assumptions of the simulation model were taken as Gupta and Jain and Sharma and Jain.[5,16]

Performance Measure

To measure the system's performance, NTJ was taken as the performance measure of the system, it is defined as sum of all jobs completed after deadline time. It is computed by Eq. (6).[(5,16)]

$$\text{NTJ} = \sum_{j=1}^{n} \delta(J_j) \quad \ldots (6)$$

where, $\delta(J_j)$ = 1 if $J_j > 0$ and $\delta(J_j)$= 0, otherwise.

Experimental Design for A Simulation-Optimization Study

Firstly, in experimentation stage, the steady-state was recognized with Welch's technique.[18] A pilot study demonstrates that after 5000 jobs, system reaches to static state. The simulation model runs for thirty replications, finishing 25,000 jobs for simulation investigation. Due to the transition phase, tasks 1–5000 were abandoned from the simulation output. The remaining 20,000 (jobs numbering 5001–25,000) completion jobs were utilized to assess system performance. This phase was followed by the use of the one-factor-at-a-time strategy for determining the reference line levels and decreasing the total number of tests.[19]

Results and Discussion

In the present study, face centered central composite design was used.[12] Design expert software creates fifty trials based on the input constraints and their levels. The shop's performance was assessed in these design points using Pro-Model® simulation software. The experimental design set and average response value of NTJ performance measure is shown in Table 3.

Analysis of variance (ANOVA) methods was used to propose the regression model between input constraints and NTJ; and estimate the legitimacy of

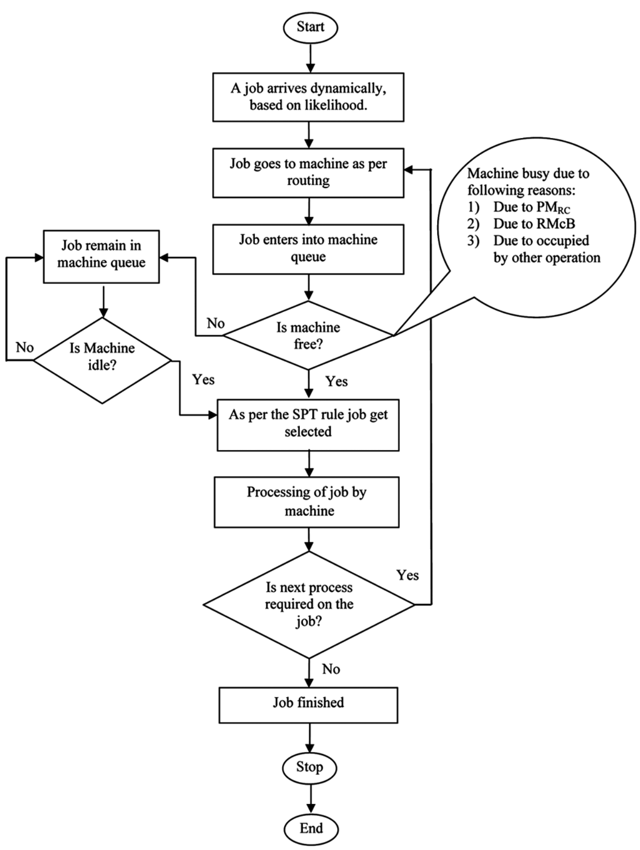

Fig. 1— Flow chart of a job flow

Table 3— Experimental design set and output responses of NTJ performance measure

Std	R_L	%McF	MTR_RMcB	F	R_FL	NTJ
1	0.74	0	1*$\bar{P}$	1	0	6035.9
2	0.9	0	1*$\bar{P}$	1	0	6983.9
3	0.74	0.1	1*$\bar{P}$	1	0	5005.9
4	0.9	0.1	1*$\bar{P}$	1	0	6416.6
5	0.74	0	10*$\bar{P}$	1	0	6035.9
6	0.9	0	10*$\bar{P}$	1	0	7061.2
7	0.74	0.1	10*$\bar{P}$	1	0	6235.5
8	0.9	0.1	10*$\bar{P}$	1	0	7315.3
9	0.74	0	1*$\bar{P}$	4	0	78.9
10	0.9	0	1*$\bar{P}$	4	0	159.1
11	0.74	0.1	1*$\bar{P}$	4	0	60.8
12	0.9	0.1	1*$\bar{P}$	4	0	155.3
13	0.74	0	10*$\bar{P}$	4	0	78.9
14	0.9	0	10*$\bar{P}$	4	0	159.1
15	0.74	0.1	10*$\bar{P}$	4	0	122.7
16	0.9	0.1	10*$\bar{P}$	4	0	220.7
17	0.74	0	1*$\bar{P}$	1	6	5201.6
18	0.9	0	1*$\bar{P}$	1	6	6366.3
19	0.74	0.1	1*$\bar{P}$	1	6	6385.9
20	0.9	0.1	1*$\bar{P}$	1	6	7338.4
21	0.74	0	10*$\bar{P}$	1	6	5201.6
22	0.9	0	10*$\bar{P}$	1	6	6366.3
23	0.74	0.1	10*$\bar{P}$	1	6	5867.7
24	0.9	0.1	10*$\bar{P}$	1	6	6972.2
25	0.74	0	1*$\bar{P}$	4	6	10.2
26	0.9	0	1*$\bar{P}$	4	6	19.4
27	0.74	0.1	1*$\bar{P}$	4	6	73.2
28	0.9	0.1	1*$\bar{P}$	4	6	95.9
29	0.74	0	10*$\bar{P}$	4	6	10.2
30	0.9	0	10*$\bar{P}$	4	6	19.4
31	0.74	0.1	10*$\bar{P}$	4	6	30.2
32	0.9	0.1	10*$\bar{P}$	4	6	47.1
33	0.74	0.05	5.5*$\bar{P}$	2.5	3	223.8
34	0.9	0.05	5.5*$\bar{P}$	2.5	3	485.3
35	0.82	0	5.5*$\bar{P}$	2.5	3	192.8
36	0.82	0.1	5.5*$\bar{P}$	2.5	3	432
37	0.82	0.05	1*$\bar{P}$	2.5	3	364.5
38	0.82	0.05	10*$\bar{P}$	2.5	3	306.7
39	0.82	0.05	5.5*$\bar{P}$	1	3	6483.4
40	0.82	0.05	5.5*$\bar{P}$	4	3	15.5
41	0.82	0.05	5.5*$\bar{P}$	2.5	0	770.6
42	0.82	0.05	5.5*$\bar{P}$	2.5	6	269.5
43	0.82	0.05	5.5*$\bar{P}$	2.5	3	293.5
44	0.82	0.05	5.5*$\bar{P}$	2.5	3	293.5
45	0.82	0.05	5.5*$\bar{P}$	2.5	3	293.5
46	0.82	0.05	5.5*$\bar{P}$	2.5	3	293.5
47	0.82	0.05	5.5*$\bar{P}$	2.5	3	293.5
48	0.82	0.05	5.5*$\bar{P}$	2.5	3	293.5
49	0.82	0.05	5.5*$\bar{P}$	2.5	3	293.5
50	0.82	0.05	5.5*$\bar{P}$	2.5	3	293.5

ANOVA Model – Fitness and Adequacy Verification regression model. A quadratic model was suggested by Design Expert® 12.0 software for NTJ performance measure at 95% confidence level to explain the system behaviour. ANOVA table for NTJ is shown in Table 4. The ANOVA table demonstrates that F-value of model is 602.24 at p-value less than 0.05, demonstrates that model is significant. It demonstrates that R_L, %McF, F, and R_FL are significant terms for NTJ. Further, it represents that R_L and F, %McF and R_FL, MTR_RMcB and R_FL, and F and R_FL are significant interaction terms, while F and R_FL are identified as significant quadratic terms for NTJ.

Further, R^2 value for NTJ performance measure is 0.9976. It demonstrates that only 0.24% of total variation cannot explain by model. Therefore, model accuracy is good. It also demonstrates that change between predicted and adjusted R^2 values is less (i.e., less than 0.0047) for NTJ. Because of this, models are very predictable. There is a practical treaty between them, proving the fitness of simulation data to generated mathematical model. Further, it also demonstrates that adequate precision value is 63.9014, which means model navigates design space. The final response equation for NTJ is represented below.

$$NTJ = 98.4783 + 52.8235 \times R\_L + 18.4526 \times \%McF + 0.544066 \times MTR\_RMcB + -68.1304 \times F + -1.29193 \times R\_FL + 17.1742 \times R\_L \times \%McF + -0.168045 \times R\_L \times MTR\_RMcB + -9.16845 \times R\_L \times F + -1.4387 \times R\_L \times R\_FL + 1.02532 \times \%McF \times MTR\_RMcB + 1.87092 \times \%McF \times F + 8.70791 \times \%McF \times R\_FL + -0.0414098 \times MTR\_RMcB \times F + -0.0723118 \times MTR\_RMcB \times R\_FL + -0.239206 \times F \times R\_FL + 3.29189 \times R\_L\text{^}2 + -455.448 \times \%McF\text{^}2 + -0.00846399 \times MTR\_RMcB\text{^}2 + 10.5576 \times F\text{^}2 + 0.401651 \times R\_FL\text{^}2 \quad \ldots (7)$$

A normal probability plot (Fig. 2) demonstrates that the model is suitable for evaluating NTJ performance indicators. All performance metrics' residuals congregate close to a straight line, showing that the mistakes follow a normal distribution regularly. As a result, the regression model closely matches the data.

Response Surface Analysis

Interaction effect plot for NTJ on input parameters is shown in Fig. 3 (a–d). Interaction effect plot

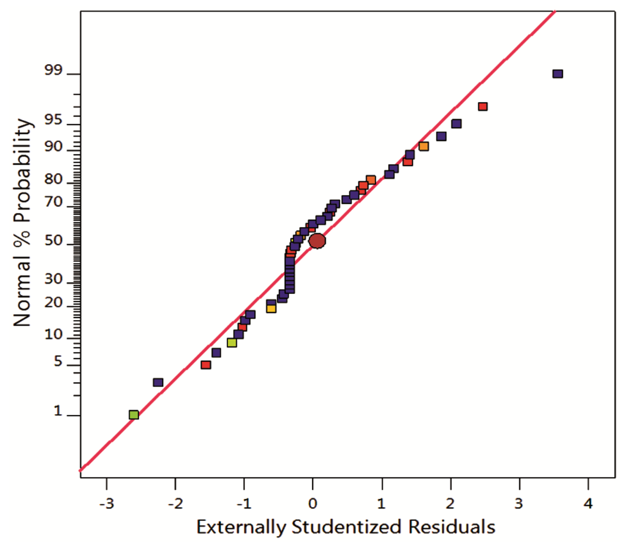

Fig. 2— shows the normal probability plot for NTJ

Table 4 — ANOVA for NTJ

Source	Sum of Squares	df	Mean Square	F-value	p-value	Remark
Model	50755.58	20	2537.78	602.24	< 0.0001	significant
A- R_L	208.03	1	208.03	49.37	< 0.0001	
B-%McF	46.67	1	46.67	11.07	0.0024	
D-F	43013.84	1	43013.84	10207.6	< 0.0001	
E-R_FL	118.42	1	118.42	28.1	< 0.0001	
AD	38.74	1	38.74	9.19	0.0051	
BE	54.6	1	54.6	12.96	0.0012	
CE	30.5	1	30.5	7.24	0.0117	
DE	37.08	1	37.08	8.8	0.006	
D^2	1395.66	1	1395.66	331.2	< 0.0001	
E^2	32.32	1	32.32	7.67	0.0097	
Residual	122.2	29	4.21			
Lack of Fit	122.2	22	5.55			
Pure Error	0	7	0			
Cor Total	50877.78	49				

R^2 = 0.9976, Adjusted R^2 = 0.9959, Predicted R^2 = 0.9912, Adeq Precision = 63.9014

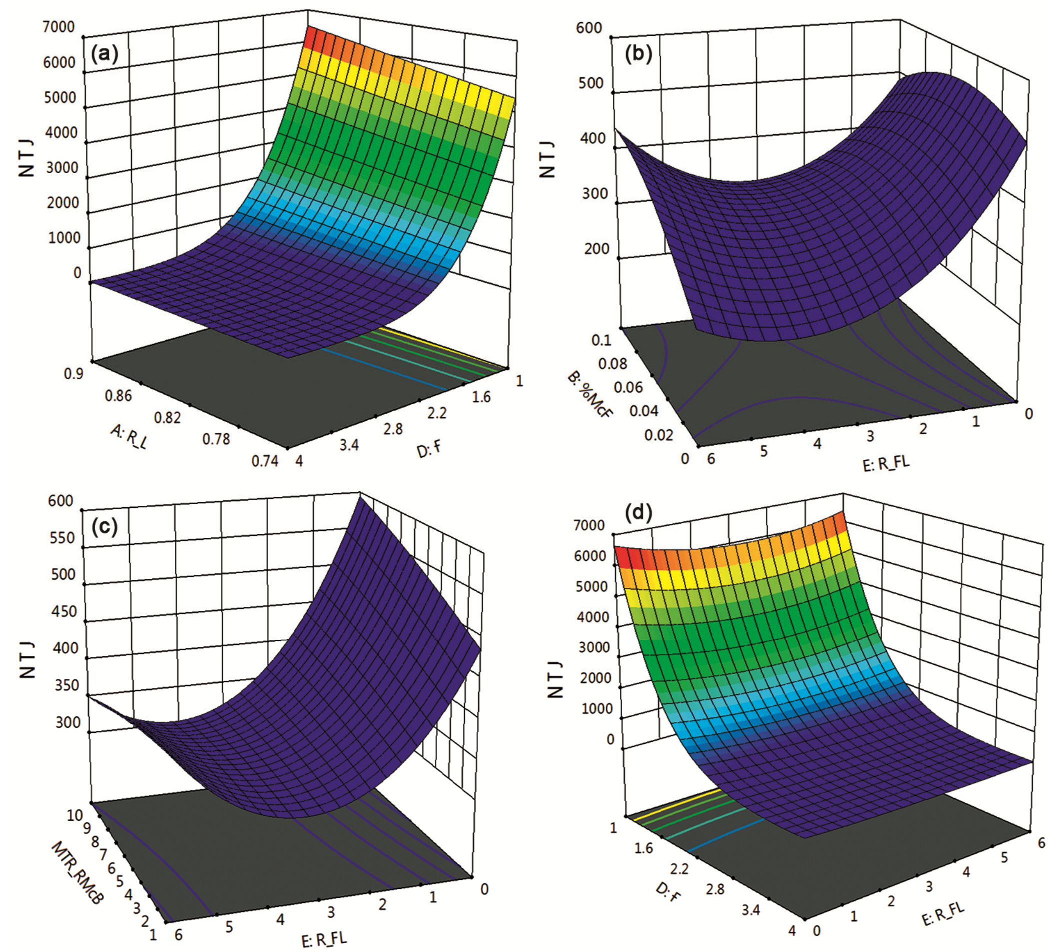

Fig. 3 — (a) Interaction plot of R_L & F (b) Interaction plot of %McF & R_FL (c) Interaction plot of MTR_RMcB & R_FL (d) Interaction plot of F & R_FL

between R_L and F demonstrated in Fig. 3 (a). It shows that lower value (L_V) of NTJ is attained at lower level (LL) of R_L, and higher level (HL) of F, i.e., 0.74, and 4, receptively. This is because, as operating time increases, the amount of time that passes between scheduled maintenance tasks increases, and job's deadline time rises. Therefore, tasks are not held up while waiting for the machine to finish. Hence NTJ decreases. A similar trend for R_L and tightness factor have been observed in past study.[12]

Interaction effect between %McF and R_FL is demonstrated in Fig. 3(b). It demonstrates that L_V of NTJ is obtained at LL of %McF and middle level (ML) of R_FL, i.e., 0% and R_FL4, respectively. This is because no machine breakdown has occurred, and there are other paths available to complete the task. Therefore, tasks are not held up while waiting for the machine to finish. Hence NTJ decreases. As R_FL rise from R_FL4 to R_FL6, NTJ increases again. The fixed configuration and intermachine rivalry in job shop reduced the improvement in NTJ. Hence, increasing R_FL improve the system performance (i.e., NTJ) up to certain limit only, i.e., R_FL4. A similar observation for RF and McB have been observed in the literature.[6,16]

Interaction effect between MTR_RMcB and R_FL is demonstrated in Fig. 3(c). It demonstrates that L_V of NTJ is obtained at LL of MTR_RMcB, and ML of R_FL, i.e., 1 × P and R_FL4, respectively. This is because of decrease in machine waiting time and availability of alternate job processing paths. Therefore, tasks are not held up while waiting for the machine to finish. Hence, NTJ decreases. A similar change in RF has been observed in past study.[16]

Interaction effect between F and R_FL is demonstrated in Fig. 3(d). It demonstrates that L_V of NTJ is obtained at HL of F, and ML of R_FL, i.e., 4

Table 5 — Optimal system parameters obtained using the desirability approach

Number	R_L	%McF	MTR_RMcB	F	R_FL	NTJ	Desirability
1	0.76	0.099	1.054	3.695	3.514	10	1
2	0.874	0.003	4.895	3.514	4.23	7	1
3	0.743	0.085	5.443	3.622	4.063	10	1
4	0.786	0.028	8.99	3.768	3.865	5	1
5	0.778	0.045	8.735	3.696	3.459	9	1
6	0.755	0.073	9.997	3.618	4.954	10	1
7	0.868	0.005	2.428	3.688	4.743	7	1
8	0.74	0	10	4	6	1	1
9	0.87	0.009	9.871	3.489	5.531	4	1
10	0.743	0.077	8.327	3.709	4.116	9	1

and R_FL4, respectively. This is because of rise in deadline time of jobs and availability of alternate job processing paths. Because of this, tasks don't have to wait around for the machine to finish processing them, and they may be completed in a timely manner. Hence, NTJ falls. A similar trend for RF and tightness factor have been observed in literature.[12,16]

Optimization Using Desirability Approach

The desirability method takes the raw response value from various performance metrics and converts it into a scalar number between 0 and 1 known as the desirability value (d_i) for that metric. The nature of the output response determines whether these numbers are organised as a maximum, minimum, or goal. The relative relevance of the objective function is represented by weight (w), which is likewise related with d_i. w may be given a value more than or equal to one, or it can be configured to be less than one. When $w = 1$, the desirability function is linear, but when $w > 1$, the attention is on the goal and when $0 < w < 1$, the emphasis is on something other than the target. For minimum response d_i is computed by Eq. (8).[(19)]

$$d_i = \begin{cases} 1 & y_i < T_i \\ ((U_i - y_i)/(U_i - T_i))^w & T_i \leq y_i \leq U_i \\ 0 & y_i > T_i \end{cases} \quad \ldots (8)$$

where, U_i represents upper limits of response y_i, and T_i represents target value.

Obtaining the desirability for NTJ is the initial stage, followed by maximizing desirability and determining the optimum value. Ten solutions are produced to find the actual optimum solution, and any of them con be considered as they all show the same desirability (Table 5).

To check the validity of the optimization results, confirmatory experiments were carried out at the parameter settings corresponding to solutions No. 1, 5, and 8 in Table 5. The simulation results for the confirmatory experiments were 8, 8, and 10, respectively, for solutions No. 1, 5, and 8. Based on these findings, the difference between the predicted and actual outcomes is less than 5%, which confirms the excellent reproducibility of the results.

Conclusions

The research work reveals that a second-order regression model is obtained to quantify the relationship between input parameters and NTJ. The results show excellent model predictability, and there is a reasonable agreement between them, proving the fitness of the simulation data to the generated mathematical model. The main effects of R_L, %McF, Ϝ, and R_FL; interaction between R_L and Ϝ, %McF and R_FL, MTR_RMcB and R_FL, and Ϝ and R_FL; and quadratic effects of Ϝ and R_FL, have significant impact on NTJ performance measure. Furthermore, Ϝ appeared as the most important influencing factor for NTJ, as shown by the higher F value (i.e., 43013.84) in ANOVA analysis. The integrated simulation-optimization approach predicts the optimal condition for system performance optimization. The confirmatory data demonstrate that error is less than 5%, confirming model can be used for future computations. The aforementioned findings will assist production managers in planning and scheduling flexible job shops in order to satisfy customer demand on time. Task cancellation, limited buffer capacity, transportation delay, and job pre-emption are only few of the additional shop aspects that may be taken into account to further develop the current work.

Acknowledgment

The authors are grateful to the Directors and Faculty members of the National Institute of Technology Kurukshetra, India, for providing the research facilities.

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