INVESTIGATING THE VALUE OF INTEGRATED OPERATIONS PLANNING CONSIDERING MULTIPLE DEPENDENT SHOP-FLOOR FUNCTIONS: REALIZING INDUSTRY 4.0

Ph.D. Thesis

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DISCIPLINE OF MECHANICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY INDORE

OCTOBER 2018

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INVESTIGATING THE VALUE OF INTEGRATED OPERATIONS PLANNING CONSIDERING MULTIPLE DEPENDENT SHOP-FLOOR FUNCTIONS: REALIZING INDUSTRY 4.0

A THESIS

Submitted in partial fulfillment of the requirements for the award of the degree
of
DOCTOR OF PHILOSOPHY

by

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DISCIPLINE OF MECHANICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY INDORE

OCTOBER 2018

INDIAN INSTITUTE OF TECHNOLOGY INDORE

CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **INVESTIGATING THE VALUE OF INTEGRATED OPERATIONS PLANNING CONSIDERING MULTIPLE DEPENDENT SHOP-FLOOR FUNCTIONS: REALIZING INDUSTRY 4.0** in the partial fulfillment of the requirements for the award of the degree of **DOCTOR OF PHILOSOPHY** and submitted in the **DISCIPLINE OF MECHANICAL ENGINEERING, INDIAN INSTITUTE OF TECHNOLOGY INDORE**, is an authentic record of my own work carried out during the time period from July 2013 to July 2018 under the supervision of Dr. Bhupesh Kumar Lad, Associate Professor, Discipline of Mechanical Engineering, Indian Institute of Technology Indore, India.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Signature of the student with date
(SANDEEP KUMAR)

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Signature of Thesis Supervisor with date

(Dr. BHUPESH KUMAR LAD)

SANDEEP KUMAR has successfully given his Ph.D. Oral Examination held on **4th October 2018.**

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Date:

PREAMBLE

Nowadays, industries are moving towards the transformation of today's factory into smart factory under the banner of Industry 4.0 or smart manufacturing. The smart manufacturing has its roots in sensing technology, digitization, artificial intelligence, and machine-to-machine communications. While these technologies are being advanced to make machines more and more intelligent, use of such intelligence in manufacturing operations planning is missing in the literature. Consequently, the present thesis focuses on operations planning perspective of the industry 4.0. In specific, following two essential but conflicting challenges of operations planning are identified and addressed in this thesis.

1) Integration of various shop-floor functions viz., production, maintenance, quality, and inventory.
2) Responsiveness of integrated operations planning in dynamic conditions created by machine failures, change in demand, uncertainty in supply, etc.

A detailed literature review presented in this thesis confirmed the need for significant advancement of the technology pertaining to integrated operations planning. Consequently, present thesis extensively contributed to the body of knowledge by developing advanced approaches for multifunction integration in realistic operations planning environments of manufacturing industries. Such integrated approaches are comprehensively investigated for various operations planning environments; it confirmed the value of integrated approaches over the conventionally done interrelated and independent approaches. Another radical advancement is made by the development of novel agent-based distributed computing approach for the integrated operations planning. The proposed agent-based approach significantly improves the responsiveness of the complex integrated operations planning decision-making. It has been developed around the inherent characteristics of next generation digital cum intelligent factory. It is concluded that the proposed integrated yet distributed operations planning approach will serve as the backbone of any next generation manufacturing planning system.

ACKNOWLEDGEMENT

I take this opportunity to express my deep sense of respect and gratitude for, Dr. Bhupesh Kumar Lad, for believing in me to carry out this research work under his supervision. His constant encouragement, friendly interactions, and constructive support have enabled this work to achieve its present form. His innovative perspective towards things and his continuous pursuit of perfection has had a profound effect on me and has transformed me majorly. He has been a father-figure to me and provided helpful career advice and suggestions, extending beyond academic boundaries, whenever needed. I feel greatly privileged to be one of his students.

The most valued, gratitude is expressed for my mother, Uttara Devi, and my father, Rambali Gupta, for receiving my ordinary feats in an ever extraordinary way and letting me be the chooser of my destiny. I would like to thank my beloved wife “Shikha” whose encouragement allowed me to finish this journey and one of the most important person in my life my daughter “Sanvi”, for their love which inspired me and was my driving force.

There are people without whom this work ‘literally’ wouldn’t have been possible. I would like to thank Amit Kumar Jain, for his dedication, Saurabh Solanki, for his sincerity and Tameshwer Nath Tiwari, for simply being himself. Thanks are also extended to Manish Rawat, Bhushan S. Purohit, Naresh Raghuwansi, Vibhor Pandhare, Pradeep Kundu, and Uday Kumar Singh for helping me out selflessly.

I would like to express my heartfelt gratitude towards my comprehensive evaluation of research progress committee members Prof. N.K. Jain (Discipline of Mechanical Engineering, IIT Indore) and Dr. Abhishek Srivastava (Discipline of Computer Science & Engineering, IIT Indore) for their interesting discussions and suggestions towards my research. Also, the anonymous reviewers who provided valuable comments and suggestions to my academic papers.

I am thankful to IIT Indore for giving me an opportunity to carry out the research work and providing all the facilities. Very special thanks to Prof. Pradeep Mathur, Director, IIT Indore, for supporting and allowing this work to be represented at various national/international platforms. I have admired him right from my initial years at IIT Indore.

I am immensely grateful to Dr. Vikas Manjrekar (AVTEC Private Limited, Pithampur, India) and Mr. Vivek Singh (AVTEC Private Limited, Pithampur, India), for providing the necessary support for this research work.

I am extremely thankful to Dr. D.L. Deshmukh (Head of Discipline of Mechanical Engineering, IIT Indore) and Dr. S.I. Kundalwal (DPGC Convener, Discipline of Mechanical Engineering, IIT Indore) for his affectionate interactions and highly supportive nature during my entire stay at IIT Indore.

I am thankful to the people of Discipline of Mechanical Engineering, IIT Indore for extending technical support and sharing their knowledge for this research work. In specific, I would like to thank Mr. Arun Kumar Bhagwaniya (Deputy Manager, Industrial and Systems Engineering), Mr. Sandeep Gour (Deputy Manager, Advanced Manufacturing Processes Lab), and Mr. Sachin Bhirodkar (Deputy Manager, Industrial and Systems Engineering) for their constant support to this research. I would also like to thank all the staff at IIT Indore, especially Ms. Jaya Vakade and Mr. Tapesh Parihar, for helping me out at so many situations.

I am thankful to the Ministry of Human Resource Development (MHRD), Department of Higher Education, New Delhi, and Royal Academy of Engineering, London, UK (Newton Bhabha Project no. HEPI\1516\10) for partial financial support. Also, to the AVTEC Private Limited, Pithampur, India for sharing of data for the research.

I would like to express my deep sense of gratitude to Priya Chouhan, Aamedh Bhargava, Tushar Rokade, Vikas Shankhala, Namit Agrawal, Maharshi Dhada, and Kshitij Bakliwal for bearing with me and always maintaining a homely atmosphere in the lab. Special thanks are extended to my colleagues, Suraj Kumar, Kuldeep Agarwal, and Manish Carpenter for their un-matched helping nature.

A heartfelt thanks to my entire Ph.D. group, with whom I have spent most of my time at IIT Indore; especially, Ashish Shukla, Hari Mohan Kushwaha, Yogesh Madaria, Prateek Kumar Jain, Karthik Thirumala, Sunil Pathak, Kapil Gupta, Gaurav Bajpai, Ankur Saxena, Vikas Sharma, and Balmukand Dhakad, for being my second family.

Lastly, I want to thank people of IIT Indore who has, in one way or another, helped me to conduct this research.

Sandeep Kumar

Dedicated to my

Parents (Rambali Gupta, Uttara Devi),

Wife (Shikha),

Daughter (Sanvi)

Mentor (Bhupesh Kumar Lad).

LIST OF PUBLICATIONS

Peer-reviewed Journals

1. **Kumar, S.**, Purohit, B.S., Manjrekar, V., Singh, V., and Lad, B.K., (2018), "Investigating the value of integrated operations planning: A case-based approach from automotive industry", *International Journal of Production Research.* DOI: 10.1080/00207543.2018.14243. [Impact factor: 2.623]
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3. Purohit, B.S., **Kumar, S.**, Lad, B.K., Manjrekar, V., and Singh, V., (2017), "Optimizing Multi Item Operations Sequencing and Batch Size for Non-Parallel Capacitated Machines: A Case Study", *International Journal of Performability Engineering,* Vol. 13, No. 5, pp. 557-568. DOI: 10.23940/ijpe.17.05.p1.557568. [Scopus Indexed, Journal Visibility Factor[1]: 0.719].

4. **Kumar, S.**, Manjrekar, V., Singh, V., and Lad, B.K., (2018), "Integrated yet distributed operations planning approach: A next generation manufacturing planning system", *Computers & Industrial Engineering, Elsevier.* [Impact factor: 3.195] (Under review)

Proceedings in International Conferences

5. **Kumar, S.**, and Lad, B.K., (2016), "Effect of maintenance resource constraints on flow-shop environment in a joint production and maintenance context", *IEEE International Conference on Industrial*

[1] Journal visibility factor, retain a similar definition as that of the impact factor.

Read more: http://www.ijpe-online.com/january-2014-a-note-on-visibility-factor-of-ijpe.html#ixzz5B2o5pANp

Engineering and Engineering Management (IEEM) 2016, 4-7 Dec., Bali, Indonesia, pp. 641-645. DOI:10.1109/IEEM.2016.7797954.

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7. **Kumar, S.**, Purohit, B.S., and Lad, B.K., (2014), "Integrated Approach for Job Scheduling and Multi-Component Maintenance Planning in a Production System", *5th International and 26th All India Manufacturing Technology, Design and Research Conference (AIMTDR) 2014*, 12-14 Dec., Guwahati, India, pp. 482 (1-6).
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NOMENCLATURE

β_j	Shape parameter of j^{th} machine
η_j	Scale parameter of j^{th} machine
BT_i	Processing time of i^{th} batch in hours
DT	Due date
μ_0	Process mean
σ	Standard deviation
δ	Process shift due to machine degradation
x_{ij}	Batch allocation decision of i^{th} batch on j^{th} machine
p_{ijk}	Batch sequencing decision of i^{th} batch at of k^{th} place on j^{th} machine
$N_{pm_{j_{i^-}}}$	Preventive maintenance decision of j^{th} machine before processing of i^{th} batch
TC_i	Tardiness penalty cost of i^{th} batch per hour
EC_i	Earliness penalty cost of i^{th} batch per hour
CT_{ij}	Completion time of i^{th} batch processing on j^{th} machine in hours
P_i	Batch manufacturing cost of i^{th} batch
C_M	Cost of raw material of a batch
C_p	Processing cost of a batch per hour
C_{OH}	Overhead cost of a batch
OT_{ij}	Operation time of i^{th} batch processing on j^{th} machine in hours
ST_i	Set-up time of i^{th} batch in hours
T_{pm_j}	Downtime of j^{th} machine due to PM in hours
T_{cm_j}	Downtime of j^{th} machine due to CM in hours
TTR_{pm_j}	Time to perform preventive maintenance on j^{th} machine
TTR_{cm_j}	Time to perform corrective maintenance on j^{th} machine
NF_{ij}	Number of failures occur during processing of i^{th} batch
Ia_{jk}	Initial age of j^{th} machine before the processing a batch sequenced at k^{th} position

α_j	Preventive maintenance restoration factor of j^{th} machine
C_{dt}	Down time cost per hour
C	Maintenance labor cost per hour
FC_{pm_j}	Fixed cost of per preventive maintenance of j^{th} machine
FC_{cm_j}	Fixed cost of per corrective maintenance action of j^{th} machine
P_{FC_1}	Probability of failure of machine due to failure consequence 1
P_{FC_2}	Probability of failure of machine due to failure consequence 2
C_{rej_i}	Rejection cost of i^{th} job
F_{rej}	Factor of cost of rejection
n	Sample size of quality inspection
f	Time between sampling for quality inspection in hours
γ	Type II error when process is out-of-control
PM_{time_j}	Decision of PM time of j^{th} machine
$\left(p_{i_{x_k}}\right)_j$	Decision of sequencing of i^{th} job for x^{th} operation k^{th} place on j^{th} machine
ST_{i_x}	Setup time of a batch of i^{th} job for x^{th} operation in hours
PT_{i_x}	Processing time of i^{th} job for x^{th} operation in hours
T	Planning horizon
D	Demand of product
$OT_{i_{x_j}}$	Batch operation time of i^{th} job for x^{th} operation processing on j^{th} machine in hours
W_{i_x}	Waiting time of a batch of i^{th} job for x^{th} operation in hours
WT_{t_j}	Waiting time for maintenance technicians on j^{th} machine
$WT_{s_{pm_j}}$	Waiting time for spare parts for PM on j^{th} machine
$WT_{s_{cm_j}}$	Waiting time for spare parts for CM on j^{th} machine
Pr_j	Priority for maintenance for j^{th} machine
C_a	Maintenance labor cost per hour in maintenance resourse constraints
$FC_{pm_{j_a}}$	Fixed cost of per preventive maintenance of j^{th} machine in

maintenance resourse constraints

$FC_{cm_{j_a}}$ Fixed cost of per corrective maintenance action of j^{th} machine in maintenance resourse constraints

CC_{i_x} Manufacturing cost of i^{th} job

LC Lost revenue per undelivered product

BS_{i_x} Decision of batch-size of i^{th} job for x^{th} operation

l_{i_x} Decision of inventory level of buffers

$J_{i_{x_j}}$ Number of i^{th} jobs produced for x^{th} operation through j^{th} machine in one shift

h Number of deliveries

P_D Number of product produced within planning horizon T

$C_{h_{i_x}}$ WIP carrying cost per hour of an item of i^{th} job for x^{th} operation

IC_{i_x} Inventory carrying cost per hour of an item of i^{th} job for x^{th} operation

$(NF_j)_{i_x}$ Number of failures occurs during processing of i^{th} job for x^{th} operation on j^{th} machine

C_F Fixed cost per sample

C_V Variable cost per sampling job

N_{pm_j} Decision of interval of PM on j^{th} machine

f_{i_x} Decision of inspection interval for i^{th} job for x^{th} operation

n_{i_x} Decision of inspection sample size for i^{th} job for x^{th} operation

ACRONYMS

CPS	Cyber-Physical Systems
IIoT	Industrial Internet of Things
Industry 4.0	Fourth industrial revolution
WIP	Work-In-Process
NP-hard	Non-deterministic polynomial-time hard
OOC	Overall Operations Cost
PM	Preventive Maintenance
CM	Corrective Maintenance
GA	Genetic Algorithm
SA	Simulated Annealing
TS	Tabu Search
PSO	Particle Swarm Optimization
ATSA	Adaptive Thermo-statistical Simulated Annealing
MAS	Multi-Agent System
FC_1	Failure consequence 1
FC_2	Failure consequence 2
ATC	Average Tardiness Cost
AEC	Average Earliness Cost
APMC	Average PM Cost
ACMC	Average CM Cost
ARC	Average Rejection Cost
IRR	Increased Rejection Rate
ARL	Average Run Length
MU	Monetary Unit
ANOVA	Analysis of Variance
μ	Mean
V	Number of iterations
TPC	Total Production Cost
SU	System Utilization

LT	Lead Time
LTs	Lead Times
EC	Earliness Cost
TC	Tardiness Cost
$PM\ C_a$	PM Cost in maintenance resourse constraints
$CM\ C_a$	CM Cost in maintenance resourse constraints
K	Initial temperature
OFV	Objective Function Value
SC	Scheduling cost
MC	Maintenance cost
DIC	Downtime inventory cost
RL	Revenue Lost
HCQ	Holding Cost in Queue
TMC	Total Maintenance Cost
PMC	PM Cost
CMC	CM Cost
PFM	Performance Model
SM	Simulation Model
OA	Optimization Algorithm
DS	Decisions Set
IF	Intensity Factor
IFs	Intensity Factors
TQC	Total Quality Cost
IC	Inspection Cost
RC	Rejection Cost
IPC	Integrated Production Cost
TC	Termination Criteria
TM	Computation time

Chapter 1

Introduction

In this introductory chapter, the background and motivation, problem, gaps, objectives, focus, and methodologies of the current research are presented to highlight the challenges and opportunities of manufacturing operations planning for next generation intelligent factories. In the end, the outline of the thesis and summary are given.

1.1 Background and motivation

Manufacturing, over the years, has evolved through three major revolutions brought out by the impact of mechanization, electricity, and information technology (Evans and Annunziata, 2012). The next big change in manufacturing has its roots in intelligence. It has paved the way for a systematic deployment of Cyber-Physical Systems (CPS), within which information from all related perspectives is closely monitored and synchronized between the physical factory floor and the cyber computational space. Such trends are fast transforming manufacturing industries to smart factories and taking them to the next generation manufacturing paradigm, namely Industry 4.0 or smart manufacturing-the application of CPS, Industrial Internet of Things (IIoT) and Computer Optimization Techniques in manufacturing enterprises. The potential of application of Industry 4.0 techniques into today's industrial practices is agreed upon by the researchers and industrial community. For instance, a joint report by the Fraunhofer Institute and the industry association 'Bitkom' said that Germany's GDP could be boosted by a cumulative 267 billion euros by 2025 after introducing Industry 4.0 (Heng, 2014). Similarly, Lee and Lapira (2013) and Lee et al. (2013) expect significant economic outcomes from the implementation of Industry 4.0 techniques into today's industrial practices of production, logistics, and services. Realizing the potential benefits of smart manufacturing a recent summit of the Confederation of Indian Industry (CII) has also launched its smart manufacturing roadmap-2025 for India.

Ideally, a smart factory is characterized by intelligent machines which are self-aware and able to make and implement decisions on their own. While a significant attention has been given to make machines intelligent through the use of sensors and algorithms like machine learning, prognostics, embedded systems, etc., the opportunities and challenges of Industry 4.0 from the operations planning point of view are not adequately discussed in the literature (Wang et al., 2016; Meissner et al., 2017). However, the numerous challenges and opportunities that the penetration of Industry 4.0 into current-day manufacturing entails should not be underestimated. Consequently, innovative operations planning system is needed to handle the challenges and opportunities offered by smart factory under Industry 4.0.

The first significant challenge for the development of such operations planning system for smart factories lies in the necessity to integrate and better management of internal value chains. The autonomous decision-making under Industry 4.0 will require lesser or no mediation of operations managers in implementing various operations planning decisions which are generally interdependent (Ivanov et al., 2016). Therefore, managerial level coordination for smooth implementation of individual decisions will be out of trend (Kumar et al., 2018). For instance, smooth implementation of a production schedule depends on the availability of machines which in turn depends on adequate maintenance. Sometimes, planned maintenance may be delayed due to tiring and un-aligned production schedule. Such delay in maintenance activity may lead to increased process variability resulting into degraded product quality. The adequate inventory level of raw materials, Work-In-Process (WIP) items, and finished products may help the organization to meet delivery commitments during machine failures and other uncertainties. Despite the interdependencies, in practice, planning of these shop-floor functions are done in isolation (Hadidi et al., 2012). This necessitates a managerial level round table discussion for fine-tuning of multiple interdependent decisions before implementations. This brings in subjectivity and may lead to sub-optimal solutions. Moreover, under the concept of Industry 4.0, advanced data analytics aim to provide shop-floor decisions without human intervention thereby eliminating the possibility of managerial level coordination. In such situation, integrated operations planning can accomplish the joint consideration of multiple dependent shop-floor functions and can facilitate autonomous decision-making at shop-floor.

Though imperative, integration of multiple shop-floor functions brings in computational complexity which poses a second challenge in terms of responsiveness of the value chain. On the other hand, Industry 4.0 advocates real-time interface of customers and suppliers with the manufacturing facilities which in turn necessitates a high level of responsiveness in the value chain to sustain in competitive economy. Therefore, quick response to dynamic conditions created by machine failures, change in demand, uncertainty in supply, etc., is important in captivating the advantages of the digitization in industries.

Thus, a novel approach is required to deal with important but conflicting challenges of "integration" and "responsiveness" of operations planning for the next generation manufacturing systems. Such a novel operations planning system should have its roots within the technology enablers of next generation manufacturing systems itself. The combination of sensors and computing infrastructures increases the intelligence at the shop-floor. Such an intelligent shop-floor powered by the ubiquity of wireless communications, is enabling the automation of more and more industrial practices, and is driving the need to replace conventional planning techniques with schemes that can utilize the capabilities of CPS and IIoT. The future is a place where intelligence will be endowed to every entity on the shop-floor and to realize this vision; it is necessary to develop new schemes that can unlock the potential of decentralized data observation and decision-making. Utilizing these characteristics of smart factory, a novel operations planning approach is required which can integrate multiple dependent shop-floor functions and also provides quick response to dynamic conditions.

1.2 Problem description

It can be comprehended from above discussion that for successful implementation of the concepts of Industry 4.0 or smart manufacturing, it is radically essential to equip the manufacturing systems with autonomous decision-support system that can deal with two essential but conflicting challenges:

1) Integration of various shop-floor functions
2) Responsiveness of operations planning in dynamic conditions

The literature review[1] shows that integrated operations planning provides significant improvisation over conventional approaches. Despite the benefit, many industries have not succeeded in utilizing integrated approaches to maximize their performance. They often fail to fully integrate the shop-floor functions efficiently and effectively (Angerhofer and Angelides, 2006). This may be due to the reason that most of the available research in literature on integrated operations planning approaches is still at exploratory stage. Most of the integrated operations planning approaches are developed considering only two shop-floor functions for simplistic and/or specific manufacturing environments. Also, the approaches ponder unrealistic assumptions like single/identical machines, same buffer capacity, ignorance of machine age, fixed maintenance interval, etc., and are illustrated for hypothetical environments. Such assumptions/limitations are not realistic and may not be valid for all types of manufacturing industries. Thus, the results of integrated operations planning approaches need to be investigated for a wide range of manufacturing scenarios.

Based on above discussion, the literature of integrated operations planning need to be advanced by:

- relaxing unrealistic assumptions,
- considering more shop-floor functions for integration,
- developing integrated approaches for real and complex manufacturing environments,

[1]*The detailed literature review and research gaps are provided in chapter 2.*

- and performing comprehensive investigation to generalize the value of integrated approaches.

The integration of multiple shop-floor functions comes with computational complexity which poses second challenge in terms of responsiveness of the value chain. For example, most of the operations planning problems are NP-hard (non-deterministic polynomial-time hard) (Tambe et al., 2013; Tambe and Kulkarni, 2015). And the integration of multiple functions exponentially increases the computational complexity. For example, solution space of a joint problem of production and maintenance of 9 jobs-5 machines is 2^{50} (see, chapter 3), which increases exponentially by adding more functions (see, chapter 4). On the other hand, extensive use of information technology is allowing customers and suppliers to directly interact with the manufacturing facility, which in turn necessitates a high level of responsiveness in the value chain to sustain in competitive economy. Therefore, quick response to dynamic conditions is important in captivating the advantages of the digitization in industries. Failure of conventional independent operations planning practices in brining global view in decision-making and limitation of integrated approaches in terms of responsiveness, often result into apparent inclination toward experience-based operations planning in industries. Such experience-based approaches may not be effective for the manufacturing systems. Consequently, next essential advancement in the literature of integrated operations planning is to develop an autonomous decision-support system which provides fast response and uses the characteristics of smart factory like distributed intelligence/computation, communication, etc.

Focusing on the above advancements, a systematic literature review[2] is carried out. Critical findings and major research gaps are as follows:

Gap 1: Evaluating decisions of more than two operations planning functions together for realistic and complex manufacturing systems entirely eludes the literature.

Gap 2: Most of the integrated approaches have considered unrealistic assumptions like single/identical machines, single operation, common

[2] *The detailed literature review and research gaps are provided in chapter 2.*

processing time, same buffer capacity, ignorance of machine age, fixed maintenance interval, etc. These assumptions have made the approaches away from real life manufacturing environments.

Gap 3: Majority of the integrated approaches are illustrated for hypothetical simplistic environments limiting their practical use. This necessitates the development of integrated approaches for real and complex manufacturing systems.

Gap 4: Researchers have developed the integrated approaches for a specific problem environment which restrict their applicability. Thus, it is required to evaluate the results of integrated approaches for various manufacturing scenarios to generalize the value of integrated operations planning.

Gap 5: The integrated approaches consume high computation time in evaluating shop-floor decisions for complex problems, and show incapability to respond quickly to dynamic conditions.

1.3 Research objective

Based on the findings from literature review, the overall research objective is as follows:

Overall Objective: Development and performance investigation of an efficient, responsive, and integrated operations planning approach considering multiple dependent shop-floor functions for diverse real-world manufacturing environments to realize Industry 4.0 in industries.

The overall objective is further divided into the following Sub Objectives (SO):

SO1: Development and performance investigation of integrated approach considering production and maintenance

SO2: Case-based investigation of the value of integrated operations planning approach

SO3: Development and performance investigation of integrated yet distributed operations planning approach for next generation manufacturing systems

1.4 Focus of the research

In this research work, four essential shop-floor functions, i.e., Production (P), Maintenance (M), Quality (Q), and Inventory (I) have been considered for integration. In chapter 3, an integrated approach considering production and maintenance planning is developed and is comprehensively investigated for sensitivity, value over independent approach, robustness and implications in various manufacturing scenarios. The approach considers random failure behaviour of machines and multiple failure consequences. Also, the approach is examined under maintenance resource constraints considering various performance measures for an automotive firm. Chapter 4 develops an integrated approach considering production, maintenance, and inventory together for a complex manufacturing environment of an automotive firm and is comprehensively investigated for sensitivity analysis, comparison of optimization algorithms, comparison with conventional approaches, efficacy analysis of integration, and the study of robustness and implications in various manufacturing scenarios. To address the second challenge, a novel agent-based integrated yet distributed operations planning approach is engineered in chapter 5. The approach considers production, maintenance, quality, and inventory together, and is tested in complex environment of an automotive firm. Moreover, the approach is comprehensively investigated for comparison of optimization algorithms, value over conventional approaches, the effect of degree of integration, performance under dynamic conditions, and robustness and implications in various manufacturing scenarios. The focus of the thesis is summarized in table 1.1.

Table 1.1 Focus of the research

Chapters	Focus on	Functions integrated	Illustrated with	Investigation	Approach
Chapter 3	Comprehensive evaluation	P+M	Numerical example	Comprehensive	Centralized
		P+M with resource constraints	Industrial case	Analyzed under various performance measures	Centralized
Chapter 4	Application, and comprehensive investigation	P+M+I	Industrial case	Comprehensive	Centralized
Chapter 5	Development of novel approach, application, and comprehensive investigation	P+M+Q+I	Industrial case	Comprehensive	Distributed

Note: ‘P’, ‘M’, ‘Q’ and ‘I’ refer to production, maintenance, quality, and inventory respectively

1.5 Methodologies and innovations

Figure 1.1 shows the overview of the proposed methodology. The three prime work done in this thesis are highlighted as follows:

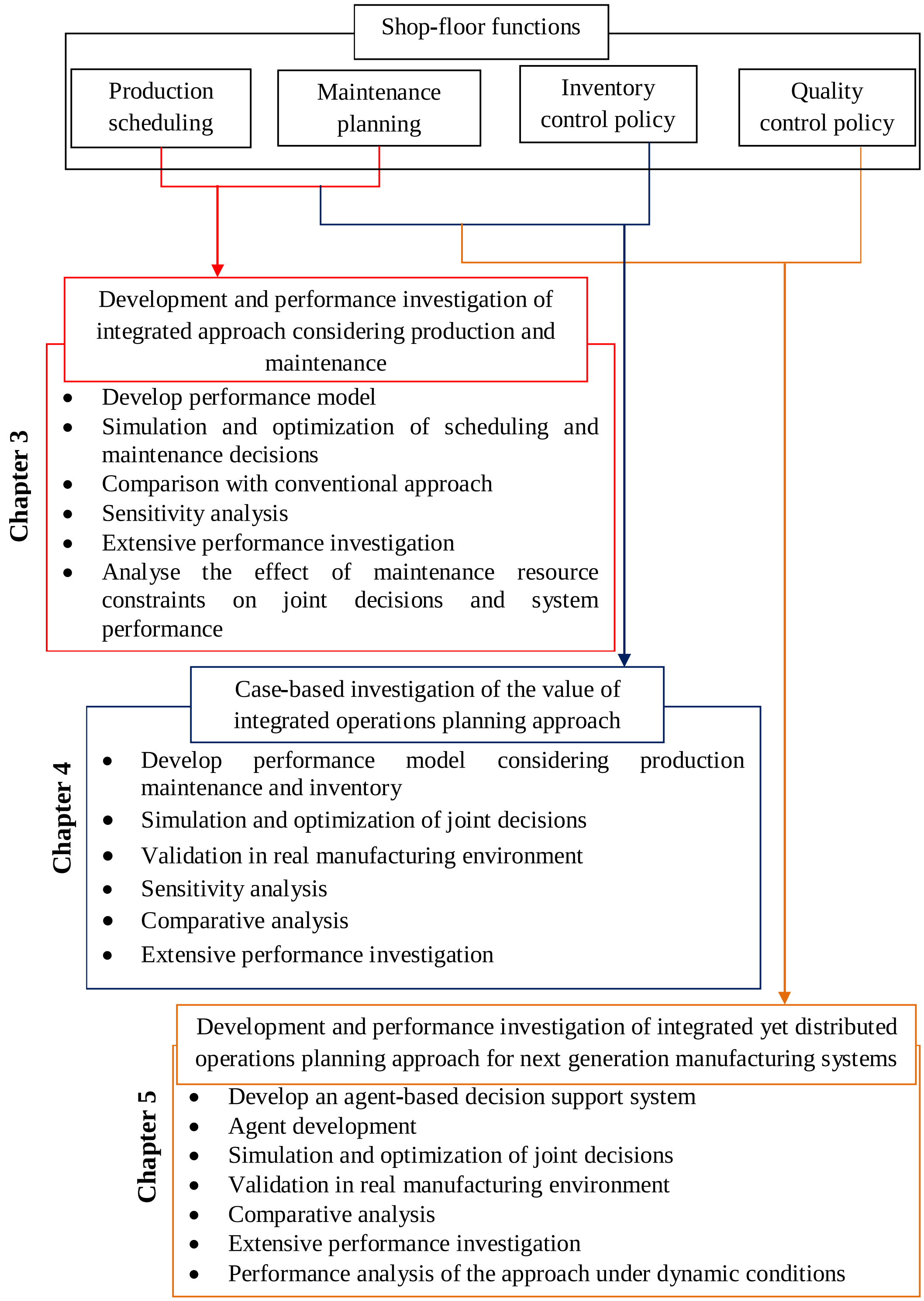


Figure 1.1 Overview of the proposed methodology

A. Development and performance investigation of integrated approach considering production and maintenance

The integrated approaches in literature consider unrealistic assumptions and are developed for simplistic manufacturing environments restricting the extensive application. To overcome this bottleneck, the first advancement progressed in this thesis is the development and comprehensive performance investigation of a more realistic integrated operations planning approach centred on the relationship between production scheduling and maintenance planning. This part of the research is a pioneering effort towards setting guidelines for industry practitioners to enable easy adaptation of the proposed approach. To do so, first, a performance model is developed to jointly optimize production and maintenance planning decisions for parallel machine system such that Overall Operations Cost (OOC) is minimized. The problem is strongly NP-hard and is of combinatorial type with large solution space (2^{50}). Also, the approach includes uncertainties in parameters like processing time, due date, times-to-repairs, etc., which further increases the computational complexity. Thus, a simulation-based optimization method is used to solve the problem. The proposed approach is illustrated through a numerical example. Also, systematic sensitivity analysis and economic comparison with conventional independent approach are carried out. Moreover, the proposed approach is comprehensively evaluated to generalize the performance over independent approach for 473 different manufacturing scenarios. These scenarios are generated by varying the number of machines and batches, machines' age, Preventive Maintenance (PM) restoration factor, quality control parameters, and due dates scenarios. Results show that the offered approach outperforms over independent approach under various scenarios. Such investigations help in evolving thumb rules for the adaption of integrated approaches in particular industrial case. Finally, the effect of maintenance resources unavailability is investigated on joint production and maintenance planning decisions and on system performance for an automotive firm considering various performance measures.

The novelty of this research is in the development of more realistic integrated operations planning approach for production and maintenance planning in industries. For the first time in the literature, the approach is comprehensively evaluated to generalize the performance over independent approach for various manufacturing scenarios. The integrated approach provides 0.6 to 35.8 percent improvements in OOC compared to independent approach for various manufacturing scenarios. The approach provides significant monetary savings to the industries having older machines and where product rejection cost is high. Thus, operations managers in such cases should be more interested in adopting integrated approaches to get improved system performances. The unavailability of maintenance resources significantly affects the joint decisions and system performance. The variations in the optimal values of different performance measures (makespan, total production cost, and system utilization) are found in the range of 14 to 30 percent.

B. Case-based investigation of the value of integrated operations planning approach

In the literature, most of the integrated approaches have considered two shop-floor functions and are illustrated for hypothetical manufacturing environments which limit the practical use of the approaches. To overcome this gap, an integrated approach considering three shop-floor functions i.e., production, maintenance, and inventory is engineered for a real and complex manufacturing environment of an automotive firm. The manufacturing environment of the firm consists of 23 different machines which processes 11 jobs. Machines are characterized by random failure behaviour, and intermediate buffers between machines are considered to ensure continuous production during disruption due to corrective or preventive maintenance actions. The approach evaluates multiple dependent operations planning decisions jointly. A performance model is developed for the joint decision-making. The problem is strongly NP-hard and is of combinatorial type with large solution space (10^{81}). Moreover, the presence of stochastic variables further increases the problem complexity. Therefore, simulation-based optimization method is used to solve the problem. Furthermore, a systematic sensitivity analysis, comparison of optimization algorithms (Adaptive

Thermo-Statistical Simulated Annealing, Hill Climb, and Random Solution), comparison with conventional approaches, and experiments to evaluate the efficacy of integration are performed. Moreover, a comprehensive performance evaluation has been carried out to analyze the robustness and implications of the proposed approach for various manufacturing scenarios. The scenarios are generated by varying machines' age, PM strategy of machines, manufacturing system (series/series-parallel), and process parameters (demand and processing time). Results of such pervasive performance investigations confirm the value of the proposed approach over conventional approaches.

The novelty of the research presented in this part is in development of an integrated approach considering production, maintenance, and inventory for real and complex manufacturing environment in flow shop configuration. An added contribution lies in the extensive performance investigation viz., sensitivity analysis, comparison of optimization algorithms, comparison with conventional approaches, efficacy analysis of integration, and the study of robustness and implications for various manufacturing scenarios. The results revealed that the integrated approach outperforms over conventional approaches and it delivers 4.2 to 21.6 percent economic improvements for various manufacturing scenarios. The benefit of the proposed approach is more prominent for the scenarios where the demand is high and uncertainty in processing time is present. The successful implementation of the approach developed in this part of the thesis will help in integrating various operations planning aspects at the decision-making stage itself, thereby reducing human intervention in coordinating and implementing various operations plans. This is believed to be one of the important requirements in realization of Industry 4.0 in industries.

The benefits increase by considering more shop-floor functions simultaneously. However, the computational complexity also increases. Therefore, novel approaches will be required to deal such complexity.

C. Development and performance investigation of integrated yet distributed operations planning approach for next generation manufacturing systems

It was observed from literature that integrated approaches consume high computation time in evaluating shop-floor decisions for complex problems and show incapability to respond quickly to dynamic conditions. Thus, in this part of the thesis, a novel agent-based integrated yet distributed operations planning approach is engineered to handle the important but conflicting challenges of integration and responsiveness for next generation manufacturing systems where intelligence at shop-floor allows distributing the computational tasks to various functional agents. The communication among the agents makes it feasible to incite global or integrated view through the coordinating agent. The approach considers multiple dependent shop-floor functions i.e., production, maintenance, quality, and inventory. It allows coordinated evaluation of shop-floor operations planning decisions viz., job sequences, batch-sizes, PM time, inspection intervals, sample sizes, and inventory levels. The problems of agents are NP-hard and are of combinatorial type with large solution space (10^{56}, 10^{46}, etc.). Moreover, the presence of stochastic variables significantly increases the problem complexity. Therefore, simulation-based optimization method is used to solve the problems. The approach is demonstrated for a representative industrial environment of an automotive firm. Also, comparison with conventional approaches, comparison of optimization algorithms, and the effect of degree of integration are analyzed. Further, the responsiveness of the approach is analyzed under unexpected shop-floor disturbances (machine failures, change in demand, and change in delivery schedule). Finally, an exhaustive performance investigation is carried out to generalize the value of the proposed approach over conventional approaches for a wide range of manufacturing scenarios. The scenarios are generated by varying machines' age, PM restoration factor, manufacturing system (series/series-parallel), and process parameters. The implication results and guidelines under various real-world industrial scenarios expand the realism of the proposed approach to the actual manufacturing systems. In succession, the approach provides dual advantage i.e., it integrates multiple dependent shop-floor functions and also improves the responsiveness of the system by distributed computation, thereby forming the basis for building an autonomous decision-support system.

The novelty of the work is in the development of an agent-based operations planning approach which integrates production, maintenance, quality, and inventory, and also provides quick response to dynamics conditions. Also, first time in literature, more than three functions are considered together for operations planning. The approach delivers a significant economic advantage (0.05 to 38.5 percent) over centralized approach under dynamic conditions. The improvisation is high in case of demand variation followed by sudden machine failures and change in delivery schedule. Also, the extensive performance investigation reveals that the proposed approach outperforms over centralized approach in terms of reduction in computation time (47 to 86 percent) for approximate same solution quality under various manufacturing scenarios. The reduction in computation time is more prominent for the scenarios where demand is high, system having old machines with low PM restoration factor. Moreover, the approach offers flexibility to choose degree of integration based on the performance and computational time of the overall approach. The approach can be used with any varying degree of asset intelligence making it easy to implement at the current industrial shop-floor and at more advanced systems. It is believed that integrated and responsive decision-making will be one of the important requirements in realization of Industry 4.0 in industries.

1.6 Thesis organization

The thesis is broadly divided into six chapters. The current chapter introduces the reader to the background of the work, outlines the research objectives and proposes the methodology with which the objectives are circumvented.

Chapter 2 presents a comprehensive literature review with emphasis on integrated approach considering two functions and three functions, case-based joint approaches, and distributed approaches, in terms of the technology driving the transformation, its benefits, its challenges and its global status.

Chapter 3 presents the development and performance investigation of integrated approach considering production and maintenance.

Chapter 4 presents case-based investigation of the value of integrated operations planning approach.

Chapter 5 presents the development and performance investigation of an agent-based integrated yet distributed operations planning approach for next generation manufacturing systems.

Chapter 6 summarizes the contributions, industrial implications and the future scope of the work.

1.7 Summary

The present thesis aims to advance the existing body of knowledge by comprehensively investigating the value of integrated operations planning approaches for various manufacturing scenarios and developing a novel agent-based integrated yet distributed approach. These approaches help in systematic expansion of intelligent operations planning in diverse real-world manufacturing environments.

Chapter 2

Literature review

To distinctly highlight the contribution of this work and its position in the available work, a systematic review of the literature with emphasis on integrated operations planning approaches, case studies on integrated operations planning approaches and distributed approach, and their application in manufacturing operations planning is carried out. In the end, findings from literature review and detailed research gaps are outlined.

2.1 Introduction

Manufacturing, over the years, has evolved through three major revolutions brought out by the impact of mechanization, electricity, and information technology (Evans and Annunziata, 2012) as depicted in figure 2.1.

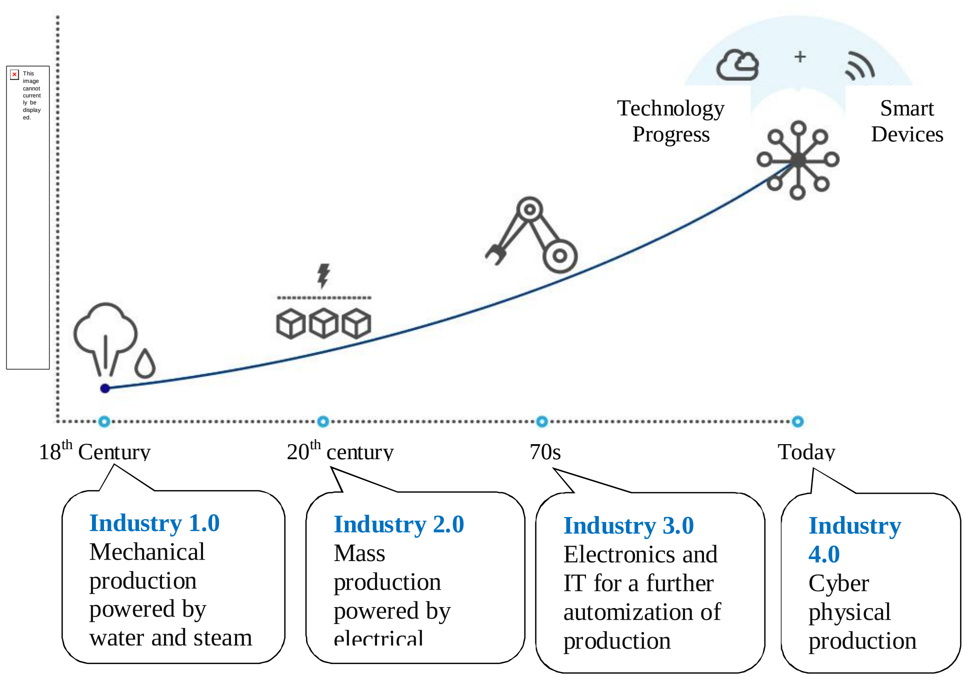


Figure 2.1 The advent of the 4th Industrial Revolution

The next big change in manufacturing has its roots in intelligence, machine-to-machine communications, and sensing technology. The role being played by computers has evolved greatly over past few years. The emergence of the computer as a smart device that can operate over the cloud, in conjunction with its miniaturization and the unstoppable spread of the Internet, makes it potent of being pervasive in all facets of life. This offers the opportunity to network assets, resources, information and people together into an Internet of Things and Services (Evans and Annunziata, 2012). The manufacturing industry is no exception to this change, and is undergoing a technological evolution that is being termed as the fourth industrial revolution or 'Industry 4.0' (Kagermann et al., 2013). Industry 4.0 forms a synonym for the transformation of today's factories into smart factories, which are intended to address and overcome the current challenges of shorter product lifecycles, highly customized products, and stiff global competition (Kagermann et al., 2013). In the same line, the present research aims to explore the notion of next industrial revolution (or Industry 4.0) from operations planning point of view. The work reported in this thesis envisages the integrated operations planning as an important requirement of the next generation intelligent factory. Accordingly, a detailed literature review of integrated operations planning is carried out. It has helped in identifying clear technology needs for the development of more realistic, complex but responsive integrated operations planning system. Specifically, the review focuses on integrated approaches that consider more than two shop-floor functions, case studies on integrated operations planning approaches and distributed decision-making and their applications in manufacturing operations planning. The same is discussed in the following sections.

2.2 Shop-floor operations planning

Modern manufacturing systems rely on efficient and effective planning of shop-floor operations. In any shop-floor, production scheduling, maintenance planning, quality control, and inventory control are critical strategic shop-floor functions which are generally interdependent. For instance, smooth implementation of a production schedule depends on the availability of machines which in turn depends on adequate maintenance. Sometimes, planned maintenance may be delayed due to tiring and un-aligned production schedule. Such delay in maintenance activity may lead to increased process variability resulting into degraded product quality. The adequate inventory level of raw materials, WIP items, and finished products may help the organization to meet delivery commitments and production during machine failures and other uncertainties. Despite the interdependencies, conventionally, planning of these shop-floor functions are done in isolation (Hadidi et al., 2012). Significant amount of literature is available on independent approaches (Dhillon, 2002; Chan and Chan, 2004; Jardine and Tsang, 2006; Yu et al., 2007; Sharma et al., 2011). Such independent planning is done by different functional teams. The resulting plans of a specific team may disrupt other functional plans. Tuning out effect of such interdependencies will impact the quality of decisions which are generally taken on shop-floor (Hadidi et al., 2012). This necessitates a managerial level round table discussion for fine-tuning of multiple interdependent decisions before implementations. This brings in subjectivity and may lead to sub-optimal solutions. These issues motivate the researchers to consider the interdependencies between shop-floor functions. Due to the complexity involved in consideration of interdependencies, some researchers have partially integrated the shop-floor functions and the approach is termed as interrelated approach. In interrelated approach, while optimizing one function, the other function/s is/are kept as a constraint. The approach is found better than the independent approach (Pandey et al., 2010; Purohit and Lad, 2015). A sufficient amount of literature can be found on interrelated approach (Qi et al., 1999; Sadfi et al., 2005; Low et al., 2008; Mosheiov and Sidney, 2010).

Though interrelated approach is better than the independent approach, the partial consideration of functional interdependencies may impose restrictions in exploring the better results. Gradually, an improvisation over interrelated approach evolved where interdependencies between allied functions are deeply examined, and all the decisions variables are simultaneously treated for overall optimization. It was termed as “Integrated Approach” and gained significant attention as it proved to be superior from previous approaches (Hadidi et al., 2012). In literature, research on integrated approaches has shown promising results from manufacturing system performance point of view. For example, considering production and maintenance together, Cassady and Kutanoglu (2003) achieved 30 percent improvement in the expected total weighted tardiness. Similarly, Pandey et al. (2011) found an average improvement of 80 percent in expected cost per unit time through integrating production and maintenance decisions. Zied et al. (2011) have obtained 6 percent improvement in total cost by combining inventory and maintenance.

The past decade and a half have witnessed significant interest from researchers towards integrated operations planning. Years 2002-2011 were the exploratory period for such research, and integrated approaches were mostly developed and investigated for single machine problem. Apart from this, assumptions like machine made up of single component, perfect or minimal repair, fixed maintenance period, etc., were also made by the researchers. During years 2011-2018, few advanced approaches in this area appeared in the literature. A detailed review is presented in next sections.

Parallel to the development of research on integrated operations planning, the growth in sensing and computing technology was shaping paradigm shift in manufacturing. This has given birth to fourth industrial revolution or Industry 4.0. Under the concept of Industry 4.0, advanced data analytics aims to provide shop-floor decisions without human intervention. Thus, managerial level coordination for smooth implementation of individual decisions will be out of trend. In such a situation, integrated operations planning approach can be seen as one of the essential requirements for successful implementation of Industry 4.0 concepts in industries. Unfortunately, integrated operations planning was never researched or imagined as a technology enabler for industry 4.0. Hence, available research on integrated operations planning fails to appreciate to the need of next generation manufacturing systems.

The present chapter first provides a detailed review of literature pertaining to integrated operations planning. It is identified that computational complexity poses a big challenge in the adaption of integrated approaches in industries. This becomes even more important in the case of Industry 4.0, where responsiveness of value chain is critical. Keeping the typical characteristics of next generation intelligent manufacturing in mind, distributed computing and decision-making is identified as one of the alternatives to overcome such challenges. Consequently, the literature pertaining to distributed approaches and their application in manufacturing operations planning are explored in this chapter.

2.3 Integrating two functions at a time

Kaabi et al. (2002) have solved the joint problem of job scheduling and PM planning such that tardiness is minimized for single machine. They considered that the machine must be maintained after continuously working for certain period. It is assumed that there exists an interval in which maintenance cost is constant. The upper and lower bounds of the interval are assumed fixed; however the same should be based on the machine health and other system specific parameters. A numerical example was presented to illustrate the approach. Cassady and Kutanoglu (2003) have proposed an integrated model considering production scheduling and PM planning for a single machine system. They assumed that the times-to-failures of machine follow Weibull distribution; the machine is minimally repaired when it fails; and PM restores the machine to as good as new state. Through a numerical illustration, authors have shown the effectiveness of the proposed model. However, their solution procedure is limited to small problems (6-jobs or less). Leng et al. (2006) and Sortrakul and Cassady (2007) further extended the work of Cassady and Kutanoglu (2003) and proposed chaotic partial swarm optimization heuristic and Genetic Algorithm (GA)-based heuristics, respectively, to solve the integrated mathematical model for single machine production scheduling and PM planning as a multi-objective optimization problem. Authors have focused more on optimization procedure rather than efficiency of the model and structural properties of optimal solution. Ji et al. (2007) have considered a single machine scheduling problem with several periodic maintenance activities and the objective was to find a schedule that minimizes the makespan, subjected to periodic maintenance and non-resumable jobs. Yulan et al. (2008) studied the joint determination of PM planning and production scheduling for a single machine with multiple objectives by simultaneously minimizing the maintenance cost, makespan, total weighted completion time of jobs, total weighted tardiness, and maximizing machine availability. They used multi-objective GA to solve the joint optimization problem. Motaghedi-Larijani et al. (2011) studied single machine scheduling problem with sequence-dependent setup times so as to minimize the total costs of tardiness and earliness of all jobs and costs related to machine processing and maintenance activities. They determined the processing times of jobs according to a deterioration function, and also planned the maintenance activities in order to reduce processing times of jobs. A new hybrid Simulated Annealing (SA) algorithm was proposed, which utilizes local heuristic search to improve the chance of obtaining better optimal solutions. Benmansour et al. (2011) focused on the integrating production and maintenance functions in the just-in-time context. They have studied the joint scheduling 'n' jobs and PM problem in a single machine to minimize the sum of earliness and tardiness costs and the maintenance cost. They have used a simulation tool to determine job scheduling and PM planning decisions. Hadidi and Rahim (2011) have developed a joint approach which integrates the decisions of preventive maintenance and job order sequencing simultaneously for a single machine. The objective was to find the job order sequence and maintenance decisions that would minimize the expected cost. In extended work (Hadidi and Rahim, 2012), authors have offered an integrated approach considering production scheduling and PM scheduling for a single machine that is subject to random failures. The objective was to determine the job schedule as well as PM schedule that minimize the total weighted expected jobs completion times. In both the works, authors assumed that the maintenance is perfect and restores the machine to an 'as good as new' condition.

It has been observed that excessive maintenance results in unnecessary costs, while inadequately maintained equipment may produce defective products resulting into high rejection cost. This has attracted attention of researchers for the joint consideration of maintenance and quality policies. For instance, Lam and Rahim (2002) have studied an integrated model for the joint economic design of $\overline{X}$ control charts and maintenance schedules, and simultaneously determined the economic production quantity and production run length for a deteriorating production system. They have evaluated the performance of the model through numerical examples. Linderman et al.

(2005) have developed an analytical model to determine optimal policy to coordinate quality control and planned maintenance, and demonstrated its economic benefits for single machine system. They assumed that the times-to-failures of machine follow Weibull distribution, and have used an $\bar{X}$ control chart to monitor the process. They found that coordinated decisions provide 0.1 to 54 percent economic improvement over uncoordinated decisions. Kuo (2006) has studied the interaction effect between machine health and product quality to obtain the joint decisions. Author considered discrete-time Markovian deteriorating machine, and assumed that machine state transition occurs at the end of a period with a fixed probability which is revealed through inspection. Zhou and Zhu (2008) developed an integrated model of control chart and maintenance management with reference to the integrated model proposed by Linderman et al. (2005). In their model, control chart was used to monitor the equipment and to provide signals that indicate equipment deterioration, while planned maintenance was scheduled at regular intervals to preempt equipment failure. Yeung et al. (2008) have developed a joint model to monitor the output of the production process and to determine when to perform corrective and condition-based maintenance so as to optimize the sample, control chart parameters, and interval for performing PM. Lad and Kulkarni (2008) stated that failure of machine tool may either stop the machine or leads to poor performance like increase rejections. Pandey et al. (2010) developed a model for obtaining optimal PM interval based on block replacement policy to incorporate the effect of rejection cost for single machine. They have compared the economic performance of the proposed joint model to conventional independent model. The proposed model outperforms over conventional model and the improvements are more significant at higher production rate, lower cost of lost production, and higher rejection cost. Bouslah et al. (2016) investigated the joint design and optimization of continuous sampling plan, make-to-stock production and PM of a stochastic production system subject to both quality and reliability deteriorations. The optimization problem was to minimize the total incurred cost under a constraint on the outgoing quality. They took into account the relationship between quality imperfection and lot sizing, and assumed a 100% inspection process upon reception.

Though joint production and maintenance policies can enhance the performance of manufacturing systems, it is still affected by unavailability of machine/s due to unexpected failure or PM. To limit the propagation of disruptions of machine's unavailability, most of the industries are keeping intermediate buffers between machines. Carrying buffers incur cost to organization; thus, inventory level of buffers needs to be optimized. Li and Zuo (2007) stated that inventory control decisions are directly linked to maintenance and should be considered simultaneously. They studied the interaction between maintenance activities and inventory control policies for single machine case where PM is considered as minimal repair. They illustrated the method through a numerical example and showed that joint maintenance and inventory optimization can save 10.2 percent of average total cost. Rezg et al. (2008) presented a joint model to determine optimal buffer size and age-based PM policy for failure-prone single machine. They illustrated the model through a numerical example, and ignored the stochastic nature of operations planning parameters like demand, processing time, etc. Radhoui et al. (2009) have coupled the quality control and PM policies for a randomly failing production system producing conforming and non-conforming units. They developed a mathematical model and combined it with simulation in order to determine, simultaneously, the optimal rate of non-conforming units observed on each lot and the optimal size of a buffer stock which minimizes the expected total cost per unit time.

Though the assumption of single machine was prevalent in the literature, limited studies have modelled the problem of integration for multiple machines in flow-shop and job-shop. For example, Allaoui et al. (2008) have studied the problem of jointly scheduling 'n' jobs and PM in a two-machine flow-shop to minimize the makespan. They considered that one of the two machines must be maintained once during the scheduling period. They showed that the problem is NP-hard, and illustrated the method through a numerical example. Similarly, Berrichi et al. (2009) proposed an integrated model to solve the combined production and maintenance scheduling problem for identical parallel machines case aiming to simultaneously optimize two criteria: the makespan and system unavailability. They assumed that times-to-failures of a machine follow exponential distribution. They have used modified GA for optimization and demonstrated the approach for hypothetical system consisting of eight machines. Dong (2013) studied more realistic identical parallel machines scheduling problem with flexible maintenance activities to minimize the total cost involved with the completion time and the unavailable time. Author proposed a branch and bound algorithm based on column generation approach. Mirabedini et al. (2014) presented PM scheduling model for parallel machines considering reliability level, PM time, and cost. They have considered two types of PM: the first type improves the reliability of jobs and machines and the second type of PM restores the machine to the as good as new condition. Lee et al. (2015) studied parallel machines scheduling problem considering single maintenance activity on each machine that minimizes the total tardiness. They developed branch and bound algorithm for small size problem and hybrid GA for large size problem. Wang and Liu (2015) investigated parallel machines scheduling problem with flexible PM activities on resources (machines and moulds) to optimize makespan and unavailability of resources. Authors have proposed a multi-objective optimization algorithm based on the non-dominated sorting GA.

The above works consider unlimited availability of maintenance resources. However, it is often impossible to perform all the desirable maintenance actions due to the limitation on maintenance resources such as spare parts, maintenance technicians, etc. (Do et al., 2015). Sometimes, situation may arise where multiple machines require maintenance and concern department may have limited technicians and spares to tackle the requirement. Due to this, maintenance of some machines may be delayed which may eventually affect the production schedule. As a consequence, decision on the quantity of maintenance resources; their provision policy and their allocation are crucial for operations planning. In the context of spare parts and maintenance planning, Van and Dekker (2011) insisted on how pivotal spare parts management was within the scope of a maintenance strategy. Panagiotidou (2014) proposed continuous and periodic review policies to supply the necessary spare parts for multiple identical machines subjected to failures. These strategies are based on a joint optimization of maintenance and spare parts ordering policies. Jin et al. (2015) proposed a policy which jointly optimizes the inventory of spares, the capacity of repair, and the maintenance under the game-theoretical framework. Safaie et al. (2010) formulated a maintenance workforce-constrained scheduling problem as a bi-objective mixed-integer programming model with the aim of simultaneously minimizing the workforce requirements and the total weighted flow time of jobs. They have assumed that the other resources such as tools, spare parts, etc., are available at the time of failure. Zhu et al. (2015) addressed a single machine scheduling problem with an option to perform a deteriorating and resource-dependent maintenance activity. They introduced the concept of controllable maintenance where the duration of the maintenance is dependent on the repair resources. Authors analyzed three regular measures viz., makespan, flow time and tardiness, and provide efficient polynomial-time algorithms to minimize the sum of each measured cost and resource cost.

In joint production and inventory context, Solimanpur and Elmi (2011) proposed an integrated approach for flow-shop group scheduling with limited buffers assuming same buffer capacity. They have developed a mathematical model with the objective of minimizing makespan and used Tabu Search (TS) algorithm to solve the problem. Wang and Wang (2013) developed an inventory based job-shop scheduling model to optimize makespan and inventory capacity simultaneously. They designed some tailor-made genetic operators and then proposed a hybrid GA to solve the problem. Van Horenbeek et al. (2013) presented the detailed literature review on joint inventory and maintenance context. They concluded that non-identical multi-machine systems are not explored for such consideration. Karimi and Davoudpour (2016) proposed a more realistic integrated approach for stage-dependent inventory planning in multi-factory scheduling with batch transportation and delivery. In scheduling systems, they have considered that only after it's processing, a job can be delivered, and the processed job should remain in the system until its batch's completion time. While on receiving at a factory, jobs should wait until their process has started. These would impose the WIP inventory cost. Also, holding cost is incurred on the jobs that are delivered to the customer before their due dates. Thus, the objective of this study was to find a schedule with trade-off among holding costs and delivery cost. Liu and Kozan (2016) have solved a job-shop scheduling problem utilizing hybrid meta-heuristic algorithm that simultaneously considers four different stage-dependent buffering requirements with the parallel use of identical-function machines. They have shown that neglecting buffer requirements in a scheduling problem often results in inapplicability in many complex real-world applications.

2.4 Integrating three functions at a time

From above discussion, it can be comprehended that during the exploratory phase, apart from the assumptions related to simplistic manufacturing environment, researchers were mostly focused on integration of only two of the functions at a time. More than two functions integration were first addressed by Pandey et al. (2011). The authors modeled the interactions between production, maintenance, and quality control policies and developed a methodology of their joint consideration for single machine case. Through numerical example of small problem size, authors concluded that integrated approach outperforms over independent approach.

Berthaut et al. (2011) proposed a joint PM and production/inventory control policy for a single machine, mono-product manufacturing cell. The inventory control policy is based on the building of a safety stock to protect against demand shortages during shutdown periods caused by corrective and preventive activities. The maintenance of the manufacturing cell is performed at failures or at scheduled periods if the time since the last maintenance action is below a specified threshold age. They assumed that failures are instantaneously detected and maintenance restores the machine to as good as new condition. Further, Nazid (2011) developed a joint production and fixed maintenance planning model for the single machine and considered inventory cost as constraint. Author modeled the problem as a linear mixed-integer programming and used optimization solver Xpress-MP. In the model, PM is carried out in time windows to restore the production line to an as good as new status. This model explicitly takes into account the reliability parameters of the system and its capacity in the development of optimal production and maintenance planning. Yedes et al. (2012) proposed joint single-vendor single-buyer strategies by integrating production, inventory, and maintenance policies. They assumed that out-of-control state is instantaneously detected;

time to repair is negligible; and maintenance is perfect. The approach was demonstrated using a numerical problem. Nourelfath and Chˆatelet (2012) developed a joint production, inventory, and maintenance model to evaluate lot-sizing and PM policy that minimizes total production cost for a system composed of a set of parallel components. They assumed two possible causes for system failure: the independent failure of single components and the simultaneous common cause failure of all components. Authors have considered an age-based perfect maintenance policy. They have shown the effectiveness of the approach by performing computational experiments. Fakher et al. (2014) developed a model by integrating production and sales planning with PM scheduling taking into account quality aspects of the production system to maximize the total profit. They have illustrated the model through numerical example, and tested the sensitivity of the model to multiple parameters. Based on the results obtained, integrated model showed between 0.5 to 20 percent improvements compared to the non-integrated models. Along these lines, Liu et al. (2015) developed a joint model considering production, inventory, and PM for a machine processing multiple products to maximize the expected profit per unit time. They have considered PM as perfect and carried out at some setup points, and have assumed fixed product's batch-size. Authors have used integer programming for optimization and conclude that production batch sizes, inventory control, and PM policy should be studied together as these are interdependent. Dellagi et al. (2017) developed a mathematical model to obtain production and PM schedule by minimizing the total cost of production, maintenance, and inventory taking into account constraint of inventory balance for single machine system. Authors also studied the effect of demand variability on smoothing penalty and production plan, inventory, and PM schedule. Nahas and Nourelfath (2018) have proposed a joint approach for a series manufacturing line composed of several machines separated by intermediate buffers of finite capacity. The aim was to find the optimal number of PM actions performed on each machine, the optimal selection of machines and the optimal buffer allocation plan that minimize the total system cost, while providing the desired system throughput level.

It can be observed that, year 2011 onwards, researchers have attempted more complex problems of integrating more than two functions. Investigations have shown more significant economic benefits for such complex problems. However, one can clearly see that the assumptions related to simplified shop-floor environment like single machine are still prevalent in the literature. Moreover, none of these research articles provides evidence of the development of such joint approaches on actual manufacturing environment.

2.5 Case studies on integrated operations planning

Tambe et al. (2013) have developed a mathematical model for opportunistic maintenance decision-making for a multi-component system at planned as well as unplanned opportunities considering the effect of failures on quality and production schedule. The approach is applied to a real-life case study of a high pressure die casting machine. Authors have used SA technique to solve complex and combinatorial problem; their work was limited to multi-component single machine case. In extended work, Tambe and Kulkarni (2015) have demonstrated the applicability of the integrated approach through a case study. They developed selective maintenance and quality control decision optimization framework considering the production schedule of the machine. They derive an optimal maintenance decision, consisting of one of the three actions (repair, replace or do-nothing) for the system components along with the optimal sample size, the acceptance number, and the time between samples by taking into account the optimal production schedule. The authors have found the problem NP-hard and solved the same using GA. Liao et al. (2016) proposed a combined production scheduling and PM model to minimize total completion time and maintenance cost for single-machine system under group production. Through a case study, they found that the model could reduce maintenance cost and completion time more effectively. Kiani and Taghipour (2017) proposed a method to optimize job sequence and PM jointly for single machine system that processes ‘n’ jobs. They tested the method through case study and concluded that optimal solution depends on the input parameters of the model, most importantly, the jobs’ processing times and the distributions of defects arrival and delay time. Cheng et al. (2017) presented a joint optimization model to optimize production lot sizing and PM threshold for a multi-component production system. They illustrated the model through a case study of a cluster tool. The results of comparative experiment have shown that the proposed strategy performs better than the individual strategies. Liu et al. (2015) proposed an integrated model considering production, maintenance, and inventory together and tested the model in a single machine system that produces six different sizes cast iron pipes alternately. Erfanian and Pirayesh (2016) developed an integrated model of aggregate production planning and maintenance planning to determine the optimal plan of production and PM in each period. They conducted a case study in a pharmaceutical company to exhibit the performance of the model. Zandieh et al. (2017) developed a joint model to determine the buffer and PM strategy in water heater production line. The model is solved for multiple objectives and an integrated simulation and meta-heuristic algorithm have been used to solve the same.

2.6 Observations

One can easily make out from the above discussion that integrated operations planning has gained significant attention from researchers in the past two decades. However, the literature lacks a comprehensive system to handle such multi-function integration. For example, only limited literature focuses on the integration of three shop-floor functions; and apparently no literature on such integration for more than three shop-floor function is available. Consideration of a realistic shop-floor environment consisting of many machines and jobs with a complex flow of materials will enhance the applicability of such approaches in industries. However, adding such complexities makes the problem computationally very challenging. More importantly, the computational complexity increases exponentially with the number of shop-floor functions considered for integration. In addition, most of the integrated operations planning problems are proved NP-hard (Tambe et al., 2013; Tambe and Kulkarni, 2015; Kaplanoglu, 2014) and are of combinatorial type. Further, it is also important for integrated approaches to ponder stochastic nature of parameters like uncertainties in machine failure, variability involved in time to repair, etc. Due to these, the integrated problem becomes extremely complex and consumes high computation time in evaluating optimized decisions. Moreover, relating this literature and observations with the discussion presented in previous chapter where the need of such integrated approaches for the next generation manufacturing systems is emphasized, a comprehensive and responsive operations planning system becomes the need for the hour. Recently, Meissner et al. (2017) concluded that distribution of computational task might be one of the alternatives to deal with the complexity associated with consideration of multiple shop-floor functions together. Moreover, as mentioned in the previous chapter, such distributed approaches are aligned with the technology enablers of Industry 4.0. Motivated from the observations, following section reviews the literature on distributed decision-making and their application in manufacturing operations planning.

2.7 Distributed approach

There are ample instances in literature where distributed approaches have been put to use to tackle complex, and dynamic problems. The approach is known for being more responsive and agile that makes them highly relevant in today's competitive market. The distributed system contains a collection of local controllers for individual resources within a manufacturing system. Local controllers are given full autonomy to make local decisions based on their local status and objectives, whereas global decisions are made through the interactions amongst local controllers (Heragu et al., 2002). Since each local controller attempts to achieve its local objectives without considering global objectives, global control decisions based on distributed approach are not always optimized. With a view to combining the positive features of integrated and distributed approaches, hybrid approach has attracted much academic attention. One of the simplest hybrid approaches is to involve a level of global control over the coordination between a set of distributed resources. This global control is usually provided by introducing a supervisory controller into distributed architecture for integrated decision-making. For instance, Anosike and Zhang (2009) have proposed an agent-based integrated decision platform for dynamic manufacturing systems. The platform enables planning and control decisions to be considered together with system reconfiguration and restructure. They solved the planning and scheduling problem using optimally controlled bidding method. The platform is tested on a simplified functional layout manufacturing system. In their extended work, Zhang and Anosike (2012) presented an agent-based modeling and control approach with a particular focus on the distributed simulation mechanism. Russell et al. (2010) stated that Multi-Agent System (MAS) can provide a new way for solving distributed, dynamic and hard problems. Where, an agent is defined as anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators. This capability makes multi-agent entities a good candidate to handle the distributed, dynamic, and complex problems. However, MAS is rarely employed for manufacturing environments and machine scheduling domain. One of the rare studies in this domain is presented by Khelifati and Benbouzid-Sitayeb (2011). They proposed a distributed approach which is using multi-agent paradigm for scheduling independent jobs and maintenance operations in the flow-shop sequencing problem. The approach introduces a dialogue between two communities of agents (production and maintenance) leading to a high level of cooperation. It also provides a framework in order to react to the disturbances occurring in the workshop. Duan et al. (2012) proposed a negotiation-based optimization method for scheduling of a manufacturing system. There are two main agent types in their paper which are manufacturers and suppliers. In their paper, Erol et al. (2012) proposed multi-agent based approach for machine scheduling together with the automated guided vehicles in a flexible manufacturing environment. The approach works under a real-time environment and generates feasible schedules using negotiation/bidding mechanisms between agents. This approach is tested on off-line scheduling problems from the literature. Lou et al. (2012) presented a multi-agent based proactive-reactive scheduling for job-shop scheduling problem. In the proactive scheduling, the objective is to generate a robust predictive schedule against known uncertainties. While in the reactive scheduling, the objective is to dynamically rectify the predictive schedule to adapt to unknown uncertainties viz., the reactive scheduling stage is actually complementary to the proactive scheduling stage. Case study showed that this scheduling mechanism generates more robust schedules than the classical scheduling mechanism. Henchiri and Ennigrou (2013) proposed a multi-agent model based on hybridization of TS method and Particle Swarm Optimization (PSO) in order to solve flexible job-shop scheduling problem. The objective was to minimize the makespan. The model was composed of Resource agents and an Interface agent. On each Resource agent, TS based local optimization process was placed to execute local diversification techniques. A global optimization process based on PSO has been integrated at the Interface agent. Polyakovskiy and M'Hallah (2014) proposed a MAS based heuristic to solve weighted earliness tardiness parallel machine problem where jobs have different processing times and distinct due dates. The MAS has three types of agents: I, G, and M. The I-agents are free jobs that need to be scheduled, whereas the G-agents are groups of jobs already assigned to machines. The M-agent acts as the system's manager of the independent intelligent I-agent and G-agent, which are driven by their own goals, fitness assessments, and context-dependent decision rules. Savino et al. (2014) proposed an agent system for a multi-objective flow-shop scheduling problem in a production context characterized by diversified, high-volume production mix. The flow-shop was characterized by multi-machine workstations, transfer batches, sequence-dependent setup times and possible re-entrant jobs. A coordination mechanism between agents and a dedicated scheduling algorithm managed by the MAS allowed to front this kind of events optimizing concurrent objectives like WIP, makespan, and buffer queues. In their work, Kaplanoglu (2014) proposed a collaborative optimization method for single machine scheduling problem with sequence-dependent setup times and maintenance constraints in a dynamic manufacturing environment. Author has used BDI (brief-desire-intention) model for agent development and SA method for optimization. The method is tested under real-time manufacturing environment where computational time plays a critical role during decision-making process. For make-to-order manufacturing system, He et al. (2014) proposed an agent bidding mechanism that is particularly designed and attempted to enhance the operational flexibility of manufacturing system in dealing with dynamic changes in business environment. They have used GA based optimization process and demonstrated the mechanism in Mexico manufacturing company.

Considering inventory–production–transportation, Long and Zhang (2014) have developed an integrated agent-based framework for modeling and distributed simulation of supply chains. They developed methods and tools to reduce the complexity and difficulty of simulation models. Zhang et al. (2014) have proposed MAS based real-time production scheduling for ubiquitous shop-floor environment. They used GA based solving method for real-time scheduling agent. Martin et al. (2016) have presented a general agent-based distributed framework where each agent implements a different meta-heuristic/local search algorithm. The approach is performed well for two benchmark problems, i.e., permutation flow-shop scheduling and capacitated vehicle routing. de Oliveira et al. (2016) proposed a coordinated decentralize optimization method for production planning and plant-wide control of Williams-Otto plant. The optimization problem is decomposed into smaller coordinated problems to ensure that the found local optimum also meets the requirements of the global system. The results for distributed optimization are satisfactory and very similar to the global optimum. Mishra et al. (2016) designed a cloud-based MAS architecture to achieve distributed production process management and control. The architecture assists manufacturing industry to establish real-time information exchange between autonomous agents. They have used algorithm portfolio which is composed of various algorithms such as GA, TS, SA, etc., and select an algorithm that results in high performance in the designed time limit. Reddy et al. (2017) proposed MAS based simulation approach for planning procurement operations and scheduling with multiple cross-docks. They conclude that with MAS framework and negotiation protocols, is a better approach rather than the conventional simulation and optimization. Recently, Upasani et al. (2017) developed agent-based distributed algorithm that performs intelligent maintenance planning for identical parallel multi-component machines in a job-shop manufacturing scenario. They have used discrete event simulation, and Brute Force Search, Memetic Algorithm and Particle Swarm methods for optimization. The cost-based technique has been used for negotiation. They found distributed approach outperforms over centralized approach.

Motivated from the two distinct spheres of radical research viz., integrated operations planning and distributed computations, the present thesis aims to develop advanced integrated approaches considering multiple dependent shop-floor functions, and a novel responsive agent-based distributed approach to solve, first time in literature, a very complex four shop-floor functions integration problem for a real-life manufacturing system. It further aims to investigate the superiority of the proposed approaches for various manufacturing scenarios and suitability over the conventional approaches.

2.8 Summary

The detailed literature review presented above is summarized in this section to explicitly highlight the need of technological advancement in the area of integrated operations planning.

1. It can be seen from above literature review that the integrated approaches are becoming important area of research. However, the current status of literature is more at the exploratory stage. For example, most of the researchers have explored the integrated approaches for single machine case. However, manufacturing industries generally have multiple machines in job-shop or flow-shop type of production environment.
2. The available work on such multi-machines cases is limited to simplistic assumptions, like fixed maintenance interval, perfect or minimal repair, ignorance of machine age, single operation, common processing time, same buffer capacity, etc. Thus, the results may not be of much practical use. Also, the effects of stochastic nature of various parameters on integrated approach are not studied in literature.
3. To the best of our knowledge, no attempt has been made to perform a comprehensive evaluation considering various manufacturing scenarios to generalize the importance of integrated approaches.
4. Most of the integrated approaches consider unlimited availability of maintenance resources. However, it is often impossible to perform all the desirable maintenance actions due to the limitation on maintenance resources such as spare parts, maintenance technicians, etc. Also, unavailability of maintenance resources affects operations planning decisions. Despite the effect, the spares provision policy and workforce

sizing for complex manufacturing environment are not studied in the literature.

5. Development of approaches considering more than three operations planning functions is not available in the literature.
6. Only limited literature is available that attempt to develop the integrated approaches for real shop-floor environment consisting of many machines and jobs with a complex flow of materials, this restricts the applicability of the integrated approaches in industries.
7. Adding such complexities make the problem computationally very challenging. More importantly, the computational complexity increases exponentially with the number of shop-floor functions considered for integration. Due to the complexity involved, integrated approaches consume high computation time in evaluating shop-floor operations planning decisions for complex problems, and show incapability to respond quickly to dynamic conditions.
8. To the best of our knowledge, the domain of integrated operations planning is never studied and developed in the context of next generation manufacturing paradigm.
9. The distributed approaches from shop-floor operations planning perspective are in initial phase of development. Very few such approaches are reported in the literature. Moreover, the reported approaches are developed for simplistic and hypothetical environments considering one or two shop-floor function only. Therefore, distributed approaches need to be explored for real, complex and dynamic manufacturing systems integrating various interdependent shop-floor functions.

These findings are summarized in the form of specific research gaps and highlighted in section 1.2 of chapter 1.

Chapter 3[3]

Development and performance investigation of integrated approach considering production and maintenance

This chapter develops and comprehensively investigate the performance of more realistic integrated operations planning approach centred on the relationship between production scheduling and maintenance planning. Moreover, the effect of maintenance resources unavailability is investigated on joint production and maintenance planning decisions for an automotive firm considering various performance measures.

Key Highlights

Purpose: The purpose of this chapter is to provide manufacturing industries with a more realistic integrated operations planning approach to evaluate production and maintenance planning decisions, and to analyze the effect of maintenance resource constraints on integrated production and maintenance planning decisions.

Findings: The integrated approach provides 0.6 to 35.8 percent improvements in overall operations cost compared to independent approach for various manufacturing scenarios. The unavailability of maintenance resources found to have significant effect on the joint decisions and system performance for the considered case. For the considered case, the variations in the optimal values of different performance measures are found in the range of 14 to 30 percent.

[3] *The work presented in this chapter is published under the title "Integrated production and maintenance planning for parallel machine system considering cost of rejection", in Journal of Operational Research Society", 2016, Vol. 68, No. 7, pp. 834-846; and under the title "Effect of maintenance resource constraints on flow-shop environment in a joint production and maintenance context", 2016, IEEE International Conference on Industrial Engineering and Engineering Management (IEEM) 2016, 4-7 Dec., Bali, Indonesia, pp. 641-645.*

Originality and Contribution: The novelty of this research is in the development of more realistic integrated operations planning approach for production and maintenance planning in industries. For the first time in the literature, the approach is comprehensively evaluated to generalize the performance over independent approach for 473 different manufacturing scenarios. These scenarios are generated by varying the number of machines and batches, machines’ age, PM restoration factor, quality control parameters, and due dates. First time in literature, the effect of maintenance resource constraints in a real manufacturing environment, for integrated production scheduling and maintenance planning is investigated.

Practical Implications: The comprehensive evaluations help the operations managers in selecting the appropriate case for adaptation of integrated approach where potential for performance improvement is higher. For example, it is identified that in case of shop-floor having older machines and high cost of rejection, the proposed approach results into more significant monetary savings to the organizations.

3.1 Introduction

It is clear from chapter 1 that production scheduling and maintenance planning are interdependent. However, in real manufacturing systems, these shop-floor operations policies are generally planned and executed separately, which may conflict their objectives and may lead to sub-optimal solutions. In order to make shop-floor operations lean, these operations policies should be integrated. In that line, chapter 2 expresses the current status of literature which is more at the exploratory stage. For example, most of the researchers have explored the integrated approaches for single machine case. While manufacturing industries generally have multiple machines in job-shop or flow-shop type of production environment. Further, the available work on multi-machine cases is limited to simplistic assumptions like fixed maintenance interval, perfect or minimal repair, ignorance of machine age, unlimited maintenance resource, common processing time, etc. Thus, the results may not be of much practical use. Similarly, the effects of stochastic nature of various parameters on integrated approach are not studied in the literature. Moreover, to the best of our knowledge no attempt has been made so far to perform a comprehensive evaluation for various manufacturing scenarios to generalize the results of integrated approaches. To overcome this bottleneck, the first advancement progressed in this thesis is in the development and comprehensive performance investigation of more realistic integrated approach for production scheduling and maintenance planning of parallel machine system considering the effect of cost of rejection. The machines have different initial ages, and are characterized by random failure behaviour; maintenance is considered imperfect; and the jobs have uniformly distributed processing times. The approach aims to determine optimal production schedule and maintenance plan such that overall operations cost is minimized. A simulation-based optimization approach is used to solve the problem; numerical investigation is performed to illustrate the approach. Further, systematic sensitivity analysis and economic comparison with conventional independent approach are performed. In addition, the approach is comprehensively evaluated to analyze its robustness and implications in various manufacturing scenarios. These scenarios are generated by varying maintenance, process and quality control parameters, number of machines, and batches. The obtained results indicate that simultaneous consideration of production scheduling and maintenance planning results into better system performance. Moreover, it helps the operations managers in selecting appropriate case for adaptation of integrated approach where potential for performance improvement is higher.

Further, the effect of maintenance resource unavailability on joint production and maintenance planning decisions for a realistic flow-shop environment is investigated considering different performance measures viz. makespan, total production cost, and system utilization.

The rest of the chapter is organized as follows. Section 3.2 presents the problem description and formulation. Section 3.3 gives details of cost models of integrated approach. Section 3.4 illustrates the approach with an example and results are discussed in section 3.5. Section 3.6 presents cost models for independent approach. A comprehensive analysis is presented in section 3.7. The effect of maintenance resource is analyzed in section 3.8. Lastly, the chapter is summarized in section 3.9.

3.2 Problem description and formulation

Consider a parallel machine system used in job-shop of a production system. The system has $'M'$ identical parallel machines $j = 1, \dots, m$. Let the age of machines at the start of planning horizon are different and the times-to-failures of machines follow a two-parameter Weibull distribution with a shape parameter β and scale parameter η. The machine failures result into two failure consequences: FC_1 and FC_2 (Pandey et al., 2011). Failure consequence 1 (FC_1) brings the machine instantly to breakdown state and is detected immediately. Failure consequence $2(FC_2)$ indicates the degradation in machine functionality and is detected after a time lag during which machine is producing items of unacceptable quality. Whenever, a machine fails, CM is performed and it results into minimal repair i.e., the machine age is restored to an age as prior to failure (Kijima, 1989). The machine also receives PM to reduce unplanned downtime losses. PM is imperfect which restores the machines by a restoration factor α i.e., restoration of α percent of machine age at the time of maintenance action (Kijima, 1989). PM decisions are evaluated before processing of each batch.

Let a set of batches $i = 1, \dots, n$ is to be scheduled non-preemptively on identical parallel machines, where each machine can process all batches. Let single operation is performed in each batch. Each batch is composed of fixed number of jobs. The batches have a given processing time BT_i and common due date DT. If a batch is delivered after its completion, it causes tardiness cost. Similarly, if a batch is processed early, it should be kept until its due date which causes earliness cost i.e., inventory cost (Jeang, 2012; Hadidi et al., 2015).

Initially, the production system is assumed to start in an in-control state producing items of acceptable quality. It is assumed in the present work that system employs a $\overline{X}$ control chart to detect the process shift with control limits at $\pm 3\sigma$, where σ is process standard deviation. It is further assumed that the process standard deviation does not change because of machine failure. The process mean may shift instantaneously due to various reasons including machine degradation, external causes, operator's mistake, etc. In this work, it is assumed that process shift occurs due to machine degradation only, i.e., due to machine FC_2. Once FC_2 happens, the process mean μ_0 shifts from its target value to new process mean $\mu_1 = \mu_0 \pm \delta\sigma$ and process is said to move in out-of-control state where, δ is some non-zero real number. At out-of-control state of process, product rejection rate increases which leads to an additional cost of rejection. Whenever process shift (due to machine degradation) is detected by control chart, corrective action is performed in order to restore the machine to in-control state.

It sounds well from above description that, machine unavailability affects the batch schedule and machine degradation affects the product quality. Thus, PM optimization and batch scheduling must be done simultaneously to reduce the effect of machine unavailability and loss of product quality such that overall operations cost is minimized.

In other words, the problem is to optimize the batch allocation decision (x_{ij}), batch sequencing decision (p_{ijk}), and PM decision $(N_{pm_{j_{i-}}})$ such that the Overall Operations Cost (OOC) is minimized.

Based on the above description, the problem is formulated as follows:

Minimize,

$$OOC = ATC + AEC + APMC + ACMC + ARC \tag{3.1}$$

The OOC includes Average Tardiness Cost (ATC), Average Earliness Cost (AEC), Average PM Cost $(APMC)$, Average CM Cost $(ACMC)$, and Average Rejection Cost (ARC).

where, the cost OOC is a function of decision variables x_{ij}, p_{ijk}, $N_{pm_{j_{i-}}}$ and other model parameters.

Decision variables

Decision of allocation:

$$x_{ij} = \begin{cases} 1, & \text{If } i^{th} \text{ batch is scheduled on } j^{th} \text{ machine} \\ 0, & \text{Otherwise} \end{cases}$$

Decision of sequencing:

$$p_{ijk} = \begin{cases} 1, & \text{If } i^{th} \text{ batch is processed at } k^{th} \text{position on } j^{th} \text{ machine} \\ 0, & \text{Otherwise} \end{cases}$$

Decision of PM:

$$\left(\mathrm{N}_{\mathrm{pm}_j}\right)_{i^-} = \begin{cases} 1, & \text{If PM performed before processing of } i^{th} \text{ batch on } j^{th} \text{ machine} \\ 0, & \text{Otherwise} \end{cases}$$

The problem is subjected to a constraint which ensures the allocation of a batch to only one machine.

$$\sum_{j=1}^{m} x_{ij} = 1, \qquad \forall\, i,\ \ x_{ij} \in \{0,1\}\ \forall\, i, j \tag{3.2}$$

The next sub-section provides the details of the cost models of integrated approach.

3.3 Development of cost models

The following assumptions are made in development of ingredient cost models:

- Each batch is available at the beginning of production period.
- Failure of machines is independent.
- Machine is available at the start of production
- Each machine processes at least one batch.
- Each machine can handle only one batch at a time.
- FC_1 and FC_2 are statically independent of each other .
- Maintenance personnel and spares are available at the time of failure.

The models for each of the ingredient costs in OOC model are developed in following sections.

3.3.1 Evaluation of Average Tardiness Cost ($\boldsymbol{ATC}$) and Average Earliness Cost ($\boldsymbol{AEC}$)

Tardiness cost incurs only when a batch is delivered after its due date. ATC can be expressed as:

$$ATC = \sum_{i=1}^{n} \sum_{j=1}^{m} max\{0,\ TC_i(CT_{ij} - DT)\} \tag{3.3}$$

Similarly, if a batch is processed before its due date, it incurs earliness cost. Mathematically,

$$AEC = \sum_{i=1}^{n} \sum_{j=1}^{m} max\{0,\ EC_i(DT - CT_{ij})\} \tag{3.4}$$

where, TC_i and EC_i are tardiness and earliness cost of i^{th} batch per hour and depends on batch manufacturing cost (P_i). Batch manufacturing cost covers cost of raw material (C_M), processing cost$(C_p \times BT_i)$, and overhead cost (C_{OH}); where, C_p is processing cost per hour and BT_i is processing time of i^{th} batch. The processing cost includes direct operator cost and other cost associated to process (power, capital, etc.). Overhead cost is 5 percent to 15 percent of the sum of raw material cost and processing cost for a batch (Feng and Zhang, 1999). While, the raw material cost is 50 percent of batch manufacturing cost (Backlund, 2013). These figures give approximate estimation of batch manufacturing cost which may vary for different industry. On the basis of percentage value of raw material cost and overhead cost, the batch manufacturing cost is found approximately three times of processing cost. Therefore,

$$P_i = 3(C_p \times BT_i) \tag{3.5}$$

CT_{ij} is completion time of i^{th} batch processing on j^{th} machine at k^{th} position and is the sum of operation time (OT_{ij}) of i^{th} batch sequenced on j^{th} machine and operations time of preceding batches. It can be expressed as:

$$CT_{ij} = \sum_{k=1}^{k} (OT_{ij}) \times x_{ij} \times p_{ijk},\ k = 1, \dots \dots, n - m \tag{3.6}$$

where, x_{ij} and p_{ijk} are decision of allocation and decision of sequencing of i^{th} batch on j^{th} machine, respectively. Value of x_{ij} and p_{ijk} ensure that i^{th} batch will process on j^{th} machine at k^{th} position. It is assumed that each machine processes at least one batch. Thus, maximum number of batches that could be process on a machine is $n - m$.

Operation time of i^{th} batch processing on j^{th} machine is sum of setup time (ST_i), processing time (BT_i), machine down time due to PM $(T_{pm_j})_{i^-}$ and CM $(T_{cm_j})_i$. Then,

$$OT_{ij} = [ST_i + (BT_i) + \{(T_{pm_j})_{i^-} + (T_{cm_j})_i\}] \tag{3.7}$$

The downtime $(T_{pm_j})_{i^-}$ of j^{th} machine due to PM depends on decision of PM $\left(N_{pm_j}\right)_{i^-}$ evaluated before processing of i^{th} batch and time needed to repair the machine (TTR_{pm_j}). Thus,

$$(T_{pm_j})_{i^-} = \left(N_{pm_j}\right)_{i^-} \times (TTR_{pm_j}) \tag{3.8}$$

The downtime $(T_{cm_j})_i$ of j^{th} machine due to CM depends on number of failures (NF_{ij}) occur during processing of i^{th} batch and time needed to repair the machine (TTR_{cm_j}). Thus,

$$(T_{cm_j})_i = NF_{ij} \times (TTR_{cm_j}) \tag{3.9}$$

For minimal repair, NF_{ij} can be calculated using formula (Cassady and Kutanoglu, 2003; Lad and Kulkarni, 2012):

$$NF_{ij} = \left[\left(\frac{(BT_i + Ia_{ji^-})}{\eta}\right)^{\beta}\right] - \left[\left(\frac{Ia_{ji^-}}{\eta}\right)^{\beta}\right] \tag{3.10}$$

where, Ia_{ji^-} is initial age of j^{th} machine before processing of i^{th} batch. β and η are shape and scale parameter of machine respectively.

Initial age (Ia_{jk^-}) of j^{th} machine before processing of a batch scheduled at k^{th} sequence is:

$$Ia_{jk^-} = [Ia_{j(k-1)^-} + BT_{k-1})] \times [1 - \alpha_j \times \left(N_{pm_j}\right)_{k^-}] \tag{3.11}$$

where, BT_{k-1} is processing time of a batch scheduled at $(k-1)^{th}$ sequence, and α_j is PM restoration factor of j^{th} machine.

3.3.2 Evaluation of Average Preventive Maintenance Cost $(\boldsymbol{APMC})$ and Average Corrective Maintenance Cost $(\boldsymbol{ACMC})$

The PM on machine incurs the downtime cost (C_{dt}) during repair of the machine, direct labor cost (C), and fixed PM cost (FC_{pm}) i.e., cost of material, lubricant, etc. Thus, average cost of PM can be expressed as:

$$APMC = \sum_{i=1}^{n}\sum_{j=1}^{m}[(TTR_{pm_j}) \times (C + C_{dt}) + FC_{pm_j}] \times \left(N_{pm_j}\right)_{i^-} \tag{3.12}$$

FC_1 brings machine breakdown state and is detected immediately. The cost to repair the machine incurs the downtime cost during repair of the machine, labor cost, and fixed CM cost (FC_{cm}). FC_{cm} includes material cost, lubricant, maintenance equipment, etc. Thus, average CM cost can be expressed as:

$$ACMC = \sum_{i=1}^{n}\sum_{j=1}^{m}[(TTR_{cm_j}) \times (C + C_{dt}) + FC_{cm_j}] \times NF_{ij} \times P_{FC_1} \tag{3.13}$$

where, P_{FC_1} is the probability of failure of machine by FC_1.

3.3.3 Evaluation of Average Rejection Cost (ARC) due to FC_2

Some time machine may fail and results FC_2 increasing the production of deformed items, in turn rejection cost. The cost due to FC_2 incur downtime cost, labor cost, fixed CM cost, and additional cost of rejection. If P_{FC_2} is probability of failure due to FC_2, the average rejection cost can be expressed as:

$$ARC = \sum_{i=1}^{n}\sum_{j=1}^{m}[(TTR_{cm_j}) \times (C + C_{dt}) + FC_{cm_j} + (IRR \times C_{rej_i} \times ARL \times f)] \times NF_{ij} \times P_{FC_2} \quad (3.14)$$

where, IRR is increased rejection rate when the process was in out-of-control state due to machine degradation; C_{rej_i} is rejection cost per job and is assumed F_{rej} times of manufacturing cost per job of i^{th} batch. F_{rej} is factor of cost of rejection and its values are different for different scenarios (see section 3.7). ARL is average run length i.e., average number of samples required to detect the shift, and f is time between samples.

IRR can be calculated as follows. If process is being monitored by $\overline{\mathrm{X}}$ control chart with a control limits of $\pm 3\sigma$ (Pandey et al., 2010). Then,

$$IRR = 1 - \varphi[3 - \delta] - \varphi[-3 - \delta] \quad (3.15)$$

where, $\varphi[.]$ is probability of standard normal cumulative distribution function and δ is process shift due to machine degradation.

The average number of samples required before the shift is detected can be given by Pandey et al. (2010).

$$ARL = \frac{1}{1 - \gamma} \quad (3.16)$$

where, γ is type II error when process is out-of-control and can be expressed as state due to machine degradation (Montgomery, 2004).

$$\gamma = \varphi\left[3 - \delta \times \sqrt{n}\right] - \varphi\left[-3 - \delta \times \sqrt{n}\right] \quad (3.17)$$

where, n is the sample size of quality inspection. Next section presents a numerical example to illustrate the integrated approach and solution method used to solve the example.

3.4 Numerical example and solution method

To illustrate the proposed approach, a numerical example is taken in which 9 batches with multiple jobs are to be scheduled on 5 identical parallel machines. Each batch has 100 jobs. Failure of machines is assumed to follow a two-parameter Weibull distribution with a shape parameter $\beta = 2$ and scale parameter $\eta = 1000$ hours. The probabilities of occurrence of failure consequences FC_1 and FC_2 due to a failure are 0.7 and 0.3 respectively. Time to carryout PM is 8 hours with a restoration factor 0.6 and time to repair for CM follows lognormal distribution with $\mu = 30$ hours and $\sigma = 10$ hours. The age of machines at the start of planning horizon is different and the reliability at the current age of machines at start of planning horizon is given in table 3.1. Table 3.1 indicates that M_1 and M_2 are comparatively new as the reliability of these machines at the start of planning horizon is higher.

The batches have uniformly distributed processing times as shown in table 3.1, fixed setup time of 5 hours, and common due date of 260 hours. Penalties for tardiness and earliness are considered as 0.2 and 0.1 percent of batch manufacturing cost per hour respectively. After processing a batch, sample of 4 jobs is inspected and time between sampling is 16 hours. It is assumed that whenever FC_2 happens it produces a process shift of 0.7σ. The cost of rejection is considered 10 times the manufacturing cost of job (Pandey et al., 2011). The cost structure is shown in table 3.1.

Table 3.1 Machines' reliability, batches' processing time and cost data

M_i	Reliability	Ia (hours)	B_i	BT_i (hours)	B_i	BT_i (hours)	Param-eters	Cost (MU)
M_1	1	0	B_1	[45,55]	B_6	[162,198]	FC_{pm}	2400
M_2	0.9	973	B_2	[72,88]	B_7	[225,275]	FC_{cm}	2000
M_3	0.65	1969	B_3	[180,220]	B_8	[117,143]	C_p	500
M_4	0.55	2319	B_4	[90,110]	B_9	[198,242]	C_{dt}	500
M_5	0.5	2497	B_5	[135,165]			C	500

Note: MU refers to monetary units

Solution space

For above example, allocation decision of 9 batches in 5 machines can be done by $2^{9\times5}$ ways, and sequencing decision of each batch in a machine can take $2^{(9-5)}$ ways. Similarly, for PM, two decisions are made to perform PM or not before the processing of each batch. Thus, total possible combinations are (2^{50}).

Solution method

The nature of the problem is a combinatorial nonlinear optimization problem. Lee and Liman (1992) demonstrated that single machine scheduling problem subject to scheduled maintenance is NP-hard. Likewise, the work of Sun and Li (2010) demonstrated that two machine scheduling problem where machines need to be maintained periodically is NP-hard. The works of (Kim et al., 2013; Zarook et al., 2014) also confirm that such combinatorial nonlinear optimization problem qualifies for NP-hard class. Since the current work considers a scenario which is an extension of the scenarios mentioned in the above references, the same is considered as NP-hard. To solve such kind of problem generally, meta-heuristic techniques like GA, PSO, SA, etc., are used. Further, the current problem also includes the uncertainties in parameters like processing time, due date, and time to repair which further increases the computational complexity. Therefore, in this work, Monte Carlo simulation-based GA is used to solve the problem. A simulation model is developed on @Risk platform (http://www.palisade.com/risk/). A GA is used with the simulation model to optimize the decision variables. The GA uses binary encoding scheme, and selects individuals from population by rank based mechanism. A uniform crossover is performed on selected individuals to produce offspring. And a non-uniform mutation is performed to produce mutated offspring. The GA parameters, population size, crossover rate and mutation rate are taken as 50, 0.75 and 0.1 respectively. The optimized results are also analyzed for varying crossover rate in the range of 0.5 to 0.8 and mutation rate in the range of 0.05 to 0.25. It was observed that the solutions obtained with different crossover rate and mutation rate did not differ significantly from each other. The run terminated when no improvement is found in last 50000 trials. The solutions obtained are within the confidence bound of 95 percent which provides an outlook for the quality of the learned local optimum against the global optimum. The entire formulation, simulation, and optimization process of integrated model is depicted in figure 3.1. The pseudo code of the same can be found in Appendix A.

In order to check the correctness of the model, first some intuitive cases were simulated. For example, integrated approach shows significant increase in OOC on increasing processing cost and down time cost. Consequently, on decreasing machines' reliability, the number of failures of machine increases; similar effect is found on decreasing PM restoration factor. This validates the correctness of the model.

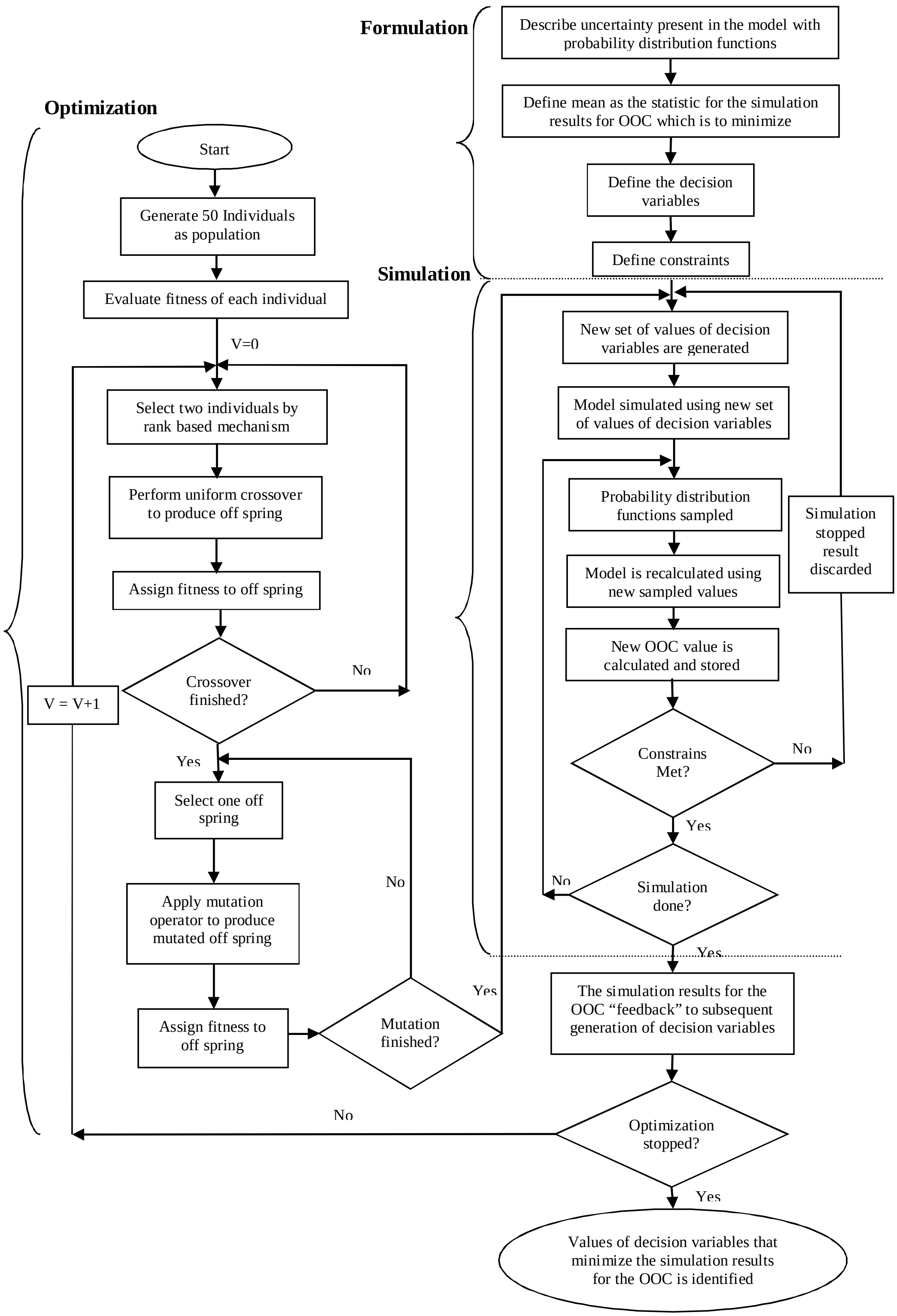


Figure 3.1 A flow chart of Monte Carlo simulation-based genetic algorithm

3.5 Results

The above example is solved by utilizing the proposed integrated approach. The obtained production and maintenance plan is summarized in figure 3.2. The corresponding OOC is 194,720 Monetary Unit (MU). The figure 3.2 shows the batch allocation on machines, sequence, and PM decisions. Where, M_i refers to machine number and PM decisions are highlighted by 'PM' while batch allocation is given by batch number (B_i).

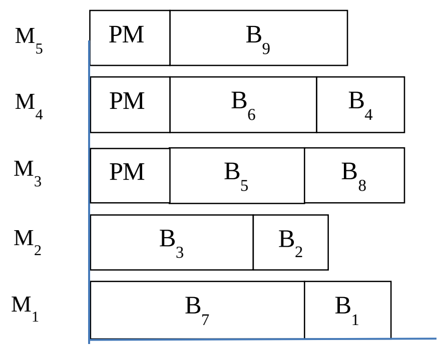


Figure 3.2 Integrated production and maintenance plan

Sensitivity analysis

Sensitivity analysis is a study to show the effect of small variation of input parameters on optimal solution. Since the cost parameters cannot always be estimated accurately, the study of effect of small variation in various cost parameters on solution is important. In the present case, downtime cost, processing cost, fixed PM cost, fixed CM cost, labor cost, tardiness cost, and earliness cost may be subjected to uncertainty.

To investigate the effect of uncertainty, one at a time sensitivity analysis is conducted with integrated model. In this, sensitivity measure was determined by adjusting parameter value by a percentage of their base-case value while keeping the values of other parameters constant. In table 3.2, basic level corresponds to the parameters values used in solving the example of previous section. Level 1 and 2 represent values of these parameters at -15 and +15 percent of basic level respectively. The result shows that model is more sensitive to processing cost, earliness cost and tardiness cost, and less sensitive to cost of downtime, fixed PM cost, fixed CM cost, and labor cost. It is also observed that the decision variables i.e., allocation, batch sequencing and PM decisions are not sensitive to variation in these parameters.

Table 3.2 Sensitivity analysis of integrated model

Parameters	Basic Level	Level 1 (-15%)	Level 2 (+15%)	Range of change in OOC in %
Processing Cost (C_p)	194,720	174,591	214,849	-10.3 to 10.3
Down time Cost (C_{dt})	194,720	190,861	198,580	-1.98 to 1.98
Fixed PM Cost (FC_{pm})	194,720	193,640	195,800	-0.55 to 0.55
Fixed CM Cost (FC_{cm})	194,720	194,441	195,000	-0.14 to 0.14
Labor Cost (C)	194,720	190,861	198,580	-1.98 to 1.98
Tardiness Cost (TC_i)	194,720	187,161	202,280	-3.88 to 3.88
Earliness Cost (EC_i)	194,720	185,343	204,097	-4.82 to 4.82

Statistical test

To analyze the statistical significance of the sensitive parameters to OOC, a statistical test, Analysis of variance (ANOVA) is performed. Higher sensitive cost parameters from figure 3.3, i.e., processing cost, earliness cost, and tardiness cost are considered at three levels i.e., −15%, basic level, (used in example of section 3.4) and + 15%, and corresponding impact on objective function is captured and analyzed. The ANOVA results are shown in table 3.3. The results show that these cost parameters have statistical significant impact on OOC at 5 percent level of significance. Thus, one should estimate the values of these parameters accurately to get clear picture of OOC and economic impact of operational policies.

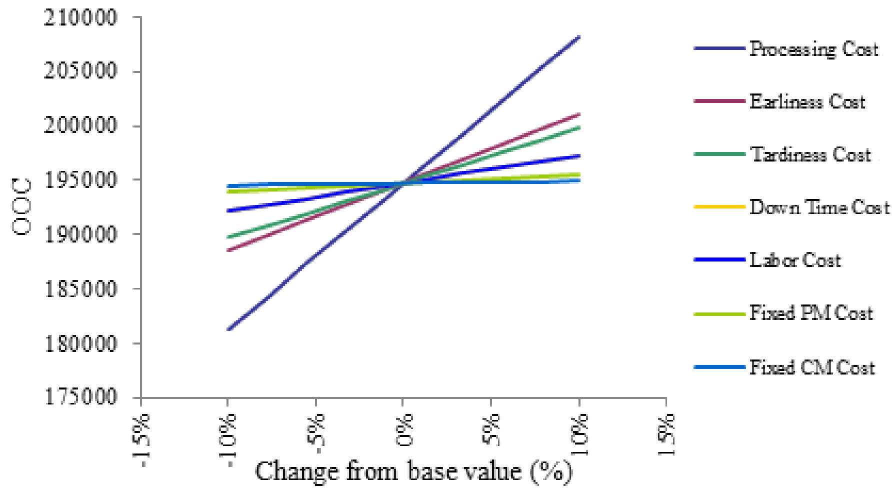


Figure 3.3 Mean of OOC vs Percentage change of cost parameters

Table 3.3 ANOVA

Source of variation	**Degrees of freedom**	**Sum of squares [Partial]**	**Mean squares [Partial]**	**F Ratio**	**P Value**
Processing Cost (C_p)	2	7.29E+09	3.65E+09	1861.99	0.000002
Tardiness Cost (TC_i)	2	1.03E+09	5.14E+08	262.6	0.000005
Earliness Cost (EC_i)	2	1.58E+09	7.91E+08	404.07	0.000003
Error	20	3.92E+07	1.96E+06		
Total	26	9.94E+09			

3.6 Comparison with independent approach

The independent approach is considered to compare the performance of the proposed integrated approach. For this, the obtained results from integrated approach are compared with that of independent approach. In independent approach, batch schedule and PM schedule are determined separately, and then OOC is calculated. While in integrated approach, these schedules are determined jointly by minimizing OOC. In independent approach, first batch allocation and sequencing decisions are determined considering conventional assumptions. This batch schedule is then used to determine the PM decisions. After that, these decisions i.e., the values of x_{ij}, p_{ijk}, and $\left(N_{pm_j}\right)_{i^-}$ are fed to Eq. (3.1) to obtain OOC. The models used in independent approach are discussed in the following sections.

3.6.1 Batch scheduling model

In this model, batch allocation decision (x_{ij}) and sequencing decision (p_{ijk}) are determined considering that machine is always available. Thus, new operation time (ot_{ij}) of a batch is sum of processing time (BT_i) and setup time (ST_i).

$$ot_{ij} = [ST_i + BT_i] \tag{3.18}$$

Similarly, new completion time (ct_{ij}) is:

$$ct_{ij} = \sum_{k=1}^{k} (ot_{ij}) \times x_{ij} \times p_{ijk},\ k = 1, \dots \dots, n - m \tag{3.19}$$

Total tardiness cost for independent approach i.e., $[TTC]_I$ is:

$$[TTC]_I = \sum_{i=1}^{n} \sum_{j=1}^{m} max\{0,\ TC_i(ct_{ij} - DT)\} \tag{3.20}$$

Similarly, Total earliness cost for independent approach i.e., $[TEC]_I$ is:

$$[TEC]_I = \sum_{i=1}^{n} \sum_{j=1}^{m} max\{0,\ EC_i(DT - ct_{ij})\} \tag{3.21}$$

The batch allocation and sequence decisions are obtained by minimizing sum of total earliness and total tardiness cost.

3.6.2 Maintenance cost model

In this model, PM decisions are determined. For this, fixed batch schedule obtained from batch scheduling model is considered. Based on batch schedule, the number of failures of machines is calculated using Eq. (3.10). Then average PM cost, average CM cost, and average rejection cost for independent approach are estimated by using Eq. (3.12), Eq. (3.13), and Eq. (3.14) respectively. The PM plan is obtained by minimizing the sum of these costs.

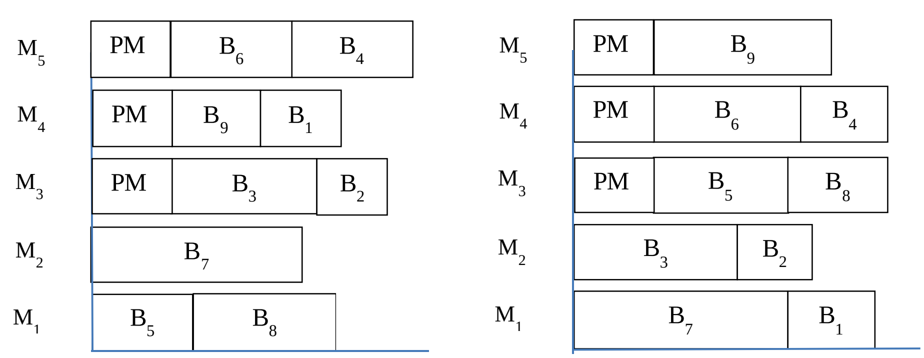
3.6.3 Tardiness and Earliness cost model

Once, batch schedule and PM schedule are obtained; the completion time (CT_{ij}) of a batch is calculated using Eq. (3.6), where the values of x_{ij} , p_{ijk}, and $\left(N_{pm_j}\right)_{i^-}$ are fixed by these schedules. Then average tardiness cost and average earliness cost for independent approach are estimated using Eq. (3.3) and Eq. (3.4) respectively.

The costs estimated from sub-sections 3.6.2 and 3.6.3 are then used to find the OOC.

Comparison

The OOC value obtained from above discussed independent approach is 205,830 MU while OOC obtained from integrated approach is 194,720 MU (see section 3.5). Thus, integrated approach shows an improvement of 5.4 percent in OOC over independent approach for the present problem settings. The production and maintenance plan obtained from independent approach is shown in figure 3.4; for comparison the plan obtained from integrated approach i.e., figure 3.2 is reproduced in figure 3.4. The batch schedule is different with batch schedule of integrated approach and PM schedules are same for both the approaches. Next section provides the comprehensive evaluation for both the approaches.



Production and maintenance plan by independent approach

Production and maintenance plan by integrated approach

Figure 3.4 Comparison of production and maintenance plan obtained from independent approach and integrated approach

3.7 Comprehensive evaluations

The results obtained in section 3.5 are specific for the scenario considered in the previous example (see, section 3.4), in terms of maintenance parameters, quality control parameters, process parameters, and number of machines and batches. In order to generalize the performance of integrated approach over the independent approach, an exhaustive evaluation is performed for 473 different scenarios. These different scenarios are generated by varying maintenance parameters, quality control parameters, and process parameters separately as shown in table 3.4. Parameter values considered in table 3.4 are varied to generate some representative scenarios of any manufacturing industry.

Table 3.4 Parameters to generate various problem scenarios

Maintenance parameters			**Quality control parameters**			**Process parameters**		
Parameters	Parameter values		Parameters	Parameter values		Parameters and its values		
Scale parameter (η)	1000, 2000 and 3000 hrs.		Process shift (δ)	0.4 and 0.6		50 sets of batch processing time ($P_1, P_2, P_3 \ldots \ldots P_{50}$), are considered.		
Shape parameter (β)	2, 2.5 and 3		Sample size (n)	2 and 4				
PM restoration factor (α)	0.4, 0.6 and 0.8		Time between sampling (f)	8 and 16		Tardiness factor (ρ)	Case DT_1 =	0.4
Reliability of machines (1 to 5) at current age	Case A_1=	1, 0.99,0.95,0.93,0.9	Factor of cost of rejection (F_{rej})	Case R_1=	1			
	Case A_2=	1,0.9,0.65,0.55,0.5		Case R_2=	5		Case DT_2=	0.2
	Case A_3=	0.65,0.63,0.6,0.55,0.5		Case R_3=	10			

3.7.1 Varying maintenance parameters

A range of values of scale parameter (β), shape parameter (η), PM restoration factor (α), and current age of machines are considered as shown in table 3.4. Three different cases of machine reliability at current age are considered as follows:

- In first case (A_1), current ages of all the five machines are either zero i.e., new machines or very less i.e., relatively new machines. To simulate this case, the reliability of machines at current age is taken as: 1, 0.99, 0.95, 0.93, and 0.9. Such case can be considered as a representative of a newly established industry where all machines are relatively new.
- In second case (A_2), some of the machines are new and some of the machines are old. Thus, the current ages of two machines are either zero or very less and rest of three machines has completed 15 to 40 percent of their life. To simulate this case, the reliability of these five machines at current age is taken as: 1, 0.9, 0.65, 0.55, and 0.5. This case may be observed in an older industry where recent up-gradation in the industry resulted into replacement of the few old machines with new machines.
- In third case (A_3), all the machines have completed 15 to 40 percent of their life. This case can be considered as a representative of an old industry. To simulate this case, the reliability of machines at current age is taken as: 0.65, 0.63, 0.60, 0.55, and 0.5.

Results

To see the effect of maintenance parameters, total 81 cases are generated by varying maintenance parameters as shown in table 3.4. All the cases are evaluated by integrated as well as independent approach. While varying the maintenance parameters; quality control, process parameters, and other parameters (processing cost, downtime cost, etc.) are set as used in example presented in section 3.4. Figure 3.5 shows OOC obtained by integrated approach and independent approach. The red area indicates the OOC obtained using integrated approach while black area shows OOC obtained using independent approach. A significant difference between red area and black area has been found for all the scenarios. This demonstrates that integrated approach always provides lesser OOC compare to independent approach for various combinations generated based on the values of various maintenance parameters.

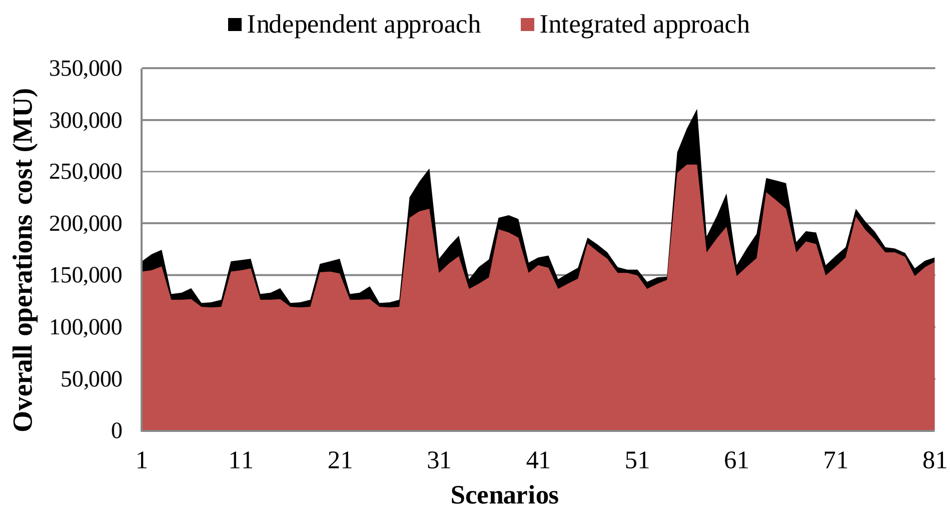


Figure 3.5 OOC obtained from integrated and independent approach on varying maintenance parameters

Out of the 81 scenarios evaluated above, table 3.5 shows lowest (L) and highest (H) improvement obtained for machines' current age cases A_1, A_2 and A_3 respectively. The results of 81 scenarios can be found in table I-1 in Appendix B.

Table 3.5 Lowest and highest improvements on varying maintenance parameters

Machine age		β	η	α	Integrated (OOC)	Independent (OOC)	Improvement (%)
A_1	L_{A_1}	2	3000	0.6	119,571	123,167	2.92
	H_{A_1}	3	1000	0.4	158,674	174,951	9.3
A_2	L_{A_2}	3	3000	0.8	145,729	148,523	1.88
	H_{A_2}	3	1000	0.4	214,402	253,168	15.6
A_3	L_{A_3}	2.5	2000	0.8	173,273	175,948	1.52
	H_{A_3}	3	3000	0.4	257,050	310,890	17.3

where, L_{A_1}, L_{A_2}, and L_{A_3} are lowest and H_{A_1}, H_{A_2}, and H_{A_3} are highest improvements for case A_1, case A_2, and case A_3 respectively. The maximum and minimum improvements obtained with various values of machine parameters are 17.3 and 1.88 percent respectively.

Observations

From varying maintenance parameters, following effects have been observed:

a. Effect of machines age: As PM is generally not required when machines are new, optimizing production and maintenance policies individually does not make significant difference. However, as the machines' age increases or machines become older, more percentage improvements have been observed using integrated approach. Thus, for older machines, optimizing production and maintenance policies individually may not be cost effective for organization and it should look for integrated approaches. It is worth citing here that post World War II, many industries were setup all over the globe. Therefore, in the present time, it is not very uncommon to witness many old machines in such industries. Thus, integrated approaches are more important relevant and have higher potential of improvement, in the present time.

b. Effect of restoration factor: For older machines restoration factors also play an important role in shop-floor operations planning. Higher improvements have been observed for older machines with low restoration factor values. In other words, if the PM policy is less effective i.e., restoration factor is low, one should think of integrated approach to take full advantages of PM policies. It is just another fact that achieving higher restoration for older machines is also a challenging task. Therefore, connecting it with case 'a' above, this observation makes the integrated operations planning an attractive option to achieve better performance from the existing manufacturing systems.

c. Effect of time to failure distribution parameters: Integrated approach results into better performance compared to independent approach for wide ranges of shape and scale parameters.

3.7.2 Varying quality control parameters

For quality control parameters, process shift, times between sampling and factor of cost of rejection have been varied over a wide range. These values are mentioned in table 3.4. Two cases of sample size viz., 2 and 4 have been considered (Pandey et al., 2010; Tambe et al., 2013). More importantly, following three cases of cost of rejection have been considered.

- In first case (R_1), the cost of rejection of a job is equal to manufacturing cost of job $(F_{rej} = 1)$ and it is considered that defected job is detected in inspection and is scraped. This case may be observed where customers do not impose any penalty for shortage in ordered quantity.
- In second case (R_2), it is considered that defected job is detected in inspection and is scraped but customer does not allow the shortage in ordered quantity; to fulfill this, same job is outsourced and it costs five times of the cost of job $(F_{rej} = 5)$.
- In last case (R_3), it is considered that defect in job is detected by the customer and it costs 10 times of manufacturing cost of job $(F_{rej} = 10)$ because of loss of goodwill of company and/or returning of whole order.

Results

To analyze the effect of quality control parameters, values of process shift due to machine degradation, sample size, time between sampling, and factor of cost of rejection have been varied for all the 6 cases shown in table 3.5. For each case, 24 combinations of quality control parameters are made and thus for six cases a total of 144 scenarios are generated. While evaluation, maintenance parameters are set as per cases from table 3.5; process parameters and other parameters are set as used in example presented in section 3.4.

Each scenario is evaluated by integrated as well as independent approach. Results show that integrated approach always provides lesser OOC compared to independent approach. Table 3.6 shows the lowest ($L_{L_{A_1}}$,$L_{H_{A_1}}$, $L_{L_{A_2}}$,$L_{H_{A_2}}$, $L_{L_{A_3}}$, and $L_{H_{A_3}}$) and highest ($H_{L_{A_1}}$,$H_{H_{A_1}}$, $H_{L_{A_2}}$,$H_{H_{A_2}}$, $H_{L_{A_3}}$, and $H_{H_{A_3}}$) improvements obtained for each case (L_{A_1}, H_{A_1}, L_{A_2}, H_{A_2}, L_{A_3}, and H_{A_3}) respectively. The results of all 144 scenarios can be found in table I-2 in Appendix B. Additionally, for higher process shift value ($\delta = 1.5$), 12 cases of table 3.6 are further analyzed.

Table 3.6 Lowest and highest improvements in varying quality control parameters

Machine age			δ	s	h	F_{rej}	Case	Integrated (OOC)	Independent (OOC)	Improvement (%)	For $\delta = 1.5$ Integrated (OOC)	Independent (OOC)	Improvement (%)
A_1	L_{A_1}	$L_{L_{A_1}}$	0.7	4	8	1	C_1	115,211	117,262	**1.75**	115,150	119,206	3.40
		$H_{L_{A_1}}$	0.5	2	16	10	C_2	127,854	134,501	4.94	123,269	129,054	4.48
	H_{A_1}	$L_{H_{A_1}}$	0.7	4	8	1	C_3	140,184	152,597	8.13	139,882	146,494	4.51
		$H_{H_{A_1}}$	0.5	2	16	10	C_4	185,644	217,858	14.8	171,856	186,002	7.61
A_2	L_{A_2}	$L_{L_{A_2}}$	0.7	4	16	10	C_5	145,729	148,523	1.88	141,919	150,706	5.83
		$H_{L_{A_2}}$	0.7	4	8	1	C_6	144,044	156,163	7.76	192,623	208,850	7.77
	H_{A_2}	$L_{H_{A_2}}$	0.7	4	8	1	C_7	191,378	226,145	15.4	185,003	188,690	1.95
		$H_{H_{A_2}}$	0.7	2	16	10	C_8	249,683	381,212	**34.5**	233,076	290,810	19.85
A_3	L_{A_3}	$L_{L_{A_3}}$	0.5	4	8	10	C_9	170,957	174,124	1.82	149,131	179,920	17.11
		$H_{L_{A_3}}$	0.7	4	8	1	C_{10}	155,182	170,566	9.02	177,751	198,207	10.32
	H_{A_3}	$L_{H_{A_3}}$	0.7	4	8	1	C_{11}	224,725	267,779	16.1	193,283	248,613	22.26
		$H_{H_{A_3}}$	0.5	2	16	10	C_{12}	330,480	492,685	32.9	311,223	456,892	31.88

Based on the results obtained, integrated approach shows 1.75 to 34.5 percent improvement compared to independent approach. The maximum improvement is obtained for the case $(H_{H_{A_2}})$ where value of factor of cost of rejection is 10, while minimum improvement is obtained for the case $(L_{L_{A_1}})$ when value of factor of cost of rejection is 1.

Observations

More improvements have been observed for small sample size with low sampling frequency at high process variability and for high value of cost of rejection. Low sample size and low sampling frequency show a lesser sensitive control chart mechanism used by the industry. This is generally a case where cost of quality monitoring is higher. The scenarios of high rejection cost can be seen in industries which produce precision components viz., firms manufacturing components for aircraft, automobile and power plants, etc. Therefore, if process variability is high, cost of rejection is higher and due to high cost of quality monitoring a stringent control chart mechanism is not feasible to employ, production manager should look for integrated operation planning to get better system performance from its existing shop-floor.

3.7.3 Varying process parameters

To evaluate the variation of process parameters, sets of mean batch processing time is randomly generated from uniform distribution in the interval [50, 250]. However, because of stochastic nature of manufacturing process, there are uncertainties regarding exact processing time, to accommodate this, an uncertainty of ±10 percent is added in each generated batch processing time. For example, three consecutive batches have mean processing time 50, 80 and 200 hours, then after adding the uncertainties viz., 50±5, 80±8 and 200±20 hours respectively. Such 50 sets of batch processing time $(P_1, P_2, P_3 \dots \dots, P_{50})$, are generated to examine the variation of processing time. The batch due dates are integer values generated from uniform distribution over $\left[A\left(1-\rho-\frac{l}{2}\right), A\left(1-\rho+\frac{l}{2}\right)\right]$ as suggested by Potts and Van (1982), where A is makespan time of system i.e., maximum completion time when batches are scheduled considering machines are always available, ρ is the tardiness factor, and l is the due date range factor respectively. Larger values of ρ indicates that the due date of batch is near to its scheduled time and vice versa. The value of l is fixed as 0.6. The tardiness factor ρ is assumed to be 0.4 for restrictive due date case (DT_1) and 0.2 for un-restrictive due date case (DT_2). These due date cases are relevant; as some industries are most of the time running short to due date of batches and for some industries there might be possibility to have early delivery of batches.

Results

To analyze the effect of process parameters, cases of minimum and maximum improvement obtained by varying quality control parameters i.e., $L_{L_{A_1}}$ and $H_{H_{A_2}}$ (see table 3.6) are evaluated for 50 sets of batch processing time $(P_1, P_2, P_3, \ldots \ldots, P_{50})$ with two due date cases (DT_1 and DT_2). Thus, a total of 200 scenarios are generated. While evaluation, maintenance parameters and quality control parameters are set as per cases from table 3.6 and other parameters are set as used in example presented in section 3.4. Each scenario is evaluated by integrated as well as independent approach. The obtained results are shown in figures 3.6(a)-3.6(d). It has been observed that integrated approach shows 0.6 to 35.8 percent improvement over independent approach.

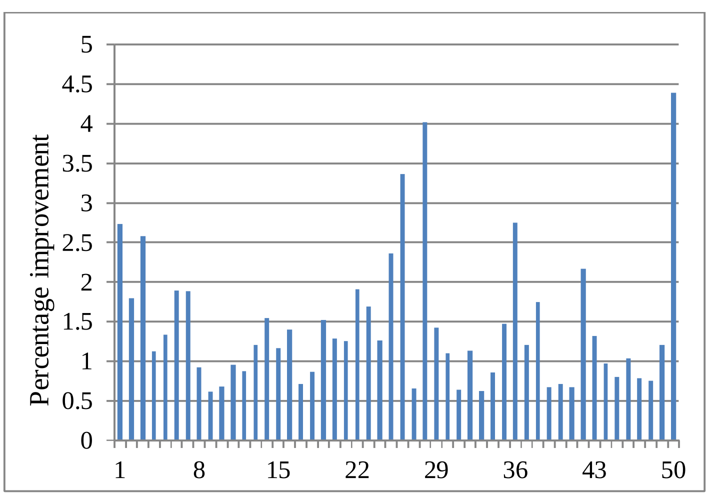


Figure 3.6(a) Comparative results of restrictive due date case (DT_1) for $L_{L_{A_1}}$

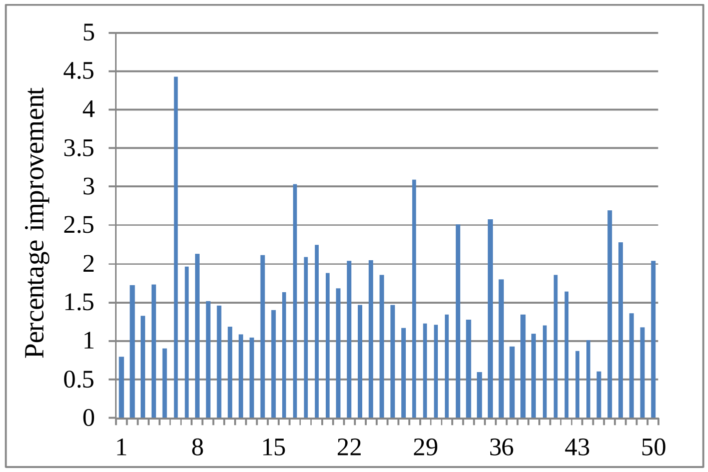


Figure 3.6(b) Comparative results of restrictive due date case (DT_1) for $H_{L_{A_2}}$

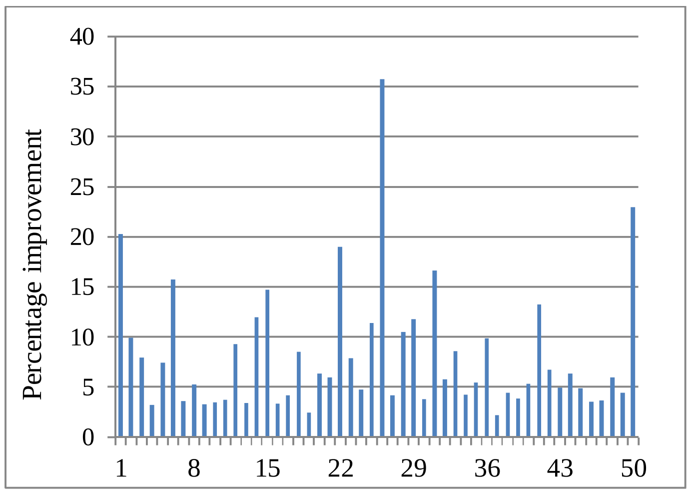


Figure 3.6(c) Comparative results of un-restrictive due date case (DT_2) for $L_{L_{A_1}}$

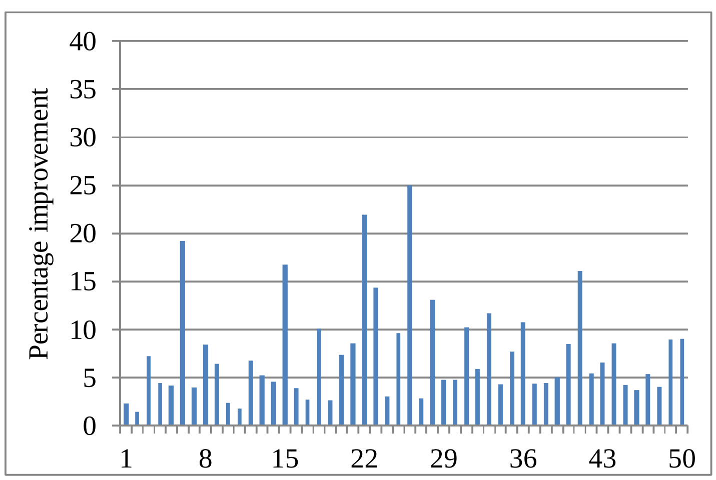


Figure 3.6(d) Comparative results of un-restrictive due date case (DT_2) for $H_{L_{A_2}}$

Observations

More improvements have been observed for restrictive due date case compared to un-restrictive case, under varying sets of batch processing time. Thus, for industries where customer imposes high penalty for late delivery of products, production manager should look for integrated approach for improved system performance.

3.7.4 Variation of number of machines and batches

Evaluation was extended to analyze the merits of integrated approach for the variation of number of machines i.e., 3 machines (M_1, M_2, and M_3) and 5 machines (M_1, M_2, M_3, M_4, and M_5), and number of batches i.e., 7 batches (B_1, B_2,……,B_7) and 9 batches (B_1, B_2,……,B_9). For this, the 12 cases of table 3.6 are considered. Each case is analyzed for machines and batches variation (3M-7B, 3M-9B, 5M-7B, and 5M-9B) by integrated as well as independent approach. Lower improvements have been observed from table 3.7 for the cases where 7 and 9 batches are to be scheduled on 3 machines compare to cases where same batches are to be scheduled on 5 machines. Also, integrated approach is found more effective for industrial environment with large number of machines and batches.

From the results of comprehensive evaluations, it is evident that integrated approach always gives better result compared to independent approach irrespective of environment and parameters. However, integrated approach becomes very important if machines are quite aged, PM is not very effective in restoring the machine age, industrial environment having large number of machines and batches. Further, it becomes more important if cost of rejection is high and due date is comparatively tighter. Finally, it can be said that as the complexity of the manufacturing environment increases; the proposed approach is more beneficial in improving system performance.

Table 3.7 Merits of integrated approach on variation of number of machines and batches

Case	3 Machines – 7 Batches			3 Machines – 9 Batches			5 Machines – 7 Batches			5 Machines – 9 Batches		
	Int. (OOC)	**Ind. (OOC)**	**Imp. (%)**	**Int. (OOC)**	**Ind. (OOC)**	**Imp. (%)**	**Int. (OOC)**	**Ind. (OOC)**	**Imp. (%)**	**Int. (OOC)**	**Ind. (OOC)**	**Imp. (%)**
C_1	131,368	133,715	1.76	354,073	364,525	2.87	89,502	93,029	3.79	115,211	117,262	1.75
C_2	137,945	140,780	2.01	361,060	373,107	3.33	96,293	102,054	5.65	127,854	134,501	4.94
C_3	144,866	148,904	2.71	382,265	394,331	3.06	99,958	106,380	6.04	140,184	152,597	8.13
C_4	168,948	178,215	5.20	416,674	435,932	4.42	127,451	134,303	5.10	185,644	217,858	14.8
C_5	146,358	150,207	2.56	381,994	409,252	6.66	106,397	112,703	5.60	145,729	148,523	1.88
C_6	140,340	142,731	1.68	358,537	377,507	5.03	97,726	101,681	3.89	144,044	156,163	7.76
C_7	170,891	177,329	3.63	419,990	432,846	2.97	129,630	136,955	5.35	191,378	226,145	15.4
C_8	201,113	206,014	2.38	464,193	482,376	3.77	173,288	201,803	14.13	249,683	381,212	**34.5**
C_9	172,332	175,671	1.90	402,061	421,222	4.55	130,823	131,669	**0.64**	170,957	174,124	1.82
C_{10}	171,958	174,212	1.29	408,805	416,201	1.78	117,323	120,939	2.99	155,182	170,566	9.02
C_{11}	161,215	164,419	1.95	424,063	430,704	1.54	108,984	111,957	2.66	224,725	267,779	16.1
C_{12}	191,473	202,056	5.24	451,536	479,727	5.88	153,615	156,388	1.77	330,480	492,685	32.9

Note: “Int.” refers for integrated approach, “Ind.” for independent approach, and “Imp.” for improvement

3.8 Effect of maintenance resource constraints in a joint production and maintenance context

Previous work shows that joint consideration of production schedule and maintenance plan is advantageous. However, the success of jointly planned production schedule depends on timely execution of planned and unplanned maintenance actions. While it is often impossible to perform all the desirable maintenance actions due to the limitation on maintenance resources such as spare parts, maintenance technicians, etc. (Do et al., 2015). Previous work considers unlimited maintenance resource. Also, the work considers a single performance measure, and is demonstrated through a numerical example. To overcome these limitations, in this section, the effect of spare parts and technicians' unavailability on joint production and maintenance planning decisions for a real flow-shop environment is investigated considering different performance measures. The performance measures considered here are makespan, Total Production Cost (TPC), and System Utilization (SU). A simulation-based optimization technique is used to obtain the optimal production and maintenance plan. Different cases of spare parts Lead Times (LTs) and technician's availability are considered for investigation in a complex industrial environment. For each case production and maintenance planning decisions are analyzed. Next sub-section presents the problem description and formulation.

3.8.1 Problem description and formulation

The joint approach is studied in the context of a firm named AVTEC Private Limited (see, chapter 4 for firm details). A section of the firm called Hard Line is considered for the study which is a kind of flow-shop. The section consists of six (m=6) non-identical machines M_j where $j = 1, \dots, m$. The machines contain multiple binary components C_{jy} where $y = 1,2 \dots, 4$. Binary means the component has two states either working or failed. The machines i.e., $M_1, M_2, \dots, M_6$ have 3, 2, 2, 4, 3 and 1 different binary components respectively, and are shown in table 3.8. For example machine M_1 has three components i.e., C_{11}, C_{12} and C_{13}. The times-to-failures of components follows two-parameter Weibull distribution with a shape parameter β_j and scale parameter η_j. Whenever a machine component fails, the machine stops production and a CM is performed on the machine to restore it back to working condition by replacing failed component. Machines also receive PM at time PM_{time_j}. In PM, operations like cleaning, lubrication, change of filters, etc., are performed. Time to carryout PM is 8 hours and time to replace the failed components for CM is μ_j hours. Fixed costs to carryout per PM and per CM are 1000 and 5000 MU respectively. The maintenance activity is dependent on availability of resources like spare parts and maintenance technicians. Unlimited maintenance resources provide instant availability but cost more. Thus, in current work, limited spare parts are considered. Similarly, limited maintenance technicians are considered here. The cost per technician per hour is 325 MU. At shop-floor, some machines are occupied more compare to others and delay in maintenance on these machines may affect production schedule. Therefore, on these machines, maintenance is needed in priority. Thus, a priority is given to occupied machines based on their load. Properties of machines are shown in table 3.8.

The above mentioned system processes six (n=6) jobs J_i where $i = 1, \dots, n$. Let these jobs are to be scheduled non-preemptively on above non-identical machines. The process flow for each job is fixed and number of operations performed in each job as O_i. The process flow is shown in table 3.8. For example, the first operation of job 1 (O_1-J_1) is on machine M_1 and second operation of same job (O_2-J_1) is on machine M_4. Each job has fixed Processing Time (PT_{i_x}), Setup Time (ST_{i_x}), Demand (D), and Batch-Size (BS_{i_x}). The job's properties are shown in table 3.8. The monthly demand is 3000 for each job. The due date (T) for all jobs is 720 hours. If a job is produced before its due date an earliness cost is imposed, and if it is processed after its due date tardiness cost is imposed. Earliness and tardiness cost for a job per hour are 0.1 percent and 0.2 percent of job manufacturing cost respectively.

The methodology for above production and maintenance planning problem with limited resources is as follows: First, optimal job schedule and PM time is obtained by minimizing makespan, minimizing TPC, and maximizing SU separately, considering unlimited maintenance resources. Then various cases ($a = 1,2,..,9$) are generated for spare parts LTs and maintenance technicians' availability, and for each case job scheduling decision and PM time are analyzed again. The obtained results are compared for different performance measures.

Table 3.8 Machine's and job's properties

M_j	C_{jy}	μ_{jy} (hours)	β_{jy}	η_{jy} (hours)	Jobs	PT_{i_x} (minutes)	ST_{i_x} (minutes)	BS_{i_x}	Cost (MU)
	C_{11}	20	2	1800	O_1-J_1	9.6	90	600	540
M_1	C_{12}	16	1.8	2000	O_1-J_2	4.2	60	500	800
	C_{13}	15	2.5	1500	O_1-J_3	2.6	42	300	620
M_2	C_{21}	10	1.5	1000	O_1-J_4	8.1	30	400	360
	C_{22}	30	2.1	1200	O_1-J_5	1.5	60	400	600
M_3	C_{31}	25	3	1800	O_1-J_6	4	30	300	450
	C_{32}	20	2.7	2400	O_2-J_4	6.8	120	200	500
	C_{41}	15	2	3000	O_2-J_1	3.2	20	500	700
M_4	C_{42}	18	1.6	1600	O_2-J_3	2.8	60	500	800
	C_{43}	14	1.8	1800	O_2-J_5	3	90	500	850
	C_{44}	16	2.1	2000	O_2-J_6	2.1	60	500	600
	C_{51}	24	1.8	1800	O_3-J_3	6.2	30	600	1000
M_5					O_4-J_4	4.1	360	300	900
	C_{52}	16	2.5	1600	O_3-J_5	1.4	60	200	1000
	C_{53}	20	3	1200	O_4-J_6	3.2	30	400	1000
M_6	C_{61}	25	2	3000	O_3-J_4	5.6	120	300	650
					O_3-J_6	1.9	90	400	800

Based on above description, the problem is formulated as follows:

Performance measure (I): Minimize,

$$\text{Makespan} = \text{Max}(CT_1, CT_2, CT_3, CT_4, CT_5, CT_6) \tag{3.22}$$

or

Performance measure (II): Minimize,

$$\text{TPC} = EC + TC + PM\ C_a + CM\ C_a \quad where\ a = 1,2,..,9 \tag{3.23}$$

or

Performance measure (III): Maximize,

$$SU = \sum_{j=1}^{m}\sum_{i=1}^{n}\sum_{x=1}^{O_i}\frac{\sum_{k=1}^{k_j}\left[OT_{i_x}\right]_{j_k}}{T} \tag{3.24}$$

where, CT_i is completion time of i^{th} job, and $\left[OT_{i_x}\right]_j$ is batch operation time of i^{th} job sequenced on j^{th} machine at k^{th} position for x^{th} operation.

Makespan is total time elapsed when all the jobs have completed their processing. While utilization defined here is a portion of available time for which the system is operating. The TPC considered here is the sum of Earliness Cost (EC), Tardiness Cost (TC), PM Cost $(PM\,C_a)$, and CM Cost $(CM\,C_a)$. Here 'a' refers to different cases of unavailability of maintenance resources. These performance measures are a function of sequencing decision $(p_{i_{x_{j_k}}})$ and PM decision (PM_{time_j}) which are defined as:

$$\left(p_{i_{x_k}}\right)_j = \begin{cases} 1, & if\ \ a\ batch\ of\ i^{th}\ \ job\ is\ sequenced\ at\ k^{th} \\ & position\ on\ \ j^{th}\ machine\ for\ x^{th} operation \\ 0, & Otherwise \end{cases}$$

Decision of PM time of j^{th} machine: PM_{time_j}

The problem is subjected to a constraint which ensures the sequencing of a batch of i^{th} job scheduled on j^{th} machine at k^{th} position for an operation.

$$\sum_{k=1}^{k_j} \left(p_{i_{x_k}}\right)_j = 1 \tag{3.25}$$

The next sub-section provides the details of the performance model.

3.8.2 Calculation of makespan and total production cost

The following assumptions are made in development of performance model:

- Each job is available at the beginning of production period.
- Each machine can handle only one job at a time.
- Failure of machine's components is independent.
- Machines are available at the start of production.
- Machine always produces items of acceptable quality

As discusses in the previous section, Makespan $= Max(CT_i)$

where, CT_i is the sum of operations time of all the operations (i.e., O_i) of the i^{th} job and can be expressed as:

$$CT_i = \sum_{j=1}^{m} \sum_{x=1}^{O_i} \left[\frac{OT_{i_x}}{BS_{i_x}}\right]_j \tag{3.26}$$

where, $\left[OT_{i_x}\right]_j$ is the sum of batch operations times of i^{th} job and preceding jobs sequenced on j^{th} machine. It can be expressed as:

$$\left[OT_{i_x}\right]_j = \sum_{k=1}^{k_j}\left[OT_{i_x}\right]_{j_k} \tag{3.27}$$

Mathematically, batch operation time of i^{th} job processing on j^{th} machine for x^{th} operation is sum of setup time (ST_{i_x}), batch processing time $(PT_{i_x} \times BS_{i_x})$, machine downtime due to PM $(T_{pm_j})_{i^-}$ and CM $(T_{cm_j})_i$, and waiting time (W_{i_x}) due to the unavailability of previous sequenced batch/es. Generally, in literature waiting time is ignored. However, it contributes significantly in completion time of job and thus should be considered with operation time. Then,

$$\left[OT_{i_x}\right]_{j_k} = [W_{i_x} + ST_{i_x} + PT_{i_x} \times BS_{i_x} + \left(T_{pm_j}\right)_{i_{x_k}-} + \left(T_{cm_j}\right)_{i_{x_k}}] \times p_{i_{x_k}} \tag{3.28}$$

The downtime $\left(T_{pm_j}\right)_{i_{x_k}-}$ of j^{th} machine due to PM before processing of a batch of ${i_x}^{th}$ job sequenced at k^{th} position occur if PM is performed before the same batch and is:

$$\left(T_{pm_j}\right)_{i_{x_k}-} = \left(N_{pm_j}\right)_{i_{x_k}-} \times (TTR_{pm_j}) + WT_{l_j} + WT_{s_{pm_j}} \tag{3.29}$$

where, TTR_{pm_j} is time to repair for PM of j^{th} machine. WT_{t_j} is waiting time for maintenance technicians and $WT_{s_{pm_j}}$ is waiting time for spare parts for PM on j^{th} machine.

where, $\left(N_{pm_j}\right)_{i_{x_k}-} = \begin{cases} 1, & \text{If PM is performed before processi} - \\ & \text{ng of a batch of } {i_x}^{th} \text{ Job on } j^{th} \text{ machine} \\ 0, & \text{Otherwise} \end{cases}$

The time of PM performed on j^{th} machine is evaluated by optimizing PM_{time_j}.

$$\sum_{y=1}^{y}\sum_{k=1}^{k_j}\left(N_{pm_j}\right)_{i_{x_k}} = 1 \text{ and } 0 \leq PM_{time_j} \leq T \tag{3.30}$$

where, y is a number of production cycles for a machine. A production cycle is defined as the total time elapsed of all sequenced jobs on a machine when each job is processed at least once.

$\left(T_{cm_j}\right)_{i_{x_k}}$ is the downtime of j^{th} machine due to CM occur during the processing of a batch of ${i_x}^{th}$ job sequenced at k^{th} position and is:

$$\left(T_{cm_j}\right)_{i_{x_k}} = \left(NF_j\right)_{i_{x_k}} \times (TTR_{cm_j}) + WT_{t_j} + WT_{s_{cm_j}} \tag{3.31}$$

$$\left(NF_j\right)_{i_{x_k}} = \begin{cases} 1, \text{ If failure occurs during process} - \\ \text{ing of a batch of } {i_x}^{\text{th}} \text{ Job on } j^{\text{th}} \text{ machine} \\ 0, \quad \text{Otherwise} \end{cases}$$

where, $WT_{s_{cm_j}}$ is waiting time for spare parts for CM on j^{th} machine.

As discussed earlier, in manufacturing system maintenance resources are limited. Also, at shop-floor, some machines are critical and may need maintenance on priority. So, a priority (Pr_j) is given to each machine based on their load.

$$Pr_j = \frac{\sum_{i=1}^{n}\left[OT_{i_x}\right]_j}{T} \tag{3.32}$$

where, T is planning horizon and its value is 720 hours. Spare parts may not be available at the time of PM and CM due to variation in Lead Time (LT) and may delay the maintenance activity. Thus, an appropriate spare parts provision policy is necessary to minimize such delay.

The ingredient costs of TPC (as mentioned in section 3.8.1) are calculated using equations below:

$$EC = \sum_{i=1}^{n} max\{0, EC_i(T - CT_i)\} \tag{3.33}$$

$$TC = \sum_{i=1}^{n} max\{0, TC_i(CT_i - T)\} \tag{3.34}$$

$$PM\ C_a = \sum_{j=1}^{m}[(TTR_{pm_j}) \times C_a + FC_{pm_{j_a}}] \times N_{pm_j}\ where\ a = \{1,2,..,9\} \tag{3.35}$$

$$CM\ C_a = \sum_{j=1}^{m}[(TTR_{cm_j}) \times C_a + FC_{cm_{j_a}}] \times NF_j \tag{3.36}$$

where, EC_i and TC_i are earliness and tardiness cost of i^{th} job per hour. a represents the cases of maintenance resources unavailability (see, section

3.8.4). C_a is labor cost. $FC_{pm_{j_a}}$ and $FC_{cm_{j_a}}$ are fixed costs to carryout per PM and per CM. Next sub-section presents solution method used to solve the problem and obtained results.

3.8.3 Solution method and results

The job sequencing and PM decisions are to be determined simultaneously for the problem presented in section 3.8.1. This problem is of combinatorial type and also strongly NP-hard (Do et al., 2015). Also, the present work considers stochastic parameters which significantly increase the problem complexity. Simulation coupled with optimization is most used method by researchers as solution methodology for such problems (Garg and Deshmukh, 2006; Sharma et al., 2011). Thus, a combined simulation and meta-heuristic approach is used in this research to solve the problem. Jobs characteristics, machines properties, process flow, etc., are coded in Witness 14 simulation platform (https://www.lanner.com/insights/blog/witness-14-has-arrived.html).

For optimization, various meta-heuristic algorithms like SA, GA, TS, etc., can be used. SA is proved beneficial over GA (Tambe et al., 2013; Tambe and Kulkarni, 2015) and ant colony algorithm (Nahas et al., 2009) in terms of quality of solution and computation time for approximately solving large combinatorial optimization problems. As the main aim of the current work is to investigate the effect of maintenance resource constraints, finding out best suitable algorithm is not targeted in this work. Here, Adaptive Thermo-statistical Simulated Annealing (ATSA) algorithm is used for optimization. It gives rapid convergence to high quality solutions using a very modest number of evaluations. To obtain the optimal algorithm parameters, initial runs are performed for varying initial temperature in the range of 500 to 5000, the cooling rate in the range of 0.90 to 0.95, cooling steps in the range of 10 to 100, and without improvement scenarios i.e., termination condition in the range of 100 to 1000 respectively. It was observed that the solutions obtained with different algorithm parameters did not differ significantly from each other. However, the optimal parameters are the one in which above problem is solved in the least time. The optimal values of initial temperature (K), cooling rate, cooling steps, and number of without improvement scenarios for termination are 1000, 0.91, 25, and 100 respectively. The complete simulation and optimization process is presented below in the form of flow chart in figure 3.7. The pseudo code of the same can be found in Appendix A.

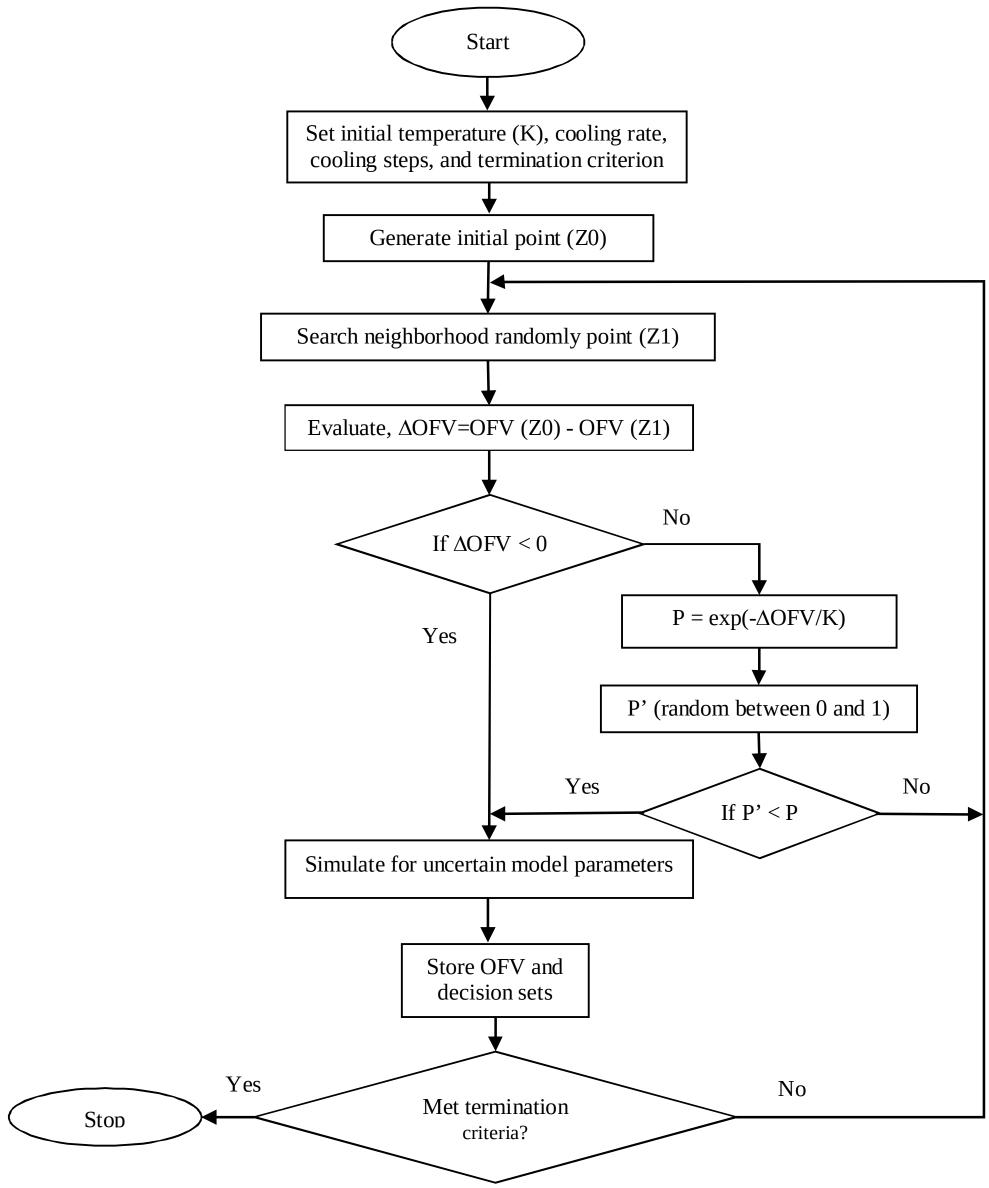


Figure 3.7 A flow chart of simulation-based Adaptive Thermo-statistical Simulated Annealing

First, the joint problem is solved considering 100 percent availability of maintenance resources i.e., α =1 (see, section 3.8.4). The optimal production sequence and PM decisions are obtained by minimizing makespan, minimizing TPC, and maximizing SU by utilizing Eq. (3.22), Eq. (3.23), and Eq. (3.24) respectively. The results are shown in table 3.9 where I, II, and III represents the results obtained by minimizing makespan, minimizing TPC, and maximizing SU respectively. The corresponding makespan is 19.2 days; TPC is 489,370 MU; and SU is 84 percent. The number of maintenance technicians required corresponding to each performance measure is 15.

Table 3.9 Obtained production sequence and PM_{time_j}

M_j	Jobs	Sequence ($p_{i_{x_k}}$)			PM_{time_j} (Weeks)			C_{jy}	Spare Quantity
		I	II	III	I	II	III		I, II, and III
M1	O_1J_1	3	2	1	2	1	2	C_{11}	5
	O_1J_2	1	1	2				C_{12}	7
	$O1J_3$	2	3	3				C_{13}	3
M2	O_1J_4	1	2	1	1	3	2	C_{21}	8
	O_1J_5	2	1	2				C_{22}	4
M3	O_1J_6	2	1	1	2	3	2	C_{31}	6
	O_2J_4	1	2	2				C_{32}	7
M4	O_2J_1	2	2	3	1	1	1	C_{41}	10
	O_2J_2	1	1	4					
	O_2J_3	3	4	1				C_{42}	6
	O_2J_5	5	3	5				C_{43}	8
	O_2J_6	4	5	2				C_{44}	3
M5	O_3J_3	1	2	2	3	2	2	C_{51}	5
	O_4J_4	3	4	3					
	O_3J_5	4	3	4				C_{52}	11
	O_4J_6	2	1	1				C_{53}	9
M6	O_3J_4	2	1	1	2	1	2	C_{61}	7
	O_3J_6	1	2	2					

3.8.4 Investigation and observations

To investigate the effect of the unavailability of spare parts and maintenance technicians on joint production and maintenance planning decisions and on performance measures, total nine cases $(a = 1,2,..,9)$ are investigated. The spare parts LTs and technician's availability is varied as 0, 1, and 2 weeks and 25 percent, 50 percent, and 100 percent respectively. In these cases, per hour cost of technician (C_a) and cost of spare parts $(FC_{pm_{j_a}}\ and\ FC_{cm_{j_a}})$ are change as per the case. For instance, to ensure 100 percent technician's availability, firm should have 15 technicians (see, previous section) i.e., 15×8×30 (number of technicians × per day working hours × number of days) working hours and it costs 325 MU per hour. On the other hand, for 50% and 25% technicians' availability cases, firm should have 7.5×8×30 hours and 3.75×8×30 hours of technicians' respectively and it costs 162.5 MU and 81.25 MU per hour. Similarly, to ensure 100% availability of spare parts, the firm procures the spare parts from supplier with zero LT i.e., instant delivery; it cost 1000 MU and 5000 MU per part for PM and CM respectively, which is 2 times more compare to the supplier with 2 week LT, and cost 1.5 times more compare to the supplier with 1 week LT. For each case, the problem of section 3.8.1 is solved using ATSA algorithm for different performance measures separately. The value of performance measures for each case and the changes in optimal production sequence and PM decisions compared to the results of section 3.8.3 are shown in table 3.10. From table 3.10, following observations have been made:

- The unavailability of maintenance resources significantly affects the joint decisions and system performance. The variations in the optimal values of different performance measures are found in the range of 14 to 30 percent.
- For performance measures I and III, the optimal values are obtained for unlimited maintenance resources case while for performance measure II, the optimal value is obtained for limited maintenance resources case i.e., case 5. It can be therefore, reasoned that total production cost gives better indication of system performance compared to makespan and system utilization. Thus, only total cost is used as performance measure in the rest of the approaches in this thesis.

Table 3.10 Results of various cases of spare parts lead time variation and technicians unavailability

Case (a)	Lead Time (Weeks)	Technician availability	I (Makespan)			II (TPC)			III (System Utilization)		
			$p_{i_{x_k}}$ change	PM_{time_j} change	Makespan (Days)	$p_{i_{x_k}}$ change	PM_{time_j} change	TPC (MU)	$p_{i_{x_k}}$ change	PM_{time_j} change	Utilization
1	0	100%	No	No	**19.2**	No	No	489,370	No	No	**84%**
2	0	75%	Yes	No	20.7	Yes	Yes	496,785	Yes	No	82%
3	0	50%	Yes	Yes	22	Yes	Yes	504,398	Yes	Yes	81%
4	1	100%	Yes	No	21.2	Yes	Yes	512,215	No	No	80%
5	1	75%	Yes	Yes	22.8	Yes	Yes	**456,862**	Yes	Yes	79%
6	1	50%	Yes	Yes	23.4	Yes	Yes	492,652	Yes	Yes	78%
7	2	100%	Yes	Yes	22.5	Yes	No	508,269	Yes	No	76%
8	2	75%	Yes	Yes	24.1	Yes	Yes	515,196	Yes	Yes	75%
9	2	50%	Yes	Yes	25	Yes	Yes	546,304	Yes	Yes	72%

3.9 Summary

In this chapter, an integrated operations planning approach is developed by considering the relationship between production and maintenance, and the performance of the approach is comprehensively investigated for various manufacturing scenarios. The purpose is to provide manufacturing industries more realistic integrated operations planning approach to evaluate production and maintenance planning decisions, and to analyze the effect of maintenance resource constraints.

3.9.1 Contributions

The major contributions from this chapter are highlighted as follows:

a) The proposed integrated approach is more realistic as it considers initial ages of machines, random failure behaviour, imperfect maintenance, uniformly distributed processing times, etc. The approach simultaneously evaluates production and maintenance planning decisions.
b) First time in the literature, the approach is comprehensively evaluated for 473 different manufacturing scenarios. The approach provides 0.6 to 35.8 percent economic improvements over independent approach under these scenarios.
c) The comprehensive evaluation helps in proposing some thumb rules for the adaptation of the proposed approach. The same are:
    - Higher improvements have been observed for machines with low restoration factor values. In other words, if the PM policy is less effective i.e., restoration factor is low, one should think of integrated approach to improve the system performance.
    - For older machines, individual optimization of production and maintenance policies may not be cost-effective for the organization and it should look for integrated approaches.
    - More improvements have been observed for restrictive due date case compared to un-restrictive case, under varying sets of batch processing time. Thus, for industries where customer imposes high penalty for

late delivery of products, the integrated may be more beneficial in improving system performance.

- The proposed approach offers more benefit for the scenarios where quality inspection sample size is small, sampling frequency is low, process variability is high, and value of cost of rejection is huge.
- The results reveal that as the complexity of the manufacturing environment increases; the proposed approach is more beneficial in improving the system performance.

d) The parameters i.e., processing cost, earliness cost, and tardiness cost are higher sensitive to the proposed integrated model and thus, one should estimate the values of these parameters accurately to get clear picture of overall operations cost and economic impact of operational policies.

e) The integrated production and maintenance approach is also offered to a flow-shop problem under maintenance resource constraints. The unavailability of maintenance resources significantly affects the joint decisions and system performance. The variations in the optimal values of different performance measures (makespan, total production cost, and system utilization) are found in the range of 14 to 30 percent.

f) For performance measures i.e., makespan and system utilization, the optimal values are obtained for unlimited maintenance resources case while for performance measure total production cost, the optimal value is obtained for limited maintenance resources case. Thus, total cost gives better idea about the overall performance of the system.

3.9.2 Research limitations and future scope

The proposed approach does not consider splitting of batch. Considering the batch splitting will increase the problem complexity but take it closer to reality. Also, inventory control is not considered in the current research, which may be a direction for further study.

Chapter 4[4]

Case-based investigation of the value of integrated operations planning approach

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Chapter 2 identified that the integration of more than two shop-floor functions for real and complex manufacturing system entirely eludes literature. Thus, this chapter intends to develop integrated operations planning approach considering production, maintenance, and inventory together for autonomous decision-making in industries. Moreover, a comprehensive performance investigation has been carried out to analyze the robustness and implications of the offered approach for various manufacturing scenarios.

Key Highlights

Purpose: The purpose is to provide manufacturing industries more realistic, validated, and generalized integrated approach for intelligent planning of shop-floor operations.

Findings: The integrated approach outperforms over conventional approaches and it delivers 4.2 to 21.6 percent economic improvements for various manufacturing scenarios. The benefit of proposed approach is more prominent for the scenarios where the demand is high and uncertainty in processing time is present. The benefits increase by considering more shop-floor functions simultaneously. However, the computational complexity also increases. Therefore, novel approaches will be required to deal with such complexity.

Originality and Contribution: First time in the literature, an integrated approach considering production, maintenance, and inventory is developed for real and

[4] *The work presented in this chapter is published under the title "Investigating the value of integrated operations planning: A case-based approach from automotive industry", 2018 in International Journal of Production Research. DOI: 10.1080/00207543.2018.1424367*

complex manufacturing environment of an automotive industry. An added contribution lies in the extensive performance investigation viz., sensitivity analysis; comparison of optimization algorithms; comparison with conventional approaches; efficacy analysis of integration; and the study of robustness and implications for various manufacturing scenarios. The successful implementation of the approach developed in this part of the thesis will help in integrating various operations planning aspects at the decision-making stage itself, thereby reducing human intervention in coordinating and implementing various operations plans. This is believed to be one of the important requirements in realization of Industry 4.0 in industries.

Practical Implications: In general, the developed approach can be applied in any manufacturing industries. However, the approach provides more economic advantages in industries, especially where various products are produced in medium or large scale through different machines; production is performed in multiple stages; demand variation is high; shop-floor has some older machines; etc.

4.1 Introduction

In literature, most of the integrated approaches have considered two shop-floor functions and are illustrated for hypothetical manufacturing environments which limit the practical use of such approaches. To overcome this gap, an integrated approach considering production, maintenance, and inventory together, with an objective of minimizing overall operations cost is developed for complex multi-machine system of an automotive industry. The production system of the industry consists of 23 different machines which processes 11 jobs. Machines are characterized by random failure behaviour, and intermediate buffers between machines are considered to ensure continuous production during disruption due to corrective or preventive maintenance actions. Due to the combinatorial nature of the problem, a meta-heuristic namely, ATSA algorithm is used to achieve near-optimal solution in less computation time. The results revealed that substantial economic benefits could be achieved through the proposed approach over conventional independent approaches. A systematic sensitivity analysis; computational comparison; and the importance of integration of various operations planning aspects are also tested. Finally, a comprehensive evaluation is performed to study the robustness and implications of the proposed approach for various production scenarios. The scenarios are generated by varying maintenance, process parameters, etc. Results of such pervasive performance investigations confirm the value of the proposed approach over conventional approaches.

The rest of the chapter is organized as follows. In the next section, the industrial case and problem formulation is presented. Section 4.3 briefly discusses the cost models used to calculate the overall operations cost. A case study with results, comparative analysis and comprehensive evaluations are presented in section 4.4. Finally, summary of this chapter is offered in section 4.5.

4.2 Industrial case

This chapter takes a case oriented path to study the importance of integrated operations planning. Consequently, the approach is first studied for the case of a firm named AVTEC Private Limited, India. The firm produces engines and transmission sets for automotive manufacturers. From the unit view, firm can broadly be divided into three main sections namely Transmission Unit, Engine Unit, and Component Section and is shown in figure 4.1. Modus operandi of key shop-floor functions (Production/Maintenance/Inventory/Quality) for all the three units was more or less similar and thus for operations planning perspective only transmission unit is considered. Further, the starting point from which material enters the unit is Soft Line. Majority of the parts travels through Heat Treatment, Sleeve Line and Hard Line only after passing from Soft Line. These cells are similar in terms of shop-floor operations planning. Thus, on transmission unit, Soft Line is considered for further study.

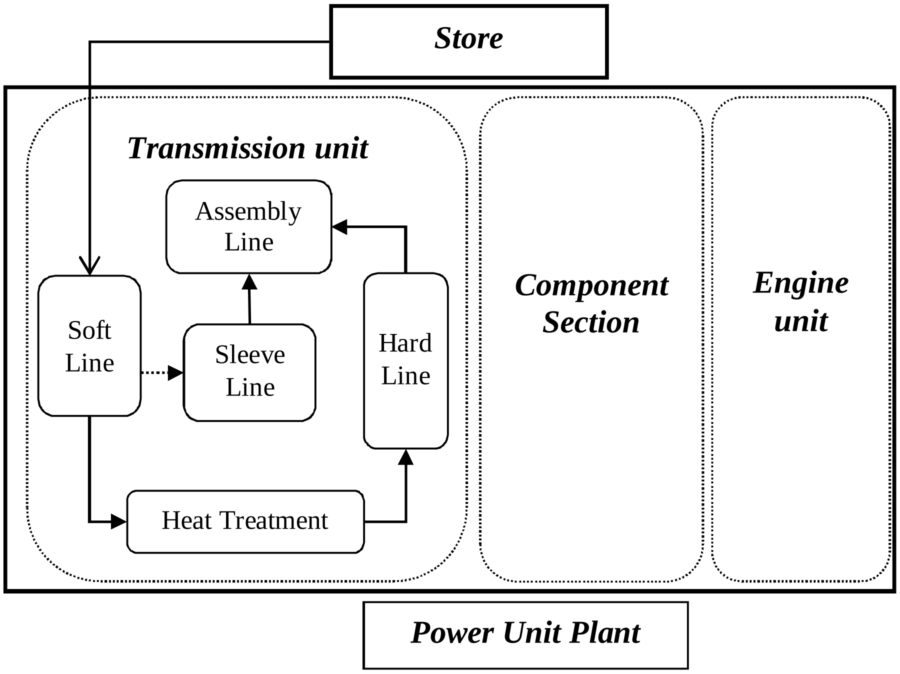

Figure 4.1 Layout of the firm

The Soft Line processes 11 different jobs (J_1, J_2…,J_{11}) like main shaft, counter gear shaft, gear low main, etc. These jobs undergo a wide range of 49 machining operations i.e., hobbing, shaping, shaving, rolling, etc. These operations are carried out on 23 non-identical machines (M_1, M_2,….,M_{23}). The jobs are assembled after their last operation to produce transmission sets. The process flow for each job is predefined by the process engineers. The process flow of main shaft is shown in figure 4.2, and process flow of all jobs is presented in table 4.1. For example, the first operation of job 1 (i.e., O_1-J_1) is scheduled on machine $M_{1,}$ the second operation (i.e., O_2-J_1) is scheduled on machine M_3 and the third operation (i.e., O_3-J_1) is scheduled on machine M_6. Thus, job 1 (i.e., J_1) is processed from machine M_1, M_3, and M_6, only. Similarly, the flow of all the jobs in different machines can be read from table 4.1.

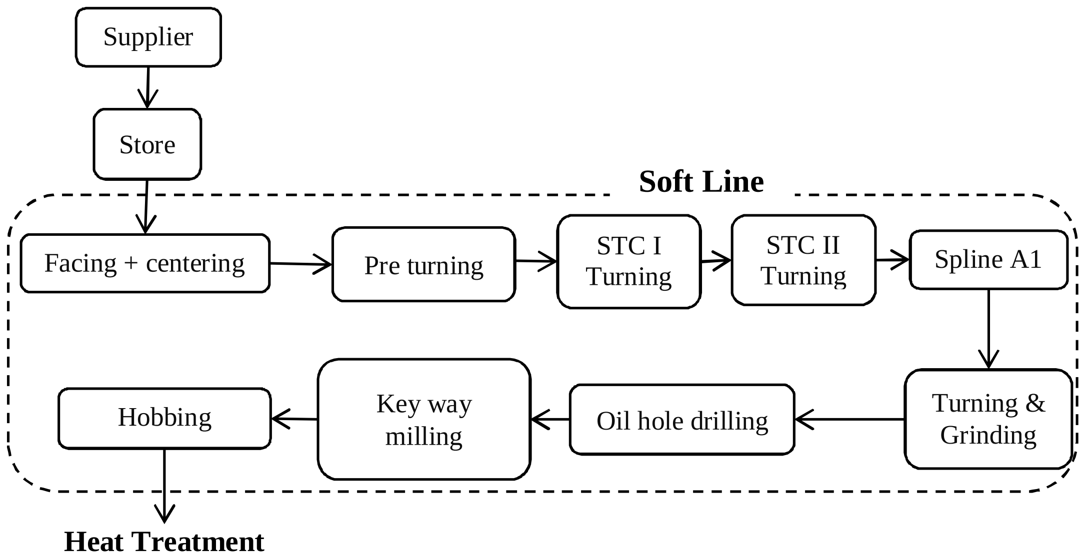

Figure 4.2 Process flow of main shaft

In table 4.1, jobs properties i.e., processing time (PT_{i_x}), setup time (ST_{i_x}), and manufacturing cost of the job (CC_{i_x}) for each operation are also presented. The sequence of these jobs on various machines and their batch-sizes are currently decided by production manager and supervisors based on their experience. An optimized job sequence of production holds prime importance for timely completion and fulfilling the demand of transmission sets. On failure to deliver on time, the firm loses revenue of undelivered transmission sets. Each job is processed in a batch for an operation. Batch-sizing is another key decision, as batches having large size will reduce the number of setups but will increase the WIP inventory carrying cost. These decisions depend on the availability of machines. Machines may be unavailable due to CM or PM. To estimate the times-to-failures distribution of machines, multiple goodness fit tests are performed on past time to failure data of machines using maximum likelihood estimation method to determine the best distribution among exponential, normal, lognormal, Gamma, and Weibull. It is found that times-to-failures of these machines follow a two-parameter Weibull distribution. Shape parameter β_j and scale parameter η_j of these distributions are shown in table 4.1. Currently, the PM plans of machines are prepared by maintenance department based on machines maintenance manual. Accordingly, machines go for PM either annually, biannually or quarterly.

Sometime this plan conflicts with production schedule which may affect the delivery commitments of the firm. The firm uses buffers with each machine. It carries semi-finished/finished items processed through the machine. Buffer supplies items to next operations when the machine is unavailable due to maintenance. Holding items in buffers will incur extra holding costs. Currently, the firm uses a 25 percent service level for buffers which may not be optimal. The interview of supervisors, operators, technicians, etc., has been performed for the understanding of the system and collection of data. Also, machine manual, maintenance logbook, process flow charts, etc., have been studied. It is clear from above discussion that job scheduling, batch-sizing, PM time, and inventory level decisions are critical for shop-floor operations planning of the firm. These vital decisions economically affect the firm and also affect the customers' commitments.

At the firm, these decisions are taken independently by concerned departments heads based on their experience or department level optimization which may not always be optimal for the firm. Moreover, these decisions are interdependent. From the literature point of view, the interdependencies among these decisions are not explored thoroughly for such real complex industrial problem. The above industrial case is a good example to showcase the value of integrated operations planning. Also, the criticality of decisions and their interdependencies may vary from company to company. Thus, generalizing the results for wide range of manufacturing scenarios is important. The same is targeted in this chapter.

Table 4.1 Machine's properties and Job's properties

Machine (β_j and η_j)	Operation-Job	PT_{i_x}(Minutes)	ST_{i_x}(Minutes)	CC_{i_x} (MU)
M_1 (2.3,700)	O_1-J_1	1.57	90	150
	O_1-J_2	1.4	90	100
	O_1-J_3	1.3	90	150
	O_1-J_4	1.8	90	100
M_2 (2.7,500)	O_2-J_{11}	4.5	0	850
M_3 (2,600)	O_2-J_5	0.6	20	150
	O_2-J_2	0.6	20	200
	O_2-J_1	0.6	20	150
	O_2-J_3	0.6	20	200
	O_2-J_4	0.6	20	250
	O_3-J_8	0.6	20	400
	O_2-J_7	0.6	20	200
M_4 (2,800)	O_1-J_{10}	1.6	90	350
	O_1-J_8	1.8	420	150
M_5 (3,540)	O_3-J_3	1.1	60	400
	O_3-J_4	1.24	60	200
	O_3-J_7	1.1	60	200
	O_5-J_8	1.1	60	400
M_6 (2.6,420)	O_3-J_1	2.1	60	400
	O_3-J_6	1.8	60	400
	O_3-J_2	1.9	60	400
M_7 (2.6,480)	O_1-J_9	7.6	60	650
M_8 (1.9,550)	O_2-J_9	8	60	800
M_9 (2,800)	O_3-J_9	2.9	60	850
	O_1-J_{11}	1.2	30	750
M_{10} (2.4,700)	O_8-J_9	2.66	0	1200
M_{11} (2.3,500)	O_4-J_{11}	8.1	0	1000
M_{12} (2.9,620)	O_4-J_9	2.33	0	920
M_{13} (1.8,460)	O_5-J_{11}	1.2	60	1150
	O_3-J_{10}	0.6	30	480
	O_2-J_6	0.6	30	200
M_{14} (1.3,450)	O_1-J_5	1.3	90	150
	O_1-J_6	1.4	90	100
	O_2-J_8	1.5	90	200
	O_1-J_7	2.3	90	100
M_{15} (2,800)	O_6-J_{11}	4.3	180	1200
M_{16} (2.6,700)	O_3-J_{11}	10.6	60	950
M_{17} (2.1,850)	O_7-J_9	1.86	45	1150
M_{18} (2.5,700)	O_7-J_{11}	1.4	60	1300
	O_5-J_{10}	1.3	60	650
	O_3-J_5	1.4	60	400
M_{19} (2.4,500)	O_9-J_9	0.56	90	1250
	O_8-J_{11}	0.56	90	1350
	O_6-J_{10}	0.6	90	700
M_{20} (2.3,600)	O_2-J_{10}	7	180	400
M_{21} (1.5,380)	O_5-J_9	1.2	30	1000
M_{22} (1.2,400)	O_6-J_9	1.3	45	1050
	O_4-J_{10}	1.6	45	1000
M_{23} (2.7,600)	O_4-J_8	2.12	0	400

4.2.1 Problem formulation

Based on the industrial case and insights from literature, a generalized shop-floor operations planning problem is formulated. Consider a flow-shop production system consisting of ‘m’ different non-parallel capacitated machines. Let the shape and scale parameters of the distribution be represented by β_j and η_j respectively where $j = 1, \ldots, m$. The decisions on when to perform PM (PM_{time_j}) on these machines in a planning horizon are evaluated. Time to carryout PM is one shift i.e., 8 hours and time to carryout CM follows a lognormal distribution with mean μ hours and standard deviation σ hours.

The system is processing a set of ‘n’ jobs. These jobs are to be scheduled non-preemptively during a given planning horizon T. The process flow for each job is fixed. Let the number of operations performed in each job is O_i where $i = 1, \ldots, n$. For all the jobs, batch-size $\left(BS_{i_x}\right)$ of an individual operation is evaluated. Let each machine is processing k_j different jobs by changing the setup. The jobs have a given processing time $\left(PT_{i_x}\right)$, setup time $\left(ST_{i_x}\right)$ and manufacturing cost $\left(CC_{i_x}\right)$ for each operation. The manufacturing cost of a job includes raw material cost, processing cost, and overhead cost. After the last operation, all the jobs are assembled to form the product. Demand (D) of product is known and fixed in the planning horizon. Customer requires the product in h number of lots with the size of $\left(\frac{D}{h}\right)$ in the interval of $\left(\frac{T}{h}\right)$. If a job is manufactured before it is required, then it has to be carried till its delivery time, causing extra carrying cost. Additionally, a buffer is attached to each machine for uninterrupted production resulting into additional carrying cost. Three different inventory levels (l_{i_x}) are considered for each buffer to evaluate optimal inventory level. The pictorial representation of the problem is shown in figure 4.3.

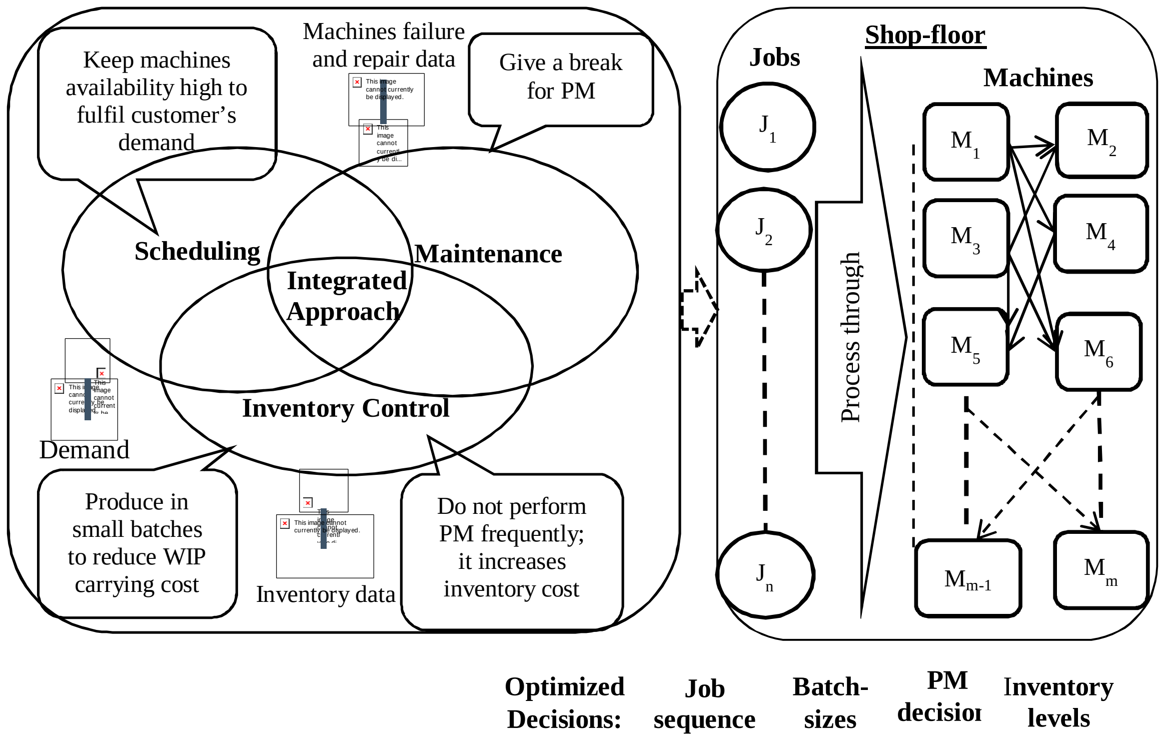

Figure 4.3 Pictorial representation of the problem

Decision variables

Sequencing decision:

$$\left(p_{i_{x_k}}\right)_j = \begin{cases} 1, & \textit{If a batch of } i^{th} \textit{ job for } x^{th} \textit{ operation is} \\ & \textit{sequenced at } k^{th} \textit{ place on } j^{th} \textit{ machine} \\ 0, & \textit{Otherwise} \end{cases}$$

Decision of batch-size of i^{th} job for x^{th} operation: BS_{i_x}

Decision of inventory level of buffers:

$$l_{i_x} = \begin{cases} L, & \textit{with } 25\% \textit{ service level} \\ M, & \textit{with } 50\% \textit{ service level} \\ H, & \textit{with } 100\% \textit{ service level} \end{cases}$$

Decision of PM time of j^{th} machine: PM_{time_j}

Assumptions

Based on the observations from the case industry some generic assumptions are made:

- A job cannot be pre-empted by another job.

- Each job is available at the start of production schedule.
- At the beginning of production schedule machines are available.
- Machine can process only one job at a time.
- The necessary maintenance resources are available.
- Machine always produces items of acceptable quality.
- Failures of machines are independent.

These assumptions are made to reduce the problem complexity and can be easily relaxed based on the particular industrial case.

The job sequencing ($p_{i_{x_k}}$), batch-sizing (BS_{i_x}), inventory level (l_{i_x}), and PM time (PM_{time_j}) decisions are evaluated simultaneously such that Overall Operations Cost (OOC) is minimized. Thus, the problem is formulated as:

Minimize:

OOC = Scheduling cost + Maintenance cost + Downtime inventory cost (4.1)

That is,

$$OOC = \sum_{i=1}^{n}\sum_{x=1}^{O_i}\sum_{k=1}^{k_j} SC(p_{i_{x_k}}, BS_{i_x}) + \sum_{j=1}^{m} MC\left(PM_{time_j}\right) + \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{x=1}^{O_i} DIC\left(l_{i_x}\right)_j \quad (4.2)$$

This is a complex equation as it consists various interdependent decision variables. For example, PM_{time_j} simultaneously affects to $p_{i_{x_k}}, BS_{i_x}$, and l_{i_x}. The equation is non-linear, and strongly NP-hard (see, section 4.4.3). In brief, the equation is explained in next section.

Subject to:

$$\frac{D}{T} \times t_1 \leq Min\left\{t_1\left(BS_{1_{O_1}}, BS_{2_{O_2}}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots, BS_{n_{O_n}}\right)\right\} \quad (4.3)$$

$$\sum_{k=1}^{k_j}\left(p_{i_{x_k}}\right)_j = 1 \quad (4.4)$$

$$\left(BS_{i_x}\right)_j \geq \left(J_{i_x}\right)_j \quad (4.5)$$

where, SC is scheduling cost, MC is maintenance cost, DIC is downtime inventory cost, D is monthly demand, T is planning horizon, t_1 is evaluation time, and $J_{i_{x_j}}$ is the numbers of i^{th} job for x^{th} operation that can be processed through j^{th} machine in one shift i.e., 8 hours.

In the above problem formulation, the objective is subjected to three constraints in which first constraint (Eq. 4.3) ensure that production at any time will be greater or equal to product demand. Second constraint (Eq. 4.4) ensures the sequencing of a job at one place on scheduled machine for an operation. The third constraint (Eq. 4.5) makes sure that minimum batch-size of any job for any operation will not be lower than the number of items that can be processed through the machine in one setup.

4.3 Development of cost models

This section provides cost models for each ingredient cost of overall operations cost.

4.3.1 Evaluation of scheduling cost

Job scheduling is one of the challenging tasks in shop-floor and has various commitments. These are: on-time product deliveries; minimize makespan; minimize WIP items; etc. Traditionally, job scheduling problems are solved for one or two of these commitments. In this work, above commitments are considered to obtain more realistic job schedule. However, for the commensurability, the performance indicators for all the functions are measure in terms of cost. Here, scheduling cost is sum of Revenue Lost (RL), Earliness Cost (EC), and Holding Cost in Queue (HCQ). That is,

$$SC = RL + EC + HCQ \tag{4.6}$$

In next sub-sections, these costs are described in detail.

4.3.1.1 Evaluation of revenue lost

Revenue lost incurs only when the product demand cannot be produced within the planning horizon. If the loss of revenue per undelivered product is LC then total revenue lost can be expressed as:

$$RL = [LC \times (D - P_D)]_T \tag{4.7}$$

where, D and P_D are demand and number of products produced within planning horizon (T) respectively.

As the product is the assembly of various jobs, P_D is equal to minimum of jobs produced in the planning horizon. Therefore,

$$P_D = Min(P_i)\ where, i = 1, \dots, n \tag{4.8}$$

where, P_i is numbers of i^{th} job produced in planning horizon. If the completion time of i^{th} job is CT_i. Then, in planning horizon, P_i is:

$$P_i = \frac{T}{CT_i} \tag{4.9}$$

Here, CT_i is the sum of operations time of all the operations (i.e., O_i) of the i^{th} job and can be calculated using Eq. (3.26) (see, chapter 3). Also, the operation time of a batch of i^{th} job for x^{th} operation on j^{th} machine i.e., $\left[OT_{i_x}\right]_j$ can be calculated using Eq. (3.27) (see, chapter 3), and $\left[OT_{i_x}\right]_{j_k}$ can be calculated using Eq. (3.28) (see, chapter 3).

As in this work, it is considered that necessary maintenance resources are available. Therefore, the downtime $\left(T_{pm_j}\right)_{i_{x_k}-}$ of j^{th} machine due to PM is estimated as follows:

$\left(T_{pm_j}\right)_{i_{x_k}-}$ depends on the decision of PM $\left(N_{pm_j}\right)_{i^-}$ evaluated before the processing of i^{th} job for x^{th} operation sequenced at k^{th} place and time required to repair the machine (TTR_{pm_j}). It is:

$$\left(T_{pm_j}\right)_{i_{x_k}-} = \left(N_{pm_j}\right)_{i_{x_k}-} \times (TTR_{pm_j}) \tag{4.10}$$

$$\left(N_{pm_j}\right)_{i_{x_k}-} = \begin{cases} 1, & If\ PM\ is\ carriedout\ earlier\ the\ processing \\ & of\ a\ batch\ of\ {i_x}^{th}\ job\ on\ j^{th}\ machine \\ 0, & Otherwise \end{cases}$$

The time of PM performed on j^{th} machine is evaluated by optimizing PM_{time_j}.

$$\sum_{y=1}^{y}\sum_{k=1}^{k_j}\left(N_{pm_j}\right)_{i_{x_k}} = 1 \text{ and } 0 \leq PM_{time_j} \leq T \tag{4.11}$$

where, y is a number of production cycles for a machine. A production cycle is defined as the total time elapsed of all the sequenced jobs on a machine when each job is processed at least once.

Similarly, the downtime $(T_{cm_j})_i$ of j^{th} machine due to CM is estimated as follows:

$(T_{cm_j})_i$ depends on the number of failures (NF_{ij}) occur during processing of a batch of i^{th} job for x^{th} operation sequenced at k^{th} place and time required to repair the machine (TTR_{cm_j}). Thus,

$$\left(T_{cm_j}\right)_{i_{x_k}} = \left(NF_j\right)_{i_{x_k}} \times (TTR_{cm_j}) \tag{4.12}$$

$$\left(NF_j\right)_{i_{x_k}} = \begin{cases} 1, & If\ failure\ occurs\ during\ process\ processing \\ & of\ a\ bacth\ of\ {i_x}^{th}\ job\ on\ j^{th}\ machine \\ 0, & Otherwise \end{cases}$$

4.3.1.2 Evaluation of earliness cost

Earliness cost incurs if a batch is manufactured before its due delivery time. Thus, it is given as follows:

$$EC = \sum_{u=1}^{h}\sum_{i=1}^{n} max\left\{0,\ EC_i \times \left(\frac{T}{h} \times u - Makespan_u\right)\right\} where\ u = \{1,2.\,h\} \tag{4.13}$$

where, EC_i is carrying cost of i^{th} job produced for u^{th} delivery. It is 0.1 percent of manufacturing cost of produced job per hour. h is the number of deliveries; $\frac{T}{h}$ is due time; and $\frac{D}{h}$ is delivery size for u^{th} delivery. Here, makespan is the maximum time taken by constituent jobs of product to finish their process to produce $\frac{D}{h}$ products for u^{th} delivery. Thus, it is:

$$Makespan_u = \left[Max\left(\frac{D}{h} \times CT_i\right)\right]_{\mathrm{u}} \quad \text{where}, i = 1, \dots, n \tag{4.14}$$

4.3.1.3 Evaluation of holding cost in queue

As discussed in previous chapter, batch of a job may have to wait in queue for its processing due to unavailability of previous sequenced batch/es. Thus, the batch will have to wait till its sequence which incurs holding cost. The average inventory model is considered here to calculate the holding cost. Thus,

$$HCQ = \sum_{i=1}^{n}\sum_{x=1}^{O_i}\frac{1}{2} \times (W_{i_x} \times BS_{i_x} \times C_{h_{i_x}}) \quad (4.15)$$

where, $C_{h_{i_x}}$is WIP carrying cost of i^{th} job for x^{th}operation per hour, and is 0.1 percent of manufacturing cost.

4.3.2 Evaluation of downtime inventory cost

A buffer is attached with each machine for uninterrupted production when machine is not available due to maintenance. Attached buffers are carrying semi-finished/finished items processed through same machines. The average inventory model is considered while calculating downtime inventory cost. It is:

$$DIC = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{k_j}\sum_{x=1}^{O_i}\frac{1}{2} \times \left[\left(T_{pm_j}\right)_{i_{x_k}-} + \left(T_{cm_j}\right)_{i_{x_k}}\right] \times \left(\frac{1}{PT_{i_x}}\right) \times IC_{i_x}) \times l_{i_x} \quad (4.16)$$

where, $(\frac{1}{PT_{i_x}})$ is production rate (items/hour) of i^{th} job for x^{th} operation, IC_{i_x} is inventory carrying cost of an item per hour, and l_{i_x} is the decision of inventory level of attached buffer.

4.3.3 Evaluation of maintenance cost

In machines, two types of maintenance actions are performed. One is PM and another is CM. The performance of maintenance function is measure in terms of maintenance cost (MC), which is the sum of corrective and preventive maintenance costs. The same is represented as below:

$$MC = PMC + CMC \quad (4.17)$$

4.3.3.1 Evaluation of PM cost

PM consists of cleaning, lubrication, changing of filters, and brushes, etc. Thus, PM cost includes the repair cost, labor cost (C), and fixed PM cost (FC_{pm}) i.e., cost of lubricant, filters, brushes, etc. Accordingly, the cost of PM can be calculated as:

$$PMC = \sum_{j=1}^{m} [(TTR_{pm_j}) \times C + FC_{pm_j}] \times N_{pm_j} \tag{4.18}$$

where, N_{pm_j} is the number of preventive actions taken in machines during the planning horizon. It is:

$$N_{pm_j} = \sum_{i=1}^{n} \sum_{x=1}^{O_i} \sum_{k=1}^{k_j} \left(N_{pm_j}\right)_{i_{x_k}-} \tag{4.19}$$

4.3.3.2 Evaluation of CM cost

The cost of CM of the machine includes labor cost and fixed CM cost (FC_{cm}). FC_{cm} includes repair/replacement cost, lubricant, maintenance equipment, etc. Thus, CM cost can be expressed as:

$$CMC = \sum_{j=1}^{m} [(TTR_{cm_j}) \times C + FC_{cm_j}] \times NF_j \tag{4.20}$$

where, NF_j is the number of failures occurring in machines during the planning horizon. It is:

$$NF_j = \sum_{i=1}^{n} \sum_{x=1}^{O_i} \sum_{k=1}^{k_j} \left(NF_j\right)_{i_{x_k}} \tag{4.21}$$

4.4 Results and discussion

First, the results for the presented industrial case (section 4.2) are obtained. Additionally, sensitivity analysis, comparative study, efficacy analysis of integration, and exhaustive investigation are carried out to generalize the results obtained from the proposed approach.

4.4.1 Input data

At, AVTEC, a monthly i.e., $24 \times 30 = 720$ hours shop-floor operations planning is performed. Time to perform PM is 8 hours, and time to carryout CM follows a lognormal distribution with mean 30 hours and standard deviation 10 hours. Fixed costs of CM and PM are 2500 and 8000 MU respectively. Labor cost for performing maintenance is 325 MU per hour. The demand for transmission sets in September month is of 3000 units, and revenue lost per undelivered product is

7500 MU. Job holding cost is 0.1 percent of job manufacturing cost per item per hour. Minimum run time for a setup is one shift i.e., 8 hours.

4.4.2 Solution space

In the above problem, sequencing decisions of 49 operations in 23 machines can be done by $(24 \times 5040 \times 2 \times 24 \times 6 \times 2 \times 6 \times 24 \times 6 \times 6 \times 2 = 1.03 \times 10^{11})$ ways. Batch-size for each operation is varied in between 200 to 600 items in the interval of 50 i.e., 8 decisions for each operation. Thus, batch-sizing decisions for 49 operations are 8^{49}. The time window for PM times is 1 week to 4 weeks. So, PM decisions for 5 machines are 4^5. Inventory levels decisions i.e., L, M, and H of attached buffers for 49 operations are 3^{49}. Thus, total possible combinations are (3.2×10^{81}). The formulation can be used with any range of decisions. However, widening the range will also increase the computational complexity.

4.4.3 Solution method

The integrated problems are well-known and proved NP-hard problems (Lee and Liman, 1992; Sun and Li, 2010; Zarook et al., 2015) and are of combinatorial non-linear optimization in nature (Kim et al., 2013). Present work considers the joint problem of production, maintenance, and inventory for complex multi-machine system with stochastic parameters which significantly increase the problem complexity. Simulation coupled with optimization is most used method by researchers as solution methodology for such problems (Garg and Deshmukh, 2006; Sharma et al., 2011). Thus, a combined simulation and meta-heuristic approach is used in this research to solve the problem. Jobs characteristics, machines properties, process flow, etc., are coded in Witness 14 simulation platform. In model, total 140 decision variables (37 sequencing, 49 batch-sizing, 49 inventory levels, and 5 PM decisions) are involved. The complexity of modeling can be seen from process flow of the jobs presented in simulation interface in figure 1 in Appendix C.

For optimization, various meta-heuristic algorithms like SA, GA, TS, etc., can be used. SA is proved beneficial over GA (Tambe et al., 2013; Tambe and

Kulkarni, 2015) and ant colony algorithm (Nahas et al., 2009) in terms of quality of solution and computation time for approximately solving large combinatorial optimization problems. La and Passannanti (2017) have used SA algorithm for faster solutions to optimize complex problem of production/inventory control and PM policies. As the main aim of the current work is to investigate the value of integrated approach, finding out best suitable algorithm is not targeted in this chapter. Here, ATSA has been used to obtain near-optimal solution. It gives quick solutions in less number of evaluations and also utilizes its experience of the problem domain to determine a cooling schedule. The cooling schedule gives the advantage over other algorithms of being able to tailor each schedule to the topology of the search space within which search begins (Debuse et al., 1999). To obtain the optimal algorithm parameters, initial runs are performed for varying initial temperature in the range of 500 to 5000, the cooling rate in the range of 0.90 to 0.95, cooling steps in the range of 40 to 100, and without improvement scenarios i.e., termination condition in the range of 200 to 1000 respectively. It was observed that the solutions obtained with different algorithm parameters did not differ significantly from each other. However, the optimal parameters are the one in which above problem is solved in the least time. The optimal values of initial temperature, cooling rate, cooling steps and termination condition are 5000, 0.91, 40, and 200 respectively. The entire simulation and optimization process of ATSA method is shown in the form of flow chart in figure 3.7 (see, chapter 3). The pseudo code of the same can be found in Appendix A.

4.4.4 Results using the proposed integrated approach

The industrial case presented in section 4.4.1 is first solved by utilizing the proposed integrated approach. The values of decision variables i.e., jobs sequences, batch-sizes, inventory levels, and PM decisions of due machines are obtained by minimizing OOC and are shown in figures 4.4(a)-4.4(d) respectively in black color. For example, sequencing decisions of the first operation of job J_1 (O_1-J_1) scheduled on machine M_1 is 2 i.e., 2^{nd} position, batch-size is 450, and attached buffer's (B1) level is 2 i.e., medium. In figure 4.4(c), buffer's (Bi) value

1, 2, and 3 means inventory level is low, medium, and high respectively. The corresponding overall operations cost is 1,089,256 MU. The sensitivity of input parameters on optimal solution is analyzed in next sub-section.

4.4.5 Sensitivity analysis

To study the effect of small variation of model parameters, a systematic sensitivity analysis is performed. Sensitivity analysis is performed for uncertainty in estimating revenue lost, earliness cost, WIP carrying cost, fixed PM cost, and fixed CM cost. In table 4.2, the basic level represents the values of cost parameters used in the industrial case in section 4.4.1, and two other levels of these parameters at -15% and +15% of the basic value. The range of change in optimal cost in percentage is shown in table 4.2. It is evident from results that above cost parameters have a statistically significant impact on OOC and OOC is more sensitive towards revenue lost, earliness cost, and WIP carrying cost. The decision variables also change with variation in these cost parameters. Consequently, production manager must compute the values of these cost parameters correctly to get an accurate value of OOC and effective decision-making.

Table 4.2 Sensitivity analysis of integrated model

Parameters	**Basic Level**	**OOC**			**Range of change in OOC in %**	**Changes in decision variables**
		Basic Level	**-15%**	**+15%**		
Revenue Lost (LC)	7500MU	1, 089,256	957,535	1,220,977	-12.1 to 12.1	Yes
Earliness Cost (EC_i)	0.1% of CC_{i_x}	1, 089,256	975,224	1,202,288	-10.45 to 10.45	Yes
Fixed PM Cost (FC_{pm})	8000MU	1, 089,256	1,081,291	1,096,221	-0.67 to 0.67	No
Fixed CM Cost (FC_{cm})	2500MU	1, 089,256	1,085,407	1,092,105	-0.32 to 0.32	No
WIP Carrying Cost ($C_{h_{i_x}}$)	0.1% of CC_{i_x}	1, 089,256	999,988	1,178,524	-8.23 to 8.23	Yes

4.4.6 Comparative analysis

The investigation further extended to compare optimization algorithms, and to evaluate the performance of the proposed approach over conventional firm's existing and interrelated approaches. While solving the problem with conventional approaches, the solution method and the constant parameter's values are kept same as used in section 4.4.1.

4.4.6.1 Evaluation for computational time and best results using different algorithms

For a better notion, the problem of section 4.4.1 is also solved by using Hill Climb and Random Solution optimization algorithms. Using Hill Climb, the integrated model is evaluated for 1000 scenarios and terminated when no improvement is found in 100 consecutive scenarios. While the model evaluated for 1000 scenarios using Random Solution algorithm. The evaluation is carried out on PC with Intel Core i7-3770 CPU @ 3.40 GHz, and obtained results are shown in table 4.3. ATSA gives 7% and 1.91% decrease in OOC compared to Hill Climb and Random Solution respectively. But, ATSA requires almost 10% and 6.5% more computational time compared to Hill Climb and Random Solution respectively. These results conclude that ATSA provides improved solution in approximate same computational time.

Table 4.3 Computation time and best results

Optimization algorithm	Computation time (hh:mm:ss)	OOC (MU)
Random solutions	00:59:12	1,110,061
Hill Climb	00:56:01	1,165,573
ATSA	01:02:54	1, 089,256

4.4.6.2 Comparison between interrelated and the proposed integrated approach

To evaluate the value of the proposed approach, the case study of section 4.4.1 is also solved by the interrelated approach. In interrelated approach, one of the operations planning variables is fixed while optimizing the values of other operations planning variables. Here, first production scheduling decisions are evaluated followed by PM decisions and inventory level decisions.

The jobs sequencing $(p_{i_{x_k}})$ and batch-sizing (BS_{i_x}) decisions are evaluated separately by minimizing scheduling cost utilizing Eq. (4.6). The completion time is calculated by using Eq. (3.26) (see, chapter 3). Here, machines un-availability is not considered while evaluation of aforementioned decisions. Thus, operation time $OT_{i_{x_k}}$ i.e., Eq. (3.28) (see, chapter 3) is modified, and now it is sum of waiting time, setup time, and batch processing time of a job. That is:

$$OT_{i_{x_k}} = [W_{i_x} + ST_{i_x} + PT_{i_x} \times BS_{i_x}] \times p_{i_{x_k}} \tag{4.22}$$

Keeping the above obtained values of $p_{i_{x_k}}$ and BS_{i_x} fixed, the PM decisions are evaluated by minimizing maintenance cost using Eq. (4.17).

Considering the values of $p_{i_{x_k}}$, BS_{i_x}, and PM decisions fixed, inventory levels of attached buffers are evaluated by minimizing downtime inventory cost using Eq. (4.16) with the same solution method.

The costs estimated above are then used to find the interrelated overall operation cost OOC. While calculating OOC, the other parameter's values are kept as used in section 4.4.1. The OOC is found 1,143,318 MU. Thus, integrated approach shows 5 percent improvement over interrelated approach as shown in figure 4.5. The sequencing, batch-sizing, inventory level, and PM decisions of due machines are shown in figures 4.4(a)-4.4(d) respectively in gray color. For example, sequencing decisions of the first operation of job J_1 (O_1-J_1) scheduled on machine M_1 is 2 (4-2) i.e., 2nd position, batch-size is 400 (850-450), and attached buffer's (B1) level is 1 (3-2) i.e., low.

4.4.6.3 Comparison between firm's existing and the proposed integrated approach

The proposed approach is also compared with firm's existing operations planning approach. For the month of September, practised operations planning decisions i.e., sequencing, batch-sizing, inventory level, and PM decisions of due machines are captured from production manager and are shown in figures 4.4(a)-4.4(d) respectively in white color. For example, sequencing decisions of the first operation of job J_1 (O_1-J_1) scheduled on machine M_1 is 3 (7-4) i.e., 3^{rd} position. At firm, inventory level of buffers of these jobs was kept at low level. The scheduling cost, downtime inventory cost, and maintenance cost are calculated by Eq. (4.6), Eq. (4.16), and Eq. (4.17) respectively. The sum of these costs i.e., OOC is found 1,202,974 MU. Figure 4.5 shows that integrated and interrelated approaches give 9.4 and 5.2 percent improvements respectively, over firm's existing planning approach.

Figure 4.4(a) Job sequencing decisions using different approaches

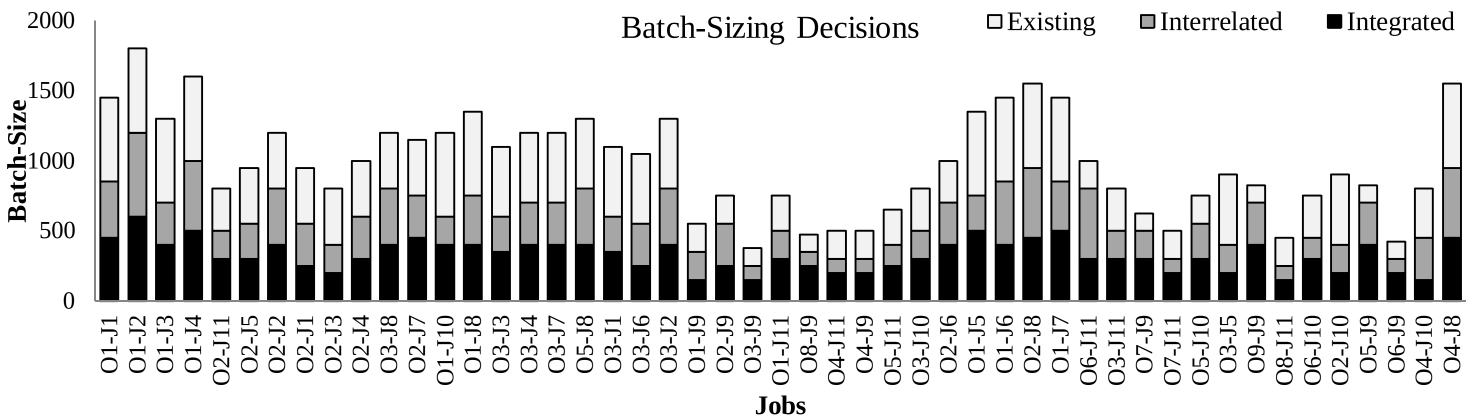

Figure 4.4(b) Batch-sizing decisions using different approaches

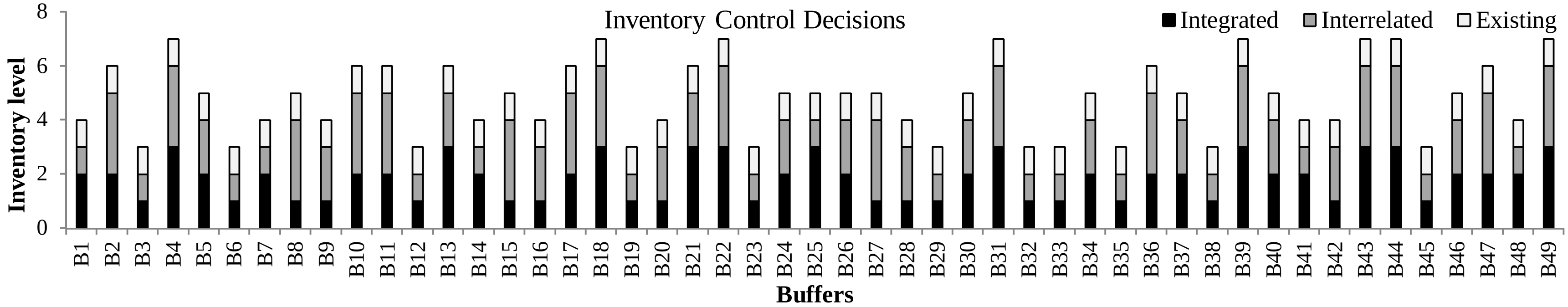

Figure 4.4(c) Inventory control decisions using different approaches

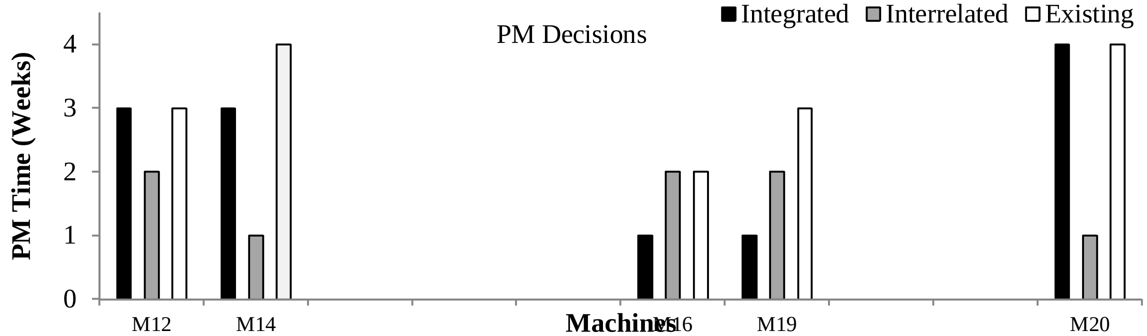

Figure 4.4(d) PM decisions using different approaches

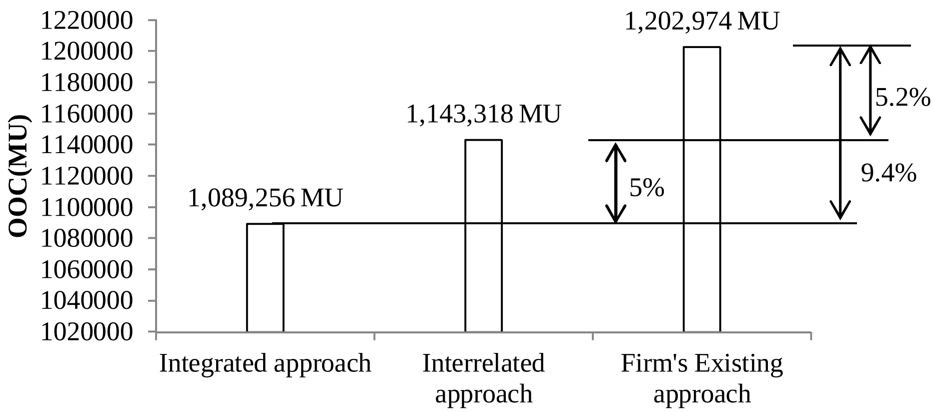

Figure 4.5 Improvement of integrated approach over interrelated approach and firm's existing approach

4.4.7 Generalizing the results for various manufacturing scenarios

The results presented in section 4.4.4 are specific to the scenario described in the case study (regarding the system, maintenance parameters, process parameters and demand). To generalize the proposed approach, an extensive evaluation is carried out to present the implication for various industrial scenarios. These scenarios are produced by varying maintenance parameters, process parameters, and considering the different types of production systems as shown in table 4.4. Moreover, to critically analyze the efficacy of the proposed approach in different scenarios, the results obtained from the proposed approach are compared with the conventional interrelated approach.

Table 4.4 Parameters to generate various manufacturing scenarios

Maintenance parameters		**System**	**Process parameters**	
Machines age	**PM**		**Demand variation**	**Processing time**
A: New (R= 1 to 0.9)	All machines		P: Low (2000)	
B: Old + New (R=0.5 to 0.95)	Selected machines	Series	Q: Medium (3000)	Uniform CT with variation of ± 10%
C: Old (R= 0.5 to 0.7)	No PM	Series-Parallel	R: High (3900)	

4.4.7.1 Varying maintenance parameters and systems

In order to set the maintenance parameters and types of systems, different cases of the current age of machines, variation in number of machines due for PM, and different kinds of production systems are considered as shown in table 4.4.

Three different cases of machine reliability at current age are considered as follow:

- In the first case (A), all machines are considered new or relatively new and have completed their 0 to 10 percent of life. To simulate this case, the reliability of machines at current age is taken between 0.9 to 1. Such case can be observed in a newly established industry where all machines are relatively new.
- For second case (B), current ages of all machines are considered high i.e., have finished 15 to 45 percent of their life. This case may be observed in an old industry running from longer time having all old machines. To simulate this case, the reliability of machines at current age is taken between 0.5 to 0.7.
- In the third case (C), it has been considered that firm has a mix of new and old machines. This case may be observed in an older industry where recent up-gradation in the industry resulted into replacement of the few old machines with new machines. The current ages of some machines are very less, and rest of machines has completed 15 to 45 percent of their life. To simulate this case, the reliability of these machines at current age is taken between 0.95 to 0.5.

Further, three different cases are considered to vary the number of machines due for PM and are as follows:

- For the first case, it has been considered that all machines are due for PM in the planning horizon. This case is representing the scenarios where machines are always needed to be in good working condition and PM performed frequently. Such scenarios are common which produces precision components viz., firms manufacturing components for aircraft, automobile, power plants, etc.

- For the second case, it has been considered that only some machines are due for PM in a planning horizon. Such as, in the case study (section 4.4.1) where only five machines (M_{12}, M_{14}, M_{16}, M_{19}, and M_{20}) are due for PM in the planning horizon.
- In the third case, no PM is performed on machines in the planning horizon. Such type of production system is common where PM is performed in a longer period (a year, two years, etc.). For example, in power plants, cement industry, etc., and it may be possible that no machines are due for PM in the planning horizon. The variation of maintenance parameters is shown in table 4.4.

Furthermore, two types of production system i.e., series and series-parallel have been considered. The production system of industrial case of section 4.2 is a kind of flow-shop and consisting of machines in series. However, in some industry where mass production is performed viz., process industries, textile industries, etc., the system has additional parallel machines for bottleneck operations. Such system can be called as series-parallel system. To generate such scenarios, same machine is added to each bottle-neck machine in the system of case presented in section 4.2. Here, a machine is considered to be bottle-neck if it process more than three jobs. From table 4.1, M_1, M_3, M_5, and M_{14} are found as such machines.

Results

The effect of maintenance parameters and system variation on the proposed approach and interrelated approach is evaluated by varying machines' age cases and the cases of number of machines due for PM for series system and series-parallel system. First, the evaluation is performed for series system i.e., 9 (1-9) scenarios. The evaluation is further carried out for series-parallel system i.e., 9 (10-18) scenarios. Figure 4.6(a) shows the percentage improvement in terms of OOC by the proposed approach.

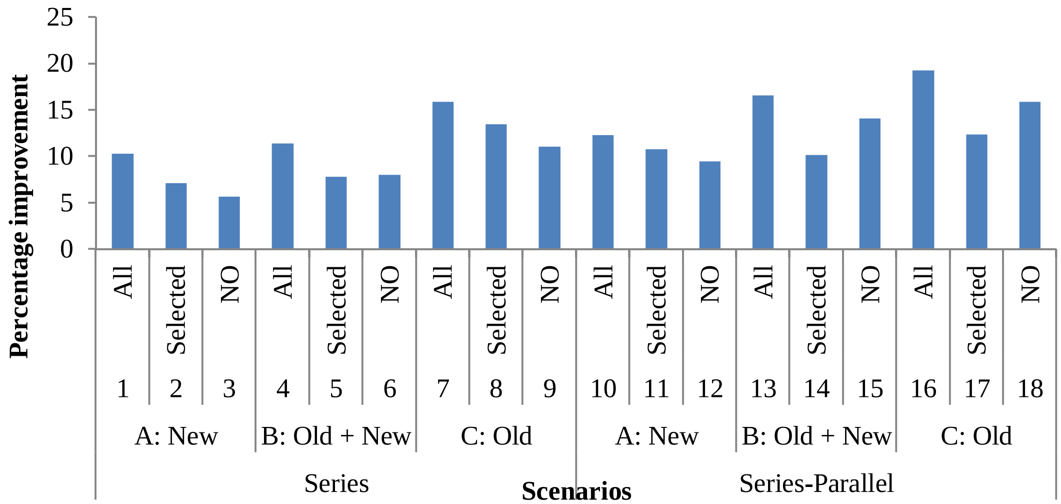

Figure 4.6(a) Percentage improvement of integrated approach over interrelated approach for variation in maintenance parameters

Observations

It can be seen from figure 4.6(a) that the proposed approach gives better performance over conventional interrelated approach for all scenarios. For series system, the benefit is more prominent for scenarios where all machines are due for PM i.e., scenarios 1, 4, and 7. The improvement is at peak for the scenario (7) where machines are old. Similar results have been obtained for series-parallel system (see, figure 4.6(a)). For instance, the improvement is more for scenarios where all machines are due for PM i.e., scenarios 10, 13, and 16, and the improvement is highest for the scenario (16) where machines are old. Figure 4.6(a) also shows that for series-parallel system, the offered approach provides better performance compared to series system. This indicates that as the complexity of the system increases, the proposed approach is more beneficial in improving system performance.

4.4.7.2 Varying process parameters

To evaluate the variation of process parameters, different cases of product demand and uncertainty in processing time are considered. Generally, in the production systems, product demands vary for different planning horizons. In the case study (see, section 4.4.1), product's demand was constant. To generalize the proposed approach three different cases of product demand viz., low (P), medium

(Q), and high (R) have been considered. At AVTEC, it was observed that in a year peak demand of transmission sets is 3900 units, moderate demand is 3000 units, and lowest is 2000 units. The variation in demand is shown in table 4.4. Also, in the production systems, there are uncertainties regarding exact processing time due to stochastic nature of manufacturing process. In the case study (see, section 4.4.1), processing time of job was constant. To generalize the approach, an uncertainty of ±10 percent is added in each job processing time of table 4.1. While evaluation of maintenance parameters, process parameters, system variation, and all other parameters (various costs, times-to-failures, etc.) are kept same as used in the case study in section 4.4.1.

Results

Out of 18 scenarios, maximum and minimum improvement scenarios of different machine age cases $(A, B \text{ and } C)$ of both the systems are further investigated. The scenarios are: 1, 3, 10 and 12 for machines age case A; 4, 5, 13 and 14 for case B, and 7, 9, 16 and 17 for case C. These are investigated for variation in demand $(P, Q \text{ and } R)$ and processing time. Thus, total 36 scenarios are evaluated. Figure 4.6(b) shows the percentage improvement in terms of OOC by the proposed approach for variation in process parameters.

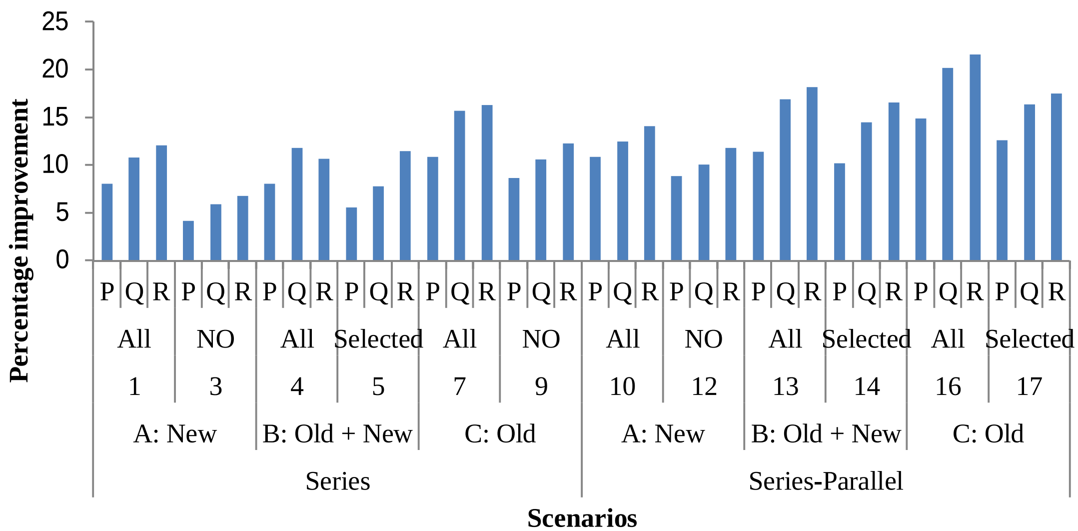

Figure 4.6(b) Percentage improvement of integrated approach over interrelated approach for variation in process parameters

Observations

It can be seen from figure 4.7(b) that the proposed approach always gives better performance in terms of percentage improvement in OOC over interrelated approach. Higher improvements are observed for the scenarios where demand is high irrespective of maintenance parameters and production system. The lowest improvement is found for series-system having low-demand with No-PM and is 4.2 percent. While highest improvement found is 21.6 percent and is for a series-parallel system with high demand and all machines are due for PM.

4.4.8 Significance of integration of shop-floor operations planning functions

To analyze the significance of integration of shop-floor functions, an evaluation was performed by varying the extent of integration. In current work, three functions: production scheduling, maintenance planning, and inventory control have been considered. Thus, the combinations are: independent optimization, integrated optimization of two functions and three functions. The possible combinations and evaluation scheme are shown in table 4.5. The evaluation is performed by the proposed approach for the highest and lowest improvement cases obtained from the variation of maintenance and process parameters i.e., cases 16 (R) and 5 (P) (see, figure 4.6(b)). The results are shown in table 4.5. Results indicate that integration of three functions gives minimum OOC followed by integration of two functions and independent optimization. However, the computation time also increases as the number of functions for integration increases. The percentage deviation from minimum OOC to the OOC obtained by other combinations is also shown in table 4.5. The deviation is maximum for independent optimization followed by integration of two functions. It is minimum for the combination of scheduling and inventory. Thus, it can be said that integrating scheduling and inventory decisions with other operations planning decisions are comparatively more important for the industrial case of section 4.2.

Table 4.5 Possible combinations and evaluation results

Functions combinations	Integrated optimization			Independent optimization			Highest and Lowest Improvement Cases	Computation time (hh:mm:ss)	OOC	Percentage deviation
	Functions	**Objective function**	**Cost estimation equations**	**Function/s**	**Objective function**	**Cost estimation equations**				
Independent optimization	-	-	-	S, I, M	SC, DIC, MC	Eq. (6), Eq. (17), Eq. (18)	16 (R)	00:14:26	1,186,150	8.72
							5 (P)	00:11:18	1,179,356	8.19
Integration of two	S and M	SC + MC	Eq. (6) and Eq. (18)	I	DIC	Eq. (17)	16 (R)	00:29:54	1,135,923	4.68
							5 (P)	00:26:42	1,141,630	5.16
	I and M	DIC + MC	Eq. (17) and Eq. (18)	S	SC	Eq. (6)	16 (R)	00:24:36	1,138,815	4.93
							5 (P)	00:21:09	1,132,207	4.37
	S and I	SC + DIC	Eq. (6) and Eq. (17)	M	MC	Eq. (18)	16 (R)	00:35:47	1, 098,780	1.46
							5 (P)	00:31:11	1, 105,648	2.07
Integration of three	S, M and I	OOC	Eq. (6), Eq. (17) and Eq. (18)	-	-	-	16 (R)	01:08:16	**1, 082,728**	
							5 (P)	00:53:37	1, 088,504	0.53

Note: ‘S’ refers to scheduling; ‘M’ for maintenance; ‘I’ for inventory; ‘SC’ for scheduling cost; ‘MC’ for maintenance cost; ‘DIC’ for downtime inventory cost

4.5 Summary

In this chapter, first time in the literature, an integrated approach considering production, maintenance, and inventory together for a realistic flow-shop environment is proposed. The approach allows joint optimization of shop-floor operations planning decisions viz. job sequences, batch-sizes, PM time, and inventory levels such that overall operations cost is minimized. This approach is evaluated in the case of an automotive industry. The effectiveness of the integrated approach is studied by comparing the results with the conventional approaches. A systematic comprehensive performance investigation was performed to verify the robustness and implication in various production scenarios.

4.5.1 Contributions

The outcomes from this chapter are highlighted as follows:

a) The results show that proposed integrated approach outperforms over conventional independent and interrelated approaches and it shows 9.4 to 5.2 percent economic improvements respectively. It is observed that there is a significant deviation in the decisions implemented based on the traditional approaches and the proposed integrated approach.

b) The results of comprehensive evaluation reveal that the proposed approach outperforms over interrelated approach and it shows 4.2 to 21.6 percent economic improvements for various manufacturing scenarios.

c) The comprehensive evaluation helps in proposing some thumb rules for the adaptation of the proposed approach. The same are:

   - Higher improvements have been observed for both series and series-parallel systems where all machines are due for PM in planning horizon. Such scenarios are common where machines are always needed to be in good working condition and PM performed frequently viz., firms manufacturing precision components for aircraft, automobile, power plants, etc.

- For industries having older machines viz., power plants, cement industry, etc., the proposed approach provide significant monetary saving compare to the conventional approach irrespective of environment and parameters.
- The benefit of proposed approach is more prominent for the scenarios where the demand is high and uncertainty in processing time is present.

d) Model is more sensitive for parameters like revenue lost, earliness cost, and WIP carrying cost. Thus, these parameters should be estimated as accurately as possible for effective decision-making.

e) For optimization, ATSA meta-heuristic provides improved solution compare to Hill Climb and Random Solution in approximate same computational time.

f) The benefits from integrated approach increases by considering more operations planning functions simultaneously. However, the computational complexity also increased with the increase in the number of decision variables. Novel approaches will be required to solve such problems. Distributed operations planning may be explored in future as one of such alternatives.

g) In general, the approach can be applied in any manufacturing industries. However, the approach provides more economic advantages in industries where various products are produced in medium or large scale through different machines; production is performed in multiple stages; demand variation is high; shop-floor has some older machines; uncertain manufacturing environment; etc. Automotive industry, process industry, household electric appliances companies, textile industry, etc., encounter such situations and may be of interest to the proposed approach.

The research presented in this chapter thoroughly investigates the importance of integrated operations planning approach for wide range of manufacturing scenarios. The successful implementation of the present approach will help in integrating various operations planning aspects at the decision-making stage itself, thereby reducing human intervention in coordinating and implementing various operations plans. This is believed to be one of the important requirements in realizing of Industry 4.0 in industries.

4.5.2 Research limitations and future scope

In the present chapter, focus is given on integrating three shop-floor functions viz., production, maintenance, and inventory. In future, quality control may be explored for integration with the current approach. For instance, machine failure may lead to reduction in process quality by shifting the process mean or increasing the dispersion, which in-turn will produce poor quality products. A stringent quality control plan may indicate timely maintenance requirement of the machines. However, considering quality control will increase the problem complexity. And to solve such problem using integrated approach will require higher computation time which will further affect the responsiveness of the approach. Therefore, novel approaches will be required to solve such problem.

Chapter 5[5]

Integrated yet distributed operations planning approach: A next generation manufacturing planning system

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In this chapter, a novel agent-based distributed operations planning approach is developed to handle the important but conflicting challenges of integration and responsiveness for next generation manufacturing systems. The approach delivers colossal reduction in computation time for approximate same solution quality for various manufacturing scenarios and offers significant economic improvements under dynamics conditions over centralized approach. The distributed approach provides flexibility to choose degree of integration based on the performance and computational time of the overall approach.

Key Highlights

Purpose: The purpose is to equip the manufacturing systems with an autonomous decision-support system that can deal with two essential but conflicting challenges viz., integration of various shop-floor functions and responsiveness to dynamic conditions.

Findings: The approach provides quick response to dynamic conditions. The extensive performance investigation reveals that the proposed approach outperforms over centralized approach in terms of reduction in computation time (47 to 86 percent) for approximate same solution under various manufacturing scenarios. The reduction in computation time is more prominent for the scenarios where demand is high, system having old machines with low PM restoration factor. Moreover, the approach delivers a significant economic advantage (0.05 to

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[5] *The work presented in this chapter is in review under the title "Integrated yet distributed operations planning approach: A next generation manufacturing planning system" from June 2018 in Computers & Industrial Engineering, Elsevier.*

38.5 percent) over centralized approach under dynamic conditions. The improvisation is high in case of demand variation followed by sudden machine failures and change in delivery schedule.

Practical Implications: The approach can be implemented in any manufacturing industry. However, it will be more beneficial in industries where machines are older; variety of job is high; process flow is complex; effectiveness of PM is poor; manufacturing environment is dynamic; etc.

Originality and Contribution: First time in the literature, a novel agent-based operations planning approach is developed which integrates production, maintenance, quality, and inventory, and also provides quick response to dynamics conditions. An added contribution lies in the extensive performance investigation viz., comparison of optimization algorithms; comparison with conventional approaches; analysis of degree of integration; efficacy analysis of integration; analysis under dynamic conditions; and generalization of the proposed approach for various manufacturing scenarios. It is believed that integrated and responsive decision-making will be one of the important requirements in realization of Industry 4.0 in industries.

5.1 Introduction

It is observed from the previous chapter that integrated approach provides better results, however requires higher computation time for complex problems, and thus shows incapability to respond quickly to dynamic conditions. Therefore, in this part of the thesis, a novel agent-based integrated yet distributed operations planning approach is engineered to handle the important but conflicting challenges of integration and responsiveness for next generation manufacturing systems where intelligence at shop-floor allows distributing the computational tasks to various functional agents. The communication among the agents makes it feasible to incite global or integrated view through the coordinating agent. The approach considers multiple dependent shop-floor functions i.e., production, maintenance, quality, and inventory. It allows coordinated evaluation of shop-floor operations planning decisions viz., job sequences, batch-sizes, PM time, inspection intervals, sample sizes, and inventory levels. The problems of agents are NP-hard and are of combinatorial type with large solution space (10^{56}, 10^{46}, etc.). Moreover, the presence of stochastic variables significantly increases the problem complexity. Therefore, simulation-based optimization method is used to solve the problems. The approach is demonstrated for an industrial case of an automotive firm. Also, comparison with conventional approaches, comparison of optimization algorithms, effect of degree of integration, and the efficacy of integration are analyzed. Further, the responsiveness of the approach is analyzed under unexpected shop-floor disturbances (machine failures, change in demand, and change in delivery schedule). Finally, an exhaustive performance investigation is carried out to generalize the value of proposed approach over conventional approaches for a wide range of manufacturing scenarios. The scenarios are generated by varying machines' age, PM restoration factor, manufacturing system (series/series-parallel), and process parameters. The implication results and guidelines under various real-world industrial scenarios expand the realism of the proposed approach to the actual manufacturing systems. In succession, the approach provides dual advantage i.e., it integrates multiple dependent shop-floor functions and also improves the responsiveness of the system by distributed computation, thereby forming the basis for building an autonomous decision-support system.

The rest of the chapter is organized as follows. Section 5.2 provides an overview of the proposed agent-based decision-support system. In section 5.3, a representative industrial scenario is presented followed by agent development in section 5.4. Results for the representative case, comparative analysis, effect of degree of integration, computational comparison, performance under dynamic conditions, and comprehensive evaluations are presented in section 5.5. Finally, the chapter is summarised in section 5.6.

5.2 An agent-based decision-support system for intelligent manufacturing

In this section, a pioneering agent-based decision-support system is put forward for next generation intelligent manufacturing. The innovative decision-support system is 'integrated' from decision variables point of view yet 'distributed' from the point of view of problems handled by individual agents. Integration helps in enchasing the advantages of joint consideration of multiple shop-floor functions while distributed approach helps in reducing the computational complexity by splitting the global problem into multiple local problems solved by multiple functional agents and finally coordinated for global output by a coordinating agent. In this work, four shop-floor functions viz., job scheduling, maintenance planning, quality control, and inventory control are considered. The distributed approach is being applied to this multi-function integration problem for the first time in literature. Each of the shop-floor functions is modelled as functional agents. Additionally, a coordination agent is considered to deal with interdependencies between these agents. The architecture of an agent is shown in figure 5.1. It contains an information unit, a decision unit, and a communication unit.

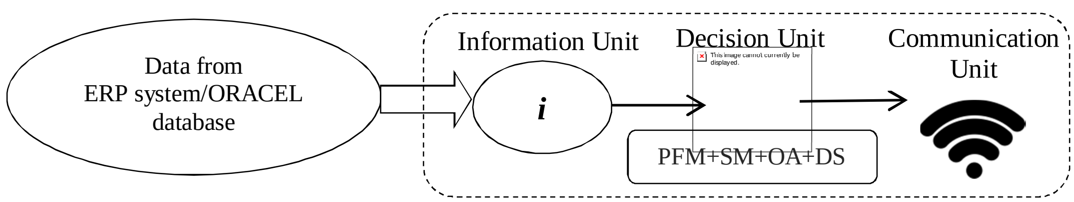

Figure 5.1 Architecture of an agent

Information unit

The central ORACLE database or any other systems used in the industry for its data collection and management, provide the required inputs to individual agents through its information unit. The inputs are of two kinds viz., static and dynamic. Static inputs include details about the system, i.e., number of machines, number of jobs to be processed, process flow, parameters like job's cycle time, setup time, times-to-failures, times-to-repairs, etc. The dynamic inputs include product demand, raw material supply, unexpected events like machine failure, operator absentees, etc. Table 5.1 provides a summary of inputs required and extracted for the current problem by the information units of each of the agents.

Decision Unit

The decision unit has four key elements viz., Performance Model (PFM), Simulation Model (SM), Optimization Algorithm (OA), and Decisions Set (DS). Decision units extract the inputs from the information units to develop performance and simulation model required by their respective agents.

A performance model is essentially a model which links goal (objective criteria) of particular agent with its decision variables and system specific parameters. For example, the performance model for scheduling agent could be a model for makespan or scheduling cost, etc. The performance models used by individual agents in this work are discussed in details in section 5.4. Each of the agents has its simulation model which incorporates the performance model of the particular agent. A simulation model is a mathematical replica of the functioning of the system (process flow, interactions and interdependencies between jobs, machines, and parameters) which is able to simulate the performance of that particular agent. These simulation models may be created on any appropriate platforms like ARENA, WITNESS, FlexSim, NetLogo, etc. If the problem is not very complex and does not involve stochastic variables, one may omit simulation model from the decision unit. Based on the nature of the problem, each functional agent will have its own optimization algorithm (e.g. Brute Force, heuristics, meta-heuristics) which utilizes the performance model and simulation model to generate a decision set consisting of multiple preferred solutions along with its relative importance measured in terms of Intensity Factor (IF). Number of solutions in a decision set decides the degree of integration and may be decided by the operations manager. The effect of varying the numbers of solutions (i.e., degree of integration) in a decision set is also studied in this chapter and is discussed in section 5.5.

Communication unit

The job of the communication unit is to transfer the decision set to other members of the network. Here, members are other agents, production manager, etc. The communication unit may use Wi-Fi, Bluetooth, lane network, etc., for transfer of the information.

5.2.1 Working of the agents

Each functional agent has just sufficient information to formulate and solve local level problems. Each functional agent acts like a selfish entity for local level decision-making; which is equivalent of saying that a functional division is not aware of decisions taken by other functional divisions while arriving on decisions pertaining to its local problem. For example, scheduling agent will not consider PM plans of the machines; maintenance agent will not consider the production schedule of the machines; and so on. These agents work in parallel, and the complex problem is distributed between them computationally to provide faster solutions. Each functional agent is assigned with separate computational power. For example, a separate processor for each functional agent is used in this research. Alternatively, the same may be hosted on a cloud by allocating separate space for each agent. Each agent solves a local optimization problem and comes up with a set of preferred solutions along with Intensity Factors (IFs) for each of the solutions in the set. IF is a measure of importance of particular solution in the set, which can be compared among all the solutions of all the agents. The global view of the system is not needed at the individual agent level, thereby reducing the computational complexity of the planning process greatly. These preferred solutions from all the functional agents along with their IFs are communicated to coordination agent. The coordination agent employs an integrated performance model and tries to optimize the overall goal of the organization based on the preferred solutions received from the functional agents. The algorithm used at coordination agent is therefore referred to as greedy algorithms. Depending on the problem size (here the total possible combinations generated from the preferred solutions received from all the agents), the coordination agent may apply any suitable optimization algorithm (e.g. Brute Force, heuristics, and meta-heuristics). Figure 5.2 shows the pictorial view of the agent-based decision-support system. Complete arrows show the initial decision-making. As soon as any disturbance is received in the system like change in the demand, machine failures, change in supply, etc., the decision-making process is repeated (shown by the dotted arrow) to dynamically update the decisions.

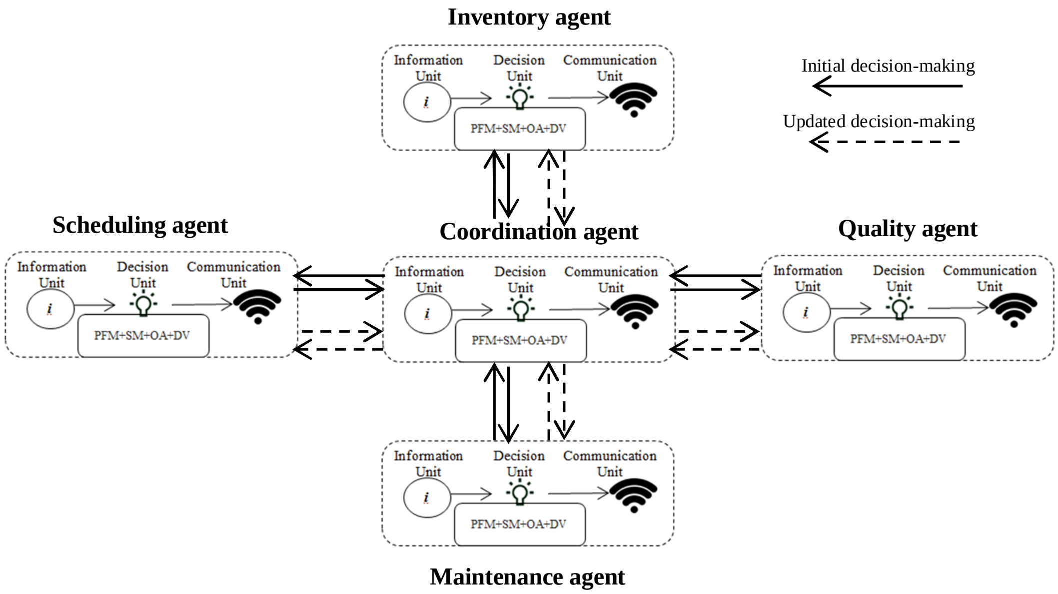

Figure 5.2 Agent-based decision-support system

5.3 A representative industrial scenario

In order to explain the development and application of the proposed decision-support system a generic industrial scenario is considered. It can be comprehended that the considered scenario is representative for the ease of understanding of the proposed approach and can be easily tuned for any other specific industrial case. In the representative industrial scenario, a production system having ‘m’ non-parallel machines processing ‘n’ jobs through predefined routes is considered. These jobs are assembled after their last operation to produce products. The jobs are to be scheduled non-preemptively during a given planning horizon T. Let the number of operations performed on i^{th} job be O_i (where, $i = 1, \dots, n$). Each job is processed in a batch for an operation. Let j^{th} machine is processing k_j (where j=1, 2,…m) different jobs. Each of the jobs has a given processing time, setup time, and operation cost at each machine. After the last operation, the job becomes ready for delivery to the assembly station to form product. Let the demand of the product be D which is required to be delivered in h number of deliveries with the size of $\frac{D}{h}$ in the interval of $\frac{T}{h}$. If a job is manufactured before it is required at the assembly station, then it will have to wait, causing extra carrying cost. The aim of the scheduling agent is to optimize sequences and batch-sizes for each job such that the scheduling related costs like revenue lost due to un-fulfillment of demand, penalty cost for early delivery, and waiting cost is minimized.

In addition, these machines may fail stochastically with times-to-failures following suitable probability distribution. In the current work, a Weibull distribution is found suitable to model the probability of machine failures. Let at the start of the planning horizon, j^{th} machine failure is characterized by shape parameters (β_j) and scale parameter (η_j) of the Weibull distribution; and initial age of the machine is a_j.

Identification of the consequences of machine failure is the key in modeling the interdependencies of machine failure and maintenance with other operations policies. Pandey et al. (2011) provided a convenient way to classify the machine failures from this perspective. The same is utilized in current research. According to Pandey et al. (2011), whenever a machine tool fails, it leads to one of the following consequences.

- Failure consequence 1 (FC_1) is detected immediately and brings the machine instantly down.
- Failure consequence 2 (FC_2) indicates the degradation in machine functionality and is detected after a time lag during which machine produces items of unacceptable quality.

Job of the maintenance agent is to selfishly think about an optimal PM schedule for the machine to mitigate the risk of sudden failures thereby reducing the downtime losses due to unexpected failures. Despite PM, machine may fail randomly which calls for CM. CM is considered as minimal i.e., the machine age is restored to an age as prior to failure (Kijima, 1989). On the contrary, PM generally helps in restoring the machine to a better state and is generally considered as imperfect (Kijima, 1989) which restores the machines by a restoration factor α i.e., restoration of α percent of machine age at the time of maintenance action. Time to carry out PM is ν hours and time to carryout CM follows a lognormal distribution with mean μ hours and standard deviation σ hours.

Initially, the production system is assumed to start in-control state (i.e., process mean (μ_0) is at its target value) producing items of acceptable quality. The process mean can shift instantly owing to machine degradation i.e., due to FC_2. Once FC_2 happens, μ_0 shifts from its target value to new process mean $\mu_1 = \mu_0 \pm \delta\sigma$, and process is said to move to out-of-control state where δ is some non-zero real number. During out-of-control state, product rejection rate increases over the normal rejection which leads to an additional cost of rejection. Whenever process shift is detected, corrective action is performed to bring the machine back to in-control state. The time lag in detection of process shift is crucial. In the present work, the $\overline{X}$ control chart mechanism with $\pm 3\sigma$ control limits is used. The detection time relies upon the power of control chart. The job of quality agent is to obtain optimal decision variables pertaining to the design parameters of control chart viz., sample size, and time between samples.

Moreover, unavailability of machines due to PM and CM can result into interruption in production. Thus, a buffer is attached to each machine for uninterrupted production which carries semi-finished/finished items processed through the machine. Carrying items in buffer result in additional carrying cost. Inventory agent works to obtain economic inventory levels of attached buffers for each operation.

It sounds well from above description that job scheduling, batch sizing, PM, inventory level, and quality control decisions are interdependent and are critical for shop-floor operations planning. These vital decisions affect economically to the organization and also affect customers' commitments. Additionally, above problem is dynamic because of disturbances like change in delivery schedule, change in demand, machine failure, etc., require re-evaluation of decisions to accommodate these changes. In current work, an agent-based distributed decision-support system is developed. It models the interdependencies and provides faster solutions in dynamic conditions. Next section provides the details on agent development. The assumptions used in the chapter are given below.

Assumptions

Following generic assumptions are made while solving the problem:

- a job cannot be pre-empted by another job;
- each job is available at the start of the production schedule;
- machine can process only one job at a time;
- at the beginning of planning period machines are available;
- the necessary maintenance resources are available;
- failures of machines are independent.

5.4 Agent development

The representative industrial scenario presented in the previous section is used to delineate the development of each agent. In specific, information unit, decision unit, and communication unit used by each of the agents are discussed in details. The decision variables used in this chapter are summarized as:

Decision variables

Sequencing decision:

$$\left(p_{i_{x_k}}\right)_j = \begin{cases} 1, & If\ a\ batch\ of\ i^{th}\ job\ for\ x^{th}\ operation\ is \\ & sequenced\ at\ k^{th}\ place\ on\ j^{th}\ machine \\ 0, & Otherwise \end{cases}$$

Decision of batch-size of i^{th} job for x^{th} operation: BS_{i_x}

Decision of inventory level of buffers of i^{th} job for x^{th} operation: l_{i_x}

Decision of interval of PM on j^{th} machine: N_{pm_j}

Decision of inspection interval for i^{th} job for x^{th} operation: f_{i_x}

Decision of inspection sample size for i^{th} job for x^{th} operation: n_{i_x}

5.4.1 Information unit

As discussed in previous section, information unit draws static and dynamic inputs from the database. The required inputs for each of the agents are presented in table 5.1.

Table 5.1 Input information

Agent	Specific static information	Common information	
		Static	**Dynamic**
Scheduling	LC, TTR_{cm_j}, $C_{h_{i_x}}$, and EC_i	Number of machines and jobs, process flow, PT_{i_x}, ST_{i_x}, η, β, initial age of machines, T, etc.	Demand, delivery schedule, machines failures
Maintenance	C, FC_{pm_j}, FC_{cm_j}, TTR_{pm_j}, TTR_{cm_j}, and α_j		
Quality	C_F, C_V, C, FC_{cm_j}, δ, P_{FC_2}, and control limits,		
Inventory	TTR_{cm_j}, and IC_{i_x}		
Coordination	Top 'n' decisions sets and IFs		

5.4.2 Decision unit

As discussed, decision unit includes performance model, simulation model, optimization algorithm, and decision sets. These constituents of decision units for each of the agents are discussed hereunder.

5.4.2.1 Performance model

In this sub-section, development of performance models for each of the agents is presented.

5.4.2.1.1 Performance model for scheduling agent

This agent is primarily concerned with the decisions related to job sequences and batch-sizes. As a selfish agent, the objective of this entity is to enhance its performance which can be evaluated using various criteria like revenue lost, on time deliveries, waiting time in queue, etc. However, for the commensurability, in the present work, the performance indicators of each of the agents are measured in terms of cost. For scheduling agent, Scheduling Cost (SC) is considered as a performance indicator. It is comprised of Revenue Lost (RL), Earliness Cost (EC) and Holding Cost in Queue (HCQ). RL incurs due to unmanufactured products against the demand in planning horizon; EC incurs due to early production of product's constituent jobs; and HCQ incurs due to holding of WIP items againts waiting time in queue. These ingredient costs are function of sequencing $(p_{i_{x_k}})$ and batch sizing (BS_{i_x}) decision variables. Thus,

$$SC = f(p_{i_{x_k}}, BS_{i_x}) \tag{5.1}$$

The constituents of scheduling cost are described below.

Revenue Lost (RL)

This cost incurs only if production is lesser than the product demand in the planning horizon. The revenue lost in the planning horizon (T) can be calculated using Eq. (4.7) (see, chapter 4).

Also, number of products manufactured in planning horizon (P_D), number of i^{th} job produced in planning horizon (P_i), completion time of i^{th} job (CT_i), and operation time of a batch of i^{th} job $\left[OT_{i_x}\right]_j$ can be estimated using Eq. (4.8) (see, chapter 4), Eq. (4.9) (see, chapter 4), Eq. (3.26) (see, chapter 3), and Eq. (3.27) (see, chapter 3) respectively.

Here, batch operation time $\left[OT_{i_x}\right]_{j_k}$ at k^{th} position includes setup time (ST_{i_x}), batch processing time $(BS_{i_x} \times PT_{i_x})$, downtime time $\left(T_{cm_j}\right)_{i_{x_k}}$ due to sudden failure of machine during the processing of a batch of i^{th} job, and waiting time (W_{i_x}) due to the unavailability of previous sequenced batch/es (see, chapter 3). Thus,

$$\left[OT_{i_x}\right]_{j_k} = [W_{i_x} + ST_{i_x} + PT_{i_x} \times BS_{i_x} + \left(T_{cm_j}\right)_{i_{x_k}}] \times p_{i_{x_k}} \tag{5.2}$$

The downtime $(T_{cm_j})_i$ of j^{th} machine depends on the number of failures $\left(NF_j\right)_{i_{x_k}}$ occurring during processing of a batch of the i^{th} job and repair time of the machine (TTR_{cm_j}). Thus,

$$\left(T_{cm_j}\right)_{i_{x_k}} = \left(NF_j\right)_{i_{x_k}} \times (TTR_{cm_j}) \tag{5.3}$$

As corrective repair is minimal; hence, $\left(NF_j\right)_{i_{x_k}}$ can be calculated using following formula (Lad and Kulkarni, 2012; Cassady and Kutanoglu, 2003):

$$\left(NF_j\right)_{i_{x_k}} = \left[\left(\frac{BS_{i_x} \times PT_{i_x} + Ia_{j_{x_k}-}}{\eta_j}\right)^{\beta_j}\right] - \left[\left(\frac{Ia_{j_{x_k}-}}{\eta_j}\right)^{\beta_j}\right] \tag{5.4}$$

where, $Ia_{j_{x_k}-}$ is initial age of j^{th} machine before processing of a batch of the $i_x{}^{th}$ job, and η_j, β_j are shape and scale parameter of j^{th} machine respectively. $Ia_{j_{x_k}-}$ of j^{th} machine can be calculated as:

$$Ia_{j_{x_k}-} = [Ia_{j_{x_{(k-1)}-}} + BS_{i_{x_{(k-1)}}} \times PT_{i_{x(k-1)}}] \tag{5.5}$$

where, $BS_{i_{x_{(k-1)}}}$ and $PT_{i_{x(k-1)}}$ are batch-size and processing time of the job respectively processed at $(k-1)^{th}$ position.

Earliness Cost (EC)

If a batch is manufactured earlier to its scheduled delivery time, it incurs earliness cost. It can be calculated using Eq. (4.13) (see, chapter 4).

Holding Cost in Queue (HCQ)

As discussed earlier, batch of a job may have to wait in queue for its processing due to unavailability of previous sequenced batch/es. Thus, the batch will have to wait till its sequence, which incurs holding cost. The average inventory model is considered here to calculate the holding cost. It can be calculated using Eq. (4.15) (see, chapter 4).

5.4.2.1.2 Performance model for maintenance agent

This agent evaluates PM schedule for machines. The performance of the agent is measured in terms of Total Maintenance Cost (TMC) which includes PM Cost (PMC) and CM Cost (CMC). These costs depend on failure and repair characteristics, fixed cost parameters and PM schedule. Thus, TMC is a function of decision variable N_{pm_j} i.e., PM schedule.

$$TMC = f(N_{pm_j}) \tag{5.6}$$

The constituents of TMC are described below.

Estimation of preventive maintenance cost

The tasks performed in PM are: cleaning, lubrication, oil change, adjustments, changing of filters, etc. Here, PMC comprises of labor cost (C) and fixed PM cost (FC_{pm}), i.e., cost of lubricant, filters, oil, etc. Therefore, PMC can be estimated as:

$$PMC = \sum_{j=1}^{m}[(TTR_{pm_j}) \times C + FC_{pm_j}] \times N_{pm_j} \tag{5.7}$$

$$N_{pm_j} = \sum_{i=1}^{n}\sum_{x=1}^{O_i}\sum_{k=1}^{k_j}\left(N_{pm_j}\right)_{i_{x_k}-} \tag{5.8}$$

$$\left(N_{pm_j}\right)_{i_{x_k}-} = \begin{cases} 1, & If\ PM\ is\ carried\ out\ earlier\ the\ processing \\ & of\ a\ batch\ of\ {i_x}^{th}\ job\ on\ j^{th}\ machine \\ 0, & otherwise \end{cases}$$

Estimation of corrective maintenance cost

The CMC includes labor cost and fixed CM cost (FC_{cm}). Where FC_{cm} is consisting of repair/replacement cost of failed component/s, oil change, tools, etc. Thus, CMC is:

$$CMC = \sum_{j=1}^{m}[(TTR_{cm_j}) \times C + FC_{cm_j}] \times NCF_j \tag{5.9}$$

where, NCF_j is the failures occur in machine in planning horizon. It is:

$$NCF_j = \sum_{i=1}^{n}\sum_{x=1}^{O_i}\sum_{k=1}^{k_j}\left(NCF_j\right)_{i_{x_k}} \tag{5.10}$$

$$\left(NCF_j\right)_{i_{x_k}} = \left[\left(\frac{D \times PT_{i_x} + IA_{j_{x_k}-}}{\eta_j}\right)^{\beta_j}\right] - \left[\left(\frac{IA_{j_{x_k}-}}{\eta_j}\right)^{\beta_j}\right] \tag{5.11}$$

$$IA_{j_{x_k}-} = [IA_{j_{x_{(k-1)}-}} + D \times PT_{i_{x(k-1)}}] \times [1 - \alpha_j \times \left(N_{pm_j}\right)_{i_{x_k}-}] \tag{5.12}$$

where, $IA_{j_{x_k}-}$ is initial age of j^{th} machine before processing of a batch of ${i_x}^{th}$ job, and α_j is PM restoration factor of j^{th} machine.

5.4.2.1.3 Performance model for quality agent

This agent evaluates inspection interval and sample size for each operation. Late inspection and small sample size may delay the detection of process shift and will lead to high rejection cost. While frequent inspection and large sample size will increase inspection cost but will help in early detection of any deviation in product quality. A tradeoff between rejection cost and inspection cost is required. Thus, the performance indicator is Total Quality Cost (TQC) which includes Inspection Cost (IC) and Rejection Cost (RC). These costs depend on inspection interval (f_{i_x}), sample size (n_{i_x}) decisions, and other parameters. Thus, TQC is function of decision variables f_{i_x} and n_{i_x}.

$$TQC = f\left(f_{i_x}, n_{i_x}\right) \tag{5.13}$$

If f_{i_x} is inspection interval, C_F is fixed cost per sample, and C_V is variable cost per job then IC is:

$$IC = \sum_{i=1}^{n}\sum_{x=1}^{O_i}\frac{PT_{i_x}}{f_{i_x}} \times (C_F + C_V \times n_{i_x}) \tag{5.14}$$

Machine may fail and results in FC_2 increasing the production of defective items which in turn incurs rejection cost. If P_{FC_2} is the probability of failure due to FC_2 then RC can be expressed as:

$$RC = \sum_{j=1}^{m}\sum_{i=1}^{n}\sum_{x=1}^{O_i}\sum_{k=1}^{k_j}\left(IRR \times C_{rej_{i_x}} \times (ARL)_{i_x} \times f_{i_x}\right) \times \left(NF_j\right)_{i_{x_k}} \times P_{FC_2} \tag{5.15}$$

where, IRR is increased rejection rate when the process was in out-of-control state due to machine degradation; C_{rej_i} is rejection cost of i^{th} job. ARL is average run length, i.e., average number of samples required to detect the shift. If process is being monitored by $\overline{X}$ control chart with a control limit of $\pm 3\sigma$, then IRR can be calculated as:

$$IRR = 1 - \varphi[3 - \delta] - \varphi[-3 - \delta] \tag{5.16}$$

where, $\varphi[.]$ is probability of standard normal cumulative distribution function and δ is process shift due to machine degradation.

The average number of samples required before the shift is detected can be given by:

$$(ARL)_{i_x} = \frac{1}{1-\gamma_{i_x}} \tag{5.17}$$

where, γ_{i_x} is type II error when process is out-of-control and can be expressed as state due to machine degradation (Montgomery, 2004).

$$\gamma_{i_x} = \varphi\left[3-\delta\times\sqrt{n_{i_x}}\right]-\varphi\left[-3-\delta\times\sqrt{n_{i_x}}\right] \tag{5.18}$$

where, n_{i_x} is sample size of quality inspection of a batch of the i^{th} job for x^{th} operation.

This agent does not consider PM plan and job schedule while arriving quality control decisions. Thus, number of failures occurs in machine $(nf_j)_{i_{x_k}}$ can be calculated as:

$$(nf_j)_{i_{x_k}} = \left[\left(\frac{D\times PT_{i_x}+ia_{j_{x_k-}}}{\eta_j}\right)^{\beta_j}\right]-\left[\left(\frac{ia_{j_{x_k-}}}{\eta_j}\right)^{\beta_j}\right] \tag{5.19}$$

$$ia_{j_{x_k-}} = [ia_{j_{x_{(k-1)}-}}+D\times PT_{i_{x(k-1)}}] \tag{5.20}$$

where, $ia_{j_{x_k-}}$ is initial age of j^{th} machine before processing of a batch of the ${i_x}^{th}$ job.

5.4.2.1.4 Performance model for inventory agent

This agent evaluates the inventory level of attached buffers. Each machine has buffer/s carrying semi-finished/finished items for uninterrupted production during machine maintenance. The performance indicator of this agent is Downtime Inventory Cost (DIC). It depends on inventory level decision (l_{i_x}) and other parameters and is function of l_{i_x}. The average inventory model is considered while calculating DIC. It is expressed as:

$$DIC = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{k_j}\sum_{x=1}^{O_i}\frac{1}{2}\times\left(\tau_{cm_j}\right)_{i_{x_k}}\times\left(\frac{1}{PT_{i_x}}\right)\times IC_{i_x})\times l_{i_x} \tag{5.21}$$

where, $(\frac{1}{PT_{i_x}})$ is production rate (jobs/hour) of i^{th} job for x^{th} operation, IC_{i_x} is inventory carrying cost of an job per hour, and l_{i_x} is the decision of inventory level of attached buffer.

This agent does not consider PM plan and job schedule while arriving inventory level decisions. Thus, downtime of machine $\left(\tau_{cm_j}\right)_{i_{x_k}}$ can be calculated as:

$$\left(\tau_{cm_j}\right)_{i_{x_k}} = \left(nf_j\right)_{i_{x_k}} \times (TTR_{cm_j}) \tag{5.22}$$

5.4.2.1.5 Performance model for coordination agent

This agent coordinates among above functional agents for integrated decision-making. The goal of this agent is to evaluate interdependent operations planning decisions, i.e., $p_{i_{x_k}}, BS_{i_x}, N_{pm_j}, f_{i_x}, n_{i_x}$, and l_{i_x} simultaneously for organization's objective. The performance indicator of this agent is Integrated Production Cost (IPC). It includes scheduling cost, maintenance cost, inventory cost, and quality cost i.e., $[SC]_c$, $[TMC]_c$, $[TQC]_c$, and $[DIC]_c$ respectively. In previous sub-sections, it is found that these ingredient costs are function of respective decision variables. Therefore, IPC is function of above decision variables.

$$IPC = f(p_{i_{x_k}}, BS_{i_x}, N_{pm_j}, f_{i_x}, n_{i_x}, l_{i_x}) \tag{5.23}$$

$$IPC = [SC]_c + [TMC]_c + [TQC]_c + [DIC]_c \tag{5.24}$$

Here, the ingredient costs are different from the costs of functional agents due to consideration of interdependencies. For instance, scheduling agent, quality agent, and inventory agent (see, section 5.4.2.1.1, 5.4.2.1.3 and 5.4.2.1.4) do not consider PM plan in the estimation of scheduling, quality, and inventory costs respectively, while coordination agent considers PM plan in estimation of these costs. Hence, some of the equations of previous sub-sections are modified. These are as follows.

$[SC]_c$ is sum of revenue lost, earliness cost, and holding cost in queue i.e., $[RL]_c$, $[EC]_c$, and HCQ. It is:

$$[SC]_c = [RL]_c + [EC]_c + HCQ \tag{5.25}$$

Here, HCQ is calculated using Eq. (4.15) (see, chapter 4). While equation of batch operation time $\left[OT_{i_x}\right]_{j_k}$ i.e., Eq. (5.2) is modified for calculation of $[RLC]_c$ and $[EC]_c$. The downtime due to PM i.e., $\left(T_{pm_j}\right)_{i_{x_k-}}$ affects the batch operation time of job and thus is added in calculation of $\left[OT_{i_x}\right]_{j_k}$. The new batch operation time is:

$$\left[ot_{i_x}\right]_{j_k} = [W_{i_x} + ST_{i_x} + PT_{i_x} \times BS_{i_x} + \left(T_{pm_j}\right)_{i_{x_k-}} + \left(t_{cm_j}\right)_{i_{x_k}}] \times p_{i_{x_k}} \quad (5.26)$$

$\left(T_{pm_j}\right)_{i_{x_k-}}$ of j^{th} machine depends on the decision of PM $\left(N_{pm_j}\right)_{i_{x_k-}}$, and time required to repair the machine (TTR_{pm_j}). It is:

$$\left(T_{pm_j}\right)_{i_{x_k-}} = \left(N_{pm_j}\right)_{i_{x_k-}} \times (TTR_{pm_j}) \quad (5.27)$$

Previously (see, section 5.4.2.1.1), PM plan is ignored in calculation of downtime due to CM. However, it is considered here. Thus, modified CM downtime equation is:

$$\left(t_{cm_j}\right)_{i_{x_k}} = \left(NMF_j\right)_{i_{x_k}} \times (TTR_{cm_j}) \quad (5.28)$$

where, $\left(NMF_j\right)_{i_{x_k}}$ is number of machine failure occurs during the processing of a batch of ${i_x}^{th}$ job. It is affected by production schedule, specifically batch-size. Thus,

$$\left(NMF_j\right)_{i_{x_k}} = \left[\left(\frac{BS_{i_x} \times PT_{i_x} + IA_{j_{x_k-}}}{\eta_j}\right)^{\beta_j}\right] - \left[\left(\frac{IA_{j_{x_k-}}}{\eta_j}\right)^{\beta_j}\right] \quad (5.29)$$

where, $IA_{j_{x_k-}}$ is calculated using Eq. (5.12) utilizing $BS_{i_{x_{(k-1)}}}$ in place of D.

Here, $[TMC]_c$ is calculated considering production schedule. It includes PM cost, and CM cost i.e., PMC and $[CMC]_c$. It is:

$$[TMC]_c = PMC + [CMC]_c \quad (5.30)$$

PMC is calculated using Eq. (5.7) while machine failure estimation Eq. (5.29) is used in place of Eq. (5.11) for calculation of $[CMC]_c$.

$[TQC]_c$ is calculated considering PM plan and production schedule, and includes inspection cost, and rejection cost i.e., $IC$and $[RC]_c$. Here, IC is calculated using Eq. (5.14).

$$[TQC]_c = IC + [RC]_c \tag{5.31}$$

While additional cost of rejection is calculated as follows:

$$[RC]_c = \sum_{i=1}^{n}\sum_{x=1}^{o_i}\sum_{j=1}^{m}\left(IRR \times C_{rej_{i_x}} \times (ARL)_{i_x} \times\ f_{i_x}\right) \times \left(NMF_j\right)_{i_{x_k}} \times P_{FC_2} \tag{5.32}$$

The PM plan and production schedule also affect the downtime inventory cost. Thus,

$$[DIC]_c = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{k_j}\sum_{x=1}^{o_i}\frac{1}{2} \times \left[\left(T_{pm_j}\right)_{i_{x_{k^-}}} + \left(t_{cm_j}\right)_{i_{x_k}}\right] \times (\frac{1}{PT_{i_x}}) \times IC_{i_x}) \times l_{i_x} \tag{5.33}$$

5.4.2.2 Simulation model for agents

Generally, real-world manufacturing operations involve many machines, jobs and complex flow of materials (see, section 5.5.1). The performance evaluation for such complex system is computationally challenging. A simulation model is commonly used in such situations. Moreover, presence of stochastic variables like time to repair, number of failures, etc., makes the simulation model necessary. In the present work, simulation models are developed on Witness 14 simulation platform. Each of the agents uses its own performance models to simulate the system behaviours for the planning horizon.

5.4.2.3 Optimization algorithm for agents

Each agent aims to optimize its decision variables for its local objective. The objective function and decision variables of each agent are mentioned in table 5.2.

Table 5.2 Objective function and decision variables

Agent	Objective function	Decision variables
Scheduling	SC	$\left(p_{i_{x_k}}\right)_j$ and BS_{i_x}
Maintenance	TMC	N_{pm_j}
Quality	TQC	f_{i_x} and n_{i_x}
Inventory	DIC	l_{i_x}
Coordination	IPC	All of the above

Here, scheduling agent is subjected to following constraints:

$$\sum_{k=1}^{k_j} \left(p_{i_{x_k}}\right)_j = 1 \quad (5.34)$$

$$BS_{i_{x_j}} \geq J_{i_{x_j}} \quad (5.35)$$

where, $J_{i_{x_j}}$ is the numbers of i^{th} job for x^{th} operation that can be processed through j^{th} machine in one shift i.e., 8 hours. The constraints, i.e., equations (5.34) and (5.35) ensure that predefined machine receives one job at one position in sequence for an operation, and minimum batch-size of a job will be greater or equal to $J_{i_{x_j}}$ respectively.

The problem of each agent is of combinatorial in nature, and is strongly NP-hard (see, section 5.5.3). Thus, a meta-heuristic, namely, ATSA technique has been used by each agent to obtain near-optimal solution for the local level problem. Depending on the problem size, each agent may use any heuristics, meta-heuristics or Brute Force Search for solving the local level problem. Additionally, the performance of the ATSA technique with Random Solution technique and Hill Climb technique is compared in this work.

5.4.3 Communication unit of each agent

Initially, each functional agent generates a set of top ‘n’ preferred solutions, along with IFs for each of the solutions in the set. These solution sets and intensity factors are communicated to the coordination agent for integrated decision-making. The coordination agent generates a coordinated (integrated) solution considering the preferences and its criticality in terms of intensity factor, received from each agent.

5.5 Results and discussion

The representative industrial scenario presented in section 5.3 was studied for the case of an automotive manufacturing firm named AVTEC Private Limited, India which produces transmission sets. The layout of the firm is divided into multiple sections which are similar in terms of shop-floor operations planning. Thus, a representative section called Soft Line is considered for further study (see, chapter 4 for firm details). Various data mentioned in section 5.3 for the specific problem of the case industry are captured and the same are given in table 4.1 (see, chapter 4) and in table 5.3, and are discussed in the following sub-section.

5.5.1 Input data

The Soft Line consists of 23 non-parallel machines i.e., m=23 (M_1, M_2,….,M_{23}). On these machines, 11 different jobs, i.e., n=11 (J_1, J_2…,J_{11}) are processed through 49 machining operations ($i.e., \sum_{i=1}^{n} O_i = 49$), and are assembled to form a transmission set (product). The routes of jobs are presented in table 4.1 (see, chapter 4). For example, job 1 requires operations on machine M_1, M_3, and M_6. The planning horizon is of 1 month i.e., 720 hours. The processing time (PT_{i_x}), setup time (ST_{i_x}), and manufacturing cost (CC_{i_x}) are presented in table 4.1 (see, chapter 4). For instance, PT_{1_1}, ST_{1_1}, and CC_{1_1} of job 1 for operation 1 are 1.57 minutes, 90 minutes, and 150 MU respectively. The demand of transmission set is D=3000 units which have to be delivered in 15 deliveries (i.e., h=15). The parameters of times-to-failures distribution of machine i.e., shape parameter (β_j) and scale parameter (η_j) are presented in table 4.1 (see, chapter 4). For instance, β_1 and η_1 for machine 1 are 2.3 and 700 hours respectively. The initial age (a_j) of machines are shown in table 5.3. The probabilities of occurrence of failure consequences FC_1 and FC_2 for the firm are 0.6 and 0.4 respectively. Time to carryout PM is υ=8 hours with a restoration factor $\alpha = 0.7$, and parameters of time to repair distribution of CM are μ=30 hours and σ=10 hours. The fixed cost of per quality inspection is C_F=30 MU and per sample checking cost is C_V=3 MU. The cost of rejection is 5 times the CC_{i_x} of job. The values of other parameters are also presented in table 5.3. The data was taken from ORACEL database of the firm by the information units of the agents.

Table 5.3 Values of parameters

D	3000	T	720 hours	$C_{h_{i_x}}$	0.1% of CC_{i_x}
$C_{rej_{i_x}}$	$5 \times CC_{i_x}$	TTR_{cm_j}	Lognormal (30, 10)	Shift time	8 hours
P_{FC_2}	0.4	C	325 MU	δ	0.7*σ
FC_{pm}	8000 MU	LC	7500MU	FC_{cm}	2500 MU

Initial age (a_j) of machines in hours

Machine	a_j	Machine	a_j	Machine	a_j	Machine	a_j
M_1	400	M_7	400	M_{13}	350	M_{19}	360
M_2	450	M_8	650	M_{14}	700	M_{20}	400
M_3	625	M_9	500	M_{15}	550	M_{21}	250
M_4	400	M_{10}	350	M_{16}	720	M_{22}	300
M_5	300	M_{11}	350	M_{17}	720	M_{23}	450
M_6	250	M_{12}	400	M_{18}	580	M_6	

5.5.2 Solution space

In the above case, scheduling agent optimizes 86 (37 sequencing + 49 batch-sizing) decision variables. The batch-size for each operation is varied in between 200 to 600 jobs in the interval of 50. Thus, solution space for scheduling agent is $1.28 \times 10^{56} (24 \times 5040 \times 2 \times 24 \times 6 \times 2 \times 6 \times 24 \times 6 \times 6 \times 2 \times 8^{49})$. Maintenance agent evaluates 23 PM decisions where each PM decision is varied in between 0 hour to 720 hours in the interval of 180 hours. So, total PM decisions are 4^{23} (7.03×10^{13}). Quality agent optimizes 98 (49 inspection interval + 49 sample size) decision variables where inspection interval and sample size are varied as 0.5, 0.75, and 1 hour, and 2, 4, and 8 respectively. The total quality control decisions are $3^{49} \times 3^{49}$ (5.72×10^{46}). Inventory agent evaluates 49 inventory level decisions for 49 operations. Each inventory level is varied as L (25 percent service level), M (50 percent service level), and H (100 percent service level); thus total decisions are 3^{49} (2.39×10^{23}). If functional agents communicate their top 10 solutions to the coordination agent then its solution space will be 10^4. While if all the four shop-floor functions are considered together and their decisions are evaluated simultaneously, then the solution space will be 1.23×10^{140}. Here, such approach is named as centralized approach. It can be seen from above discussion that the problem size of the centralized approach is very large. The same is divided into multiple smaller problems in the distributed approach. This provides the whole genesis of the proposed approach. However, it is important and interesting to see the quality of solutions over the evaluation time. The same is discussed in details in the following sub-section.

5.5.3 Solution method

It is clear from the above discussion that problem handled by each agent is of combinatorial in nature. Literature has also classified problems related to job scheduling, maintenance planning, quality and inventory control as NP-hard (Tambe et al., 2013; Tambe and Kulkarni, 2015; Zarook et al., 2015). Moreover, consideration of stochastic parameters significantly increases the problem complexity. To solve such complex, NP-hard, and combinatorial problems, simulation together with optimization is widely used technique by researchers (Garg and Deshmukh, 2006; Sharma et al., 2011). For optimization, numerous meta-heuristic algorithms like SA, GA, ant colony, etc., can be used. It is proved that SA provides quality solution in lesser computation time over GA, (Tambe et al., 2013; Tambe and Kulkarni, 2015) and ant colony (Nahas et al., 2009), for large combinatorial optimization problems. Here, ATSA technique has been used by each agent to obtain near-optimal solution. This technique provides faster solutions in less number of iterations and also uses its experience of the problem domain to decide a cooling schedule. The cooling schedule gives the advantage over other algorithms of being able to tailor each schedule to the topology of the search space (Debuse et al., 1999). The entire simulation and optimization process of ATSA method is shown in the form of flow chart in figure 3.7 (see, chapter 3). The pseudo code of the same can be found in Appendix A.

5.5.4 Selection of algorithm parameters and termination criteria

In order to obtain algorithm parameters, initial runs are performed for each agent for varying initial temperature (K) in the range of 500 to 5000, cooling rate in the range of 0.90 to 0.95, and cooling steps in the range of 10 to 100. As the results for different parameters scenarios do not differ significantly from each other, therefore, based on least computation time, these algorithm parameters are chosen as: initial temperature=5000; cooling rate= 0.95; and cooling steps= 25.

The computational time is a major factor in the proposed approach. And Termination Criteria (TC) has a significant effect on the computational time. Therefore, it is important to study the effect of termination criteria on quality and evaluation time of the solution for different agents and centralized approach. Initial runs are performed for each agent and centralized approach, with termination criteria as 0.1 percent or less improvement in 20, 50, 100, 150, and 200 trials. The progress of trials of functional agents, coordination agent, and centralized approach are shown in figures 5.3(a)-5.3(c) and in table 5.4. The value in the bracket shown against the name of each agent or centralized approach in table 5.4 is the value of solution space of the respective problem. It can be seen from table 5.4 that functional agents and coordination agent show no improvement in best Objective Function Value (OFV) achieved after TC=50 and TC=20 respectively. Running the models of these agents for higher TC will consume computation time without any significant improvement in OFV. For instance, best OFV for inventory agent is obtained at 166 trails for TC=50, then optimization process completes in 216 trials with computation time 0.198 hour; and it is completed in 266 trails for TC=100 with computation time 0.282 hour without any improvement in OFV and so on. The similar behaviour is observed for other agents (see, figures 5.3(a)-5.3(b)). Table 5.4 also shows that centralized approach gives slightly better OFV for higher TC, at the cost of high computation time. Computation time directly affects the responsiveness of the planning approach which is a vital criterion to sustain in competitive economy. For TC=50 and TC=200 it takes 2 hours and more than 5 hours of computation time respectively with the 3.7 percent improvement in OFV. Consequently, functional agents and coordination agent, due to relatively smaller problem size, may be run for smaller TC to save the computation time without affecting the OFV. However, due to the larger problem size, higher TC value is required for the centralized approach. Thus, TC for functional agents and coordination agent are chosen 50 and 20 respectively; the same is chosen as 50 for the centralized approach to save the computational time. One can choose higher TC for centralized approach to get better solution but this will increase the computational time significantly.

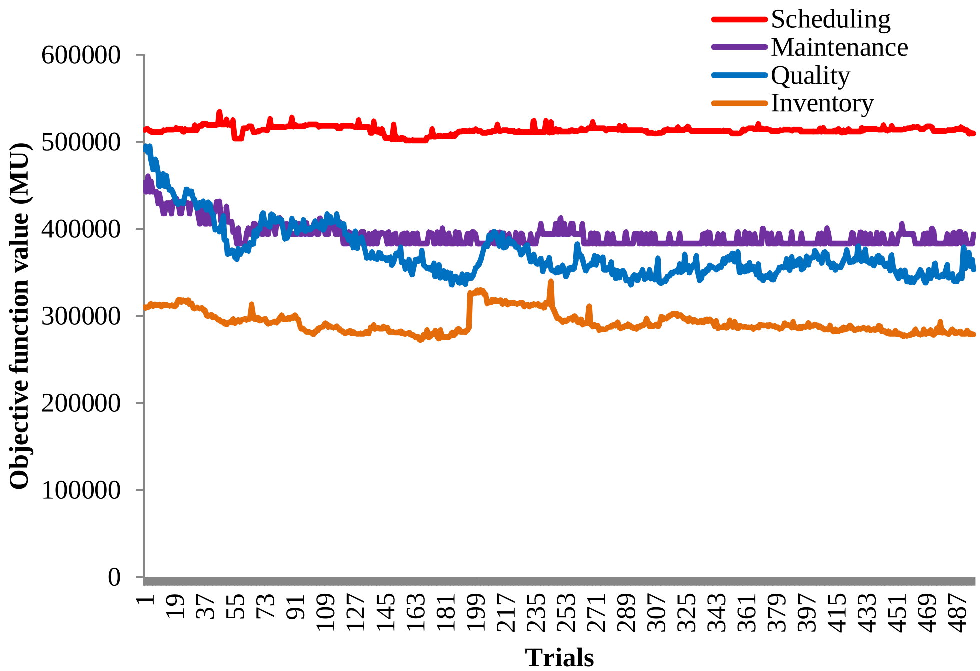

Figure 5.3(a) Progress of trials of functional agents

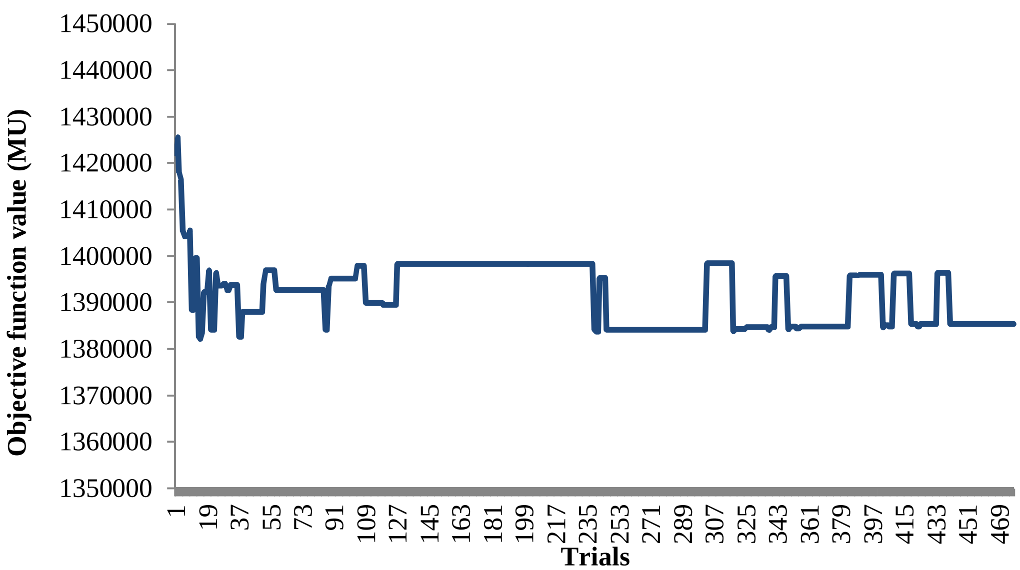

Figure 5.3(b) Progress of trials of coordination agent

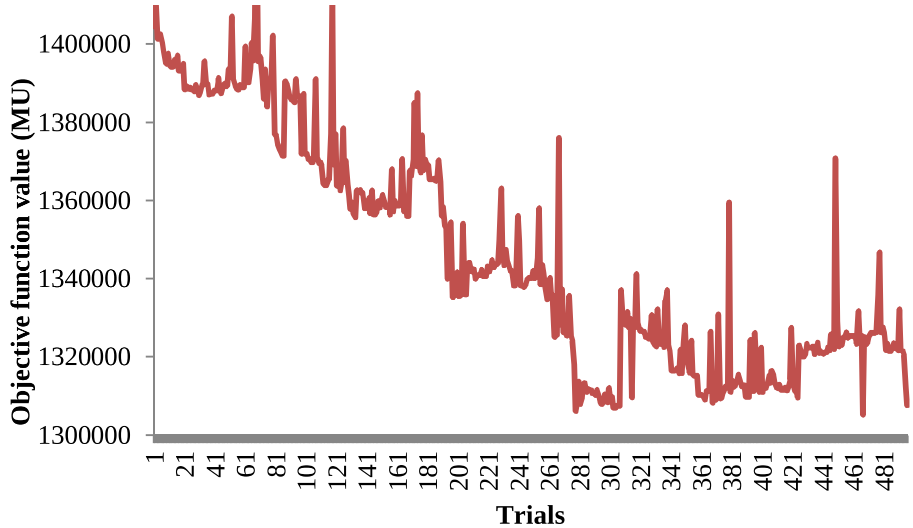

Figure 5.3(c) Progress of trials of centralized approach

5.5.5 Results using integrated yet distributed approach

Table 5.5 shows the top 10 solutions and corresponding IFs from the functional agents i.e., scheduling agent, maintenance agent, quality agent, and inventory agent. As these agents are running in parallel, the total computational time taken by the functional agents is the maximum of these time values. From table 5.4, the maximum computation time is taken by scheduling agent which is equal to 0.211 hour i.e., 12 minutes 41 seconds. The coordination agent runs the optimization algorithm based on the top 10 solutions received from each of the agents considering their criticality and generates the best possible combination for the proposed integrated problem. The final solution is indicated in bold in table 5.5. The IPC achieved through the optimal solution received from the coordination agent is 1,382,130 MU. The evaluation time of coordination agent is 0.215 hour i.e., 12 minutes 55 seconds (see, table 5.4). Thus, the total computation time for the distributed approach is sum of maximum computation time taken by the functional agents and computation time taken by the coordination agent, which is equal to 25 minutes and 36 seconds (12 minutes 41 seconds + 12 minutes 55 seconds).

Table 5.4 Results from successive trials

TC	Integrated yet distributed approach										Centralized approach (10^{140})	
	Scheduling Agent (10^{56})		Maintenance Agent (10^{13})		Quality Agent(10^{46})		Inventory Agent(10^{23})		Coordination Agent (10^{4})			
	OFV	TM	OFV	TM	OFV	TM	OFV	TM	OFV	TM	OFV	TM
20	525,514	0.164	428,319	0.113	365,179	0.157	290,750	0.142	**1,382,130**	0.215	1,389,787	0.643
50	**503,383**	0.211	**382,865**	0.180	**335,900**	0.207	**273,055**	0.198	1,382,130	0.441	**1,356,264**	2.04
100	503,383	0.493	382,865	0.251	335,900	0.452	273,055	0.282	1,382,130	0.573	1,306,156	3.75
150	503,383	0.628	382,865	0.435	335,900	0.584	273,055	0.537	1,382,130	0.816	1,306,156	4.25
200	503,383	0.826	382,865	0.596	335,900	0.770	273,055	0.743	1,382,130	0.984	1,305,161	> 5

Note: "TC" refers to termination criterion; "OFV" refers to objective function value; and "TM" refers to computation time in hours

Table 5.5 Top ten results of functional agents

IF rank	Scheduling cost (MU)	Total maintenance cost (MU)	Total quality cost (MU)	Downtime inventory cost (MU)
1	503,383	382,865	335,900	**273,055**
2	503,393	396,382	**336,963**	274,004
3	510,671	**400,800**	338,100	275,825
4	510,768	405,919	338,335	276,365
5	511,216	408,062	340,846	277,962
6	511,941	417,348	342,491	278,196
7	512,539	417,371	343,011	278,466
8	**513,021**	417,537	343,380	279,171
9	513,043	419,437	343,459	279,225
10	513,074	423,854	344,095	279,486

The corresponding sequencing, batch-sizing, quality control, and inventory level decisions of jobs are shown in figures 5.4(a)-5.4(e), respectively in black color. For example, sequencing decisions of job 1 for operation 1 (O_1-J_1) is 2nd position; batch-size is 600; inspection interval is 1 hour; sample size is 4 and buffer (B1) level is medium. In figure 5.4(e), buffer's (Bi) value 1, 2, and 3 means inventory level is low, medium, and high respectively. Similar PM decisions can be read from figure 5.4(f) in black color.

5.5.5.1 Comparison with firm's existing approach

A closer interaction with industries can easily reveal that due to the inherent complexity and dynamic nature of such operations planning problem in real industrial environment, many of the firms over a period of time, arrive at its experience-based operations planning practice. The same was also observed in the present case. By nature, such practices are highly subjective and independent as they are highly influenced by the local observations and experience of the concern heads of the functional divisions. Though, a multi-divisional heads' meeting is generally practised to consider the interdependencies of the decisions, the subjectivity can be ruled out. Moreover, such multi-divisional meetings consume significant time of the managers. In the current case, it is observed that on an average such meetings take 40 minutes to arrive at final decisions.

To evaluate the performance of such experience-based approach, the actual implemented plan of the month of September is compared with the proposed integrated yet distributed approach. The decisions taken by the firm's existing experience-based approach is shown in figures 5.4(a)-5.4(e) in dark gray color. For instance, sequencing decisions of job 1 for operation 1 (O_1-J_1) is 3^{rd} position (5-2), batch-size is 600 (1200-600); inspection interval is 0.75 (1.75-1) hour; sample size is 2 (6-4) and attached buffer's (B1) level is 1 (3-2) i.e., low. Similarly, the PM decisions of machines are shown in figure 5.4(f) in dark gray color. It can be observed that there is a significant deviation in the decisions implemented based on the existing approach and the proposed integrated yet distributed approach. The percentage improvement in the objective function value using the proposed approach is 21.6 percent, as can be seen from figure 5.5. It can also be seen that proposed approach not only gives better results but is able to arrive at such improved decision in significantly lesser (36 percent) time than that spent on inter-departmental meetings.

5.5.5.2 Comparison with interrelated approach

Conventionally in literature, interrelated approach is used to solve operations planning problems involving multiple shop-floor functions (Low et al., 2008; Mosheiov and Sidney, 2010; etc.). In such approach, while optimizing the decisions of a function, decisions of other interdependent function/functions are kept fixed. To evaluate the importance of the proposed approach, the case of section 5.5.1 is also solved by the interrelated approach. The steps for interrelated approach are as follows:

Step I: First, jobs sequencing $(p_{i_{x_k}})$ and batch-sizing (BS_{i_x}) decisions are evaluated by minimizing scheduling cost (Eq. (5.1)).

Step II: Keeping scheduling decisions fixed, PM decisions are evaluated by minimizing total maintenance cost using Eq. (5.30).

Step III: Keeping above decisions fixed, inspection interval (f_{i_x}) and sample size (n_{i_x}) decisions are evaluated by minimizing the total quality cost (Eq. (5.31)).

Step IV: Considering above decisions fixed, inventory levels (l_{i_x}) of attached buffers are evaluated by minimizing downtime inventory cost (Eq. (5.33)).

Step V: The decisions obtained in above steps are then used to estimate IPC (Eq. (5.24)).

The decision variables obtained through interrelated approach are shown in figures 5.4(a)-5.4(e), respectively in light gray color. For example, sequencing decisions of job 1 for operation 1 (O_1-J_1) is 3 (8-5) i.e., 3rd position, batch-size is 300 (1500-1200); inspection interval is 0.75 (2.5-1.75) hour; sample size is 2 (8-6) and attached buffer's (B1) level is 3 (6-3), i.e., high. Similarly, PM decisions of machines can be read from figure 5.4(f) in light gray color. It can be seen from figure 5.5 that the proposed approach provides 16.3 percent improvement in IPC and a colossal reduction in evaluation time of 50.8 percent over interrelated approach for the considered case. Further, it can also be seen from figure 5.5 the interrelated approach takes significantly higher time than the presently used experience-based planning. Also, the experience-based planning practice is able to arrive at the decisions reasonably closer to the conventionally available interrelated approach. This motivates and justifies the genesis of such experience-based planning in industries.

5.5.5.3 Comparison with centralized approach

All the existing literature (Pandey et al., 2011; Dong, 2013; etc.) on integrated approach use a centralized computational and optimization system to solve such problems. To evaluate the importance of the proposed approach, the case of section 5.5.1 is solved by the centralized approach. The performance model of Eq. (5.24) is used for the same. As this approach evaluates above decisions simultaneously, the number of possible combinations for the case problem becomes (10^{140}) (see, section 5.5.2). The optional decisions pertaining to sequencing, batch-sizing, quality control, and inventory level are shown in figures 5.4(a)-5.4(e), respectively in white color. For example, sequencing decisions of job 1 for operation 1is 4 (12-8), i.e., 4th position, batch-size is 450 (1950-1500); inspection interval is 1 (3.5-2.5) hour; sample size is 4 (12-8), and attached buffer’s (B1) level is 2 (8-6), i.e., medium. Similarly, PM decisions of machines are shown in figure 5.4(f) in white color.

Figure 5.5 shows that centralized approach though provides least value of IPC; the proposed approach provides closer (only 1.88 percent poor) solution at approximately 80 percent lesser time.

Generally, in industries, time required to arrive at the solution is another major concern for a production manager besides the quality of the solution. This is becoming increasingly important for the next generation intelligent or smart factories. In specific to the operations planning, quality of the solution impacts the effective utilization of the resources and performance of the system whereas the timeliness of the solution impacts the responsiveness. Thus, the proposed approach can be seen as the backbone of next generation intelligent factory.

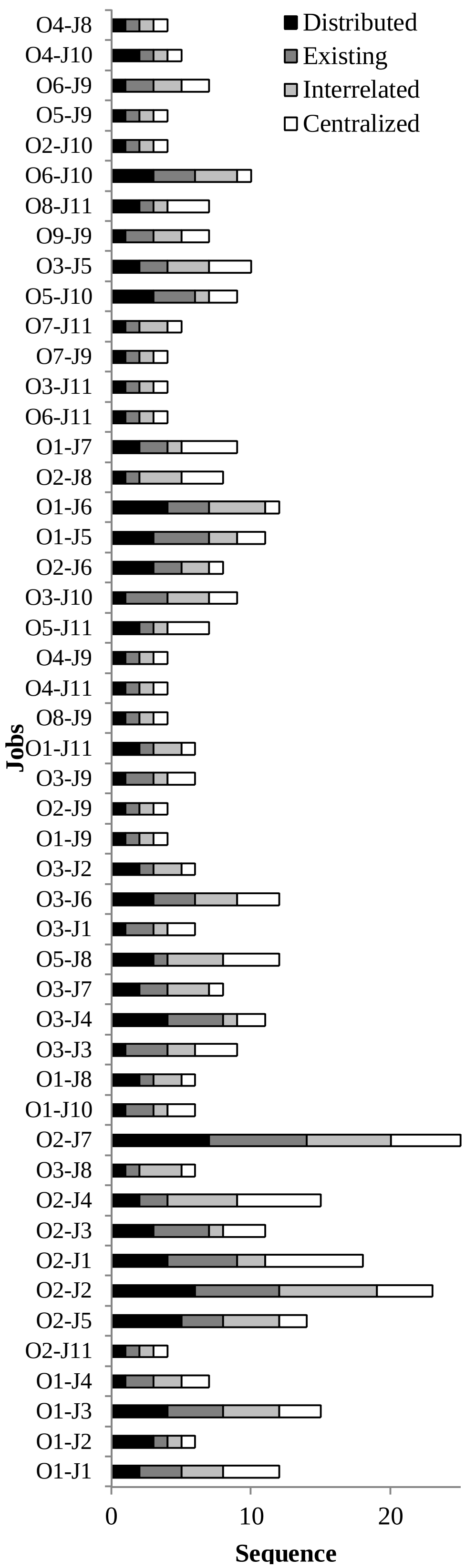

Figure 5.4(a) Sequencing decisions using different approaches

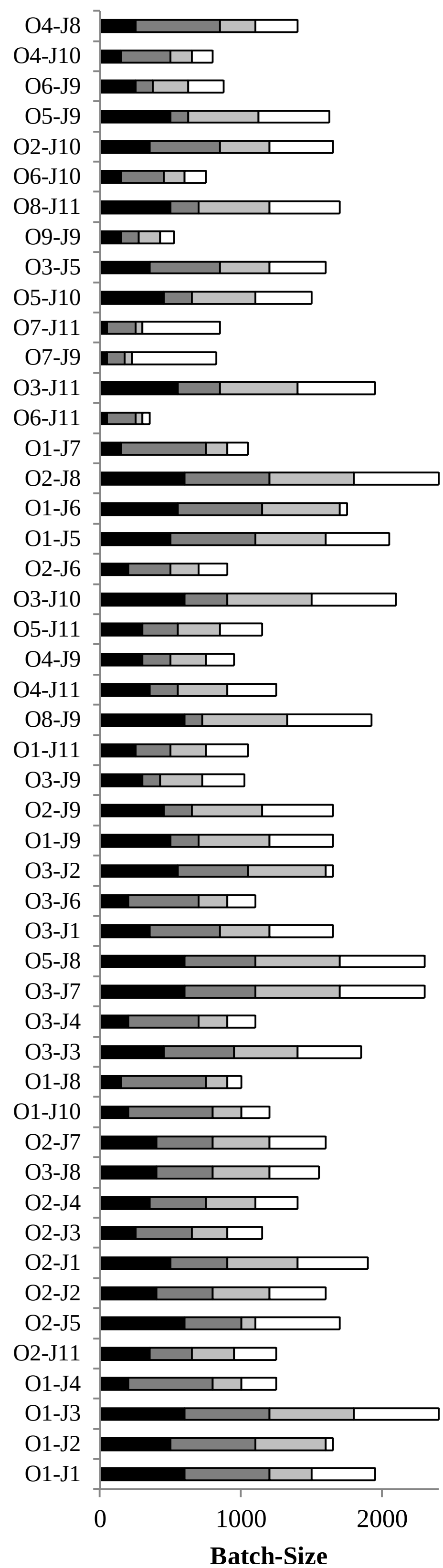

Figure 5.4(b) Batch-Sizing decisions using different approaches

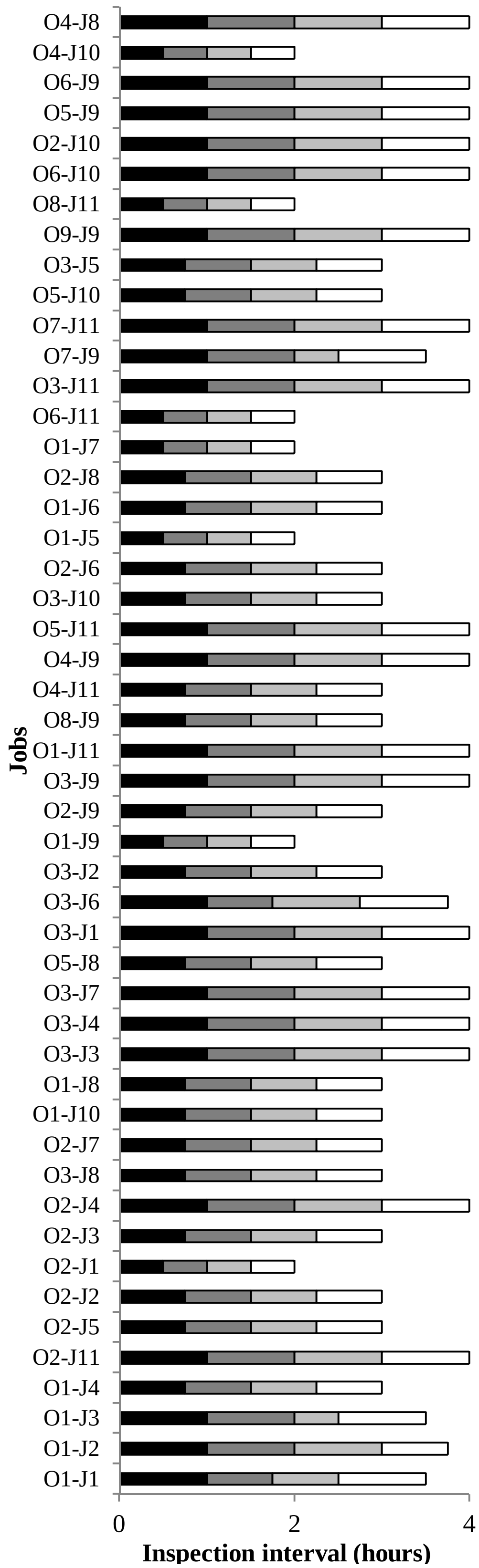

Figure 5.4(c) Inspection interval using different approaches

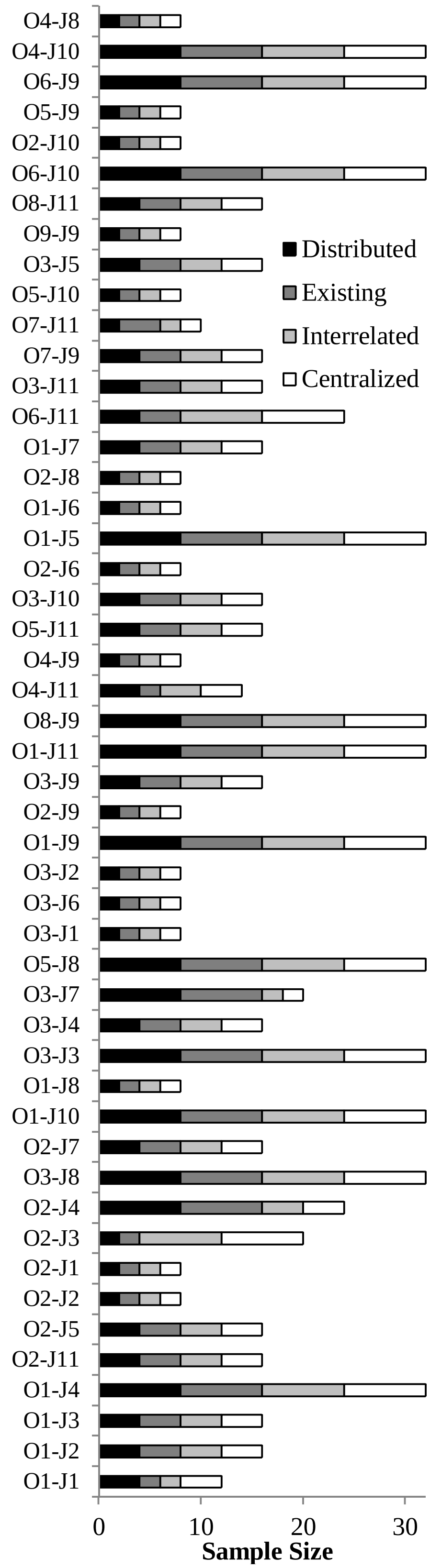

Figure 5.4(d) Sample size decisions using different approaches

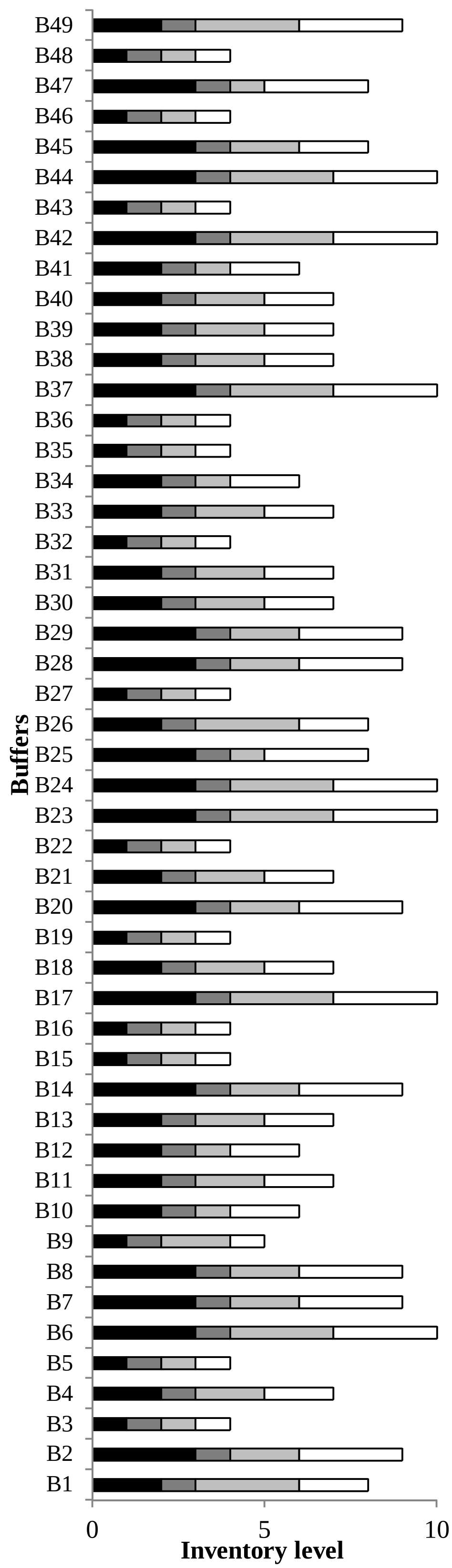

Figure 5.4(e) Inventory control decisions using different approaches

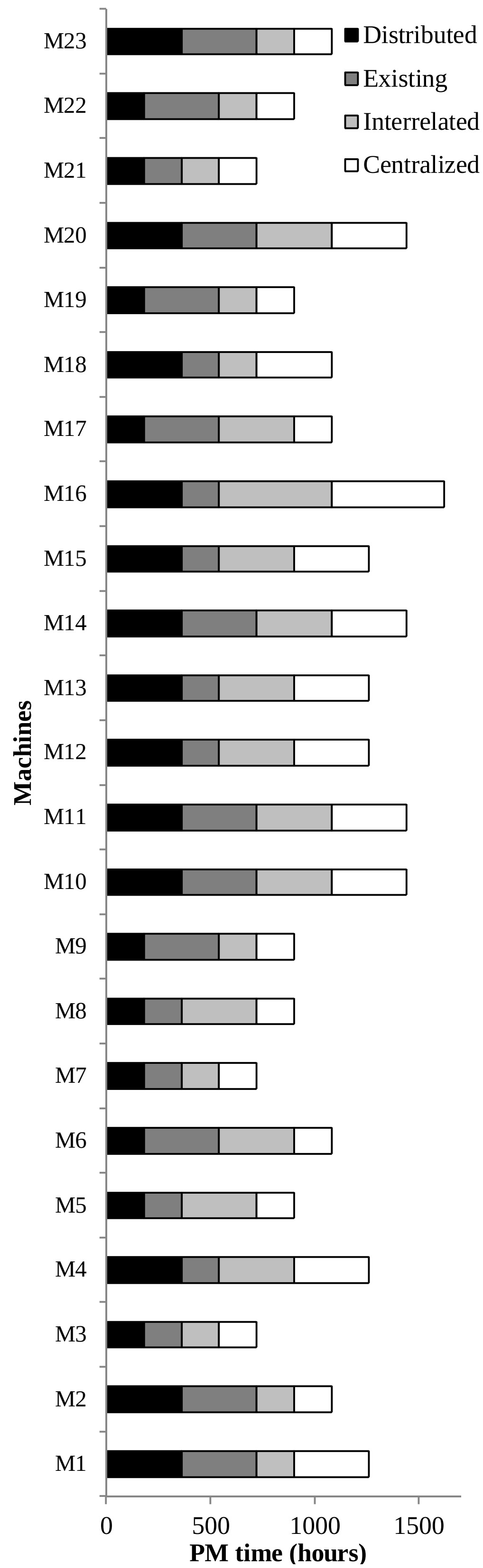

Figure 5.4(f) PM decisions using different approaches

5.5.5.4 Effect of degree of integration

The proposed approach provides flexibility to the analyst to choose the degree of integration by varying the number of solutions which are returned by the functional agents to the coordination agent for further evaluation. The analyst may even choose to communicate different numbers of solutions from different agents to coordination to give different weight to different functions. Higher the numbers of solutions evaluated at coordination agent, higher is the degree of integration. Theoretically, if very large numbers of solutions are returned from each of the functional agents, the coordination agent solution will reach closer to the solution of the centralized approach. However, it will also increase the computational time. To see the effect of degree of integration, in the present work, solution quality and computational time of following cases are compared with that of centralized approach.

Case 1: top 10 solutions are evaluated at coordinating agent

Case 2: top 5 solutions are evaluated at coordinating agent

Case 3: top 3 solutions are evaluated at coordinating agent

The results are summarized in figure 5.5.

It can be seen from figure 5.5 that, even with the smaller degree of integration (i.e., only with top 3 solutions from each agent), the distributed approach, performs better than the experience-based planning or conventionally done interrelated approach. As expected, the performance of distributed approach, in terms of the quality of solution, improves with the increase in the degree of integration and it reaches closer to the centralized integrated approach performance. With 10 solutions from each agent evaluated at coordinating agent, the performance is reasonably close to the centralized approach at the same time the computational time performance is approximately 80 percent better than the centralized approach. This shows the importance of the distributed approach.

For all further discussion and analysis, the results with 10 solutions are used.

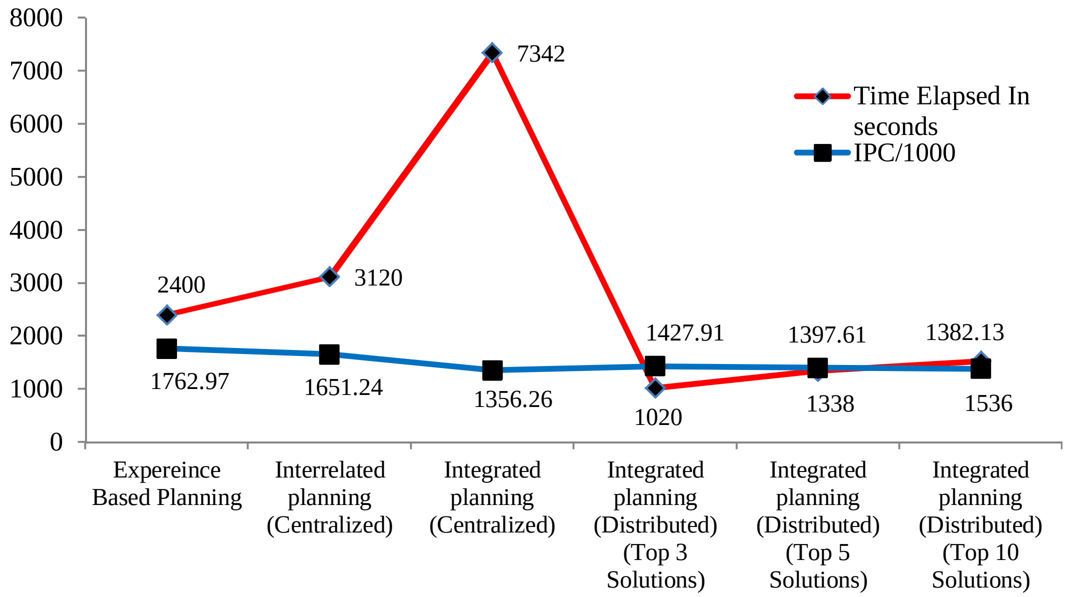

Figure 5.5 Performance of integrated yet distributed approach over conventional approaches

5.5.5.5 Evaluation of different algorithms for the proposed approach

For better notion, the same problem is also evaluated using Hill Climb and Random Solution optimization algorithms. The evaluation is carried out on computers with Intel (R) Core i7-4790 CPU @ 3.60 GHz., 4GB RAM. The results are summarized in table 5.6. ATSA provides 13.4 percent and 17.1percent reduction in IPC over Hill Climb and Random Solution respectively in approximate same computation time. Based on this, ATSA algorithm may be adopted to get improved solution in reasonable time compared to other algorithms.

Table 5.6 IPC and elapsed computation time

Optimization algorithm	IPC (MU)	Computation time (mm:ss)
Random solutions	1,663,626	30:00
Hill Climb	1,486,410	22:17
ATSA	1,382,130	25:36

5.5.6 Performance of the proposed approach in dynamic manufacturing conditions

The performance of the proposed approach is further analyzed in dynamic manufacturing conditions for the case of section 5.5.1. Here, dynamic conditions are considered due to the variation in demand, delivery schedule, and sudden machine failure. Here, demand and delivery schedules are considered as external dynamic varying parameters. Customer can update these parameters at any time in planning horizon. The sudden machine failure is considered as internal dynamic parameter. The variation in these parameters will affect net demand, delivery commitments, number of deliveries, initial age of machine, length of planning horizon, effective items to be manufactured for each operation, etc. This may further affect the decisions of agents. Thus, in case of any change in above varying parameters, each agent re-evaluates their decisions for remaining planning horizon.

As change in these varying parameters affect other parameters of the model. The value of affecting parameters needs to be re-calculated for re-evaluation. The event of change in demand, delivery schedule, and sudden machine failure is represented by $p, q,$ and r respectivery. The re-calculation of varying parameters is formulated as:

Remaining planning horizon: $T_g = T - T_{g^-} \qquad where, g \in (p, q, r)$ (5.36)

Initial age of machines:

$$(Ia_j)_g = [Ia_j + \sum (BS_j)_{g^-} \times (PT_j)_{g^-}] \times [1 - \alpha_j \times \left(b_{pm_j}\right)_{g^-}] \tag{5.37}$$

In case of change in demand, updated demand is: $D_u = (D_p - P_D)_{T_p}$ (5.38)

In same case, effective items to be manufactured for each operation:

$$\left(WIP_{i_x}\right)_p = D_u - \left(WIP_{i_x}\right)_{p^-} \tag{5.39}$$

For other cases, $(WIP_{i_x})_s = D - \left(WIP_{i_x}\right)_{s^-} \qquad where, s \in (q, r)$ (5.40)

In case of change in delivery schedule, updated number of delivery: h_q

After the events, T_g is remaining planning horizon, T_{g^-} is the time at which event occurs, $(Ia_j)_g$ is the updated initial age of the machine, and $\left(b_{pm_j}\right)_{g^-}$ is the information about machine PM; it is 1 if PM is performed and 0 if not. After the event p, D_u is updated demand, and $(WIP_{i_x})_p$ is current status of WIP. While after the event q and r, $(WIP_{i_x})_s$ is the current status of WIP. Before the event p, $(P_D)_{T_p}$ is numbers of product delivered.

The updated decisions are obtained by repeating the entire distributed decision-making approach after replacing the values of D to D_u, T to T_g, h to h_q, Ia_j to $(Ia_j)_g$ and D to $(WIP_{i_x})_s$ in the performance models of agents i.e., equations {(4.7, see chapter 4) and (4.14, see chapter 4)}, {(4.7, see chapter 4), (4.9, see chapter 4) and (4.13, see chapter 4)}, {(4.13, see chapter 4) and (4.14, see chapter 4)}, {(5.4), (5.5), (5.11) and (5.12)}, and (5.11).

In order to generate the cases for dynamic conditions, variations in dynamic parameters have been induced at different phases of planning horizon (720 hours) i.e., phase 1 or early stage of the planning horizon (between 0 to 1st week: 150 hours), phase 2 (between 1st week to 2nd week: 300 hours), phase 3 (between 2nd week to 3rd week: 450 hours) and phase 4 or last stage of the planning horizon (between 3rd week to 4th week: 550 hours). The variations are shown in table 5.7. For example, customer varies the demand from 3000 to 3900, i.e., 30 percent at 150 hours of planning horizon. It is assumed that one variation occurs at a time. Generally, as time passes in planning horizon, the amount of change reduces; the same is considered here. The demand is varied between ±30 to ±20 percent, ±20 to ±15 percent, ±15 to ±10, percent, +5 to +20 percent in above four phases respectively. Similarly, changes in delivery schedules are made. The sudden machine failure cases are generated randomly such that 30 percent machines (7 machines i.e., M_1, M_2, M_9, M_{15}, M_{16}, M_{18}, and M_{22}) fail at 200 hours, 20 percent machines (4 machines i.e., M_2, M_9, M_{15}, and M_{18}) fail at 350 hours, and 10 percent (2 machines i.e., M_1 and M_{16}) and fail at 500 hours. Table 5.7 presents the details of dynamic variations considered in this analysis.

Table 5.7 Dynamic variation in parameters

<table>
<tr><th>Parameters</th><th>0 to 1^{st} week (150 hrs.)</th><th>1^{st} week to 2^{nd} week (300 hrs.)</th><th>2^{nd} week to 3^{rd} week (450 hrs.)</th><th>3^{rd} week to 4^{th} week (550 hrs.)</th><th>Machine failure (Random)</th></tr>
<tr><td rowspan="4">Demand</td><td>30%</td><td>20%</td><td>15%</td><td>20%</td><td rowspan="3">30%</td></tr>
<tr><td>-30%</td><td>-20%</td><td>-15%</td><td>15%</td></tr>
<tr><td>20%</td><td>15%</td><td>10%</td><td>10%</td></tr>
<tr><td>-20%</td><td>-15%</td><td>-10%</td><td>5%</td><td rowspan="2">20%</td></tr>
<tr><td rowspan="3">Delivery schedule</td><td>-50%</td><td>-50%</td><td>-50%</td><td>-50%</td></tr>
<tr><td>-20%</td><td>-20%</td><td>-20%</td><td>-20%</td><td rowspan="2">10%</td></tr>
<tr><td>100%</td><td>100%</td><td>100%</td><td>100%</td></tr>
</table>

Note: % refers to percent

Whenever above disturbance occurs production is stopped and re-planning steps listed below are followed.

1- Calculate remaining planning horizon for the all cases and net demand in case of demand variation using equations (5.36) and (5.38) respectively.
2- Estimate initial age of machines using Eq. (5.37).
3- Calculate effective items to be manufactured for each operation for events p, and (q, r) using Eq. (5.39) and Eq. (5.40) respectively.
4- Update number of deliveries in case of delivery schedule change.
5- Provide above information as input to the model of each functional agent, and evaluate top ‘n’ decision sets for remaining planning horizon.
6- Communicate top ‘n’ decision sets to coordination agent, and re-evaluate coordinated decision sets for remaining planning horizon.

Conventionally, in case of such disturbances, generally, production manager do not disturb initial plan due to the high re-planning time taken by conventional approaches and adjusts the variations at the end of the planned schedule. However, due to significant reduction in the time taken by proposed approach the re-planning is feasible. Here, the performance of proposed approach has been compared with the centralized approach with the variations adjusted at end of the already running schedule. Figure 5.6 reveals that proposed approach outperforms over the conventional practice of adjusting the dynamic variations at the end of the existing schedule. For various cases of induced dynamic variation, 0.05 to

38.5 percent economic improvements are reported over the conventional practice for the present problem. The improvement is high in case of demand variation followed by sudden machine failure and change in delivery schedule. The performance is highest in case of large demand variation (30 percent and 20 percent) as the centralized approach is not able to meet updated demand due to the initial scenario of plan which leads to high revenue lost. The proposed approach, through re-planning, meets the updated demand to some extent in case of 30 percent demand change and meets entire demand for 20 percent variation in the original demand. Thus, an industry where demand is expected to vary significantly with time, it is important to adopt an approach which can quickly re-evaluate all its operations planning decisions. Industry 4.0 advocates direct interaction of customers with the industrial systems, through the CPS. It is therefore expected that such large demand variations will be more common in next generation intelligent factories; the distributed approach, therefore, becomes an obvious choice for such smart factories.

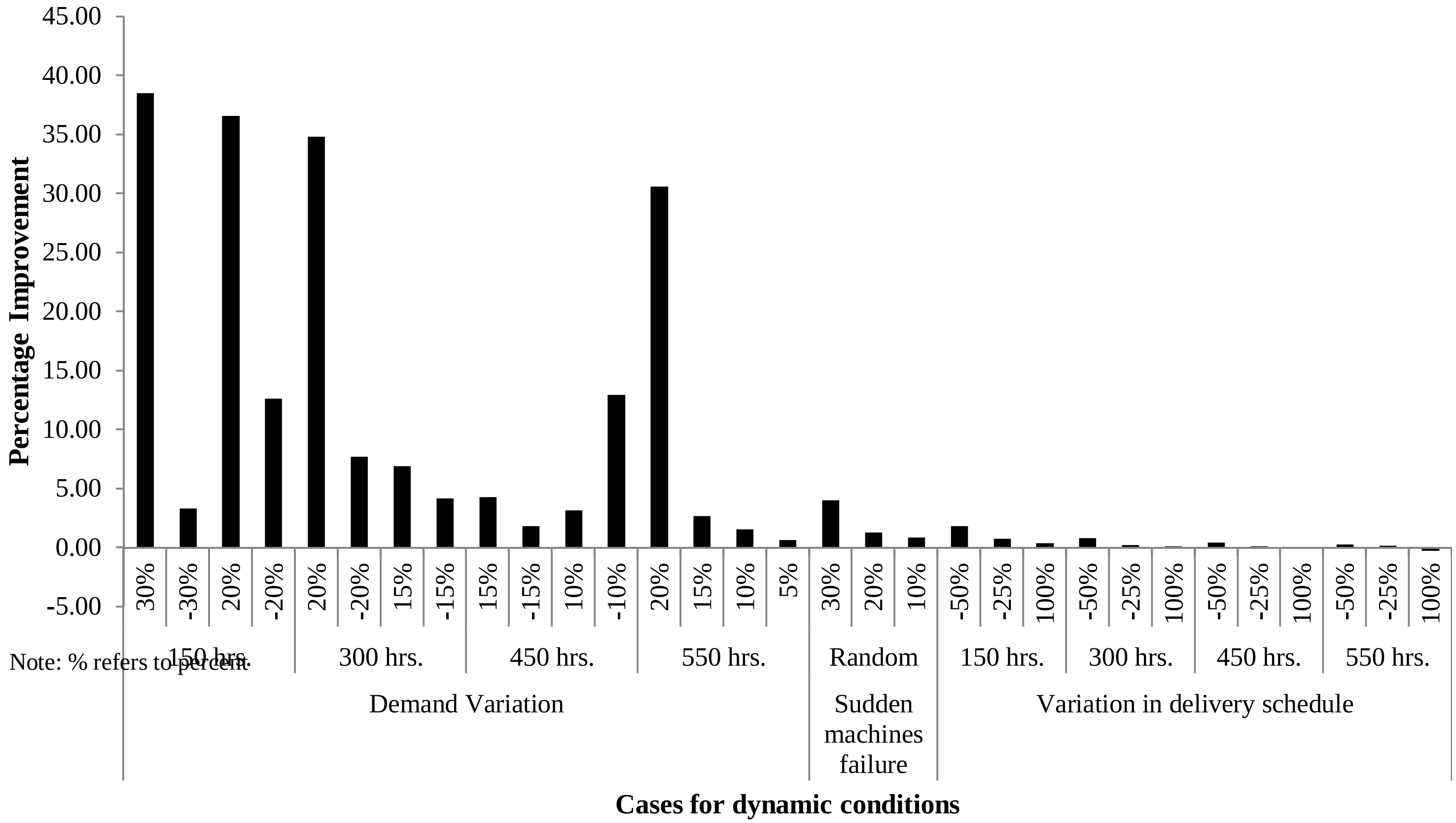

Figure 5.6 Performance of the proposed approach over centralized approach (disturbance is adjusted at last) under dynamic conditions

5.5.7 Generalizing the proposed approach for various manufacturing scenarios

The investigation performed in previous sub-sections is specific to the manufacturing environment described for the case of section 5.5.1 in terms of system, maintenance parameters, and process parameters. Now to generalize the results, the approach is extensively evaluated for wide range of manufacturing scenarios. These scenarios are generated by varying machines' current age, PM restoration factor, product demand, processing time, and by considering different types of production systems as shown in table 5.8. Additionally, each scenario is also solved by centralized approach to analyze the value of the proposed approach in terms of solution quality and computation time.

***Setting of maintenance parameters*:** In order to generate cases for machine's current age, machine reliability has been varied. For case one, it has been considered that current ages of all machines are high i.e., having completed 15 to 45 percent of their life. The corresponding reliability of machines at current age lies in between 0.5 to 0.7. This case is illustrative of an old company having all old machines. In the second case, there is a mix of old and new machines. This case is representative of an older company where due to up-gradation some new machines are added. The current ages of some machines are very less i.e., have finished only 0-10 percent of their life and rest of machines has finished 15 to 45 percent of their life. Consequently, the reliability of machines at current age is considered in between 0.5 to 0.95 (see, chapter 3).

Moreover, in industries, PM effectiveness may also vary. It depends on the restoration factor used for PM. Here, three cases of PM restoration factors viz., 0.4 (B), 0.6 (O) and 0.8 (G) are considered. The variation of maintenance parameters is shown in table 5.8. For example, restoration factor of 0.4 indicates that the PM will restore 40 percent of machine age at the time of maintenance action.

***Various production systems*:** The production system of case (section, 5.5.1) is a kind of flow-shop and consisting of machines in series. However, in some industry where mass production is performed viz., process industries, textile industries, etc., the system has additional parallel machines for bottleneck operations. Such system can be called as series-parallel system. To generate such scenarios, same machine is added to each bottle-neck machine in the system of case presented in section 5.5.1. Here, a machine is considered to be bottle-neck if it processes more than three jobs. From table 4.1 (see, chapter 4), M_1, M_3, M_5, and M_{14} are found as such machines.

***Setting of process parameters*:** In manufacturing industry, product demand varies commonly. In the case firm, i.e., AVTEC, yearly peak, medium and lowest demand of product is 3900, 3000 and 2000 units respectively. The case (section 5.5.1) is presented for a particular month with fixed demand. Thus, to generalize the proposed approach, three different cases of product demand viz., low, medium and high have been considered. The variation of demand is shown in table 5.8.

Additionally, due to scholastic nature of manufacturing process, there are uncertainties regarding exact processing time of a machining operation. However, in case (section, 5.5.1), processing time of each operation was fixed. Thus, to generalize the approach, an uncertainty of ±10 percent is added in processing time of each operation of table 4.1 (see, chapter 4).

Table 5.8 Parameters to generate various manufacturing scenarios

Maintenance parameters			**Process parameters**	
Machines	**PM restoration factor (α)**	**System**	**Demand variation**	**Processing time**
Old (R= 0.5 to 0.7)	0.4 (B)	Series	Low (2000)	Uniform CT with variation of ± 10%
	0.6 (O)		Medium (3000)	
Old + New (R=0.5 to 0.95)	0.8 (G)	Series-Parallel	High (3900)	

Thus, total 36 different manufacturing scenarios are generated. While evaluation of a scenario, the other parameters' values (various costs, times-to-failures, etc.) are kept same as used in section 5.5.1. The obtained results for 36 (1-36) different scenarios are presented in figure 5.7.

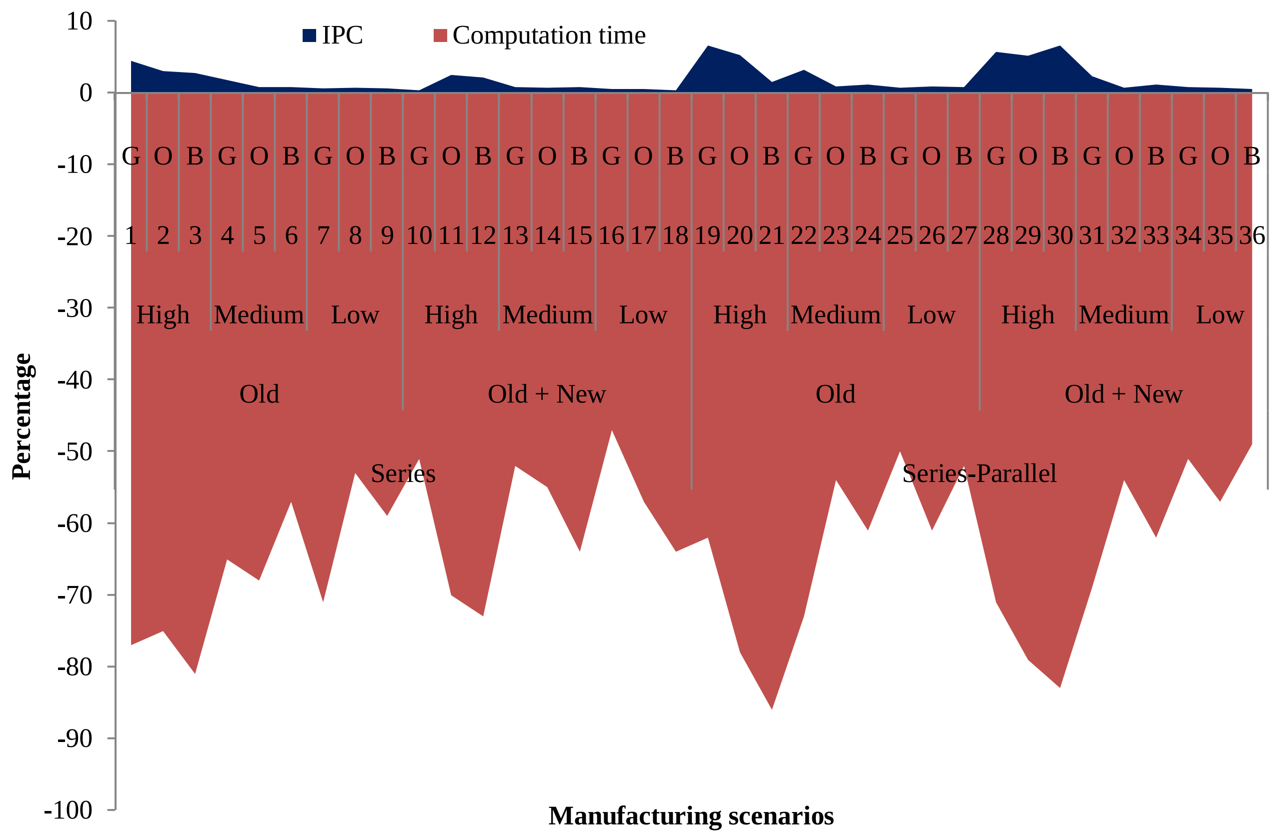

Figure 5.7 Performance of the proposed approach over centralized approach for various manufacturing scenarios

Observations

The portion above X-axis shows percentage improvement in IPC by centralized approach over the proposed approach. While the portion below X-axis displays percentage reduction in computation time by the proposed approach over centralized approach. It is evident from figure 5.7 that for most of the scenarios, the proposed approach provides approximately same solution quality in very less computation time (47 to 86 percent) over centralized approach. The lowest reduction in computation time i.e., 47 percent is found for series-system with low demand and having high restoration factor i.e., scenario 16. The solution quality obtained by the proposed approach for this scenario is slightly poor (only 0.5 percent) over centralized approach. While highest reduction in computation time found is 86 percent and is for a series-parallel system with high demand having low restoration factor, i.e., scenario 21. For this scenario, the difference of solution quality between centralized and the proposed approach is 1.5 percent. Also, it is evident from figure 5.7 that when demand is high, the reduction of computation time is high. A similar pattern is found with system having old machines and low restoration factor. Therefore, it can be comprehended from the analysis that the proposed approach becomes more advantageous when the manufacturing system is complex in terms of machines' age, effectiveness of maintenance actions, high demand, series-parallel system, etc.

5.6 Summary

Present chapter can be seen as an attempt to explore the notion of next industrial revolution (or Industry 4.0) from operations planning point of view. The works reported in this chapter first time envisage the integrated operations planning as an important requirement of the next generation intelligent factory. In this chapter, a novel agent-based integrated yet distributed operations planning approach for next generation manufacturing systems is proposed. The approach deals with two essential but conflicting challenges in operations planning viz., integration and responsiveness. The approach is in line with the inherent characteristics of any intelligent factory like distributed intelligence and communications.

First time in the literature of integrated operations planning, more than three shop-floor function viz., production, maintenance, quality, and inventory are integrated together. The approach is demonstrated for a complex and dynamic industrial environment of an automotive plant. The effectiveness of the proposed approach is studied by comparing the results with the conventional approaches. Also, comparison of optimization algorithms, and the effect of degree of integration are analyzed. Further, the responsiveness of the approach is analyzed under unexpected shop-floor disturbances like machine failures, change in demand, and change in delivery schedule. Finally, an exhaustive performance investigation is carried out to generalize the value of the proposed approach over centralized approach for a wide range of manufacturing scenarios.

5.6.1 Contributions

The outcomes of the work are highlighted hereunder:

a) The proposed approach provides 21.6 percent improvement in Integrated Production Cost (IPC) with 36 percent reduction in computation time over firm's existing planning approach. A significant deviation in the decisions implemented based on the existing planning approach and the proposed approach is observed.

b) The proposed approach provides 16.3 percent improvement in IPC and a colossal reduction in evaluation time of 50.8 percent over interrelated approach. It is found that the interrelated approach takes significantly higher time than the experience-based planning. Also, the experience-based planning practice is able to arrive at the decisions reasonably close to the conventionally available interrelated approach. This motivates and justifies the genesis of such experience-based planning in industries.

c) The proposed approach provides flexibility to choose degree of integration based on the performance and computational time of the overall approach. Even with the smaller degree of integration, the proposed approach performs better than the experience-based planning and conventionally done interrelated approach. Industry 4.0 advocates real-time interface of customers and suppliers with the manufacturing facility which in turn necessitates a high level of responsiveness. In such situation, operations manager can choose low degree of integration for faster solution.

d) The proposed approach gives quick response to dynamic conditions created by machine failures, change in demand, and uncertainty in delivery schedule. Also, it shows 0.05 to 38.5 percent economic improvements over centralized approach under the dynamics conditions. The improvisation is high in case of higher demand variation. In Industry 4.0, manufacturing facility will receive variation in demand more frequently due to speedy interaction between customers and the facility. This makes the approach highly suitable for next generation intelligent factory.

e) For various manufacturing scenarios generated by varying machines' age, demand, maintenance effectiveness, processing times, etc., the proposed approach confirms 47 to 86 percent reduction in computational time over the conventionally done centralized approach without any significant loss in the quality of solution.

f) Comprehensive investigation reveals that the proposed approach becomes more advantageous when the manufacturing system is complex in terms of machines' age, effectiveness of maintenance actions, high demand, series-parallel system, etc.

g) The approach can be implemented in any manufacturing industry. However, it will be more beneficial in industries where machines are older; variety of jobs is high; process flow is complex; effectiveness of PM is poor; manufacturing environment is dynamic; etc.

h) The approach can be used with any varying degree of asset intelligence making it easy to implement at the current industrial shop-floor and at more advanced systems. It is believed that integrated and responsive decision-making will be one of the important requirements in realization of Industry 4.0 in industries.

5.6.2 Research limitations and future scope

The present chapter can lead to number of potential extensions; as it is conceded for flow-shop. Though, it is motivating to extend the current research towards other manufacturing systems. Planning of raw materials is not considered in the current work, considering this will make the problem more complicated but take it closer to reality. The present work distributes the computational tasks at shop-floor function level; it is challenging but can be explored for distributing the tasks at machine level. In this chapter, it is considered that machine is made of single component; considering the machine made of multi-component may be a direction for future research.

Chapter 6

Conclusion

Objective of this chapter is to provide a summary of the work reported in this thesis in terms of research contributions and utility of the research. In the end, limitation and future scope of the present work are given.

6.1 Summary

The outcomes of the research in this work advance the existing body of knowledge by comprehensively investigating the value of integrated operations planning approaches for various manufacturing scenarios and developing a novel agent-based integrated yet distributed approach. These approaches help in the systematic expansion of intelligent operations planning in diverse real-world manufacturing environments. In general, this research work can be assessed as follows:

6.1.1 Research contributions

The present research resulted in a number of contributions which can be summarized as follows:

a) First time in the literature, the problem of integrated operations planning for more than three shop-floor functions is tackled in this thesis.
b) First time in the literature, integrated operations planning research is discussed and explored in the context of next generation manufacturing paradigm i.e., Industry 4.0.
c) A novel integrated yet distributed operations planning approach is developed. The novel approach can deal with two essential but conflicting challenges viz., integration of various shop-floor functions and responsiveness to

dynamic conditions, of any next generation intelligent manufacturing system. The proposed integrated yet distributed approach gives quick response to dynamic conditions created by machine failures, change in demand, and uncertainty in delivery schedule. Also, it shows 0.05 to 38.5 percent economic improvements over centralized approach under the dynamics conditions, for various cases considered in this thesis. The improvement is high in case of demand variation followed by sudden machine failure and change in delivery schedule. In addition, the proposed approach provides flexibility to choose the degree of integration based on the performance and computational time of the overall approach. Even with the smaller degree of integration, the proposed approach performs better than the experience-based planning and conventionally done interrelated approach.

d) An advanced integrated operations planning approach considering three shop-floor functions viz., production, maintenance, and inventory is developed for complex manufacturing system of an automotive industry. The approach facilitates autonomous decision-making at shop-floor.

e) Various simplistic assumptions made in the literature, are relaxed throughout the thesis and more realistic integrated operations planning approaches are developed. For example, all the approaches proposed in this thesis consider realistic job-shop or flow-shop systems, considers the initial age of machines, random failure behaviour, imperfect maintenance, stochastic parameters, etc.

f) All the approaches are comprehensively evaluated for various manufacturing scenarios generated by varying maintenance parameters, process parameters, quality control parameters, etc. This helps in generalizing the results and help the operations managers in selecting a suitable case for the immediate adaption of the offered integrated approaches. The outcomes of extensive value investigations are as follows:

- Comprehensive value investigation is performed on integrated approach considering production and maintenance for 473 different manufacturing scenarios. The results reveal that the approach provides 0.6 to 35.8 percent economic improvements over independent approach for various manufacturing scenarios.

- The results of comprehensive performance investigation carried out on integrated approach considering production, maintenance, and inventory show 4.2 to 21.6 percent economic improvements over conventional approaches for various manufacturing scenarios.
- For various manufacturing scenarios, the proposed integrated yet distributed approach confirms 47 to 86 percent reduction in computational time over the conventionally done centralized approach without any significant loss in the quality of solution.
- In general, it is concluded that integrated operations planning approaches give improved system performance for manufacturing industies having older machines, low maintenance effectiveness, higher cost of rejection, restrictive due dates, complex system configruation, demand is high, and uncertainty in processing time is present, etc. In other words, the integrated operatiosn planning approaches deliver better system performance with the inctrese complexity of the manufacturing system.

g) The integrated production and maintenance approach is analyzed under maintenance resource constraints. The results show that the unavailability of maintenance resources significantly affects the joint decisions and system performance. The variations in the optimal values of different performance measures are found in the range of 14 to 30 percent, for the considered cases.

h) In addition, sensitivity analysis, comparison of optimization algorithms, comparison with conventional approaches, efficacy analysis of integration, and analysis of the effect of degree of integration are carried out in this thesis.

i) The offered integrated models, in general, found to be more sensitive for rejection cost, revenue lost, earliness cost, and WIP carrying cost. Therefore, these parameters should be computed and controlled accurately for effective decision-making.

j) While most of the integrated operations planning approaches in literature consider hypothetical cases for illustration, the present research develops the integrated approaches for real-world complex industrial problems.

k) For optimization, the performance of various optimization algorithms viz. Adaptive Thermo-Statistical Simulated Annealing (ATSA), Hill Climb and Random Solution is compared. The ATSA provides improved solution compared to other two algorithms in approximate same computational time.

In essence, the outcomes of the research in this thesis advance the existing body of knowledge by comprehensively investigating the value of integrated operations planning approaches for various manufacturing scenarios and developing a novel agent-based integrated yet distributed approach. This work forms the basis for building an autonomous decision-support system for joint consideration of several critical strategic operational policies viz., production scheduling, maintenance planning, quality control, and inventory control under dynamic manufacturing environments; realizing a holistic view of intelligent operations planning in industries under Industry 4.0. The results of integrated yet distributed operations policy are a breakthrough in the field of operations planning, Industrial Engineering, and Industry 4.0.

6.1.2 Utility and industrial implications of the research work

The outcomes of the present research will help manufacturing industries in the following manner:

1. World over industries is looking forward for the adaption of Industry 4.0 or smart manufacturing. In such situation, to the least, research presented in this thesis gives raise to a new dimension of Industry 4.0. It strongly advocates exploring novel methods and system to optimize and manage shop-floor operations. In other words, operations planning perspective of Industry 4.0 is brought to the forefront of Industry 4.0 research. It is therefore expected that the research will have long-term industrial implications.

2. The successful implementation of the present approaches will help in integrating various operations planning aspects at the decision-making stage itself, thereby reducing human intervention in coordinating and implementing various operations plans. This is believed to be one of the important requirements in realizing of Industry 4.0 in industries. Moreover, the integrated yet distributed approach makes it more in line with the typical characteristic of Industry 4.0.
3. Industry 4.0 advocates real-time interface of customers and suppliers with the manufacturing facility. It is therefore expected that large demand variations will be more common in the case of next generation intelligent factories; the integrated yet distributed approach, therefore, becomes an obvious choice for such smart factories. Furthermore, the flexibility of choosing the degree of integration will help operations manager in efficient and fast decision-making.
4. Failure of conventional operations planning practices in bringing global view in decision-making and limitation of integrated approaches in terms of responsiveness, often result into apparent inclination toward experience-based planning in industries. Thus, the novel integrated yet distributed approach will be highly suitable as it considers global view in terms of various functions of the organizations and at the same time provides faster solutions. This also reduces the subjectivity involved in the conventional decision-making process.
5. Integrated operations planning may not result into same performance improvement for all the manufacturing industries. The results of comprehensive evaluation obtained by varying parameters related to maintenance, process, and quality control help the operations managers in evolving thumb rules for easy adaption of integrated approaches for their respective shop-floors.

   For example, operations managers working with a shop-floor having older machines, low maintenance effectiveness, high cost of quality rejection, should preferentially go for integrated operations planning. Similarly, the proposed approaches are more beneficial for restrictive due date case compared to un-restrictive due date case. Therefore, in industries where customers impose high penalty for late delivery of products, production manager should look for the proposed approaches for extracting better system performance.

6. Lastly, the research equips the manufacturing industries with autonomous decision-support system that allows high level responsiveness to the dynamic conditions for various real-world manufacturing environments.

6.2 Limitation and future scope of the research work

The advanced integrated approaches developed in this research have a good potential for application in the manufacturing industry. Any such research study aimed at meeting the academic requirements in a somewhat limited duration is bound to suffer from certain limitations. This research is also not an exception. Moreover, the limitations of the present research offer an excellent scope for future research.

In the present research, offered approaches have been developed considering a single component machine. Extending the current research by considering the failure and repair characteristics of each of the components will help in making the investigation more realistic, especially from the maintenance point of view. It will further allow consideration of failure dependencies, opportunistic maintenance, etc. Also, maintenance resource and spares inventory consideration will become more important in such cases. From dependency point of view, it will be interesting to model the effect of failure of various components on process quality. Multiple critical to quality characteristics will naturally come into consideration in such cases. All these will make the investigation more practical but at the same time, it will also significantly increase the computation complexity. Extending the distributed decision-making at functional level to machine or/and component level will solve the problem. When the problem is extended to component level, the integration of manufacturing operations planning with another sphere of research, namely, Prognostic and Health

Management (PHM), will be natural extension of current work. It will help in more accurate maintenance planning at the same time will closely relate with Industry 4.0 paradigm. Eventually, the core domain of Industry 4.0 research, which increasingly focuses on developing digital twin and platform for machine-to-machine communications, can be utilized to build up more advanced intelligent operations planning system for next generation manufacturing.

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Appendix A

Simulation-based Genetic Algorithm

Input: Size 'e' of population, crossover rate 'f', mutation rate 'g'
Output: Minimum OOC
// **Formulation**
setParameters();
Define mean as the statistic for the simulation results;
defineDecisionVariables();
defineConstraints();
// **Simulation based optimization**
Initialize ( );
Generate_ random ( ) e individuals;
Compute _fitness (u) $\forall$ u $\in$ e;
1 ***for V=1 to termination do***
2 Select two individuals u_a & u_b from population by using rank based mechanism;
3 Generate u_c & u_d; by uniform crossover on u_a & u_b under rate f;
4 Select one off spring; apply non-uniform mutation under rate g; // Generate new decision variables
// **Simulation**
5 Determine sample of uncertain parameters using probability distribution functions;
6 Recalculate the model using new sampled values and new decision variables;
7 Calculate and store the new value of **OOC**;
8 ***If*** Solution is unfeasible **then**
9 Repeat simulation from step 5;
10 ***Endif***
// Increment
11 Update u: = u+1
12 ***Endfor***
// resulting minimum OOC
13 return OOC

Simulation-based Adaptive Thermo-statistical Simulated Annealing

```
Input: Set algorithm parameters();
K = Initialize Temperature;
Z0 = Generate_Initial_Solution();
X = 0 // iteration count;
while(!Stopping_condition(Z0, t, X))
        Z1 = Neighbor (Z0) // find a neighbor of Z0
         ΔOFV=OFV (Z0) - OFV (Z1)
        if(α < 0)
          Z0 = Z1 // If Z1 is better than Z0 // accept it
        else if(rand() < temp_Func(Z0, Z1, t, X))
          Z0=Z1//if α > 0 // accept with probability exp(-ΔOFV/K)
          Simulate(Z1) // for uncertain model parameters
        end if
        Annealing_Schedule(Z0, K, X) // anneal the temp
        X = X + 1 // increment
end while
Output: Minimum OFV
```

Appendix B

Table I-1 Results of variation in maintenance parameters

Scenarios	Machine age	β	η	α	Integrated (OOC)	Independent (OOC)	Improvement (%)
1	A_1	2	1000	0.4	153,797	163,583	5.98
2	A_1	2.5	1000	0.4	155,058	170,344	8.97
3	$\boldsymbol{A_1}$	**3**	**1000**	**0.4**	**158,674**	**174,951**	**9.3 ($\boldsymbol{H_{A_1}}$)**
4	A_1	2	2000	0.4	126,701	131,782	3.86
5	A_1	2.5	2000	0.4	126,329	133,581	5.43
6	A_1	3	2000	0.4	126,929	137,344	7.58
7	A_1	2	3000	0.4	119,548	123,167	2.92
8	A_1	2.5	3000	0.4	119,189	124,102	3.96
9	A_1	3	3000	0.4	119,415	126,245	5.41
10	A_1	2	1000	0.6	153,797	163,583	5.98
11	A_1	2.5	1000	0.6	155,058	164,784	5.9
12	A_1	3	1000	0.6	156,530	166,139	5.78
13	A_1	2	2000	0.6	126,701	131,782	3.86
14	A_1	2.5	2000	0.6	126,329	133,581	5.43
15	A_1	3	2000	0.6	126,929	137,344	7.58
16	$\boldsymbol{A_1}$	**2**	**3000**	**0.6**	**119,571**	**123,167**	**2.92 ($\boldsymbol{L_{A_1}}$)**
17	A_1	2.5	3000	0.6	119,189	124,102	3.96
18	A_1	3	3000	0.6	119,415	126,245	5.41
19	A_1	2	1000	0.8	153,250	161,012	4.82
20	A_1	2.5	1000	0.8	153,941	163,366	5.77
21	A_1	3	1000	0.8	151,699	165,947	8.59
22	A_1	2	2000	0.8	126,701	131,782	3.86
23	A_1	2.5	2000	0.8	126,329	133,581	5.43
24	A_1	3	2000	0.8	126,929	139,219	8.83
25	A_1	2	3000	0.8	119,548	123,167	2.92
26	A_1	2.5	3000	0.8	119,189	124,102	3.96
27	A_1	3	3000	0.8	119,415	126,245	5.41
28	A_2	2	1000	0.4	205,705	225,266	8.68
29	A_2	2.5	1000	0.4	212,059	240,461	11.8
30	$\boldsymbol{A_2}$	**3**	**1000**	**0.4**	**214,402**	**253,168**	**15.60 ($\boldsymbol{H_{A_2}}$)**
31	A_2	2	2000	0.4	152,639	166,368	8.25
32	A_2	2.5	2000	0.4	161,601	178,654	9.55
33	A_2	3	2000	0.4	168,788	188,356	10.4
34	A_2	2	3000	0.4	136,850	146,073	6.31
35	A_2	2.5	3000	0.4	142,220	158,218	110
36	A_2	3	3000	0.4	148,019	165,458	10.5
37	A_2	2	1000	0.6	194,720	205,830	5.38
38	A_2	2.5	1000	0.6	191,487	208,057	7.96
39	A_2	3	1000	0.6	186,204	204,609	9
40	A_2	2	2000	0.6	152,639	162,644	6.15
41	A_2	2.5	2000	0.6	159,940	167,510	4.52
42	A_2	3	2000	0.6	157,581	169,154	6.84

Results of variation in maintenance parameters (continued)							
Scenarios	**Machine age**	$\boldsymbol{\beta}$	η	$\boldsymbol{\alpha}$	**Integrated (OOC)**	**Independent (OOC)**	**Improvement (%)**
43	A_2	2	3000	0.6	136,850	146,073	6.31
44	A_2	2.5	3000	0.6	142,220	152,154	6.53
45	A_2	3	3000	0.6	146,684	157,718	7
46	A_2	2	1000	0.8	180,682	186,649	3.2
47	A_2	2.5	1000	0.8	172,887	179,708	3.8
48	A_2	3	1000	0.8	165,862	172,216	3.69
49	A_2	2	2000	0.8	152,639	158,145	3.48
50	A_2	2.5	2000	0.8	152,226	155,687	2.22
51	A_2	3	2000	0.8	150,221	155,276	3.26
52	A_2	2	3000	0.8	136,850	144,029	4.98
53	A_2	2.5	3000	0.8	142,220	148,058	3.94
54	$\boldsymbol{A_2}$	**3**	**3000**	**0.8**	**145,729**	**148,523**	**1.88 ($\boldsymbol{L_{A_2}}$)**
55	A_3	2	1000	0.4	248,798	268,965	7.5
56	A_3	2.5	1000	0.4	256,811	291,679	12
57	A_3	3	1000	0.4	166,833	190,518	12.4
58	A_3	2	2000	0.4	171,994	187,512	8.28
59	A_3	2.5	2000	0.4	185,969	207,511	10.4
60	A_3	3	2000	0.4	196,759	229,145	14.1
61	A_3	2	3000	0.4	149,454	159,758	6.45
62	A_3	2.5	3000	0.4	157,895	175,358	9.96
63	$\boldsymbol{A_3}$	**3**	**3000**	**0.4**	**257,050**	**310,890**	**17.3 ($\boldsymbol{H_{A_3}}$)**
64	A_3	2	1000	0.6	230,691	244,297	5.57
65	A_3	2.5	1000	0.6	222,437	241,866	8.03
66	A_3	3	1000	0.6	214,154	239,139	10.4
67	A_3	2	2000	0.6	171,994	182,367	5.69
68	A_3	2.5	2000	0.6	182,526	192,495	5.18
69	A_3	3	2000	0.6	180,374	191,241	5.68
70	A_3	2	3000	0.6	149,844	159,758	6.21
71	A_3	2.5	3000	0.6	158,457	169,444	6.48
72	A_3	3	3000	0.6	167,343	177,224	5.58
73	A_3	2	1000	0.8	207,001	214,085	3.31
74	A_3	2.5	1000	0.8	194,058	201,815	3.84
75	A_3	3	1000	0.8	184,450	192,169	4.02
76	A_3	2	2000	0.8	172,578	177,393	2.71
77	$\boldsymbol{A_3}$	**2.5**	**2000**	**0.8**	**173,273**	**175,948**	**1.52 ($\boldsymbol{L_{A_3}}$)**
78	A_3	3	2000	0.8	168,167	171,494	1.94
79	A_3	2	3000	0.8	149,454	156,514	4.51
80	A_3	2.5	3000	0.8	157,895	164,248	3.87
81	A_3	3	3000	0.8	162,784	167,326	2.71

Table I-2 Variation of quality control parameters in lowest and highest improvement scenarios of varying maintenance parameters

Scenarios	Machine age		δ	s	h	F_{rej}	Integrated (OOC)	Independent (OOC)	Improvement (%)
1	A_1	L_{A_1}	0.5	2	8	1	115,636	117,829	1.86
2	A_1	L_{A_1}	0.5	2	8	5	118,208	121,339	2.58
3	A_1	L_{A_1}	0.5	2	8	10	121,423	125,726	3.42
4	A_1	L_{A_1}	0.5	2	16	1	116,279	118,706	2.04
5	A_1	L_{A_1}	0.5	2	16	5	121,423	125,726	3.42
6	$\boldsymbol{A_1}$	$\boldsymbol{L_{A_1}}$	**0.5**	**2**	**16**	**10**	**127,854**	**134,501**	**4.94** $(\boldsymbol{H_{L_{A_1}}})$
7	A_1	L_{A_1}	0.5	4	8	1	115,302	117,373	1.76
8	A_1	L_{A_1}	0.5	4	8	5	116,537	119,059	2.12
9	A_1	L_{A_1}	0.5	4	8	10	118,081	121,166	2.55
10	A_1	L_{A_1}	0.5	4	16	1	115,610	117,794	1.85
11	A_1	L_{A_1}	0.5	4	16	5	118,081	121,166	2.55
12	A_1	L_{A_1}	0.5	4	16	10	121,170	125,380	3.36
13	A_1	L_{A_1}	0.7	2	8	1	115,555	117,718	1.84
14	A_1	L_{A_1}	0.7	2	8	5	117,802	120,785	2.47
15	A_1	L_{A_1}	0.7	2	8	10	120,611	124,618	3.22
16	A_1	L_{A_1}	0.7	2	16	1	116,116	118,485	2
17	A_1	L_{A_1}	0.7	2	16	5	120,611	124,618	3.22
18	A_1	L_{A_1}	0.7	2	16	10	126,230	132,285	4.58
19	$\boldsymbol{A_1}$	$\boldsymbol{L_{A_1}}$	**0.7**	**4**	**8**	**1**	**115,211**	**117,262**	**1.75** $(\boldsymbol{L_{L_{A_1}}})$
20	A_1	L_{A_1}	0.7	4	8	5	116,131	118,505	2
21	A_1	L_{A_1}	0.7	4	8	10	117,270	120,059	2.32
22	A_1	L_{A_1}	0.7	4	16	1	115,448	117,573	1.81
23	A_1	L_{A_1}	0.7	4	16	5	117,270	120,059	2.32
24	A_1	L_{A_1}	0.7	4	16	10	119,571	123,167	2.92
25	A_2	L_{A_2}	0.5	2	8	1	134,324	144,474	7.03
26	A_2	L_{A_2}	0.5	2	8	5	142,084	147,136	3.43
27	A_2	L_{A_2}	0.5	2	8	10	146,373	150,464	2.72
28	A_2	L_{A_2}	0.5	2	16	1	136,575	145,139	5.9
29	A_2	L_{A_2}	0.5	2	16	5	146,373	150,464	2.72
30	A_2	L_{A_2}	0.5	2	16	10	150,325	157,120	4.32
31	A_2	L_{A_2}	0.5	4	8	1	133,155	144,128	7.61
32	A_2	L_{A_2}	0.5	4	8	5	137,479	145,406	5.45
33	A_2	L_{A_2}	0.5	4	8	10	142,885	147,007	2.8
34	A_2	L_{A_2}	0.5	4	16	1	134,236	144,447	7.07
35	A_2	L_{A_2}	0.5	4	16	5	142,885	147,007	2.8
36	A_2	L_{A_2}	0.5	4	16	10	146,618	150,202	2.39
37	A_2	L_{A_2}	0.7	2	8	1	134,040	144,389	7.17
38	A_2	L_{A_2}	0.7	2	8	5	141,908	146,716	3.28
39	A_2	L_{A_2}	0.7	2	8	10	145,332	149,624	2.87
40	A_2	L_{A_2}	0.7	2	16	1	137,400	144,971	5.22

Variation of quality control parameters in lowest and highest improvement scenarios of varying maintenance parameters (continued)									
Scenarios	**Machine age**		**δ**	**s**	**h**	**F_{rej}**	**Integrated (OOC)**	**Independent (OOC)**	**Improvement (%)**
41	A_2	L_{A_2}	0.7	2	16	5	145,332	149,624	2.87
42	A_2	L_{A_2}	0.7	2	16	10	149,424	155,439	3.87
43	$\boldsymbol{A_2}$	$\boldsymbol{L_{A_2}}$	**0.7**	**4**	**8**	**1**	**144,044**	**156,163**	**7.76 ($\boldsymbol{H_{L_{A_2}}}$)**
44	A_2	L_{A_2}	0.7	4	8	5	144,987	154,505	6.16
45	A_2	L_{A_2}	0.7	4	8	10	139,984	146,165	4.23
46	A_2	L_{A_2}	0.7	4	16	1	133,668	144,279	7.35
47	A_2	L_{A_2}	0.7	4	16	5	139,984	146,165	4.23
48	$\boldsymbol{A_2}$	$\boldsymbol{L_{A_2}}$	**0.7**	**4**	**16**	**10**	**145,729**	**148,523**	**1.88 ($\boldsymbol{L_{L_{A_2}}}$)**
49	A_3	L_{A_3}	0.5	2	8	1	158,137	171,083	7.57
50	A_3	L_{A_3}	0.5	2	8	5	170,087	174,282	2.41
51	A_3	L_{A_3}	0.5	2	8	10	174,125	178,281	2.33
52	A_3	L_{A_3}	0.5	2	16	1	162,712	171,882	5.34
53	A_3	L_{A_3}	0.5	2	16	5	174,125	178,281	2.33
54	A_3	L_{A_3}	0.5	2	16	10	180,219	186,278	3.25
55	A_3	L_{A_3}	0.5	4	8	1	155,760	170,667	8.73
56	A_3	L_{A_3}	0.5	4	8	5	163,772	172,204	4.9
57	$\boldsymbol{A_3}$	$\boldsymbol{L_{A_3}}$	**0.5**	**4**	**8**	**10**	**170,957**	**174,124**	**1.82 ($\boldsymbol{L_{L_{A_3}}}$)**
58	A_3	L_{A_3}	0.5	4	16	1	157,957	171,051	7.66
59	A_3	L_{A_3}	0.5	4	16	5	170,957	174,124	1.82
60	A_3	L_{A_3}	0.5	4	16	10	173,885	177,966	2.29
61	A_3	L_{A_3}	0.7	2	8	1	157,560	170,982	7.85
62	A_3	L_{A_3}	0.7	2	8	5	169,395	173,777	2.52
63	A_3	L_{A_3}	0.7	2	8	10	173,355	177,271	2.21
64	A_3	L_{A_3}	0.7	2	16	1	161,557	171,681	5.9
65	A_3	L_{A_3}	0.7	2	16	5	173,355	177,271	2.21
66	A_3	L_{A_3}	0.7	2	16	10	178,680	184,259	3.03
67	$\boldsymbol{A_3}$	$\boldsymbol{L_{A_3}}$	**0.7**	**4**	**8**	**1**	**155,182**	**170,566**	**9.02 ($\boldsymbol{H_{L_{A_3}}}$)**
68	A_3	L_{A_3}	0.7	4	8	5	161,969	171,699	5.67
69	A_3	L_{A_3}	0.7	4	8	10	168,777	173,116	2.51
70	A_3	L_{A_3}	0.7	4	16	1	156,803	170,849	8.22
71	A_3	L_{A_3}	0.7	4	16	5	168,777	173,116	2.51
72	A_3	L_{A_3}	0.7	4	16	10	172,347	175,948	2.05
73	A_1	L_{A_1}	0.5	2	8	1	141,959	154,743	8.26
74	A_1	L_{A_1}	0.5	2	8	5	152,949	168,030	8.98
75	A_1	L_{A_1}	0.5	2	8	10	165,587	184,639	10.3
76	A_1	L_{A_1}	0.5	2	16	1	144,706	158,064	8.45
77	A_1	L_{A_1}	0.5	2	16	5	165,587	184,639	10.3
78	$\boldsymbol{A_1}$	$\boldsymbol{L_{A_1}}$	**0.5**	**2**	**16**	**10**	**185,644**	**217,858**	**14.8 ($\boldsymbol{H_{H_{A_1}}}$)**
79	A_1	L_{A_1}	0.5	4	8	1	140,531	153,016	8.16
80	A_1	L_{A_1}	0.5	4	8	5	145,810	159,398	8.52

Variation of quality control parameters in lowest and highest improvement scenarios of varying maintenance parameters (continued)

Scenarios	Machine age		δ	s	h	F_{rej}	Integrated (OOC)	Independent (OOC)	Improvement (%)
81	A_1	L_{A_1}	0.5	4	8	10	152,408	167,376	8.94
82	A_1	L_{A_1}	0.5	4	16	1	141,851	154,612	8.25
83	A_1	L_{A_1}	0.5	4	16	5	152,408	167,376	8.94
84	A_1	L_{A_1}	0.5	4	16	10	165,605	183,331	9.67
85	A_1	L_{A_1}	0.7	2	8	1	141,612	154,323	8.24
86	A_1	L_{A_1}	0.7	2	8	5	151,215	165,933	8.87
87	A_1	L_{A_1}	0.7	2	8	10	163,219	180,446	9.55
88	A_1	L_{A_1}	0.7	2	16	1	144,013	157,226	8.4
89	A_1	L_{A_1}	0.7	2	16	5	163,219	180,446	9.55
90	A_1	L_{A_1}	0.7	2	16	10	181,096	209,470	13.5
91	$\boldsymbol{A_1}$	$\boldsymbol{L_{A_1}}$	**0.7**	**4**	**8**	**1**	**140,184**	**152,597**	**8.13** $(\boldsymbol{L_{H_{A_1}}})$
92	A_1	L_{A_1}	0.7	4	8	5	144,077	157,303	8.41
93	A_1	L_{A_1}	0.7	4	8	10	148,943	163,186	8.73
94	A_1	L_{A_1}	0.7	4	16	1	141,157	153,774	8.2
95	A_1	L_{A_1}	0.7	4	16	5	148,943	163,186	8.73
96	A_1	L_{A_1}	0.7	4	16	10	158,674	174,951	9.3
97	A_2	L_{A_2}	0.5	2	8	1	189,524	231,995	18.3
98	A_2	L_{A_2}	0.5	2	8	5	204,296	268,224	23.8
99	A_2	L_{A_2}	0.5	2	8	10	223,653	313,510	28.7
100	A_2	L_{A_2}	0.5	2	16	1	192,295	241,052	20.2
101	A_2	L_{A_2}	0.5	2	16	5	223,653	313,510	28.7
102	A_2	L_{A_2}	0.5	2	16	10	258,476	401,361	33.8
103	A_2	L_{A_2}	0.5	4	8	1	186,216	227,288	18.1
104	A_2	L_{A_2}	0.5	4	8	5	193,901	244,689	20.8
105	A_2	L_{A_2}	0.5	4	8	10	205,556	266,440	22.9
106	A_2	L_{A_2}	0.5	4	16	1	188,137	231,638	18.8
107	A_2	L_{A_2}	0.5	4	16	5	205,556	266,440	22.9
108	A_2	L_{A_2}	0.5	4	16	10	222,282	309,943	28.3
109	A_2	L_{A_2}	0.7	2	8	1	187,789	230,851	18.7
110	A_2	L_{A_2}	0.7	2	8	5	201,771	262,506	23.1
111	A_2	L_{A_2}	0.7	2	8	10	219,257	302,075	27.4
112	A_2	L_{A_2}	0.7	2	16	1	191,285	238,765	19.9
113	A_2	L_{A_2}	0.7	2	16	5	219,257	302,075	27.4
114	$\boldsymbol{A_2}$	$\boldsymbol{L_{A_2}}$	**0.7**	**2**	**16**	**10**	**249,683**	**381,212**	**34.5** $(\boldsymbol{H_{H_{A_2}}})$
115	$\boldsymbol{A_2}$	$\boldsymbol{L_{A_2}}$	**0.7**	**4**	**8**	**1**	**191,378**	**226,145**	**15.4** $(\boldsymbol{L_{H_{A_2}}})$
116	A_2	L_{A_2}	0.7	4	8	5	185,711	238,977	22.3
117	A_2	L_{A_2}	0.7	4	8	10	198,462	255,016	22.2
118	A_2	L_{A_2}	0.7	4	16	1	187,128	229,353	18.4
119	A_2	L_{A_2}	0.7	4	16	5	198,462	255,016	22.2
120	A_2	$\boldsymbol{L_{A_2}}$	0.7	4	16	10	214,402	287,094	25.3

Variation of quality control parameters in lowest and highest improvement scenarios of varying maintenance parameters (continued)

Scenarios	Machine age		δ	s	h	F_{rej}	Integrated (OOC)	Independent (OOC)	Improvement (%)
121	A_3	L_{A_3}	0.5	2	8	1	228,201	275,172	17.1
122	A_3	L_{A_3}	0.5	2	8	5	249,734	320,964	22.2
123	A_3	L_{A_3}	0.5	2	8	10	276,649	378,204	26.9
124	A_3	L_{A_3}	0.5	2	16	1	235,584	286,620	17.8
125	A_3	L_{A_3}	0.5	2	16	5	276,649	378,204	26.9
126	$\boldsymbol{A_3}$	$\boldsymbol{L_{A_3}}$	**0.5**	**2**	**16**	**10**	**330,480**	**492,685**	**32.9** ($\boldsymbol{H_{H_{A_3}}}$)
127	A_3	L_{A_3}	0.5	4	8	1	225,504	269,223	16.2
128	A_3	L_{A_3}	0.5	4	8	5	235,746	291,217	19
129	A_3	L_{A_3}	0.5	4	8	10	248,674	318,710	22
130	A_3	L_{A_3}	0.5	4	16	1	227,989	274,721	17
131	A_3	L_{A_3}	0.5	4	16	5	248,674	318,710	22
132	A_3	L_{A_3}	0.5	4	16	10	274,529	373,696	26.5
133	A_3	L_{A_3}	0.7	2	8	1	227,522	273,727	16.9
134	A_3	L_{A_3}	0.7	2	8	5	246,336	313,738	21.5
135	A_3	L_{A_3}	0.7	2	8	10	269,853	363,751	25.8
136	A_3	L_{A_3}	0.7	2	16	1	232,225	283,730	18.2
137	A_3	L_{A_3}	0.7	2	16	5	269,853	363,751	25.8
138	A_3	L_{A_3}	0.7	2	16	10	316,888	463,778	31.7
139	$\boldsymbol{A_3}$	$\boldsymbol{L_{A_3}}$	**0.7**	**4**	**8**	**1**	**224,725**	**267,779**	**16.1** ($\boldsymbol{L_{H_{A_3}}}$)
140	A_3	L_{A_3}	0.7	4	8	5	232,351	283,997	18.2
141	A_3	L_{A_3}	0.7	4	8	10	241,884	304,270	20.5
142	A_3	L_{A_3}	0.7	4	16	1	226,631	271,833	16.6
143	A_3	L_{A_3}	0.7	4	16	5	241,884	304,270	20.5
144	A_3	L_{A_3}	0.7	4	16	10	257,050	344,816	25.5

Appendix C

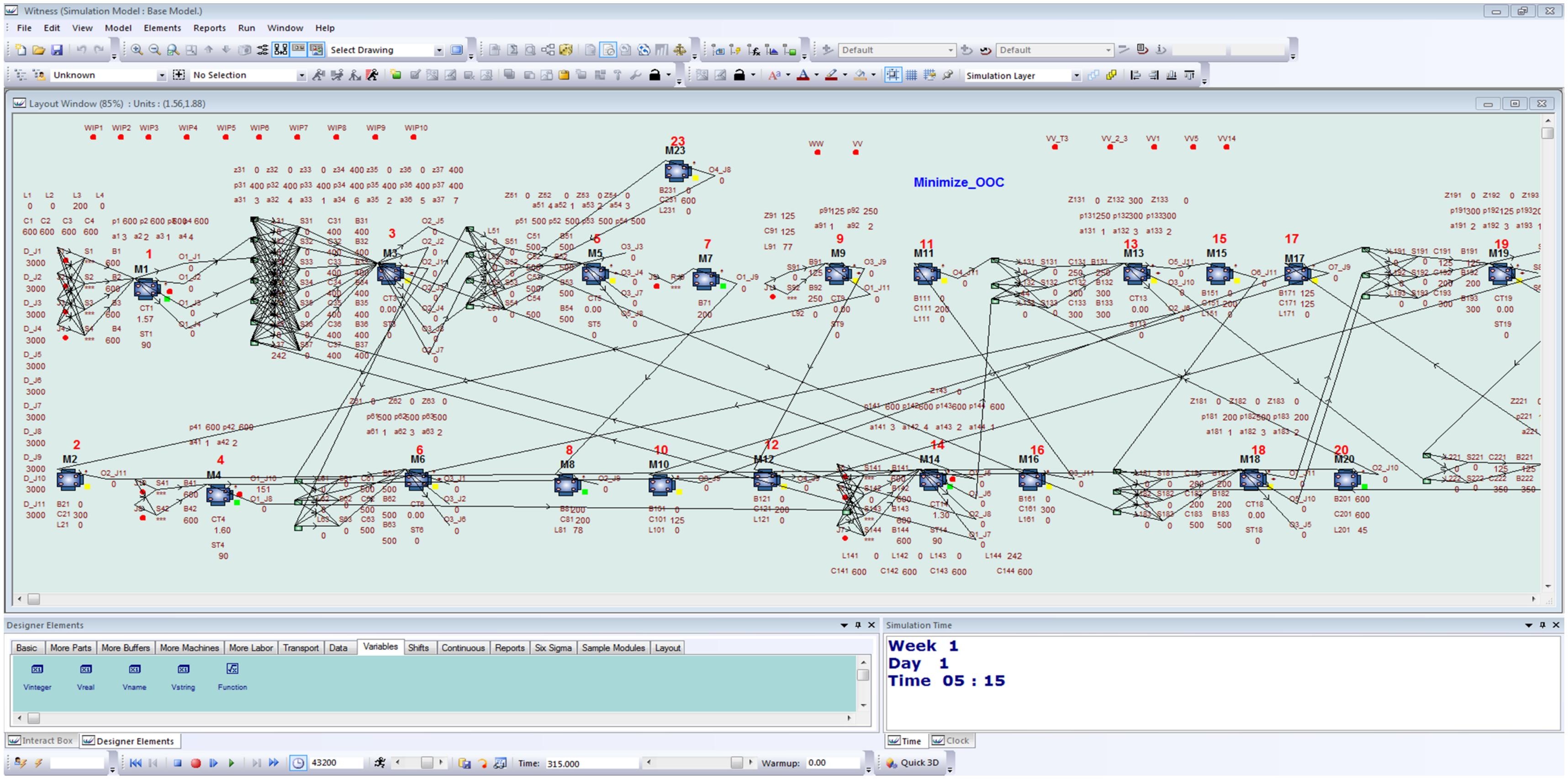

Figure 1 Simulation interface