Investigating the Degradation and Upgradation models of Flexible Unit Systems for Smart and Sustainable Production

Submitted in partial fulfilment of the requirements

for the award of the degree of

Doctor of Philosophy

by

SAMALA THIRUPATHI

Roll No: 719065

Under the Supervision of

Dr. Vijaya Kumar Manupati
Assistant Professor, MED

Department of Mechanical Engineering
NATIONAL INSTITUTE OF TECHNOLOGY
WARANGAL – 506004
Telangana State, INDIA.

Oct - 2022

THESIS APPROVAL FOR Ph.D.

This thesis entitled **"Investigating the Degradation and Upgradation models of Flexible Unit Systems for Smart and Sustainable Production"** by **Mr. Samala Thirupathi** is approved for the degree of Doctor of Philosophy.

____

____

____

Examiner

Dr. Vijaya Kumar Manupati
Assistant Professor, Department of Mechanical Engineering, NIT Warangal
Supervisor

Prof. Suresh Babu. V
Head, Department of Mechanical Engineering, NIT Warangal
Chairman

NATIONAL INSTITUTE OF TECHNOLOGY

WARANGAL – 506 004, Telangana State, INDIA

CERTIFICATE

This is to certify the thesis entitled **"Investigating the Degradation and Upgradation models of Flexible Unit Systems for Smart and Sustainable Production"** submitted by **Mr. Samala Thirupathi** for, Roll No. 719065, to **National Institute of Technology, Warangal** in partial fulfilment of the requirements for the award of the degree of **Doctor of Philosophy in Mechanical Engineering** is a record of bonafide research work carried out by him under our supervision and guidance. This work has not been submitted elsewhere for the award of any degree.

Place: Warangal.

Date:

Dr. Vijaya Kumar Manupati
Supervisor
Assistant Professor,
Department of Mechanical Engineering,
National Institute of Technology,
Warangal, Telangana State.

NATIONAL INSTITUTE OF TECHNOLOGY

WARANGAL – 506 004, Telangana State, INDIA

DECLARATION

This is to certify that the work presented in the thesis entitled **"Investigating the Degradation and Upgradation models of Flexible Unit Systems for Smart and Sustainable Production"**, is a bonafide work done by me under the supervision of **Dr. Vijaya Kumar Manupati**, Assistant Professor, Department of Mechanical Engineering, NIT Warangal, India has not been submitted for the award of any degree to any other University or Institute.

I declare that this written submission represents my ideas in my own words and where ever others ideas or words are included have been adequately cited and referenced with the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will cause for disciplinary action by the institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Place: Warangal.
Date:

Samala Thirupathi
Roll No. 719065

AKNOWLEDGEMENTS

I would like to express my sincere gratitude and profound indebtedness to **Dr. Vijaya Kumar Manupati,** Assistant Professor of Mechanical Engineering Department, National Institute of Technology, Warangal for giving me an opportunity to carry out doctoral work under his esteemed supervision. This work is a reflection of his thoughts, ideas, and concepts. **Dr. Vijaya Kumar Manupati** looks at things in the right perspective, and it has truly been a learning experience working with him. I owe a lot to him for making me a part of the continuity of the profession.

I extend my sincere gratitude to **Prof. N. V. Ramana Rao,** Director, National Institute of Technology Warangal, India for providing the necessary facilities and encouragement throughout my work.

I am thankful to **Prof. Suresh Babu V,** Head, Department of Mechanical Engineering, NIT Warangal and other faculty members for their encouragement and support extended during this period.

It's my great opportunity to express my deepest gratitude to the Departmental Scrutiny Committee members, **Dr. Suresh Babu V,** Professor, Department of Mechanical Engineering, **Dr. Subhash Chandra Bose,** Associate Professor, Department of Mechanical Engineering, and **Dr. Ilaiah Kavati,** Assistant Professor, Department of Computer Science and Engineering, for their adeptness and many discussions during this research period.

I express my sincere thanks to my co-scholars **Veerababu Ramakurthi, Malliswari Karanam,** NIT Warangal for their support and help in completion of this thesis.

I would like extend my heartfelt thanks to **Mr. B. Rangilal, Mr. G. Ilaiah,** technical staff of Production Engineering Lab and **Mr. M. V. Vijay Kumar** office staff of Mechanical Engineering Department, NIT Warangal for their constant help and encouragement.

A Special dept of deep gratitude to my father **Samala Rajesham,** and my mother **Samala Laxmi** for their unceasing sacrifices, endeavours and encouragement.

Finally, I would like to acknowledge the help given by all the persons who have directly or indirectly supported the work.

Samala Thirupathi

Research Publications

International Journals

1. Samala, Thirupathi; Manupati, Vijaya K.; Varela, Maria L.R.; Putnik, Goran. 2021. "Investigation of Degradation and Upgradation Models for Flexible Unit Systems: A Systematic Literature Review" Future Internet, Vol.13, No. 3: 57. https://doi.org/10.3390/fi13030057, **IF: 3.64, ESCI**

2. Samala, Thirupathi, Vijaya Kumar Manupati, Jose Machado, Shubham Khandelwal, Katarzyna Antosz. “A Systematic Simulation approach for the evaluation of process parameters on Semi-Fully flexible machine systems”, Electronics, Vol.11(2), https://doi.org/10.3390/electronics11020233 , **IF:2.6, SCI**

3. Samala, Thirupathi, Vijaya Kumar Manupati, Bethalam Brahma Sai Nikhilesh, Maria Leonilde Rocha Varela, and Goran Putnik. "Job adjustment strategy for predictive maintenance in semi-fully flexible systems based on machine health status" Sustainability, Vol.13, No. 9 (2021): 5295. https://doi.org/10.3390/su13095295, **IF: 3.251, SCI**

4. Samala Thirupathi, Vijaya Kumar Manupati. “An Integrated Meta-Learning based predictive scheduling approach for Remaining Useful Life of flexible unit systems”, Reliability Engineering and Systems Safety. (Communicated).

5. Samala Thirupathi, Vijaya Kumar Manupati, Bethalam Brahma Sai Nikhilesh, Jose Machado, MLR Varela. “Integration of Cyber Physical Systems for Flexible systems”, “Smart Manufacturing Technologies for Industry 4.0: Integration, Benefits, and Operational Activities”, CRC Press, Taylor and Francis group, (Accepted).

ABSTRACT

Flexible Unit Systems (FUS) is an assembling structure wherein there is some proportion of flexibility permits the system to react if there should be an event of changes, regardless of whether predicted or unpredicted. This work proposes the degradation, residual life distribution, workload adjustment, upgradation, predictive maintenance of flexible unit systems that gives a wide guide of the main explored look into issues in flexible units and future research openings on the point. An example of 43 scholarly articles distributed in peer-evaluated worldwide diaries up to 2020 comprises the information base of the examination. After a detailed review, few major performance parameters of manufacturing systems such as throughput rate, throughput time, system utilization, availability, average stay time, and maximum stay time which affect the manufacturing systems are shown great importance in its performance and maintaining the final product quality. Ranking of those parameters from the most influenced parameter to the least one is utmost requirement for overall assessment particularly when the applications are complex. An integrated Multi Criteria Decision Making (MCDM) – Technique of Order Preference by Similarity to the Ideal Solution (TOPSIS) method has been used to ranking in which these parameters can influence various manufacturing expenditures.

Based on these Identified and ranked parameters, we developed a stochastic linear degradation model to find the real-time degradation coefficient of each machine in a system at every instance. We established a textile industry case study for single product category with the key assumptions. Hence, a Bayesian approach is deployed to update prior distribution of degradation coefficient to get posterior distribution with the help of measurements that are collected in real-time and then predicting Remaining Useful Life (RUL) of machines from degradation signals. With the available health status value of each machine and their corresponding degree of flexibility, the dynamic job adjustment strategy is applied to achieve the maximum output for the system. Along with that, the maintenance of machines is also important to ensure the system to run efficiently. In extension, the maintenance prediction for the FUS has been proposed and Meta learning based intelligent Cyber-Physical System (I-CPS) architecture as a higher-level environment for ML based predictive maintenance has been executed with the help of predictive simulation.

Further, learning the maintenance prediction which determines the degree of the maintenance necessity between 0 and 1 has been proposed and RUL has been estimated for 3 months, 4 months, and 5 months of training data respectively. From here, the simulation analysis has been conducted to find the throughput time for equal, random, and proposed workload adjustment strategies on 4 flexible configurations. Further, Criticality Index (CI) of each machine has been predicted by considering the predicted maintenance as an input with the collected data. The CI from 1 to 5 indicated which machine is under more critical or less critical and based on the index, and estimated maintenance time is required for combined machines or multiple machines or individual machines with respect to CI. Here, the RUL is the length of time a machine is likely to operate before it is going to failure, and CI indicates the level of criticality of a machine. Further, the predicted RUL and CI will be giving the health information about the machine which helps in enhancing the throughput rate of every machine. The machine which need to go for maintenance first has been decided based on decision matrix. Finally, Workload adjustment for a system whose individual machines RUL, and CI has known has been proposed for throughput enhancement.

Keywords: Flexible Unit Systems, Degradation, Remaining Useful Life, Workload strategy, Upgradation, Predictive Maintenance, Machine Learning, Criticality Index.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

FUS	Flexible Unit Systems
RUL	Remaining Useful Life
JIT	Just In Time
MCDM	Multi-Criteria Decision Making
TOPSIS	Technique of Order Preference by Similarity to the Ideal Solution
CPS	Cyber Physical Systems
PPC	Production Planning and Control
MM	Maintenance Management
PLC	Product Life Cycle
I-CPS	Intelligent – Cyber Physical Systems
CI	Criticality Index
PROMETHEE II	Preference Ranking Organization Method for Enrichment Evaluation
ML	Machine Learning
SLR	Systematic Literature Review
KPI	Key Performance Indices
IIoT	Industrial Internet of Things
PHM	Prognostics and Health Management
MTBF	Mean Time Between Failure
MTTR	Mean Time To Run

NOMENCLATURE

(a,b) or (q,r)	Position and stage of a machine
N	Number of machines
D	Demand per unit time
$C_{(q,r)}$ or $C_{(a,b)}$	Capacity of a machine with respect to position q or a and stage r or b
$O_{(q,r)}(x)$ or $A_{(a,b)}(x)$	Jobs Assigned on a machine q,r or a,b at the time x
$TH(x)$	The system's throughput at time x
$\tilde{N}(x)$	Number of operational machines at the time x
$A_{(q,r)}(x)$ or $B_{(a,b)}(x)$	The amplitude for degradation wave of q,r or a,b at the time x
$i_{(q,r)}(x)$ or $i_{(a,b)}(x)$	The instantaneous degradation rate of the machine q,r or a,b at the time x
$W_{(q,r)}(x)$ or $W_{(a,b)}(x)$	degradation error of Brownian motion for machine q,r or a,b at the time x
$\alpha_{(q,r)}(x)$ or $\alpha_{(a,b)}(x)$	Degradation coefficient for machine q,r or a,b
$\beta_{(q,r)}$ or $\beta_{(a,b)}$	Mean of prior distribution of $\alpha_{(q,r)}$ or $\alpha_{(a,b)}$,
$\gamma^2{}_{(q,r)}$ or $\gamma^2{}_{(a,b)}$	The variance of prior distribution of $\alpha_{(q,r)}$ or $\alpha_{(a,b)}$.
δx	Sampling interval.
$W_{(q,r)}(x_{u-1})$	Column vector that constitutes the number of jobs of a machine q,r from x_0 to x_{u-1}.
$\delta A_{(q,r)}(x_u)$ or $\delta B_{(a,b)}(x_u)$	Column vector that constitutes increments in degradation of machine q,r or a,b observed from time intervals x_0 to x_{u-1}

$p(.)$	Probability density function for distribution.
$\beta_{(q,r)}(x_u)$	Mean of posterior distribution for $\alpha_{(q,r)}$ updated at x_u.
$\gamma^2{}_{(q,r)}(x_u)$	Variance of the posterior distribution of $\alpha_{(q,r)}$ updated at x_u.
$F_{(q,r)}$	Pre-defined failure threshold for a machine q,r.
$IG(.)$	An inverse Gaussian distribution for the cumulative distribution function
$\mu_{(q,r)}(x_u)$	The mean variable of the conditional residual life distribution of machine q,r computed at x_u.
$S_{(q,r)}(x_u)$	The shape parameter of the conditional residual life distribution of machine q,r computed at x_u
$di_{(q,r)}(x_u)$ or $di_{(a,b)}(x_u)$	Degradation indicator of the machine q,r or a,b which is identified with the severity of degradation.
$E_{(q,r)}\delta x$ or $L_{(a,b)}x$	Repair time of a machine q,r or a,b
Z	Throughput time
t_p	Processing time for a job on a machine
t_s	Setup time of a machine
$U_{(a,b)}$	Time to produce n number of jobs on a machine a,b

Chapter 1

Introduction

1.1 Manufacturing Systems

A manufacturing system can be the combination of various machines, equipment, and the humans that are bound by the information flow. In a factory, various manufacturing processes assembled together to produce a desired product. The manufacturing system takes certain inputs and transforms those inputs into the final product for the customer. Nowadays, the manufacturing industries are also facing the different challenges of keeping their competitiveness in the market requirements and technological evolution. In this unique circumstance, profound research activity need to be addressed to the development of smart factories in manufacturing sector. In order to make a factory smarter, smart devices are to be used such as sensors, drives, motors, switches and relays etc. A smart factory is defined as it is an exceptionally digitized shop floor that persistently gathers and shares the data through associated machines, gadgets and production systems. With its tremendous applications in businesses, for example automotive and transportation, packaging and process industries such as oil and gas, the smart factory relied upon to encounter enormous growth in coming years. Generally, the manufacturing systems can be designed differently according to the company's strategy, boundary conditions, and the goals mentioned in [1].

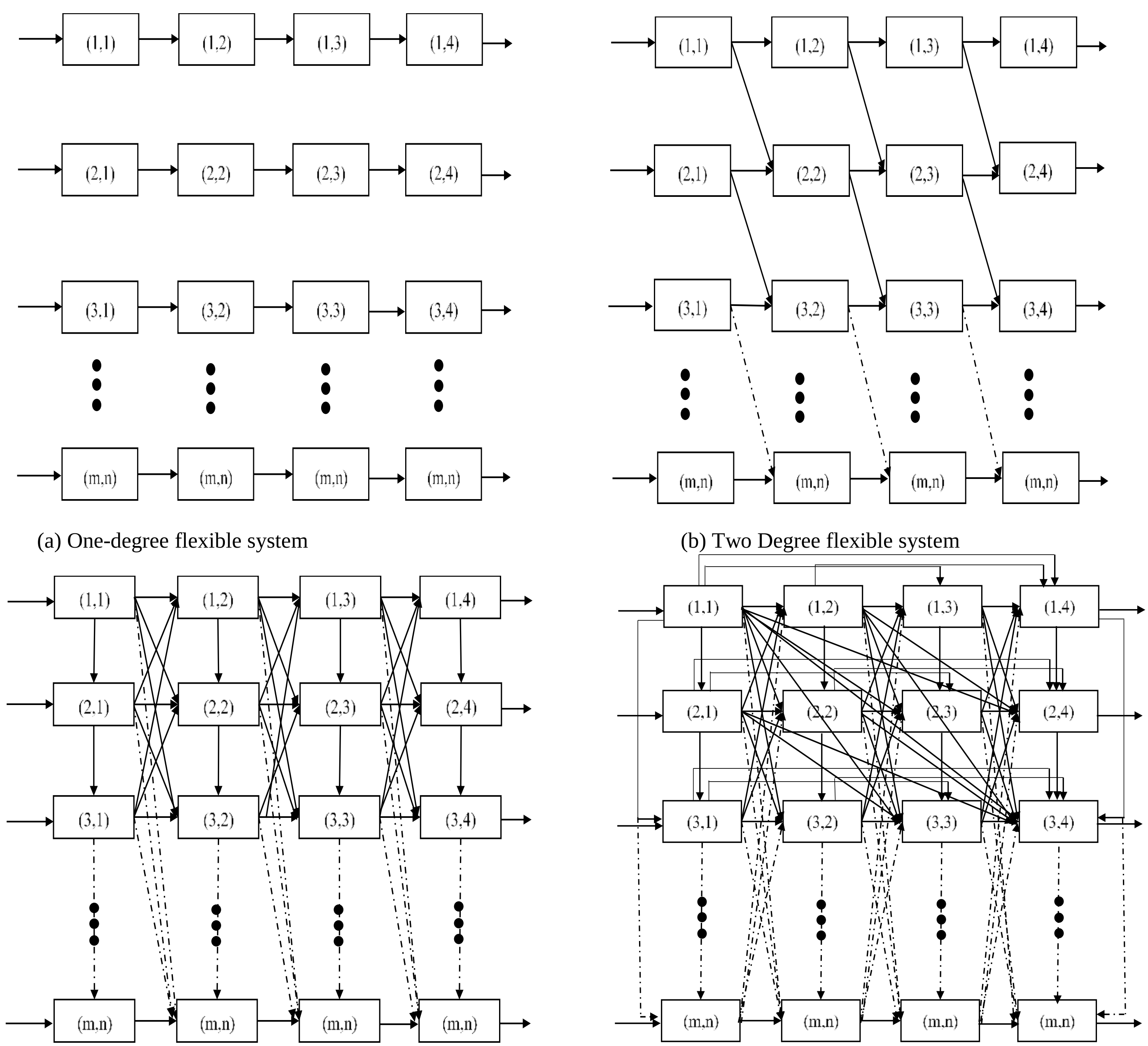
1.2 Flexible Unit Systems (FUS)

The recent requirements such as shorter product life cycles, high production rates, jobs complexity, quality products, and cost effectiveness are the most significant factors for any manufacturing industry. Considering all the foregoing requirements, in addition, according to the current market demand and society needs there is a need to enhance the systems capabilities by maintaining it under control from system breakdowns and several external forces that have not been considered as a highest priority in the past decade. To accomplish these challenges, there is a need for high machine availability, flexibility, accessibility of the manufacturing processes. The flexibility in the manufacturing system configuration is necessary for complex products to cope with the system responsiveness. Better responsiveness shows a significant level of impact in increasing the efficiency of the system but seldom makes a system more expensive [2-6]. According to

Chryssolouris et al. [7], the flexibility of a manufacturing system, can be defined in terms of its sensitivity to change, where the sensitivity of the system decreases, the system to incorporate flexibility increases. However, not just machines but the layout of the machine's configuration, type of operations, and the type of products produced also have an impact on the manufacturing system flexibility. For example, a well-known cell production unit situated in japan is famous for its flexibility, operates with just a couple of human operators, manufacturing items themselves. Flexible complex manufacturing systems usually consist of multiple machines, which operate individually or simultaneously in a particular configuration to achieve the required demand.

In theory, Ji-wen sun et al. [8] stated that the proper choice of machine configuration greatly impacts the manufacturing system concerning its machine reliability and system reliability. As a result, numerous scholars have published articles by optimizing the configurations to get better productivity [9-11]. In addition, they require fewer workers to work them contrasted with other manufacturing flexibilities. Furthermore, in a flexible manufacturing environment, the identical machines are designed with a certain level of redundancy that if in case of any unexpected event the system cultivates a certain level of common redundancy to compensate. For instance, the capacity of the machines has always kept a value higher than the usual number of jobs assigned so that, if in the system a machine fails, the other operating machines can be delegated with the number of jobs more than they are usually assigned to keep up with system necessities. In the U.S. organizations according to Federal Reserve, the normal repetition for manufacturing industries has been evaluated to be around 20% [12]. Whereas such a repetition structure by design endeavors to give a vigorous production scheme, it isn't uncommon and due to that, an enormous number of machines tend to degrade at a similar rate, particularly when an equal number of workloads is allocated to those machines [13]. As a result, it will certainly lead to simultaneous multiple machine failures and system necessities being unsatisfied.

Among all the existing manufacturing systems configurations, the semi-fully flexible real-time configurations also called as FUS, i.e., one-degree, two-degree, semi-flexible, and fully flexible configurations have been proposed in this research. The above-mentioned configuration provides routing flexibility, so the system can use two or more machines to perform the same task, and the system's ability to handle a large number of changes, such as a substantial increase in capacity and machine failure [3]. Each of the models illustrated in Figure 1.1 (a–d) have a different level of flexibility. In this research, we deliberated the degree of flexibility as the ability of a machine to adjust the assigned number of jobs for completion in response to failure or maintenance.



(a) One-degree flexible system

(b) Two Degree flexible system

(c) Semi-flexible system

(d) Fully flexible system

Figure 1.1 (a-d) Flexible Configurations

For instance, Figure 1.1 (a) presents a one-degree flexible environment, here machines work individually and simultaneously in a linear path to fulfil the necessity of the system, but if the machine (1,1) fails, the pending assigned jobs on the machine (1,1) can be processed by the adjacent machine (1,2) depending upon the availability of the machine, stating one-degree flexibility. Figure 1.1 (b) articulates a two-degree flexible environment, here the availability of machines for job adjustment increases, i.e., in case of failure in the machine (1, 1), the adjacent machine (1, 2) or machine (2, 2) can process the pending jobs of the machine (1, 1). Followed by this are semi-flexible and fully flexible configurations in Figure 1.1 (c), (d) respectively, where the options for workload adjustment are more in comparison to one-degree and two-degree flexible systems.

1.2.1 Performance Parameters

This section explains an overview of performance parameters which influence the flexible systems and their ranking. Generally the manufacturing systems are disrupting due to their own natural characteristics or unexpected downtimes, their health management for machines is considered as a most confound approach for better performance, mentioned by [14]. From the various literature [15, 16], it was shown that majorly six performance parameters need to be considered which influence the above mentioned four configurations performance. These parameters influence the flexible machine system’s performance, as machine availability can be an important determinant of delivery speed and delivery dependability because unexpected machine downtime will not only increase lead time but also disrupt the production plan [16]. Such disruptions can be detrimental to a Just-in-Time (JIT) manufacturing environment. Along with that, the average stay time of jobs, maximum stay time of jobs, maintenance costs, and production cost force firms to analyze the performance of their systems systematically and efficiently about the availability of the machines [17]. The simulation analysis for the performance parameters helps in visualize and understanding of systems behavior of real-time manufacturing systems mentioned by [18].

A method needs to be used for ranking the performance parameters from most influenced to least influenced which furtherly can help on increasing in manufacturing systems performance and product quality. The integrated MCDM method considers all standards and the importance that decision-makers place to determine the most satisfactory solution based on its performance evaluation [19]. The literature [19, 20] mentioned that different MCDM techniques have been used to solve the problems related to decision making or ranking among the alternatives. An entropy method has been presented by the [21] and it has been utilized for finding the weight of each criterion. From the past literature, it has been observed that an integrated MCDM methodology based on the TOPSIS method has been utilized to rank the parameters. Among the various MCDM techniques, the TOPSIS method is best suited for decision-making problems since it has been observed that the TOPSIS method has been preferred for considering the quantitative criteria mentioned by [22]. The main principle of the TOPSIS method is the selected alternative should be in the shortest distance from the positive ideal solution and the largest distance from the negative ideal solution. To determine the attribute weight for the TOPSIS method the Entropy method is frequently utilized [23]. Generally, the Entropy method is used to calculate the weights of each criterion when decision-makers having conflicting views on the value of weights.

1.2.2 Integration of Cyber Physical Systems for FUS

With the advancement of sensors, actuators, data acquisition systems, communication, and the latest network technologies, the manufacturing field transforming into the digital age. Hence, there is a need to integrate Cyber Physical System (CPS) with traditional Production Planning and Control (PPC) and the Maintenance Management (MM) for manufacturing industries. CPS is the integration of physical processes with the computation, information, and communication technologies, as the systems immersed with the physical components and interact with those physical processes. Generally, the physical part consists of human/material/machine/environment, which executes the manufacturing activities, and the cyber part consists of the embedded systems in which it is a combination of input/output peripheral devices, computer processes, and computer memory [24]. PPC is a tool, which helps in integrating and coordinating the entire manufacturing activities in a manufacturing system. The production plan handles the materials planning, capacity planning, and operations scheduling and the control portion oversees the actual production process to meet the production targets. The main aim of production planning and control is to minimize direct and indirect costs [25]. The maintenance management is the process of maintaining a firm's assets and resources. The main purpose of maintenance management is to make sure that production runs in an efficient way and that assets of a firm are used effectively [26].

In this context, the industries need CPS proficiencies for improving the usage of resources and increasing the operator safety [27]. The integration of CPS with the PPC and MM help industries in fulfilling the different needs such as efficient systems, reduction in systems building cost, operational cost, and development of new innovative system capabilities and mostly it has been recognized in manufacturing, energy, and medical domains [28,29]. Among various maintenance strategies, the condition-based strategy is dependent on the present condition and it needs to determine, consequently, times of the necessities can be predicted with the help of predictive maintenance technique at an early stage [30-32]. These maintenance techniques help in improving several challenges that affect the FUS' efficiency and performance in the view of the breakdown of machines, maintenance issues, sudden interruptions due to natural characteristics, etc. [33]. The integration CPS for FUS shown in Figure 1.2.

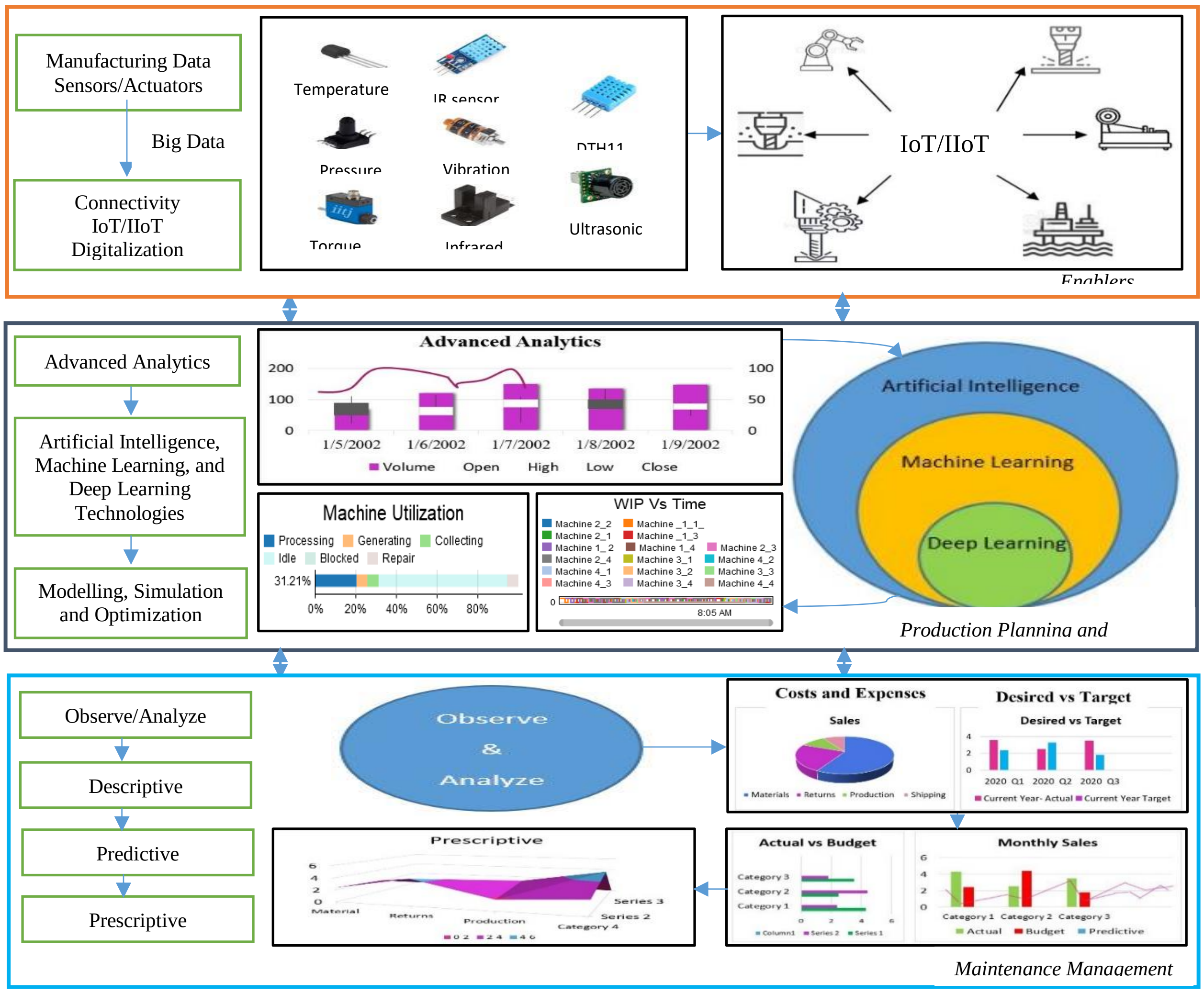


Figure 1.2 Integration of CPS on flexible systems

The challenges for integrating the CPS for a manufacturing system has been observed from four viewpoints: improving the production, reconfiguration, information technology, and standardization. A 5C architecture with five levels VIZ., connection, conversion, cyber, cognition, and configuration to overcome some of the challenges mentioned above. Here, the accuracy and reliability measurements of FUS can be obtained by connecting various sensors to the units, and it has concerned with the connection level and connection level is the first level of 5C architecture in integration of CPS. The measurement data into the useful information conversion is taken care of by the conversion level. More data can be obtained by connecting sensors to a greater number of machines and it has been emphasized by the cyber level. The statistics and visual information to assist users to make decisions will be known by the cognition level. Finally, the feedback back to the physical system according to the decisions made will be known by the configuration level.

There were limited frameworks and approaches available in the context of integration of CPS across Product life cycle (PLC). In this research, an integrated CPS with their traditional PPC and MM for several flexible configurations that can cater the needs of recent production industries has been proposed. This work also concerns how Industry 4.0 integrates the CPS regarding maintenance activities and various needs for a company to reach the ideal factory.

1.2.3 Degradation

Generally the manufacturing systems subjected to degradation where the machines life comes down to full health condition to failed condition. Although, a good amount of research investigated component level and machine level degradation on system performance, but a significant research gap exists on the unit-level analysis for controlling the degradation of machines in turn to enhance the system-level performance. In this research, a stochastic linear degradation model has been developed to find the real-time degradation coefficient of each machine in a system at every instance. Consequently, an assumption considered as that the degradation rate of each machine is a random variable following a normal distribution to apprehend the deviation in the degradation process due to natural characteristics. Further, a Bayesian approach has deployed to predict the remaining useful life of the machines and their corresponding value.

1.2.4 Remaining Useful Life (RUL)

Estimation of Remaining Useful Life (RUL) helps in understanding the degradation behavior of a manufacturing system at various stages, and it also helps in maintaining the system health status. To handle the customized orders that are low in volume, frequent demand shifts, and long-lead times current manufacturing systems configurations are not only capable enough to manage the production process. Moreover, every machine in the production system has its own health status therefore its RUL. Predicting the RUL of each machine which is a key point for understanding the system behavior in parallel and hybrid configurations [13]. In line with this purpose, a multi-stage RUL based on real time data has been proposed and the time features has been extracted from the collected raw sensory data to classify the machine's health status. Similarly, a novel mission reliability based RUL prediction method is developed in a serial manufacturing system [34]. Later, an empirical analysis for predicting the RUL based on the condition monitoring data has been presented by developing a model degradation using the data driven prognostics based ML techniques [35]. It is noted that, based on the RUL of a system, a workload adjustment strategy helps in improving productivity in the manufacturing industries.

1.2.5 Workload Adjustment strategy

Workload adjustment strategy can be utilized for controlling the pace of degradation of machines in a parallel and hybrid configuration was proposed by [36]. Based on the mentioned problematic condition, [37, 38] proposed a method to control the disruptions and to predict the failure time of each machine in a parallel configuration by adjusting the workloads on individual machines. This transformation leads to a lot of studies and concepts on the maintenance methodologies related to the manufacturing systems [39]. The health status of a machine can be evaluated by the conventional prognostics and diagnostics approaches and these are essential in the case of machine health management in Industry 4.0 [40, 41]. With the available health status value of each machine and their corresponding degree of flexibility, the workload adjustment methodology can be applied to achieve the maximum output from the system. This study presents a method to assign the number of jobs dynamically in a real-time flexible manufacturing environment to overcome simultaneous multiple machine breakdown in a system for achieving higher production. The problem here is designed in such a way that it considers all the real-time system configurations in a flexible environment. Altogether, this study provides prescriptive analytic for a manufacturing system, utilizing a dynamic job adjustment strategy.

1.2.6 Predictive Maintenance

Machine maintenance is generally defined as four ways, "reactive maintenance", preventive maintenance, predictive maintenance, and proactive maintenance [42, 43]. The main objective of maintenance of manufacturing systems is to minimize the downtime of machines, unscheduled maintenance and to make sure that production facilities keep running as smooth as possible. This is a real challenge to the many industries and they are facing the difficulties in defining of maintaining and execute the schedules. It will show a large impact on the efficiency of production facilities and cost increment, because of shutting down the manufacturing machines until the problem has been resolved. At that particular time, the continuous advancement in research and development can be involved in with the new intelligent solutions for decision making, especially with the predictive maintenance in machine learning. It has been observed from the literature that many researchers considered only vibration data into the consideration for their studies for the detection of damages. A very few researchers use one or more features such as temperature, pressure, and sound. In addition it is not common to use only one machine learning algorithm comparatively in modeling the collected data. In this study, 30 major machine learning algorithms has been trained, tested and validated in which algorithm is providing better F1 score to predict the maintenance and not to have maintenance has been identified. For this, the semi double loop machine learning based Intelligent – Cyber Physical Systems architecture for predict the maintenance has been used [44].

1.2.7 Criticality Index (CI)

Due to the customer requirements for a various customized products, the companies not only plan for the maintenance activities of the machines, but also issues need to be considered related to the business goals. Based on the above mentioned reason, the major issue for any company is a machine's Criticality Index (CI) [45]. Criticality index of a machine is the most important category in the manufacturing industry in case of maintenance management of a system. The CI of machines or devices used in manufacturing industry can be structured a set of activities to identify failures which impacts on companies goals [46]. The CI defined as it is the level of critical referring to the machines with the highest or lowest importance for maintenance.

The Remaining Useful Life (RUL) and Criticality Index (CI) will be providing the health status of a particular machine which will help in enhancing the throughput rate of every machine by adjusting the workloads. RUL is the length of time a machine is likely to operate before it is going to failure. And CI indicates the level of criticality of a machine to know the time required for the maintenance. Workload adjustment for a system whose individual machines RUL, and CI has known has been proposed and validated by throughput enhancement.

1.3 Organization of Thesis

Chapter 1: Introduction

In this chapter, the research preliminaries and the conceptual background of the research area has been explained. This chapter also includes the motivation for the research and scope of the research. The thesis organized into eight chapters and contents of each chapter are presented below in brief.

Chapter 2: Literature Review

A Systematic Literature Review has been conducted to find the literature related to modelling and analysis of FUS. Literature review attempts to give detailed information unit degradation model to predict the RUL. The workload adjustment strategy for single product category, and multi-product category has been discussed based on predicted RUL. The prediction of CI for combined machine strategy, multiple machine strategy, and individual machine level strategy has been discussed. Finally, workload adjustment strategy by combining of RUL and CI based on the decision matrix has also reviewed.

Chapter 3: Development of realistic configurations ranging from Semi-Flexible to Fully-Flexible systems and identifying the performance measures

In this chapter, The FUS performance parameters has been identified and analyzed by conducting simulation analysis and further, the simulation results has been validated with the experimental results. Thereafter, MCDM Entropy method has been used to identify the weights of each parameter and then TOPSIS method has been used to rank the parameters. Finally, the rankings from the TOPSIS method are compared with the PROMETHEE method rankings.

Chapter 4: Development of workload strategy for linear degradation model on single product category

In this chapter, an approach has been developed using each machine's degradation information to predict the machine's RUL. based on the RUL information the job adjustment strategy of single product category where machines with a lower health status will be given a high number of jobs to perform is proposed. The objectives of the proposed model are to reduce simultaneous machine failures by slowing down the pace of degradation of machines, to improve the average occurrence of the first failure time of machines, and to decrease the loss of production.

Chapter 5: Workload Adjustment strategy on Meta Learning based CPS approach for Predictive Maintenance in Flexible systems based on Machine status indications

In this chapter, the workload adjustment strategy of multi-product category from the FUS has been proposed. Initially, the maintenance of individual machines has been predicted based I-CPS architecture. Further, the RUL of an individual machines has been known with the help of predicted maintenance. Finally, the workload adjustment strategy has been applied based on RUL has been executed along with the other two benchmark strategies i.e. equal, and random workload strategy.

Chapter 6: Development of Criticality Index prediction for multi-product category for identifying machine status indicators

In this chapter, two original and innovative contributions has been presented. The model of machine learning based approach for predictive maintenance in FUS and the CI prediction of each machine with the help of Meta learning based I-CPS architecture as a higher-level environment for ML based maintenance prediction execution.

Chapter 7: Enhancing the Throughput of Flexible Configurations using novel Hybrid Degradation model

In this chapter, the workload adjustment strategy on flexible unit configurations has been proposed by combining of RUL, and CI. The quick maintenance of machine has been preferred based on decision matrix in which the machine is having low RUL and CI. The proposed methodology has enhanced the throughput of system compared to workload adjustment applied on single product category, and multi product category without considering CI for flexible configuration.

Chapter 8: Conclusions, and Future Scope

This chapter reports the research contributions of degradation and upgradation models of FUS. The results obtained from the analysis shown that the throughput time is most influenced parameter. The tools, techniques, and approaches used in this research can help for researchers for predicting the system behavior there by improving the health status of their system. The RUL and CI of each individual machines are predicted which provides the health status of machine. In this research, we specially focused on instantaneous degradation rate is proportional to the workload, but in reality such relationships may not be appropriate. In future, a study is needed to perform the workload adjustment strategy when the degradation rate and the workload having different relationships. A study also required to aim at the creation of a software for the frequent observation of the criticality index of machines.

Chapter 2

Systematic Literature Review

2.1 Systematic Literature Review

This thesis reviews the state-of-the-art degradation of manufacturing flexible systems through RUL, workload adjustment strategy, and CI in case of single and multi-product category and the maintenance predictions for smart factories. Smart factory research is an interdisciplinary class that is performed by researchers from various backgrounds mentioned in [47]. The scenery of scientific literature on the idea of the "smart factory", which in recent years gaining more consideration from academics and experts. Smart factories consolidate modern organization, cloud, and supervisory terminals with smart shop floor objects, for example, conveyers, products, and machines [47, 48].

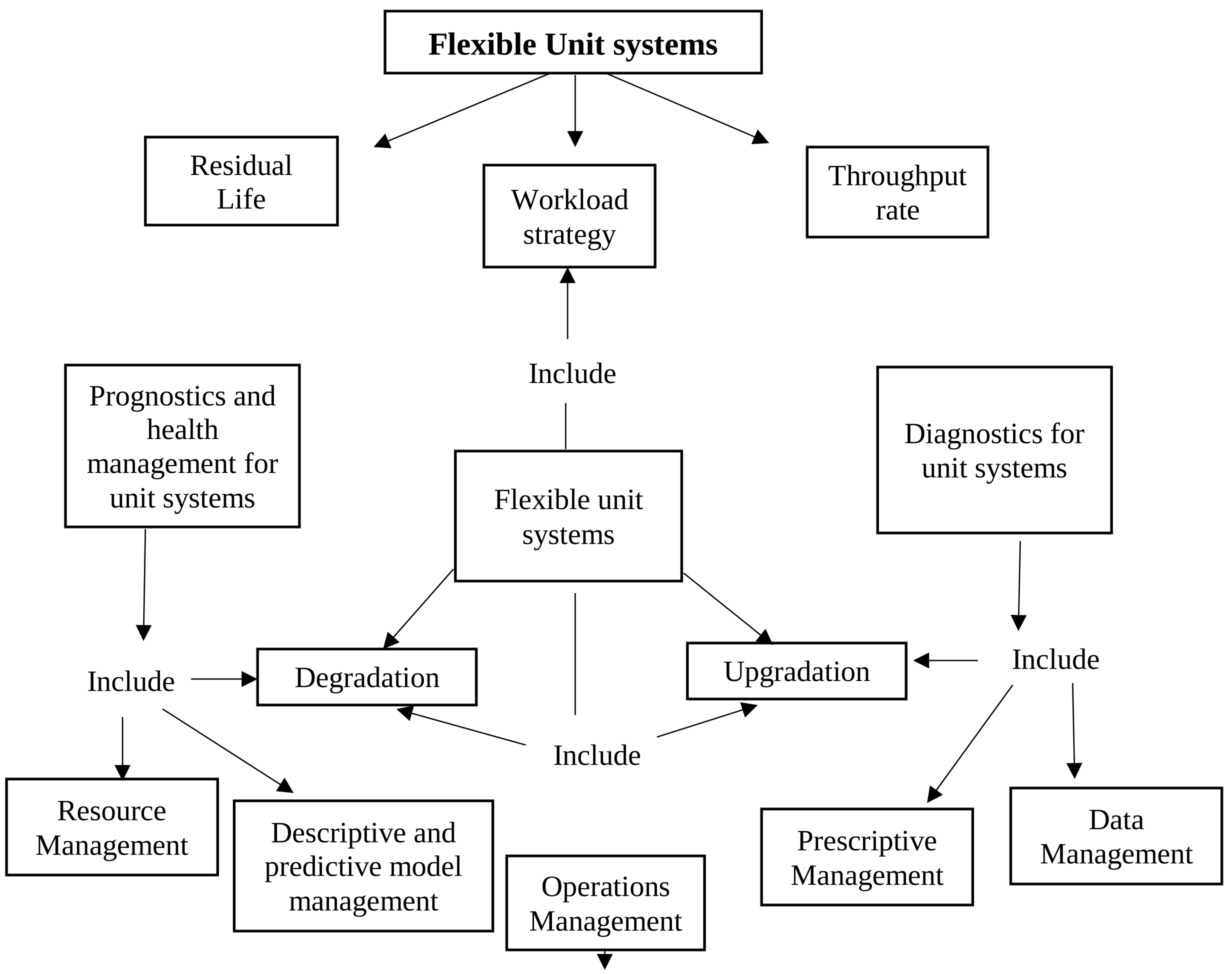


Figure 2.1 Framework addressing the topics effects the flexible unit systems

Smart factories and smart manufacturing technologies give us additional information for understanding the connection between working conditions and machine degradation and failures. For example, rough starts and stops may be the reason for recurring misalignments problems in a machine. With this information, integration of CPS with respect to production planning and control and maintenance management can improve the production rate. The common factors from different studies that affect the FUS are degradation rate, residual life distribution, workload strategy, upgradation, and predictive maintenance. Given this scenario, A Systematic Literature Review (SLR) with respect to the degradation and upgradation models for FUS has been conducted to stimulate the future investigations. The analysis of the reviewed literature, a comprehensive conceptualization has been developed shown in Figure 2.1.

The research followed the SLR is a basic scientific activity that delivers a clear and comprehensive overview compared to descriptive literature reviews. The formation of a basic framework for an in-depth analysis and a scientific process can be possible by using the SLR. It has been observed from the systematic literature followed a sequence of five steps are as follows.

1) Formation of questions;
2) Finding the studies;
3) Study preference and evaluation;
4) Investigation and combination;
5) Reporting and using the results.

Step1. Formation of Questions

RQ1. What is the role of degradation, residual life distribution, workload strategy, upgradation, and predictive maintenance on flexible unit systems?

RQ2. How to integrate the degradation and upgradation models to the flexible unit systems?

Step2. Finding the studies

This step concerns how to find and choose the bibliographic database or search engine, additionally search strings. The research questions have been considered in this search for literature reviews. Following similar literature reviews [49-51] and three bibliographic databases i.e. Web of Science, Scopus and Science Direct a remarkable quantity of published literature on degradation rate, residual life distribution, workload strategy, upgradation, and predictive maintenance including very relevant important journals in this area has been considered.

Table 2.1 Search string and Number of results from Web of science

Search String	Search Field	Date of Search	No. of Results
“Flexible unit systems (or) Flexible machine systems” and “Degradation (or) Degradation Rate”	Topic	11-08-2020	273
“Flexible unit systems (or) Flexible machine systems” and “Residual Life (or) Residual Life Distribution”	Topic	11-08-2020	34
“Flexible unit systems (or) Flexible machine systems” and “Workload strategy (or) Workload adjustment”	Topic	11-08-2020	42
“Flexible unit systems (or) Flexible machine systems” and “Upgradation”	Topic	11-08-2020`	2
“Flexible unit systems (or) Flexible machine systems” and “Predictive Maintenance”	Topic	11-08-2020	41

Table 2.2 Search string and Number of Results from Scopus

Search String	Search Field	Date of Search	No. of Results
“Flexible unit systems (or) Flexible machine systems” and “Degradation (or) Degradation Rate”	Article title, abstract, keywords	04-09-2020	178
“Flexible unit systems (or) Flexible machine systems” and “Residual life (or) Residual life Distribution”	Article title, abstract, keywords	04-09-2020	9
“Flexible unit systems (or) Flexible machine systems” and “Workload strategy (or) Workload adjustment”	Article title, abstract, keywords	04-09-2020	14
“Flexible unit systems (or) Flexible machine systems” and “Upgradation”	Article title, abstract, keywords	04-09-2020	1
“Flexible unit systems (or) Flexible machine systems” and “Predictive Maintenance”	Article title, abstract, keywords	04-09-2020	9

Table 2.3 Search string and Number of Results from Science direct

Search String	Date of Search	No. of Results
“Flexible unit systems (or) Flexible machine systems” and “Degradation (or) Degradation Rate”	18-09-2020	152
“Flexible unit systems (or) Flexible machine systems” and “Residual life (or) Residual life Distribution”	18-09-2020	124
“Flexible unit systems (or) Flexible machine systems” and “Workload strategy (or) Workload adjustment”	18-09-2020	84
“Flexible unit systems (or) Flexible machine systems” and “Upgradation”	18-09-2020`	101
“Flexible unit systems (or) Flexible machine systems” and “Predictive Maintenance”	18-09-2020	193

Tables 2.1, 2.2, and 2.3 shows the search strings searched in data bases and the results obtained using the three mentioned databases. However, after sorting the selecting research articles and by selecting the publication title between 2009-2020 shows 603 number of articles for the search string “Flexible unit systems (or) Flexible machine systems and Degradation (or) Degradation rate”, 167 articles for the search string “Flexible unit systems (or) Flexible machine systems and Residual Life Distribution (or) Residual life”, 140 articles for the search string “Flexible unit systems (or) Flexible machine systems and workload strategy (or) workload adjustment”, 104 articles for the search string “Flexible unit systems (or) Flexible machine systems and Upgradation” and 243 articles for the search string “Flexible unit systems (or) Flexible machine systems and Predictive Maintenance” respectively.

Step3. Study preference and Evaluation

In this step, filtering criteria was explicated, to choose only relevant studies to add in the review, in which the studies actually addressed the research questions. From 1995 to 2008 articles were excluded because they were just consigned to the small percentage of the examples. 11 years (2009-2020) of related studies was initiated to focus on recent studies, methodologies, and technologies. The article journals of document type have been sorted from the search results and at best articles distributed in peer-reviewed journals in English were contemplated and Bortolini et al., (2018) [49] argue that enclosing the search towards the peer-reviewed journals, and the results can be improved because rigorous processes to such articles are subject before publication.

This exercise reduces the number of journal articles to 198. After checking the duplicates (initially in each search string and after, taking into consideration all search strings set together), titles, abstracts of the selected journal articles were analyzed for relevance, further the number of articles reduced to 106. Articles qualified for review must fulfill the five major criteria (i) articles related to finding the Degradation level of manufacturing systems (ii) articles related to finding the residual life of manufacturing systems (iii) articles related to be adjustment strategy of workload to reduce the degradation level of manufacturing systems (iv) articles related to upgradation of manufacturing systems. (v) Articles had to be focused on predictive maintenance of manufacturing systems. At this step, the number of articles for investigation was 106. At last, a more examined analysis of the 66 articles was made with the full gratified review.

Step4. Investigation and Combination

In this step, the content of each paper was analyzed concerning identifying the key issues. Through full-content review, different articles were excluded, because those are not as per the specified research focus of this study. In this way, the number of definite articles for the investigation have been reduced to 43, as recorded in Table 2.4.

Table 2.4 Summary of articles preferences and evaluation.

Bibliographic database analysis	Search1	Search2	Search3	Search4	Search5	Total
Web of sciences	273	34	42	2	41	392
Scopus	178	9	14	1	9	211
Science Direct	152	124	84	101	193	654

	Inclusion/Exclusion criteria of Web of sciences					
Date Range	193	29	26	1	28	277
Document type	191	29	26	1	28	275
Research Area	175	26	23	1	26	251
Language	174	26	22	1	26	249
	Inclusion/Exclusion criteria of Scopus					
Date Range	155	9	11	1	6	182
Document Type	130	6	7	1	6	150
Research Area	109	6	6	1	6	128
Language	96	6	6	1	6	115
After checking the duplicates (in each search)	113	22	36	3	24	198
After checking the duplicates (in all search)	106					
Analysis of (Abstract and Title)	66					
After a detailed article analysis	59					

Step5. Reporting and using the results

The data contained in 59 articles was summarized and then prepared with connected categories, for example, methodologies used in their research and various key findings. The list of journals related to the number of articles published as well as the year of publication are noted.

Reliability engineering and systems safety, International Journal of Advanced Manufacturing Technology, IEEE Transactions on automation science and engineering, Journal of Intelligent Manufacturing, IFAC online, CIRP Annals: Manufacturing Technology, and IEEE Transactions on Reliability contributed to 55% of the total articles published related to factors (degradation, residual life distribution, workload strategy, upgradation, and predictive maintenance) related to the manufacturing systems. Other journals like the Journal of Computers & Industrial Engineering, IIE Transactions, Journal of manufacturing systems, Procedia Manufacturing, European Journal of Operations Research and few other journals contribute to 45% of the total journal articles published related to factors affecting the manufacturing systems.

The relevant data has been collected and studies are arranged dependent on five factors, which are mentioned in the research methodology. Only these five relationships are formulated because these five are the common factors that will affect the flexible unit systems in different ways mentioned in the recognized studies, connection, conversion, cyber, cognition, and configuration. The integration of the CPS approach with the production plan and MM of flexible configurations contribution is important and it can improve the productivity [52].

The discussion in this section has been focused on detailed literature of the CPS approach with the PPC and MM as well as several challenges that affect the system's efficiency and performance of realistic flexible configuration systems. CPS became more popular in the context of the fourth industrial revolution (Industry 4.0). The main drivers for the development of CPS are as security, competitiveness, social needs, etc. for reduction in development costs [53] and time with the improvement in designing of the products to make systems safer, increment in productivity, and reduction in maintenance cost. The relation between the designed product and manufacturing system plays a key role in the evolution of Industry 4.0 [54-55]. For building of CPS an 8C architecture by considering the 3C facets along with the 5C architecture provided guidelines for a smart factory has been proposed in [56].

PPC is the planning for the production and manufacturing of various modules in an industry. Generally increasing in shorter PLC and the challenges facing by the employees as a result of technological changes require to upgrade their practice-related training and qualifications. Given the above-mentioned situation, the cost objectives influence by the numerous interactive mechanisms. The decisions need to be made in the frame of PPC and targeted as these objectives have to consider the reason of technical considerations. From the past literature it has been clarified that the CPS in the view of PPC is an advantage in case of cost reduction [57]. Similarly, [58] investigation has shown that production planning is essential for manufacturing systems for reducing the overall cost. Along with that, [59] presented a method to the production and maintenance plan on a manufacturing system to minimize the cost and maximize the reliability.

The literature in the past have shown that inadequate maintenance practices also affect the industry's competitiveness by reducing the reliability of production facilities and lowering equipment availability. To solve the above-mentioned problems, industrial systems' maintenance is an important part of asset management strategy that aims to maintain better levels of efficiency. Generally, maintenance will lead to the monitoring of physical processes with the help of sensors and it is a basic function of CPS. It has been identified how industry 4.0 integrate CPS regarding maintenance management and the requirements for industries to reach the ideal smart factory. Thus, the impact of maintenance mainly on profitability and productivity, which are the two most important business performance aspects. Along with that many industries are seeking to facilitate performances assets and gain a safer, more sustainable environment with the help of better asset management strategies. Moreover, the industry may face various challenges with the integration of CPS to the manufacturing industry, and it can be listed as data protection, data security, and strategic planning, etc. [60-62]. [63] Worked on aiming to review the literature on the CPS for manufacturing the fourth industrial revolution for a complete understanding of its challenges, and various used techniques in his domain. But many industries are facing the various breakdown problems and research focusing on machine breakdown has also grown significantly in the past few years. In manufacturing systems, the uncertainty in machine breakdown has a severe effect on the system in context to his production planning, maintenance planning and system predicted output [64]. To overcome this, Koh and Sameh [65] intended to represent the stochastic nature of such interruption. Later, Yan and Jay [66] designed a prognostic algorithm to capture this process of machine failure as the degradation process stating it as a single staged process and tried to predict the residual life of the machines.

2.2 Degradation of manufacturing systems

The degradation of a manufacturing systems is defined as the condition of degrading or being degraded. The degradation information of a manufacturing systems will help in knowing the performance of manufacturing the products. Although, system degradation is not a single staged process in real life but instead a multi-staged process following a Poisson distribution, mentioned in [67]. With this information, a multi-stage stochastic degradation model was proposed to the performance of a system using Bayesian updating methods to extract real-time data from machines and update the degradation model for finding the Residual Life Distribution for degraded machines [68]. Following this, numerous research was carried towards the modeling of the degradation process with an insight to capture the degradation coefficient [69]. Later, Bian and Gebraeel [70] formulated a stochastic model for the degradation process of inter-dependent parts in a multi-component system. Hao et al. [37] adopted the stochastic model and proposed a prognostics method to predict the residual life of each component in a composite manufacturing system by modeling degradation signals as an instantaneous stochastic process.

Among those literature, Gebraeel et al., [71] implemented Bayesian method for updating parameters and to predict the RUL of a bearing component. Hao et al., [38] and Song et al., [72] adopted the stochastic model and proposed a prognostic method to predict the residual life of each component in a composite manufacturing system by modeling degradation signals as an instantaneous stochastic process. The functional form of degradation endeavors to explain probabilistically the progression of the physical degradation process. Various techniques have been explained by Bian et al., [73], and they has modeled the evolution of degradation signals based on sensors data to estimate lifetime distribution. Later, Deutsch et al., [74] research focused on prediction of RUL of a rotating element with big data by presenting a deep learning based technique based on the degradation data. Their technique has been tested and validated by collecting the data from a gear test rig. Similar work has been carried out by Ren et al., [75], a deep learning based method has been proposed to predict the RUL of a bearing component combined with the deep neural network and deep auto encoder. Further, supervised and unsupervised data analysis techniques have been used [76, 77] for the maintenance of a vessel based on its condition in a diesel-electric gas propulsion plant.

In machine level, a case study has been presented for finding the degradation level on monitoring of industrial pumps by [78]. In their work, vibration data has been collected from a chemical plant on 30 industrial pumps for a period of 2.5 years and applied random forest algorithm and found Key Condition Indices (KCIs) for condition based monitoring. Similarly, data analysis and simulation tools have been used to analyze the machine failure data, system failures prediction, and a novel procedural approach has been proposed by [79]. Later, to reduce the impact of the degradation process on machine performance, and machining precision using sensory data such as emission rate, maintenance rate, as well as production rate as the performance indices has been identified by [80, 81]. In general, the system degradation is not a single staged process instead it is a multi-stage process in real life. Li et al., [82] proposed a method for predicting the RUL by changing the degradation rate of systems, and cause signal jumps at condition to change points as the two factors. With this information, a multi-stage stochastic degradation model was proposed by using Bayesian updating methods to extract real-time data from machines and update degradation model for finding the RUL for degraded machines. Further, numerous research was carried towards the modeling of the degradation process with an insight to capture the degradation [83]. Another paper mentioned with various techniques for predicting the RUL and understanding the progression of degradation in machines [84-88].

2.3 Workload Adjustment

The objective of workload strategy is to manage the remaining useful lifetime of various unit systems to accomplish some sort of optimality. A dynamic workload adjustment technique has been proposed by [13] to locate the most extreme workload of the higher degraded machines in manufacturing systems to satisfy the production necessities on parallel configurations as well as various benchmark instances and simulation tests have been led to assess degradation rate. [36] explored that the effects of various workload adjustment methodologies on a system execution by a mathematical study utilizing the agent-based simulation. Studies have shown that the higher the workload to the machine, accelerate the degradation and vice versa. To prevent the overlap of machine failure within a period of time [36] developed a method to control the degradation and predicted failure time of each machine by adjusting the workload. Few studies [13], [35] and [36] addresses the phenomena of controlling the pace of degradation among the machines in a real-time manufacturing environment. Their studies proposed a workload strategy dynamically to control the degradation rate by predicting the residual life on parallel and hybrid configurations.

The workload adjustment strategy also helps in reducing the overlap of the machine failures that the most degraded machines need to be identified and adjust the workload to fulfill the necessary requirements [35]. A similar work has been carried out, where the workload adjustment strategy has been tested and validated on hybrid configuration by [13, 37]. The allocation of a number of jobs is especially important to obtain the better throughput. A mixed integer linear programming for the workload adjustment strategy has been proposed by minimizing the loads on maximum number of machines in a semiconductor manufacturing front end fab [89]. Similarly, a workload allocation approach has been proposed and a case study of aerospace enterprise has been demonstrated by validating the proposed approach [90]. Further, a sensitivity analysis has been performed by proposing a mixed integer linear programming where the workload on each machine has been adjusted dynamically in a manufacturing company for satisfying the requirements [91].

2.4 Predictive Maintenance

Nowadays, predictive maintenance is considered as the key point for many manufacturing industries because of a major part of the operational cost and system failure impacts on product quality and equipment availability. [92] Explained that Predictive maintenance considers close past information for predicting future tendencies, biases, behaviors, etc. through correlation. He et al., (2017) [93] introduced that Predictive maintenance is an analytic technique to eliminate prospective failures and improve the mission dependability of production systems. Consequently, a coordinated Predictive Maintenance procedure considering item degree, mission dependability state was proposed reasoning of prediction and manufacturing. Spendla et al., (2017) [94] proposal focused on predictive maintenance of manufacturing systems to improve the production process quality.

Dong et al., (2019) [95] have attempted to work on a flexible structure of a versatile manufacturing system to satisfy different needs and item varieties and to build up a PHM structure for assembling with different online sensors and flexible structures utilizing different sensors-based degradation data for registering and predicting each machine's time to failure. For example, Traini et al., (2019) [96] discussed the execution predictive maintenance of a milling cutting tool information the collection as validation of a structure. Yildirim et al., (2016) [97] expanded the adaptive predictive generator maintenance model presented by incorporating unit commitment. From the different literature on predictive maintenance, it can be concluded that the predictive maintenance of the machines allows to extend the machine’s life and to lower maintenance costs by addressing the problems before they cause machine failures.

The predictive maintenance has significantly benefited with the use of ML prediction algorithms and real-time fault detection based on the technological advancements such as sensors utilization in manufacturing systems. The predictive maintenance (PM) is a focal point for many manufacturing industries to reduce the operational costs [98]. A systematic implementation of machine learning (ML) algorithms for PM has been proposed to identify the fault detections of a machine before its failure in a Small and Medium Enterprise (SME) [99]. The Predictive Maintenance for machine learning models has been proposed and the models were evaluated by the accuracy, precision and F1 score for classifying the ML algorithms [100].

Many authors have explained that the equipment replacement is based on the maintenance costs and many companies were struggling to implement AI and ML-based predictive maintenance techniques. The main benefit of the predictive maintenance technique with the help of the ML approach is to improve the performance of the machines. The ML tool helps in data-driven recommendations and decision makings based on the input data provided. Later, a data-driven PM technique is developed for a production line to improve the performance of a manufacturing system as the data has been generated from the IoT-based sensors in real-time, and the predictions of machine failures and the maintenance requirement detected using ML methods (Ayvaz et al., 2021) [101].

2.5 Criticality Index (CI)

The criticality index of machines or devices used in manufacturing industry can be structured a set of activities to identify failures which impacts on companies goals [46]. Criticality of a machine is used as a comprehensive measure to estimate the various actions and to highlight the differences between each individual machine and action strategies [102].

The literature described about the assessing the machine's criticality index [103]. Due to the quality and method of data acquisition there is an uncertainty related to the time between failures and time to repair of machines [104] and all assessment criteria are equally important into the consideration. Considering the above issues, a novel method of machine's criticality index is proposed in this objective. In the area of manufacturing systems the factors which are redundancy, workload breakdown time of a machine and impact on throughput as factors has been indicated.

It has been observed from various literature that it is important to find the weightage of each criterion to find the health status of a machine in a manufacturing system. Based on the above issue, a novel model of criticality index assessment of a machines is proposed as the first criterion [105]. The usage of an index method is proposed and demonstrated based on a Cuban heat exchanger battery to rank the investment in a manufacturing company [46]. Later, in following of finding the criticality index, the effectiveness of reliability is investigated to identify the most critical manufacturing machine to improve the performance by developing a discrete event simulation model [106]. Similarly, an embedded multiple case study method is adopted and investigated for improving the productivity with the help of smart maintenance techniques by incorporating the main objective of maintenance organization as productivity [107]. The main goal of this work is to find the criticality assessment of a machine and the criticality assessment of tools in machinery to increase productivity.

Few more studies as the part CI is introduced to rank and prioritize various parts involved in the manufacturing of different products as an algorithm is developed to obtain the compound global index which shows the index of a part in a manufacturing machine. A method was proposed to improve the productivity of equipment by focusing on equipment's criticality evaluation and daily maintenance [106]. Later, a strategy is presented on the impact of maintenance and it is considered one of the competitive factors on critical equipment [107].

2.6 Motivation of the Research

Although manufacturing industries are adapted to face few challenges, many industries are incapable to meet the pace of change to keep up with the current global competition. Most factories are composed of resources such as machines, and automatic devices that are properly integrated but not always connected. To handle the customized orders that are low in volume, and long-lead times, current manufacturing systems configurations may not be capable enough to manage the production process. Therefor the flexible unit systems has been motivated us to conduct various analysis and these configurations has been proposed in this research for fulfilling customer requirements. Moreover, every machine in the production system has its own health status therefore its remaining useful life (RUL) has an important to maximize the production rate and also its degradation status is highly responsible for the operational performance of the production system. The maintenance prediction with the help of machine learning also plays the major role has been proposed in this research. Finally predicting the criticality index which gives the maintenance time for combined, multiple, and individual machines, and workload adjustment strategy on flexible unit configurations by combining of RUL, and CI drive us to conduct this research.

2.7 Objectives of the Thesis

- To develop different realistic Configurations ranging from semi-flexible to fully-flexible systems and to identify the most influenced performance measure
- To develop mathematical models and job adjustment strategy for linear degradation model on single product category of the proposed flexible systems.
- To develop the workload adjustment strategy on multiple product category for Flexible systems.
- To develop the criticality index for multi-product category for identifying the machine status indicators.
- To enhance the throughput of flexible configurations using novel upgraded hybrid degradation model.

Chapter 3

Development of realistic Configurations ranging from Semi-Flexible to Fully-Flexible systems and identifying the performance measures

3.1 Introduction

Due to recently emerged technologies from Industry 4.0, industries not only benefited but simultaneously throw challenges during execution. Regardless of technology advancements and functionalities, recent manufacturing systems are vulnerable and challenge enough to unexpected disruptions like machine breakdown, power fluctuations, loss of data, Interoperability, etc. Monitoring of complex manufacturing systems and to deal with these unexpected disruptions is a complex and challenging task. The Prognostics and Health Management (PHM) is the maintenance policy that helps for the better health care of complex machine systems aiming at reducing the time and cost for maintenance, manufacturing processes, and unexpected disruptions. Prognostics and Health Management also combines sensing and elucidate the performance related parameters to assess the system health and diagnose different types of failures. In this situation, few major performance parameters of manufacturing systems such as throughput rate, throughput time, system utilization, availability, average stay time, and maximum stay time which affect the manufacturing systems are of great importance in its performance and maintaining the final product quality.

Ranking of those parameters from the most influenced parameter to the least one is utmost requirement for overall assessment particularly when the applications are complex and advanced. The ranking of parameters is a tedious task, because of complicated relationships exist between decision criteria for ranking the alternatives. It is a type of integrated Multi Criteria Decision Making (MCDM) problem in which these parameters can influence various manufacturing expenditures [108, 109]. The main driving force for this research work is to improve the performance of manufacturing systems, maximize the production rate of the semi-fully flexible machine systems and priory identification of degradation of systems and their health status by ranking of various parameters.

The real-time semi-fully flexible machine configurations are of one-degree flexible configuration, two-degree flexible configuration, semi-flexible configuration, and fully flexible configurations, in which the identical machines operate simultaneously to process the given number of jobs. In addition, the performance analysis of flexible machine systems of the above-mentioned parameters has shown great importance in systems efficiency. Among various mentioned parameters, the throughput rate (summation of all workloads from all the units) is an important parameter for the designing and operations of presented configurations. Similarly, various manufacturing costs along with the processing time, inspection time, and moving time drives the firms to effectively analyse the performance of semi-fully flexible machine systems in terms of throughput time. In general, systems degrade with certain rate over a period of time where its performance varies while processing similar kind of operations. In fact, the machine is considered as failed when its degradation level crosses the pre-defined failure threshold. Hence, predicting of residual life will be of great help to the shop floor manager to reroute the processes efficiently. Residual life of a machine can be defined as the machine can work until a catastrophic interruption [110]. Another key parameter influences the process in the shop floor is machine availability, it deals with the probability of machines working without breakdown. In addition, the average stay time is the mean processing time taken to complete the jobs on a single machine and the maximum stay time is the maximum processing time taken to complete the jobs on a single machine also affects the flexible machine systems.

The experimental analysis is based on the real system, which provides the accurate results compared to the simulation results [111]. The simulation model solves real-world problems safely and efficiently. The performance parameters analysis provided by the simulation helps in visualization, understanding, and quantification of real time manufacturing systems scenarios. Various techniques have been applied in the past literature [112] to make the decisions or rank the alternatives and it has been observed that one of the popular methods is integrated MCDM method but few researches has been done in the field of ranking the parameters with the Technique of Order Preference by Similarity to the Ideal Solution (TOPSIS) method.

3.2 MCDM (Multi-Criteria Decision Making)

In this research, the performance process parameters have been analysed using the simulation analysis approach and then the results have been validated with the real-time experimental calculation results. Later, an integrated MCDM method has been selected to rank the parameters, because MCDM is a well-known technique to solve the complex real-life scenario problems of diverse alternatives with several criteria to rank or choose the best or worst alternative.

From the various literature, it has been observed that different MCDM techniques can be used for solving decision-making problems, but the TOPSIS method is best suited and since it has been observed that the TOPSIS method has been preferred for considering the quantitative criteria. The Entropy method has been used in conjunction with the TOPSIS method respectively. The Entropy method has been applied to calculate the weightage of each criterion and the TOPSIS method has been used for evaluating the alternatives (parameters) based on these criteria. Various key parameters which influence the Flexible machine systems are shown in below Figure 3.1.

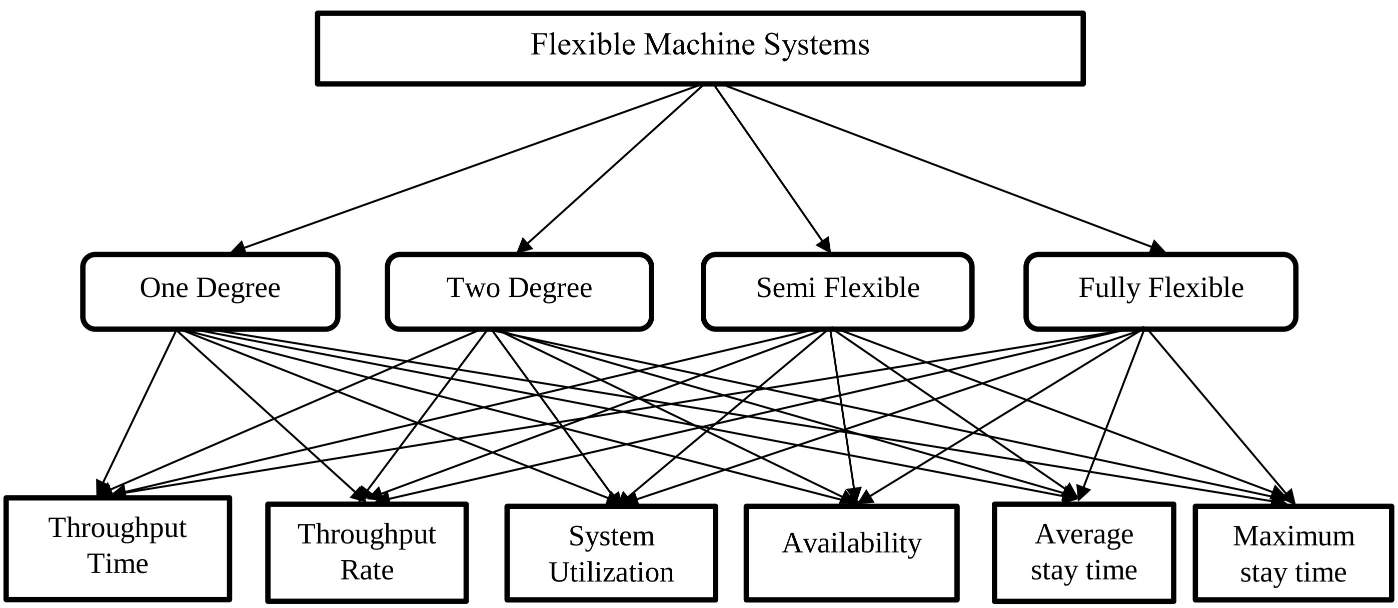


Figure 3.1 Identified Parameters which influence the flexible configurations

3.3 Methodology

In the experimentation analysis, the number of jobs has been taken as 5000 and the values of each individual parameter have been evaluated. Later, the simulation analysis has been conducted with the help of simulation software by varying the number of jobs from 100 to 5000.

The obtained simulation results are mostly nearby the experimental values. Finally ranked the parameters of simulation results that influence the flexible machine systems from most to least. Figure 3.2 outlines the overview of the integrated MCDM based simulation approach.

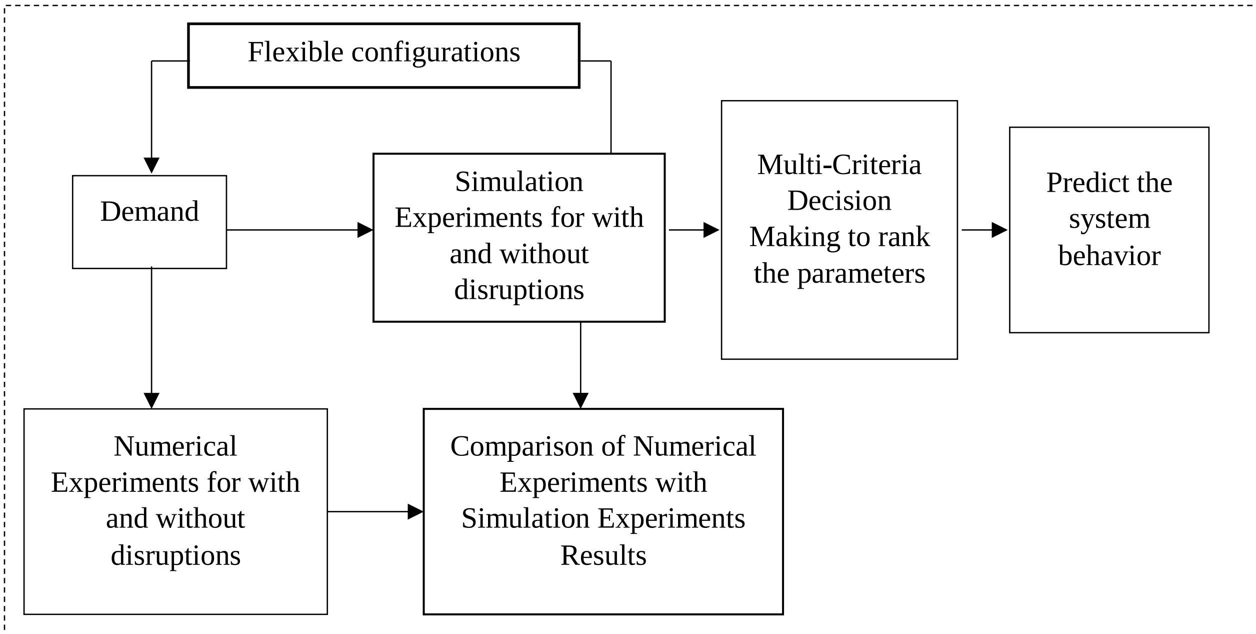
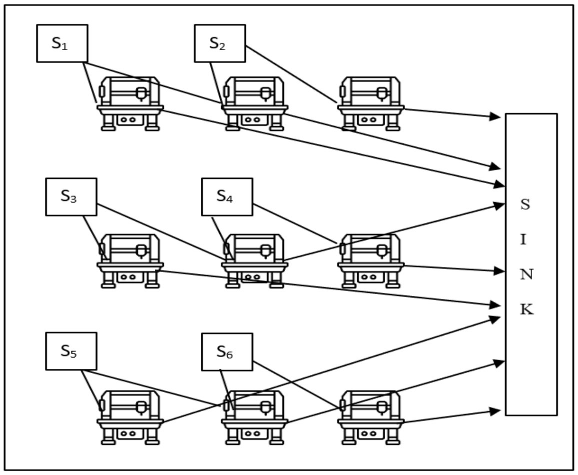
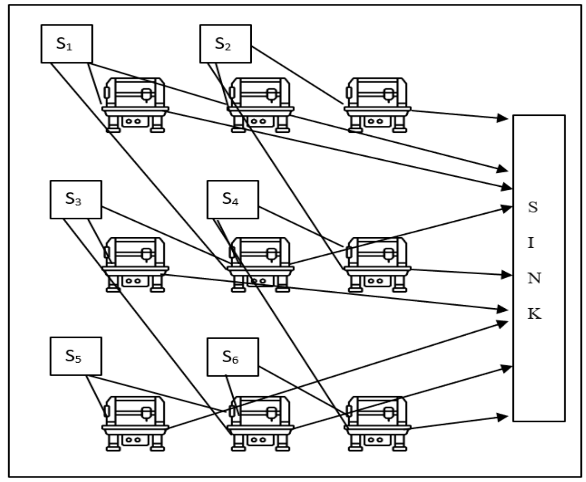


Figure 3.2 Overview of an integrated MCDM based simulation approach

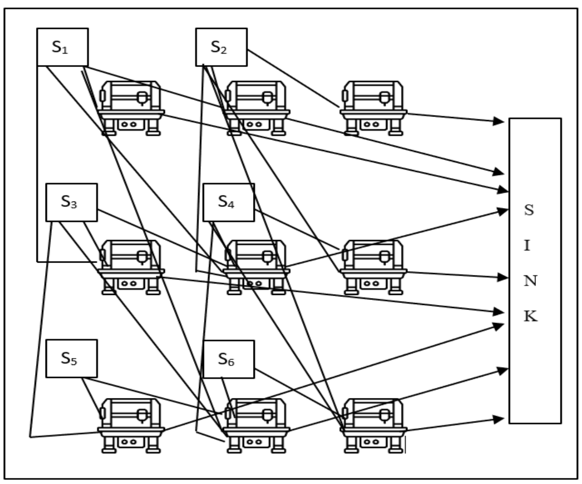
Here, S1, S2… S6 indicates the sources from where the jobs can be assigned to the processors. The flexible machine systems consist of N number of identical machines in which the system has to operate simultaneously to complete the given number of jobs shown in Figure 3.3 (a-d). Figure 3.3 (a) presents the one-degree flexible system in which if any machine will fail then the remaining number of jobs can be adjusted on an adjacent connected machine. Figure 3.3 (b) represents the two-degree flexible system in which if any machine fails then the remaining number of jobs can be adjusted on two adjacent connected machines depending upon the availability of machines. Here, the availability of machines has been increased in the case of two-degree flexible configuration compared to one-degree flexible configuration. Figure 3.3 (c), (d) represents the semi-flexible and fully flexible machines in which the availability of machines is more compared to the one-degree flexible system, two-degree flexible system.

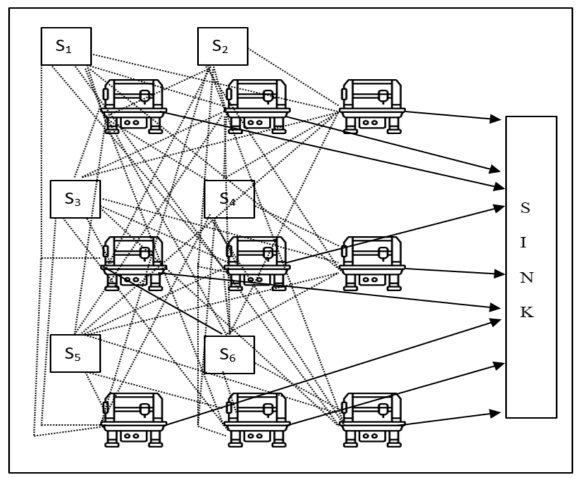




a. One-Degree Flexible System

b. Two-Degree Flexible System





c. Semi Flexible System

d. Fully Flexible System

Figure 3.3 (a-d) Flexible configuration machine systems

3.3.1 Experimental Analysis

The values of each parameter have been calculated by considering the number of jobs as 5000 and it was mentioned below in Table 3.1 since to get that level our majority of machine breakdown at least once. Throughput time is the actual time taken to manufacture a product and it can be calculated by multiplying the average stay time by the total number of jobs per machine, similarly, throughput rate is the rate at which units move from start to finish and it can be calculated by dividing the output by throughput time. The availability is the amount of time in which the machine actually runs and is available for production, and it can be calculated by Equation 3.1.

$$Availability = \frac{MTBF}{MTBF + MTTR} \qquad (3.1)$$

The average stay time and maximum stay time can be calculated from the bell curve by considering a 99.97% confidence level since the processing time follows the normal distribution. The system utilization can be defined as the proportion of time that the manufacturing system has been used, and system utilization is calculated by Equation 3.2.

$$Utilization = \frac{Actual\ Output}{Maximum\ Level\ Output} \qquad (3.2)$$

Table 3.1 Experimentation matrix of various parameters for 5000 number of jobs

	Without Breakdown				**With Breakdown**			
Criteria/ Parameters	One degree	Two degrees	Semi Flexible	Fully Flexible	One degree	Two degrees	Semi Flexible	Fully Flexible
Throughput Time (Sec)	362133.33	362133.33	380133.33	369333.33	521600	550400	539600	550400
Throughput/ Hour	49.70	49.70	47.35	48.73	34.50	32.70	33.35	32.70
System Utilization (%)	99.41	99.410	94.70	97.47	69.01	65.40	66.71	65.40
Availability	1	1	1	1	0.9999	0.9999	0.9999	0.9999
Average stay time(s)	600	600	600	600	600	600	600	600
Max stay time(s)	690	690	690	690	86400	86400	86400	86400

3.3.2 Simulation Analysis

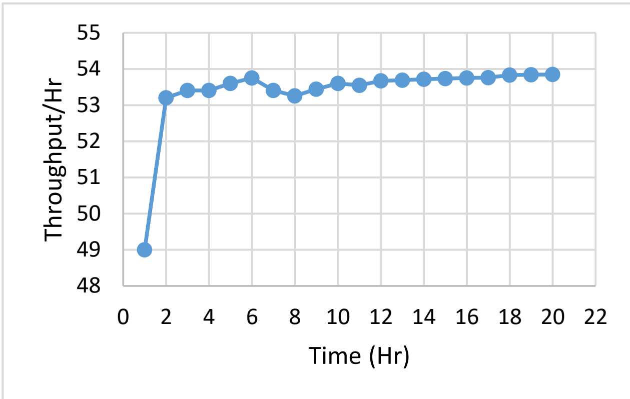
The simulation analysis was conducted on a *PC* with Intel Corei3-7100 U (2.40 GHz), running under windows 10 professional operating system with 8GB RAM. The images of various configurations from a single degree to fully flexible as shown in Figure 3.3 (a-d) The processing time and mean time between failures (MTBF), Mean Time to Repair (MTTR) follows the normal distribution, and the time required to repair a machine has been considered as constant.

Warmup period

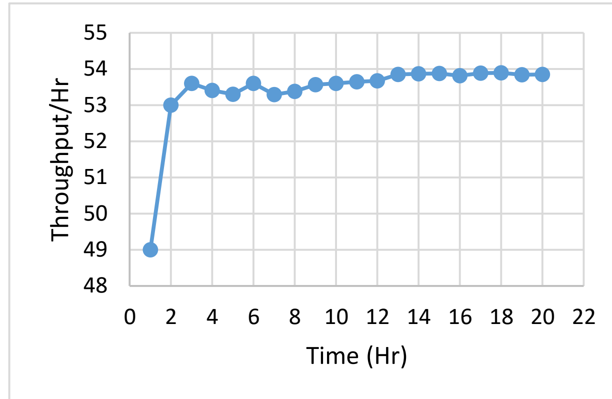
The number of replications for the simulation has been determined as 20 and the length of each replication is 1hr with a warmup period is 8hours for one-degree flexible configuration and has been shown in Figure 3.4 (a) by without breakdown of machines. The warmup period for two-degree flexible configuration, semi-flexible, and fully flexible configurations without the breakdown of machines are as 8hours, 13hours, and 10hours as shown in Figure 3.4 (b), (c), (d) respectively. Similarly, warm-up period with the breakdown of machines for various configurations is shown in Figure 3.5 (a-d). The warmup period for one-degree, two-degree flexible configuration, semi-flexible, and fully flexible configurations in the view of the breakdown of machines are as 6hours, 14hours, 11hours, and 14hours as shown in Figure 3.5(a), (b), (c), (d) respectively. The warmup period can be obtained by applying Welch's procedure [113] to estimate the steady state mean. Here the technique often suggested for these kinds of problems is called the *warmup period* or also called initial data deletion. The main idea here is to delete the initial observations from the run and using of remaining observations to get the steady-state. The number of replications has been calculated with the help of the following Equation 3.3. [113].

$$\bar{X}(n) \pm t_{n-1,1-\alpha/2} \frac{s}{\sqrt{n}} \tag{3.3}$$

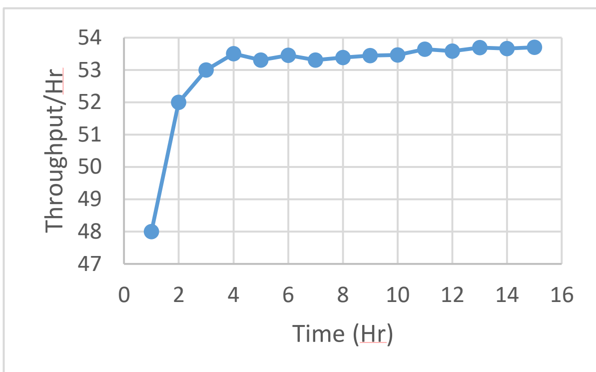
Where $\bar{X}(n)$ represents the sample mean, S represents sample standard deviation, and n represents the number of replications, and $t_{n-1,1-\alpha/2}$ is the upper and $1-\alpha/2$ critical points where the warmup period is in case of breakdown for one-degree configuration is 6hrs. Then the desired confidence interval for 95% confidence level is $6 \pm t_{19,0.025} \frac{7.504}{\sqrt{20}}$. From the results it has been observed that, the 20 number of simulations are enough from the initial approach mentioned in [113]. The warmup period has been identified from the plot as shown in figure below for various configurations.



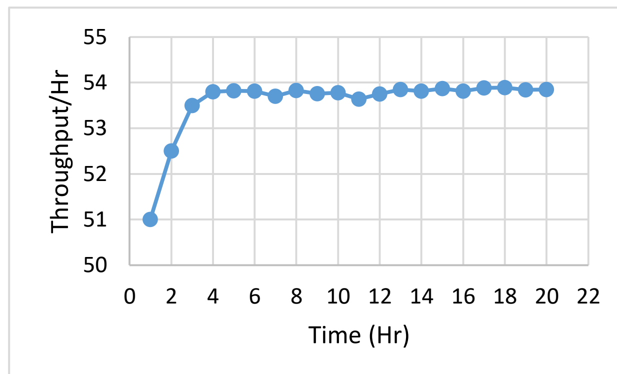
(a) One Degree



(b) Two Degree

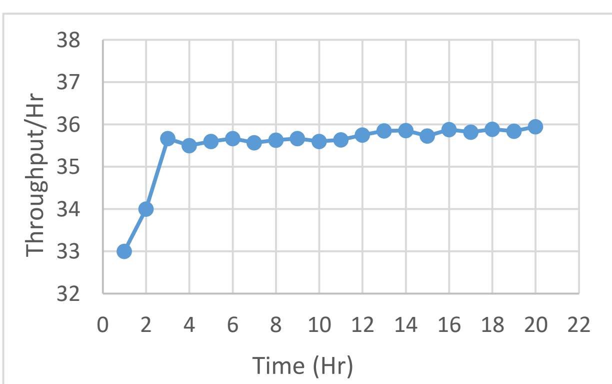


(c) Semi Flexible

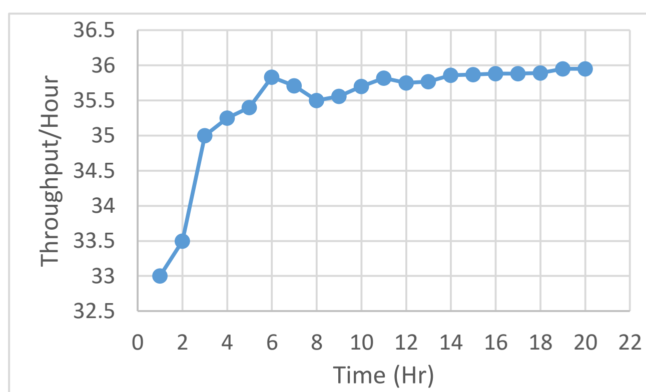


(d) Fully Flexible

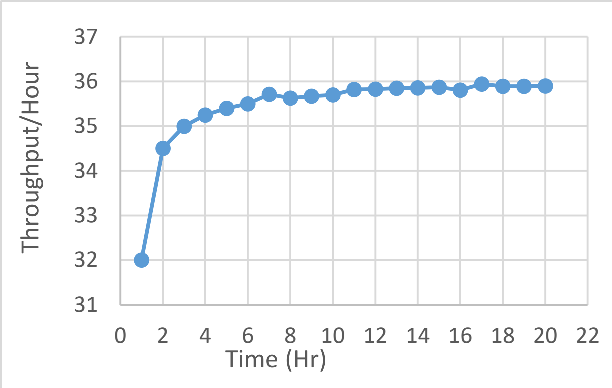
Figure 3.4 (a-d) Warm up period for flexible configurations without breakdown



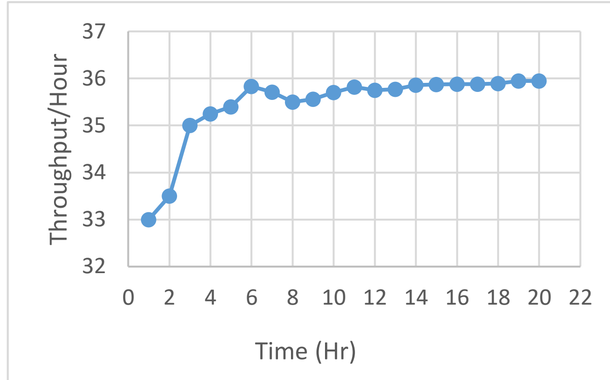
(a) One Degree



(b) Two Degree



(c) Semi Flexible



(d) Fully Flexible

Figure 3.5 (a-d) Warm up period for flexible configurations without breakdown

Various parameters such as Throughput Rate (TR) in (throughput/hour), Throughput Time (TT) in (Seconds), System Utilization (SU) in (%), Availability (A), Average stay time (T_{avg}) in (Seconds) Maximum stay time (T_{max}) in (Seconds) values have been generated with the help of simulation software for one degree, two-degree, semi-flexible, and fully flexible configurations without and with the breakdown of machines. The number of machines has been varied from 100 to 5000 and the simulation results has been presented for various configurations in Tables 3.2, 3.3, 3.4, and 3.5 respectively.

Table 3.2 Comparative Simulation Matrix of One-degree Configuration without and with breakdown of machines.

	One Degree Flexible (without breakdown)						**One Degree Flexible (with breakdown)**					
No. of Jobs	TR	TT	SU	A	T_{max}	T_{avg}	TR	TT	SU	A	T_{max}	T_{avg}
100	50.85	35879.61	100	1	674.91	601.19	35.13	31848.98	66.67	1	669.4	600.2
200	52.71	42459.19	100	1	678.82	599.2	35.52	41867.61	66.67	1	678.82	598.18
300	53.25	49082.4	100	1	678.82	599.58	35.79	51772.82	66.67	1	683.74	600
400	53.56	55685.86	100	1	683.74	599.66	35.75	61883.3	66.67	1	683.74	599.8
500	53.94	90973.22	100	1	695.33	600.5	35.88	71771.32	66.67	1	683.74	599.82
700	53.96	104299.78	100	1	695.33	600.36	35.92	91749.3	66.67	1	683.74	599.88
900	54.09	117499.95	100	1	701.54	600.38	35.86	111943.09	66.67	1	695.33	600.36
1100	53.87	131110.14	100	1	712.62	601.32	35.9	131893.71	66.67	1	695.33	600.17
1300	53.89	144439.91	100	1	712.62	600.79	35.93	151868.42	66.67	1	701.74	600.41
1500	53.91	157769.41	100	1	712.62	600.56	35.9	172038.72	66.67	1	712.62	601.12

1800	53.97	177659.53	100	1	712.62	600.49	35.93	201928.04	66.67	1	712.62	600.72
2100	53.97	197681.64	100	1	712.62	600.13	35.92	232050.95	66.67	1	712.62	600.6
2400	54	217589.93	100	1	712.62	600.12	35.93	262070.93	66.67	0.99	712.62	600.37
2700	53.98	237683.2	100	1	712.62	600.12	35.95	291977.9	66.66	0.98	712.62	600.24
3000	54.02	257528.86	100	1	712.62	599.99	35.93	322222.42	66.66	0.97	712.62	600.24
3400	53.97	54381.48	100	1	712.62	600.21	35.98	361781.14	66.68	0.97	86981.14	625.41
3700	53.62	305999.59	99.33	1	712.62	600.26	35.96	391993.21	66.68	0.96	86981.14	623.48
4100	51.89	342068.53	96.07	1	712.62	600.13	35.96	432017.34	66.68	0.95	86981.14	621.35
4500	49.95	381923.46	92.46	1	712.62	599.83	35.98	471830.77	66.69	0.94	87012.33	638.61
5000	48.09	431921.51	89.01	1	712.62	599.87	36	521598.36	66.69	0.94	87012.33	651.7

Table 3.3 Comparative Simulation Matrix of Two-degree Configuration by without and with breakdown of machines

	Two Degree Flexible (without breakdown)						**Two Degree Flexible (with breakdown)**					
No of Jobs	TR	TT	SU	A	T_{max}	T_{avg}	TR	TT	SU	A	T_{max}	T_{avg}
100	50.85	35879.61	100	1	674.91	601.19	50.85	35879.61	100	1	674.91	601.19
200	52.71	42459.19	100	1	678.82	599.2	52.71	42459.19	100	1	678.82	599.2
300	53.25	49082.4	100	1	678.82	599.58	53.25	49082.4	100	1	678.82	599.58
400	53.56	55685.86	100	1	678.82	599.66	53.56	55685.86	100	1	678.82	599.66
500	53.66	62347.22	100	1	683.74	600	53.66	62347.22	100	1	683.74	600
700	53.78	75659	100	1	683.74	600.19	53.78	75659	100	1	683.74	600.19
900	53.71	89121.68	100	1	695.33	600.26	53.71	89121.68	100	1	695.33	600.26
1100	53.79	102424.66	100	1	695.33	600.2	53.79	102424.66	100	1	695.33	600.2
1300	53.86	115686.21	100	1	695.33	600.41	53.86	115686.21	100	1	695.33	600.41
1500	53.73	129300.36	100	1	712.62	601.18	53.73	129300.36	100	1	712.62	601.18
1800	53.8	149244.62	100	1	712.62	600.74	53.8	149244.62	100	1	712.62	600.74
2100	53.84	169217.09	100	1	712.62	600.64	53.84	169217.09	100	1	712.62	600.64
2400	53.86	189221.03	100	1	712.62	600.41	53.86	189221.03	100	1	712.62	600.41
2700	53.93	209043.09	100	1	712.62	600.26	53.93	209043.09	100	1	712.62	600.26
3000	53.93	229064.06	100	1	712.62	600.25	53.93	229064.06	100	1	712.62	600.25
3400	53.94	255711.11	100	1	712.62	600.03	53.94	255711.11	100	1	712.62	600.03
3700	53.93	275769.78	100	1	712.62	600.13	53.93	275769.78	100	1	712.62	600.13
4100	53.9	302657.47	99.71	1	712.62	600.31	53.9	302657.47	99.71	1	712.62	600.31
4500	52.55	337049.76	97.41	1	712.62	600.23	52.55	337049.76	97.41	1	712.62	600.23
5000	50.28	386801.83	93.14	1	712.62	599.87	50.28	386801.83	93.14	1	712.62	599.87

Table 3.4 Comparative Simulation Matrix of Semi flexible Configuration by without and with breakdown of machines.

	Semi Flexible (without breakdown)						**Semi Flexible (with breakdown)**					
No of Jobs	TR	TT	SU	A	T_{max}	T_{avg}	TR	TT	SU	A	T_{max}	T_{avg}
100	50.85	53879.61	100	1	674.91	601.19	35.35	49783.91	66.67	1	669.4	600.75
200	52.71	60459.19	100	1	678.82	599.2	35.55	59852.27	66.67	1	678.82	598.46
300	53.25	67082.4	100	1	678.82	599.58	35.67	69877.89	66.67	1	678.82	599.8
400	53.56	72685.86	100	1	678.82	599.66	35.77	79858.19	66.67	1	683.74	599.69
500	53.66	80347.22	100	1	683.74	600	35.75	89944.35	66.67	1	683.74	599.85
700	53.78	93659	100	1	683.74	600.19	35.87	109852.47	66.67	1	683.74	599.95
900	53.71	107121.68	100	1	695.33	600.26	35.89	129878.71	66.67	1	695.33	600.35
1100	53.79	120424.66	100	1	695.33	600.2	35.94	149797.73	66.67	1	695.33	600.15
1300	53.86	133686.21	100	1	701.41	600.41	35.91	169916.44	66.67	1	701.54	600.44
1500	53.73	147300.36	100	1	712.62	601.18	35.84	190257	66.67	1	712.62	601.13
1800	53.8	167244.62	100	1	712.62	600.74	35.9	220097.42	66.67	1	712.62	600.73
2100	53.84	187217.09	100	1	712.62	600.64	35.91	250140.05	66.67	1	712.62	600.59
2400	53.86	207221.03	100	1	712.62	600.41	35.95	279925.42	66.67	1	712.62	600.36
2700	53.93	227043.09	100	1	712.62	600.26	36.35	307012.44	67.46	0.99	712.62	600.23
3000	53.93	247064.06	100	1	712.62	600.25	37.26	329437.19	69.12	0.98	712.62	600.24
3400	53.94	273711.11	100	1	712.62	600.03	38.27	359391.17	70.97	0.97	712.62	600.03
3700	53.93	293769.78	100	1	712.62	600.13	38.63	384447.19	71.62	0.96	87010.2	623.48
4100	53.92	320521.68	100	1	712.62	600.31	38.92	418792.05	71.21	0.95	87010.2	621.37
4500	52.69	354260.59	97.6	1	712.62	600.23	39.17	453145.31	72.62	0.95	87010.2	638.59
5000	50.39	403982.15	93.3	1	712.62	599.87	38.77	503929.54	71.81	0.95	87010.2	634.44

Table 3.5 Comparative Simulation Matrix of Fully flexible Configuration by without and with breakdown of machines.

	Fully Flexible (without breakdown)						**Fully Flexible (with breakdown)**					
No of Jobs	TR	TT	SU	A	T_{max}	T_{avg}	TR	TT	SU	A	T_{max}	T_{avg}
100	50.85	43079.61	100	1	674.91	601.19	35.13	60648.37	66.67	1	669.4	600.49
200	52.71	49659.19	100	1	678.82	599.2	35.6	70625.13	66.67	1	678.82	598.21
300	53.25	56282.4	100	1	678.82	599.58	35.75	80613.69	66.67	1	683.74	600.06
400	53.56	62885.86	100	1	683.74	599.66	35.84	90575.8	66.67	1	683.74	599.74
500	53.66	69547.22	100	1	683.74	600	35.8	100676.19	66.67	1	683.74	599.91

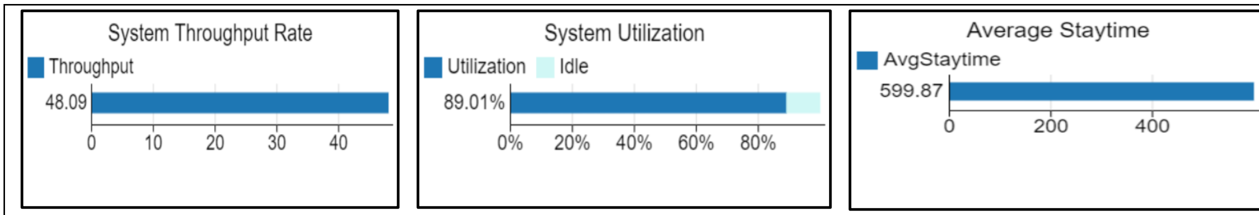
700	53.78	82859	100	1	683.74	600.19	35.89	120618.59	66.67	1	683.74	600
900	53.71	96321.68	100	1	695.33	600.26	35.89	140663.51	66.67	1	695.33	600.32
1100	53.79	109624.66	100	1	695.33	600.2	35.91	160686.28	66.67	1	695.33	600.2
1300	53.86	122886.21	100	1	701.41	600.41	35.89	180798.96	66.67	1	701.54	600.44
1500	53.73	136500.36	100	1	712.62	601.18	35.85	201020.24	66.67	1	712.62	601.13
1800	53.8	156444.62	100	1	712.62	600.74	35.89	230963.02	66.67	1	712.62	600.75
2100	53.84	176417.09	100	1	712.62	600.64	35.92	260855.44	66.67	1	712.62	600.58
2400	53.86	196421.03	100	1	712.62	600.41	35.94	290798.12	66.67	1	712.62	600.34
2700	53.93	216243.06	100	1	712.62	600.26	35.95	320764.93	66.67	1	712.62	600.21
3000	53.93	236264.06	100	1	712.62	600.25	36.25	348339.64	67.24	0.9971	712.62	600.22
3400	53.94	262911.11	100	1	712.62	600.03	37.33	378258.36	69.22	0.9872	712.62	600.01
3700	53.93	282969.78	100	1	712.62	600.13	38.02	400784.56	70.48	0.9829	712.62	600.12
4100	53.92	309721.68	100	1	712.62	600.31	38.75	431342.46	71.84	0.9748	87037.7	621.37
4500	53.94	336339.16	100	1	712.62	600.23	38.99	465935.58	72.26	0.9726	87037.7	619.41
5000	53.95	369613.81	100	1	712.62	599.87	39.33	508033.76	72.86	0.9557	87037.7	617.15

The collected values of the parameters' effect on FUS have been represented in Table 3.6. These values have been generated by the simulation procedure for various configurations without and with machines breakdown by considering the number of jobs as 5000. Initially different normally distributed Mean Time Between Failures (MTBF) values for the different machines (processors) and constant Mean Time to Repair (MTTR) as 1 day and normally distributed processing time has been considered to get random failure.

Table 3.6 Collected values of the parameters effect on flexible machine systems for 5000 number of jobs

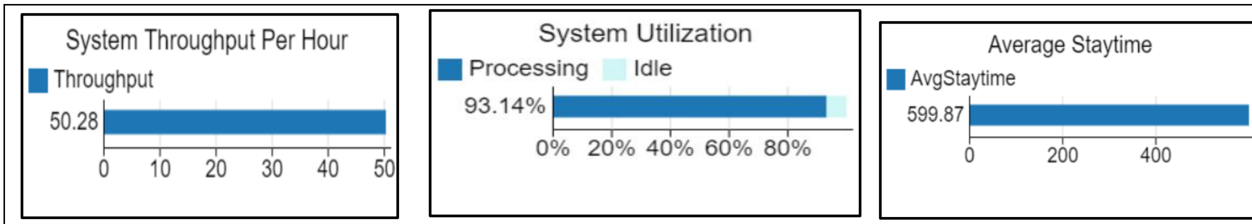
	Without the Breakdown				**With Breakdown**			
Criteria/Parameters	One degree	Two degrees	Semi Flexible	Fully Flexible	One degree	Two degrees	Semi Flexible	Fully Flexible
Throughput Time	431921.51	386801.83	403982.15	369613.81	521598.36	572693.84	503929.54	508033.76
Throughput rate	48.09	50.28	50.39	53.95	36	34.46	38.77	39.33
System Utilization (%)	89.01	93.14	93.76	100	66.69	63.84	71.81	72.86
Availability	1	1	1	1	0.9423	0.9488	0.9505	0.9557
Average stay time(s)	599.87	599.87	599.87	599.87	651.7	634.41	634.33	617.15
Maximum stay time(s)	712.62	712.62	712.62	712.62	87012.33	87037.73	87010.28	87037.73

Figures 3.6 (a), (b), (c), (d) represents the simulation results of various parameters (throughput rate, system utilization, and average stay time) for various configurations without the breakdown of machines. Similarly, Figures 3.7 (a), (b), (c), (d) represents the simulation results of the above-mentioned parameters with the breakdown of machines. These simulation results have been generated by arranging the machines as per the configuration and data has been provided in the simulation software with the help of MTBF, MTTR, and processing time for each machine.



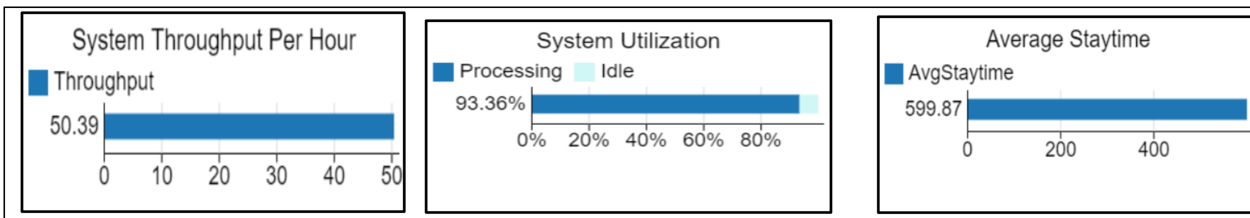
a. System Throughput Rate b. System Utilization c. Average Stay time

(a) One Degree



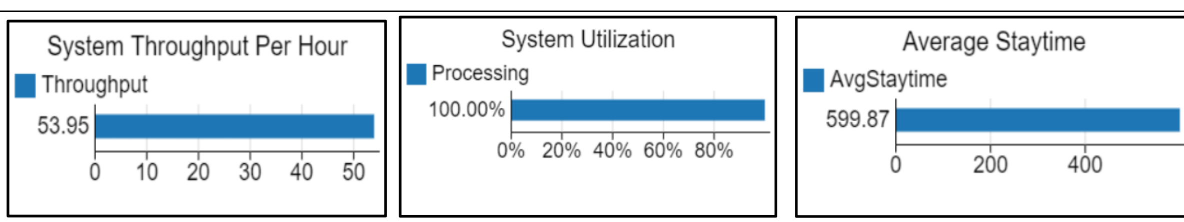
a. System Throughput Rate b. System Utilization c. Average Stay time

(b) Two Degree



a. System Throughput Rate b. System Utilization c. Average Stay time

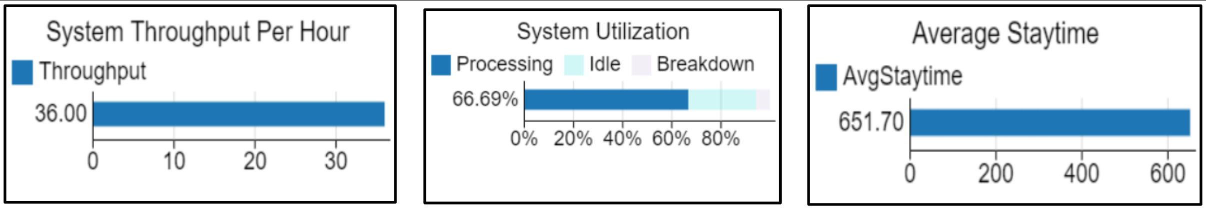
(c) Semi Flexible



a. System Throughput Rate b. System Utilization c. Average Stay time

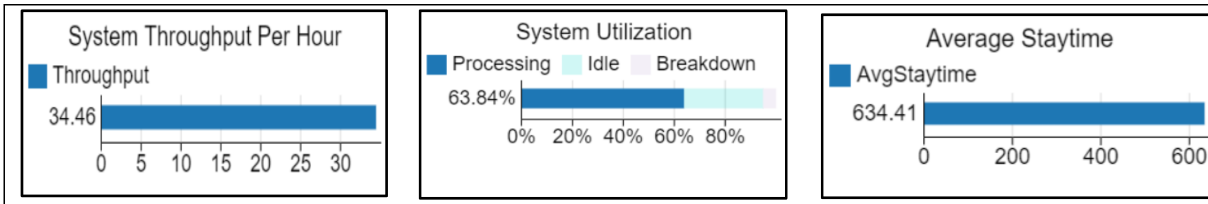
(d) Fully Flexible

Figure 3.6 (a-d) Simulation results by without breakdown of machines



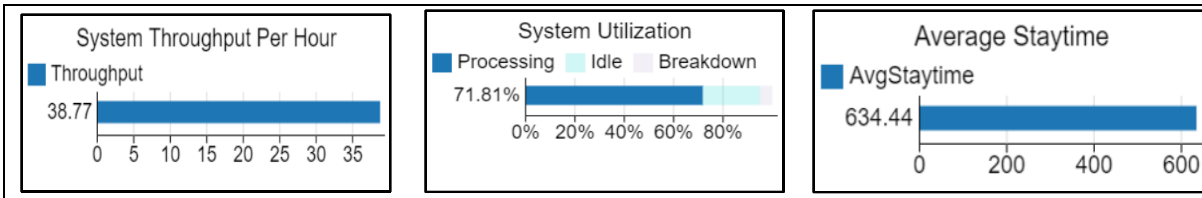
a. System Throughput Rate b. System Utilization c. Average Stay time

(a) One-degree



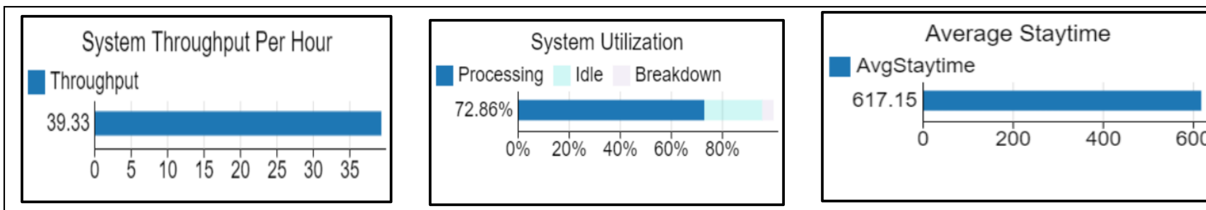
a. System Throughput Rate b. System Utilization c. Average Stay time

(b) Two-degree



a. System Throughput Rate b. System Utilization c. Average Stay time

(c) Semi Flexible



a. System Throughput Rate b. System Utilization c. Average Stay time

(d) Fully Flexible

Figure 3.7 (a-d) Simulation results by with breakdown of machines

3.3.3 Proposed Entropy weight based TOPSIS method

In this research, frequently used normalization methods including the entropy and TOPSIS methods, as these two methods are used in combination with each other have been analyzed for the collected simulation data. The entropy method is used to calculate the weights of each criterion when decision-makers having conflicting views. The weights calculating by the entropy method as also called objective weights. The entropy method shows how much different alternatives approach one another in respect to a certain criterion. The best advantage of an entropy method is the avoidance of human factors interference on the weights of indicators. With this advantage, the entropy method has been widely utilized in recent years. The entropy method consists of four steps mentioned below. The equations from 4 to 7 are the formulas to calculate the weights of each criterion are as follows [114]. The TOPSIS method is used to find the ranking for each individual alternative. The TOPSIS method is used to get the solution, which is near to the positive ideal solution and far from the negative ideal solution. The application of the TOPSIS method in ranking various factors that affect the FUS has been reported in the literature. Various steps involved in the entropy and TOPSIS methods have been explained below with the help of equations from 3.4 to 3.14 are as follows [114].

3.4 Results and Discussion

Weights calculation by Entropy Method

Step 1. Normalize the Decision matrix

The performance value of a^{th} alternative and b^{th} criteria in Equation 3.4 is indicated by $A_{ab} = (a = 1, 2, ..., m; \;\; b = 1, 2, ..., n)$ and the normalized matrix has been shown in Table 3.7.

$$B_{ab} = \frac{u_{ab}}{\sum_{a=1}^{m} u} \tag{3.4}$$

Table 3.7 Normalized Matrix for the collected values of the parameters.

	Without Breakdown				With Breakdown			
Criteria/Parameters	One degree	Two degrees	Semi Flexible	Fully Flexible	One degree	Two degrees	Semi Flexible	Fully Flexible
Throughput Time	0.271253077	0.242917253	0.253706747	0.232122923	0.247642492	0.27190141	0.239253756	0.241202342
Throughput rate	0.23723546	0.248039071	0.248581718	0.266143752	0.242326333	0.231960151	0.260971998	0.264741519
System Utilization (%)	0.236785401	0.247772073	0.249421404	0.266021122	0.242332849	0.231976744	0.2609375	0.264752907
Availability	0.25	0.25	0.25	0.25	0.248150001	0.249861744	0.25030943	0.251678824
Average Stay time	0.25	0.25	0.25	0.25	0.256818477	0.250004926	0.2499734	0.243203197
Maximum Stay time	0.25	0.25	0.25	0.25	0.249964988	0.250037956	0.249959099	0.250037956

Step 2. Entropy value of E_b for b^{th} criteria

Entropy value E_j of b^{th} criteria can be obtained by Equation 3.5 and has shown in Table 3.8.

$$E_b = -K \sum_{a=1}^{x} B_{ab} \ \ln(B_{ab}) \qquad\qquad b = 1, 2, ..., x \qquad (3.5)$$

Where, $K = 1/\ln x$ is a constant to satisfy the condition $0 \le E_b \le 1$ and 'b' indicates the number of alternatives or factors.

Table 3.8 Entropy values.

	E_b	
Parameters	**Without Breakdown**	**With Breakdown**
Throughput Time	0.9988008	0.999082245
Throughput Rate	0.999384207	0.998999198
System Utilization	0.999373203	0.999000837
Availability	0.999999999	1.000035853
Average Stay Time	0.999999999	0.999911288
Maximum Stay Time	0.999999999	1.000045018

Step 3. The degree of divergence of average information

The degree of divergence of average needs to be find out by the Equation 3.6. The degree of diversity value matrix has been calculated and shown in Table 3.9.

$$D_b = \ |1 - E_b| \qquad (3.6)$$

Table 3.9 Degree of divergence values.

	D_b	
Parameters	Without Breakdown	With Breakdown
Throughput Time	0.0011992	0.000917755
Throughput Rate	0.000615793	0.001000802
System Utilization	0.000626797	0.000999163
Availability	1E-09	3.58532E-05
Average Stay Time	1E-09	8.87123E-05
Maximum Stay Time	1E-09	4.50179E-05

Step 4. The weight of entropy of b^{th} criteria

The weightages of b^{th} criterion can be calculated by Equation 3.7 and represented in Table 3.10.

$$B_b = \frac{D_b}{\sum_{b=1}^{y} D_b} \qquad (3.7)$$

Table 3.10 Weights of all criteria.

	B_b	
Parameters	Without Breakdown	With Breakdown
Throughput Time	0.491114421	0.297267459
Throughput Rate	0.25218903	0.324167048
System Utilization	0.256695321	0.323636175
Availability	4.09535E-07	0.011613119
Average Stay Time	4.09535E-07	0.028734577
Maximum Stay Time	4.09535E-07	0.014581622

Ranking the parameters by TOPSIS Method

Step1. Normalization of decision matrix.

The normalization matrix can be calculated by the Equation 3.8 mentioned below. The normalized decision matrix has been formed and shown in Table 3.11.

$$N_{ab} = \frac{u_{ab}}{\sqrt{\sum_{a=1}^{x} u^2}} \qquad b = 1, 2...., y; \qquad a = 1, 2, ..., x\ ; \tag{3.8}$$

Table 3.11 Normalized Matrix of the collected values

	Without Breakdown				With Breakdown			
Criteria/Parameters	One degree	Two degrees	Semi Flexible	Fully Flexible	One degree	Two degrees	Semi Flexible	Fully Flexible
Throughput Time	0.541602229	0.485025007	0.50656804	0.463472318	0.494614631	0.5430668	0.477859868	0.481751765
Throughput rate	0.474063957	0.495652646	0.49673701	0.531830952	0.483954322	0.463251831	0.521191918	0.528720096
System Utilization (%)	0.47315782	0.495112003	0.498407788	0.531578272	0.483968414	0.463286003	0.521124184	0.528744019
Availability	0.5	0.5	0.5	0.5	0.496293694	0.499717136	0.500612497	0.50335125
Average Stay time	0.5	0.5	0.5	0.5	0.51354176	0.499917187	0.499854147	0.48631625
Maximum Stay time	0.5	0.5	0.5	0.5	0.499929971	0.500075907	0.499918193	0.500075907

Step2. Construct the weighted normalized decision matrix.

The associated weights W_b to be multiplied with the normalized matrix and taken from each parameter to be obtained by following Equation 3.9. The weighted normalized decision matrix is formed and shown in Table 3.12.

$$V_{ab} = N_{ab} W_b \qquad b = 1, 2....., y \qquad a = 1, 2....., x \tag{3.9}$$

Table 3.12 Weighted normalized decision matrix.

	Without Breakdown				With Breakdown			
Criteria/Parameters	One degree	Two degrees	Semi Flexible	Fully Flexible	One degree	Two degrees	Semi Flexible	Fully Flexible
Throughput Time	0.265988665	0.238202775	0.24878287	0.227617939	0.147032834	0.161436088	0.142052189	0.143209123
Throughput rate	0.119553729	0.12499816	0.125271625	0.134121932	0.156882044	0.15017097 9	0.168953246	0.171393633
System Utilization	0.121457398	0.127092934	0.127938947	0.136453655	0.156629686	0.14993611	0.168654638	0.171120692
Availability	2.04768E-07	2.04768E-07	2.04768E-07	2.04768E-07	0.005763518	0.005803275	0.005813672	0.005845478
Average stay time	2.04768E-07	2.04768E-07	2.04768E-07	2.04768E-07	0.014756405	0.014364909	0.014363097	0.013974092
Maximum stay time	2.04768E-07	2.04768E-07	2.04768E-07	2.04768E-07	0.00728979	0.007291918	0.007289618	0.007291918

Step3. Determining Positive Ideal solution and Negative Ideal Solution

The positive ideal solution and the negative ideal solution to be determined by using below Equations 3.10, 3.11 respectively. The positive ideal and negative ideal solution matrix is formed and shown in Table 3.13.

$$\{V_1^+, V_2^+, \ldots\ldots, V_n^+\} \;=\; \{(Max\ V_{ab} \mid b \in K), (Min\ V_{ab} \mid b \in K^{|}) \mid \quad a = 1, 2, \ldots., x\} \qquad (3.10)$$

$$\{V_1^-, V_2^-, \ldots\ldots, V_n^-\} \;=\; \{(Min\ V_{ab} \mid b \in K), (Max\ V_{ab} \mid b \in K^{|}) \mid \quad a = 1, 2, \ldots., x\} \qquad (3.11)$$

Where K is the index of set of benefit criteria and $K^{|}$ is the index of cost criteria.

Table 3.13 Matrix of Positive and Negative ideal solution.

	Without Breakdown		With Breakdown	
Parameters	$V_j +$	$V_j -$	$V_j +$	$V_j -$
Throughput Time	0.227618218	0.265988992	0.142052189	0.161436088
Throughput Rate	0.134122097	0.119553876	0.171393633	0.150170979
System Utilization	0.136453823	0.121457548	0.171120692	0.14993611
Availability	2.04768E-07	2.04768E-07	0.005845478	0.005763518
Average Stay Time	2.04768E-07	2.04768E-07	0.013974092	0.014756405
Maximum Stay Time	2.04768E-07	2.04768E-07	0.007289618	0.007291918

Step 4. Finding the Euclidean Distance from positive ideal solution & negative ideal solution.

The Euclidean distance from positive ideal solution and negative ideal solution to be computed by the below Equations 3.12, 3.13 respectively. The Euclidian distance matrix from positive ideal solution & negative ideal solution is formed and shown in Table 3.14.

$$S_i^+ = \{\sum_{b=1}^{y}(V_{ab} - V_b^+)^2\}^{1/2} \qquad b = 1, 2...., y; \qquad a = 1, 2, ..., x \; ; \tag{3.12}$$

$$S_i^- = \{\sum_{b=1}^{y}(V_{ab} - V_b^-)^2\}^{1/2} \qquad b = 1, 2...., y; \qquad a = 1, 2, ..., x \; ; \tag{3.13}$$

Table 3.14 Euclidian Distance Matrix.

Criteria/Parameters	Without Breakdown		With Breakdown	
	S_i^+	S_i^-	S_i^+	S_i^-
Throughput Time	0.002032267	0.002540462	0.02004696	0.0302557
Throughput rate	0.000373814	0.000274561	0.02582523	0.02912409
System Utilization	0.000385022	0.000298649	0.0257848	0.02905122
Availability	0	0	9.75202E-05	0.000103988
Average stay time	0	0	0.00095712	0.00095915
Maximum stay time	0	0	3.25684E-06	3.13322E-06

Step 5. Calculating the relative closeness (performance score)

The relative closeness to be calculated from the ideal solution by using below mentioned Equation 3.14.

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \qquad a = 1, 2, ..., x \; ; \; 0 \le C_i \le 1 \tag{3.14}$$

The Equation 3.14 indicates the relative closeness in which the higher value indicates best rank and lower value indicates worst rank. The relative closeness value matrix is formed based on obtained value and ranked the parameters with as shown in Tables 3.15 (a), (b).

Table 3.15 (a) Matrix of Relative closeness and ranking of the parameters.

Without Breakdown			
Criteria/Parameters	$S_i^+ + S_i^-$	$C_i = \frac{S_i^-}{S_i^+ + S_i^-}$	Rank
Throughput Time	0.004572729	0.555568101	1
Throughput rate	0.000648376	0.423460029	3
System Utilization	0.000683671	0.43683168	2
Availability	0	-	4
Average stay time	0	-	4
Maximum stay time	0	-	4

Table 3.15 (b) Matrix of Relative closeness and ranking of the parameters.

With Breakdown			
Criteria/Parameters	$S_i^+ + S_i^-$	$C_i = \frac{S_i^-}{S_i^+ + S_i^-}$	**Rank**
Throughput Time	0.050302734	0.60147362	1
Throughput rate	0.054949332	0.530017304	2
System Utilization	0.054836051	0.529783342	3

Availability	0.000201509	0.516049358	4
Average stay time	0.001916273	0.50053063	5
Maximum stay time	6.39006E-06	0.490327135	6

3.5 Conclusions

In this research, the maximum number of jobs has been taken as 5000 in the real-time experiment and obtained the values of mentioned six parameters such as throughput rate, throughput time, system utilization, availability of machines, maximum stay time, and average stay time. To compare these experimental results, the simulation analysis was also conducted with the help of simulation software by varying the number of jobs from 100 to 5000 by considering with and without the breakdown of machines for various configurations. Later, the entropy method has been utilized for simulation results to compute the weights of each criterion, and the integrated MCDM – TOPSIS method has been employed to rank the parameters from the most affected parameter to the least affected parameter by considering the breakdown and without the breakdown of machines. From the obtained results it has been observed that the Throughput Time is the most affected performance parameter and maximum stay time is the least affected performance parameter on flexible machine systems in case of breakdown condition and Throughput Time is the most affected performance parameter and Availability, average stay time, and maximum stay time are the least affected performance parameter on flexible machine systems without breakdown condition.

Chapter 4

Development of workload strategy for linear Degradation model on single product category

4.1 Introduction

Although production industries are adapted to face a certain level of challenges, many firms are incapable to meet the accelerated pace of change to keep up with the current global competition, and technological advancements. Digital transformation driven by smart manufacturing is the basis of the current paradigm shift. Most factories are composed of resources such as machines, assembly lines, and automatic devices that are properly integrated but not always connected. In order to make a factory smarter, the Industrial Internet of Things (IIOT) platform has emerged as a new and innovative concept that enables Industry 4.0 key enabling technologies. To handle the customized orders that are low in volume, frequent demand shifts, and long-lead times current manufacturing systems configurations are not capable enough to manage the production process. Moreover, every machine in the production system has its own health status therefore its remaining useful life (RUL). Its' degradation status is highly responsible for the operational performance of the production system [115, 116].

In this unique circumstance, profound research activity is addressed for the development of smart factories in the Industrial world. Although the maximum rate of production of a particular machine designed with more than actual, according to the reports from the Federal Reserve Board, the United States fabrication industries are facing nearly 20 percent of redundancy which is an alarming issue for the production system industries [7]. However, this isn't uncommon due to an enormous number of machines tend to degrade at a similar rate, particularly when an equal number of workloads are allocated to those machines [13]. Therefore, evaluation of systems performance in real-time by capturing performance of a machine is a challenge. Although, a good amount of research investigated on component level and machine level degradation on system performance, however, a significant research gap exists on the unit-level analysis for controlling the degradation of machines in turn to enhance the system-level performance. The proper choice of machine configuration greatly impacts the production system concerning its machine reliability and system reliability. As a result, numerous scholars have published articles by optimizing the configurations to get better productivity

4.2 Degradation Problem Description

We develop a linear degradation model for proposed configurations associated with their manufacturing flexibility ranging from a single degree to fully flexible systems to control the pace of degradation among the machines for preventing the system from failure and indirectly controlling the loss of production of the system. To highlight the main idea, these systems undergo various analyses to predict the RUL of the machines that further improves the throughput through the minimization of the average degradation level. We define "throughput rate" as the overall output of the system, i.e., $\mathrm{TH(x)} = \sum_{q=1,r=1}^{N(x)} O_{(q,r)}(x)$ where denoted by TH(x) represents the throughput rate at the time x and $N(x)$ presents the number of machines. Here, we assume that the machines in the system are identical in nature. Now, let the number of operating machines at time x , be $\tilde{N}(x)$, then the maximum throughput rate becomes $\sum_{q=1,r=1}^{\tilde{N}(x)} C_{(q,r)}$, where $C_{(q,r)}$ indicates the "capacity" of a machine q,r at time x. The throughput rate of a system concerning demand is defined as $TH(x) = \min\left[\sum_{q=1,r=1}^{\tilde{N}(x)} C_{(q,r)}, D\right]$ where D stands for "Demand". If demand of the system is less than capacity $\sum_{q=1,r=1}^{\tilde{N}(x)} C_{(q,r)} \geq D$, then the throughput rate can be considered as equal to the demand, $TH(x) = D$. Alternatively, when the capacity of the operating machines is lower than the demand, $\sum_{q=1,r=1}^{\tilde{N}(x)} C_{(q,r)} \leq D$ then the throughput rate becomes equal to the maximum capacity of the operating machines $TH(x) = \sum_{q=1,r=1}^{\tilde{N}(x)} C_{(q,r)}$, which in turn possibility of assigning the maximum amount of jobs to the machines. Here, $0 \leq O_{(q,r)}(x) \leq C_{(q,r)}$, for $q,r \in 1, 2, \ldots, N$, $O_{(q,r)}(x)$ denotes assigned jobs for the machine q,r at time x acts as a control variable. When machine breakdown occurs the job processed on the machine becomes zero with the machine q,r at the time x , i.e. $O_{(q,r)}(x) = 0$

4.3 System Model Description

Yoram et al. [3] pointed out the impact of various configurations on manufacturing system performance in terms of productivity, reliability, and life cycle cost. Among all the existing manufacturing systems configurations, we considered flexible real-time configurations, i.e., one-degree, two-degree, semi-flexible, and fully flexible configurations as explained in previous chapters. Flexible unit systems consist of N identical machines operating simultaneously to process the assigned number of jobs. Here, when a job arrives, it has to be assigned to any available machines in the following configuration to be completed. To recap, the main highlight of this research work is to determine the number of jobs that are to be assigned to each machine based on the health status of a machine at a unit time from the following assumptions.

1. Demand is constant in the system, whereas, the resulting amount of jobs can vary on machines at a certain time.
2. The degradation coefficient for m, n machines, i.e., $\lambda_{(m,n)}$ is unknown and random. For that, we assumed "Machines to machines variability" to capture the uncertainty in the manufacturing environment.
3. At a time, only one job can be handled on one machine.
4. Once a machine initiates the processing of a job, the obstruction of its processing is not allowed.
5. Machine failure concerning its degradation rate is only considered.

4.4 Proposed Degradation Framework

We proposed a framework of the methodology followed in this research depicted in Figure 4.1. The framework depicts a tool for decision-making by delivering the condition of the machine at each decision epoch and predicting the real-time health status of machines in a manufacturing flexible systems scenario. Recall, the machines are identical in nature, where the assignment of the jobs on each machine is carried out based on the capacity and the demand of the system. Though the machines are identical in nature, their degradation rate differs not only concerning the number of jobs and demand but also due to the natural characteristics such as processing variations, friction, material inhomogeneity, etc. These characteristics provide information about the real-time degradation rate of each machine, denoted as $i_{(q,r)}(x)$. With the available degradation information of each machine, a linear stochastic differential equation is developed as follows.

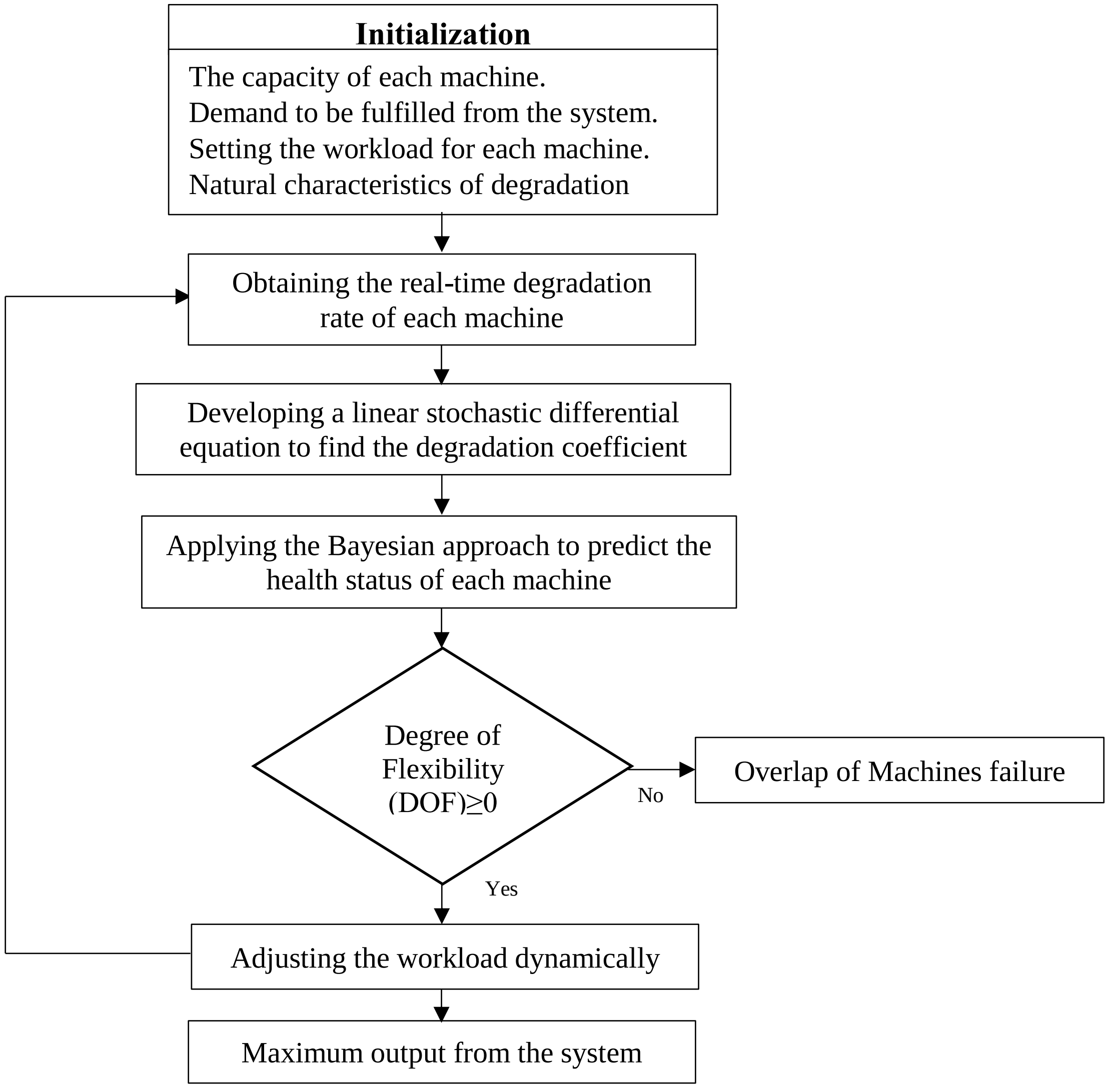


Figure 4.1 Proposed Degradation framework

$$dA_{(q,r)}(x) = \alpha_{(q,r)} O_{(q,r)}(x)dt + dW_{(q,r)}(x) \tag{4.1}$$

Here, $A_{(q,r)}(x)$ represents the amplitude of degradation signals for the machine q, r at the time x, and $W_{(q,r)}(x)$ is a Brownian motion error function. The formulation of Equation 4.1 is inspired by the modeling of degradation efforts in the absence of prior degradation information [117]. The main idea here is to develop a job assignment strategy to effectively control acceleration in the degradation rate of machines by considering this relationship shown in Equation 4.1. Based on the past research efforts made on characterizing the relationship between degradation rate and amount of jobs assigned through several mathematical assumptions and historical data, we considered a special case stating real-time degradation rate is directly proportional to jobs assigned as, shown in Equation 4.2 below.

$$i_{(q,r)}(x) = \alpha_{(q,r)} O_{(q,r)}(x) \tag{4.2}$$

Where, $\alpha_{(q,r)}$ is considered as the degradation coefficient of the machine q, r. From Equation 4.2, Equation 4.1 can be rewritten as below in Equation 4.3.

$$dA_{(q,r)}(x) = \alpha_{(q,r)} O_{(q,r)}(x)dt + dW_{(q,r)}(x) \tag{4.3}$$

Furthermore, the condition monitoring of systems is executed at discrete observation epochs [38] therefore we performed the sampling of job adjustment in discrete epochs i.e., $x_1 - x_0 = x_2 - x_1 = ... = x_u - x_{u-1} = \delta x$ where the sampling interval is kept constant and x_u denotes the latest observation epoch. Then, $A_{(q,r)}(x_u)$ is the amplitude of degradation signal of the machine q, r at time x_u and the corresponding job assigned is $O_{(q,r)}(x_{u-1})$. To facilitate solving the formulation in Equation (3) can be simplified as below in Equation 4.4.

$$\delta A_{(q,r)}(x_u) = \alpha_{(q,r)} O_{(q,r)}(x_{u-1})\delta t + W_{(q,r)}(x_u) - W_{(q,r)}(x_{u-1}) \tag{4.4}$$

From the properties of Brownian motion $W_{(q,r)}(x_u) - W_{(q,r)}(x_{u-1}) \sim N(0, d^2_{(q,r)}\delta x)$. Next, we have the corresponding jobs assigned as $O_{(q,r)}(x_{u-1})$ and degradation coefficient $\alpha_{(q,r)}$, the conditional distribution developed by Manupati et al., [36] is expressed as below in Equation 4.5.

$$\delta A_{(q,r)}(x_u) \mid O_{(q,r)}(x_{u-1}), \alpha_{(q,r)} \sim N(\alpha_{(q,r)} O_{(q,r)}(x_{u-1})\delta x, d^2_{(q,r)}\delta x) \tag{4.5}$$

As per the characteristics of the Wiener process, Brownian motion has an independent increment stating $\delta A_{(q,r)}(x_1), ..., \delta A_{(q,r)}(x_u)$ are statistically independent [36]. As a result, the probability density function of amplitude function can be evaluated as below in Equation 4.6.

$$p(\delta A_{(q,r)}(x_u) \mid O_{(q,r)}(x_{u-1}), \alpha_{(q,r)}) = \prod_{i=1}^{u} p(\delta A_{(q,r)}(x_i) \mid O_{(q,r)}(x_{i-1}), \alpha_{(q,r)}) \tag{4.6}$$

Where $\delta A_{(q,r)}(x_u) = [\delta A_{(q,r)}(x_1), ..., \delta A_{(q,r)}(x_u)]$ and $O_{(q,r)}(x_{u-1}) = [O_{(q,r)}(x_0), ..., O_{(q,r)}(x_{u-1})]$. Here random variable $\alpha_{(q,r)}$ is modelled whose prior distribution was normal distribution with mean $\beta_{(q,r)}$, and variance $\gamma^2_{(q,r)}$ .This prior distribution is updated to get posterior distribution with help of Bayesian approach by the use of measurements that are collected in real-time [37]. Then the posterior distribution's mean and variance of degradation coefficient $\alpha_{(q,r)}$ are represented in Equation 4.7, and Equation 4.8.

$$\beta_{(q,r)}(x_u)=\frac{\gamma^2_{(q,r)}\sum_{i=1}^{u}\delta A_{(q,r)}(x_i)O_{(q,r)}(x_{i-1})+\beta_{(q,r)}d^2_{(q,r)}}{\gamma^2_{(q,r)}\sum_{i=1}^{u}[O_{(q,r)}(x_{i-1})]^2\delta x+d^2_{(q,r)}} \tag{4.7}$$

$$\gamma^2_{(q,r)}(x_u)=\frac{d^2_{(q,r)}\gamma^2_{(q,r)}}{\gamma^2_{(q,r)}\sum_{i=1}^{u}[O_{(q,r)}(x_{i-1})]^2\delta x+d^2_{(q,r)}} \tag{4.8}$$

Next, the posterior mean of degradation coefficient assists in updating the residual life distribution of each machine that follows Inverse Gaussian (IG) distribution developed [37] as shown below in Equation 4.9.

$$P(T_{(q,r)}\le x\,|\,A_{(q,r)}(x_u),O_{(q,r)}(x_u),\alpha_{(q,r)})\sim \mathrm{IG}(x;\mu_{(q,r)}(x_u),S_{(q,r)}(x_u)) \tag{4.9}$$

where IG(t;.,.) indicates the cumulative distribution function with $\mu_{(q,r)}(x_u)=(F_{(q,r)}-A_{(q,r)}(x_u))/(\alpha_{(q,r)}O_{(q,r)}(x_u))$, $S_{(q,r)}(x_u)=([F_{(q,r)}-A_{(q,r)}(x_u)]^2)/(d^2_{(q,r)})$ as the mean parameter and the shape parameter of an IG distribution respectively. Here, to estimate $\alpha_{(q,r)}$ at a certain decision epoch we propose to replace $\alpha_{(q,r)}$ with the posterior mean $\beta_{(q,r)}(x_u)$ which in turn helps in finding the approximated mean parameter of the IG distribution i.e., $\mu_{(q,r)}(x_u)=(F_{(q,r)}-A_{(q,r)}(x_u))/(\beta_{(q,r)}(x_u)O_{(q,r)}(x_u))$. Here, $(F_{(q,r)}-A_{(q,r)}(x_u))/\beta_{(q,r)}(x_u)$ is the health status of the machine q,r at the time x represented by $di_{(q,r)}(x_u)$, As a result, predicted residual life (mean parameter of IG distribution) can be shown below in Equation 4.10.

$$\mu_{(q,r)}(x_u)=\frac{di_{(q,r)}(x_u)}{O_{(q,r)}(x_u)} \tag{4.10}$$

After finding each machine's health status value $di_{(q,r)}(x_u)$, the degree of flexibility of the system is checked according to which the number of jobs is assigned dynamically to prevent the simultaneous multiple machines failure is the primary objective of this study. This procedure repeats for every trail until maximum throughput is achieved.

4.5 Development of a Jobs Adjustment Methodology

We formulate our dynamically assigning jobs methodology as a minimization problem that controls the degradation of machines by modifying the remaining task at hand. Given the posterior mean of the degradation coefficient $\alpha_{(q,r)}$ of functioning machines $\beta_{(1,1)}(x_u)...\beta_{\tilde{N}(u)}(x_u)$ and corresponding degradation levels, $A_{(1,1)}(x_u)...A_{(\tilde{N}(u))}(x_u)$ the average degradation of all machines at next decision epoch are minimized by adjusting the jobs $O_{(1,1)}(x_u)...O_{(\tilde{N}(u))}(x_u)$ as shown in Equation 4.11 and it is summation of two parts. The first part $\sum_{q=1,r=1}^{\tilde{N}(x_u)}[\beta_{(q,r)}(x_u)O_{(q,r)}(x_u)\delta x]$ indicates the incremental growth in the degradation rate of the system concerning time. Whereas, the second part $A_{(q,r)}(x_u)$ measures the degradation signal amplitude of the machine q,r at the time x.

Objective function: Minimize *Z*,

Where

$$Z = \frac{1}{\tilde{N}(x_u)} \sum_{q=1,r=1}^{\tilde{N}(x_u)} [\beta_{(q,r)}(x_u)O_{(q,r)}(x_u)\delta x + A_{(q,r)}(x_u)] \tag{4.11}$$

Subjected to constraints:

$$\sum_{q=1,r=1}^{\tilde{N}(x_u)} O_{(q,r)}(x_u) = \min\left(\sum_{q=1,r=1}^{\tilde{N}(x_u)} C_{(q,r)}, D\right) \tag{4.12}$$

$$O_{(1,1)}x_{(u)} \geq ... \geq O_{(\tilde{N}(x_u))}(x_u) \tag{4.13}$$

$$0 \leq O_{(q,r)}(x_u) \leq C_{(q,r)}, \qquad q,r \in 1,...,N \tag{4.14}$$

$$\frac{E_{(q,r)}\delta x}{4}[O_{(q,r)}(x_u)+O_{(q,r+1)}(x_u)]^2 \le di_{(q,r+1)}x_{(u)}O_{(q,r)}(x_u)-di_{(q,r)}(x_u)O_{(q,r+1)}(x_u)$$

$$\text{for } q \in 1,2,\ldots,\ \tilde{N}(x_u)$$

$$r \in 1,2,\ldots,\ \tilde{N}(x_u)-1 \qquad (4.15)$$

$$\frac{E_{(q,r)}\delta x}{4}[O_{(q,r)}(x_u)+O_{(q+1,r+1)}(x_u)]^2 \le di_{(q+1,r+1)}x_{(u)}O_{(q,r)}(x_u)-di_{(q,r)}(x_u)O_{(q+1,r+1)}(x_u)$$

$$\text{for } q \in 1,2,\ldots,\tilde{N}(x_u)-1$$

$$r \in 1,2,\ldots,\tilde{N}(x_u)-1 \qquad (4.16)$$

$$\frac{E_{(q,r)}\delta x}{4}[O_{(q,r)}(x_u)+O_{(q+1,r)}(x_u)]^2 \le di_{(q+1,r)}x_{(u)}O_{(q,r)}(x_u)-di_{(q,r)}(x_u)O_{(q+1,r)}(x_u)$$

$$\text{for } q \in 1,2,\ldots,\tilde{N}(x_u)-1$$

$$r \in 1,2,\ldots,\tilde{N}(x_u) \qquad (4.17)$$

$$\frac{E_{(q,r)}\delta x}{4}[O_{(q,r)}(x_u)+O_{(q+a,r+1)}(x_u)]^2 \leq di_{(q+a,r+1)}x_{(u)}O_{(q,r)}(x_u)-di_{(q,r)}(x_u)O_{(q+a,r+1)}(x_u)$$

$$\text{for } r=1$$

$$q \in 1,2,...,\tilde{N}(x_u)$$

$$a \in 1,2,...,\tilde{N}(x_u)-1 \qquad (4.18)$$

$$\frac{E_{(q,r)}\delta x}{4}[O_{(q,r)}(x_u)+O_{(q,r+a)}(x_u)]^2 \leq di_{(q,r+a)}x_{(u)}O_{(q,r)}(x_u)-di_{(q,r)}(x_u)O_{(q,r+a)}(x_u)$$

$$\text{for } r=1$$

$$\mathrm{q} \in 1,2,....,\tilde{N}(x_u)$$

$$a \in 1,2,...,\tilde{N}(x_u)-1 \qquad (4.19)$$

$$\frac{E_{(q,r)}\delta x}{4}[O_{(q,r)}(x_u)+O_{(q+a,r+b)}(x_u)]^2 \leq di_{(q+a,r+b)}x_{(u)}O_{(q,r)}(x_u)-di_{(q,r)}(x_u)O_{(q+a,r+b)}(x_u)$$

$$\text{for } q,r \;=\; 1$$

$$a \in 1,2,...,\tilde{N}(x_u)-1$$

$$b \in 0,1,2,...,\tilde{N}(x_u)-1 \qquad (4.20)$$

The purpose of the objective function is to ensure that, on average, the failure of all machines occurs at the slowest rate, shown in Equation 4.11.

Recall, in the system, when the demand of the system is lower than its capacity, the throughput rate is equivalent to demand. Conversely, if the capacity is less than its system's demand, then the system's capacity becomes the throughput rate. This constraint is determined as presented in Equation 4.12. Despite the fact, the flexibility in a system develops a certain amount of robustness for production, it will become ineffectual if the simultaneous breakdown occurs in multiple machines exceeding a certain limit. So to prevent the multiple machines failure at a time, we proposed a method that assigns machines having poorer health status, with a greater workload. The fundamental assumption of this approach is that a greater workload speeds up the process of degradation and thus distinguishes these machine's anticipated failure time from the others i.e., assigning $O_{(1,1)}(x_u) \geq O_{(1,2)}(x_u) \geq \ldots \geq O_{(q,r)}(x_u)$ for machines having health status $di_{(1,1)}(x_u) \leq di_{(1,2)}(x_u) \leq \ldots \leq di_{(q,r)}(x_u)$, where $O_{(q,r)}(x_u), di_{(q,r)}(x_u)$ and denotes the number of jobs assigned and health status respectively of machine q,r calculated at time x_u, be $\tilde{N}(x_u)$

indicating the number of functional machines computed at time x_u ., This method as a constraint is reflected in Equation 4.13. Constraint in Equation 4.14 refers to the allotment of the non-negative quantity of jobs to the respective machines.

To intercept the system from breakdown, the key challenge is to prevent overlap of machine failure. The solution to this problem is that the failure of a machine should occur after the repair of another machine as stated in Equation 4.21 as for a one-degree flexible system.

$$\mu_{(q,r)}(x_u) + E_{(q,r)}\delta x \le \mu_{(q,r+1)}(x_u) \tag{4.21}$$

From Equation (10), Equation (21) can be rewritten as shown in Equation 4.22.

$$E_{(q,r)}\delta x O_{(q,r)}(x_u) O_{(q,r+1)}(x_u) \le di_{(q,r)}(x_u) O_{(q,r)}(x_u) - di_{(q,r+1)}(x_u) O_{(q,r+1)}(x_u) \tag{4.22}$$

While solving, it results in non-convex quadratic programming equations which are NP-hard in nature. An algorithm has been proposed by [118-121] that provides an optimal solution to the non-convex quadratically constrained quadratic programming problems by finding a convex space, covering the original non-convex space. Later on literature addressed certain challenges that arise while optimizing non-convex problems, and further proposed a cutting plate strategy to recognize strong cuts to select and generate to improve solutions by using branch and cut algorithm. The drawback of using this mentioned approach for our problem is that an optimal solution may not be feasible to the non-convex space providing misleading results. In this research, we search for a convex subspace in the nonconvex space so that until unless there is an optimal solution, it falls under the feasible region and prevents overlap of machine failures. Based on Hao et al. [37], we utilized the Arithmetic mean- Geometric mean inequality to convert the non-convex form from which constraint in Equation 4.15 is generated.

For a one-degree flexible system, the overlap of machine failure is controlled by Equation 4.15. Recall, as flexibility increases the availability of machines for adjusting jobs increases. As a result, for a two-degree flexible environment, the problem is controlled by Equation 4.15 and 4.16. Similarly, Equation 4.15, 4.17, and 4.18 prevents the intersection of machine failure in the semi-flexible system. Whereas, in a fully flexible system the problem is tried to be controlled using constraints in Equation 4.19 and 4.20.

4.5.1 Case Study

In this section, a case study provided to evaluate the performance of the proposed configurations and the effectiveness of the method adopted with a fabric weaving Industry [122]. The related data are collected from the zone Surat situated in the northern region of India. This industry consists of power loom machines that operate identically to weave fabrics from the thread. The factors that influence the productivity of power looms are equipment factor, technological factor, and manufacturing flexibility.

Data gathering and Parameters setting

In this research, 1460 power loom machines degradation data were considered to validate and verify proposed model. These 1460 machines process under 4 proposed configurations with 3 different instances until there is a catastrophic interruption. The number of machines and the degree of flexibility for a particular configuration with different instances and flexibilities is shown in Table 4.1. An effective arrangement of machines in the configurations has an impact on increasing the performance. In this study, the machine arrangement is planned for each configuration in a particular instance in such a way that maximum production and highest productivity must be achieved. For example, in instance 1 for a one-degree flexible system, the number of machines 70 arranged in the sequence 10 rows and 7 columns. To capture the real-world characteristics of the power looms, we considered the following parameter settings stated in Table 4.2.

Experimental Study

Table 4.1 Experimental data

Serial No.	Degree of Flexibility	No. of Machines (Instance 1)	No. of Machines (Instance 2)	No. of Machines (Instance 3)
1	One Degree	70	90	110
2	Two Degree	80	120	140
3	Semi Flexible	100	140	160
4	Fully Flexible	100	150	200

Parameters for the case study

Table 4.2 Parameters for the case study

Parameters	**Unit**
Production of Jobs	Kg/day
The capacity of each machine	48kg/day
Demand for One Degree Flexible system	3400kg/day
Demand for Two Degree Flexible system	4000kg/day
Demand for Semi-Flexible system	5000kg/day
Demand for Fully Flexible system	5250kg/day
The prior mean of degradation coefficient of each machine	5.97×10^{-8} inch/kg
Diffusion parameter of the Brownian motion error	2.03×10^{-5} inch/day
Failure threshold of each machine	0.004

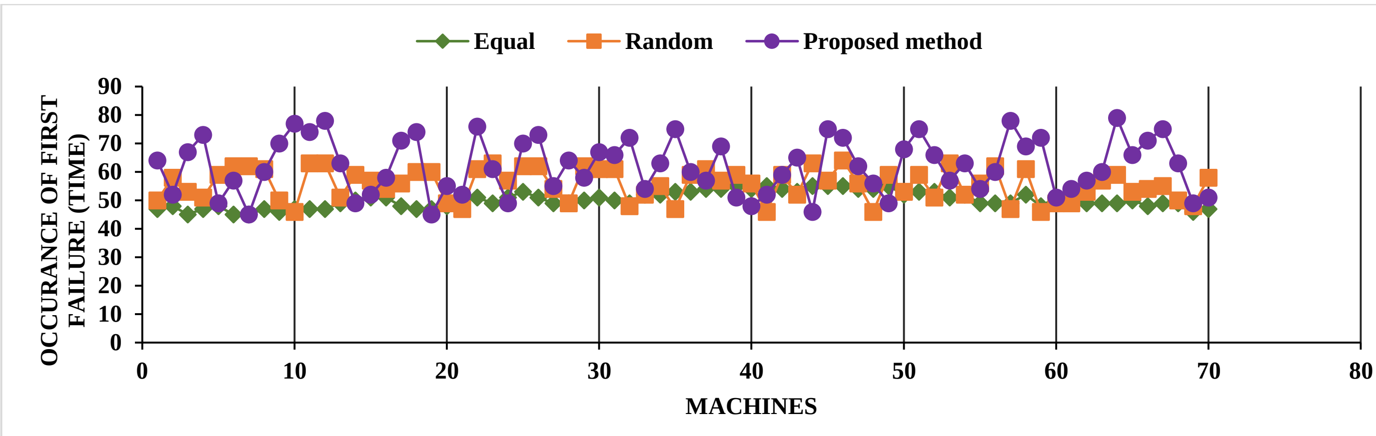
Experiment Procedure

We investigated the performance of our approach concerning effectiveness in increasing the residual life of machines by comparing our strategy with two other benchmark strategies mentioned in [13] i.e., 1) jobs are assigned equally to each machine, and 2) Assignment of jobs is done randomly among the machines in a given particular configuration. To be more specific, on each observation epoch, for the first benchmark, an equal number of jobs are assigned to each machine in the system, while in benchmark 2, all possible solutions of the number of jobs assignment are identified, and randomly one is selected from the entire solution sets. Next, for the proposed methodology, based on the degradation framework in section 3, the rate of degradation of each machine on each decision epoch was calculated. Further based on the health status of the machine, the number of jobs was assigned to it following the methodology in section 4. The experimentation on each configuration in each instance simultaneously was conducted for 350 days. The observation time for each decision epoch was considered as 1 day.

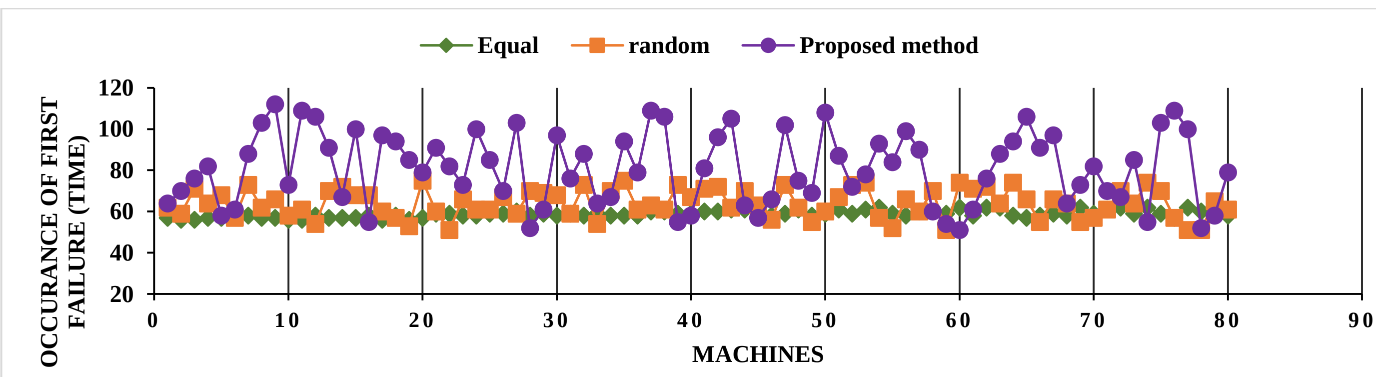
To examine the performance and enumerate the results, we contemplated two performance indices: 1) The occurrence of a failure in machines for the first time and 2) Loss of Production. Since the objective of this research is to find degradation information of machines, so these indices are more informative for our proposed manufacturing configurations as the loss of production will be influenced if multiple machines breakdown occurs. Here, the maintenance time for a repaired machine is considered as 3 days according to power loom industry data.

4.6 Results and Discussion

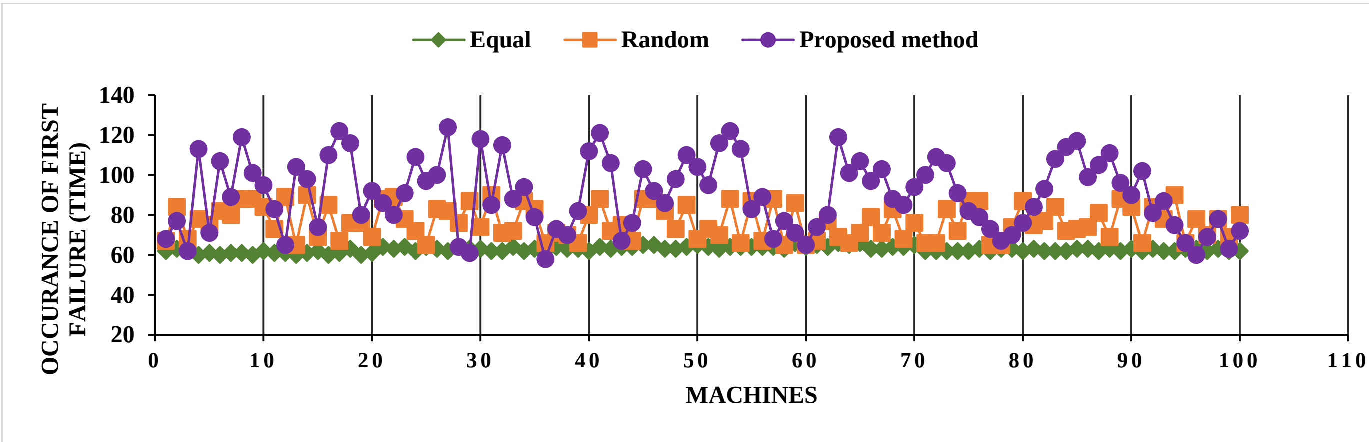
In this section, for 3 different instances of 4 flexible configurations, we ran 12 experiments. For every condition, we plotted the graph by considering the two performance indices as shown in Figures 4.2, 4.3, 4.4, and 4.5. The following discussions can be made based on the results obtained.



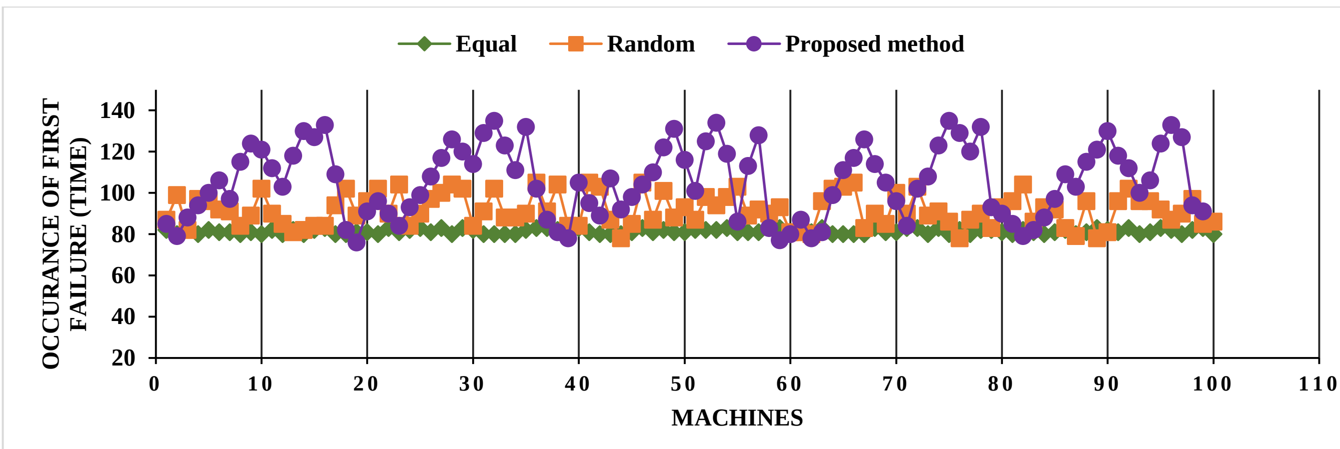
(a)



(b)



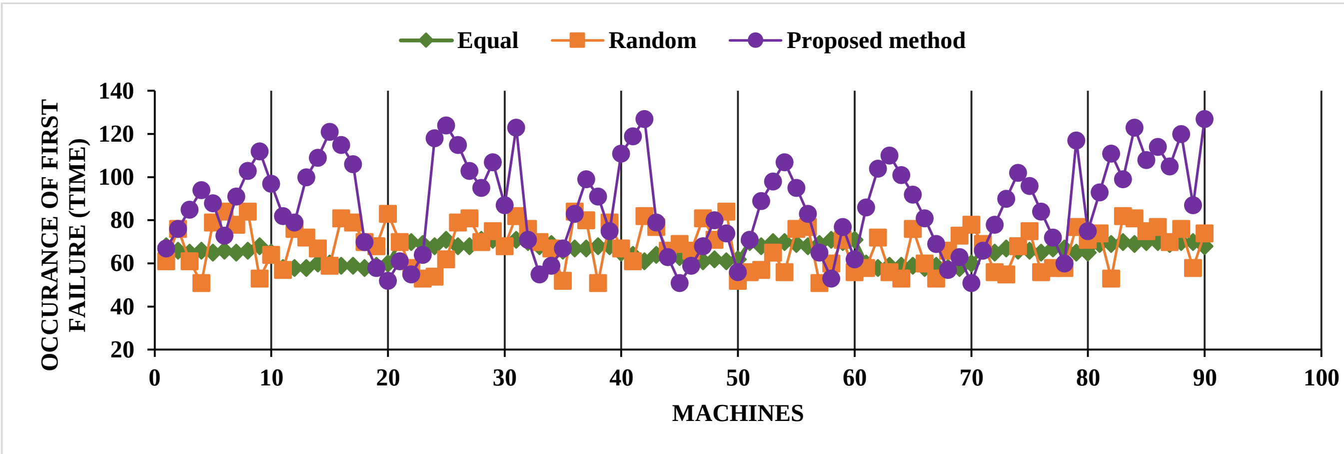
(c)



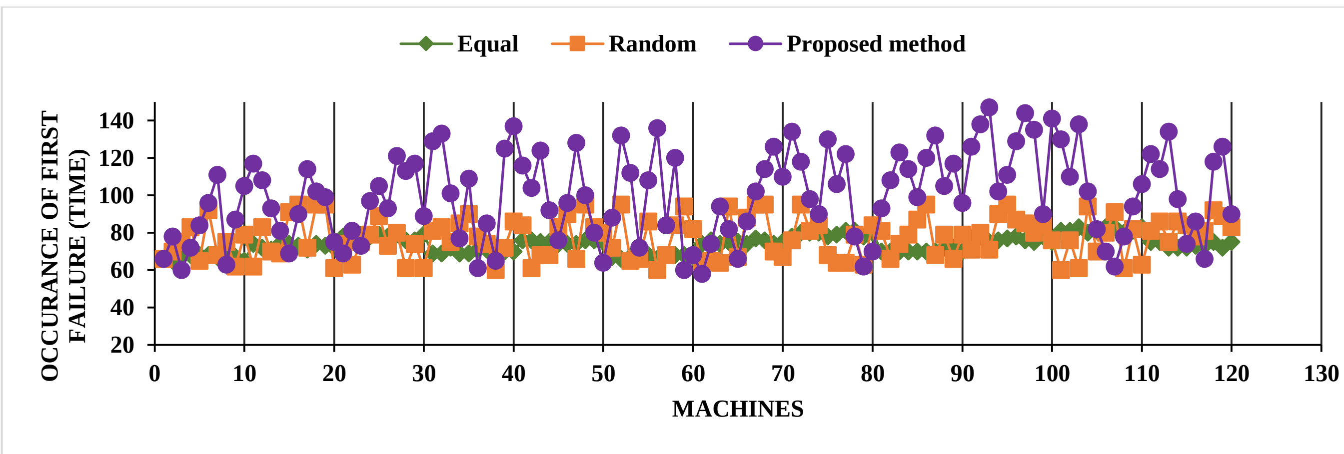
(d)

Figure 4.2 (a-d) Occurrence of Machines failure in the system (Instance 1)

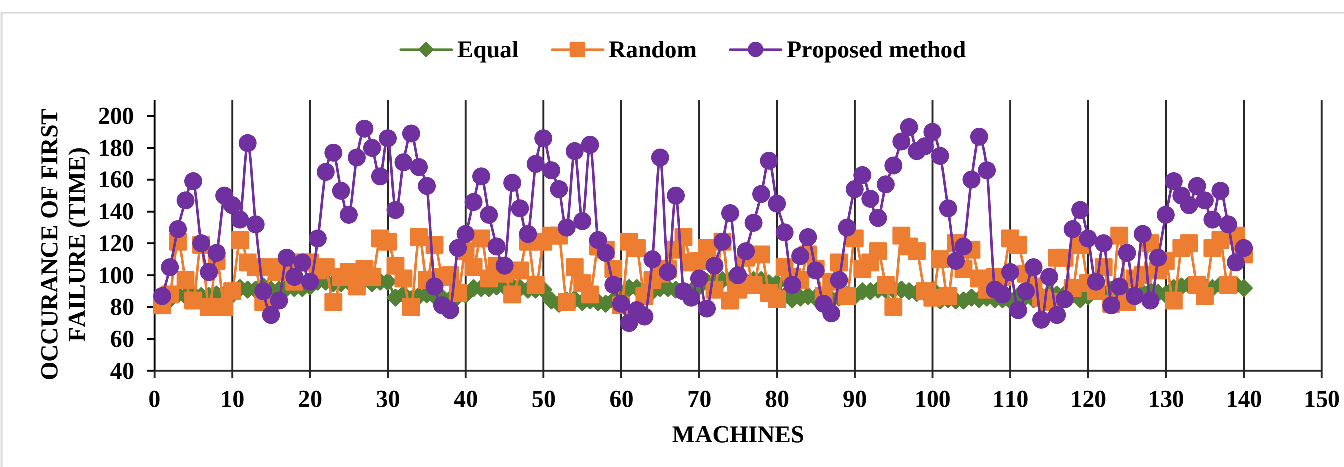
Figure 4.2 (a-d) depicts the experimental results for the first instance of machine configurations. As the demand is high, the machines are made to work up to their limit, accelerating the degradation process resulting in machine life. Figure 4.2 (a) shows the result of a one-degree flexible system. From the plot, it should be noticed that when an equal number of jobs are assigned to all the machines in the configuration, the rate of degradation remains similar in all the machines that lead to failure within a short period i.e., between 41th – 50th day. Whereas, when the random workload was assigned a deviation in the range was found between 40th – 65th day. While in the proposed methodology it was found that in a row (10 machines) there was a gap of at least 3 days (repair time) in between any two machines failure. Figure 4.2 (b) presents the graph of a two-degree flexible system. Here, similar results were observed when the number of jobs was assigned equally and randomly while in the proposed method a certain level of robustness was found. The result of the semi-flexible system and fully flexible system is articulated in Figure 4.2 (c) and (d) respectively. Recall, as flexibility increases the availability of machines for adjusting the remaining jobs increases. As a result, here in Figure 4.2 (c-d) when an equal amount of jobs is assigned, the graph depicts almost a straight line stating very close failure times of machines.



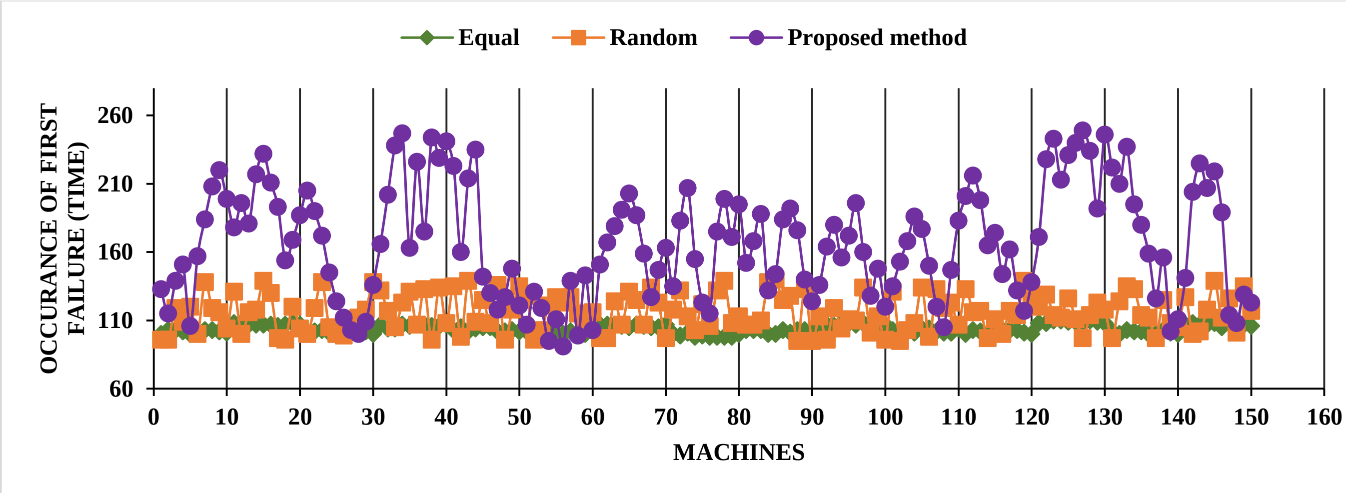
(a)



(b)



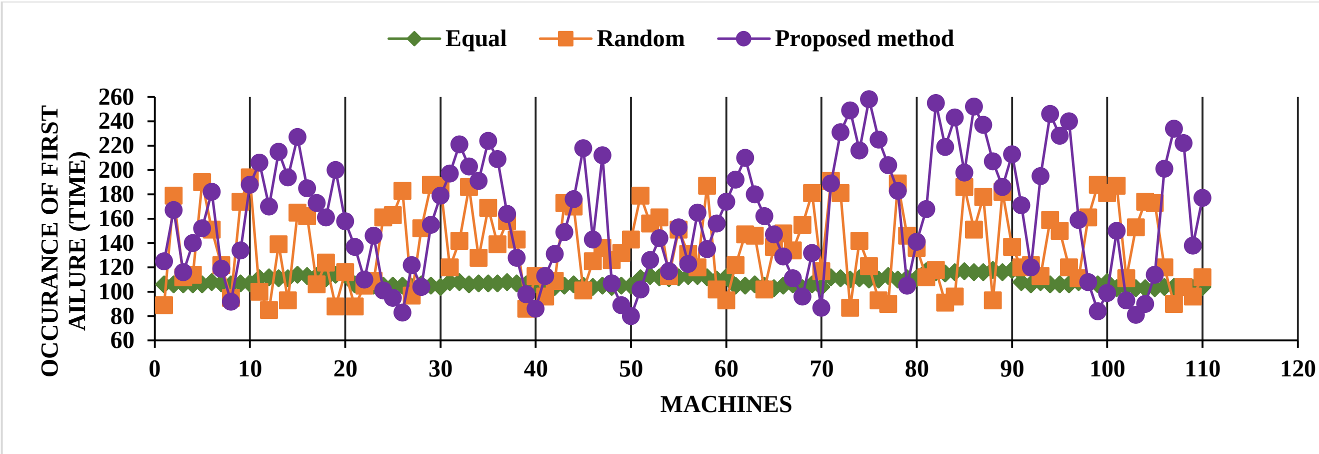
(c)



(d)

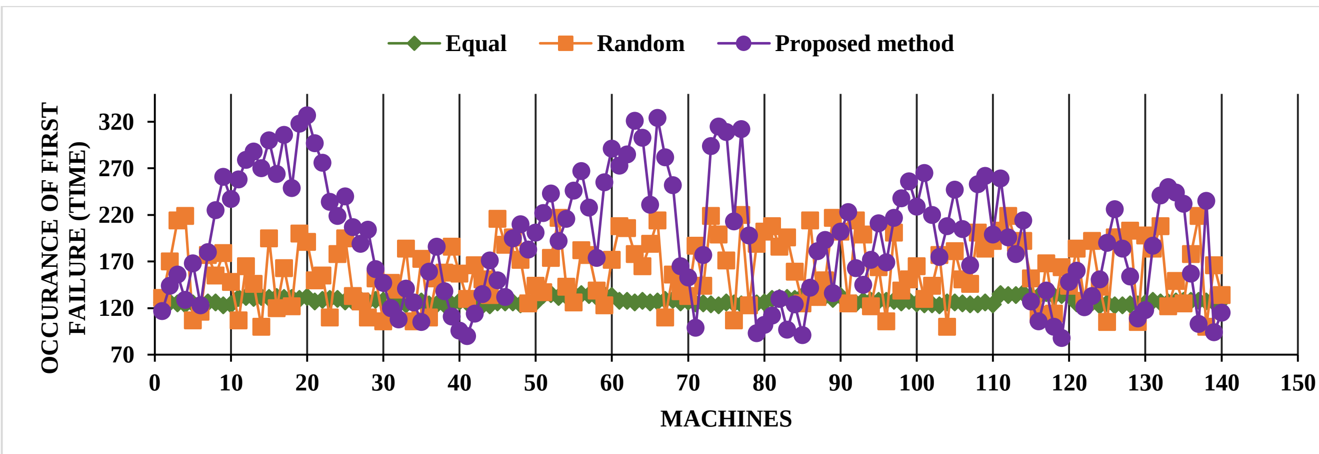
Figure 4.3 (a-d) the occurrence of Machines failure in the system (Instance 2)

The results for Instance 2 are illustrated in Figure 4.3 (a-d). Here, as the number of machines more while the demand being constant, a rise in the average life span of machines was observed. In a one-degree flexible system, as shown in Figure 4.3 (a), it was found that machines in a row tend to fail at the same time when an equal number of jobs were assigned to the system. From Figure 4.3 (a) it is visible as one machine in the row fails, the others tend to fail at a similar range of days. For example, machines 1-10 fail approximately between 65th – 67th day while machines 11-20 fail approximately in a range 55th – 60th day. Whereas in the random assignment of jobs the machines tend to fail randomly, increasing the efficiency of the system somewhat improved than equal workload. While in the proposed method, the tendency of multiple machines breakdown reduced drastically increasing the efficiency of the system. Similar but slightly better results were observed in Figure 4.3 (b) as the degree of flexibility increased compared to Figure 4.3 (a). In a semi-flexible system and fully flexible system results are shown in Figure 4.3 (c) and Figure 4.3 (d) respectively, a hike in points in the plot was appeared for the proposed method, stating robust in machine-to-machine variability. On contrary, the performance of the other two assignment techniques reduced as the machine-to-machine variability decreased.



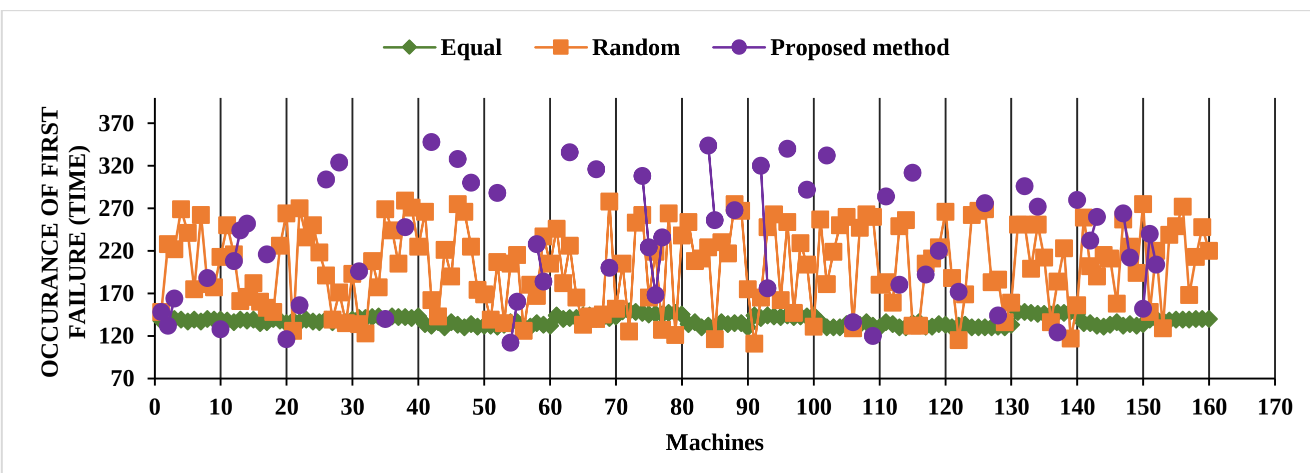
Equal
Random
Proposed method
OCCURANCE OF FIRST AILURE (TIME)
MACHINES

(a)



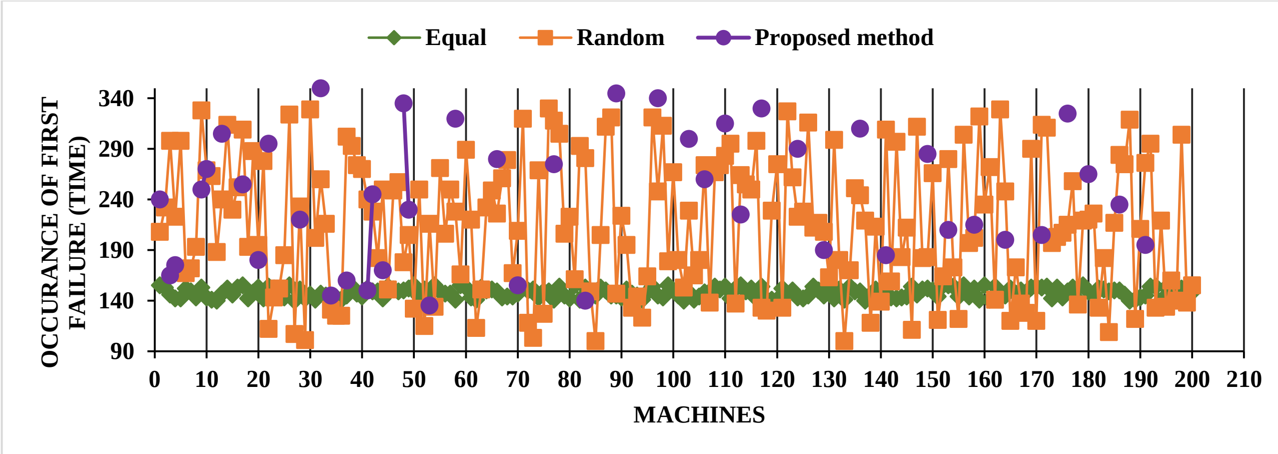
Equal
Random
Proposed method
OCCURANCE OF FIRST FAILURE (TIME)
MACHINES

(b)



Equal
Random
Proposed method
OCCURANCE OF FIRST FAILURE (TIME)
Machines

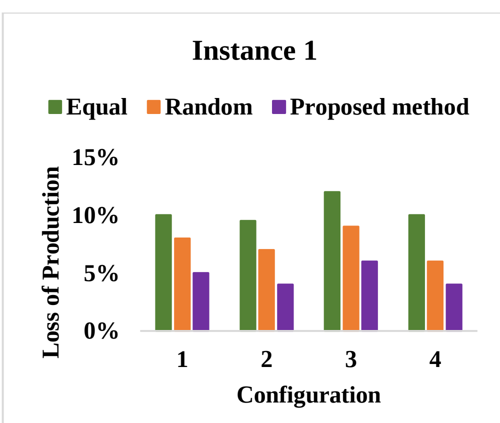
(c)

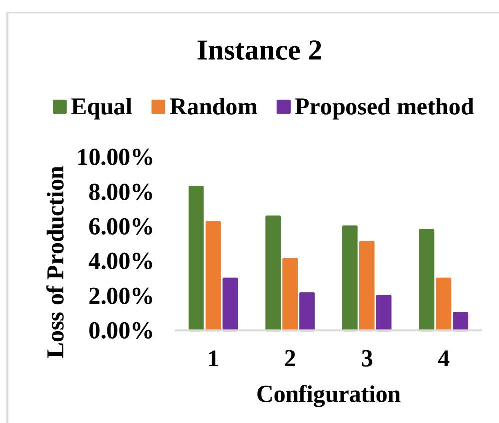


(d)

Figure 4.4 (a-d) Occurrence of Machines failure in the system (Instance 3)

Figure 4.4 (a-d) plots the results for Instance 3. Compared to the other two instances a certain level of increased efficiency of the system is observed. Figure 4.4 (a) and (b) illustrates the result of a one-degree flexible system and two-degree flexible system respectively. It can be observed that here when an equal amount of jobs the results were the same as Figure 4.3 (a), (b) but as the number of machines were more the average time of breakdown was increased. While in the case of random assignment of jobs the deflection in points was in a higher range reducing the possibility of multiple machines breakdown but less compared to the proposed methodology. In the case of semi-flexible system and fully flexible system articulated in Figure 4.4 (c) and (d), the number of points presenting the machines for the proposed method in the plot was less in comparison to the number of machines considered in Instance 3, depicting that not all machines failed during the experimentation. It was found that in the observed time only 58 machines failed in a semi-flexible system while in a fully flexible system the count was 44.





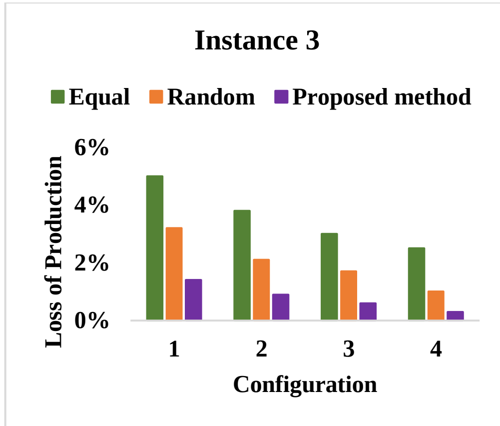


Figure 4.5 Percentage Loss of Production

In Figure 4.5, numbers 1, 2, 3 and 4 on horizontal axis indicates one degree, two degree, semi flexible and fully flexible configurations. Based on the experimental results illustrated in Figures 4.2, 4.3, 4.4, and 4.5, the performance of equal assignment of jobs is found to be worst in all the 3 instances. When the random assignment of jobs was carried the machines tend to fail randomly, showing slightly better results than the equal assignment of workload reducing the possibility of multiple failures of machines but still, it failed to control the overall degradation rate resulting in a system breakdown. In all the 3 instances proposed method showed an effective impact on the efficiency of the system by reducing the degradation process of each machine. When the number of machines was less the system exhibited a similar degradation process as a result several machines tend to fail at a similar range of time.

4.7 Conclusions

The stochastic nature of the degradation process always brings challenges to accurately predict the residual life of machines in a system. First, each configuration of machines in a system has a different level of flexibility which varies the degradation rate of one in comparison to others, thus making it difficult to formulate a degradation model. Second, the workload adjustment in such a system is dependent on the type of configuration which makes it hard to frame an ideal dynamic workload adjustment strategy. Corresponding to these two major challenges, in this research, we proposed a degradation model framework that explicates the degradation process and predicts the health status of any machine regardless of the system configuration. The major contribution of this research is the multiply configurations dynamic jobs adjustment strategy that can be applied to any manufacturing systems depending upon their flexibility. We applied a Bayesian approach that utilizes the real-time degradation information from the machine to predict the health status of the machine at each decision epoch. Then based on the degradation condition of the machines, our job assignment methodology assigns the jobs to the machines to prevent the overlap of machines failure in the system. Later, the stochastic degradation model was adapted numerically to evaluate the performance of a real-time manufacturing environment. We compare our proposed method with the other two benchmark strategies, specifically equal job adjustment and random job adjustment. The outcomes depicted that our method consistently shows a certain level of robustness by preventing the overlap of machine failure in each instance and reducing the loss in production to fulfill the required demand. The average percentage of loss in production is 4.75% in case of proposed model, which is reduced compared to average of 10.5% obtained in case of equal job adjustment, and average of 7.5% in random job adjustment in instance1. Similarly average percentage of loss in production is 2% in case of proposed model, which is reduced compared to average of 6.67% in case of equal job adjustment and average of 4.61% in random job adjustment in instance2. The average percentage of loss in production is 0.75% in case of proposed model which is reduced compared to average of 3.75% in case of equal job adjustment and average of 2% in random job adjustment in instance3.

Chapter 5

Development of workload strategy on multi-product category of flexible configurations

5.1 Introduction

Recent industries efficiency and effectiveness depend on smooth flow of production without any interruptions. The equipment maintenance is apparent in the shop floor to offset the problems related to product quality, production cost and loss of productivity. However, conventional maintenance procedures lack effective mechanism to tackle real time disruptions. Recently emerged Artificial Intelligence (AI) and Machine Learning (ML) techniques transform the traditional maintenance system to an advanced one that can able to capture the machines status and further process the machines information in a real-time environment to improve the system performance. Out of many maintenance strategies available corrective, preventive, and predictive maintenance are considered as effective ones.

Selection of an appropriate maintenance strategy depends on the context of the problem and desired objective function. From various strategies mentioned above, it has been observed that the effective maintenance concerned with respect to manufacturing systems is by minimizing the downtime of machines, unscheduled maintenance and uninterrupted production facilities. Additionally, defining of maintenance schedules and execution of activities is a real challenge. In other words, breakdown of any machine may leads to shutting down of the facility which shows huge impact on efficiency and cost of production. Hence, there is a need of effective mechanism not only for handling the above mentioned disruptive activities but also to understand and predict the systems behavior priory. Recent advancements proved the effectiveness of ML approach on Predictive Maintenance (PM) where the intelligent solutions guide the decision maker to take the necessary action without damage.

In conventional CPS, the machines are integrated with IoT/IIoT devices responsible to generate mountains of data is connected to the data acquisition system to transform and transfer the data into tools and techniques for further analysis. Ultimately the analyzed data reached to maintenance manager for further action. In this work, a semi double loop machine learning based I-CPS (Intelligent – Cyber Physical Systems) architecture [44] has been used that act as an alternative to the conventional CPS. Due to the limitations in conventional CPS i.e., deploying of

IoT/IIoT devices for every task in the industries is a cost affair and employees working under such situations need additional skills where identifying of skilled labor is one of the challenging tasks in current industries. Hence, industries are not ready to transform their existing setup. The alternative solution to handle the above issues and make the system effective is by introducing the recently proposed I-CPS architecture. The advantage with this architecture is, it allows the decision maker to implement the meta-learning by improving the intelligence of the system and by creating new and effective algorithms.

Motivation drawn from the fact that the adapted meta-learning approach is having its ability to adapt the system behavior and improve the system's intelligence through improved learning algorithms. In this research work, the I-CPS model is instantiated in three different combinations i.e., the combined machines, multiple machines, and individual machine level. Here, the developed models behavior and the related information has been trained and tested with supervised learning based machine learning repository, after learning some algorithms that are not qualified are discarded due to their poor performance, among others the best performed five algorithms has been chosen further for future analysis. Based on the analysis, the health status i.e., RUL of each machine can be evaluated. Further, with simulation experiments by adjusting the workload adjustment strategy, the performance of the system has been improved by reducing the throughput time.

5.2 Problem Description

System model description

The proposed flexible configurations with one degree, two degree, semi-flexible, and fully flexible configurations are considered. The one-degree flexibility represents in which, if any machine fails, then the pending jobs can be assigned to the adjacent machine. Whereas in two-degree flexibility represents if any machine fails, the pending jobs can be re-routed to adjacent machines of two stages.. Similarly semi-flexible as well as fully flexible configurations where the availability of machines are more in case of semi-flexible than one degree and two degree flexible configurations and more in case of fully flexible.

Here, the workload for the machines, i.e., the assigned number of jobs, acts as the control variable, and the workload must be in the range of 0 to machine capacity. As mentioned earlier, we utilize the production data to predict the residual life of the machine for which the set-up time, processing time and the repair time of each machine has been considered by assuming all the machines are identical in nature. As a result, the Equation 5.1 representing time required to produce n number of jobs can be written as follows:

$$U_{a,b} = \left(n * t_p\right) + t_s + (L_{a,b} * x) \tag{5.1}$$

Here, time to produce n number of jobs = setup time of a machine (t_s)+ repair time of a machine $(L_{a,b})$ + processing time per n number of jobs(t_p).

The degradation model is adopted from [37], where Bayesian approach is used to predict the rate of degradation of a machine and the corresponding mean and the shape parameters of Inverse Gaussian (IG) distribution helps in finding the degradation coefficient of the machine a, b at the time x represented by $\alpha_{(a,b)}(x)$. For notational convenience we define $di_{(a,b)}(x_u) = U_{a,b}/\beta_{(a,b)}$. Such that, $\mu_{(a,b)}(x_u)$, an estimation of predicted residual life can be calculated using Equation 5.2.

$$\mu_{(a,b)}(x_u) = \frac{di_{(a,b)}(x_u)}{A_{(a,b)}(x_u)} \tag{5.2}$$

Based on machine's health status value $di_{(a,b)}(x_u)$, the workload adjustment strategy is then implemented to reduce the simultaneous machines failure by indirectly reducing the throughput time. Here, the main objective is to minimize the throughput time by adjusting the number of jobs on each machine based on the predicted health status from Equation 5.3. Thus, the objective function for minimizing overlap of machine failure to reduce the throughput time can be formed as follows;

Minimization of throughput time (Z):

$$Z = \frac{1}{N(x_u)} \sum_{a=1,b=1}^{N(x_u)} \left[\beta_{(a,b)}(x_u) A_{(a,b)}(x_u) \delta x + U_{a,b}\right] \tag{5.3}$$

Subjected to constraints

$$\sum_{a=1,b=1}^{N(x_u)} A_{(a,b)}(x_u) = min\left(\sum_{a=1,b=1}^{N(x_u)} C_{(a,b)}, D\right) \tag{5.4}$$

$$A_{(1,1)} x_{(u)} \geq \cdots \geq A_{(N(x_u))}(x_u) \tag{5.5}$$

$$0 \leq A_{(a,b)}(x_u) \leq C_{(a,b)}, \qquad a, b \in 1, \dots, N \tag{5.6}$$

$$\mu_{(a,b)}(x_u) + L_{(a,b)} \delta x \leq \mu_{(a.b+1)}(x_u) \tag{5.7}$$

$$\frac{L_{(a,b)}\delta x}{4}\left[A_{(a,b)}(x_u) + A_{(a,b+1)}(x_u)\right]^2 \leq di_{(a,b+1)}x_u A_{(a,b)}(x_u) - di_{(a,b)}(x_u)A_{(a,b+1)}(x_u) \quad for\ a \in 1,2,\ldots.,N(x_u), \quad b \in 1,2,\ldots.,N(x_u)-1 \tag{5.8}$$

$$\frac{L_{(a,b)}\delta x}{4}\left[A_{(a,b)}(x_u) + A_{(a+1,b+1)}(x_u)\right]^2 \leq di_{(a+1,b+1)}x_u A_{(a,b)}(x_u) - di_{(a,b)}(x_u)A_{(a+1,b+1)}(x_u) \quad for\ a \in 1,2,\ldots.,N(x_u)-1, \quad b \in 1,2,\ldots.,N(x_u)-1 \tag{5.9}$$

$$\frac{L_{(a,b)}\delta x}{4}\left[A_{(a,b)}(x_u) + A_{(a+1,b)}(x_u)\right]^2 \leq di_{(a+1,b)}x_u A_{(a,b)}(x_u) - di_{(a,b)}(x_u)A_{(a+1,b)}(x_u) \quad for\ a \in 1,2,\ldots.,N(x_u)-1, \quad b \in 1,2,\ldots.,N(x_u) \tag{5.10}$$

$$\frac{L_{(a,b)}\delta x}{4}\left[A_{(a,b)}(x_u) + A_{(a+m,b+1)}(x_u)\right]^2 \leq di_{(a+m,b+1)}x_u A_{(a,b)}(x_u) - di_{(a,b)}(x_u)A_{(a+m,b+1)}(x_u) \quad for\ b=1, \quad a \in 1,2,\ldots.,N(x_u), \quad b \in 1,2,\ldots.,N(x_u)-1 \tag{5.11}$$

$$\frac{L_{(a,b)}\delta x}{4}\left[A_{(a,b)}(x_u) + A_{(a,b+m)}(x_u)\right]^2 \leq di_{(a,b+m)}x_u A_{(a,b)}(x_u) - di_{(a,b)}(x_u)A_{(a,b+m)}(x_u) \quad for\ b=1, \quad a \in 1,2,\ldots.,N(x_u), \quad b \in 1,2,\ldots.,N(x_u)-1 \tag{5.12}$$

$$\frac{L_{(a,b)}\delta x}{4}\left[A_{(a,b)}(x_u) + A_{(a+m,b+n)}(x_u)\right]^2 \leq di_{(a+m,b+n)}x_u A_{(a,b)}(x_u) - di_{(a,b)}(x_u)A_{(a+m,b+n)}(x_u) \quad for\ b=1, \quad a \in 1,2,\ldots.,N(x_u)-1, \quad b \in 1,2,\ldots.,N(x_u)-1 \tag{5.13}$$

Constraint mentioned in Equation 5.4 states that when the capacity of the system is greater than demand, the throughput of the system will be equal to the demand and conversely, if demand is greater than capacity then throughput will be equal to capacity. Constraint mentioned in Equation 5.5 articulates that higher workload to be assigned to machines with lower health status, and vice versa. Constraint mentioned in Equation 5.6 ensures the workload need to be in the range between 0 to capacity of the machine. Constraint mentioned in Equation 5.7 prevents the overlapping of machine failures. Considering the situation of different configurations, the overlapping of machine failure constraint is developed depending upon the configurations. Equation 5.8 represents the overlap of machine failures for one-degree flexible configuration. Equation 5.9 and Equation 5.11 represents the overlap of machine failures can be controlled in two-degree flexible configuration. Similarly, Equation 5.10, Equation 5.12, and Equation 5.13 prevents the overlap of machines failure in the semi-flexible system. Whereas, in a fully flexible system the problem is tried to be controlled using constraints in Equation 5.12 and Equation 5.13.

5.3 Methodology

The framework which is an integration approach of data preparation, machine learning model and workload adjustment strategy has been proposed to identify the KPI's responsible for residual life of a system. The proposed model starts with data collection followed with data transformation for data pre-processing to perform data preparation. Primarily, after articulating the problem definition the respective data has been gathered Via sensory information. It is necessary to remove the inaccurate, unbalanced, and bias information from collected data through sensors integrated on the machines. We have performed data pre-processing by formatting, cleaning and sampling before data transformation. In data transformation, normalizing, decomposition, and aggregation steps need to be performed before sending the data to the ML model. While developing a ML model, the prepared data undergoes three different stages namely training, testing, and validation as shown in Figure 5.1.

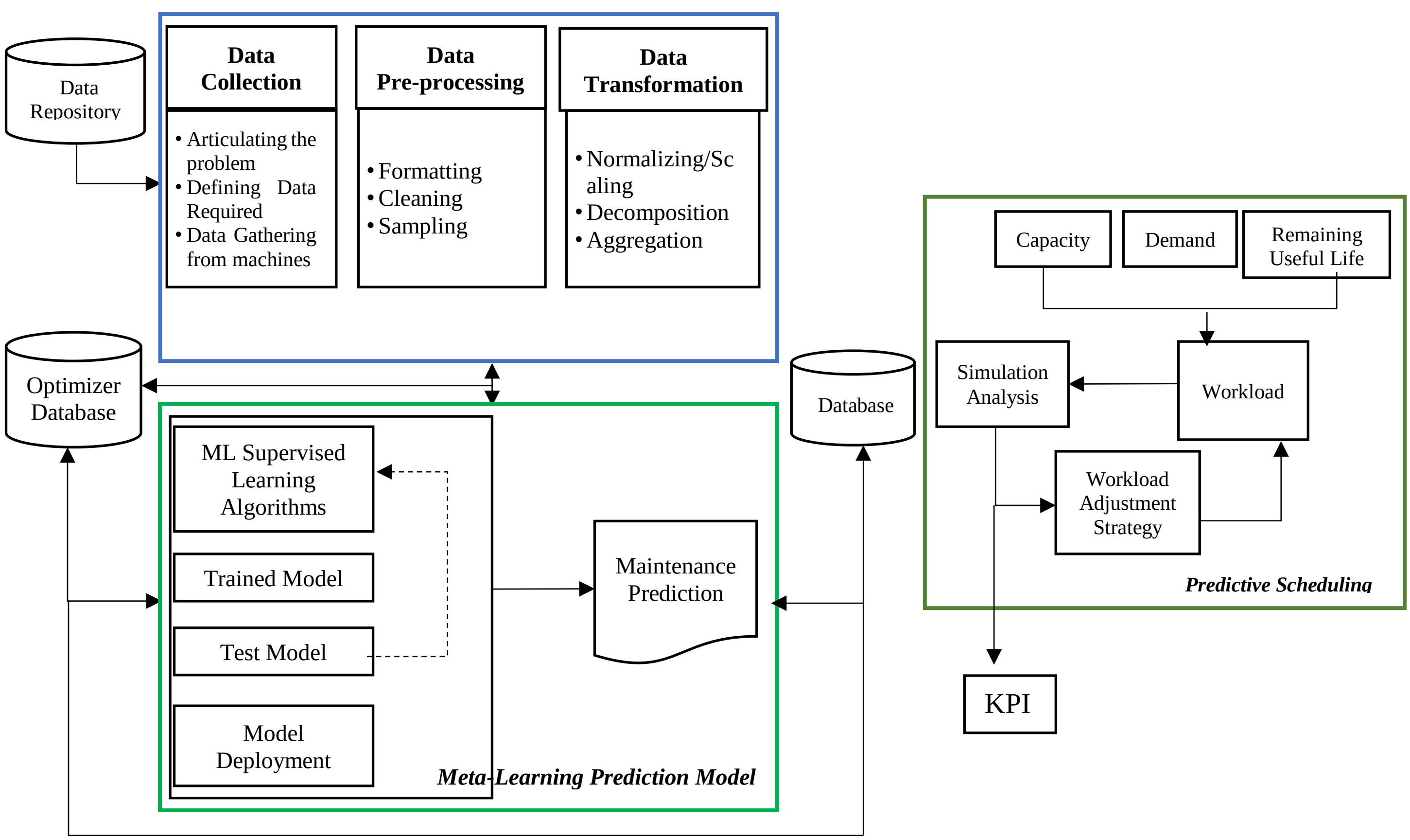


Figure 5.1 Framework for developing workload adjustment strategy based on predicted RUL

In the second stage i.e., machine learning prediction model, the prepared data is tried to fit with numerous machine learning algorithms particularly supervised learning algorithms available in the MATLAB repository. During this process some algorithms automatically discarded due to their poor performance, where the best fit algorithms called for modelling further known as double loop for modelling the parameters using training, testing and validating the model parameters for improving the accuracy thereby reduce the error. In other words, the double loop learning model or Meta learning model inferred as two separate ML algorithms in two loops. Learning algorithms in the first loop are the object algorithms, where the learning algorithms in second loop are adjusted or modified first loop algorithms used to improve the model parameters for better accuracy is shown as an I-CPS architecture in Figure 5.2.

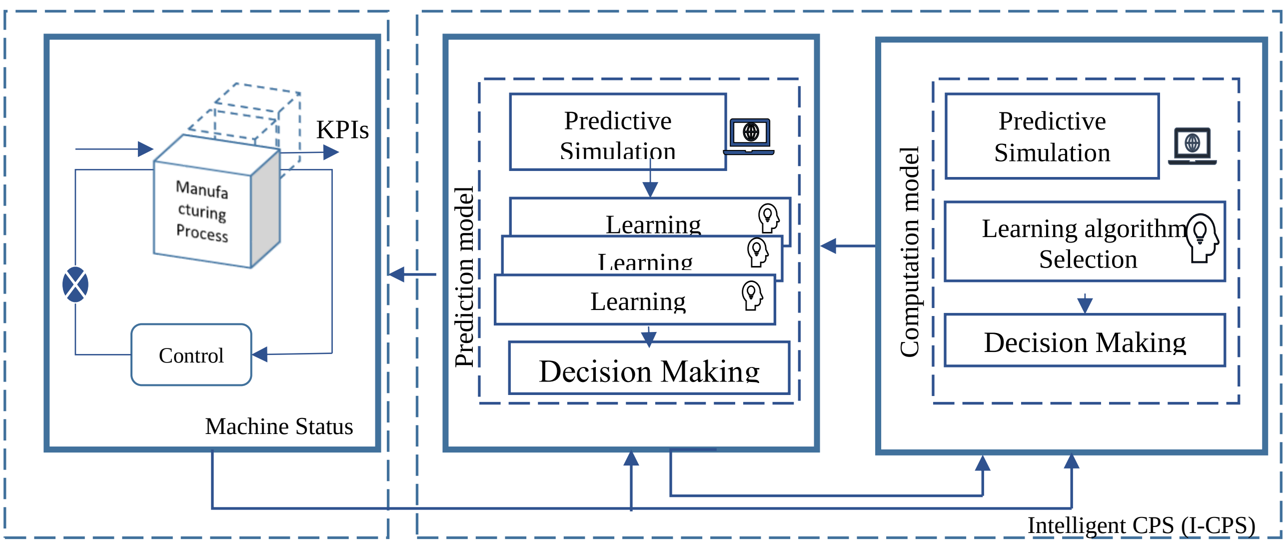


Figure 5.2 Intelligent Cyber Physical Systems (I-CPS) architecture

In the third stage, predictive simulations has been performed using the RUL from the predicted maintenance can be taken as an input along with the capacity of each unit, and demand for each configuration from the collected data. The goal of dynamically adjusting the workload on each unit is to reduce the overlap of machine failures and to increase the throughput of each unit. To achieve this goal, we have used the workload adjustment strategy that allocates the more number of jobs on worse health status. The main reason underlying this strategy is that the more jobs on worse health status machine will degrades faster and leads to failure and thus the expected failure time of each machine to other will be different [36,37].

5.4 Experimentation

In this section, we proposed three strategies i.e., combined machine strategy, multiple machines strategy, and individual machine strategy to analyze four different realistic configurations for implementing the proposed approach. The detailed description of proposed strategies and configurations are as follows:

Strategy 1. Combined Machine:

In this strategy, the group of machines are considered as a single machine and their information is considered as one data set to perform different analysis of the system. Here, to perform the machine learning based modelling operations i.e., training, testing and validation, we have chosen the best performing supervised machine learning algorithm from the repository to conduct the analysis. As we assume that the considered training data is from single machine information, the available maintenance information is plenty to conduct required analysis. But, due to lack of specific machine data it is quite difficult to predict which machine is required for maintenance.

Strategy 2. Multiple Machines

In this strategy, similarly like combined machine strategy a single ML algorithm has been used to train, test and validate the data. But, unlike the combined strategy here the Machine ID has been considered as an additional input which helps in identifying the maintenance requirement for a particular machine.

Strategy 3. Individual machine

Here, we have collected the training data of every single machine in the system for prediction due to their unique behavior. Thereafter, with all the supervised machine learning algorithms available in the repository we have trained each machine separately to predict the most suitable algorithm for the respective machine. One can realize from below tables that due to this analysis each machine ID have their respective ML algorithm.

5.4.1 Experimentation settings for maintenance prediction

The Meta-learning ML based CPS approach for the prediction of maintenance has been validated in real life industry in this research. Data of 12 machines were considered to validate the proposed model. The 12 machines are operating under four configurations called one degree flexible, two degree flexible, semi flexible, and fully flexible configurations. The machine IDs are considered from 1 to 12 in each configuration. A period of 6 months' data has been collected to predict the maintenance required and maintenance not required. A total of 30,427 batches of manufacturing data from 12 machines has been considered in each configuration. Among the 6 months of data, the holdout data has been taken in 3 variances in which 17% (1 month), 33% (2 months), 50% (3 months) for testing of different set of algorithms, the input data variables as well as output of the program are shown in Table 5.1.

Table 5.1 Data variables involved in ML Program.

Variable of Input	Extracted Features	Output
1. Machine ID	1. Total working time of machine	Maintenance requirement (1/0)
2. Shift	2. Total number of setups	
3. Shift Date	3. Total quantity of a machine	
4. Material	4. Total work time of a machine after last maintenance	
5. Quantity	5. Total quantity of a machine after last maintenance	
6. Production Time	6. Total number of setups after previous maintenance	
7. Time/piece		
8. Maintenance Time		
9. Setup		

5.4.2 Experimentation settings for workload adjustment strategy

The proposed framework for workload adjustment strategy followed in this research is shown in Figure 5.3. The machines are identical where the workload on machines can be assigned based on the demand and capacity of each machine. The processing variations in machines will provide the information about the characteristics of degradation rate which helps in finding the degradation coefficient. Later, the Bayesian approach applied to predict the residual life of each individual machine. Further, the workload is adjusted dynamically on machines to minimize the throughput time.

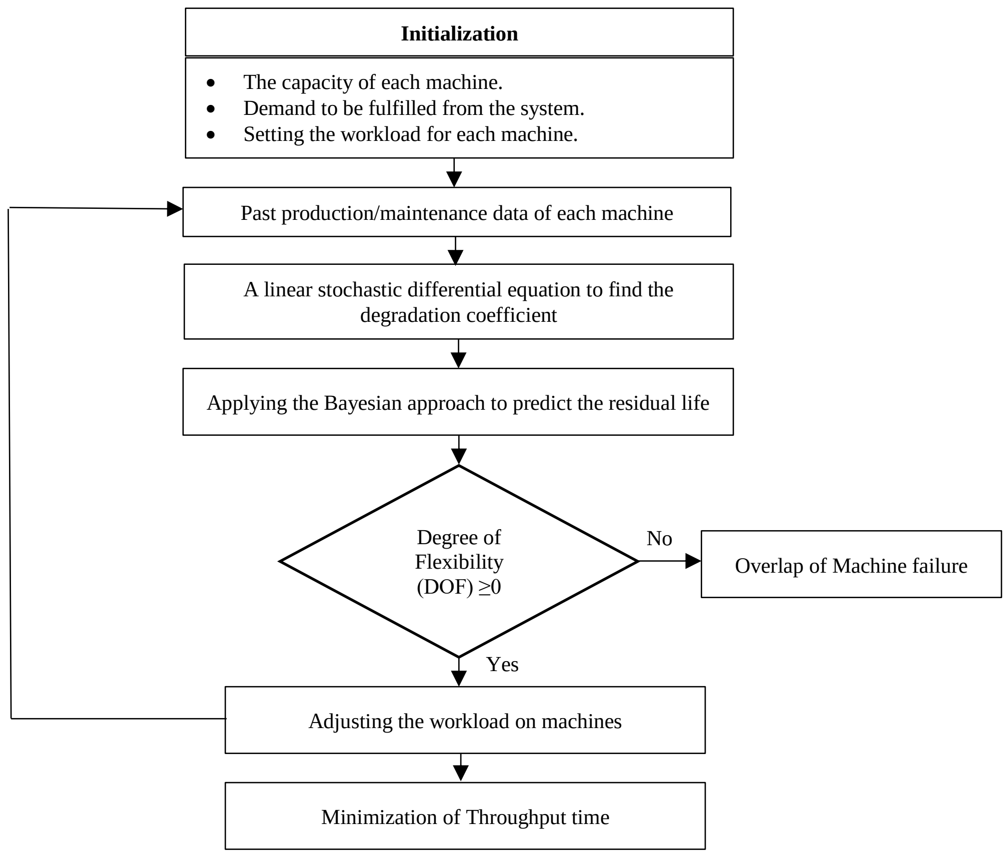


Figure 5.3 Framework for workload adjustment strategy

The total number of machines are 12 for each configuration, in which the machine ID from 1 to 12 is considered. The data has been collected over a period of 6 months and a total of 30,427 batches of data for 54000 number of jobs. The demand of each configuration, and capacity of each identical machine as parameters for the experimentation shown in Table 5.2.

Table 5.2 Parameters for the experimentation

Parameters	Unit
The capacity of each machine	4500 jobs/day
Demand for One Degree Flexible system	54000 jobs/day
Demand for Two Degree Flexible system	54000 jobs/day
Demand for Semi-Flexible system	54000 jobs/day
Demand for Fully Flexible system	54000 jobs/day

5.5 Experimental Results and Discussion

5.5.1 Results for Maintenance prediction

The Confusion Matrix (CM) is a tool helps for predictive analysis in ML and it can be deployed for checking the performance of a classification-based ML model. The CM is an *N*N* matrix which helps in evaluating the performance of a model, where *N* indicates the number of target classes. Here, *2*2* CM has considered and F1 score has been calculated for predicting the maintenance required or not required. Three strategies have been applied for predicting the maintenance of machines named as combined strategy, multiple machines strategy, and individual machine strategy [44].

Table 5.3 Results for the various learning algorithms for 17%, 33%, and 50% holdout for predictive models under 3 strategies for one degree flexible configuration.

Learning Algorithm	Accuracy	F1 Score (Maintenance Prediction)	F1 Score (No Maintenance Prediction)
Strategy 1. Combined Machines			
Decision Tree fine	94.32%	0.0909	0.9767
Naïve Bayes (Kernel)	94.02%	0.1388	0.9775
SVM (Quadratic)	95.74%	0.1176	0.9805
Neural Network (Medium)	94.6%	0.24	0.9720
Ensemble (RUS Boosted)	67.47%	0.1061	0.9811
SVM (Cubic)	94.31%	0.1449	0.9705
Strategy 2. Multiple Machines			
Decision Tree (Medium)	95.45%	0.05	0.98

Naïve Bayes (Kernel)	91.19%	0.16	0.98
SVM (Quadratic)	96.04%	0.11	0.98
Neural Network (Medium)	93.75%	0.21	0.97
Ensemble (RUS Boosted)	65.5%	0.13	0.85
SVM (Cubic)	94.01%	0.23	0.98
Strategy 3. Individual Machine Level (Average F1)			
Multi algorithm learning model	98.04%	0.6733	0.991

Table 5.3 presents the results of top 5 algorithms from a total of 30 algorithms which are predictive models with highest F1 score and accuracy for the above mentioned 3 strategies for one degree flexible configuration. From the Table 5.3, it has been observed that in strategy 1, the Neural network (Medium) has been predicted the highest F1 score as 0.24, where the 24% of chance is there for the maintenance requirement according to the algorithm predicted. The Ensemble (RUS Boosted) algorithm has been predicted the highest F1 score as 0.9811 for the no maintenance prediction in which the 0.9811 indicated that the 98.11% of chances as there is no maintenance is required. In strategy 2, the neural network (medium) has been predicted highest F1 score as 0.21 for maintenance requirement, and Decision Tree (Medium), Naïve Bayes(Kernel), and SVM (Quadratic) has been predicted the highest F1 score as 0.98 for not to have the maintenance. In strategy 3, multi algorithm learning model has been predicted 0.6733 as highest F1 score to have the maintenance, 0.991 as F1 score to not to have the maintenance, and the 98.04% as accuracy has been achieved.

Table 5.4 Results for the various learning algorithms for 17%, 33%, and 50% holdout for predictive models under 3 strategies for two degree flexible configuration.

Learning Algorithm	Accuracy	F1 Score (Maintenance Prediction)	F1 Score (No maintenance Prediction)
Strategy 1. – Combined Machines			
Decision Tree fine	95.27%	0.0754	0.9757
Naïve Bayes (Gaussian)	89.76%	0.0833	0.9458
Naïve Bayes (Kernel)	94.6%	0.1739	0.9761

SVM (Cubic)	94.03%	0.2222	0.9798
SVM (Quadratic)	95.61%	0.0625	0.9775
KNN (Fine)	96.13%	0.2	0.9803
Strategy 2. – Multiple Machines			
Decision Tree (Fine)	92.85%	0.0975	0.9783
Naïve Bayes (Gaussian)	93.27%	0.1785	0.9649
Naïve Bayes (Kernel)	94.88%	0.1025	0.9736
SVM (Cubic)	94.49%	0.123	0.9797
SVM (Quadratic)	95.75%	0.0434	0.9782
KNN (Fine)	96.02%	0.2222	0.9795
Strategy 3. – Individual Machine Level (Average F1)			
Multi algorithm learning model	96.43%	0.5422	0.9815

Table 5.4 presents the results of top 5 algorithms from a total of 30 algorithms which are predictive models with highest F1 score and accuracy for the above mentioned 3 strategies for two degree flexible configuration. From the Table 5.4, it has been observed that in strategy 1, the SVM (Cubic) has been predicted the highest F1 score as 0.1739 for maintenance required, and the SVM (Cubic) algorithm has been predicted the highest F1 score as 0.9798 for the no maintenance required. In strategy 2, the Naïve Bayes (Gaussian) algorithm has been predicted the highest F1 score as 0.21 for maintenance requirement, and SVM (Cubic) is giving highest F1 score for not to have the maintenance. In strategy 3, multi algorithm learning model has been predicted 0.5422 as F1 score to have maintenance, and 0.9815 as F1 score to not to have the maintenance, and the 96.43% of accuracy has been achieved.

Table 5.5 Results for the various learning algorithms for 17%, 33%, and 50% holdout for predictive models under 3 strategies for semi flexible configuration.

Learning Algorithm	Accuracy	F1 Score (Maintenance Prediction)	F1 Score (No Maintenance Prediction)
Strategy 1. – Combined Machines			
Decision Tree Coarse	95.74%	0.12	0.9782

Naïve Bayes (Kernel)	94.89%	0.10	0.9737
SVM (Linear)	96.2%	0.13	0.9806
SVM (Cubic)	95.17%	0.32	0.9750
Ensemble (Random Search with 1K Learner)	95.91%	0.07	0.9791
Ensemble (Random Search with 30K Learner)	96.31%	0.13	0.9811
Strategy 2. – Multiple Machines			
Ensemble (Boosted)	96.06%	0.2	0.9798
Decision Tree (Medium)	95.76%	0.1887	0.9782
Naïve Bayes (Gaussian)	94.3%	0.1	0.9729
SVM (Cubic)	94.64%	0.2308	0.9722
Naïve Bayes (Kernel)	95.17%	0.1	0.9752
Strategy 3. – Individual Machine Level (Average F1)			
Multi algorithm learning model	96.9%	0.5491	0.9840

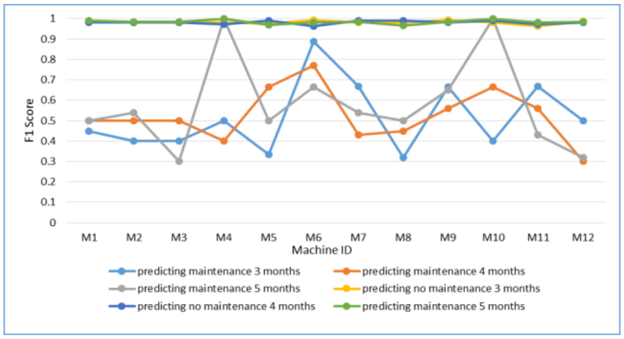
Table 5.5 presents the results of top 5 algorithms from a total of 30 algorithms which are predictive models with highest F1 score and accuracy for the above mentioned 3 strategies for semi-flexible configuration. From the Table 5.5, it has been observed that in strategy 1, the SVM (Cubic) has been predicted the highest F1 score as 0.32 for maintenance required, and the SVM (Linear) algorithm has been predicted the highest F1 score as 0.9706 for the no maintenance prediction. In strategy 2, the SVM (Cubic) has been predicted the highest F1 score as 0.2308 for maintenance required, and Ensemble (Boosted) has been predicted the highest F1 score as 0.9798 for not to have the maintenance. In strategy 3, multi algorithm learning model has been predicted 0.5491 as highest F1 score to have maintenance, and 0.9840 as highest F1 score to not to have the maintenance, and the 96.9% of accuracy has been achieved.

Table 5.6 Results for the various learning algorithms for 17%, 33%, and 50% holdout for predictive models under 3 strategies for fully flexible configuration.

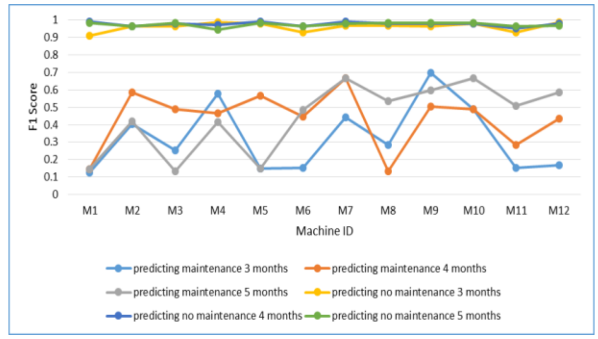
Learning Algorithm	Accuracy	F1 Score (Maintenance Prediction)	F1 Score (No Maintenance Prediction)
Strategy 1. – Combined Machines			
Ensemble (Random Search with 30K learner)	96.35%	0.13	0.9813
Decision Tree Course	96.02%	0.12	0.9796
Naïve Bayes (Kernel)	95.32%	0.15	0.9759
SVM (Linear)	96.14%	1	0.9803
SVM (Cubic)	95.17%	0.32	0.9749
Ensemble (Random Search with 1K Learner)	96.31%	0.13	0.9811
Strategy 2. – Multiple Machines			
Ensemble (Bagged)	95.76%	0.12	0.9782
Decision Tree (Medium)	95.45%	0.2	0.9766
SVM (Cubic)	94.32%	0.16	0.9705
Naïve Bayes (Kernel)	93.47%	0.14	0.9660
Neural Network (Narrow)	90.2%	0.12	0.9481
Strategy 3. – Individual Machine Level (Average F1)			
Multi algorithm learning model	97.49%	0.6625	0.9857

Table 5.6 presents the results of top 5 algorithms from a total of 30 algorithms which are predictive models with highest F1 score and accuracy for the above mentioned 3 strategies for fully flexible configuration. From the Table 5.6, it has been observed that in strategy 1, the SVM (Cubic) has been predicted the highest F1 score as 0.32 for maintenance required, and the Ensemble (random search with 30K learner) algorithm has been predicted the highest F1 score as 0.9813 for the no maintenance prediction. In strategy 2, the SVM (Cubic) has been given the highest F1 score as 0.16 for maintenance requirement, and Ensemble (Bagged) has been predicted the highest F1 score as 0.9782 for not to have the maintenance. In strategy 3, multi algorithm learning model has

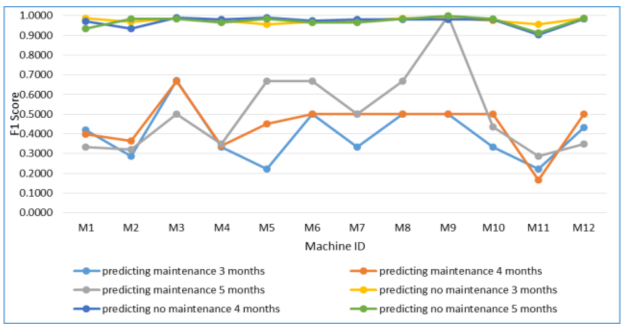
been predicted 0.6625 as F1 score to have maintenance, 0.9857 as F1 score to not to have the maintenance, and the 97.49% of accuracy has been achieved.



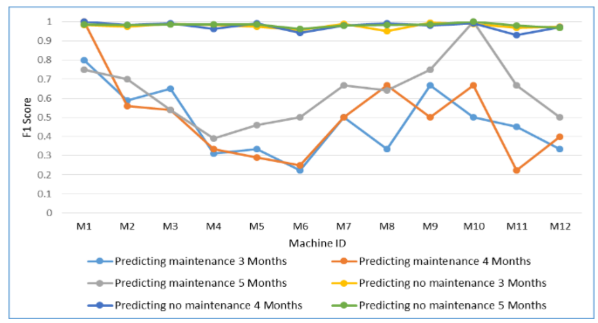
(a) One Degree



(b) Two Degree



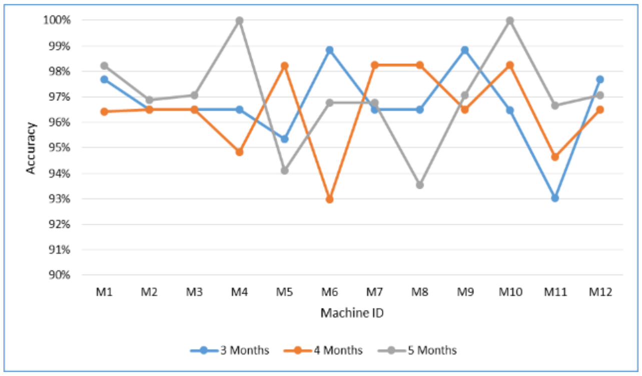
(c) Semi Flexible



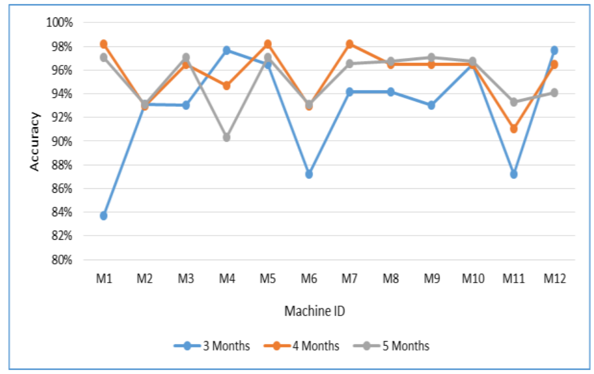
(d) Fully Flexible

Figure 5.4 (a-d) F1 score of maintenance prediction and of no maintenance prediction when required for individual machines for the strategy 3 for various flexible configurations

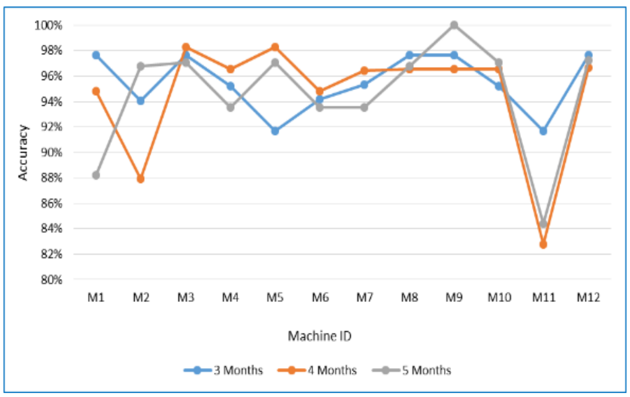
Figure 5.4 (a-d) shows the individual machine strategy for the prediction of maintenance requirement of four proposed flexible configurations. Here, the M1 to M12 represents the machine ID from 1 to 12 as shown in figure above. The training data set has been taken in 3 different periods such as 3 months training, 4 months training, and 5 months training and the other time period among the 6 month of data has been considered for testing the model. Figure 5.4 (a) represents the maintenance prediction for the one degree flexible systems where the F1 score is more than 0.9 for not to have the maintenance, and 0.48 to have the maintenance. Figure 5.4 (b) represents the maintenance prediction for the two degree flexible system as F1 is score is more than 0.9 to not to have the maintenance, and 0.38 is the average F1 score to have the maintenance. Similarly, Figure 5.4 (c), Figure 5.4 (d) represents the maintenance prediction for the semi-flexible, and fully flexible systems respectively, where the F1 score is greater than 0.9 in case of no maintenance prediction, and the average F1 score is 0.4 for semi flexible, and 0.48 for fully flexible systems.



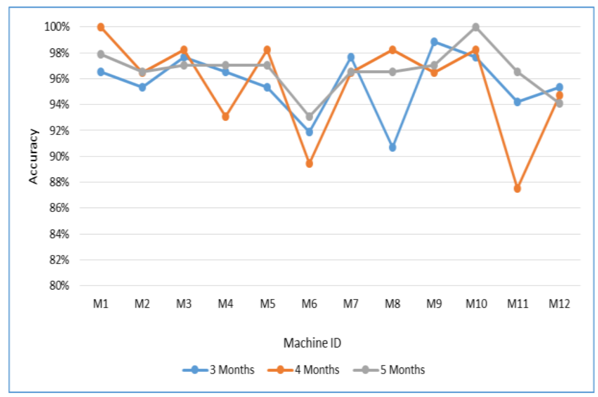
(a) One Degree



(b) Two Degree



(c) Semi Flexible



(d) Fully Flexible

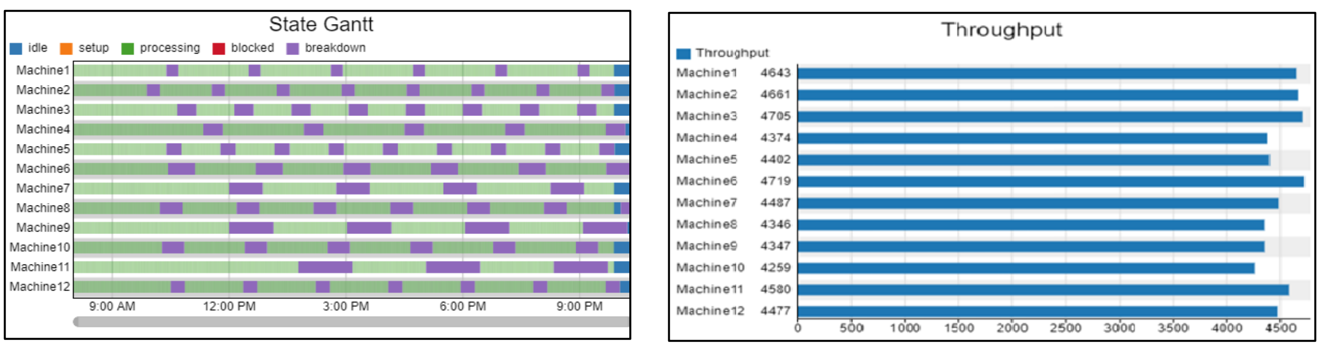
Figure 5.5 (a-d) Accuracy of an individual machine maintenance prediction for the strategy 3 for flexible configurations

The accuracy for each machine from machine ID 1 to machine ID 12 as shown in Figure 5.5 (a-d) for each configuration from one degree flexible to the fully flexible systems. Figure 5.5 (a) represents one degree flexible system and the accuracy has been achieved between the ranges of 90-100% for 12 number of machines with the predicted ML algorithms. Figure 5.5 (b) represents the accuracy obtained for two degree flexible system, and it is ranging between 83-100% with the predicted algorithms. Figure 5.5 (c), Figure 5.5 (d) represents the accuracy results for the semi-flexible system, and fully-flexible system respectively and the accuracy has been achieved between the range of 82-100%, and 87-100% respectively.

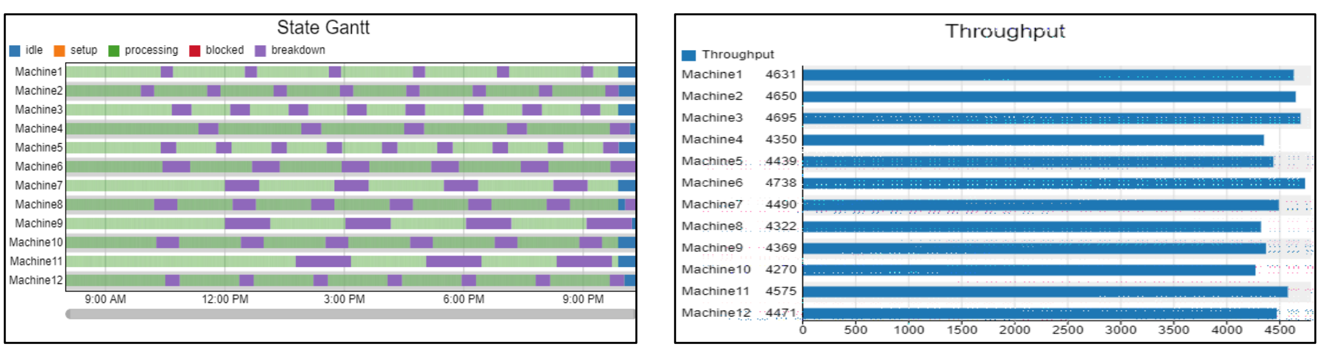
5.5.2 Results of Workload Adjustment strategy

To be part of it, based on the predicted maintenance the RUL has been identified and the simulation environment is created using simulation software for workload adjustment strategy. The validation of proposed approach has been shown by the simulation results of state Gantt, and throughput on four different configurations such as one degree, two degree, semi flexible, and fully flexible. The simulation helped in showing each individual machine and the number of jobs processed as throughput. State Gantt shown the machine performance based on time in which performance time, breakdown time, and idle time of machines.

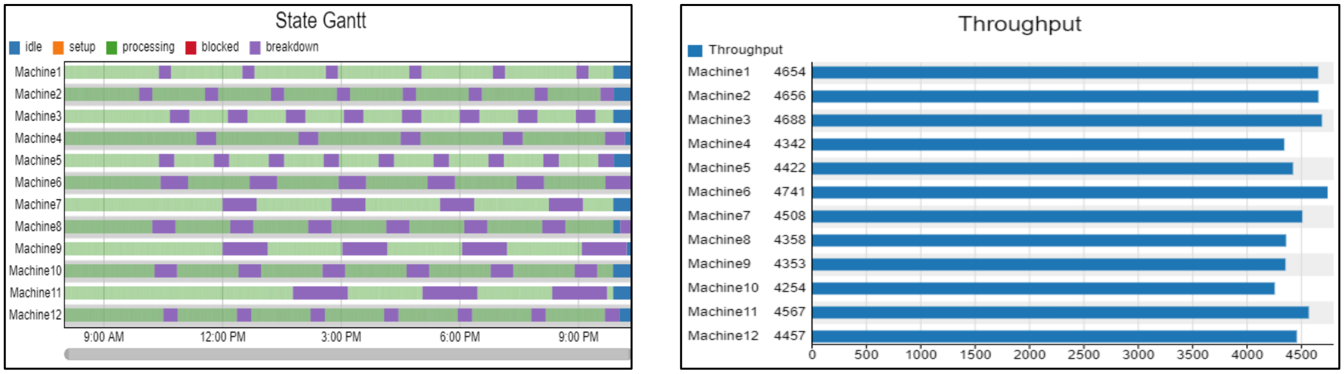
In this section, the dynamic workload adjustment strategy has been implemented (Hao et al., 2015) [37] with the other two benchmark strategies i.e. equal workload, and random workload has been enumerated. We considered two key performance indices (KPI) as Throughput and performance of machines based on time as State Gantt.



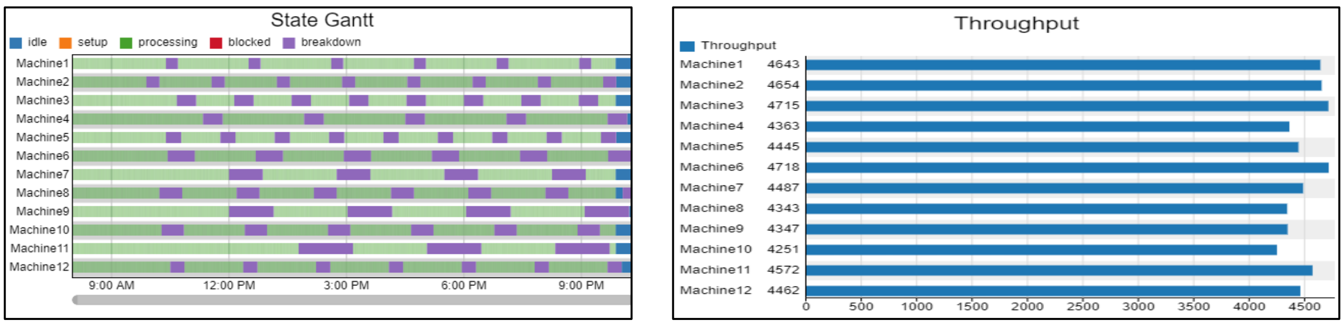
(a) One Degree



(b) Two Degree



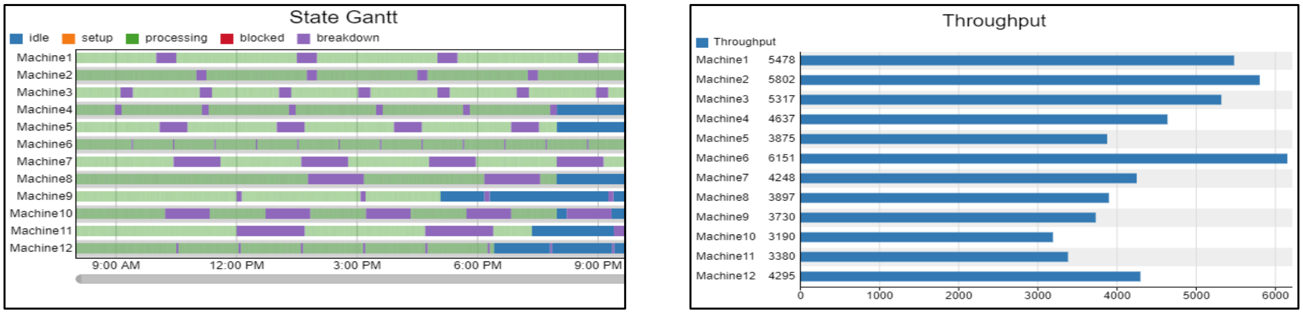
(c) Semi Flexible



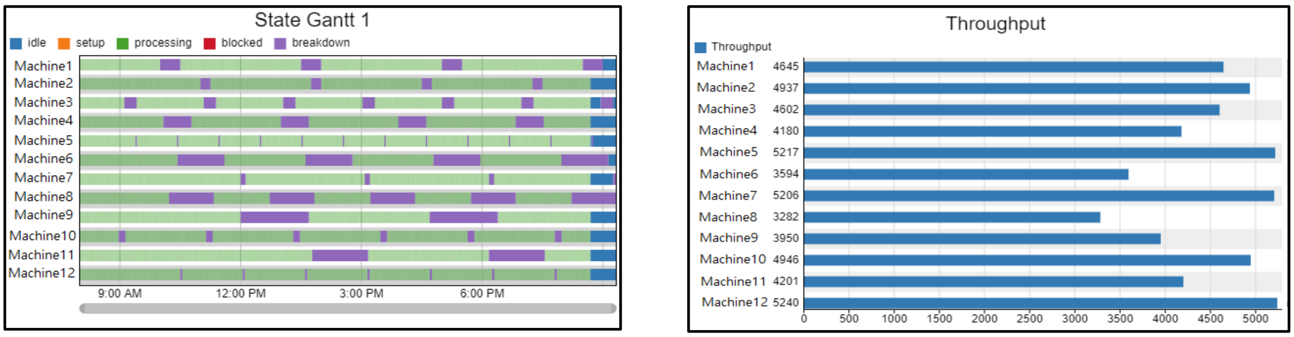
(d) Fully Flexible

Figure 5.6 (a-d) Equal strategy as equal number of jobs has been distributed on every machine

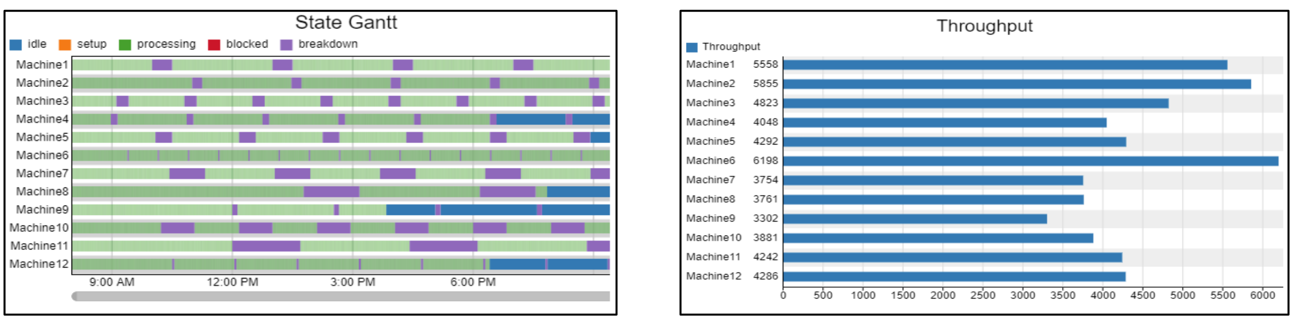
The above Figure 5.6 (a-d) shows the simulation program outcomes for one degree to fully flexible configurations for processing the 54000 number of jobs in equal strategy. In equal strategy, the equal number of jobs has been distributed on each machine where Figure 5.6 (a) represents the one degree flexible system and clearly shows that it has taken 51757 seconds to complete the demand. Figure 5.6 (b) represents the two degree flexible system where it taken 51756 seconds to complete the number of jobs. Figure 5.6 (c), and Figure 5.6 (d) represents the semi-flexible, and fully flexible systems respectively, and it has been observed that it almost taken same amount of time to complete the number of jobs as first two configurations. From the figures it is clearly observed that in case of equal strategy, the machines are ultimately fails in an equal phase and the workload allocated to the machines leads to the overlap of machine failure.



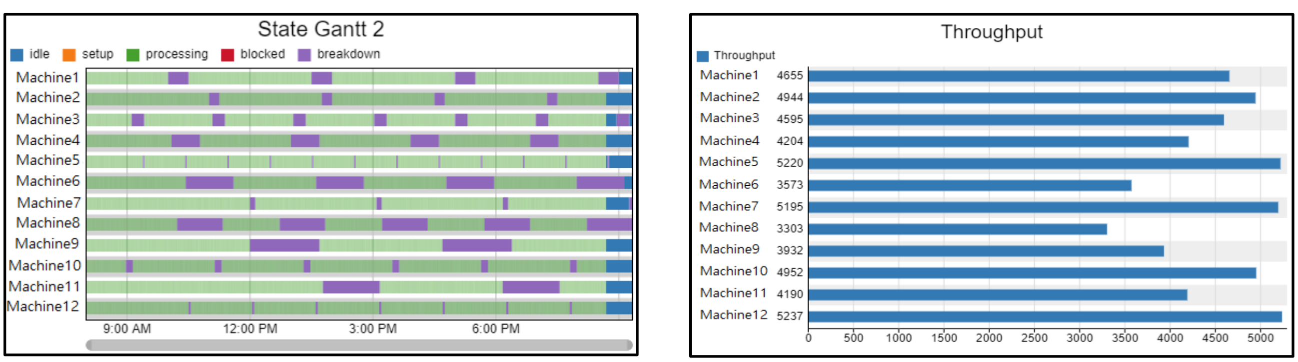
(a) One degree



(b) Two degree



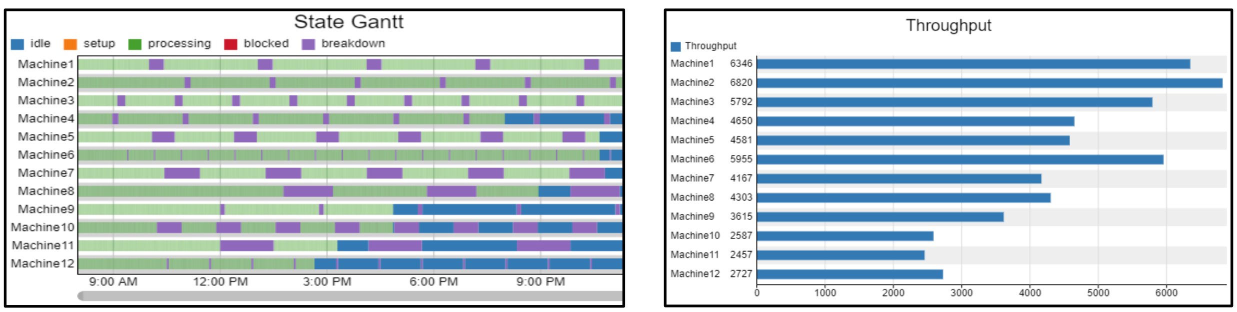
(c) Semi-Flexible



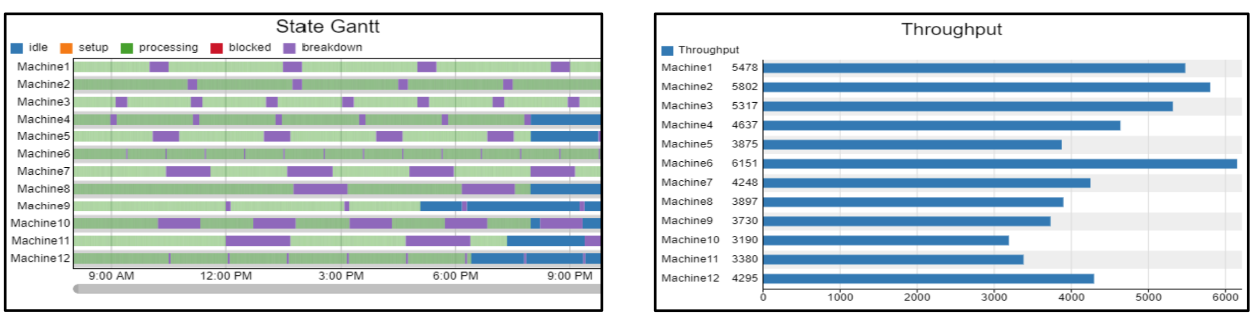
(c) Fully-Flexible

Figure 5.7 (a-d) Random strategy as the random number of jobs has been distributed on every machine in various configuration.

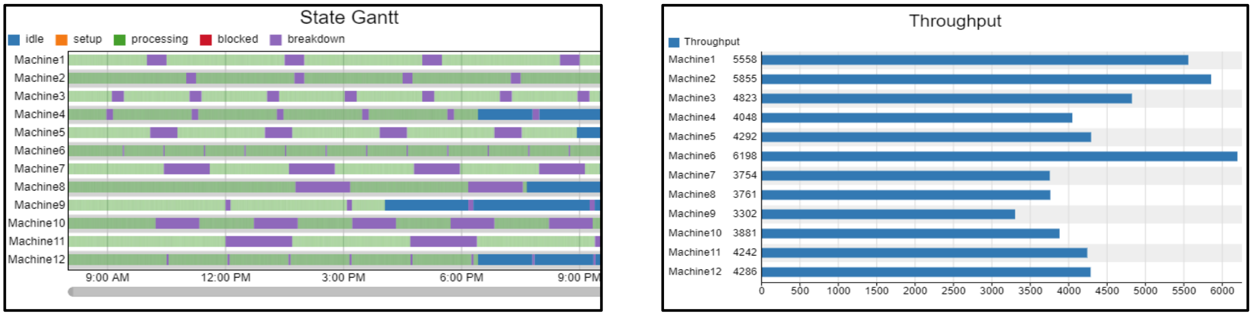
Figure 5.7 (a-d) shows the performance of simulation for random strategy for one degree to fully flexible configurations for processing 54000 number of jobs. Figure 5.7 (a) shows the one degree flexible system in random strategy, where the jobs has been allocated on machines randomly. It has taken 48960 seconds to process the number of jobs. Figure 5.7 (b) represents the two degree flexible system where it has taken 47880 seconds to process the jobs. Similarly, Figure 5.7 (c), and Figure 5.7(d) represents the semi-flexible, and fully flexible system where it has taken 48296 seconds, and 47996 seconds to process the 54000 number of jobs respectively. In the random strategy as the jobs has been distributed randomly irrespective of machine condition. One could clearly comprehend that the tendency of various machine failures overlap was reduced to a certain level because of random failures.



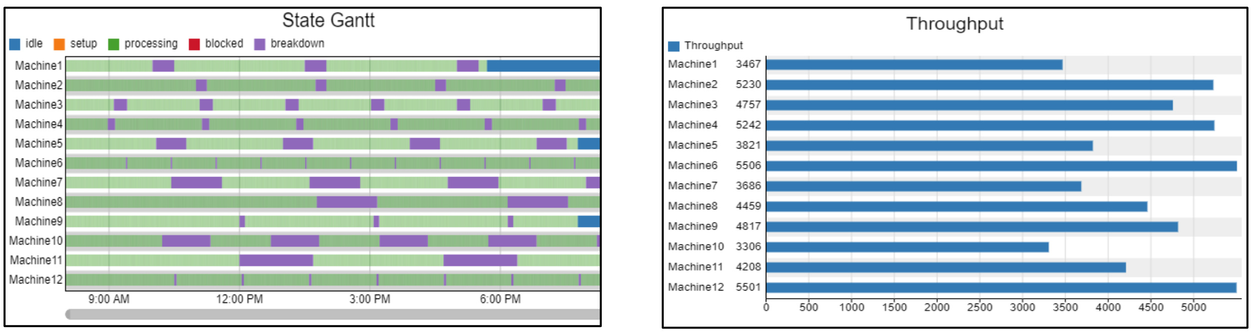
(b) one degree



(a) Two degree



(c) Semi-Flexible



(d) Fully-Flexible

Figure 5.8 (a-d) Workload adjustment strategy for flexible configurations

Figure 5.8 (a) represents the results of proposed methodology of throughput and Gantt chart for one degree flexible configuration and it has been observed that the workload adjustment strategy has been taken 52865 seconds to complete the number of jobs. Figure 5.8 (b) represents the two degree flexible system where it has been taken 47843 seconds to complete the number of jobs. Figure 5.8 (c), and Figure 5.8 (d) represents the semi-flexible, and fully-flexible configurations as 47376 seconds, 46946 seconds has been taken to process the jobs. As in proposed methodology, a dynamic workload has been carried out based on the predicted remaining useful life which has been taken from the maintenance predicted and the tendency of individual machine failure was purely improved resulted in the completion of the workload allocated on the machines.

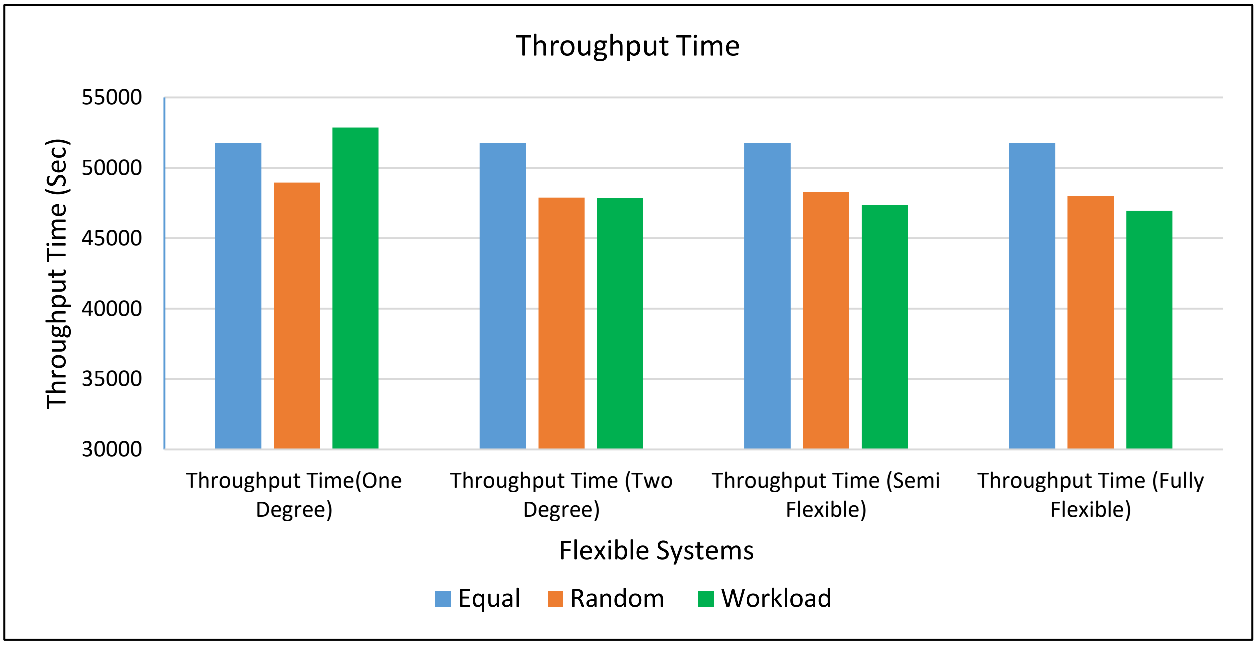


Figure 5.9 Throughput time comparison for three strategies

The proposed methodology that integrates the workload for the flexible configurations applied to residual life. It mainly consists of throughput time based on workload adjustment for each strategy as shown in Figure 5.9. In dynamic workload adjustment, the capacity of each machine and demand has been considered to allocate the workload on each individual unit. Here the total amount of operations at its peak, performed efficiently by each machine in a unit time called as capacity. From the Figure 5.9, it has been observed that the throughput time for processing 54000 number jobs, in equal strategy for the processing the demand almost equal throughput time around 51756 seconds has been taken for various configurations. Similarly in the random strategy taken 47996 seconds from the fully flexible configuration is taken less amount of time taken than the other configurations to complete the number of jobs. Workload adjustment strategy results shown in which 46946 seconds has been taken for fully flexible configuration which is less for processing the same number of jobs on each configuration among 3 strategies.

5.5.3 Sensitivity Analysis

The sensitivity analysis assists in understanding how the uncertainty in the model's output is varying by changing the coefficient of the parameters. It also helps in simplifying the models and identifying the research priorities and plays a major role as a tool to assess the model validity. Here, the throughput time has been generated with the help of simulation for flexible configurations for three strategies i.e., equal strategy, random strategy, and proposed workload strategy by varying the number of jobs from 1000 to 54000 units. The results for these three strategies have been shown in Tables 5.7, 5.8, 5.9 respectively.

Table 5.7 Comparative simulation matrix of equal strategy for flexible configurations

Equal Strategy				
No of Jobs	**One Degree Flexible Throughput Time (Seconds)**	**Two Degree Throughput Time (Seconds)**	**Semi Flexible Throughput Time (Seconds)**	**Fully Flexible Throughput Time (Seconds)**
1000	697	697	697	697
2000	1402	1402	1403	1403
3000	2118	2116	2118	2118
5000	3536	3534	3535	3534
10000	7100	7096	7101	7100
15000	11742	11740	11742	11742
20000	16290	16287	16291	16288
30000	26425	26423	26424	26426
40000	35861	35855	35858	35853
50000	45630	45628	45626	45623
54000	51757	51756	51756	51758

Table 5.8 Comparative simulation matrix of random strategy for flexible configurations

Random Strategy				
No of Jobs	**One Degree flexible Throughput Time (Seconds)**	**Two Degree flexible Throughput Time (Seconds)**	**Semi Flexible Throughput Time (Seconds)**	**Fully Flexible Throughput Time (Seconds)**
1000	697	697	697	697
2000	1400	1403	1402	1403
3000	2115	2118	2118	2118
5000	3532	3528	3536	3595
10000	7096	7306	7218	7232

15000	11738	12196	11953	11925
20000	16187	15864	15920	15765
30000	26258	25044	24845	24925
40000	33671	33458	33380	33326
50000	42573	42376	42380	42337
54000	48960	47880	48296	47996

Table 5.9 Comparative simulation matrix of workload adjustment strategy for flexible configurations

Workload adjustment Strategy				
No of Jobs	**One Degree flexible Throughput Time (Seconds)**	**Two Degree flexible Throughput Time (Seconds)**	**Semi Flexible Throughput Time (Seconds)**	**Fully Flexible Throughput Time (Seconds)**
1000	699	696	698	698
2000	1403	1399	1386	1381
3000	2185	2183	2176	2168
5000	3537	3510	3501	3485
10000	7156	7228	7206	7180
15000	11846	11994	11742	11695
20000	16847	15688	15454	15286
30000	26953	24918	24698	24315
40000	35510	33392	33023	32601
50000	45272	42355	41982	41351
54000	52865	47843	47376	46946

On the basis of simulation results, it can be observed that the throughput time is varying linearly by increasing the number of jobs from 1000 to 54000 jobs for one-degree flexible configuration to fully flexible configurations. In equal strategy, the similar time has been followed to process the number of jobs. In random strategy, each configuration processed randomly by increasing the number of jobs and in the workload adjustment strategy, the throughput time has reduced from one degree to fully flexible configurations.

5.6 Conclusions

Primarily, the main research hypothesis is examined that the predicting the maintenance requirement and predicting the no maintenance requirement of the flexible configurations. Based on the predicted maintenance requirement of machines, the RUL has been examined and workload adjustment strategy has been applied. Initially, 12 machines data of each configuration has been collected from single degree to fully flexible configuration. The demonstration, based on the system implementation shown very good predictions and better results has been achieved under 3 different strategies and various machine learning algorithms. Results shown that the accuracy varied from 82% to 100% under 3 strategies for 4 configurations, and the F1 score is varied from 0.9 to 1 for prediction in maintenance required, and 0.1 to 1 for prediction in not to have maintenance. Further we focused on dynamic adjustment on the workload control the throughput time of all units in a complex system based on RUL by predicted maintenance requirement. To validate the methodology, a simulation environment created and workload adjustment strategy has been applied and compared with the other two benchmark strategies in achieving the lower throughput time. The results clearly shown out methodology consistently outperformed than other two strategies in case of minimization of throughput time. The proposed workload adjustment strategy has been taken 46946 seconds for fully flexible configuration which is less than the other two benchmark strategies in any configuration. Finally, it can be concluded that with the workload adjustment strategy has been given better results than other strategies in flexible configurations.

Chapter 6

Development of Criticality Index prediction for multi-product category for identifying machine status indicators

6.1 Introduction

Due to the customer requirements for specific and individual products, the technologies used in their industries underwent a paradigm shift by introducing various latest technologies such as artificial intelligence, machine learning, cyber-physical systems, and maintenance management. Recent requirements such as high-quality products, and customized products are the major factors for most of the manufacturing industries to improve the production rate. Considering the foregoing requirements, the flexibility of a manufacturing system needs to be enhanced where flexibility plays a major role to perform production faster. The flexible unit systems (FUS) with one-degree flexible, two-degree flexible, semi-flexible, and fully flexible systems have been considered. Therefore, the major issue for any company is a machine's criticality index. Criticality index of a machine is the most important category in the manufacturing industry in case of maintenance management of a system. The CI defined as it is the level of critical referring to the machines with the highest or lowest importance for maintenance.

To improve the productivity of a company, the companies not only plan for the maintenance activities for manufacturing systems but also issues that affect the business goals in the industry. Therefore, the major issue for any company is predicting the machine's CI with the help of ML techniques. Finding the CI of each individual machine in complex flexible configurations is the most important category for the manufacturing industry along with the maintenance management of a system. The main reason to predict or evaluates the CI of machines or devices used in the manufacturing industry with a set of activities to identify failures that impact companies' goals. Predicting the machine's CI is possible to prior the action of maintenance of machines in a flexible machine system. The criticality of a machine is used as a comprehensive measure to estimate the various actions and to highlight difference between the individual machine and its action strategy.

The literature described assessing the machine's CI as an important parameter to improve in quality of products. Due to the method of collecting the data and the quality of product, there is uncertainty related to the time between failures of machines and time to repair of various machines and considered as all assessment criteria are considered as equally important [111]. By considering the above issues, a novel method of prediction of criticality index of machines is proposed in this objective with the predicted maintenance into consideration. Initially, the maintenance of machines in flexible systems is predicted with the help of ML algorithms and the I-CPS architecture is used for ML-based predictions [45]. The I-CPS implies the usual applications of the ML models, and in this case, learning of criticality index predictive models.

In the area of manufacturing systems, the factors such as breakdown time of a machines, redundancy, and workload are impact on throughput as factors are indicated. Henceforth, in this research, the ML-based approach is utilized to process the data of various configurations. Here, different ML techniques have been proposed to classify the collected data. Later, the confusion matrix has been generated for evaluating the data as the confusion matrix is the tabular way of visualizing the performance of the predicted model. The criticality level of a machine is checked by choosing a grading scale from 1 to 5 and subjectively assigning numbers. The estimated time of maintenance for the machines for each criticality index needs to be considered. Later, F1 score and accuracy is evaluated from the confusion matrix to rank the ML algorithms for identifying which algorithm is providing the highest F1 score and accuracy. Finally, the CI is predicted from day 1 to day 100 based on the method used to predict the criticality index of a machine.

6.2 Problem Description

The flexible configurations with one degree, two degree, semi-flexible, and fully flexible configurations has considered for the criticality index analysis in this problem. Here, the criticality index need to be predicted as a prediction output, and the output must be in the range of 0 to 5. As mentioned earlier, we utilize the production data for training, testing, and validation to predict the maintenance requirement for the machines and then to predict the CI of each machine.

List of notations

μ	Expected Value
X	Random Variable
σ	Standard Deviation
m	Number of standard deviations from the mean

For example, the decision tree algorithm needs a proper decision making to the classification point as it decide to split a main node into two or more sub nodes and the naive Bayes algorithm is works on the theory of conditional probability. The mathematical model behind the random forest algorithm are explained as the random forest algorithm stands on the theory of Chebyshev's in equality combination of mean and standard deviation. Thus the objective function for prediction of criticality index as per the random forest algorithm is to understand the system health status as shown in Equation 6.1.

Prediction of criticality index combination of mean and standard deviation (P):

$$P(|X-\mu| > m\sigma) \leq \frac{1}{m^2} \tag{6.1}$$

6.3 Methodology

Machines criticality index is a complex concept and which depends on many factors. In general "intuition" may not be sufficient to make the decision about which machine is more important, and which machine is less important. At this particular time, it is necessary to build a method which supports the decision makers to identify the machines in an appropriate way in the machine criticality assessment process. The main aim of this research is to obtain a criticality index for a machine for the maintenance prioritization demands, using the collected production data. Therefore, an explanatory sequential method was chosen to predict the CI of each machine as explained. The framework which is an integrated approach on data preparation, and machine learning prediction for the criticality index for each individual machine as shown below in Figure 6.1. The initial step of model implementation starts with data collection, data pre-processing, and data preparation. Here the data from 12 machines are considered for validating the proposed model. The data has been collected over a period of 6 months, considering the different variables mentioned in the above table. We have processed cleaning, and sampling by removing the inaccurate and unbalanced data before data transformation. The normalization and aggregation of data are performed before sending the data to develop an ML model. The basic ML model consists of training, testing, and validation as shown below in Figure 6.1.

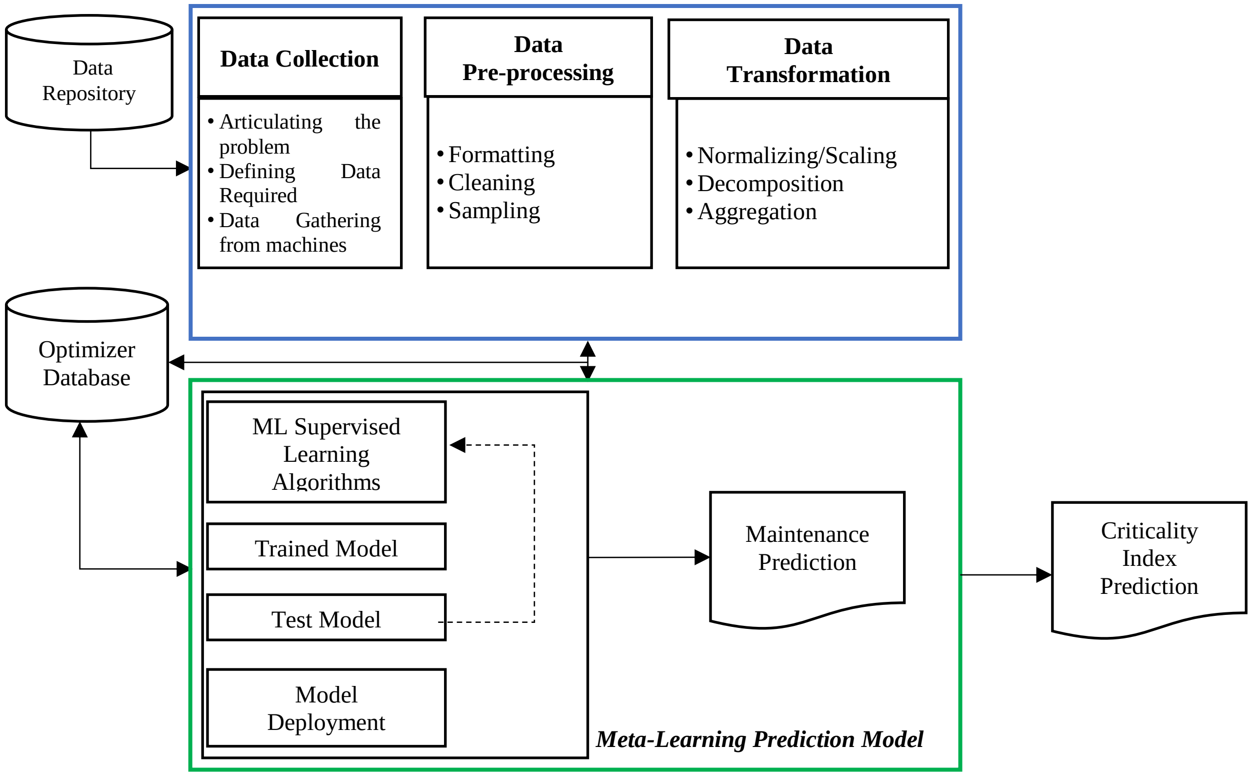


Figure 6.1 Framework for developing the ML model to predict the criticality index

The input data variables such as Machine ID, shift, shift date, material, quantity, production time, time per piece, time for maintenance, and set up is considered [45]. Later, the data is imported, and tried to develop an algorithm that performs supervised learning algorithms. The maintenance requirement of machines is predicted with the help of various ML algorithms by performing the necessary steps. Few algorithms are eliminated due to poor performance which is providing less accuracy. Amongst all algorithms, the top 5 best algorithms are noted which are trained, tested, and validated with the highest F1 score, and better accuracy. Here, the I-CPS architecture is utilized as a double-loop learning model as two separate two loops. The first loop algorithms are considered objective algorithms, and the second loop algorithms are modified first-loop algorithms. The double loop ML algorithm is used to improve the accuracy and model parameters. Later, the predicted maintenance is considered as an extra input for predicting the criticality index of machines. We have considered 1 month, 2 months, and 3 months of data amongst 6 months of data is used for testing in different set of ML algorithms.

6.4 Experimentation

We proposed three strategies in this study i.e., combined machine strategy, multiple machines strategy, and individual machine strategy, and these strategies are adopted to analyze four different realistic configurations for implementing the proposed methodology [44]. From the three strategies, the combined machines strategy is considered as the single machine data, multiple machines is considered as the single machine data along with the machine ID as an extra input for the predictions, and the individual machine strategy considered as it is to train the data separately for each machine for the predictions [44].

6.4.1 Experimentation settings for criticality index prediction

The Meta-learning based ML approach is utilized for predicting the criticality index of each machine and validated. Data from 12 machines were collected and these 12 machines are operating under four configurations called one-degree flexible, two-degree flexible, semi-flexible, and fully flexible. The machine ID from 1 to 12 from each configuration is considered. The additional extracted features as total work time of the machine, Total work quantity of the machine, Total number of setups, total work time of the machine after previous maintenance, and the total number of setups after previous maintenance is taken and the criticality index considered as predicted output [46]. A total of 30,427 batches of manufacturing data from these machines from each configuration and amongst 6 months of data 1 month, 2 months, and 3 months of data have been utilized for testing in three conditions for a different set of ML algorithms. Initially, the maintenance requirement for each individual machine is predicted. Later, the criticality index for each individual machine has been predicted in four configurations by taking the predicted maintenance as an input along with the input data and the input data has shown below in Table 6.1.

Table 6.1 Data variables involved in ML Program

Variable of Input	Extracted Features	Output
10. Machine ID	4. Total working time of machine	Maintenance requirement (1/0)
11. Shift	5. Total number of setups	
6. Shift Date	12. Total quantity of a machine	
13. Material	4. Total work time of a machine after last maintenance	

14. Quantity	5. Total quantity of a machine after last maintenance	
15. Production Time	6. Total number of setups after previous maintenance	
16. Time/piece		
17. Maintenance Time		
18. Setup		

6.5 Experimental Results and Discussion

Confusion Matrix

Figure 6.2 shows the 5*5 confusion matrix for the CI. CI of each machine has been predicted by considering the predicted maintenance as an input with the collected data. The CI from 1 to 5 indicated which machine is more critical or less critical based on the index, and estimated maintenance time is required for combined machines or multiple machines, or individual machines with respect to CI as shown in Table 6.2. The information on CI ranges from 1 to 5 and has been collected from the shop floor manager in industry. The formulas for calculating the precision, accuracy, and F1 score from the obtained confusion matrix as mentioned in below Equations 6.2, 6.3, 6.4.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{6.2}$$

$$Accuracy = \frac{(True\ Positive + True\ Negative)}{(True\ Positive + False\ Positive + True\ Negative + False\ Negative)} \tag{6.3}$$

$$F1\ Score = \frac{2 * Precision * Accuracy}{(Precision + Accuracy)} \tag{6.4}$$

Real CI

Predicted CI

TP_1	**E_{21}**	**E_{31}**	**E_{41}**	**E_{51}**
E_{12}	**TP_2**	**E_{32}**	**E_{42}**	**E_{52}**
E_{13}	**E_{23}**	**TP_3**	**E_{43}**	**E_{53}**
E_{14}	**E_{24}**	**E_{34}**	**TP_4**	**E_{54}**
E_{15}	**E_{25}**	**E_{35}**	**E_{45}**	**TP_5**

Figure 6.2. Criticality Index for 5*5 matrix

The TP_1, TP_2, TP_3, TP_4, and TP_5 indicate the True Positive of the prediction class for the CI from 1 to 5 and the E_{21} to E_{45} are the True negatives and the false positives and false negatives for their respective prediction classes, and the true classes for the CI shown above Figure 6.2. The true positive defines the label belongs to the class of correctly predicted, False positive does not belong to the class but is predicted as positive, true negative does not belong to the class, predicted correctly, and finally, false negative does not belong to the class, predicted as negative. From the predictions of CI, the estimated time for maintenance of a machine information is collected from the shop floor manager is shown below in Table 6.2.

Table 6.2 Criticality Index estimated time

Criticality Index	Estimated time for maintenance (seconds)
1	0-999
2	1000-4999
3	5000-9999
4	10000-19999
5	20000+

The estimated time for maintenance in (seconds) for respective CI has been taken from the shop floor manager from the industry. The estimated time range is 0-999 seconds for CI 1, 1000-4999 seconds for CI 2, 5000-9999 seconds for CI 3, 10000-19999 seconds for CI 4, and greater than 20000 seconds for CI 5 as shown below in Table 3. Three strategies have been applied for predicting the criticality index of machines named as combined machine strategy, multiple machine strategy, and individual machine strategy.

Table 6.3 presents the results of the top 6 algorithms (out of 30) that output the predictive models with the highest F1 score and the accuracy for the above-mentioned 3 strategies for one-degree flexible configuration. It has been observed that in strategy 1 i.e. combined machines strategy, for one-degree flexible configuration, the Cosine KNN is giving the highest F1 score as 0.7288 as the 72.88% of chances are there for the criticality index according to the algorithm predicted and SVM (Quadratic) algorithm is giving the highest accuracy as 98.3%. In strategy 2, i.e multiple machines strategies, the neural network (Trilayered) is giving the highest F1 score of 0.6731 for the criticality index and the KNN medium is giving the highest accuracy at 98.9% for one-degree flexible configuration. In strategy 3, i.e multi-algorithm level model, the algorithm has given an F1 score of 0.636, and an accuracy of 98.04% has been achieved.

Table 6.3 Results for the criticality index prediction in case of one degree flexible configuration

Learning Algorithm	Accuracy	F1 Score to predict maintenance
Strategy 1. – Combined Machines		
Cosine KNN	97.90%	0.7288
Neural Network (Medium)	96.90%	0.7179
Decision Tree (Fine)	97.70%	0.7076
Neural Network (Bilayered)	97.5%	0.6621
SVM (Quadratic)	98.3%	0.5934
Strategy 2. – Multiple Machines		
Neural Network (Trilayered)	98.6%	0.6731
KNN (Medium)	98.9%	0.6422
Ensemble Subspace (KNN)	96.9%	0.6249
Fine KNN	98.3%	0.6014
SVM Linear	98.6%	0.5802
Strategy 3. – Individual Machine Level (Average F1)		
Multi algorithm learning model	98.04%	0.636

Further, the criticality index range has been taken from 1 to 5, where 1 indicates the lower critical level which requires a lower amount of time for the maintenance of a machine is required, and 5 indicates the higher critical machine which requires a higher amount of time for the maintenance. The predicted criticality index for 100 days for 12 number of machines has explained. The CI has been predicted when the 12 machines of one-degree configuration are performing the operations under the given input is shown in Figure 6.3. The average criticality index of one degree flexible configuration is obtained as 1.09667. The average and standard deviation summation is equal to 1.63136, and the difference between averages to the standard deviation is equal to 0.56198.

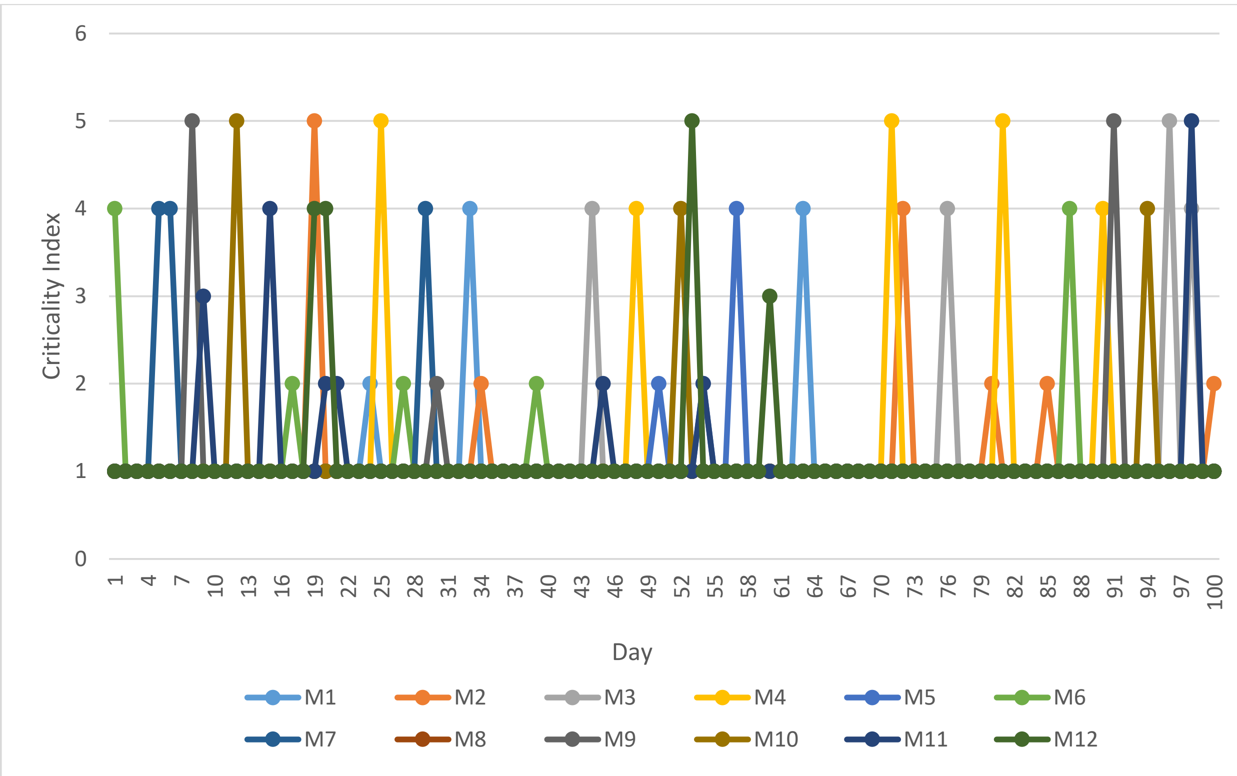


Figure 6.3 Criticality Index prediction for One degree flexible configuration

Table 6.4 presents the results of the top 5 algorithms (out of 30) that output the predictive models with the highest F1 score and the accuracy for the mentioned 3 strategies for two-degree flexible configuration. It has been observed that in strategy 1 i.e. combined machines strategy, for two-degree flexible configuration, the neural network (medium) is giving the highest F1 score of 0.696 as the 69.6% of chances are there for the criticality index according to the algorithm predicted and KNN (medium) algorithm is giving the highest accuracy as 98.4%. Similarly in strategy 2, i.e multiple machines strategy, the Ensemble Boosted Trees is giving the highest F1 score as 0.9744 for the criticality index and SVM (Quadratic) is giving highest accuracy at 98.3% for two-degree flexible configuration. In strategy 3 i.e multi-algorithm learning model has given an F1 score of 0.6395 and an accuracy has 97.57% has been achieved.

Table 6.4 Results for the Criticality index prediction for the two degree configuration

Learning Algorithm	Accuracy	F1 Score to predict maintenance
Strategy 1. – Combined Machines		
Neural Network (Medium)	98.10%	0.696
Ensemble RUS Boosted Trees	97.50%	0.631
Neural Network (Trilayered)	97.20%	0.588
SVM Medium (Gaussian)	98.3%	0.597
Medium KNN	98.4%	0.563
Strategy 2. – Multiple Machines		
Ensemble Boosted Trees	97.4%	0.9744
Ensemble Subspace KNN	96.9%	0.7366
Neural Network (Bilayered)	97.6%	0.7285
SVM (Quadratic)	98.3%	0.6496
Linear Discriminant	98.0%	0.6322
Strategy 3. – Individual Machine Level (Average F1)		
Multi algorithm learning model	97.57%	0.6395

The CI has been predicted from day 1 to day 100 as when 12 number of machines of two-degree configuration are performing the operation under the given input is shown in Figure 6.4. The average criticality index of a two-degree flexible configuration for 12 number of machines is obtained as 1.0725. The average and standard deviation summation is equal to 1.5054, and the difference between averages to the standard deviation is equal to 0.6396.

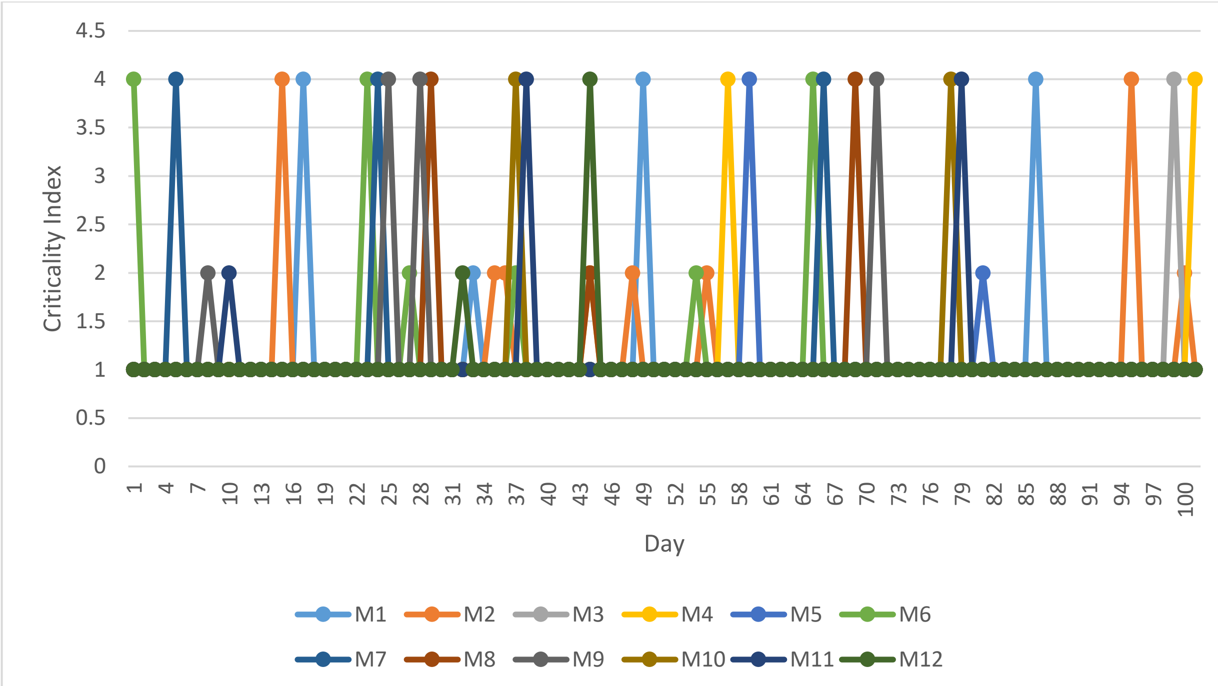


Figure 6.4 Criticality Index for Two degree flexible configuration

Table 6.5 presents the results of the top 5 algorithms (out of 30) that output the predictive models with the highest F1 score and the accuracy for the mentioned 3 strategies for semi-flexible configuration. It has been observed that in strategy 1 i.e. combined machines strategy, for semi-flexible configuration, the neural SVM (Quadratic) is giving the highest F1 score as 0.6461 as the 64.61% of chances are there for the criticality index according to the algorithm predicted and KNN (medium) algorithm is giving the highest accuracy as 97.4%. In strategy 2, i.e multiple machines strategy, the Weighted KNN is giving the highest F1 score as 0.6138 for the criticality index and SVM coarse Gaussian is giving highest accuracy as 92.53% for semi-flexible configuration. In strategy 3, i.e multi-algorithm learning model has been given an F1 score of 0.6406 and an accuracy as 97.96% has been achieved.

Table 6.5 Results for the criticality index prediction in case of semi flexible configuration

Learning Algorithm	**Accuracy**	**F1 Score to predict maintenance**
Strategy 1. – Combined Machines		
SVM Quadratic	97.00%	0.6461
Decision Tree Medium	96.30%	0.560
Medium KNN	97.40%	0.5521

Ensemble Bagged Trees	97.2%	0.5372
Ensemble Boosted Trees	97.2%	0.5115
Strategy 2. – Multiple Machines		
Weighted KNN	92.15%	0.6138
Decision Tree Fine	92.06%	0.5351
Ensemble Bagged Trees	92.25%	0.5326
Ensemble Boosted Trees	92.06%	0.5319
SVM Coarse Gaussian	92.53%	0.5214
Strategy 3. – Individual Machine Level (Average F1)		
Multi algorithm learning model	97.96%	0.6406

The CI has been predicted from day 1 to day 100 when 12 machines of semi degree configuration are performing the operations under given input is shown in Figure 6.5. The average criticality index of semi degree for 12 machines is obtained as 1.07083. The average and standard deviation summation is equal to 1.53198, and the difference between averages to the standard deviation is equal to 0.60968.

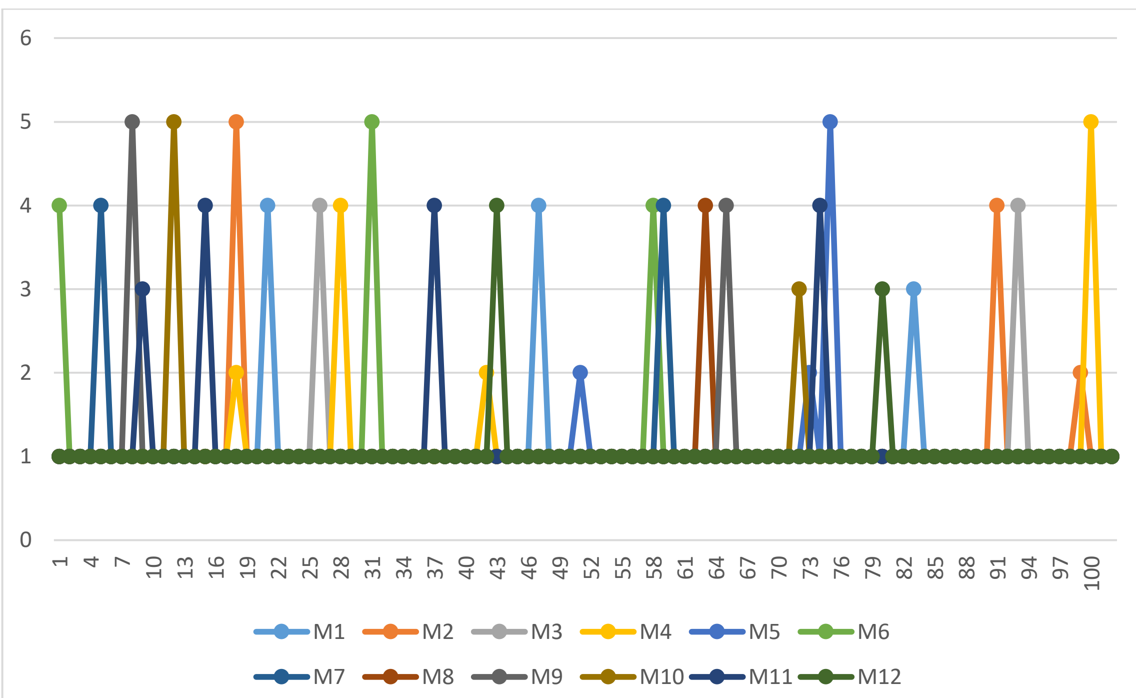


Figure 6.5 Criticality Index for Semi flexible configuration

Table 6.6 presents the results of the top 5 algorithms (out of 30) that output the predictive models with the highest F1 score and the accuracy for the mentioned 3 strategies for fully flexible configuration. It has been observed that in strategy 1, i.e. combined machines strategy, for fully flexible configuration, the neural SVM (medium Gaussian) is giving the highest F1 score as 0.6422 as the 64.22% of chances are there for the criticality index according to the algorithm predicted and SVM (medium Gaussian), and the weighted KNN (medium) algorithm is giving the highest accuracy as 97.5%. In strategy 2, i.e multiple machines strategy, the SVM course Gaussian algorithm is giving highest F1 score as 0.6166 for the criticality index and SVM coarse Gaussian and weighted KNN algorithms are giving the highest accuracy as 93.6% for semi-flexible configuration. In strategy 3, i.e multi-algorithm learning model has been given an F1 score of 0.5774 and an accuracy as 98.15% has been achieved.

Table 6.6 Results for the criticality index prediction in case of fully flexible configuration

Learning Algorithm	Accuracy	F1 Score to predict maintenance
Strategy 1. – Combined Machines		
SVM Medium Gaussian	97.50%	0.6422
Ensemble Bagged Trees	97.30%	0.6113
Weighted KNN	97.50%	0.5946
SVM Quadratic	97.4%	0.5641
Decision Tree Medium	96.3%	0.56
Strategy 2. – Multiple Machines		
SVM Coarse Gaussian	93.6%	0.6166
Neural Network	93.41%	0.5869
Weighted KNN	93.6%	0.5709
Decision Tree Coarse	93.41%	0.5486
SVM Linear	93.5%	0.4316
Strategy 3. – Individual Machine Level (Average F1)		
Multi algorithm learning model	98.15%	0.5774

The CI has been predicted from day 1 to day 100 when 12 number of machines of fully configuration are performing the operations under given input is shown in Figure 6.6. The average criticality index of semi degree for 12 machines is obtained as 1.03746. The average and standard deviation summation is equal to 1.2847, and the difference between averages to the standard deviation is equal to 0.6283.

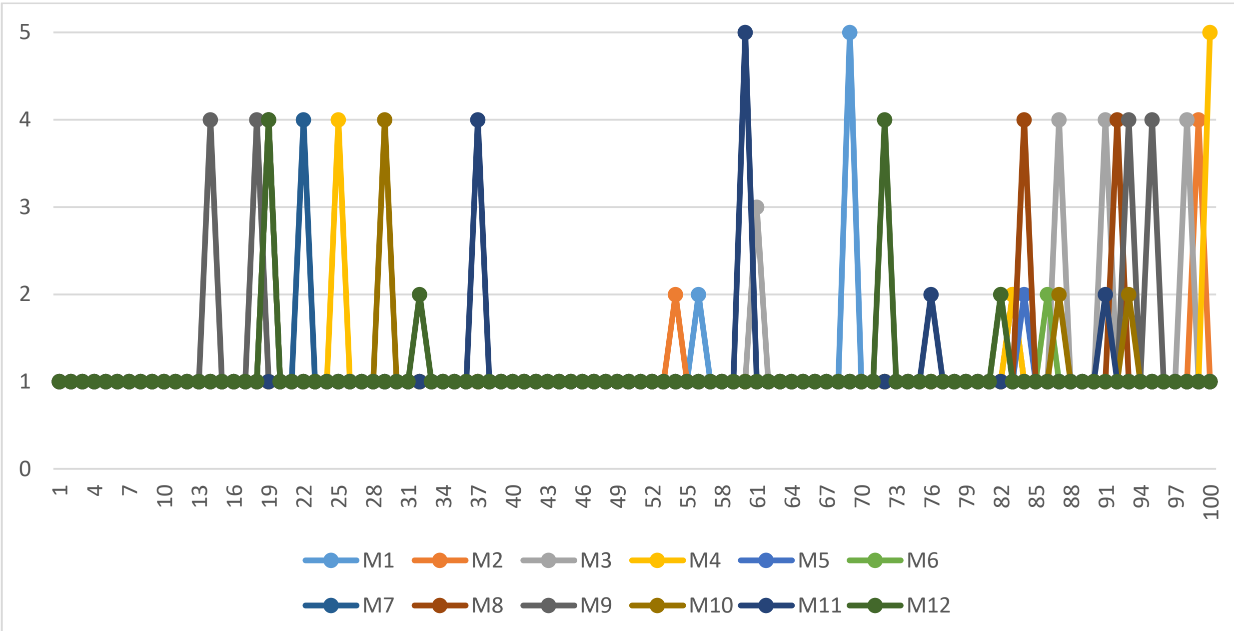


Figure 6.6 Criticality Index for Fully flexible configuration

6.6 Conclusions

Predicting the criticality index of a machine is an important experiment to understand the machine behavior. Primarily, the main hypothesis of this work is examined that the predicting the criticality index of each individual machine in the complex flexible configurations. Initially, 12 machines data of each configuration has been collected from single degree to fully flexible configurations. The demonstration, based on the system implementation shown very good predictions and better results has been achieved for predicting the criticality index under 3 different strategies and various machine learning algorithms. From the results, it has been observed that the accuracy has been achieved in the range from 92% to 98.9% under 3 strategies for 4 configurations, and F1 score for predicting the criticality index varied from 0.43 to 0.9744. Few machines were not identified as critical machines, which indicates that the machines are working in good condition and there is no maintenance is required for those machines. Amongst, four configurations, the less number of machines are identified as critical in case of fully flexible configurations compared to other configurations. In general, higher the criticality index for a machine will indicates the high amount of time is required for the maintenance.

Chapter 7

A novel upgraded hybrid degradation model for maximum throughput in flexible configurations

7.1 Introduction

Manufacturing systems can be designed with various configurations such as series configuration, parallel configuration, and hybrid configuration. When it comes to the complex products to manufacture, the flexibility of manufacturing systems will play a major role to complete the demand as early as possible. The FUS, which are flexible enough to produce the complex parts is considered in this problem. Generally, throughput analysis is important for the design, operation and management of manufacturing systems [123, 124]. The maximum number of parts produced can be affected by the reliability of the workstations, and the cycle time (the time required to complete all the operations). The throughput can be defined as the maximum number of items processed in a unit time [37]. Most papers analyzed throughput for manufacturing systems using simulation or analytical methods. In general, the simulation and analytic methods are two different methods to estimate and analyze the throughput performance of various manufacturing systems. as per the authors knowledge, the simulation analysis has been widely using in various manufacturing systems analysis due to the robustness and the capacity of modeling large and complex systems.

This study analyzes and enhances the throughput of flexible systems with the help of hybrid degradation model which has been combined with RUL and CI of each individual machine. The throughput achieved by the hybrid degradation model has been compared with the real time data method which was used in 4th chapter of this research and production data method which was used in 5th chapter of this research work.

7.1.1 Remaining Useful Life (RUL)

A machine's or a component's residual life estimation during its operation based on its present condition is very important in order to find its health condition. The residual life of a manufacturing machine was characterized as remaining useful time till its level of degradation arrives at a predefined failure threshold. [38] Proposed a remaining useful life prediction by introducing the degradation rate changing to transition function and it jumps the degradation signals towards the measurement function. The neural network can also be used to decide the residual life of a machine's component regarding a number of residual operations. For example, in the manufacturing industry the usage of a prognostic health management system for deciding the residual life of milling cutters in a high-speed milling machine depends on externally measured conditions has been mentioned in [125].

The Prediction of the life of a complex manufacturing system needs an exact estimation of degradation conditions of its constituent parts as well as an adequate understanding of how these stages progress in the future. Those difficulties become more entangled whenever parts of a machine are associated. Si et al., (2013) [126] proposed degradation method to anticipate the remaining useful life of machines utilizing a recursive channel calculation. Zhang et al., (2018) [127] survey is on ongoing modeling improvements of the wiener-process strategies for degradation information examination, remaining useful life estimation as their implementation in the empirics of the health management of manufacturing systems. Mosallam et al., (2014) [128] presented two stages of an information-driven strategy for remaining useful life prediction. It is noted that, based on the residual life of a manufacturing unit a workload adjustment strategy will be helpful to maintain the production rate.

7.1.2 Criticality Index (CI)

Due to the customer requirements for a product, the technologies used in their industries, the companies not only must plan for the maintenance activities, but also issues which affects the business goals. Therefore, the major issue for any company is a machine's criticality index. Criticality index of a machine is the most important category in the manufacturing industry in case of maintenance management of a system. The criticality index of machines or devices used in manufacturing industry can be structured a set of activities to identify failures which impacts on companies goals [46]. Criticality of a machine is used as a comprehensive measure to estimate the various actions and to highlight the differences between each individual machine and action strategies.

The predicted remaining useful life and Criticality index will be giving the whole health information about the machine which helps in enhancing the throughput rate of every machine. RUL is the length of time a machine is likely to operate before it is going to failure. And CI indicates the level of criticality of a machine. Workload adjustment for a system whose individual machines RUL, and CI has known has been proposed and validated by throughput enhancement.

7.2 Problem Description

We developed a linear degradation model for proposed configurations for single degree to fully flexible systems to control the degradation of machines for controlling the loss of production of the system. To highlight the main idea, these systems undergo various analyses to predict the RUL and to predict the Criticality Index of each machines that further improves the throughput by minimizing the average degradation level. We define "throughput rate" as the overall output of the system, denoted by TH(x) and it represents the throughput rate at the time x and $N(x)$ presents the number of machines. Based on the operating machines $\tilde{N}(x)$, the maximum throughput rate becomes $\sum_{q=1,r=1}^{\tilde{N}(x)} C_{(q,r)}$, where $C_{(q,r)}$ indicates the "capacity" of a machine q, r at time x. The throughput rate of a system by considering the demand is defined as $TH(x) = \min\left[\sum_{q=1,r=1}^{\tilde{N}(x)} C_{(q,r)}, D\right]$ where D stands for "Demand". If the capacity is less than the demand, then throughput is equal to capapcity, and if the demand is less than the capacity, then the throughput is equal to the demand. Further, The RUL has been predicted by using the Equations 4.1 to Equation 4.10.

Along with the RUL, the method for predicting the criticality index is used as a prediction output, and the output must be in the range of 0 to 5 which is used for Equation 6.1. As mentioned earlier, we utilized the production data for training, testing, and validation to predict the maintenance requirement for the machines and then to predict the CI of each machine. For example, The mathematical model behind the random forest algorithm are explained as the random forest algorithm stands on the theory of Chebyshev's in equality combination of mean and standard deviation. Thus the objective function for prediction of criticality index as per the random forest algorithm is to understand the system health status as shown in Equation 6.1.

7.3 Experimentation

We define throughput as the maximum number of items processed in a unit time from the system. Here, we assume that the machines in the system are identical in nature. Now, the capacity of each machine and the demand for the each configuration need to be known for operating machines for finding the throughput. The throughput can be concerning about the demand is defined as if the demand is less than the capacity, then the demand is equal to the throughput and if the demand is more than the capacity, then the capacity is equal to the throughput. The framework for developing the Hybrid Degradation model is shown in Figure 7.1.

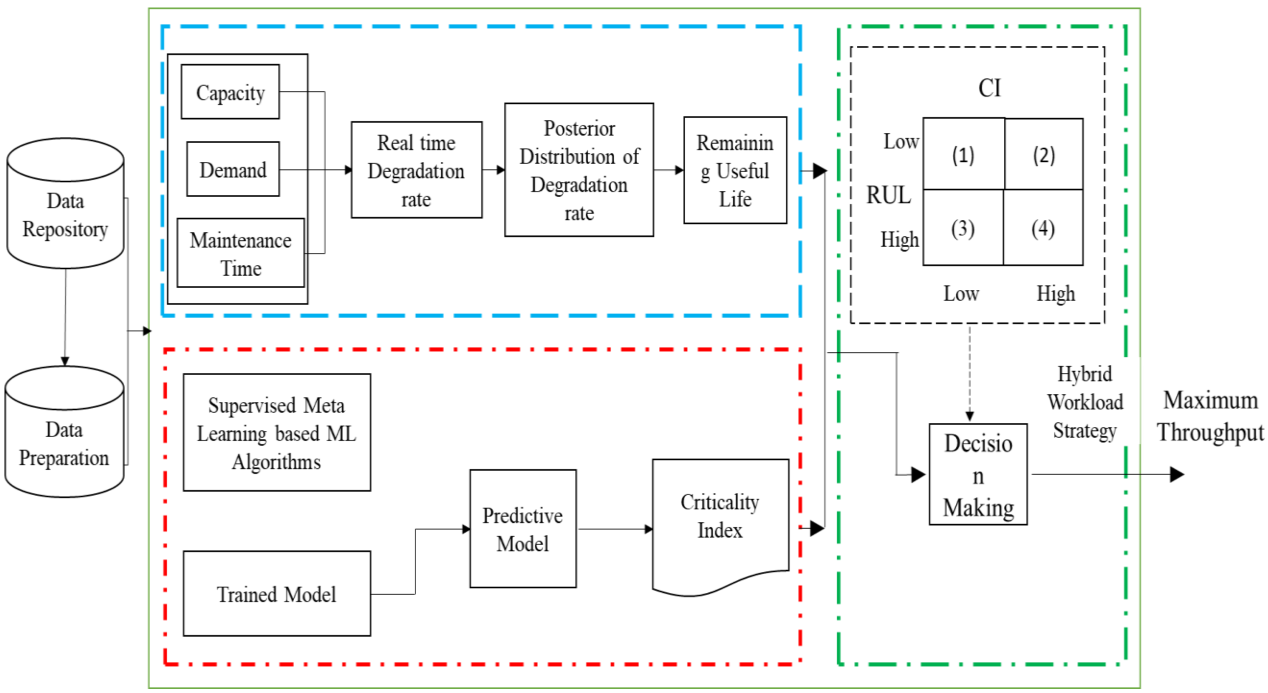


Figure 7.1 Framework for developing the Hybrid Degradation model

7.3.1 Decision Making

The decision making by combining of RUL and CI as shown in Figure 7.2. The Decision making has been considered based on the machine which has lower RUL and CI as first preference for the maintenance because the machine will take the lower maintenance time than other conditions mentioned in the decision criteria. Low RUL and High CI of a machine has been considered second preference for the maintenance. High RUL and low CI of a machine has been considered as the third preference and High RUL and high CI of a machine has been considered as the last preferred for the maintenance requirement for fulfilling the necessities.

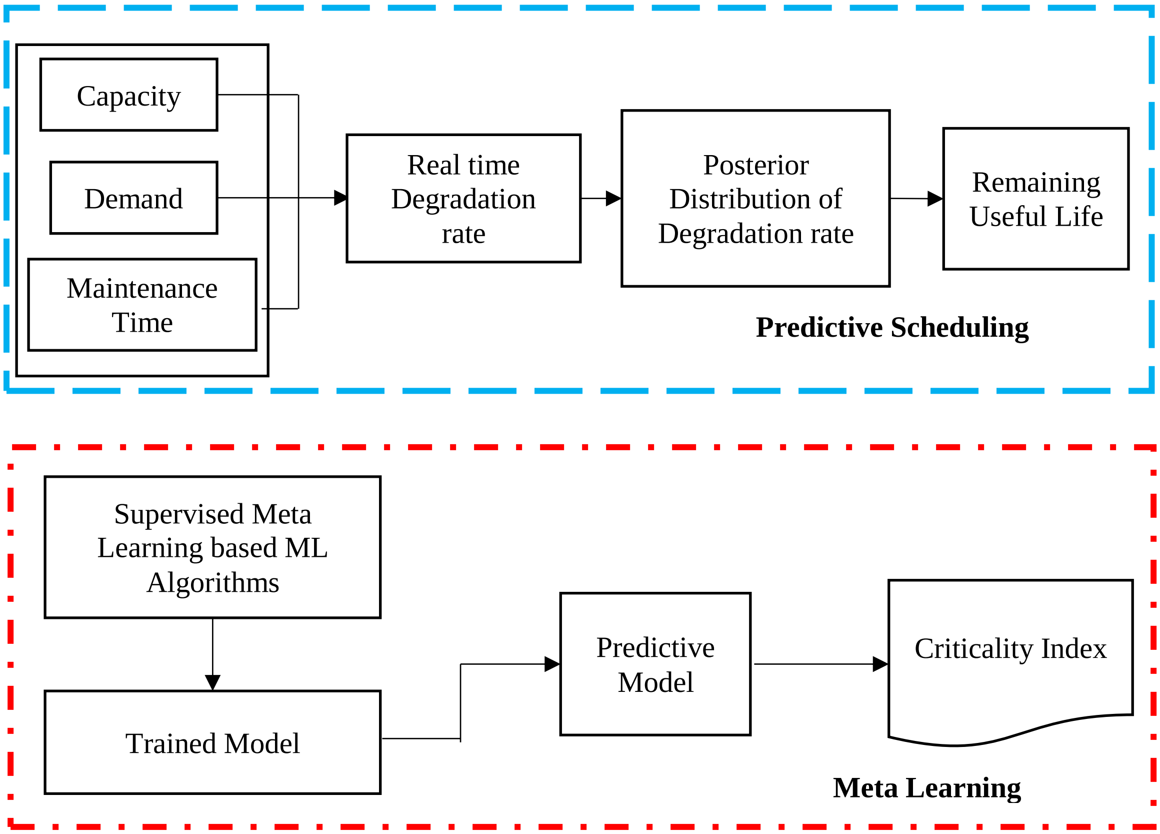


Figure 7.2 Decision making criteria for hybrid degradation model

7.4 Results and Discussions

Figure 7.3 shows the throughput for the hybrid degradation model comparison with the real time data method and production data method for one degree flexible configuration. When the time of manufacturing has been considered as 1 day, the 1053 number of products has been manufactured which is almost equal when compared with the other two methods i.e. real time data method and production data method. In time comparison, when the number of days are increasing from 1 to 9, the number of products processed has been raised to 8909 which is higher than other two methods in one degree flexible configuration.

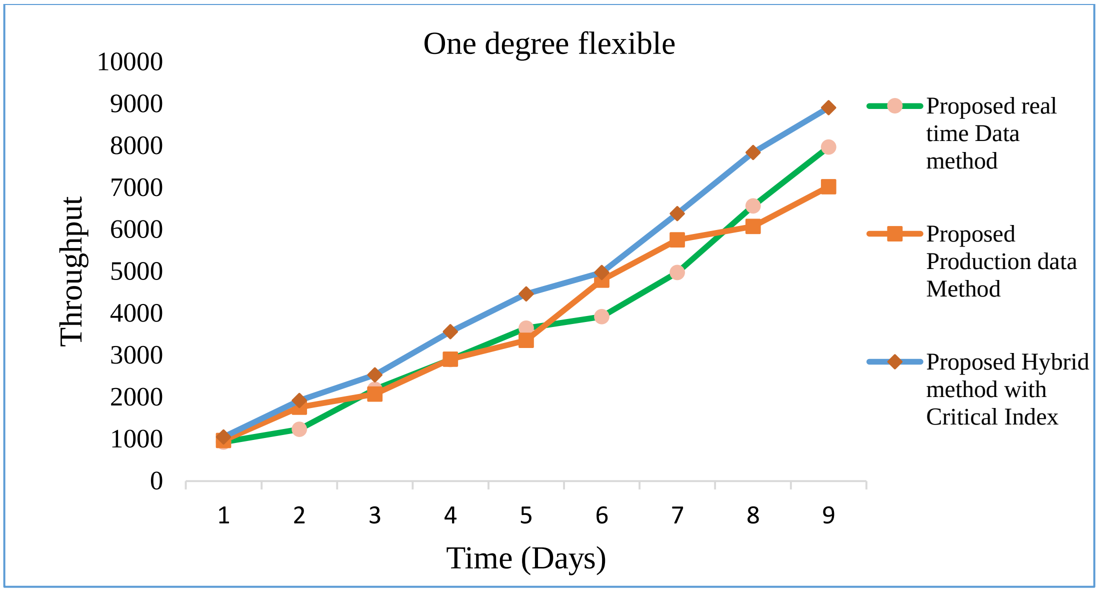


Figure 7.3 Throughput comparison between proposed method with other real time data method and production data method for one degree flexible configuration

Figure 7.4 shows the throughput of the hybrid degradation model for two degree flexible configuration in comparison with the real time data method and production data method. When the time of manufacturing has been considered as 1 day, the 1132 number of products has been manufactured which is almost equal when compared with the other two methods i.e. real time data method and production data method. In time comparison, when the number of days are increasing from 1 to 9, the number of products processed has been increased to 12985 which is higher than other two methods in two degree flexible configuration.

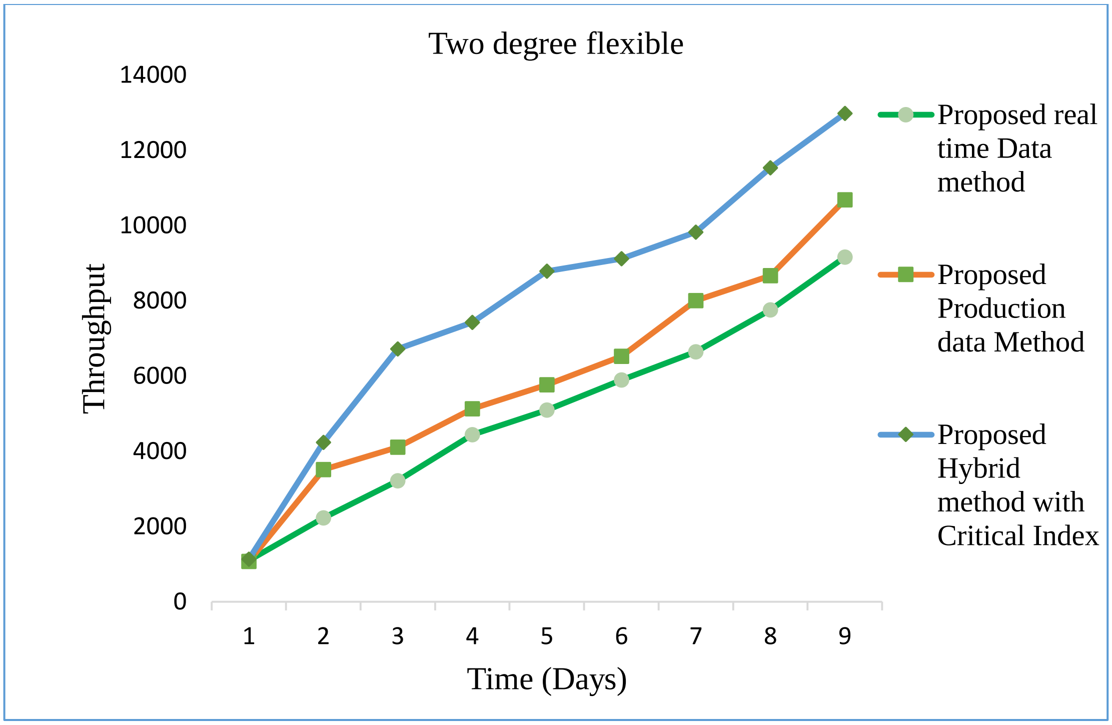


Figure 7.4 Throughput comparison between proposed method with other real time data method and production data method for two degree flexible configuration

Figure 7.5 shows the throughput of the hybrid degradation model for semi flexible configuration in comparison with the real time data method and production data method. When the time of manufacturing has been considered as 1 day, the 1576 number of products has been manufactured which is slightly greater when compared with the other two methods i.e. real time data method and production data method. In time comparison, when the number of days are increasing from 1 to 9, the number of products processed has been increased to 14448, which is higher than other two methods in semi flexible configuration.

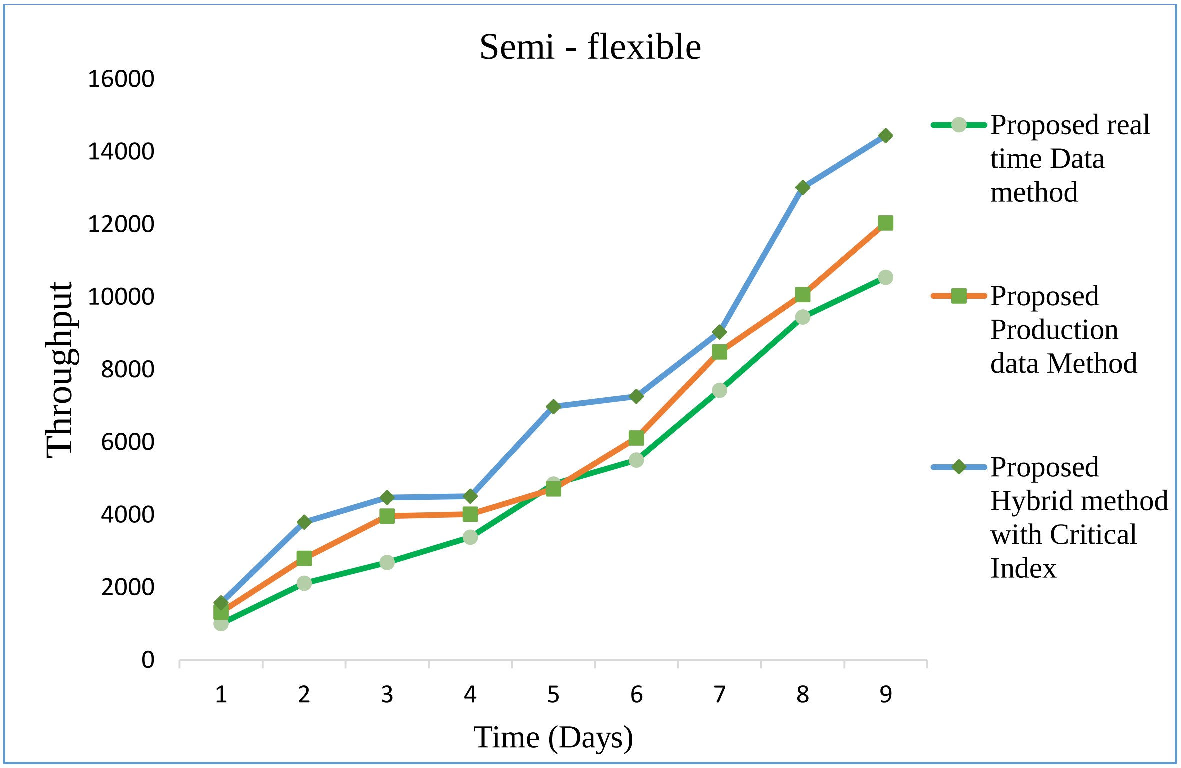


Figure 7.5 Throughput comparison between proposed method with other real time data method and production data method for semi flexible configuration

Figure 7.6 shows the throughput of the hybrid degradation model for fully flexible configuration in comparison with the real time data method and production data method. When the time of manufacturing has been considered as 1 day, the 1270 number of products has been manufactured which is almost equal when compared with the other two methods i.e. real time data method and production data method. In time comparison, when the number of days are increasing from 1 to 9, the number of products processed has been increased to 15604, which is higher than other two methods in fully flexible configuration.

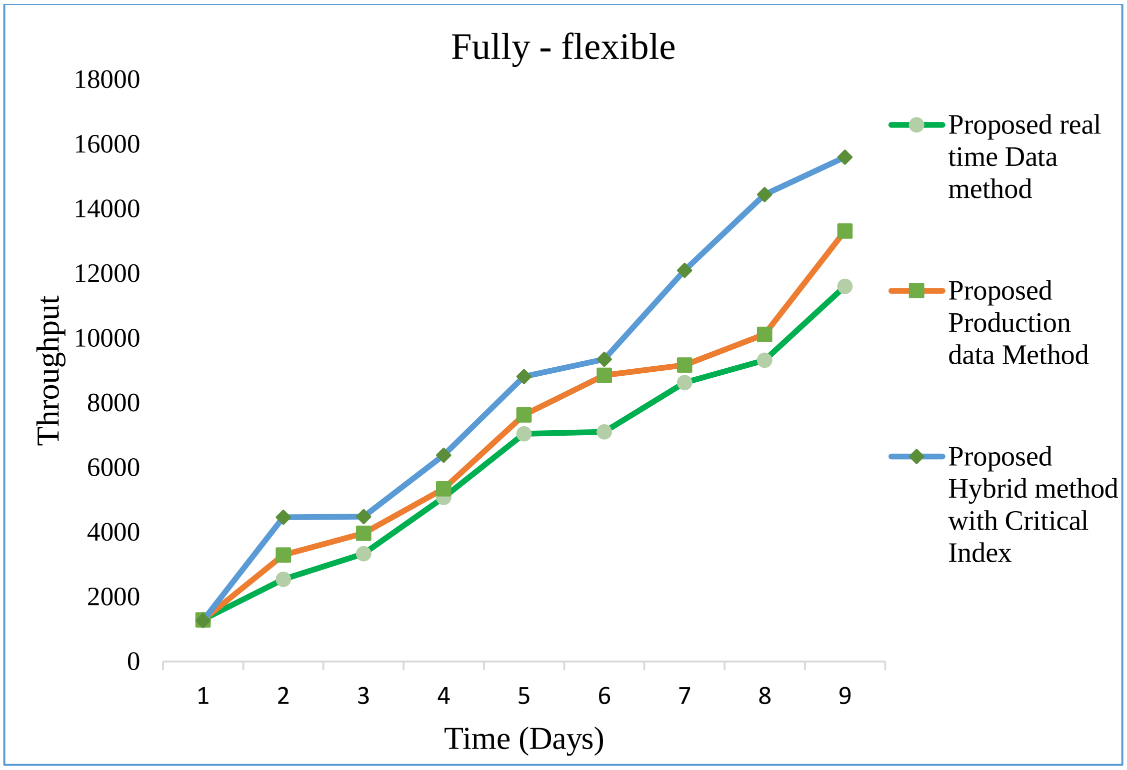


Figure 7.6 Throughput comparison between proposed method with other real time data method and production data method for fully flexible configuration

7.5 Conclusions

The proposed hybrid degradation model manufactured 15,604 number of jobs in fully flexible configuration which is higher than other two benchmark strategies. In one degree flexible configuration, the 1053 number of products has been manufactured which is almost equal when compared with the other two methods i.e. real time data method and production data method on day1. In two degree flexible configuration, the 1132 number of products has been manufactured which is almost equal when compared with the other two methods i.e. real time data method and production data method for the day 1.

Chapter 8

Conclusions and Future Scope

8.1 Conclusions

The flexible systems analysis shown an interest to understand the system behavior. Majorly six performance parameters has been identified which influence the four flexible configurations. Based on the identified parameters, the entropy based TOPSIS method has been used to rank the parameters. The Throughput rate shown as most influenced parameter, further which was used for predicting the RUL and workload adjustment strategy has been proposed on single product category. The maintenance requirement has been predicted using ML and RUL has been identified based on maintenance prediction then workload adjustment has been proposed on multi-product category. The criticality index of each machine has been predicted for understanding

The following conclusions can be drawn from the obtained results.

- The Throughput Time is the most affected performance parameter and maximum stay time is the least affected performance parameter on flexible machine systems in case of breakdown condition and Throughput Time is the most affected performance parameter and Availability, average stay time, and maximum stay time are the least affected performance parameter on flexible machine systems without breakdown condition.
- The average percentage of loss in production is 4.75% in case of proposed model, which is reduced compared to average of 10.5% obtained in case of equal job adjustment, and average of 7.5% in random job adjustment in instance1. Similarly average percentage of loss in production is 2% in case of proposed model, which is reduced compared to average of 6.67% in case of equal job adjustment and average of 4.61% in random job adjustment in instance2. The average percentage of loss in production is 0.75% in case of proposed model which is reduced compared to average of 3.75% in case of equal job adjustment and average of 2% in random job adjustment in instance3.
- The workload adjustment strategy in case of multi-product category, the results clearly shown out that the workload adjustment methodology consistently outperformed than other

two strategies in case of minimization of throughput time. The proposed workload adjustment strategy has been taken 46946 seconds for fully flexible configuration which is less than the other two benchmark strategies in any configuration.

- The criticality index prediction results shown that the accuracy varied from 92% to 98.9% under 3 strategies for 4 configurations, and F1 score for predicting the criticality index varied from 0.43 to 0.9744.

8.2 Future Scope

- A study is needed to perform the workload adjustment strategy when the degradation rate and the workload having different relationships.
- In the future, the proposed parameters ranking methodology using entropy based TOPSIS method can help firm management to take verdicts refining the performance parameters of various proposed flexible systems and understand the manufacturing system behavior and its influencing parameters in normal and various uncertain conditions.
- The criticality index prediction which determines the degree of the maintenance necessity can be done for more applications.
- In future, investigation of new learning paradigms, various algorithms can be utilized to predict the criticality index.
- A study also required to aim at the creation of a software for the frequent observation of the criticality index of machines.

References

1. Lafou, M., Mathieu, L., Pois, S. and Alochet, M. (2015). Manufacturing system configuration: Flexibility analysis for automotive mixed-model assembly lines. IFAC-PapersOnLine, 48(3), pp.94-99.
2. Chan, F.T. (2001). The effects of routing flexibility on a flexible manufacturing system. International Journal of Computer Integrated Manufacturing, 14(5), pp.431-445.
3. Koren, Y., Hu, SJ., Weber TW. (2012) Impact of manufacturing system configuration on performance. CIRP annals 47(1):369-372. https://doi.org/10.1016/S0007-8506(07)62853-4
4. Kaplan R.S. (1998) Cost & effect: using integrated cost systems to drive profitability and performance. Harvard Business Press.
5. Devise, O., Pierreval, H., (2000) Indicators for measuring performances of morphology and material handling systems in flexible manufacturing systems. International Journal of Production Economics 64(1-3):209-218. https://doi.org/10.1016/S0925-5273(99)00059-6
6. Maier-Speredelozzi, V., Hu, SJ. (2002). Selecting manufacturing system configurations based on performance using AHP. TECHNICAL PAPERS-SOCIETY OF MANUFACTURING ENGINEERS-ALL SERIES-.
7. Chryssolouris, G., Georgoulias, K. and Michalos, G. (2012). Production systems flexibility: theory and practice. IFAC Proceedings Volumes, 45(6), pp.15-21. https://doi.org/10.3182/20120523-3-RO-2023.00442
8. Sun, JW., Xi, LF., Du, SC., Ju, B. (2008). Reliability modeling and analysis of serial-parallel hybrid multi-operational manufacturing system considering dimensional quality, tool degradation and system configuration. International Journal of production economics 114(1):149-164. https://doi.org/10.1016/j.ijpe.2008.01.002
9. Azadeh, A., Kolaee, MH., Sheikhalishahi, M. (2016). an integrated approach for configuration optimization in a CBM system by considering fatigue effects. The International Journal of Advanced Manufacturing Technology 86(5-8):1881-1893. https://doi.org/10.1007/s00170-015-8204-x
10. Bednar, S., Rauch E. (2019). Modeling and application of configuration complexity scale: concept for customized production. The International Journal of Advanced Manufacturing Technology 100(1-4):485-501. https://doi.org/10.1007/s00170-018-2659-5

11. Benderbal, HH., Benyoucef, L., (2019) Machine layout design problem under product family evolution in reconfigurable manufacturing environment: a two-phase-based AMOSA approach. The International Journal of Advanced Manufacturing Technology 104(1-4):375-389. https://doi.org/10.1007/s00170-019-03865-1
12. Otoo, M., Collins, J. (2011). Industrial Production and Capacity Utilization: The 2010 Annual Revision.
13. Chandra, A., Ahsan, M., Lahiri, S., Panigrahi, S., Manupati, V., Costa, E. (2017). Degradation modeling to predict the residual life distribution of parallel unit systems on benchmark instances. In World Congress on Engineering: 783-787. http://www.iaeng.org/publication/WCE2017/WCE2017_pp783-787.pdf
14. Alexandru, A.M., De Mauro, A., Fiasché, M., Sisca, F.G., Taisch, M., Fasanotti, L., Grasseni, P. (2015). A smart web-based maintenance system for a smart manufacturing environment. In 2015 IEEE 1st International Forum on Research and Technologies for Society and Industry Leveraging a better tomorrow (RTSI). 579-584. IEEE. https://doi.org/10.1109/RTSI.2015.7325160
15. Lopes, I.D.S., Figueiredo, M., Sá, V. (2020). Criticality evaluation to support maintenance management of manufacturing systems. https://doi.org/ 10.24867/IJIEM-2020-1-248
16. Shagluf, A., Longstaff, A.P., Fletcher, S. (2014). Maintenance strategies to reduce downtime due to machine positional errors. In Proceedings of Maintenance Performance Measurement and Management (MPMM) Conference 2014. Imprensa da Universidade de Coimbra. http://dx.doi.org/10.14195/978-972-8954-42-0_25
17. Swamidass, P.M. (2000) Encyclopedia of production and manufacturing management. Springer Science & Business Media. https://doi.org/10.1007/1-4020-0612-8
18. Law, A.M.; Kelton, W.D. (2000). Simulation modeling and analysis (Vol. 3). New York: McGraw-Hill. https://doi.org/10.1177/003754979306100508
19. Kazimieras., Zavadskas, E., Antucheviciene, J., Chatterjee, P. (2019). Multiple-criteria decision-making (MCDM) techniques for business processes information management. https://doi.org/10.3390/info10010004
20. Khan, S.A., Chaabane, A., Dweiri, F.T. (2018). Multi-criteria decision-making methods application in supply chain management: A systematic literature. Multi-criteria methods and techniques applied to supply chain management. 1. http://dx.doi.org/10.5772/intechopen.74067

21. Chodha, V., Dubey, R., Kumar, R., Singh, S., Kaur, S. (2021). Selection of industrial arc welding robot with TOPSIS and Entropy MCDM techniques. Materials Today: Proceedings. https://doi.org/10.1016/j.matpr.2021.04.487

22. Kaynak, S., Altuntas, S., Dereli, T. (2017). Comparing the innovation performance of EU candidate countries: an entropy based TOPSIS approach. Economic research-Ekonomska istraživanja. 30(1), pp.31-54. https://doi.org/10.1080/1331677X.2016.1265895

23. Ding, L., Shao, Z., Zhang, H., Xu, C., Wu, D. (2016). A comprehensive evaluation of urban sustainable development in China based on the TOPSIS-entropy method. Sustainability. 8(8), p.746. https://doi.org/10.3390/su8080746

24. He, K., & Jin, M. (2016). Cyber-Physical systems for maintenance in Industry 4.0. https://www.diva-portal.org/smash/get/diva2:1071443/FULLTEXT01.pdf

25. Rossit, D. A., Tohme, F., & Frutos, M. (2019). Production planning and scheduling in Cyber-Physical Production Systems: a review. International journal of computer integrated manufacturing, 32(4-5), 385-395. https://doi.org/10.1080/0951192X.2019.1605199

26. Schreiber, M., Vernickel, K., Richter, C., & Reinhart, G. (2019). Integrated production and maintenance planning in cyber-physical production systems. Procedia CIRP, 79, 534-539. https://doi.org/10.1016/j.procir.2019.02.095

27. Neal, A. D., Sharpe, R. G., van Lopik, K., Tribe, J., Goodall, P., Lugo, H., & West, A. A. (2021). The potential of industry 4.0 Cyber Physical System to improve quality assurance: An automotive case study for wash monitoring of returnable transit items. CIRP Journal of Manufacturing Science and Technology, 32, 461-475. https://doi.org/10.1016/j.cirpj.2020.07.002

28. Okolie, S. O., Kuyoro, S. O., & Ohwo, O. B. (2018). Emerging Cyber-Physical Systems: An Overview. https://doi.org/10.32628/CSEIT183862

29. Yaacoub, J. P. A., Salman, O., Noura, H. N., Kaaniche, N., Chehab, A., & Malli, M. (2020). Cyber-physical systems security: Limitations, issues and future trends. Microprocessors and Microsystems, 77, 103201. https://doi.org/10.1016/j.micpro.2020.103201

30. Hozdić, E. (2015). Smart factory for industry 4.0: A review. International Journal of Modern Manufacturing Technologies, 7(1), 28-35. https://modtech.ro/international-journal/vol7no12015/Hozdic_Elvis.pdf

31. Yildirim, M., Gebraeel, N. Z., & Sun, X. A. (2019). Leveraging Predictive Analytics to Control and Coordinate Operations, Asset Loading, and Maintenance. IEEE Transactions on Power Systems, 34(6), 4279-4290. https://doi.org/10.1109/TPWRS.2019.2922380
32. Von Birgelen, A., Buratti, D., Mager, J., & Niggemann, O. (2018). Self-organizing maps for anomaly localization and predictive maintenance in cyber-physical production systems. Procedia CIRP, 72, 480-485. https://doi.org/10.1016/j.procir.2018.03.150
33. Barthelmey, A., Störkle, D., Kuhlenkötter, B., & Deuse, J. (2014). Cyber physical systems for life cycle continuous technical documentation of manufacturing facilities. Procedia Cirp, 17, 207-211. https://doi.org/10.1016/j.procir.2014.01.050
34. Han, X., Wang, Z., Xie, M., He, Y., Li, Y., Wang, W. (2021). Remaining useful life prediction and predictive maintenance strategies for multi-state manufacturing systems considering functional dependence. Reliability Engineering & System Safety, 210:107560. https://doi.org/10.1016/j.ress.2021.107560
35. Almeida, J.C., Ribeiro, B., Cardoso, A. (2021). Empirical Analysis for Remaining Useful Life Estimation via Data-Driven Models. IFAC-PapersOnLine. 55(6):222-227. https://doi.org/10.1016/j.ifacol.2022.07.133
36. Manupati, VK., Panigrahi, S., Ahsan, M., Lahiri, S., Chandra, A., Thakkar, JJ., Putnik, G., Varela, MLR. (2019) Estimation of manufacturing systems degradation rate for residual life prediction through dynamic workload adjustment. Sādhanā 44(2):30. https://doi.org/10.1007/s12046-018-0991-y
37. Hao, L., Liu, K., Gebraeel, N., Shi, J. (2015). Controlling the residual life distribution of parallel unit systems through workload adjustment. IEEE Transactions on Automation Science and Engineering. 14(2). pp.1042-1052. https://doi.org/10.1109/TASE.2015.2481703
38. Ajukumar, V.N.; Gandhi, O.P. (2013). Evaluation of green maintenance initiatives in design and development of mechanical systems using an integrated approach. Journal of cleaner production. 51, 34-46. https://doi.org/10.1016/j.jclepro.2013.01.010
39. Lee, G.Y., Kim, M., Quan, Y.J., Kim, M.S., Kim, T.J.Y., Yoon, H.S., Min, S., Kim, D.H., Mun, J.W., Oh, J.W, Choi, I.G. (2018). Machine health management in smart factory: A review. Journal of Mechanical Science and Technology. 32(3), pp.987-1009. https://doi.org/10.1007/s12206-018-0201-1

40. Lee, J., Bagheri, B., Kao, H.A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manufacturing. letters, 3, pp.18-23. https://doi.org/10.1016/j.mfglet.2014.12.001

41. Yang, HL., Chang, TW., Choi, Y. (2018) Exploring the research trend of smart factory with topic modelling. Sustainability 10(8):2779. https://doi.org/10.3390/su10082779

42. Wang, H., Ye, X., & Yin, M. (2016). Study on predictive maintenance strategy. International Journal of U- and e- Service, Science and Technology, 9(4), 295–300. https://doi.org/10.14257/ijunesst.2016.9.4.29

43. K¨oksal, M., & Uzun, A. (2016). Bakım Planlaması. Retrieved from Seçkin Yayıncılık website: http://web.bilecik.edu.tr/bulent-turan/files/2016/03/bakim_onarim.pdf

44. Putnik, G.D., Manupati, V.K., Pabba, S.K., Varela, L. & Ferreira, F. (2021). Semi-Double-loop machine learning based CPS approach for predictive maintenance in manufacturing system based on machine status indications. CIRP Annals, 70(1), pp.365-368. https://doi.org/10.1016/j.cirp.2021.04.046

45. H. Hu, D. Munoz, J. Bagnell, and M. Hebert. (2013). Efficient 3-D scene analysis from streaming data, in Proc. IEEE International Conference on Robotics and Automation, Karlsruhe, Germany, 2297– 2304. https://doi.org/10.1109/ICRA.2013.6630888

46. Ledón, R.A., Garcia, J.A., Gomes, L.F.A.M., Delgado, F.M. and Lago, O.F., EQUIPMENT CRITICALITY INDEX: A DEA-BASED MULTI-CRITERIA APPROACH TO SETTING INVESTMENT PRIORITIES FOR INDUSTRIAL PRODUCTION PROCESSES. http://www.din.uem.br/~ademir/sbpo/sbpo2004/pdf/arq0140.pdf

47. Strozzi, F., Colicchia, C., Creazza, A., Noè, C. (2017). Literature review on the 'Smart Factory'concept using bibliometric tools. International Journal of Production Research. 55(22):6572-6591. https://doi.org/10.1080/00207543.2017.1326643

48. Wang, S., Wan, J., Zhang, D., Li, D., Zhang, C. (2016). Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination. Computer Networks 101:158-168. https://doi.org/10.1016/j.comnet.2015.12.017

49. Bortolini, M., Galizia, F.G. and Mora, C. (2018). Reconfigurable manufacturing systems: Literature review and research trend. Journal of Manufacturing Systems, 49, 93-106. https://doi.org/10.1016/j.jmsy.2018.09.005

50. Carvalho, T.P., Soares, F.A., Vita, R., Francisco, R.D.P., Basto, J.P. and Alcalá, S.G. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. Computers & Industrial Engineering, 137, 106024. https://doi.org/10.1016/j.cie.2019.106024
51. Colicchia, C., & Strozzi, F. (2012). Supply chain risk management: a new methodology for a systematic literature review. Supply Chain Management: An International Journal, 17(4), 403–418. http://dx.doi.org/10.1108/13598541211246558
52. Jiang, J. R. (2018). An improved cyber-physical systems architecture for Industry 4.0 smart factories. Advances in Mechanical Engineering, 10(6), 1687814018784192. https://doi.org/10.1177%2F1687814018784192
53. Cui, X. (2021). Cyber-Physical System (CPS) architecture for real-time water sustainability management in manufacturing industry. Procedia CIRP, 99, 543-548. https://doi.org/10.1016/j.procir.2021.03.074
54. Hehenberger, P., Vogel-Heuser, B., Bradley, D., Eynard, B., Tomiyama, T., & Achiche, S. (2016). Design, modelling, simulation and integration of cyber physical systems: Methods and applications. Computers in Industry, 82, 273-289. https://doi.org/10.1016/j.compind.2016.05.006
55. Yan, J., Zhang, M., & Fu, Z. (2019). An intralogistics-oriented Cyber-Physical System for workshop in the context of Industry 4.0. Procedia manufacturing, 35, 1178-1183. https://doi.org/10.1016/j.promfg.2019.06.074
56. Saldivar, A. A. F., Li, Y., Chen, W. N., Zhan, Z. H., Zhang, J., & Chen, L. Y. (2015). Industry 4.0 with cyber-physical integration: A design and manufacture perspective. In 2015 21st international conference on automation and computing (ICAC) (pp. 1-6). IEEE. https://doi.org/10.1109/IConAC.2015.7313954
57. Seitz, K. F., & Nyhuis, P. (2015). Cyber-physical production systems combined with logistic models–a learning factory concept for an improved production planning and control. Procedia Cirp, 32, 92-97. https://doi.org/10.1016/j.procir.2015.02.220
58. Meissner, H., & Aurich, J. C. (2019). Implications of cyber-physical production systems on integrated process planning and scheduling. Procedia Manufacturing, 28, 167-173. https://doi.org/10.1016/j.promfg.2018.12.027

59. Ebrahimipour, V., Najjarbashi, A., & Sheikhalishahi, M. (2015). Multi-objective modeling for preventive maintenance scheduling in a multiple production line. Journal of Intelligent Manufacturing, 26(1), 111-122. https://doi.org/10.1007/s10845-013-0766-6

60. Boyes, H., Hallaq, B., Cunningham, J., & Watson, T. (2018). The industrial internet of things (IIoT): An analysis framework. Computers in industry, 101, 1-12. https://doi.org/10.1016/j.compind.2018.04.015

61. Kanisuru, A. M. (2017). Sustainable Maintenance Practices and Skills for Competitive Production System. In Skills Development for Sustainable Manufacturing. IntechOpen. https://dx.doi.org/10.5772/intechopen.70047

62. Giaimo, F., Andrade, H., & Berger, C. (2020). Continuous experimentation and the cyber–physical systems challenge: An overview of the literature and the industrial perspective. Journal of Systems and Software, 170, 110781. https://doi.org/10.1016/j.jss.2020.110781

63. Dafflon, B., Moalla, N., & Ouzrout, Y. (2021). The challenges, approaches, and used techniques of CPS for manufacturing in Industry 4.0: a literature review. The International Journal of Advanced Manufacturing Technology, 1-18. https://doi.org/10.1007/s00170-020-06572-4

64. Glazebrook, KD. (1987) Evaluating the effects of machine breakdowns in stochastic scheduling problems. Naval Research Logistics (NRL) 34(3):319-335. https://doi.org/10.1002/1520-6750(198706)34:3%3C319::AID NAV3220340303%3E3.0.CO;2-5

65. Koh, SCL., Saad, SM. (2003). MRP-controlled manufacturing environment disturbed by uncertainty. Robotics and Computer-Integrated Manufacturing 19(1):157-171. https://doi.org/10.1016/S0736-5845(02)00073-X

66. Yan, J., Koc, M., Lee, J. (2004). A prognostic algorithm for machine performance assessment and its application. Production Planning & Control 15(8):796-801. https://doi.org/10.1080/09537280412331309208

67. Ni, X., Zhao, J., Zhang, X., Lv, X., Zhao, J. (2014) System degradation process modeling for two-stage degraded mode. In 2014 Prognostics and System Health Management Conference (PHM-2014 Hunan) IEEE :186-189. https://doi.org/10.1109/PHM.2014.6988160

68. Gebraeel, NZ., Lawley, MA., Li, R., Ryan, JK. (2005) Residual-life distributions from component degradation signals: A Bayesian approach. IiE Transactions 37(6):543-557. https://doi.org/10.1080/07408170590929018
69. Zhou, RR., Serban, N., Gebraeel, N. (2011). Degradation modeling applied to residual lifetime prediction using functional data analysis. The Annals of Applied Statistics 5:1586-1610. https://www.jstor.org/stable/23024864
70. Bian, L., Gebraeel, N. (2012) Computing and updating the first-passage time distribution for randomly evolving degradation signals. IIE Transactions 44(11):974-987. https://doi.org/10.1080/0740817X.2011.649661
71. Bian, L., Gebraeel, N. (2014). Stochastic modeling and real-time prognostics for multi-component systems with degradation rate interactions. Iie Transactions, 46(5):470-482. https://doi.org/10.1080/0740817X.2013.812269
72. Song, C. and Liu, K. (2018). Statistical degradation modeling and prognostics of multiple sensor signals via data fusion: A composite health index approach. IISE Transactions, 50(10), pp.853-867. https://doi.org/10.1080/24725854.2018.1440673
73. Bian, L., Gebraeel, N., Kharoufeh, JP. (2015). Degradation modeling for real-time estimation of residual lifetimes in dynamic environments. Iie Transactions, 47(5):471-486. https://doi.org/10.1080/0740817X.2014.955153
74. Deutsch, J. and He, D. (2017). Using deep learning-based approach to predict remaining useful life of rotating components. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 48(1), pp.11-20. https://doi.org/10.1109/TSMC.2017.2697842
75. Ren, L., Sun, Y., Cui, J. and Zhang, L. (2018). Bearing remaining useful life prediction based on deep autoencoder and deep neural networks. Journal of Manufacturing Systems, 48, pp.71-77. https://doi.org/10.1016/j.jmsy.2018.04.008
76. Cipollini, F., Oneto, L., Coraddu, A., Murphy, A. J., & Anguita, D. (2018). Condition based maintenance of naval propulsion systems: Data analysis with minimal feedback. Reliability Engineering & System Safety, 177, 12–23. https://doi.org/10.1016/j.ress.2018.04.015
77. Man, J. and Zhou, Q. (2018). Prediction of hard failures with stochastic degradation signals using Wiener process and proportional hazards model. Computers & Industrial Engineering, 125, pp.480-489. https://doi.org/10.1016/j.cie.2018.09.015

78. Amihai, I., Gitzel, R., Kotriwala, A.M., Pareschi, D., Subbiah, S. and Sosale, G. (2018). An industrial case study using vibration data and machine learning to predict asset health. In 2018 IEEE 20th Conference on Business Informatics (CBI), 1, pp. 178-185. IEEE. https://doi.org/10.1109/CBI.2018.00028

79. Matyas, K., Nemeth, T., Kovacs, K. and Glawar, R. (2017). A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. CIRP Annals, 66(1), pp.461-464. https://doi.org/10.1016/j.cirp.2017.04.007

80. Ben-Salem, A., Gharbi, A., Hajji, A. (2015). Environmental issue in an alternative production–maintenance control for unreliable manufacturing system subject to degradation. The International Journal of Advanced Manufacturing Technology, 77(1-4):383-398. https://doi.org/10.1007/s00170-014-6454-7

81. Ye, Z., Cai, Z., Zhou, F., Zhao, J., Zhang, P. (2019). Reliability analysis for series manufacturing system with imperfect inspection considering the interaction between quality and degradation. Reliability Engineering & System Safety, 189:345-356. https://doi.org/10.1016/j.ress.2019.05.005

82. Li, N., Gebraeel, N., Lei, Y., Bian, L., Si, X. (2019). Remaining useful life prediction of machinery under time-varying operating conditions based on a two-factor state-space model. Reliability Engineering & System Safety, 186:88-100. https://doi.org/10.1016/j.ress.2019.02.017

83. Gao, Z., Hu, Q.G. and Xu, X.Y. (2020). Residual Lifetime Prediction with Multistage Stochastic Degradation for Equipment. Complexity, https://doi.org/10.1155/2020/8847703

84. Ayad, S., Terrissa, L.S. and Zerhouni, N. (2018). An IoT approach for a smart maintenance. In 2018 International Conference on Advanced Systems and Electric Technologies (IC_ASET), 210-214. IEEE. https://doi.org/10.1109/ASET.2018.8379861

85. Nemeth, T., Ansari, F., Sihn, W., Haslhofer, B. and Schindler, A. (2018). PriMa-X: A reference model for realizing prescriptive maintenance and assessing its maturity enhanced by machine learning. Procedia CIRP, 72, 1039-1044. https://doi.org/10.1016/j.procir.2018.03.280

86. Jin, W., Liu, Z., Shi, Z., Jin, C. and Lee, J. (2017). CPS-enabled worry-free industrial applications. In 2017 Prognostics and System Health Management Conference (PHM-Harbin, 1-7. IEEE. https://doi.org/10.1109/PHM.2017.8079208

87. Lee, J., Jin, C. and Bagheri, B. (2017). Cyber physical systems for predictive production systems. Production Engineering, 11(2), pp.155-165. https://doi.org/10.1007/s11740-017-0729-4

88. Terrissa, L.S., Meraghni, S., Bouzidi, Z. and Zerhouni, N. (2016). A new approach of PHM as a service in cloud computing. In 2016 4th IEEE International Colloquium on Information Science and Technology (CiSt), 610-614. IEEE. https://doi.org/10.1109/CIST.2016.7804958

89. Ghasemi, A., Azzouz, R., Laipple, G., Kabak, K.E., Heavey, C. (2020). Optimizing capacity allocation in semiconductor manufacturing photolithography area–Case study: Robert Bosch. Journal of Manufacturing Systems, 54:123-137. https://doi.org/10.1016/j.jmsy.2019.11.012.

90. Zhou, B., Bao, J., Li, J., Lu, Y., Liu, T., Zhang, Q. (2021) A novel knowledge graph-based optimization approach for resource allocation in discrete manufacturing workshops. Robotics and Computer-Integrated Manufacturing, 71:102160. https://doi.org/10.1016/j.rcim.2021.102160.

91. Firat, M., De Meyere, J., Martagan, T., Genga, L. (2022). Optimizing the workload of production units of a make-to-order manufacturing system. Computers & Operations Research. 138:105530. https://doi.org/10.1016/j.cor.2021.105530.

92. Menezes, B.C., Kelly, J.D., Leal, A.G. and Le Roux, G.C. (2019). Predictive, prescriptive and detective analytics for smart manufacturing in the information age. IFAC-PapersOnLine, 52(1), 568-573. https://doi.org/10.1016/j.ifacol.2019.06.123

93. He, Y., Gu, C., Chen, Z. and Han, X. (2017). Integrated predictive maintenance strategy for manufacturing systems by combining quality control and mission reliability analysis. International Journal of Production Research, 55(19), 5841-5862. https://doi.org/10.1080/00207543.2017.1346843

94. Spendla, L., Kebisek, M., Tanuska, P. and Hrcka, L. (2017). Concept of predictive maintenance of production systems in accordance with industry 4.0. In 2017 IEEE 15th International Symposium on Applied Machine Intelligence and Informatics (SAMI), 000405-000410. IEEE. https://doi.org/10.1109/SAMI.2017.7880343

95. Dong, Y., Xia, T., Fang, X., Zhang, Z. and Xi, L. (2019). Prognostic and health management for adaptive manufacturing systems with online sensors and flexible structures. Computers & Industrial Engineering, 133, 57-68. https://doi.org/10.1016/j.cie.2019.04.051

96. Traini, E., Bruno, G., D'Antonio, G. and Lombardi, F. (2019). Machine Learning Framework for Predictive Maintenance in Milling. IFAC-PapersOnLine, 52(13), 177-182. https://doi.org/10.1016/j.ifacol.2019.11.172
97. Yildirim, M., Sun, X.A. and Gebraeel, N.Z. (2016). Sensor-driven condition-based generator maintenance scheduling—Part I: Maintenance problem. IEEE Transactions on Power Systems, 31(6), 4253-4262. https://doi.org/10.1109/TPWRS.2015.2506600
98. Jimenez-Cortadi, A., Irigoien, I., Boto, F., Sierra, B., Rodriguez, G. (2019). Predictive maintenance on the machining process and machine tool. Applied Sciences, 10(1):224. https://doi.org/10.3390/app10010224
99. Welte, R., Estler, M., Lucke, D. (2020). A method for implementation of machine learning solutions for predictive maintenance in small and medium sized enterprises. Procedia CIRP 93:909-914. https://doi.org/10.1016/j.procir.2020.04.052
100. Cakir, M., Guvenc, M.A., Mistikoglu, S. (2021). The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system. Computers & Industrial Engineering, 151:106948. https://doi.org/10.1016/j.cie.2020.106948
101. Ayvaz, S., Alpay, K. (2021). Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. Expert Systems with Applications, 173:114598. https://doi.org/10.1016/j.eswa.2021.114598
102. Hosseini, S.M.S., Shahanaghi, K. and Shasfand, S. (2021). Resistive maintenance and equipment criticality indexes. Nexo Revista Científica, 34(02), pp.744-758. https://doi.org/10.5377/nexo.v34i02.11559
103. Jasiulewicz–Kaczmarek, M., Antosz, K., Żywica, P., Mazurkiewicz, D., Sun, B. and Ren, Y. (2021). Framework of machine criticality assessment with criteria interactions. Eksploatacja i Niezawodność, 23(2). http://doi.org/10.17531/ein.2021.2.1
104. Djassemi, M. and Seifoddini, H. (2019). Analysis of critical machine reliability in manufacturing cells. Journal of Industrial Engineering and Management, 12(1), pp.70-82. http://dx.doi.org/10.3926/jiem.2757
105. Gopalakrishnan, M., Skoogh, A., Salonen, A. and Asp, M. (2019). Machine criticality assessment for productivity improvement: Smart maintenance decision support. International Journal of Productivity and Performance Management. https:doi.org/10.1108/IJPPM-03-2018-0091

106. Saidy, C., Panavas, L., Harik, R., Bayoumi, A.M. and Khoury, J. (2017). Development of a Part Criticality index in inventory management. In IFIP International Conference on Product Lifecycle Management (pp. 184-195). Springer, Cham. https://doi.org/10.1007/978-3-319-72905-3_17
107. Onawoga, D.T. and Akinyemi, O.O. (2010). Development of equipment maintenance strategy for critical equipment. The Pacific Journal of Science and Technology, 11(1), pp.328-342.
108. Aghaie, M., Fazli, S. (2012). An improved MCDM method for maintenance approach selection: A case study of auto industry. Manag. Sci. Lett. 2, 137–146. http://dx.doi.org/10.5267/j.msl.2011.09.012
109. Emovon, I., Oghenenyerovwho, O.S. (2020). Application of MCDM method in material selection for optimal design: A review. Results Mater. 7, 100115. https://doi.org/10.1016/j.rinma.2020.100115
110. Hao, L., Gebraeel, N., Shi, J. (2015). Simultaneous signal separation and prognostics of multi-component systems: the case of identical components. IIE Transactions. 47(5), pp.487-504. https://doi.org/10.1080/0740817X.2014.955357
111. Lugaresi, G., Alba, V.V., and Matta, A. (2021). Lab-scale models of manufacturing systems for testing real-time simulation and production control technologies. Journal of Manufacturing Systems. 58, pp.93-108. https://doi.org/10.1016/j.jmsy.2020.09.003
112. Tan, T., Mills, G., Papadonikolaki, E., Liu, Z. (2021). Combining multi-criteria decision making (MCDM) methods with building information modelling (BIM): A review. Automation in Construction. 121, p.103451. https://doi.org/10.1016/j.autcon.2020.103451
113. Mavi, R.K., Zarbakhshnia, N., and Khazraei, A. (2018). Bus rapid transit (BRT): A simulation and multi criteria decision making (MCDM) approach. Transport Policy. 72, pp.187-197. https://doi.org/10.1016/j.tranpol.2018.03.010
114. Ding, L., Shao, Z., Zhang, H., Xu, C., Wu, D. (2016). A comprehensive evaluation of urban sustainable development in China based on the TOPSIS-entropy method. Sustainability. 8(8), p.746. https://doi.org/10.3390/su8080746
115. Kang, Z., Catal, C., Tekinerdogan, B. (2021). Remaining useful life (RUL) prediction of equipment in production lines using artificial neural networks. Sensors, 21(3), p.932. https://doi.org/10.3390/s21030932

116. Al-Khayyal, FA., Larsen, C., Van Voorhis, T. (1995). A relaxation method for nonconvex quadratically constrained quadratic programs. Journal of Global Optimization, 6(3):215-230. https://doi.org/10.1007/BF01099462
117. Gebraeel, N., Elwany, A., Pan, J. (2009). Residual life predictions in the absence of prior degradation knowledge. IEEE Transactions on Reliability, 58(1):106-117. https://doi.org/10.1109/TR.2008.2011659
118. Audet, C., Hansen, P., Jaumard, B., Savard, G. (2000). A branch and cut algorithm for nonconvex quadratically constrained quadratic programming. Mathematical Programming, 87(1):131-152. https://doi.org/10.1007/s101079900106
119. Boukouvala, F., Misener, R., Floudas, CA. (2016). Global optimization advances in mixed-integer nonlinear programming, MINLP, and constrained derivative-free optimization, CDFO. European Journal of Operational Research, 252(3):701-727. https://doi.org/10.1016/j.ejor.2015.12.018
120. Murty, KG., Kabadi, SN. (1985). Some NP-complete problems in quadratic and nonlinear programming, 39:117-129. https://doi.org/10.1007/BF02592948
121. Baltean-Lugojan, R. (2019). Exploiting structure in nonconvex quadratic optimisation. https://doi.org/10.1007/978-3-030-18500-8_7
122. Shaikh, SR., Dulange, SR. (2013). A study of factors affecting productivity of Power Loom Industries. International Journal of Engineering Research & Technology (IJERT), 2(12):2278-0181. https://doi.org/ 10.35940/ijeat.C6550.029320
123. Li, J., E. Blumenfeld, D., Huang, N., and M. Alden, J. (2009). Throughput analysis of production systems: recent advances and future topics. International Journal of Production Research, 47.14 (2009): 3823-3851. https://doi.org/10.1080/00207540701829752
124. Imseitif, J., Tang, H. and Smith, M. (2019). Throughput analysis of manufacturing systems with buffers considering reliability and cycle time using DES and DOE. Procedia Manufacturing, 39, pp.814-823. https://doi.org/10.1016/j.promfg.2020.01.423
125. Das, S., Hall, R., Herzog, S., Harrison, G., Bodkin, M. and Martin, L. (2011). Essential steps in prognostic health management. In 2011 IEEE Conference on Prognostics and Health Management 1-9. IEEE. https://doi.org/10.1109/ICPHM.2011.6024332

126. Si, X.S., Wang, W., Hu, C.H., Chen, M.Y. and Zhou, D.H. (2013). A Wiener-process-based degradation model with a recursive filter algorithm for remaining useful life estimation. Mechanical Systems and Signal Processing, 35(1-2), 219-237. https://doi.org/10.1016/j.ymssp.2012.08.016
127. Zhang, Z., Si, X., Hu, C. and Lei, Y. (2018). Degradation data analysis and remaining useful life estimation: A review on Wiener-process-based methods. European Journal of Operational Research, 271(3), 775-796. https://doi.org/10.1016/j.ejor.2018.02.033
128. Mosallam, A., Medjaher, K. and Zerhouni, N. (2016). Data-driven prognostic method based on Bayesian approaches for direct remaining useful life prediction. Journal of Intelligent Manufacturing, 27(5), 1037-1048. https://doi.org/10.1007/s10845-014-0933-4