Agent Based Production Scheduling in Job Shop Manufacturing System

Ph.D. Thesis

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by

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DECLARATION

I, Om Ji Shukla, declare that the thesis titled, **"Agent Based Production Scheduling in Job Shop Manufacturing System"** and the work presented in it, are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this university.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this university or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself, jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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CERTIFICATE

This is to certify that the thesis entitled, **"Agent Based Production Scheduling in Job Shop Manufacturing System"** being submitted by Om Ji Shukla (Id No. 2013RME9540) is a bonafide research work carried out under my supervision and guidance in fulfillment of the requirement for the award of the degree of **Doctor of Philosophy** in the Department of Mechanical Engineering, Malaviya National Institute of Technology, Jaipur, India. The matter embodied in this thesis is original and has not been submitted to any other University or Institute for the award of any other degree.

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Abstract

The manufacturing sector has seen dynamic changes during the last few years, namely the move from product-oriented local economy to customer-driven global economy. In this environment, manufacturing systems have been required to deliver highly flexible, demand-driven and customized products. In this highly competitive scenario, agent based technology can play an important role in making highly responsive production scheduling systems in order to meet dynamic and uncertain changes in demand. Hence, this thesis develops an agent based simulation model of job-shop manufacturing system (JMS) for real time production scheduling. Therefore, first of all this research work offers a review of multi agent system (MAS) for production scheduling problems in manufacturing systems. It provides comparative advantages of MAS over traditional approaches in this area. This study identifies different key issues which are involved in implementing MAS in production scheduling and simultaneously various MAS platforms are found out through related literature. In addition to this, the research also presents a conceptual framework for implementing MAS concept in production scheduling systems.

In the present time, Discrete event simulation (DES) software tool is very known to engineers in designing a manufacturing system layout and production lines, it facilitates to get a good solution for the analysis and validation of any problem. In this research work, DES software tool 'SimEvents' has been used for developing simulation model of JMS. Further performance measures of this discrete event simulation model of JMS is analyzed using different job dispatching rules. The first-in-first-out (FIFO), last-in-first-out (LIFO), shortest processing time (SPT) and longest processing time (LPT) are considered for examining six performance measures i.e. mean flow time, mean tardiness, standard deviation of flow time, standard deviation of tardiness, production output and work-in-process for three jobs. Simulation results reveal that dispatching rule SPT has provided best performance for the measures such as mean flow time, production output and work-in-process for all the three jobs while the best performance of LPT rule is obtained for the measures mean tardiness, standard deviation of flow time and standard deviation of tardiness. LIFO rule has shown lower performances in standard deviation of flow time and mean flow time measures for all the three jobs.

In a cut throat competitive environment, effective production is one of the key issues which can be addressed by efficient production scheduling in the manufacturing system. Hence this study develops an agent-based architecture for job-shop manufacturing system (JMS). This architecture facilitates real time production scheduling as well as provides a MAS platform on which multiple agents will interact to each other. A case study of three jobs and six machine types of JMS has been considered in this study for implementing the concept of MAS. In addition to develop an agent based architecture, an agent based simulation modeling approach is also presented in this study which provides ten steps for developing agent based model of JMS. This approach facilitates the integration of discrete event model of JMS with agent based architecture.

SimEvents with Stateflow functions libraries simulation tool is used for developing agent based job-shop manufacturing system model. In which SimEvents is used for developing simulation model of JMS and Stateflow is used for developing agent based architecture. This study also analyzes the performance of agent based job-shop manufacturing system (ABJMS) model using different performance measures such as mean flow time, mean tardiness, standard deviation of flow time, standard deviation of tardiness, production output, work-in-process. The statistical analysis of simulation results reveal that among most of the performance measures, agent based job-shop manufacturing system (ABJMS) model with SPT rule perform well while FIFO rule provides lower performance. Finally this study evaluates the ABJMS model with JMS model using maximum utilization and average utilization of machines. The comparative analysis of ABJMS with JMS model shows that casting and shaper machines are over utilized, whereas both maximum and average utilizations of planer, lathe machine, drilling machine and polishing machine in ABJMS model are greater than JMS model.

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Abbreviations

MS	Manufacturing System
JMS	Job-Shop Manufacturing System
ABJMS	Agent Based Job-Shop Manufacturing System
MAS	Multi Agent System
JSSP	Job Shop Scheduling Problem
AI	Artificial Intelligence
DAI	Distributed Artificial Intelligence
CMS	Cellular Manufacturing System
PSO	Particle Swarm Optimization
TS	Tabu Search
GA	Genetic Algorithm
SA	Simulated Annealing
HGA	Hybrid Genetic Algorithm
HSA	Hybrid Simulated Annealing
ABC	Artificial Bee Colony
ANN	Artificial Neural Network
FMS	Flexible Manufacturing System
FBS	Filtered Beam Search
MOORA	Multi Objective Optimization on the basis of Ratio Analysis
FMCDM	Fuzzy Multi Criteria Decision Making
IPPS	Integrated Process Planning and Scheduling
MES	Manufacturing Execution System
MILP	Mixed Integer Linear Programming
FIPA	Foundation for Intelligent Physical Agents
AC	Agent Coordinator

AC & N	Agent Coordination and Negotiation
CNP	Contract Net Protocol
FANN	Feed-forward Artificial Neural Networks
DES	Discrete Event Simulation
DPPW	Dynamic Processing Plus Waiting Time
FIFO	First In First Out
LIFO	Last In First Out
SPT	Shortest Processing Time
LPT	Longest Processing Time
MFT	Mean Flow Time
MT	Mean Tardiness
SDFT	Standard Deviation of Flow Time
SDT	Standard Deviation of Tardiness
PO	Production Output
WIP	Work-In-Process
JA	Job Agent
SUA	Shop Utilization Agent
DDA	Dispatching Date Agent
JWA	Job Weightage Agent
SA	Scheduling Agent
MU	Machine Utilization
OT	Operation Time
TAT	Total Available Time

List of Symbols

P_i is the processing time of job entity i

C_i is the completion time of job entity i

D_i is the dispatching date of job entity i

A_i is the arrival time of job entity i

n_j is the number of completed entities of job j from zero starting time to simulation ending time

ne_j is the number of job entities of job j entered into the system

$F\bar{T}_j$ Mean flow time of jth job

FT_i Flow time of job entity i

$\bar{T}_j$ Mean tardiness of jth job

T_i Tardiness of job entity i

$SDFT_j$ Standard deviation of flow time of jth job

SDT_j Standard deviation of tardiness of jth job

PO_j Production output of jth job

WIP_j Work-In-Process of jth job

Chapter 1

Introduction

1.1 Introduction

During recent years, the fast development of technology has resulted fierce market competition. The manufacturing organisations have to gradually shift their policy making methods from product-oriented to customer-oriented due to diversified demands and individualistic desires of the customers, shorter product life cycles and increasing volatility of products. In order to survive the competition, the industries are in acute need of manufacturing systems with fault tolerant ability, agility and more flexibility to deal with high level of unpredictable situations and uncertainties (Dominici, 2008). The dynamic adaptive nature and responsiveness of new manufacturing systems can fulfil the requirements of present manufacturers (Zhang et al., 2000). The research shows that several manufacturing systems have been emerged with time. Some of these are holonic manufacturing system (HMS), based on holons (Koestler, 1989) and investigated by Seidel et al. (1994); biological manufacturing system, introduced by Ueda (1993); fractal factory, introduced by Warnecke (2003); distributed manufacturing systems (Peklenik and Jerele, 1992) and networked manufacturing system (Yan, 2000; Manupati et al., 2016). These manufacturing systems are more adaptable to frequent changing environment. The Intelligent manufacturing system built on multi agent system (MAS) is one such distributed manufacturing system relating to the artificial intelligence domain which can support above mentioned characteristics.

Production scheduling is one of the main activities in a production system which deal with time span of production processes and job priority decisions. In a nutshell, production scheduling is an optimization process in which limited resources are assigned over time in both parallel and sequential manufacturing activities (Zweben and Fox, 1994). Scheduling problems are usually NP-hard in nature (Morton and Pentico, 1993; Pinedo, 1995). The researchers have addressed different types of scheduling problems in manufacturing systems to enhance its performance (de Fátima Morais et al., 2014; Wang and Usher, 2005; Manupati et al., 2016; Jana et al., 2013; Wong et al., 2006). The scheduling process can be dynamic (i.e. a decision has to be made immediately or for a predetermined time) or static (i.e. the schedule is constructed before execution), depending on the system requirements. The static scheduling processes have limitations over dynamic scheduling in real time information exchange (Ouelhadj and Petrovic, 2009). There are three components of a scheduling problem (Wang and Usher, 2005): (a) specific job characteristics, which represents number of operations and the precedence relationships among operations, (b) a machine environment, representing the type of manufacturing system and (c) one or more optimal conditions, which are the scheduling objectives. Common goals are minimizing mean flow time, mean tardiness, makespan, mean lateness and work in process.

In order to cope with highly competitive business environment, it is essential to generate efficient production schedules to deal with real time production requirements. The dynamic changes can be introduced in the manufacturing system from either outside such as suppliers end and customers end or inside the manufacturing system such as real time events occur on the shop floor (Wang et al., 2008a). In a real-time system environment, process times tend to vary, new orders receive, some orders get denied, non scheduled maintenance of machines etc. Such hindrances produce delay in products delivery, higher rework processes and decreases the performance of a manufacturing system. To handle with these issues, scheduling systems need to take effective decisions in real time such as reorganize the production plan and reform the production schedules accordingly. The general approach to facilitate these decisions does not provide coherent interactions across all stakeholders to generate optimum production. An essential rethink is needed towards the process, a manufacturing system is modeled and controlled to provide such type of interactions across several decision stages.

This study is dealt with real-time production scheduling at shop floor level. Thus, this research uses an agent based simulation modeling approach for real-time production scheduling in job-shop manufacturing system (JMS). This novel methodology would enable manufacturing enterprises to prioritize different job types for real time production scheduling within existing system constraints. SimEvents and Stateflow both software tools together propose an integrated decision platform on which production scheduling is being executed. Thus SimEvents, a discrete event simulation tool provides simulation modeling of JMS and Stateflow provides agent based architecture which has the capability to facilitate the communication among developed agents and take required decisions. The remaining part of this chapter provides an overview of manufacturing system, multi agent system (MAS), drivers & barriers of agent technology in manufacturing system, research rationale, research objectives and thesis outline.

1.2 Overview and motivation

This section describes both application area and technique or approach used in this research work.

1.2.1 Manufacturing system

A manufacturing system in which manufacturing equipments are arranged in a certain manner. The flow chart of a manufacturing system is shown in Figure 1.1. The manufacturing system has a physical layout while production control operates on manufacturing philosophies. Other important elements of the manufacturing system are methods of information, energy, and material transfer. The physical layout of the manufacturing system is normally divided into two areas:

a) *Processing area*, which is used for manufacturing the components; and

b) *Assembly area*, which is used for assembling the components.

In manufacturing sector, four basic methods are used to organize the processing area for discrete manufacturing: the job shop, project shop, cellular system and flow line.

In a *Job shop*, machines with the same or similar material processing capabilities are grouped together. For example the lathes form a turning work center, the milling machines form milling work center, and so forth.

In a *Project shop*, a product's position remains fixed during manufacturing because of its size and/or weight. Materials, people, and machines are brought to the product as needed. Applications of project shops can be found in the aircraft & shipbuilding industries and in bridge & building construction.

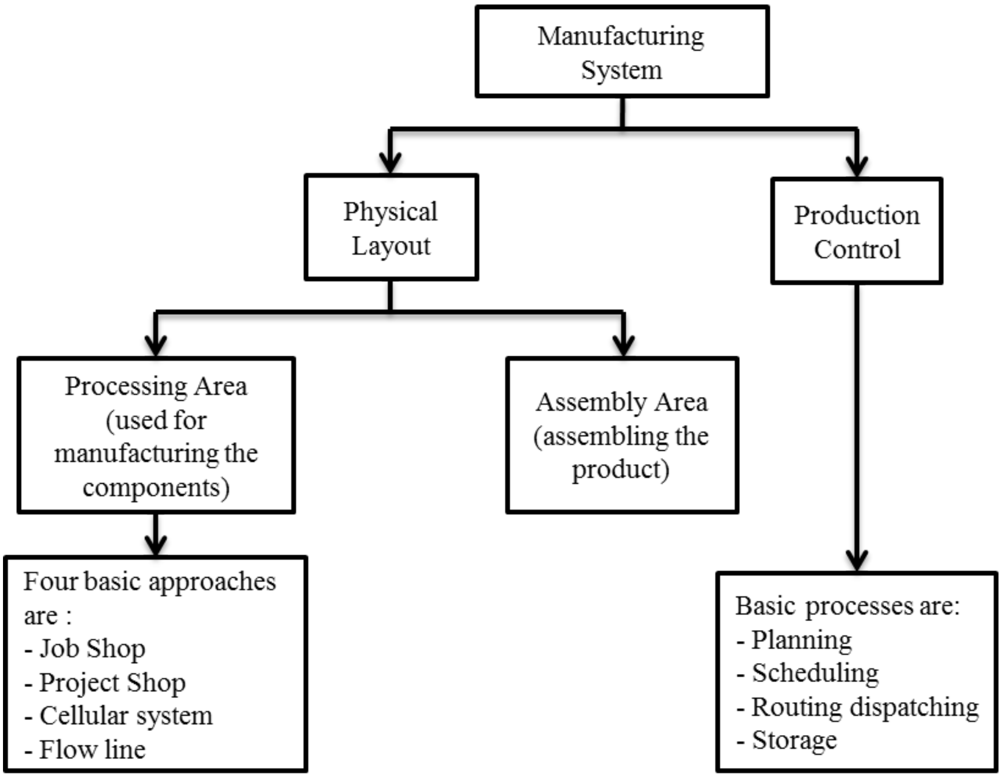

Figure 1.1: The flow chart of manufacturing system

In *Cellular manufacturing systems* organized according to the cellular plan, the equipment or machinery is grouped according to the process combinations that occur in families of parts. Each cell contains machines that can produce a certain family of parts. The cellular manufacturing system is highly automated and flexible.

In *Flow line*, equipments or machines are arranged as per the operating sequences of the product to be manufactured. A transfer line consists of a sequence of machines, which are typically dedicated to one particular part or at the most a few very similar parts/products. Only one product is produced at a time.

Production planning and control: Different approaches adopted for handling materials, components assemblies, and sub-assemblies, from their initial stage to the finished product stage in a structured and efficient way are called production control. It also includes activities such as planning, scheduling, routing dispatching, storage, etc. Production control depends on the experience of the manager to worker level human resources, and methods or procedures used for efficient control.

1.2.2 Agents and multi agent system

1.2.2.1 Basic properties of agents

More accepted definition of ‘agent’ defines an agent as a computer system which is situated in some environment and is capable of flexible autonomous action in this environment to meet its design objectives (Wooldridge, 2009; Wooldridge and Jennings, 1995). An agent in software applications can be defined as a computational agent which acts autonomously to achieve its objective (Brenner et al., 2012; Weiss, 1999). In agent based modeling, an agent is defined as an individual with autonomy, interacting behaviour, self-motivation, decision making ability, goal oriented behaviour and learning ability (Macal and North, 2009; Baykasoglu and Gorkemli, 2017). The most important properties of computational agents are as follows (Leitão, 2009; Jennings et al., 1998).

a.) *Autonomous*: agents operate without direct intervention of humans or others and they control both their actions and internal states.

b.) *Social*: agents interact with their environment and humans or other agents in order to achieve their tasks.

c.) *Reactive*: agents perceive their environment and respond in a timely manner to changes that occur in it.

d.) *Proactive*: agents do not simply act in response to their environment but are able to modify their goal directed behaviour by taking initiatives.

1.2.2.2 Multi agent system

Multi agent system (MAS) is a network of agents which interact and communicate to each other to reach common objectives while simultaneously each agent pursues individual goals (Chen et al., 2004; Monostori et al., 2006). MAS allows a new method that solves the issues in design and implementation stages of dynamic, decentralized and complex distributed manufacturing systems (Parunak, 1998). In MAS, since each agent has system’s partial view, the agents need to be able to communicate to each other for achieving pre-defined objectives. The agents’ interaction among themselves needs a suitable agent communication language, interaction protocols and negotiation mechanisms.

After describing of both application area and technique or approach used in this research work, two questions have been arisen; why job shop is chosen instead of other manufacturing systems and why agents and MAS are used to solve such problems. The job shop manufacturing system is highly flexible as compare to other manufacturing systems which needs quick response to handle dynamic events occurring in the system. Agents and MAS are software systems and they put efforts to achieve global objective through their local goals and coordination & negotiation. Hence agents and MAS are needed to solve such dynamic problem in this research work.

1.3 Factors affecting implementation of agent technology in an industry

While reviewing the literature related to agent based technology in manufacturing systems, some factors are found which affect the implementation of agent technology. The factors which drive its implementation are drivers and which hinder the implementation of agent technology are barriers.

1.3.1 Description of drivers

The drivers of agent technology are semantic web, grid computing, peer-to-peer computing, ambient intelligence, self-systems & autonomic computing, web services & service oriented computing and complex systems. The detailed explanation of each driver is given below.

1. **Semantic web**

   Berners-Lee et al. (2001) described semantic web as a developed version of present web on which data is stored and structured in a manner that it can be read by computers for the automatic processing in different applications. García-Sánchez et al. (2009) presented an ontology based framework that integrates two technologies; intelligent agents and semantic web services for analysing benefits of their grouping. Hence Semantic web and agent technologies are intimately connected and enable to handle complex agent based computing in manufacturing systems.

2. **Grid computing**

   Foster and Kesselman (2003) referred the grid as a high performance computing environment for supporting large distributed systems, information handling and knowledge management. Grid computing provides a virtual infrastructure to users with integrating data and computing resources for solving various types of problems (Khan et al., 2017). The grid provides heterogeneous, distributed, unpredictable and autonomous resources. The flexibility is more generally the main benefit of grid computing (Garg et al., 2010).

3. **Peer-to-peer computing**

   Peer-to-Peer (P2P) computing provides an extensive sort of environments, systems, and technologies that share distributed resources to accomplish a function in a decentralized way. Milojicic et al. (2002) surveyed the field of P2P computing systems and applications by analyzing the design and implementation issues of P2P systems. This survey has helped the researchers by proposing potential benefits of P2P systems as a strong alternative for the requirements of anonymity, scalability and fault resilience. Purvis et al. (2003) presented a multi-agent based approach that supports multiple trader agents in electronic trading environments on multiple P2P computing platforms. Thus P2P computing drives multi-agent technology in manufacturing systems.

4. **Ambient intelligence**

   Ambient intelligence (AmI) is a popular research topic due to its transparency, characteristics and intelligence. AmI can be described as an environment of large number of components which are independent and distributed interacting to each other and have characteristics of flexibility, autonomous, responsiveness, pro-activeness and so on which are the same as agents have. The AmI considers numerous different aspects and technologies in manufacturing domain (Sanders and Tewkesbury, 2009). Robinson et al. (2015) described the intelligent systems using AmI for monitoring energy consumption and knowledge management technologies in manufacturing system. Hence AmI drives the agent technology in manufacturing systems.

5. **Self-systems and autonomic computing**

   The computation systems which are able to cope themselves called as self-systems that include some features such as self-organisation, self-management, self-configurable, self-awareness, and self-repair. Autonomic computing is defined as self-organising behaviour of distributed computing resources adapting to uncertain changes. Barbosa et al. (2015) proposed a multi-agent based adaptive holonic control architecture for distributed manufacturing systems, inspired by biological and evolutionary theories. A two dimensional self-organized mechanism inspired by hierarchical and heterarchical control approaches was designed to handle unexpected events and modifications.

6. **Web services and service oriented computing**

   This technology provides a standard way for interoperation between different software applications running on different platforms. According to Booth et al. (2013) web services came out as the greatest option for remote execution of functionality due to its features like ubiquity, independence of operating system and programming language. Thus web services & service oriented computing provide a well-established infrastructure which is widely accepted for supporting agent interactions using XML and HTTP interfaces in multi-agent manufacturing systems.

7. **Complex systems**

   A complex system contains a large number of interacting components whose collective activity is non-linear with interdependency between components. Hsu et al. (2016b) presented a study to understand the complexity in selection of project team member using agent-based modeling. Agent technologies conceptualise the complex systems as consisting independent components which act, learn or evolve to interact with their surroundings. This conceptualisation includes the computer simulations of the systems operation and behaviours and design of control through agent concepts (Luck et al., 2005). Thus agent technologies give a proper way to handle increasing complexity in the modern manufacturing systems.

Thus it can be said that these drivers motivate the application of agent based technology in manufacturing systems.

1.3.2 Description of barriers

The barriers are required investment, scalability, skilled engineers, high complexity, lack of awareness, interoperability, afraid of complex terminologies, fear of failure, requirement of new approach and availability of commercial platform. The detailed explanation of these barriers are given below.

1. **High investment**

   The high investment is a major barrier in the implementation of agent based manufacturing system. Although it provides the flexibility in the manufacturing system, but the cost incurred in making the system interoperable is too high which restricts the application of agent technology in the manufacturing system (Marik and McFarlane, 2005).

2. **Scalability**

   Scalability is defined as the ability to change in size or scale and its plays an important role in reconfigurable manufacturing system (Renzi et al., 2014).

3. **Lack of technical expertise**

   Lack of technical expertise is a very important factor for agent based systems. If control and system engineers are given technical training on design, operations and control of agent based systems, then it will become easy to implement agent based solutions in manufacturing systems (Marik and McFarlane, 2005).

4. **High complexity**

   The introduction of an agent technology makes the system complex as self organizing and self learning capabilities introduce more complexity to agent based systems, and hence this factor is another barrier in this area (Leitão et al., 2013).

5. **Lack of top management involvement**

   This factor affects more the implementation of agent technology in the manufacturing systems. Resistance of the top management to adopt new technology, change in the present investments, conventional manufacturing ways and habits create hindrance to the implementation of agent technology in its industry (Bousbia and Trentesaux, 2002).

6. **Interoperability**

   This is a key factor in the development of distributed and heterogeneous production control applications. The solution to those issues needs standard platforms that support transparent communication between distributed control components or applications. Ontologies play a decisive role to support interoperability problems. However, the development of an ontology may take from a few hours up to months or even years depending on the choice of the language, the covered topics, and the level of formality and precision (Leitão, 2009).

7. **Afraid of complex terminologies**

   Afraid of terminologies such as ontologies, self organization, emergence, distributed thinking and learning. The introduction of agent technology in the system also brings out the different types of difficult terminologies which are harder to understand (Paolucci and Sacile, 2016).

8. **Fear of failure**

   As the cost requirement is too high in deploying an agent technology, it is always a fear of failure for the top management due to probable losses in its implementation, and hence this is one of the major barrier in the application of agent technology (Farmer and Foley, 2009).

9. **New approach required**

   Agent technology works on the foundation of flexibility and adaptability. Therefore the agent technology based manufacturing system requires a new way of thinking for solving related problems (Metzger and Polakow, 2011).

10. **Commercial platform**

    The application of agent-based solutions requires the migration towards autonomous and independent controllers communicating asynchronously (if required) among themselves in a peer-to-peer way. However, this migration problem remains unsolved (Marik and McFarlane, 2005). Therefore, a commercial platform is needed for an agent based system which can provide interaction among different agents on that platform.

A manufacturing organization has to take in to account of these ten barriers before implementation of agent technology in its manufacturing system. Thus, it can be said that these factors are much important for the manufacturers who adopt agent technology to implement in their plants.

1.4 Research rationale

The concept of MAS is still discussed today, though it was started two decades ago. In the early 90's, the agents theory appeared when research in distributed artificial intelligence (DAI) had just started (Bond and Gasser, 2014). Two decades ago or so, agent concept shifted the focus on mainstream research in artificial intelligence from aim-seeking to rationality, from expertise in narrow domains to sharable and reusable knowledge, from ideal to resource-bound reasoning (Monostori et al., 2006). All these developments led to current research scenario in the agent paradigm of computing.

In the present scenario, the effectiveness of static scheduling has been reduced as it is inflexible and less responsive to immediate changing circumstances. MAS has been considered as an important technology which is highly responsive during disturbances and can work in real time situations for dynamic and distributed systems (Wong et al., 2006; Barenji et al., 2014). Job shop production involves complexity in optimization of the scheduling of different jobs but it becomes more complex when real time events are added to this. Thus it is felt that agent based technology may provide some new outlook to the problem of real time production scheduling in JMS.

Agent based technology consists of a number of agents which interact and communicate with each other to achieve a common goal. It is widely dependent upon agent based modeling and simulation tool i.e. MAS platform which ensures reliable communication among agents. There are many MAS platforms available such as AnyLogic, JADE, MACSimJX, MASON, Netlogo, SimEvents etc. Since production scheduling in job-shop manufacturing system involves discrete-events. Out of available agent based simulation tools, SimEvents involves communication among agents via discrete-events (Abar et al., 2017). Hence, SimEvents together with Stateflow functions libraries based multi-agent simulation modeling approach may be most suitable agent based simulation tool for this problem.

1.5 Research objectives

The literature review shows that the majority of the research work done has focused on solving job-shop scheduling optimization problem using MAS concept. Mostly the nature of the solution is based on mathematical modeling. Simulation based solutions are also found in literature but the solution perspective of making real time manufacturing system together with resolving job-shop scheduling problem using local or global intelligence of agents has been ignored. Hence there is a research scope towards this perspective to resolve production scheduling issues.

In this study, the research work related to agent based production scheduling has been thoroughly investigated. In which traditional and MAS based approaches are compared and some key issues found in the literature are also investigated. A conceptual framework has been proposed for MAS based production scheduling on the basis of literature review. Further a discrete event simulation model has been developed for JMS using SimEvents simulation tool. An agent based architecture has been proposed for real time production scheduling in JMS using Stateflow functions. Finally an agent based simulation model has also been developed for JMS using integration of SimEvents model and Stateflow functional charts.

The formal research objectives pertaining to this thesis work can be stated as follows:

1. To develop a simulation model for production scheduling in job-shop manufacturing system.
2. To propose agent based architecture for real-time production scheduling in job-shop manufacturing system.
3. To develop integrated agent based simulation model for job-shop manufacturing system.

1.6 Thesis organization

The thesis is organized in six chapters. Further to this Introduction, the remaining thesis is organized in five further chapters. A brief overview of each chapter is presented below.

Chapter 2 presents a comprehensive literature review on agent based production scheduling in manufacturing system. It describes different types of approaches to solve production scheduling problems. The advantages of agent based approaches over traditional approaches are also discussed. Apart from covering various types of agent based modeling & simulation tools or MAS platforms reported in the literature, the chapter also describes different key issues involved during MAS implementation in production scheduling systems. It reports vast research work done by various researchers comprehensively in different subsections. This chapter also proposes a conceptual framework for MAS based production scheduling in manufacturing system.

Chapter 3 focuses on achieving first objective of the present research. It describes the development of discrete-event simulation model of JMS and its component operations using SimEvents simulation tool. It discusses the different performance measures of JMS. This chapter also evaluates all discussed performance measures of JMS with comparing four job dispatching rules through statistical analysis of simulation results.

Chapter 4 proposes agent based architecture for real time production scheduling in JMS. It also discusses background and overview of MAS architecture with citing some examples given by other researchers. This chapter describes the overview of agents with its Stateflow based agent models. It achieves second objective of this study.

Chapter 5 develops agent based simulation model of JMS for real time production scheduling. It covers the third objective of this research work. This chapter describes the integrated agent based platform of SimEvents together with Stateflow charts for production scheduling in real time events occur at JMS.

Chapter 6 concludes the present study with a discussion of contributions made and limitations of this research work as well as the future research directions.

Figure 1.2 provides a flow of the thesis in the form of a block diagram highlighting the major portions covered in each chapter.

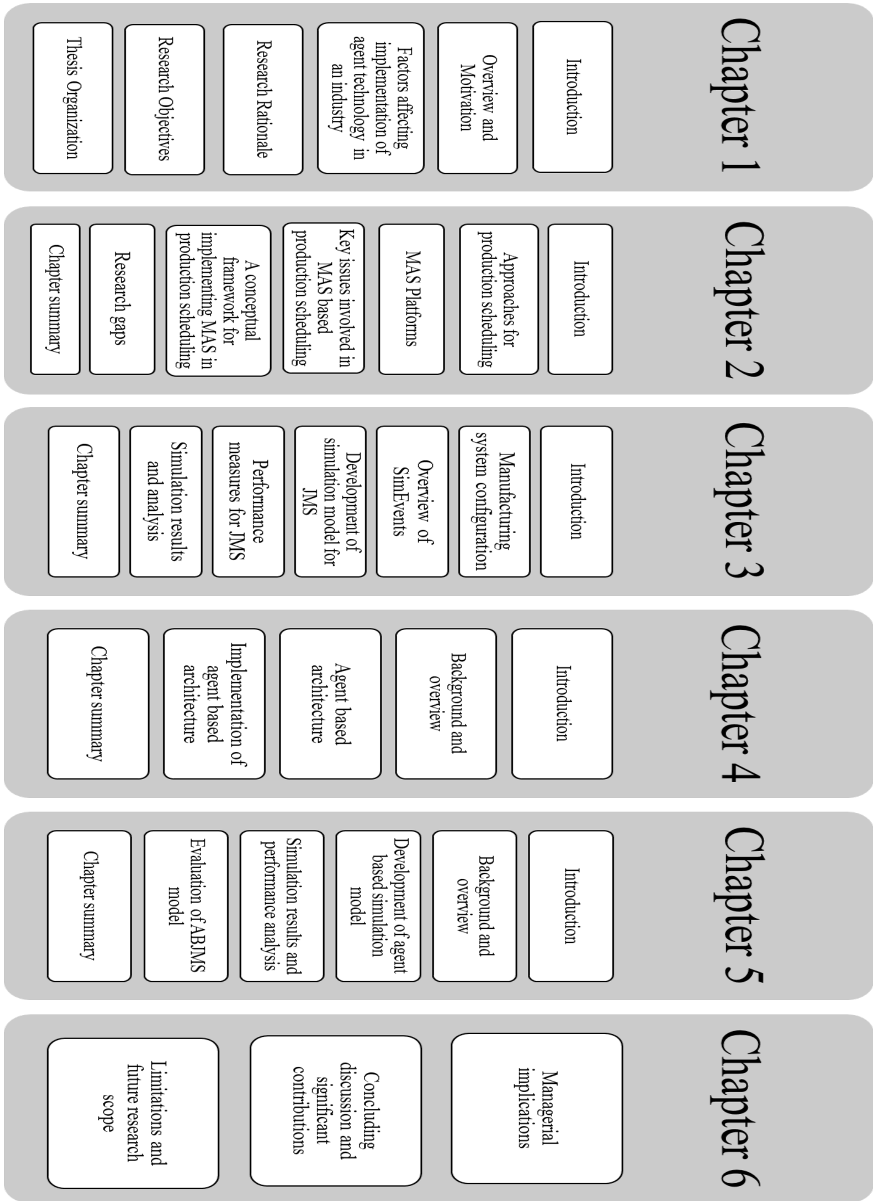

Figure 1.2: Block diagram of thesis organization

Chapter 2

Literature review

2.1 Introduction

This chapter provides a state-of-the-art review of multi-agent system based production scheduling in manufacturing system. The purpose of this chapter is twofold: first, perform a critical analysis of MAS based production scheduling in manufacturing system related content and second, identification of research gaps from the literature review. For this purpose, at first the production scheduling in manufacturing system domain is investigated to find the research gaps and future scope. Next, on the basis of observations from this portion of the review, a separate focused review was conducted for agent based production scheduling in different manufacturing systems related content. Initially, 183 research papers are taken from peer-reviewed international journals which were used for synthesizing the review process. This chapter discusses literature related to agent based production scheduling systematically. The remaining chapter is organized as follows: Section 2.2 describes the traditional & MAS based approaches for production scheduling and potential advantages of MAS based approaches. Section 2.3 provides the different MAS platforms for various production scheduling problems. Section 2.4 discusses key issues involved in MAS based production scheduling. Section 2.5 describes a conceptual framework for implementing MAS in production scheduling. Section 2.6 discusses research gaps found from literature review. Section 2.7 provides chapter summary.

2.2 Approaches for production scheduling

2.2.1 Traditional approaches

The problems of production scheduling have been widely described by the researchers through many methods: constraint propagation techniques, heuristics, meta heuristics such as Tabu search, genetic algorithm, simulated annealing, neural networks, fuzzy logic etc. This subsection discusses various production scheduling problems using different traditional approaches.

The traditional approaches include methods such as mixed integer programming which was used by Zweben and Fox (1994) to formulate a model for job shop scheduling problem where each job is provided with multiple process plans and the model based on objective of minimizing production makespan seeks to integrate the selection of machines for each job and the sequencing of jobs on each machine. Alternatively, Celikbilek and Süer (2015) proposed a mixed integer mathematical model for concurrent optimization problem of production scheduling and transportation mode decisions in a cellular manufacturing system (CMS). Cell loading performs on the outcome of CMS design whereas the CMS design considered the probabilistic demand environment. The another approach 'right-shift heuristic' was used to define predictable schedules by O'Donovan et al. (1999) and Mehta (1999) while Kutanoglu and Sabuncuoglu (2001) considered various schedule repair heuristics in the case of machine failures in their literature as the schedule repair heuristics are much useful for rerouting the jobs to their alternative machines. Nof and Hank Grant (1991) described several rescheduling techniques for machine breakdown, new job arrival in a manufacturing cell and process time variations.

Production scheduling is an important tool for the manufacturing system which can very much affect the productivity. In order to get optimal solutions, most of the scheduling problems fall into the case of NP-hard combinatorial problems. The researchers focused on design of multi-objective evolutionary algorithms to solve a variety of production scheduling problems (Gen and Lin, 2014). To solve job shop scheduling problem (JSSP), Nowicki and Smutnicki (2005) described an approximate Tabu search (TS) algorithm based on big valley phenomenon which considers only local search. For solving the same JSSP, Meeran and Morshed (2012) proposed a hybrid method of genetic algorithm (GA) and Tabu Search (TS) which combines intensified local search and diversified global search capabilities of TS and GA respectively. Further, an improved JSSP was presented by Jia et al. (2011) through the analysis of working data, precedence constraints, processing performance index, working procedure & so on. They also proposed a novel algorithm which is decode select string (DSS), decoding GA based on operation coding modes. The superiority and effectiveness of the proposed method was verified by the simulation experiments and it worked well with JSSP. Banharnsakun et al. (2012) proposed a Best-so-far Artificial Bee Colony (Best-so-far ABC) based effective method for solving JSSP. This method uses the biased solution toward the Best-so-far solution rather than a neighbouring solution as in the ABC method. Jong and Lai (2015) developed a GA based mould-manufacturing scheduling navigation system. The searching capabilities of GA was used by this study to determine the sequence of component processing with limited machines during mould manufacturing and calculated the makespan of the components currently planned in the industry.

Hence, a relative investigation of traditional methods for production scheduling have been discussed and simultaneously the relationship between research works of several authors have also been explained above. There are a number of research works in the literature on dynamic production scheduling problems. These problems can be solved by a.) modeling and simulation related approaches, b.) artificial intelligence (AI) based approaches and c.) MAS based approaches. First two approaches come under traditional methods in which dispatching decision rule is selected by simulation and any AI technique respectively, where as third one 'MAS based approaches' is discussed in the next subsection. Above discussed studies clearly state that the decision response time is one of the major issues for production scheduling under dynamic conditions. The authors have tried to improve the efficiency of production scheduling systems through traditional methods but to reduce decision response time effectively is yet to be done.

2.2.2 MAS based approaches

In the past decade, a number of researchers have applied MAS concepts in attempts to solve production scheduling problems. This section provides a detailed review in a structured manner in the following subsections.

2.2.2.1 Techniques and methodologies

Detailed literature review related to techniques and methodologies adopted or developed in MAS based production scheduling is as follows.

In the machine scheduling related issues, Li et al. (2014) proposed an agent technology based intelligent scheduling algorithm called as ABISA for resolving uniform machine scheduling problem in which agents are coordinated to each other by token ring mechanism. The algorithm performed excellent in solution quality through examination of 1800 random problem instances. On the other hand, Kaplanoğlu (2014) proposed a collaborative multi-agent based optimization method for single machine scheduling problem under sequence dependent setup times and maintenance constraints. Further, Lou et al. (2010) proposed a heuristic negotiation-based distributed scheduling approach through multi-agent based platform using market mechanism for solving task-machine assignment problem. One of the main points of discussion was the formation of a virtual job shop in which service providers and clients can share information and different service providers can collaborate with each other through the PpU platform. A case was also discussed, which validated the proposed approach.

When it comes to dynamic scheduling problem, Wang et al. (2008b) formulated a hybrid approach which integrates multi-agent approach with filtered beam-search (FBS)-based heuristic algorithm in a Flexible Manufacturing System (FMS) shop floor consisting of multiple manufacturing cells. The agents are embedded with FBS based algorithm which improved the generation procedure of branches to obtain optimal or sub-optimal schedules quickly. Jana et al. (2013) described a methodology which dealt with negotiation based task allocation of the resources for dynamic scheduling in an agent based holonic manufacturing system. Multi Objective Optimization on the basis of Ratio Analysis (MOORA) technique was used for scheduling priority under Fuzzy Multi Criteria Decision Making (FMCDM) environment. Renna (2011) proposed a coordination approach based on multi-agent system for dynamic scheduling in a cellular manufacturing system. The architecture is based on the evaluation of internal index (failure time and machine efficiency) and external index (workload of the machines). A simulation environment was used to implement the proposed approaches and evaluate the performance measures. Zhenqiang et al. (2012) adopted a methodology which is aimed to solve imbalance problem of resource capacity in production scheduling system using multi-agent dynamic scheduling. Under this methodology, firstly bottleneck resources are found out in the production line followed by the analysis of the inherent mechanism in bottleneck resource and then description of the production scheduling process based on bottleneck resource using bottleneck resource agent.

Process planning and scheduling were executed in a sequential manner in the traditional approaches which hindered the productivity improvement and agility of the manufacturing systems (Kumar and Rajotia, 2003). To overcome these issues, an integrated process planning and scheduling (IPPS) system was proposed which improved manufacturing efficiency through reduction in work-in-process, scheduling conflicts and flow time and improving resource utilization (Lee and Kim, 2001). To facilitate IPPS functions in a manufacturing system, Li et al. (2010) proposed an agent based approach with an evolutionary algorithm. This algorithm has been used to optimize the process and manage the interaction among agents. Shukla et al. (2008) discussed IPPS problem using bidding based MAS. In this study, tool cost was taken a dynamic quantity rather than a constant as it was being considered in the traditional integrated process. The proposed mechanism of MAS also optimized machine utilization and enabled optimum process plan and production schedule using hybrid Tabu-SA algorithm through optimization agent. As the efficiency in agent-based manufacturing system becomes very important, recent literature is trying to combine MAS based approaches with other optimization techniques like GA, Tabu-search, neural network etc. and other mathematical modeling techniques (Shen et al., 2006b).

MAS based approaches with simulation experiments became more efficient as per recent research works. Sudo and Matsuda (2013) experimented with the manufacturing efficiency by changing the layout of a factory using agent-based autonomous production scheduling, using the virtual factory on a multi-agent simulation system. Rolón and Martínez (2012) proposed an agent-oriented methodology for design and verification of a manufacturing execution system (MES) which favors emergent scheduling and local execution control for agility and responsiveness. The agents adopted monitor-analyze-plan-execution loop for interactions among them. Lam and Ip (2011) proposed an agent based approach for scheduling problems in manufacturing systems. In this approach, a sales agent, a scheduling agent and a production agent were developed and a constraint prioritized schedule was generated through agents autonomous communication to fulfill customer orders and customer change orders, as well as to achieve a better scheduling performance result.

2.2.2.2 System models and frameworks

Researchers have developed and presented various models and frameworks to satisfy the needs of next generation manufacturing systems which are explained as follows:

In dynamic scheduling, quick response should be made whenever event occurs in the manufacturing system. Thus response time plays a major role in dynamic scheduling. MAS based approaches facilitate a rapid response to a dynamic event and which is achieved by decision making through agent coordination and negotiation processes. Notably Xiang and Lee (2008) proposed an efficient agent based dynamic scheduling model for real-world manufacturing systems with different kinds of products, processes and disturbances. In this study, insect-inspired coordination integrated with agents was used with the help of ant colony intelligence to make autonomous agents adaptive to changes in the circumstances and give efficient global performance. Zattar et al. (2010) proposed a multi agent system model for on-line adaptation of a process plan with alternatives and real time routing of job orders of parts composed by machining operations in a job-shop environment using operation-based time-extended negotiation protocols. Erol et al. (2012) proposed agent based system for dynamic and simultaneous scheduling of AGVs and machines in manufacturing systems. This system works under a real time environment and generates feasible schedules using negotiation mechanisms among agents. Giordani et al. (2013) proposed two levels decentralized multi-agent system framework for dynamic factory layout with a set of mobile robots. At the first level in production planning, the agents are tasks which compete for robots (resources), solved by iterative auction based negotiation protocol and at second level, in scheduling, the agents are robots which reallocate themselves to different tasks that are solved by a distributed version of the Hungarian Method. Guo and Zhang (2009b) developed a scheduling system based on multiple agents for intelligent manufacturing. The proposed system comprises of different autonomous agents that are capable of communicating to each other and making decisions based on their knowledge. Wang et al. (2008a) proposed a framework which consists of distributed shop floor control structure, dynamic distributed scheduling algorithm and system integration using an agent based service oriented approach. In this framework, scheduler agent, real time control agent and resource agents were developed. The authors used JADE (agent development platform in Java) for the implementation of this real time scheduling system.

Further research works show that MAS based approaches have been adopted with some other mathematical modeling and different algorithms for solving production scheduling related issues. Polyakovskiy and M'Hallah (2014) proposed a precedence based mixed integer linear programming (MILP) model for solving minimum weighted earliness and tardiness parallel machine scheduling problem using deterministic heuristic based multi agent system. Guo and Zhang (2010) developed an agent based scheduling system for intelligent manufacturing. This generic system is based on theories of MAS and DAI (distribute artificial intelligence). This intelligent manufacturing system contained a set of intelligent agents who are responsible for one or more activities and interacting with other related agents in planning and executing their responsibilities. Chen (2011) developed a self-adaptive agent-based fuzzy-neural system which integrates dispatching, performance evaluation & reporting and scheduling policy optimization to enhance the performance of scheduling jobs in a wafer fabrication factory. In this research work, each agent develops and modifies its own scheduling algorithm to adapt it to the local conditions unlike in the past studies.

Huang and Liao (2012) proposed a multi-agent based architecture to provide intelligent support for negotiation in a distributed parallel machine scheduling application in an electro etching process which involves many parallel machines with three distinct voltages. Mainly two types of agents i.e. scheduling and management agents were used in negotiation protocol and embedded decision model. As a result, it was shown in this paper that the architecture can solve large problems with little time consumption i.e. a 100-job and 10-machine problem can be solved within 300s to obtain a good solution. Zhang et al. (2014) presented an overall architecture of multi-agent based real-time production scheduling to address the problem of real time feedback of ubiquitous shop floor environment during manufacturing execution stage. GA based solving method was used for optimizing and improving the efficiency. Guo and Zhang (2009a) proposed architecture of Intelligent Manufacturing System based on Multi-agent. The production workshop scheduling problem was discussed under the constraints of machine tools, workers, and robots. Chou et al. (2013) presented the overall architecture of a bio-inspired mobile agent based integrated system inspired by autonomic nervous system which demonstrated the self-configuration property of the system for flexible autonomic job shop scheduling. The property is comprised of; a) automatically assigning the order to the most capable cell for manufacturing purposes and b) after order assignment the amount of each work piece on each machine is automatically arranged so that the total energy consumption of the manufacturing cell reaches the minimum.

Thus, the relationship between the research works of various authors have been discussed above. As mentioned in previous subsection, decision response time is the governing factor for dynamic production scheduling. Hence, the response decisions in MAS based approaches are very quick to dynamic events occurring in manufacturing systems and they put efforts to achieve global objective through local goals of agents and their coordination & negotiation. On the other hand, intelligent algorithms have been used by several authors in their research works as the nature of scheduling problems is too complex. Hence, to optimize the schedules under uncertain conditions, intelligence is required in the scheduling system. Therefore multi-objective evolutionary algorithms like hybrid GA, hybrid SA, improved PSO, ANN, TS and hybrid of GA& TS and Best-so-far ABC were adopted by the researchers in their scheduling problems. An intelligent algorithm can work efficiently in real manufacturing systems as it can update itself according to users' requirements. Various authors have considered MAS based approaches with intelligent algorithms in their scheduling systems. This type of hybrid nature of MAS approaches improves the global effectiveness of the production scheduling systems. Thus decentralized nature of MAS facilitates the production scheduling system to be more responsive in modern settings.

2.2.3 Advantages of MAS over traditional approaches

Traditional approaches (include analytical, heuristic or metaheuristic) unexpectedly face problems when these methods are applied to real life dynamic situations. This is happened due to centralized nature of theoretical models which has rigid and static framework used by these approaches. Since traditional methods do not adequately fulfill the requirements of the manufacturing systems in the present competitive scenario in terms of agility, flexibility, expansibility and adaptability in dynamic situations. Hence a new intelligent method based on MAS fulfills the gap left by the traditional approaches. MAS suggests an innovative distributed solution approach to scheduling problems which is more efficient and adaptable to real-time dynamic environments. Some other advantages of MAS over traditional approaches related to production scheduling are as follows (Leitão, 2009; Shen et al., 2006b).

a.) MASs are able to tolerate uncertainty due to parallel computation through a number of agents which may provide robustness and high efficiency to production scheduling systems.

b.) MAS approaches have maintainability which can easily be used to maintain multiple component-agents due to production scheduling system's modularity.

c.) MASs are more flexible as compare to traditional methods, having several abilities and can adaptively resolve current problem of the production scheduling systems.

d.) MAS based production scheduling systems use agents which update their rules by learning capabilities to provide better performance compare to traditional approaches.

e.) MASs lead to cooperative production scheduling by improving local performance to global performance through trade-off between individual agents.

f.) MAS based methods have highly robust response to disturbances in production scheduling as compare to traditional methods.

g.) MASs may provide manufacturing systems with high fault tolerance and higher reliability through real time dynamic production scheduling.

2.3 MAS Platforms

MAS platform is defined as the surroundings in which agents live, like human beings in the universe and also MAS platform ensures reliable communication among agents and provides multiple communication protocols, languages, and communication media (Sujil et al., 2016). The agent technology is widely dependent upon MAS platforms. Such platforms presume the existence of standards that reflect the agreement of developers on which basic functionality should be presented (Shen et al., 2006a). The Foundation for Intelligent Physical Agents (FIPA), founded in 1996, is an international standardization organization promoting the development and specification of agent technologies. Some of the FIPA compliant MAS platforms are JADE, FIPA-OS and ZEUS (Owliya et al., 2013). Most recently developed MAS based manufacturing systems are Java-based systems. Many MAS platforms are found in literature which have used traditional programming languages such as C/C++, Java, LISP, SmallTalk, Prolog and Netlogo to develop MAS based manufacturing systems.

This literature review shows that JADE has been the most favorite agent platform used by the researchers due to its characteristics; interoperability, user friendly nature, uniformity and portability (Komma et al., 2011; Martin et al., 2016). While

C/C++ coded platform was the second most favorite MAS platform. On the other hand, some authors have used simulation packages and programming language environment to build makeshift platforms for agents' communication. Renna (2011) used Arena simulation package while Sudo and Matsuda (2013) used simulator 'Artisoc' for developing their MAS. While, Java coded environment (Baffo et al., 2013; Chen, 2011) and Java based template (Lou et al., 2010; Srivastava et al., 2008) have also been used by different authors to develop MAS for their scheduling problems. Different MAS platforms used in literature are shown in Table 2.1.

Table 2.1: Different MAS Platforms

Platform	**Authors**
JADE	Martin et al. (2016); Barenji et al. (2016a); Nouiri et al. (2015); Asadzadeh (2015); Savino et al. (2014); Hsieh and Lin (2014); Huang and Liao (2012); Wong et al. (2012); Rajabinasab and Mansour (2011); Komma et al. (2011); Zattar et al. (2010); Chen and Chen (2010); Xiang and Lee (2008); Wang et al. (2008a); Wang et al. (2008b); Valero et al. (2008).
C/C++ coded platform	Polyakovskiy and M'Hallah (2014); Li et al. (2014);Giordani et al. (2013); Chou et al. (2013); Zhenqiang et al. (2012); Li et al. (2010); Liu et al. (2007); Wu and Weng (2005); Ouelhadj et al. (2004); Maione and Naso (2003); Lažanskỳ et al. (2001); Archimede and Coudert (2001).
JACK	Barenji et al. (2016b); Kaplanoğlu (2014); Erol et al. (2012).
AnyLogic	Baykasoglu and Gorkemli (2017); Lam and Ip (2011).
JAVA coded environment	Baffo et al. (2013); Chen (2011).
FIPA compliant platform	Frey et al. (2003); Pechoucek et al. (2002).
Matlab coded platform	Reddy et al. (2017).
Discrete event system platform	Hsu et al. (2016a).

Platform	**Authors**
Simulator "Artisoc"	Sudo and Matsuda (2013).
Repast	Owliya et al. (2013).
JSP program	Jana et al. (2013).
Netlogo	Rolón and Martínez (2012).
RIDER software system	Papakostas et al. (2012).
ORIN2.0 (open robot interface for network)	Nejad et al. (2011).
ARENA simulation package	Renna (2011).
STEP	Guo and Zhang (2010).
PpU agent platform	Lou et al. (2010).
Embedded extensible application script language (EXASL)	Kang and Choi (2010).
JATLite (Java Agent Template Lite)	Srivastava et al. (2008).
Intel Mini Fab	Yoon and Shen (2008).
Zeus	Mönch and Stehli (2006).
JAVA DEVELOPMENT KIT (JDK) package	Nigro et al. (2003).
UML (Unified Modelling Language)	Chan and Zhang (2002).
KQML + LALO(Langage dAgents Logiciel Objet) programming environment	Caridi and Sianesi (2000).
Microsoft Visual Studio Model-View-Controller (MVC) + ASP.NET technology	Cupek et al. (2016).
MALLET (Multi-Agent Logic Language for Encoding Teamwork) + CAST (Collaborative Agents for Simulating Teamwork)	Mishra et al. (2016).

2.4 Key issues involved in MAS based production scheduling

Shen et al. (2003) discussed key issues for agent cooperative systems such as system architecture, communication, agent structure, agent coordination and negotiation, agent organization, learning, optimization, system dynamics, conflict resolution, overall system control, ontology management, legacy systems integration and external interfaces. This section evaluates most relevant key issues involved in MAS based production scheduling.

2.4.1 Agent encapsulation

Agent encapsulation defines the process in which the agents are used to encapsulate. There are two approaches for agent encapsulation in MAS based production systems; Functional decomposition and Physical decomposition approach (Shen et al., 2006a). The researchers build the agents in their production scheduling applications using these two approaches.

In *functional approach*, no explicit relationship exists between agents and physical entities. The agents are used as functional modules such as those for process planning, scheduling, order acquisition, material handling. Guo and Zhang (2009a) and Guo and Zhang (2010) developed a multi-agent-based scheduling system for intelligent manufacturing. They used functional agents for all the resources in their multi agent systems. Martin et al. (2016) proposed an agent based distributed framework which makes use of two types of agents i.e. launcher agent and meta-heuristic agent and these agents were used functionally in solving flow shop scheduling problem and capacitated vehicle routing problem discussed in their article.

In *physical approach*, there exists an explicit relationship between an agent and a physical entity. The agents are used to represent entities in physical form such as machines, operators, products, tools, parts and operations. Renna (2011) has taken machine agents as physical entities in the proposed MAS architecture for dynamic scheduling. Some authors used combined approach, consisting of functional and physical decomposition approach in their agent based systems. Komma et al. (2011) suggested different agent modeling in manufacturing on JADE reactive architecture. In this agent modeling, different agents are having functional

Table 2.2: Different agent encapsulation approaches

Agent encapsulation approaches	Authors
Functional approach	Wang and Usher (2005); Guo and Zhang (2009a); Kang and Choi (2010); Guo and Zhang (2010); Chen (2011); Lam and Ip (2011); Rolón and Martínez (2012); Wong et al. (2012); Sudo and Matsuda (2013); Martin et al. (2016); Nouiri et al. (2015); Zhang and Wang (2016); Reddy et al. (2017).
Physical Approach	Wang et al. (2008b); Renna (2011); Nejad et al. (2011); Hsu et al. (2016a); Barenji et al. (2016a); Barenji et al. (2016b); Baykasoglu and Gorkemli (2017).
Hybrid of functional and physical Approach	Wang et al. (2008a); Valero et al. (2008); Yoon and Shen (2008); Xiang and Lee (2008) ; Shukla et al. (2008); Guo and Zhang (2009b); Lou et al. (2010); Zattar et al. (2010); Li et al. (2010); Rajabinasab and Mansour (2011); Erol et al. (2012); Zhenqiang et al. (2012); Huang and Liao (2012); Owliya et al. (2013); Chou et al. (2013); Baffo et al. (2013); Jana et al. (2013); Giordani et al. (2013); Savino et al. (2014); Li et al. (2014); Kaplanoğlu (2014); Zhang et al. (2014); Polyakovskiy and M'Hallah (2014); He et al. (2014) .

and physical decomposition. Shukla et al. (2008) and Jana et al. (2013) have used both functional and physical approach in agents formation for their MAS architecture. Several authors have considered these agent encapsulation approaches in their MAS architectures as given in Table 2.2.

2.4.2 Agent organization

Agent organization is defined as an architecture in which agents are arranged in a particular fashion. Shen et al. (2003) and Shen et al. (2006a) discussed MAS architectures for agent organization in MAS based production systems; hierarchical, federation, autonomous and heterarchical. These MAS architectures have been discussed by various authors in the literature as given in Table 2.3. Here the aim of the researchers is to select suitable MAS architecture to provide best arrangement of agents so that the flow of information could be streamlined in production scheduling. These MAS architectures are explained and reviewed with respect to production scheduling as follows.

Table 2.3: Different MAS architectures for agent organization

MAS architectures	Authors
Hierarchical architecture	Mönch and Zimmermann (2007); Xiang and Lee (2008); Yoon and Shen (2008); Kang and Choi (2010); Nejad et al. (2011); Wong et al. (2012) ; Rolón and Martínez (2012) ; Chou et al. (2013); Giordani et al. (2013); Savino et al. (2014); Polyakovskiy and M'Hallah (2014); Zhang et al. (2014); Zhang and Wang (2016); Barenji et al. (2016b); Baykasoglu and Gorkemli (2017).
Federation architecture	Wang et al. (2008a); Guo and Zhang (2009a); Li et al. (2010); Erol et al. (2012); Huang and Liao (2012); Reddy et al. (2017).
Autonomous agent architecture	Caridi and Sianesi (2000); Valero et al. (2008); Shukla et al. (2008); Lam and Ip (2011); Renna (2011); Zhenqiang et al. (2012); Baffo et al. (2013); Owliya et al. (2013); Sudo and Matsuda (2013); Li et al. (2014); Kaplanoğlu (2014); Martin et al. (2016); Hsu et al. (2016a); Barenji et al. (2016a).
Heterarchical architecture	Cavalieri et al. (2000); Maione and Naso (2003); Wang and Usher (2005); Zattar et al. (2010); Chen (2011); Cupek et al. (2016) .
Hybrid architecture	Wang et al. (2008b);Guo and Zhang (2009b); Guo and Zhang (2010); Lou et al. (2010); Rajabinasab and Mansour (2011); Jana et al. (2013); He et al. (2014).

In *hierarchical architecture* (as in Figure 2.1, the agents (A) are placed in a network in a hierarchical manner and decision making occurs from high level to lower levels. Agent coordinator (AC) at level 1 gathers information from level 2 agents and passes the decision to level 2 agents. Similarly level 2 agents gather information from level 3 agents and pass the decision to level 3 agents. The main disadvantage is that the upper and lower movement of the information results increase the response time which leads to lower degree of robustness.

Federation architecture is of three kinds: facilitator, mediator and broker. In a *facilitator federation architecture*, the agents communicate to each other through the facilitator (as shown in Figure 2.2). The facilitator provides a reliable communication layer, routes messages among agents based on the contents of the messages, and coordinates the control of the multi-agent activities.

In *mediator federation architecture* (as in Figure 2.3), besides coordinating the communication among the agents and the control of the multi-agent activities, the

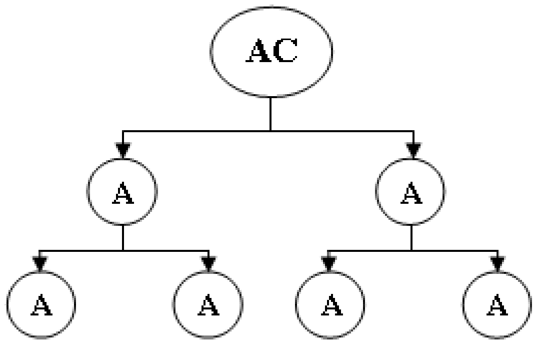

Figure 2.1: Hierarchical architecture

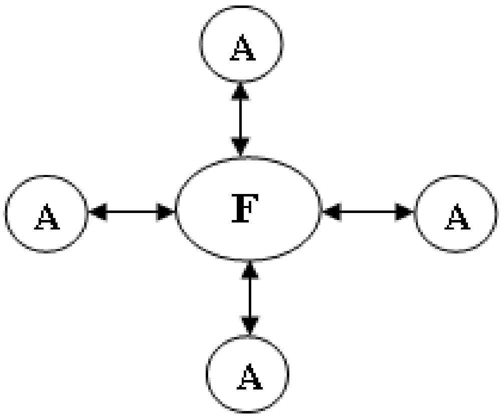

Figure 2.2: Facilitator federation architecture

mediator is able to search for relevant agents according to the agents requirements and assists in setting up communication among them.

In *brokers federation architecture*, any agent can contact any broker in the same system to find service agents for completing a concerned task. This architecture is similar to facilitator architecture.

Every agent in the *autonomous architecture* can communicate directly with other as shown in Figure 2.4. The agents in this architecture are more complex and are required to have knowledge of the environment and other agents.

No master-slave relationships exist between agents in *heterarchical* architecture (as in Figure 2.5). According to (Naso and Turchiano, 2004; Cavalieri et al., 2000), the agents in heterarchical architecture operate in full autonomy and are capable of achieving global objectives. The demerit of this architecture is highly distributed decision making process through which the agents can face system problems.

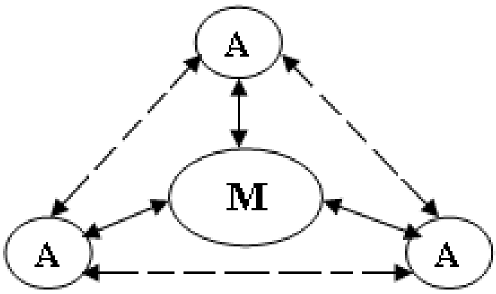

Figure 2.3: Mediator federation architecture

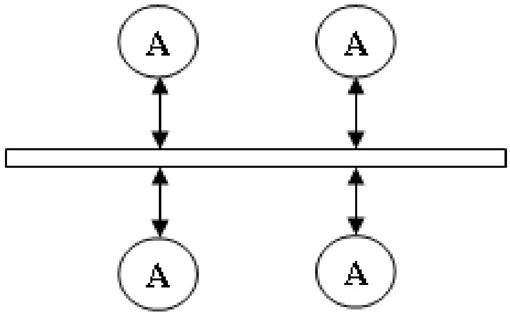

Figure 2.4: Autonomous architecture

Guo and Zhang (2010) proposed a MAS in intelligent manufacturing for scheduling optimization. A hybrid of hierarchical and autonomous architecture has been considered in the proposed system. Giordani et al. (2013) used hierarchical architecture in the proposed multi agent system while Chen (2011), Zattar et al. (2010) and Wang and Usher (2005) have used heterarchical architecture in their developed systems. More number of authors such as Jana et al. (2013), Wang et al. (2008b), Lou et al. (2010), Rajabinasab and Mansour (2011) have adopted hybrid MAS architectures in their works.

2.4.3 Agent coordination and negotiation

Coordination is the most important activity for successful operation in MAS based production scheduling, that is very complex in nature and whose stability is essential. Two types of interaction/coordination (Owliya et al., 2013) among agents could be taken as:

a) Direct coordination: Agents directly communicate and exchange messages with each other. The most common coordination & negotiation mechanisms are con-

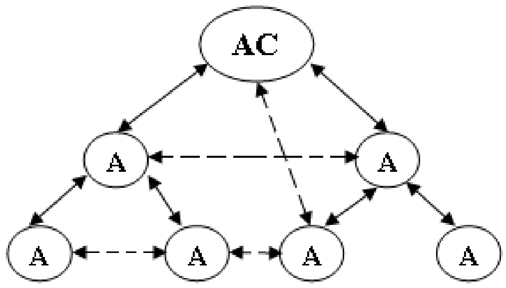

Figure 2.5: Heterarchical architecture

tract net protocol (CNP) (Jana et al., 2013) and its modified versions, such as Auction-based CNP, Market-driven CNP, and Extended CNP.

b) Indirect coordination: Agents do not communicate directly but leave messages for others or collect through their environment anonymously. For example the insect-inspired coordination (Cicirello and Smith, 2001). Two types of insect-inspired coordination are found in literature: Ant-inspired coordination that refers to the coordination inspired by cooperative ant foraging behaviour and Wasp-like coordination referring to the coordination inspired by division of labour and task allocation behaviour in a wasp colony.

The agent coordination mechanisms and negotiation protocols have been used by many authors as given in Table 2.4. Some authors used other than above two coordination mechanisms such as iterative auction based negotiation protocol (Giordani et al., 2013), uncertain finite automaton negotiation process (Guo and Zhang, 2009a), iterative & hierarchical agent bidding mechanism (He et al., 2014), interaction goal hierarchy mechanism (Rolón and Martínez, 2012), operation-based time-extended negotiation protocols (Zattar et al., 2010), negotiation protocol based on a FIPA-ACL (Huang and Liao, 2012), scheduling algorithm based coordination mechanism (Savino et al., 2014), bidding mechanism using temporal constraint sets (Yoon and Shen, 2008), uncertain finite automaton negotiation (Guo and Zhang, 2009b), token-ring mechanism (Li et al., 2014), bid competitive mechanism (Zhang et al., 2014), migration policy i.e. communication through migrants (Nouiri et al., 2015), fuzzy constraint-directed negotiation (FCN) mechanism (Hsu et al., 2016a) etc.

Table 2.4: Different agent coordination and negotiation mechanisms

Mechanisms	**Authors**
Direct AC & N mechanism	Lažanskỳ et al. (2001); Wang and Usher (2005); Wang et al. (2008a); Wang et al. (2008b); Shukla et al. (2008); Valero et al. (2008); Lou et al. (2010); Li et al. (2010); Guo and Zhang (2010); Chen (2011); Komma et al. (2011); Erol et al. (2012); Kang and Choi (2010); Wong et al. (2012); Jana et al. (2013); Owliya et al. (2013); Giordani et al. (2013); Sudo and Matsuda (2013); Hsieh and Lin (2014); Martin et al. (2016); Zhang and Wang (2016); Barenji et al. (2016a); Barenji et al. (2016b); Reddy et al. (2017);Baykasoglu and Gorkemli (2017).
Indirect AC & N mechanism	Xiang and Lee (2008); Rajabinasab and Mansour (2011).
Other AC & N mechanisms	Chou et al. (2013); Baffo et al. (2013); Polyakovskiy and M'Hallah (2014); Guo and Zhang (2009a); He et al. (2014); Rolón and Martínez (2012); Zattar et al. (2010); Huang and Liao (2012); Nejad et al. (2011); Yoon and Shen (2008); Guo and Zhang (2009b); Li et al. (2014); Kaplanoğlu (2014); Zhang et al. (2014); Lam and Ip (2011); Savino et al. (2014); Hsu et al. (2016a); Nouiri et al. (2015).

2.4.4 Agent learning

Manufacturing system problems operate in dynamic and real-time environments. During the process, some problems always occur such as failures of tools or machines & material shortages and new machines or tools may need to be added into the operating manufacturing environment. Thus, MAS based production scheduling must be capable of adapting to frequently changing environments. Therefore learning can play an effective role in MAS based production scheduling by adding learning capabilities in agents to improve their performance (Arviv et al., 2016). Cooperative behaviour can be made more efficient in production scheduling systems if agents adapt to information about their partners and environment, by learning the partners' knowledge and strategic behaviours. Agent learning is much needed in following circumstances: system failures, changes in system configuration and improvement of system capabilities (Shen et al., 2000).

In MAS based production scheduling, learning opportunities come where direct or indirect communication occurs between agents. Training agents may be the

Table 2.5: Different agent learning approaches

Agent learning approaches	**Authors**
Reinforcement learning	Drakaki and Tzionas (2017); Martin et al. (2016); Arviv et al. (2016); Wauters et al. (2015); Mahdavi et al. (2013); Aissani et al. (2012); Wang et al. (2012); Csáji et al. (2006); Wang and Usher (2005); Aydin and Öztemel (2000).
Genetic Algorithm based learning	Lee et al. (2015); Pendharkar (1999).
Neural network based learning	Chen (2011); López-Ortega and Villar-Medina (2009).
Case based reasoning	Navarro et al. (2012); Mikos et al. (2010); Shen et al. (2000).
Filtered beam search based learning algorithm	Wang et al. (2008b).
Weighted sum of processing time based learning	Wu (2014).
Other supervised learning approaches	Wu et al. (2016); Wang et al. (2003).

main source of learning for the agent based learning systems. Pendharkar (1999) proposed a multi-agent framework using GA based learning approach for dynamic scheduling environments. Wang and Usher (2005) investigated the application potential of Q-learning, a reinforcement learning algorithm to a single machine dispatching rule selection problem. Martin et al. (2016) proposed a distributed agent based framework for Permutation Flow-shop Scheduling and Capacitated Vehicle Routing in which each agent adapts continuously during the process using a cooperation protocol based on reinforcement learning and pattern matching. Wauters et al. (2015) proposed a learning-based optimization approach for the problem of resource-constrained multi-project scheduling. In this approach, a group of managers played a simple sequence learning game using reinforcement learning. López-Ortega and Villar-Medina (2009) described a MAS for enhancing production planning by supervised learning of machine agent which is achieved through feed-forward artificial neural networks (FANN) with the back propagation algorithm. Different agent learning examples are given in Table 2.5.

Thus, key issues involved in MAS based production scheduling are reviewed exhaustively. From the discussed literature, it can be inferred that all the key issues collectively work for minimizing decision response time and improving effectiveness of MAS based production scheduling.

2.5 Conceptual framework for implementing MAS in production scheduling

This chapter provides a comprehensive review on MAS based production scheduling in manufacturing systems. Based on this review, a conceptual framework has been developed for providing structured procedure to implement MAS in production scheduling. The framework consists of input elements, different MAS platforms and key issues of MAS. The proposed framework is shown in Figure 2.6. A job shop scheduling problem (JSSP) as an example is considered for the description of each component of the framework which is given in the following subsections.

2.5.1 Input elements to MAS based production scheduling

A number of input elements are essential to develop MAS based production scheduling. In this step, there may be chosen various types of input elements such as scheduled time of each operation, number of machines, machines types, type of jobs, promised order, each job sequence and service failure time of each machine to develop MAS for considered job-shop production scheduling problem. The role of these elements in production scheduling are very important. Every operation has its scheduled processing time of completion. The number of machines in each machine type for a manufacturing system indicates single machine or multi-machine production scheduling. Type of jobs indicates the number of production lines e.g. if two types of jobs have to be produced then two production lines would be required in the manufacturing system. Each job will be having its operation sequence in each production line. The demand or promised order is a very important component in production scheduling process. This value can vary with respect to time and it must be fulfilled within due time. Another important element is service failure time (or time distribution) of each machine that increases the total make span. The values of these input elements must be correctly given as the intelligent behaviour of MAS based production scheduling will introduce agility into the system.

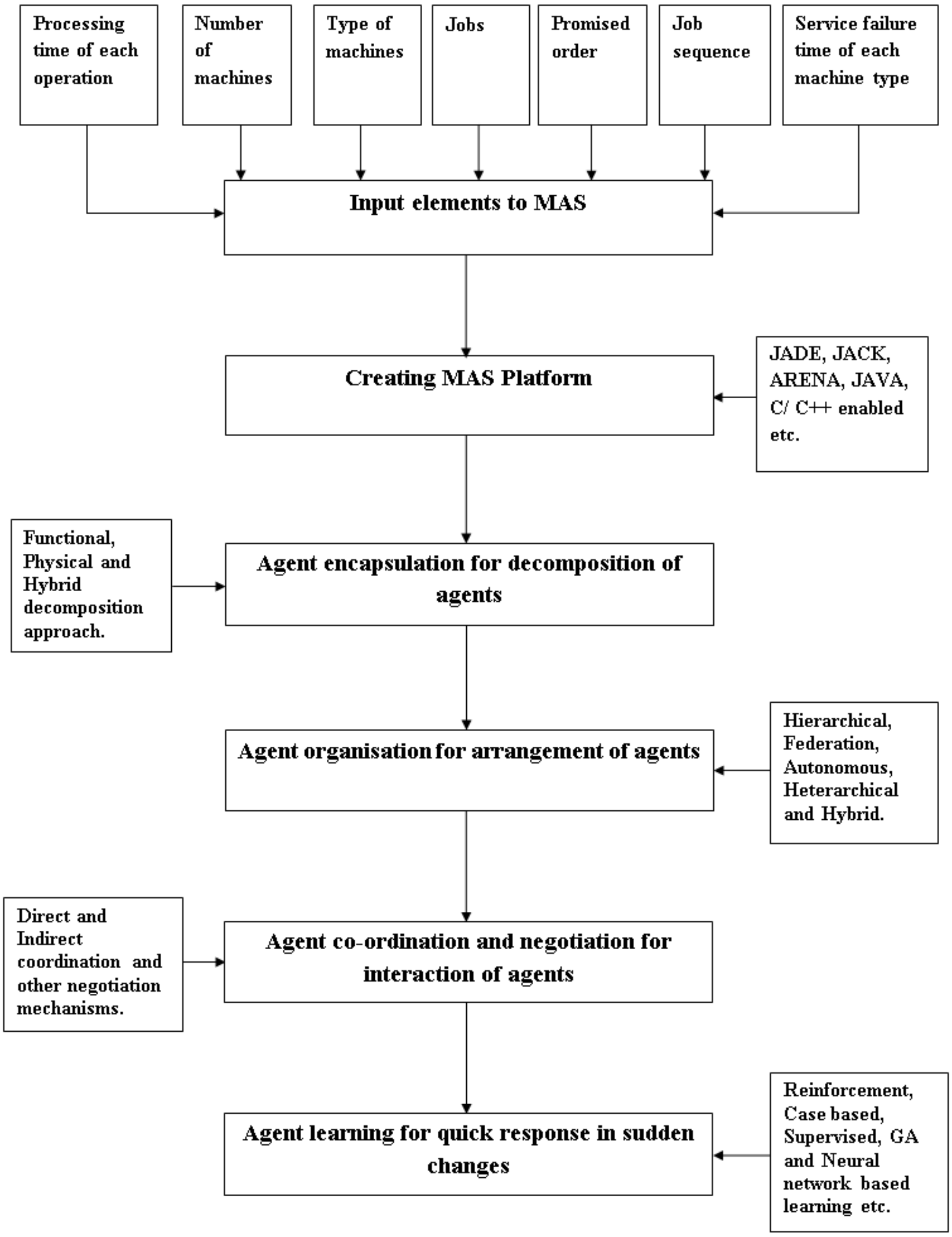

Figure 2.6: A conceptual framework for developing MAS based production scheduling

2.5.2 MAS platform for agent based production scheduling

A MAS platform provides a place where all involved agents communicate locally and globally with each other and with the agent coordinator. Different types of MAS platforms used by several researchers have been discussed in section 2.4 of this chapter. After choosing desired input elements, it is required to have a suitable MAS platform to create agents and facilitate communication among different agents for considered production scheduling example. This MAS platform will have some agents that support different processes of production scheduling. Many researchers adopted different MAS platforms (as given in Table 2.1) in their research articles which indicate its importance in agent based production scheduling. Suitable MAS platform for this scheduling problem can be selected from available MAS platforms (as discussed in Table 2.1). Hence selected MAS platform would provide the base for developing MAS based production scheduling.

2.5.3 Agent encapsulation for decomposition of agents

Agent encapsulation provides the decomposition details about the agents i.e. functional and physical. It means that, the agents can act as functional modules like process planning, scheduling etc. and as physical entities like machines, operators, products, tools etc. In this step, decomposition of the agents would be chosen as either functional or physical for considered JSSP. If some agents in JSSP do any function and some agents act as physically then this JSSP will have hybrid decomposition approach. Hence agent encapsulation would play an important role in defining the working of agents for MAS based JSSP.

2.5.4 Agent organization for arrangement of agents

After assigning the nature of agents in considered JSSP, different agents would be organized in this step. Agent organization provides various MAS architectures; hierarchical, federation, autonomous and heterarchical architectures which describe the structure of different agents in the MAS framework. How the agents would be organized for the particular problem of production scheduling, has to be decided after assigning the nature of agents i.e. agent encapsulation. The MAS architecture for this JSSP would decide the communication process among different agents. Such as in hierarchical architecture, the agents are communicated among themselves in hierarchy and decision making occurs from top to bottom. Similarly in other MAS architectures, agents communicate as per their working nature which has been discussed in section 2.4.2. Thus agent organization is the important factor from agents communication point of view for developing MAS based production scheduling.

2.5.5 Agent coordination and negotiation for interaction of agents

Agent coordination is the backbone of successful implementation of MAS in production scheduling. After arrangement of agents in an organized form, MAS would be needed suitable coordination and negotiation mechanism (s) in this step. The chosen agent coordination and negotiation mechanism (s) would facilitate interaction among different agents in MAS based JSSP. There are two coordination mechanisms i.e. direct and indirect (Owliya et al., 2013) and some other mechanisms also exist which are described in section 2.4.3. The chosen agent coordination & negotiation mechanism (s) would ensure to fulfill local and global objectives of each agent in MAS.

2.5.6 Agent learning for quick decision response under sudden changes

Agent learning is one of the important step in developing MAS based production scheduling. It provides learning abilities to the agents to increase the future performance of the manufacturing systems (Shen et al., 2006a). Most of the disturbances and changes in manufacturing systems are those which can not be predicted in advance. This form of complexity in the systems can be reduced or avoided by learning of the agents. Aissani et al. (2012) adopted a multi-agent approach based on reinforcement learning to take accurate short-term decisions under environmental fluctuations for adaptive scheduling in multi-site companies. Similarly different kinds of other learning techniques used by several researchers in MAS based production scheduling, has been discussed in section 2.4.4. Hence in this step, appropriate agent learning technique is selected which would provide quick response to sudden changes in MAS based JSSP.

Thus after following all six steps, this conceptual framework would facilitate the development of MAS for considered JSSP.

2.6 Research gaps

As discussed in above sections, job shop production scheduling problems were solved by traditional approaches using heuristic and meta-heuristic such as heuristic based algorithm (Lou et al., 2010; Wang et al., 2008b), Tabu search (Nowicki and Smutnicki, 2005), GA (Meeran and Morshed, 2012; Jia et al., 2011), artificial bee colony (Banharnsakun et al., 2012) etc. and simulation based approaches (Sudo and Matsuda, 2013; Rolón and Martínez, 2012). Hence the researchers focused on solving production scheduling problems using different techniques but manufacturing system oriented studies for production scheduling using simulation based approaches have been ignored in the related literature. Other than this, many production scheduling related studies were solved by the concept of MAS using various general agent based simulation tools. Though job shop production scheduling is discrete event based problem but no researcher has tried to address this type of problem using such type of agent based simulation tool which applicable for the discrete event systems. Hence based on detailed literature review, few research gaps are identified and discussed below.

1. It is found that traditional approaches with heuristic and meta-heuristic have been adopted in most of the production scheduling related problems. Although some researchers have also performed simulation based studies in scheduling. But there is a much scope to discuss production scheduling in manufacturing system using simulation based approaches.

2. The literature shows that existing research have focused on wide spectrum of scheduling problems such as dynamic, distributed, decentralized and parallel machine scheduling etc. Out of these, real time production scheduling problems are needed to be discussed more.

3. Many MAS platforms are discussed in the literature. But the researchers have focused only few agent based simulation tools. Thus there is a much scope for testing other agent based simulation tools which should be based on type of problems such as discrete, continuous and other specific type.

2.7 Chapter summary

This chapter has provided a review of MAS applications in the field of production scheduling. It described traditional and MAS based approaches for solving various production scheduling problems. The MAS based approaches are successfully employed to cope with a wide spectrum of scheduling problems such as dynamic, distributed, decentralized and parallel machine scheduling in manufacturing systems. The extant literature seems to confirm that the MAS based computing can provide potential advantages in terms of computing time, production costs, robustness and efficiency. The chapter further offered different MAS platforms and a brief taxonomy of key issues in MAS based production scheduling, characterizing the research contributions thematically. The detailed review of key issues in agent based production scheduling has been described under four categories; agent encapsulation, agent organization, agent coordination and negotiation and agent learning. These issues of MAS examined different production scheduling applications. Further a conceptual framework for implementing MAS in production scheduling has also been proposed in this chapter. This framework embodies input elements to agent based scheduling system, MAS platforms and the key issues of MAS. Each step in this framework is described adequately using an example of JSSP. Hence, this conceptual framework is able to answer some important questions in the modeling of MAS based production scheduling system complexity. These questions would include how agents reduce decision response time under uncertain situations in production scheduling; and how the agents optimize the schedules in dynamic conditions. This chapter tries to answer above mentioned queries with relevant literature.

Chapter 3

Modeling and simulation of job shop manufacturing system

3.1 Introduction

In the job-shop system, the different job types arrive continuously at the different set of machines in a random manner. Each job has a set of processes that has to be processed on different machines in a fixed route (Rangsaritratsamee et al., 2004). The job shop consists of different jobs in which a job get processed on one machine and then proceeds to another machine for next process, simultaneously other jobs already waiting for that machine to complete its present task. Thus the formation of a queue of jobs is built in front of that machine. Hence, the priority of jobs is involved at each machine to get processed in job-shop scheduling process. The dispatching rules are considered for providing the order of jobs in the job-shop manufacturing system (JMS). Hence, it is required to create simulation model for analyzing the performance of JMS in real time. The DES based approach plays an important role to develop simulation model of JMS.

DES is one of the most flexible tools and techniques which analyzes the dynamic nature of manufacturing systems and evaluates various strategies in operation for decision support in the manufacturing problems. As a computer simulation tool the use of discrete event simulation has been increased in recent years. Numerous researchers have adopted simulation in designing and operating the manufacturing systems which has increased the research interest in this topic. Many real case problems in which successful applications of simulation implemented have proved the effectiveness of simulation in solving various practical manufacturing issues.

Several studies have discussed different aspects of modeling and simulation to the manufacturing system applications. For example, Wang et al. (2016) provided a DES analysis of dynamic FMS in their article by examining the two decisions: the part launching into the system for production and finding the order sequence for collection of the completed parts. Imran et al. (2017) have proposed an integration approach of discrete event simulation and genetic algorithm to solve mathematical model for minimizing value added work in process. Mousavi et al. (2016) presented a hierarchical framework for assessment of energy and water consumption in a manufacturing system and a simulation analysis was done on a pharmaceutical company as a case industry. Nylund and Andersson (2010) have discussed modeling and simulation in respect of distributed manufacturing system using hierarchy of the communication of the services and described formally as a digital manufacturing system. Liraviasl et al. (2015) proposed a framework for decentralized control and collaborative decision making in reconfigurable manufacturing system using AnyLogic agent based simulation modeling method and DES. Thus these examples showed successful applications of simulation in various manufacturing systems.

This chapter focuses on simulation modeling of the JMS using SimEvents (a Simulink toolbox in Matlab). Dynamic processing plus waiting time (DPPW) due date assignment method and four dispatching rules are considered for the investigation. The performance of the JMS is evaluated and analyzed statistically using different measures.

In this chapter, Section 3.2 describes configuration details of the manufacturing system with assumptions made and considered due date assignment method. Section 3.3 discusses about DES tool 'SimEvents'. Section 3.4 presents simulation modeling of JMS & its component operations. Section 3.5 describes performance measures of JMS. Section 3.6 discusses the simulation results and analysis. Finally in Section 3.7, chapter summary is provided.

3.2 Manufacturing system configuration

A realistic job-shop manufacturing system configuration has been investigated in this research work (Agha, 1993). In the present work, a JMS consisting of six machines and three jobs is chosen. These six machines are not identical and perform different operations. The six machines are (1) casting unit, (2) planer, (3) lathe machine, (4) shaper, (5) drilling machine and (6) polishing machine.

The overview of JMS is shown in Figure 3.1. The JMS is producing three jobs (products) which are processed under six manufacturing operations i.e. casting, planing, turning, shaping, drilling and polishing. Job-1 (J1) follows the processing sequence of casting-planing-turning-polishing, whereas Job-2 (J2) follows shaping-drilling-turning and the processing sequence of casting-shaping-drilling-planing-polishing is followed by Job-3 (J3). The job arrival distribution for three jobs is Poisson and the mean values of the same are given in Table 3.1. The description of the three jobs and six machines with respective processing times which are mean values of exponential distribution, as provided in Table 3.2. The important characteristics of the considered JMS in this research activity are given as follows.

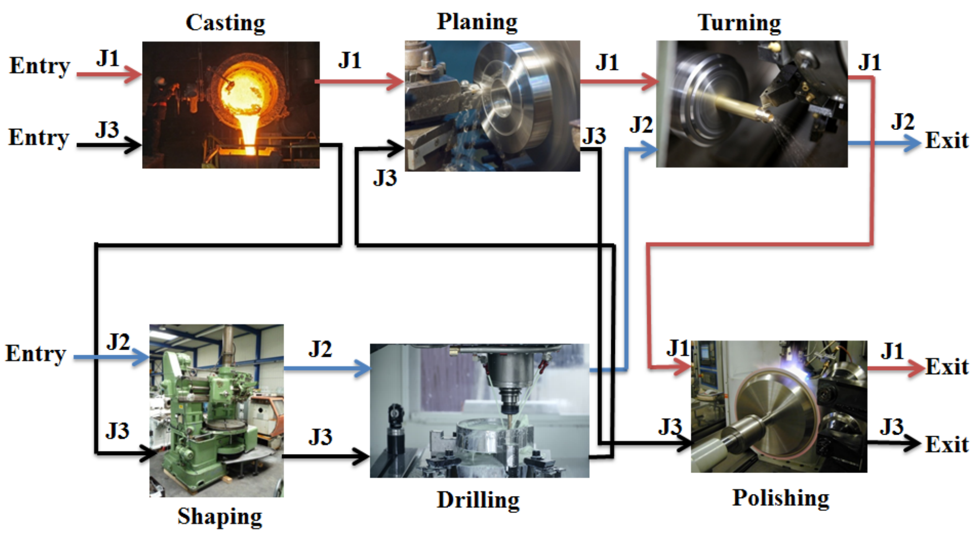

Figure 3.1: Schematic diagram of the Job Shop Manufacturing System

Table 3.1: Description of arrival distribution and processing sequence of three jobs

	Job1	Job2	Job3
Arrival times (in seconds)	9	8.2	7
Processing sequence	1-2-3-6	4-5-3	1-4-5-2-6

3.2.1 Assumptions

This research work considers following assumptions to develop simulation model for job-shop manufacturing system:

- Each machine type consists only one machine in the manufacturing system.

Table 3.2: Description of three jobs with respective processing times (in seconds)

Operation	Job1	Job2	Job3
Casting	125	-	235
Planing	35	-	30
Turning	20	65	-
Shaping	-	105	250
Drilling	-	90	50
Polishing	60	-	25

- Only one operation occurs at a time on any job entity.
- every job entity visit the same machine only once but the job which has several entities visits same machine number of times.
- Machine breakdown or maintenance does not occur.
- Queue length on any machine is limited.
- The manufacturing system can handle three jobs at a time.
- Job entities arrive stochastically (Poisson distribution).
- Job entities get processed stochastically (Exponential distribution).

3.2.2 Dispatching date assignment of jobs

Each job entity needs its assigned dispatching date when it arrives at the machine for processing. In this study, dynamic processing plus waiting time (DPPW) method has been adopted which was proposed by (Enns, 1995). Dispatching date of job entity = Arrival time + Total processing time + (expected waiting time per operation)(number of operations). Thus the formula for dispatching date of a job entity is given as follows (Vinod and Sridharan, 2011).

$$Di = Ai + \sum_{j=1}^{n_i} p_{ij} + \{\frac{J_t \mu_p}{n_m \rho} - \mu_p\} n_i \qquad \forall i \tag{3.1}$$

Where

D_i is the dispatching date of job entity i

A_i is the arrival time of job entity i on the machine type

p_{ij} is the processing time of operation j of job entity i

J_t is the number of uncompleted jobs in the system at time t

n_i is the number of operations in job entity i

n_m is the number of machines type of m

μ_p is the mean processing time per operation (here p denotes processing)

ρ is the shop utilization which is average utilization of all the machines over a period of time. While the machine utilization is defined as the proportion of time that a machine is actually in operation.

3.3 Overview of SimEvents

In recent years, simulation has become a suitable methodology for solving realistic problems. Like Di Gironimo et al. (2015) simulated the model for the manufacturing process of a high speed train using DES application tool and had done virtual production planning for the same. Robinson (2004) explains the comparison between simulation and different modeling methods. SimEvents is chosen for the present study among available DES software tools in the market due to complex nature of JMS. The SimEvents software tool provides a DES engine and block library for Simulink. DES involves discrete items which are called as entities in SimEvents. Entities can pass through a network of queues, servers, gates, and switches during a simulation. Entities can carry data, known as attributes in SimEvents tool. In a DES, an event is an instantaneous discrete incident that changes a state variable, an output, and/or the occurrence of other events. Events can not be represented through graphically but their occurrence can be observed through their consequences using Instantaneous Event Counting Scope block (Zelenka, 2010).

With the discussion of related research application of Simulink/ SimEvents in manufacturing, Omar et al. (2016) proposed a hybrid simulation model of continuous and discrete modes for predicting energy consumption and flows in automotive production lines using Simulink and SimEvents. Sachdeva et al. (2008) described multi-criteria optimization framework for determining optimal preventive maintenance schedules. The authors have interfaced Simulink simulation tool box with genetic algorithm for optimization and availability, maintenance cost and life cycle costs are considered as the criteria for optimization. He et al. (2012) proposed a modeling method which is solved in Simulink environment and implemented to optimize task oriented energy consumption in machining manufacturing system. In recent years, the use of SimEvents is increasing in research problems as it has wide-range of analytical tools and built-in modeling capabilities which make it most suitable than other simulation tools for DES (Ravitz et al., 2016).

3.4 Development of simulation model for JMS

The JMS consists of six machines: casting, planing, turning, shaping, drilling and polishing. The three different jobs (products) were being produced in this JMS. Due to complex nature of the production process in MS, the MS model is developed and simulated using SimEvents (a Simulink toolbox of MATLAB). Simulation model of the manufacturing system is shown in Figure 3.2. This simulation model handles with the scheduling of job types on different machine types using various dispatching rules. This study used four dispatching rules from the literature. These are first in first out (FIFO), last in first out (LIFO), shortest processing time (SPT) and longest processing time (LPT).

3.4.1 Casting operation

The casting units facilitate this operation in the MS. It is the first process for jobs J1 and J3 while J2 is not processed under this operation. The SimEvents model of casting process is shown in Figure 3.3, which comprises of ‘Set attribute’ block for set processing time on each generated entity, ‘Event based random number’ block for generating process time distribution, ‘Priority queue’ block for dispatching the job entities, ‘Input switch’ and ‘Output switch’ blocks for scheduling two jobs and ‘Single server’ block for a number of casting units.

3.4.2 Planing operation

The planers provide the facility for planing operation in the MS. For job J1, this is the second task while for job J3, planing occurs in the fourth processing sequence. It’s SimEvents model is shown in Figure 3.4, which consists of set processing

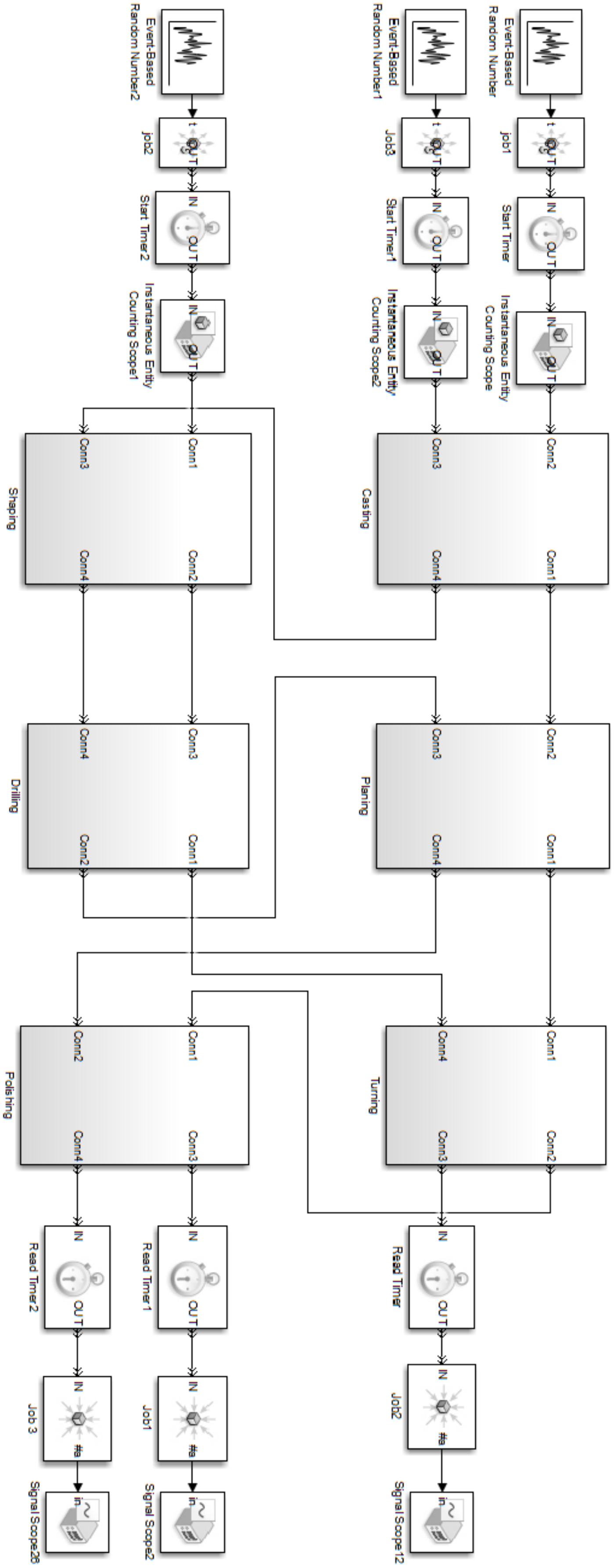

Figure 3.2: Simulation model of JMS

time distribution using 'Set attribute' & 'Event based random number' blocks, job dispatching rule using 'Priority queue' block, and production scheduling of both jobs J1 & J3 using 'Input switch' & 'Output switch' blocks.

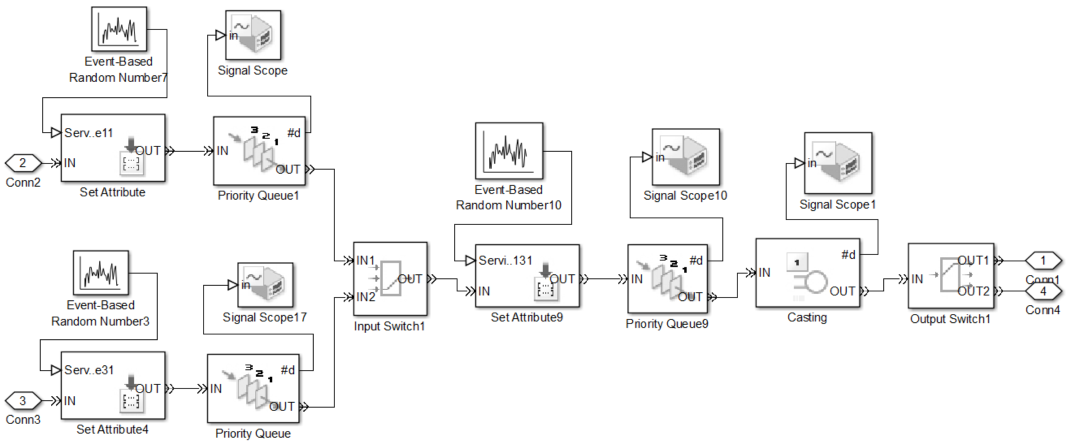

Figure 3.3: SimEvents model of casting operation

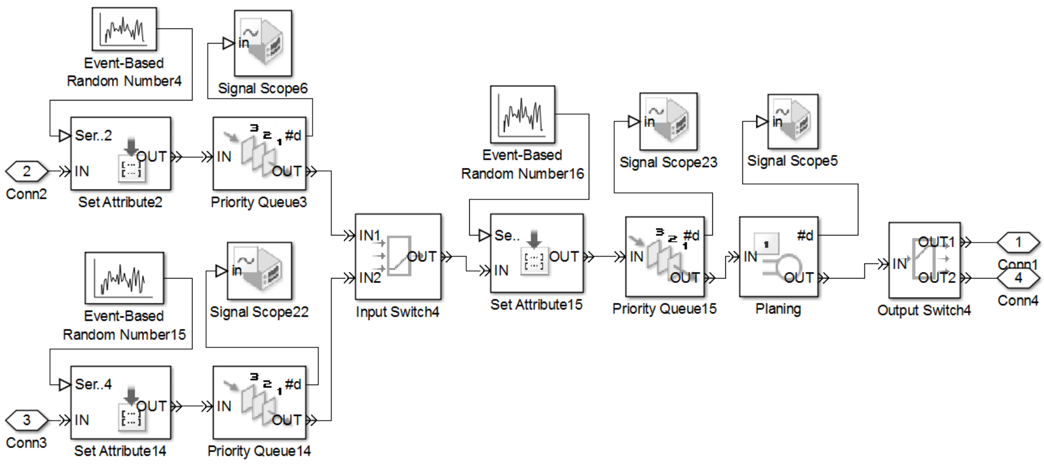

Figure 3.4: SimEvents model of planing operation

3.4.3 Turning operation

The manufacturing system consists of lathe machines which facilitate turning operation for the jobs. Both jobs J1 and J2 have been processed under turning operation in their third processing sequence. The model of turning operation is shown in Figure 3.5, which comprises of different SimEvents blocks such as 'Set attribute', 'Event based random number', 'Priority queue', 'Single server' and 'Input switch' & 'Output switch' for part production of both jobs J1 and J2.

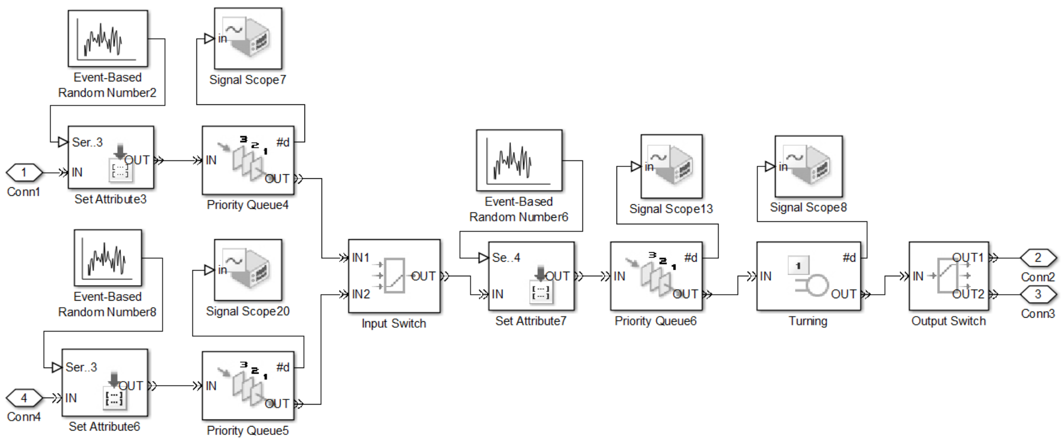

Figure 3.5: SimEvents model of turning operation

3.4.4 Shaping operation

The shapers provide shaping operation in the MS. Jobs J2 & J3 are being processed in shaping operation in their first & second tasks respectively. The model of shaping operation is shown in Figure 3.6, that consists of different SimEvents blocks for part production of both jobs through set the processing time distribution, job priority rule and suitable switching criterion for scheduling of both jobs.

3.4.5 Drilling operation

A number of drills facilitate drilling operation in the MS. Jobs J2 & J3 are being processed through this drilling process in their second & third processing sequences respectively. The model of drilling operation is shown in Figure 3.7, that comprises of various SimEvents blocks which are 'Set attribute' block, 'Event based random number' block, 'Input switch' & 'Output switch' block, 'Job priority queue' block and 'Single server' block. These blocks are combined into one model and give output as drilled parts.

3.4.6 Polishing operation

The polishing machines provide polishing operation to the jobs. Jobs J1 and J3 are being processed under this operation in their fourth and fifth tasks. The SimEvents model of polishing operation is shown in Figure 3.8, which is the combination of various SimEvents blocks that facilitate part production of the jobs.

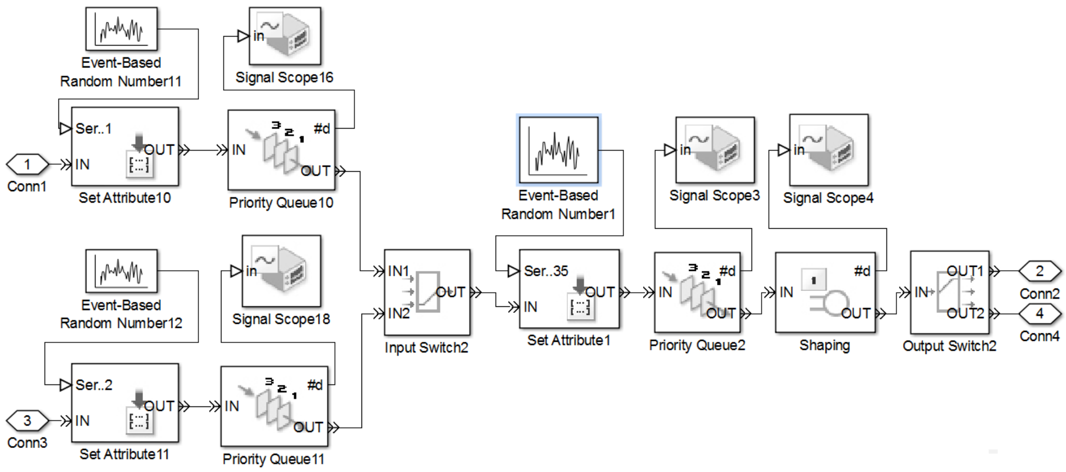

Figure 3.6: SimEvents model of shaping operation

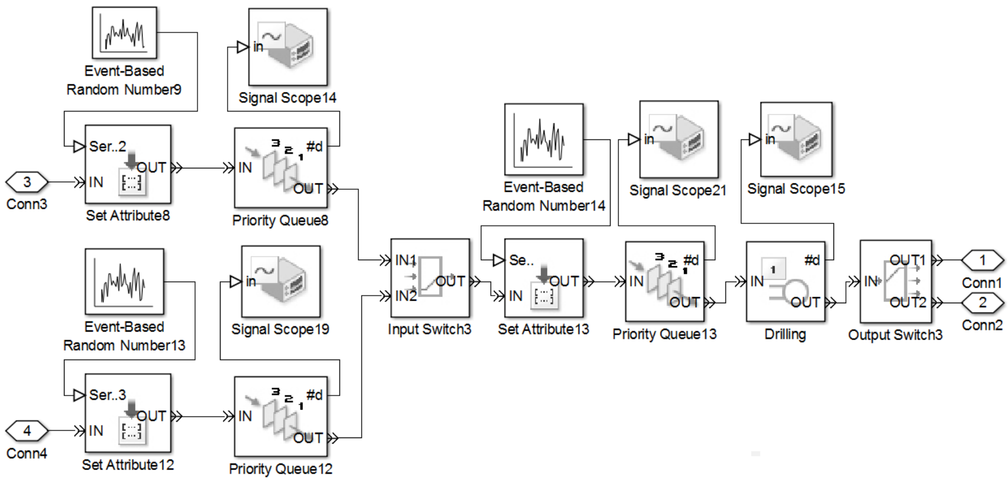

Figure 3.7: SimEvents model of drilling operation

3.5 Performance measures for JMS

After completion of all operations in the simulation model, it consolidates the simulation outputs for the performance measurements. The purpose of selecting the performance measures is to evaluate the effect of different dispatching rules on the performance of JMS. The notations used are given below.

P_i is the processing time of job entity i

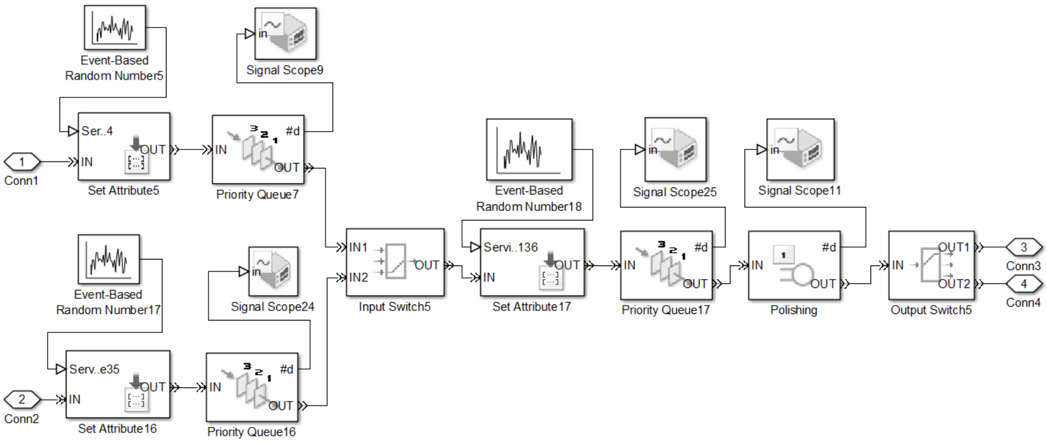

Figure 3.8: SimEvents model of polishing operation

C_i is the completion time of job entity i

D_i is the dispatching date of job entity i

A_i is the arrival time of job entity i

n_j is the number of completed entities of job j from zero starting time to simulation ending time

ne_j is the number of job entities of job j entered into the system.

The performance measures are explained as follows.

1. Mean flow time ($\bar{FT_j}$): The average time a job spends in the manufacturing system.

   Flow time of job entity i, $FT_i = C_i - A_i$

$$\bar{FT_j} = \frac{1}{n_j}[\sum_{i=1}^{n_j} FT_i] \tag{3.2}$$

2. Mean tardiness ($\bar{T_j}$): The average tardiness of a job.

   Tardiness of job entity i, $T_i = Max\{0, L_i\}$

   Where L_i is the lateness of job entity i, $L_i = C_i - D_i$

$$\bar{T_j} = \frac{1}{n_j}[\sum_{i=1}^{n_j} T_i] \tag{3.3}$$

3. Standard deviation of flow time ($SDFT_j$):

$$SDFT_j = \sqrt{\frac{\sum_{i=1}^{n_j}(FT_i - \bar{FT})^2}{(n_j - 1)}} \tag{3.4}$$

4. Standard deviation of tardiness (SDT_j):

$$SDT_j = \sqrt{\frac{\sum_{i=1}^{n_j}(T_i - \bar{T})^2}{(n_j - 1)}} \tag{3.5}$$

5. Production output (PO_j): Number of completed job entities within simulation time.

$$PO_j = n_j \tag{3.6}$$

6. Work-In-Process (WIP_j): Number of job entities which are under rework process.

$$WIP_j = ne_j - n_j \tag{3.7}$$

$$\%WIP_j = [\frac{ne_j - n_j}{ne_j}] \times 100 \tag{3.8}$$

3.6 Simulation results and discussion

The simulation is lasted for 8 hours as a working shift (one day). The aim of the simulation experimentation is to investigate the effect of dispatching rules on the performance of the JMS producing three jobs. In this research work, DPPW method has been adopted to assign the dispatch dates of different jobs. Four job dispatching rules i.e. FIFO, LIFO, SPT and LPT are considered for dispatching the job entities waiting to be operated on machines. Since FIFO is generally used as a benchmark while SPT is popularly used rule for job shop scheduling and a very effective rule for minimizing mean flow time as well as tardiness (Rajendran and Holthaus, 1999; Chen and Matis, 2013). There are 12 different scenarios arising out of the combinations of the four dispatching rules and three jobs. Hence, graphical analysis is carried out using simulation results (Table 3.3-3.8) for 12 experiments. The analysis of performance measures for three jobs using simulation results is given in the following subsections.

3.6.1 Mean flow time

Table 3.3 and Figure 3.9 provide simulation and graphical results of mean flow time (MFT) respectively for different combinations of dispatching rules and job types. The LIFO rule has provided the worst performance (highest MFT values) for three job types. While the SPT rule provides the best performance (lowest MFT values) among available rules for all three job types. Job type J1 shows high MFT performance in FIFO, SPT and LPT dispatching rules while job type J2 shows same in LIFO. Job type J3 indicates lowest MFT measures in FIFO, LIFO and LPT while J2 indicates same measures in SPT. Considering MFT performance, the following ranking is obtained:

For J1: LIFO <FIFO <LPT <SPT

For J2: LIFO <FIFO <LPT <SPT

For J3: LIFO <FIFO <LPT <SPT

Table 3.3: Simulation results of MFT (in seconds)

Jobs	FIFO	LIFO	SPT	LPT
J1	13691.22	15204.87	12613.35	13253.66
J2	13881.61	15159.27	12896.02	13477.78
J3	13918.22	15449.80	12675.33	13530.36

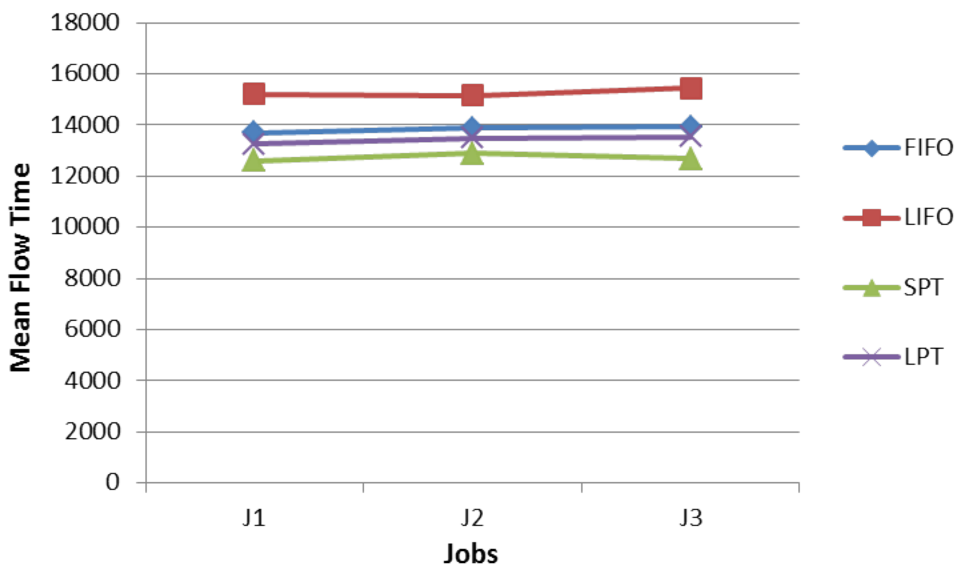

Figure 3.9: Mean Flow Time

3.6.2 Mean tardiness

Simulation and graphical results of mean tardiness (MT) performance are given in Table 3.4 and Figure 3.10 respectively. It is found that LPT rule has provided better performance for all three jobs in MT measures among all four dispatching rules. Although SPT rule has shown low MT measures in all job types. Job type J1 and J3 have highest MT values in SPT rule while J2 has high MT value in LIFO rule. Considering the MT performance of all dispatching rules for three job types, the following ranking is found:

For J1: SPT <LIFO <FIFO <LPT.

For J2: LIFO <SPT <FIFO <LPT

For J3: SPT <FIFO, LIFO, LPT

Table 3.4: Simulation results of MT (in seconds)

Jobs	FIFO	LIFO	SPT	LPT
J1	548.18	588.80	1277.10	0
J2	4018.56	4498.11	4408.33	1949.39
J3	0	0	399.65	0

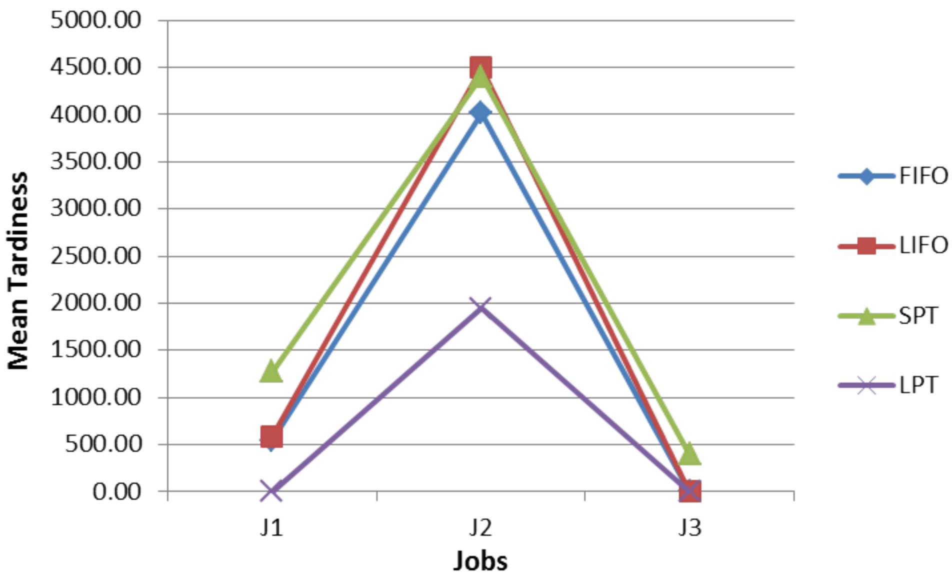

Figure 3.10: Mean Tardiness

3.6.3 Standard deviation of flow time

Table 3.5 and Figure 3.11 has provided simulation and graphical results for standard deviation of flow time (SDFT) measures respectively. LPT rule has shown lowest values of SDFT for all three job types. A similar pattern is found for LIFO and FIFO rules as in case of mean flow time performance which have too higher values in standard deviation of flow time measure for three job types. The SDFT performance wise ranking of all four dispatching rules is as follows:

For J1: LIFO <FIFO <SPT <LPT

For J2: LIFO <FIFO <SPT <LPT

For J3: LIFO <FIFO <SPT <LPT

Table 3.5: Simulation results of SDFT (in seconds)

Jobs	FIFO	LIFO	SPT	LPT
J1	8407.58	8698.38	7970.12	7234.42
J2	8492.99	8634.02	8169.86	7441.59
J3	8292.82	8530.04	7951.13	6950.82

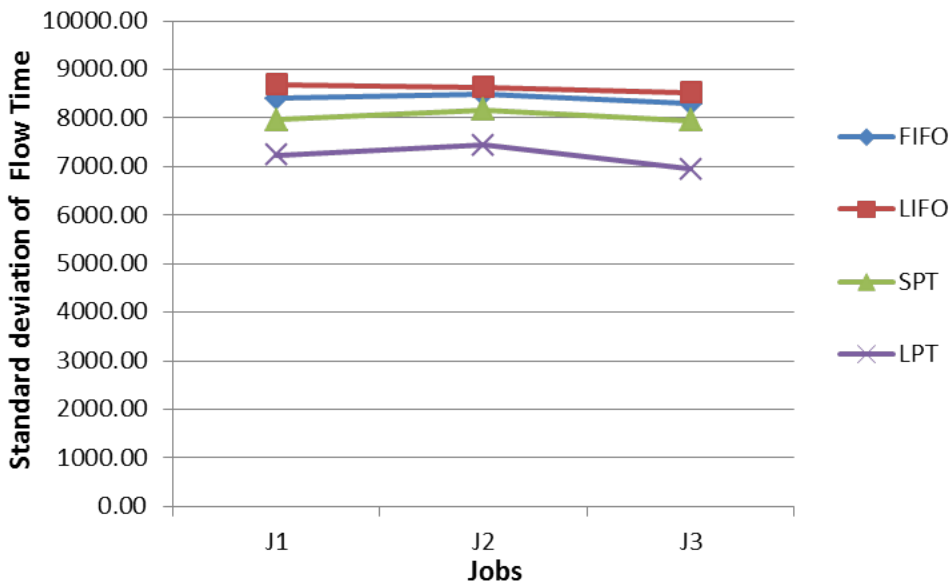

Figure 3.11: Standard Deviation of Flow Time

3.6.4 Standard deviation of tardiness

The simulation and graphical results for the performance measure of standard deviation of tardiness (SDT) for four dispatching rules is as shown in Table 3.6 and Figure 3.12 respectively. As observed in mean tardiness, the LPT rule has zero SDT values for J1 and J3 and lowest SDT value for J2 among all four rules. SPT rule provides higher SDT values for all three jobs. The ranking of SDT performance measure for all four dispatching rules is as follows:

For J1: SPT <FIFO <LIFO <LPT.

For J2: SPT <LIFO <FIFO <LPT

For J3: SPT <FIFO, LIFO, LPT

Table 3.6: Simulation results of SDT (in seconds)

Jobs	FIFO	LIFO	SPT	LPT
J1	1405.84	1331.62	2732.93	0
J2	5490.68	5714.14	5990.46	3724.69
J3	0	0	1209.77	0

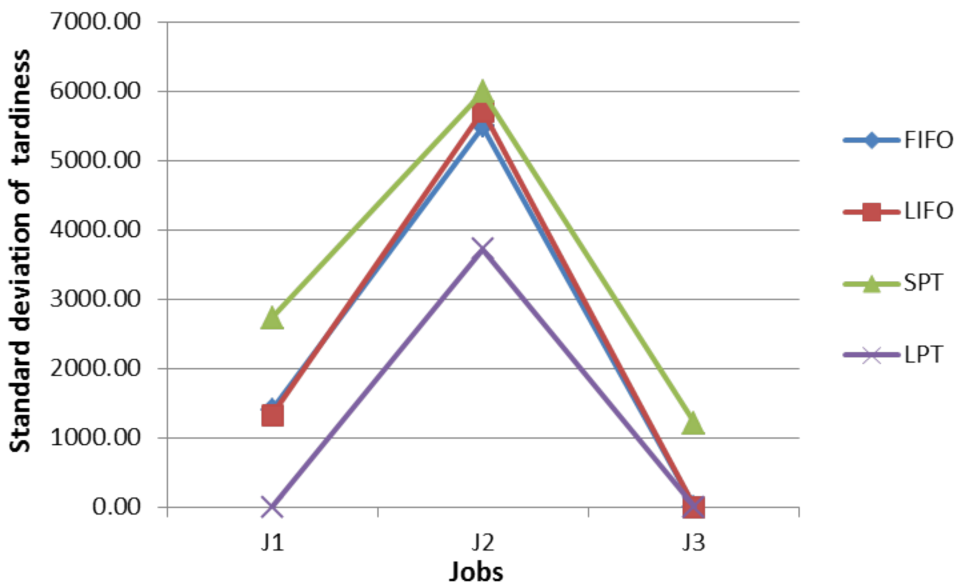

Figure 3.12: Standard Deviation of Tardiness

3.6.5 Production output

Table 3.7 and Figure 3.13 provide simulation and graphical results of the production output (PO) respectively for three job types in case of all four dispatching rules. The SPT rule provides best performance (i.e. highest number of completed jobs in 8 hours) in production output of jobs for all three job types while LPT rule shows lowest performance among all four rules. The performance ranking of all four rules in production output of jobs measure is as follows:

For J1: LPT <FIFO <LIFO <SPT

For J2: LPT <FIFO <LIFO <SPT

For J3: LPT <FIFO <LIFO <SPT

Table 3.7: Simulation results of PO

Jobs	FIFO	LIFO	SPT	LPT
J1	49	54	114	29
J2	49	53	115	29
J3	48	53	113	28

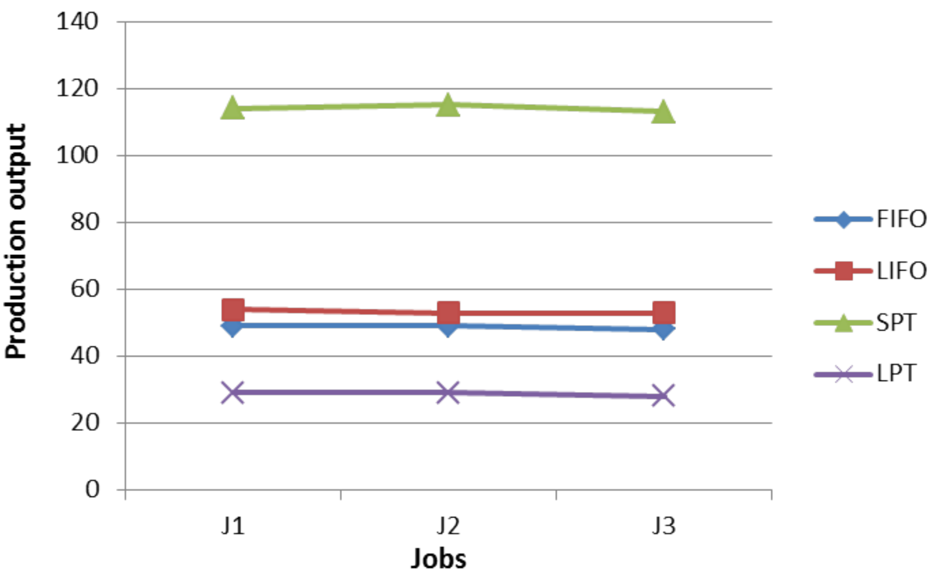

Figure 3.13: Production output

3.6.6 Work-In-Process

The simulation and graphical results for work-in-process (WIP) in all four dispatching rules are provided in Table 3.8 and Figure 3.14 respectively. The LPT rule provides worst performance (i.e. largest percentage of WIP) for all three job types among all four rules. In case of WIP measures, the best performance (lowest percentage of WIP) is provided by SPT rule for all three job types. The ranking among dispatching rules in case of WIP measures is given as follows:

For J1: LPT <FIFO <LIFO <SPT

For J2: LPT <FIFO <LIFO <SPT

For J3: LPT <FIFO <LIFO <SPT

Table 3.8: Simulation results of WIP (in %)

Jobs	FIFO	LIFO	SPT	LPT
J1	78.32	68.42	61.62	84.82
J2	72.16	69.71	53.44	79.43
J3	78.76	76.34	61.82	85.26

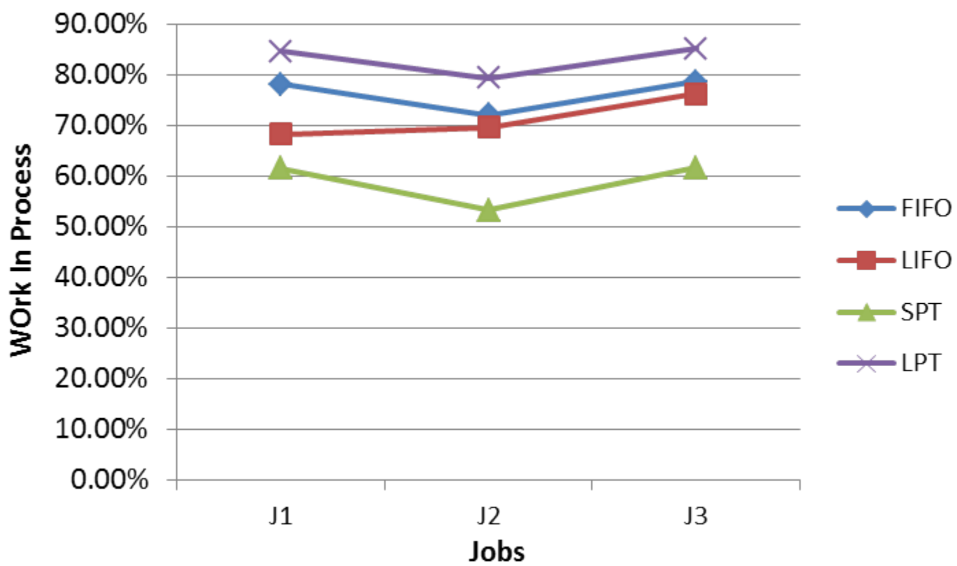

Figure 3.14: Work-In-Process

3.7 Chapter summary

In this chapter, a DES model of three jobs and six machines JMS has been created using SimEvents toolbox of Simulink library in MATLAB. The effects of DPPW, a dispatch-date assignment method and dispatching rules on the performance of JMS have been analyzed in this research work. The dispatching rules such as FIFO, LIFO, SPT and LPT are considered for examining six performance measures i.e. mean flow time, mean tardiness, standard deviation of flow time, standard deviation of tardiness, production output and work-in-process for three jobs J1, J2 and J3. The statistical analysis of the simulation results reveal some results on performance measures for dispatching rules. These results can be discussed in following points:

1. The dispatching rule SPT has provided best performance for the measures such as mean flow time, production output and work-in-process for all the three jobs. The second best performance of SPT rule has been obtained in standard deviation of flow time measure while lowest performance of SPT rule is found in mean tardiness, standard deviation of tardiness measures.

2. The best performance of LPT rule is obtained for the measures mean tardiness, standard deviation of flow time and standard deviation of tardiness. Although LPT is the next best dispatching rule for mean flow time measure, while it shows lowest performance in production output and work-in-process.

3. The FIFO rule is obtained as second best dispatching rule for mean tardiness measure for jobs J1 and J2. For job J3, FIFO has zero value of MT and SDT measure which shows best performance.

4. The dispatching rule LIFO provides second best performance in production output and work-in-process measures for all three jobs. LIFO rule has zero SDT value for job J3. LIFO rule has shown lower performances in SDFT and MFT measures for all the three jobs.

The results presented in this chapter must be depicted for JMS under given experimental conditions. In this job-shop scheduling problem, real time events occur. Hence, further JMS is investigated with real time production scheduling using the concept of multi-agent system. The agent based architecture for real time production scheduling in JMS is proposed in the next chapter.

Chapter 4

Development of agent based architecture

4.1 Introduction

Effective production is one of the major requirements in today's highly competitive scenario. It refers to the type of production in a company which meets the customer requirements and strives to maintain customer satisfaction. This type of efficient production can be achieved through real time production scheduling in the manufacturing system. Production scheduling is a decision making process that allocates optimum resources and leads to increased capacity utilization and profit for the company . In this study, job-shop scheduling is considered for investigation as it is one of the most complex combinatorial optimization problems. Hence it requires an intelligent approach which can deal with real time events.

This chapter aims at achieving the second objective of this study which introduces an agent-based architecture for real time production scheduling in JMS. This architecture is developed using the multi-agent system (MAS) concept. The MAS incorporates various agents which have autonomous, social, reactive and pro-active behaviour to achieve a common goal. MAS can handle any unforeseen situations in an efficient manner by taking smart decisions and managing global communication. With the architecture developed in this study, the agents communicate to each other to fulfill the following objectives:

1. to provide real time information in JMS.

2. to prioritize the different jobs for processing on machines; and

3. to facilitate dynamic production scheduling.

This agent framework comprises five main agents which participate in decision making directly or indirectly under an environment that has less human interference. Each agent in this agent based architecture has been developed through Stateflow functional libraries in Simulink. This chapter is organised as follows: Section 4.2 discusses background and overview. Section 4.3 proposes the agent based architecture and Section 4.4 describes implementation of the agent architecture. The chapter summary is provided in Section 4.5.

4.2 Background and overview

In the present scenario, production industry has to adopt different approaches to address dynamic nature of the changes taking place in the increasingly complex manufacturing systems. Monostori et al. (2006) described different agent based manufacturing application domains through a comprehensive survey. The authors emphasised methodological issues of multi-agent systems and implemented in industrial systems. Time to time, the researchers have been introduced agent based frameworks for production control in the complex manufacturing systems. Van Brussel et al. (1998) developed a holonic reference architecture i.e. PROSA with hierarchical and heterarchical control approaches for manufacturing systems. Heikkilä et al. (2001) described agent architecture manAge using various control algorithms for flexible control in manufacturing. This framework based system was implemented in Java language and that showed desired flexibility. Fan and Wong (2003) developed agent architecture for the control of a flexible assembly cell (a type of cellular flexible manufacturing system). Here the aim of the researchers was to establish an agent control system which is capable of handling dynamic changes in the flexible assembly cell. Lim and Zhang (2003) introduced a multi-agent architecture for agile manufacturing in which process planning and production scheduling are integrated. This architecture was able to dynamically optimise the manufacturing resources utilisation. Further in this discussion, Mishra et al. (2016) proposed a self-reactive multi-agent framework based on cloud computing technology for distributed manufacturing system. This agent framework enabled to rectify internal and external discrepancies in a manufacturing system through interaction of autonomous agents. Mönch and Stehli (2006) presented a MAS framework for production control in complex manufacturing systems. This framework included distributed hierarchical decision making processes.

Lüder et al. (2017) proposed an agent based production control architecture for improving the performance of complex manufacturing systems in terms of output, delivery reliability, resource utilization and others. This architecture facilitated the communication between customer orders and resources within a manufacturing system (a car body shop) so that the agents can provide the best schedule and order sequence under disturbances. Manupati et al. (2016) described a framework of mobile-agent based negotiation approaches to integrate different manufacturing functions (process planning and scheduling) in a network based manufacturing system. Li et al. (2014) proposed an agent-based intelligent scheduling algorithm for a NP-hard uniform machine scheduling problem to minimize total completion time. Here the agents were coordinated through token ring mechanism. Tonelli et al. (2017) presented a multi-agent based framework for modelling and simulation analysis of sustainable manufacturing. A case of semi-automated food production line was described here.

When it comes to dynamic nature in production systems, Nejad et al. (2011) proposed a multi-agent based architecture of a dynamic manufacturing system for process planning and scheduling of multiple jobs. A negotiation protocol was used for process plans and scheduling of production resources. He et al. (2014) presented a hierarchical agent bidding mechanism enables self-organized manufacturing resources and fulfilling cost-efficiently customer orders within structural constraints of manufacturing systems in production planning and scheduling. Proceed to discussion about real time processes, Zhang et al. (2014) presented a multi-agent based architecture for providing timely feedback information of shop floor. This leads to real time production scheduling in the manufacturing system. The authors used wireless devices for collecting and processing of real time data in the shop floor. Wang et al. (2008a) proposed a real time distributed production scheduling architecture at the shop floor level which was facilitated by agent based service oriented shop floor integration approach. Chen and Tu (2009) proposed an agent based framework for monitoring and controlling the dynamic production using RFID technology and ontology. The authors addressed real time events using RFID which were responded by multi-agent system.

In the past, researchers have adopted several approaches to resolve various types of complexities in manufacturing systems. Most of these approaches have addressed dynamic behaviour of manufacturing systems. In MAS based research problems, all the agents have to communicate each other on the same platform but how those agents will be interacting; this is the main issue in all research problems. Although in this study, an automated system is introduced, this will bring various stakeholders (in terms of agents) of JMS on the same platform. The communication flow among different agents is also addressed in this research. The proposed automated system is an agent based framework for JMS. The researchers have resolved real time scheduling issues in their research problems using various methods. This study also incorporates real time events during production scheduling using a new method. The strength of this architecture is its ability to update real time production scheduling decisions on the basis of updated tardiness values of each job.

4.3 Agent based architecture

In the proposed agent based architecture, there are five principal agents: job agent (JA), shop utilization agent (SUA), dispatching-date agent (DDA), job weightage agent (JWA) and scheduling agent (SA). The agent based architecture for JMS is as shown in Figure 4.1. These agents interact and exchange data/information among them to achieve the objectives mentioned in the Section 4.1. In a broader sense, the agents can be categorised in two types: decision making and information sharing agents. Decision making agents, as the name implies, are responsible for executing decisions and they have to be specified procedure. Information sharing agents share the data or information with other agents to facilitate the execution of decisions.

The main agents are briefly summarized in Table 4.1 based on data/ information sources and destinations and final outcome achieved. Detailed description of each agent is discussed in following subsections.

4.3.1 Job agents

Three job agents (JAs) for three job types i.e. JA1 for job1, JA2 for job2 and JA3 for job3 have been used in the proposed agent framework. The JAs adopted functional approach for agent encapsulation which means there is no explicit relationship between agents and physical entities. JAs provide the information regarding number of uncompleted job entities of each job type and total processing

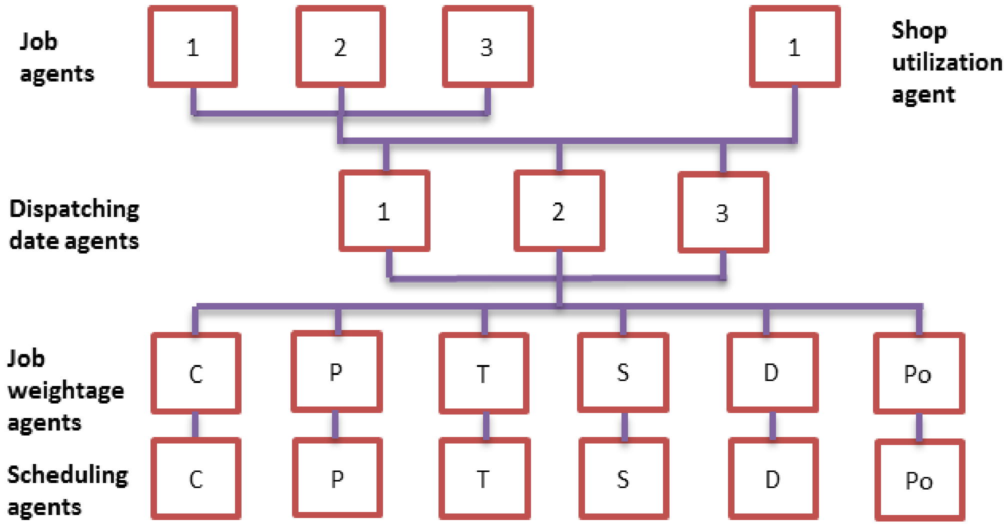

Figure 4.1: Agent based architecture for JMS

Table 4.1: Brief description of agents

Agents	**Data/ Information received from**	**Data/ Information given to**	**Final outcome**
Job agents	Machines	DDAs	Updated job related information
Shop utilization agent	Machines	DDAs	Updated machine utilization records
Dispatching date agents	JAs and SUA	JWAs	Updated dispatch date records of each job
Job weightage agents	DDAs	SAs	Updated job priority values assigned to each job
Scheduling agents	JWAs	Manufacturing system (i.e. shop floor)	Updated production scheduling plan

time spent for each job type to the due-date agents. Total processing time may be calculated as below:

$$TP = P_{O1} + P_{O2} + P_{O3} + ... + P_{Oj} \tag{4.1}$$

Where TP is the total processing time spent by a job and P_{Oj} is the processing time of j^{th} operation. Hence this study uses JAs as information agents in production planning of each job. Each JA updates it timely. It creates a new JA if a new job type enters into the manufacturing system. The Stateflow model of job agent is as shown in Figure 4.2.

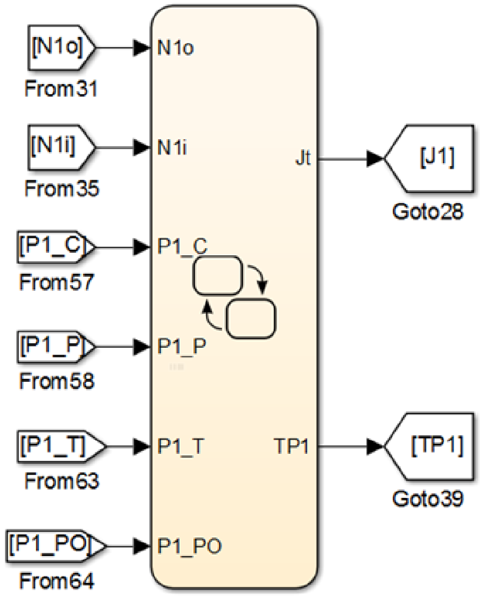

Figure 4.2: Stateflow model of a job agent

4.3.2 Shop utilization agent

Shop utilization agent (SUA) is the only agent which has been used in agent based job-shop manufacturing system (ABJMS) for providing information regarding shop utilization to DDAs. The Stateflow model of SUA is as shown in Figure 4.3. SUA contains the real time information of each machines utilization in the shop. SUA has been used as an information agent and acts as a functional module for production planning in this study. Shop utilization can be obtained as follows:

$$U = (U_1 + U_2 + U_3 + ... + U_m)/m \qquad (4.2)$$

Where U is the shop utilization, m is the number of machines in the shop and U_m is the utilization of m^{th} machine.

4.3.3 Dispatching date agents

This study uses three dispatching date agents (DDAs) which are responsible for imparting information regarding dispatch dates of each job type to the JWAs. These DDAs have been modeled in Stateflow which can be shown in Figure 4.4.

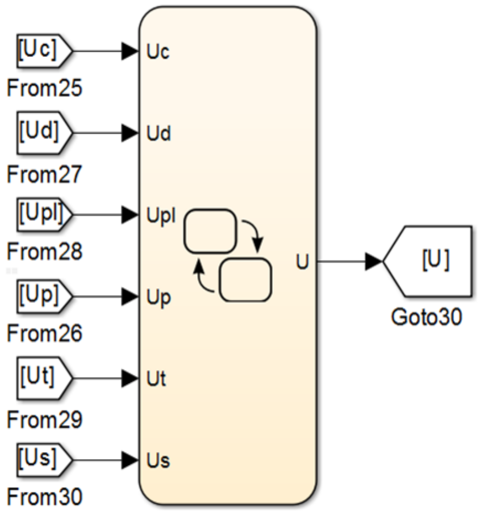

Figure 4.3: Stateflow model of a shop utilization agent

DDAs are also used as information agents and act as the functionaries for production planning. Each DDA collects the information of several parameters such as mean processing time per operation, number of machines in the manufacturing system, number of uncompleted jobs, shop utilization, total processing time and number of operations in each job from two agent types (JAs and SUA). According to dynamic processing plus waiting time (DPPW) method, dispatch date of each job is formulated as follows (Vinod and Sridharan, 2011):

$$Di = Ai + \sum_{j=1}^{n_i} p_{ij} + \{\frac{J_t \mu_p}{n_m \rho} - \mu_p\} n_i \tag{4.3}$$

Where D_i, dispatching date of job i; A_i, arrival time of job i in the shop; p_{ij}, processing time of operation j of job i; J_t, uncompleted jobs in the shop at time t; n_i, number of operations in job i; n_m, number of machines; μ_p, the Mean processing time per operation ; ρ, the shop utilization ;

4.3.4 Job weightage agents

This study uses job weightage agents (JWAs) for each operation. Here six JWAs are used for six operations such as $JWA_{Casting}$, $JWA_{Planing}$, $JWA_{Turning}$, $JWA_{Shaping}$, $JWA_{Drilling}$ and $JWA_{Polishing}$. A new JWA will be created if a new operation is added into the system. For instance, $JWA_{Casting}$ contains the information on due dates, late fines, completion times and arrival times of Job1 and Job3 as these two jobs are being processed on casting operation. On the other hand, all job

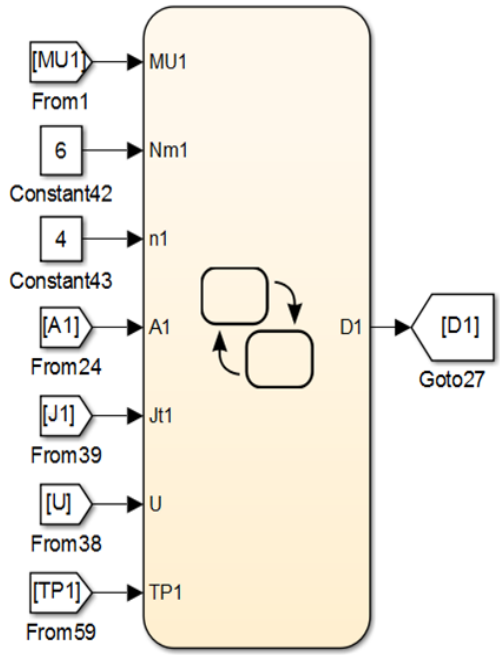

Figure 4.4: Stateflow model of a dispatching date agent

weightage agents act as information agents responsible for imparting updated information to SAs. This JWA optimize the tardiness value and provides the job priority value to respective SA. The Stateflow model of JWA is shown in Figure 4.5. Job weightage value or priority value for each job can be calculated as follows:

$$JW_i = \begin{cases} (T_{now} + C_i - D_i) f_i, & (T_{now} + C_i) > D_i \\ 0, & (T_{now} + C_i) \leq D_i \end{cases} \tag{4.4}$$

Where JW_i is job weightage value for job type i; C_i is the average time spent in the manufacturing system for job type i; D_i is the dispatching date (time) for job i; f_i is the fine per time unit for delay the job i with respect to dispatching time; and T_{now} is the current time.

4.3.5 Scheduling agents

The responsibility of a scheduling agent (SA) is to execute and monitor the scheduling of jobs in real time. In this study, six scheduling agents such as $SA_{Casting}$, $SA_{Planing}$, $SA_{Turning}$, $SA_{Shaping}$, $SA_{Drilling}$ and $SA_{Polishing}$ are used for all six operations. All SAs act as decision making agents responsible for scheduling two jobs on the basis of job weightage value which updates in real time. The SA chooses the job with the highest job weightage value which is obtained from equation

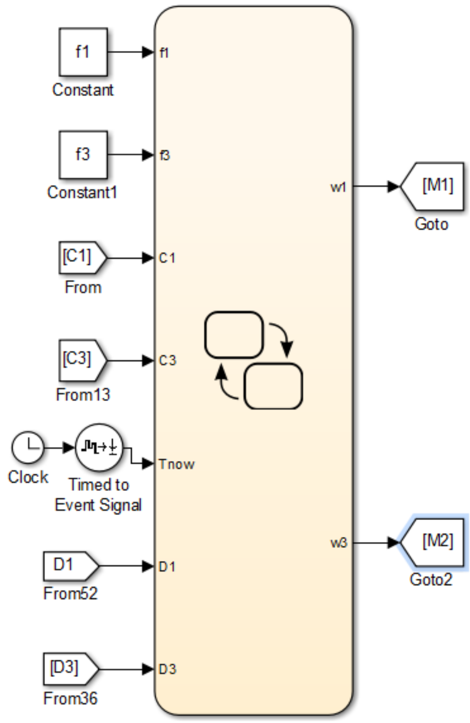

Figure 4.5: Stateflow model of a job weightage agent

(4.4). SAs are also functionally encapsulated since they are involved in production scheduling process. The Stateflow model of SA is as shown in Figure 4.6.

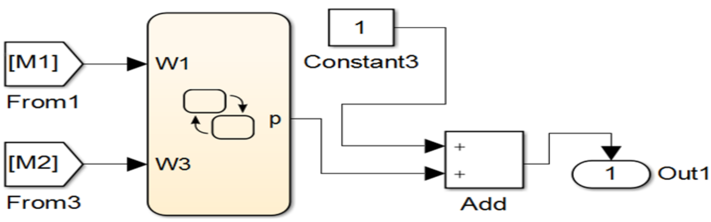

Figure 4.6: Stateflow model of a scheduling agent

The communication flow chart of the agent based architecture for JMS is illustrated in Figure 4.7.

4.4 Implementation of agent based architecture

This study uses Stateflow as a MAS platform to develop agent based framework for JMS. In the preliminary implementation, Stateflow is used to model the behaviour of each agent and then integrate all agents into the simulation model of JMS. Stateflow is an integrated tool of Matlab-Simulink and is used for developing

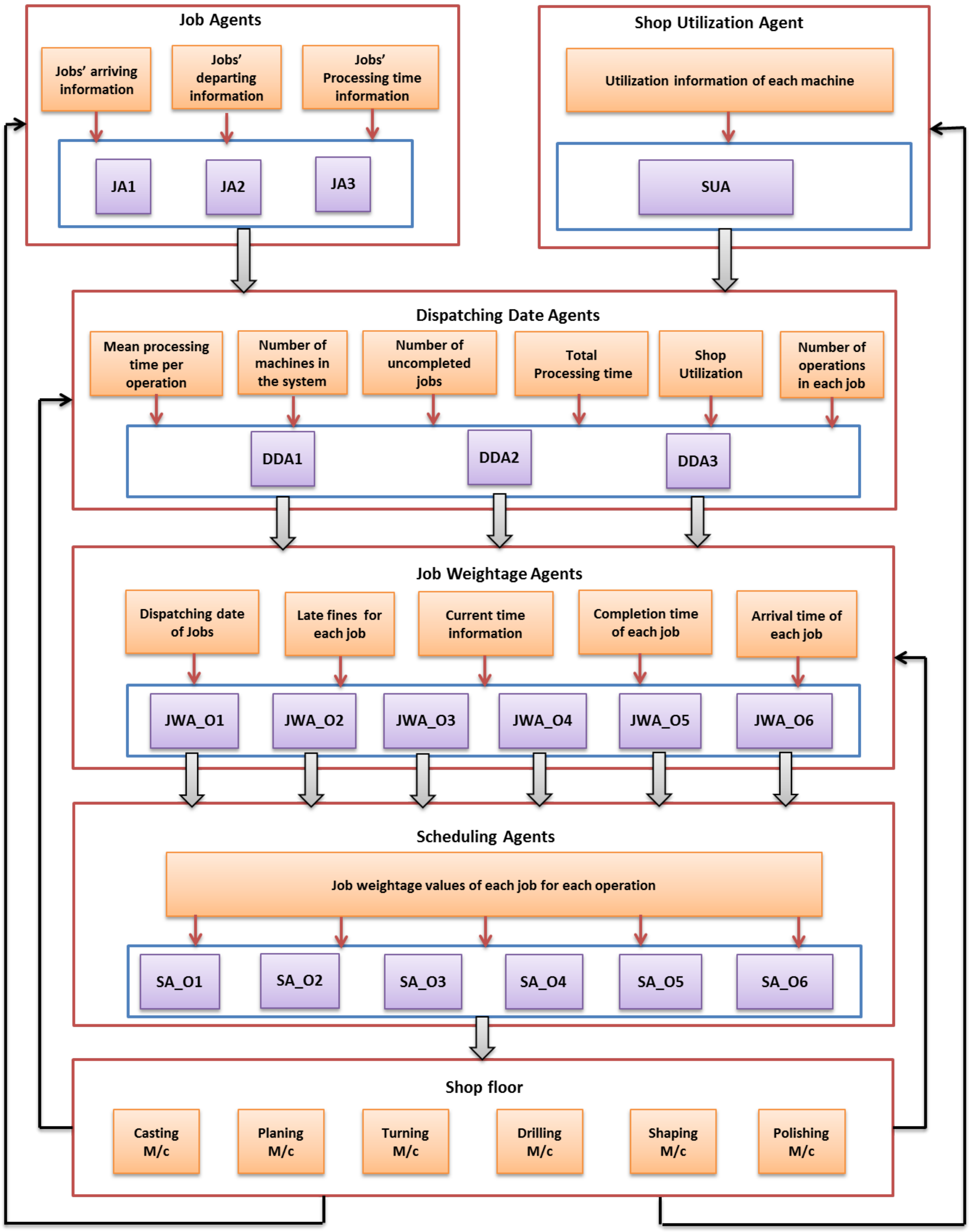

Figure 4.7: Communication flow chart of agent architecture for JMS

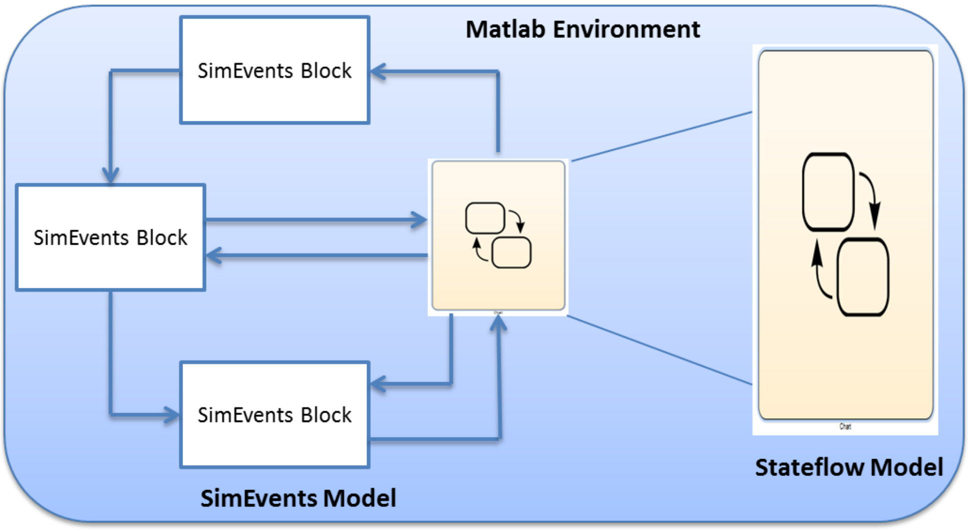

Figure 4.8: Interaction of Stateflow with SimEvents model in Matlab environment

embedded reactive systems that consist of behavioural logic, supervision & control. This modeling tool is the extension of Simulink in a design environment for designing state machines and flow charts. Stateflow enables the graphical representation of hierarchy, parallelism and transition between them; hierarchy allows an organisational structure of complex systems, and parallelism in the system enables two or more parallel states simultaneously (Yoon et al., 2011).

In Stateflow, the agents communicate among themselves by sending messages and these messages are exchanged in '.data' form. Initially the JA and SUA receive the data/ information from a simulated model of the JMS which is built on SimEvents (a Simulink block set of Matlab). The integration of Stateflow in Matlab environment and its interaction with SimEvents model can be understood by Figure 4.8. JA will calculate the total average time spent in the system and number of uncompleted jobs and then send these values in the form of messages to each DDA. Simultaneously SUA will also send shop utilization value in message form to DDA. After these activities, the DDA will utilise some real time information received from JMS simulated model and some data values in message form received from JA and SUA and then it will send updated dispatch-date value to JWA. JWA will send the job weightage value to respective SA in the message form. Thereafter the SA will decide which job goes first for production on the basis of updated job weightage value.

The communications between DDAs & JWAs and JWAs & SAs have been presented in Figure 4.9 and Figure 4.10 respectively. Figure 4.9 shows DDAs of each job type send dispatching date values to respective JWAs. While Figure 4.10

shows job weightage values of each job type are sent to respective SAs from corresponding JWAs. In Figure 4.10, CSA, PSA, TSA, SSA, DSA and PoSA refer to the scheduling agents for casting, planing, turning, shaping, drilling and polishing operations respectively. In this MAS application, the method of message sending and receiving, which is essential for agent communication, handled by 'Message Viewer'. In Stateflow environment, all the agents are capable of receiving and sending messages in real time. A message queue capacity must not overflow. To avoid this situation, queue capacity can be increased through model explorer of receiver agents in SimEvents model.

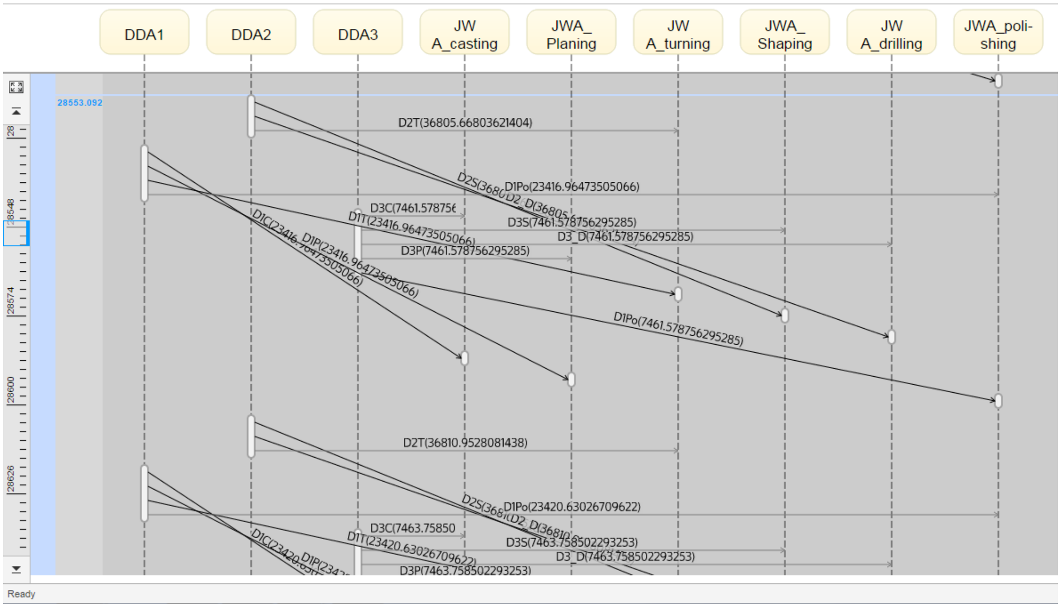

Figure 4.9: Communication between DDAs and JWAs

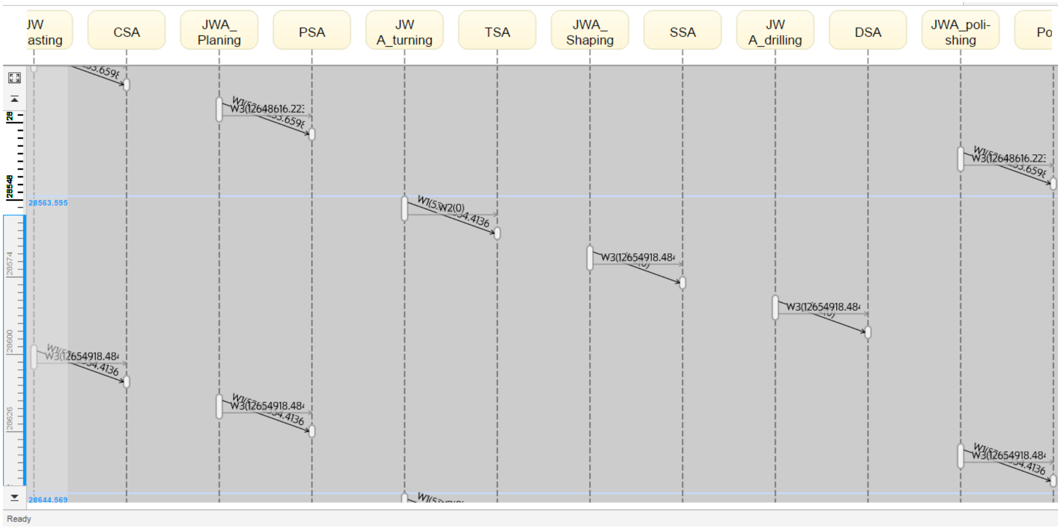

Figure 4.10: Communication between JWAs and SAs

4.5 Chapter summary

The MAS concept has been applied in this research work and all the manufacturing system related tasks are executed by agents which are having autonomous behavior and are capable of communicating with each other for making decisions. The architecture developed in this chapter facilitates dynamic production scheduling and minimizes the production related problems through different agents. It allows real time data sharing among agents which enables dynamic behavior in the JMS. It also provides updated job weightage value which facilitates real time production scheduling in JMS. The agent based architecture has been easily built on Stateflow platform with its features. All the agents perform their roles simultaneously and it provides autonomy to respective agents. The agents run their logics and simultaneously communicate with other agents when it is required. For evaluating this MAS application, a case study of JMS which comprises five principal agents is tested and its simulation modeling is discussed in the next chapter.

Chapter 5

Agent based simulation modeling for job shop manufacturing system

5.1 Introduction

As today's global market has become more dynamic, manufacturing organizations require a manufacturing system which can quickly adapt and respond rapid changes. Production scheduling is one of the important activity in a manufacturing system which deal with time span of production processes and job priority decisions. In order to cope with highly competitive business environment, it is essential to generate efficient production schedules to deal with real time production requirements. The dynamic moderations in the manufacturing system can be introduced from either outside such as suppliers' side and customers' side or inside the manufacturing system such as real time events occur on the shop floor (Wang et al., 2008a). In a real-time system environment, process times tend to vary, new orders receive, some orders get denied, non scheduled maintenance of machines etc. Such hindrances produce delay in products delivery, higher rework processes and decreases the performance of a manufacturing system. To handle with these issues, scheduling systems need to take effective decisions in real time such as reorganize the production plan and reform the production schedules accordingly. The general approach to facilitate these decisions does not provide coherent interactions across all stakeholders to generate optimum production.

Hence, this chapter aims at achieving third objective of this study which introduces agent based simulation modeling approach for real-time production scheduling in JMS. This novel methodology would enable manufacturing enterprises to prioritize different job types for real time production scheduling within existing system constraints. This study uses agent based modeling and simulation software tool 'SimEvents' with Stateflow functions libraries which proposes an integrated decision platform on which real time production scheduling could be executed. SimEvents, a discrete event simulation tool provides simulation modeling of JMS and Stateflow provides multi-agent system (MAS) architecture which has the capability to facilitate the communication among developed agents and take required decisions.

The chapter is structured as follows: Section 5.2 describes the background and overview for this chapter. Section 5.3 describes development of agent based simulation model for JMS. Section 5.4 discusses simulation results and performance analysis of agent based job-shop manufacturing system (ABJMS) model. Section 5.5 provides evaluation of ABJMS model followed by chapter summary in Section 5.6.

5.2 Background and overview

In the context of agent based modeling applications for production scheduling, Table 5.1 provides a review of recent research works which deal with MAS based solution for complex manufacturing problems.

Table 5.1: Recent research works on agent based simulation modeling

Authors	**Description**
Baykasoglu and Gorkemli (2017)	Handling dynamic part demand arrivals in virtual cellular manufacturing using Anylogic MAS platform on which four types of agents; part, part family, clustering manager and machine agents are interacted.
Reddy et al. (2017)	Discussed planning procurement operations and scheduling (vehicle routing problem) with multiple cross-docks using procurement, allocation, milling and scheduling agents.

Authors	Description
Martin et al. (2016)	To solve two problem domains, permutation flow-shop scheduling and capacitated vehicle routing using two types of agents: launcher and metaheuristic agents through JADE platform enabled multi-agent based distributed framework.
Barenji et al. (2016a)	Investigating the potential enhancement of flexible assembly line performance through the implementation of RFID-enabled multi-agent scheduling and control system. Here JADE platform provides a space on which shop management agents, agent managers, shop monitoring and command agents, station control agents, station monitoring agents, agent machine interfaces, and manufacturing resource agents are communicated.
Barenji et al. (2016b)	To design a Prometheus methodology based decision making system for a real manufacturing flow line of a SME using multi-agent based dynamic scheduling system under dynamic customer demands and internal disturbances. JACK platform facilitates the interaction among manager agent, shop manager agent, cell agent, material handling system (MHS) agent, scheduler machine agent, MHS resource agent, and machine resource agent.
Zhang and Wang (2016)	Efficient production schedules for re-entrant manufacturing systems under unbalanced workload and dynamic uncertainty are developed by using collaborative scheduling agent, several task management agents, certain resource capacity management agents; a multi-agent production control system (MAPCS) and a multi-agent fundamental information management system (MAFIMS) are deployed to cooperate with these agents using CNP based scheduling algorithm.
Cupek et al. (2016)	To focus on simulation based planning through multi-agent architecture of manufacturing execution systems for a short-series production scheduling, MVC provides a platform on which HUB a communication centre, client agent, order agent, supervisor agent and six work place agents are communicated.

Authors	**Description**
Mishra et al. (2016)	Cloud computing technology integrates eleven autonomous agents (purchase order collection agent, supplier selection agent, planning agent, material planning agent, transport agent, administrative agent, forecasting agent, maintenance agent, knowledge base agent, design agent and negotiation agent), multiple clients and different suppliers on a single platform for real time and quick exchange of information.
Hsu et al. (2016a)	An agent-based fuzzy constraint-directed negotiation (AFCN) mechanism is used to model scheduling problem using interaction between job agents and resource agents on discrete event system platform.
Nouiri et al. (2015)	Flexible job-shop scheduling problem is aimed to minimize maximum completion time which is achieved by two multi-agent particle swarm optimization (MAPSO) architectures considering the communication among boss agent, synchronization agent, execute agents on JADE platform..
Asadzadeh (2015)	Agent-based model for job-shop scheduling problem using local search genetic algorithm is implemented on JADE MAS platform and considered agents (management agent, processor agent, local search agent and elite local search agent) are built on it.
Polyakovskiy and M'Hallah (2014)	MAS^H, a deterministic heuristic based on MAS is developed for weighted earliness tardiness parallel machine problem and modeled in C-coded environment which provides the interaction among I-agents (free jobs), G-agents (group of jobs) and M-agents (system's manager).
He et al. (2014)	A hierarchical agent bidding mechanism enables self-organized manufacturing resources and fulfilling cost-efficiently customer orders within structural constraints of manufacturing systems in production planning and scheduling.

Authors	Description
Savino et al. (2014)	This study described multi-objective flow-shop modeling and scheduling problem through MAS with a dedicated scheduling algorithm. JADE platform facilitates the co-ordination between agents.
Li et al. (2014)	Minimization of total completion time in uniform machine scheduling problem is achieved through intelligent scheduling algorithm called as ABISA based agent technology. The agents are coordinated through token ring mechanism.

In recent years, the application of MAS has been thoroughly examined in manufacturing area by the researchers. Thus in the intelligence-connected era, MAS is an effective solution for modeling and simulating the manufacturing systems to deal with seamless communications at different decision stages. These agent based models were modeled in different MAS platforms such as JADE, Jack, Anylogic, C/C++ coded platform, Java coded environment, discrete event platforms etc. Various MAS platforms have already been discussed in chapter 2. Out of these MAS platforms, this study uses SimEvents with Stateflow function libraries which is most suitable MAS platform for dealing with discrete events type data sharing among agents. Thus detailed discussion of agent based simulation modeling is provided in this chapter.

5.3 Development of agent based simulation model

The agent based simulation modeling is described for job-shop manufacturing system in this section. The procedure for developing agent based simulation model is given in Figure 5.1 and discussed below in 10 steps.

1. *Create simulation model of JMS*: Discrete-event simulation model of JMS is generated using SimEvents (a Simulink block set in Matlab). This step can be seen as the structural development of JMS in which all the operations involved in production process of three job types are modeled.

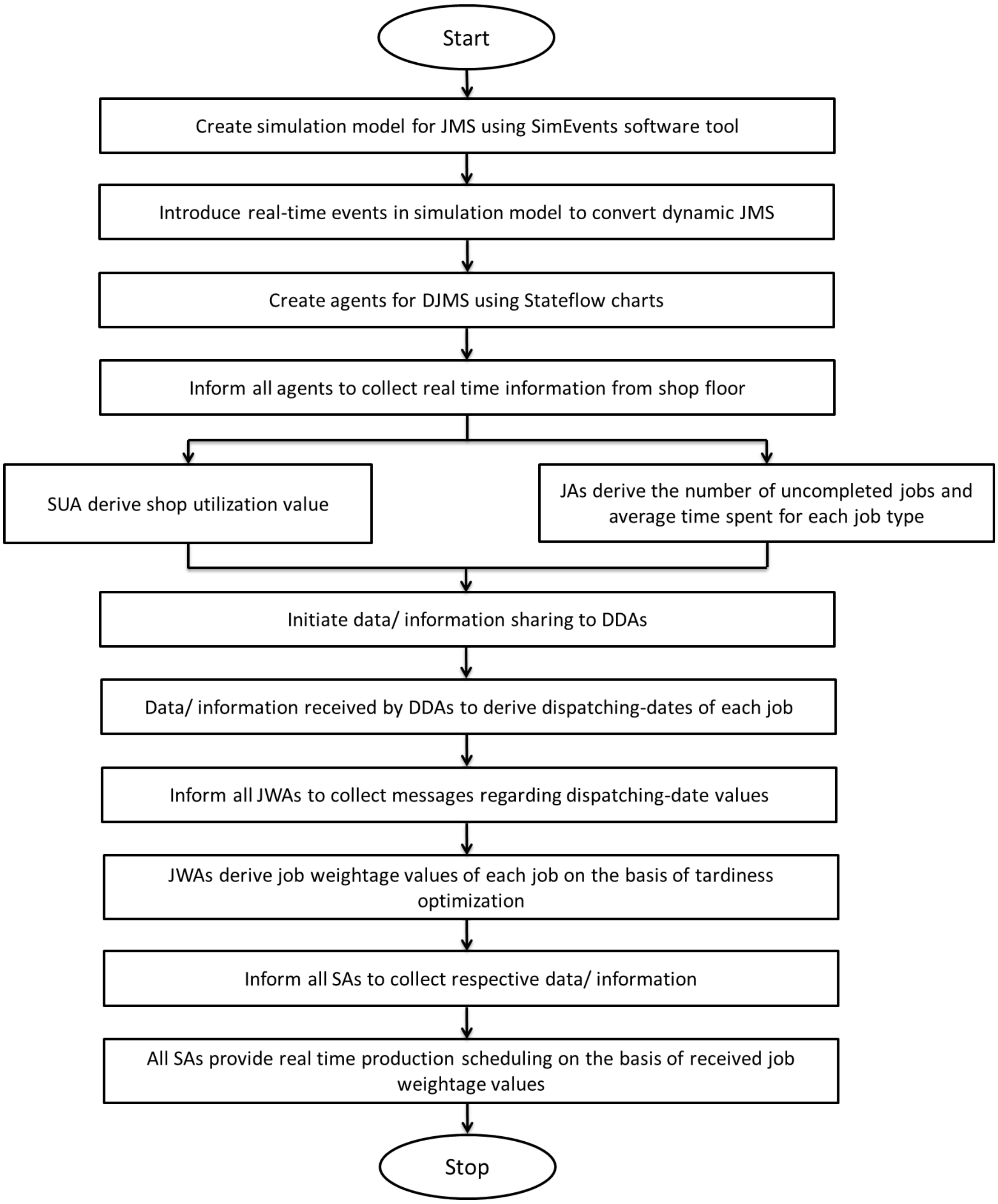

Figure 5.1: Procedure for developing agent based simulation model

2. *Introduce dynamic behaviour in JMS*: Real time events and varying processing times are introduced on the shop floor which convert in to dynamic JMS. Here dynamic nature is derived from real time events occur at the shop floor events of the manufacturing system.

3. *Create agents in JMS*: In this step, the functional agents are created in JMS using Stateflow charts (a Simulink block set in Matlab). In JMS, one shop utilization agent, three job agents and three due date agents according to number of job types, six job weightage agents and six scheduling agents as per number of operations are developed in the simulation model.

4. *Collection of real time information*: As simulation starts, simulation coordinator informs to respective agents to collect real-time information from shop floor. Global simulation clock begins at time zero. As clock starts, real-time events occur at shop floor such as processing of each job type on respective machines according to its processing sequence with stochastic processing times and real-time information exchange among agents. Utilization value of each machine is provided to SUA through 'Goto' and 'From' Simulink blocks on each time step. Similarly the information about number of processed & unprocessed jobs and average time spent for each job type are provided to respective job agents. The average time spent in the system can be obtained using 'Start timer' and 'Read timer' blocks in SimEvents block set.

5. *Initiate data sharing to respective agents*: In this step, SUA provides the shop utilization value and JAs provide total processing times spent and number of uncompleted jobs for respective job types to DDAs using Stateflow charts. On the other hand, DDAs received required data from shop floor too such as completion time of each job, number of machines, number of processes involved in production of each job type etc.

6. *Generation of dispatching date values for each job*: Dispatching date agents (DDAs) generate dispatching date values for each job type using dynamic processing plus waiting time (DPPW) method. For obtaining these values, DDAs collect the data about arrival times of each job, number of operations in each job, number of machines from shop floor and the data about mean processing times per operation, total processing time for each job and shop utilization from respective agents.

7. *Collection of messages for respective JWAs*: In this step, simulation coordinator informs all job weightage agents (JWAs) to collect the data about due

date values for each job from DDAs. Other required data is also taken from shop floor in real time.

8. *Generation of job weightage values for each job*: JWAs calculate the job weightage values on the basis of real time tardiness values using "If-Then-Else" rules. T_{now} is used for current time updates in job weightage calculation.

9. *Inform all scheduling agents to collect the information*: In this step, simulation coordinator informs all scheduling agents (SAs) to collect the messages regarding job weightage values of different job types from respective JWAs.

10. *Generate real-time production scheduling*: According to updated incoming messages of job weightage values, the scheduling agent of an operation schedules two job types using "If-Then-Else" rules.

In this agent based job shop manufacturing system (ABJMS), functionally decomposed agents are used which perform different functions in JMS model. The agent based simulation process is facilitated by Stateflow which is integrated in Matlab environment and interacted with simulation model in SimEvents. The complex simulation model of JMS in SimEvents is as shown in Figure 5.2 and Stateflow model of agents is as shown in Figure 5.3. The interaction of agents with JMS can be understood through Figure 5.4. The purpose of presenting the simulation model of JMS with all workstations in Figure 5.2 is showing the complexity of JMS simulated model though the texts are illegible in the figure due to software constraints. Similarly other figures are also needed to represent here though these are not clear. In simulation process, each agent has an input queue for receiving messages. An incoming message arrives on each time, the communication interface receives all messages in the queue sorted as per time. The message queue capacity which is given in communication interface that must be fixed according to number of incoming messages within global simulation time. If at an instant, message queue length is higher than message queue capacity then the simulation process will give error immediately. The simulation process is driven by simulation engine which processes receiving messages as per their incoming sequence in the input queue and updates both states of messages i.e. internal and external accordingly and send resulting messages to the simulation coordinator. The simulation coordinator continuously updates the queue and simulation clock and sends the message to its destination. The interaction of agents with respective machines in different manufacturing operations is described below.

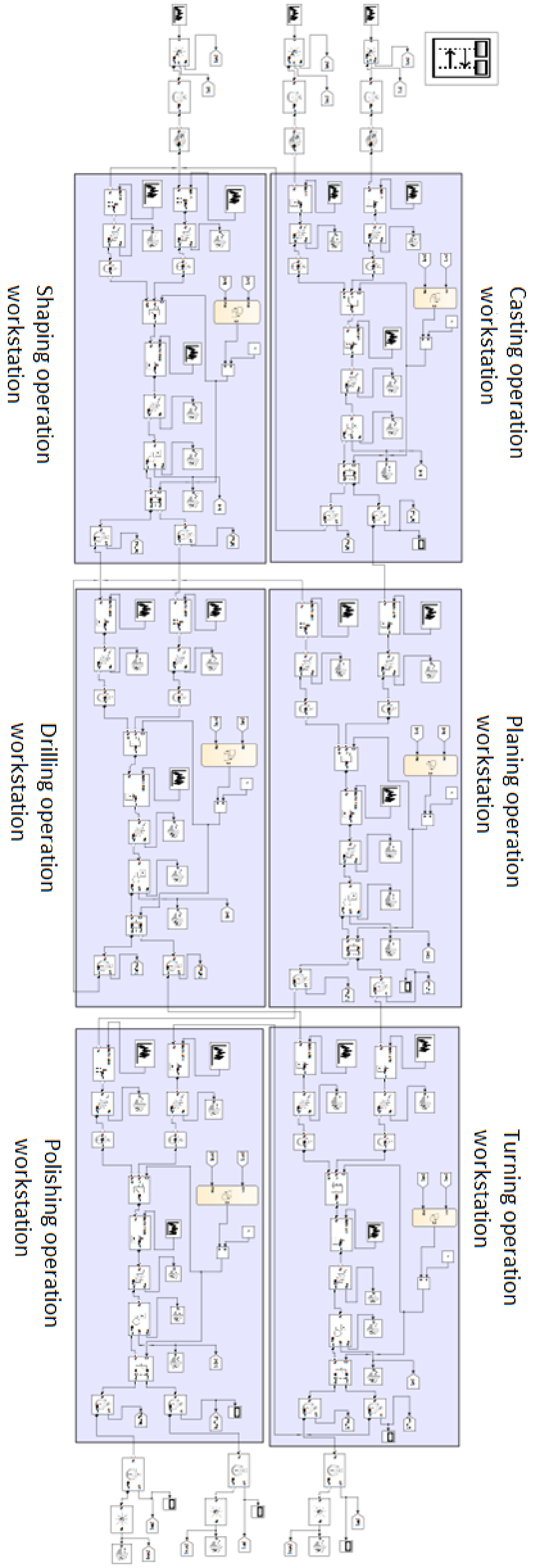

Figure 5.2: Simulation model of JMS in SimEvents

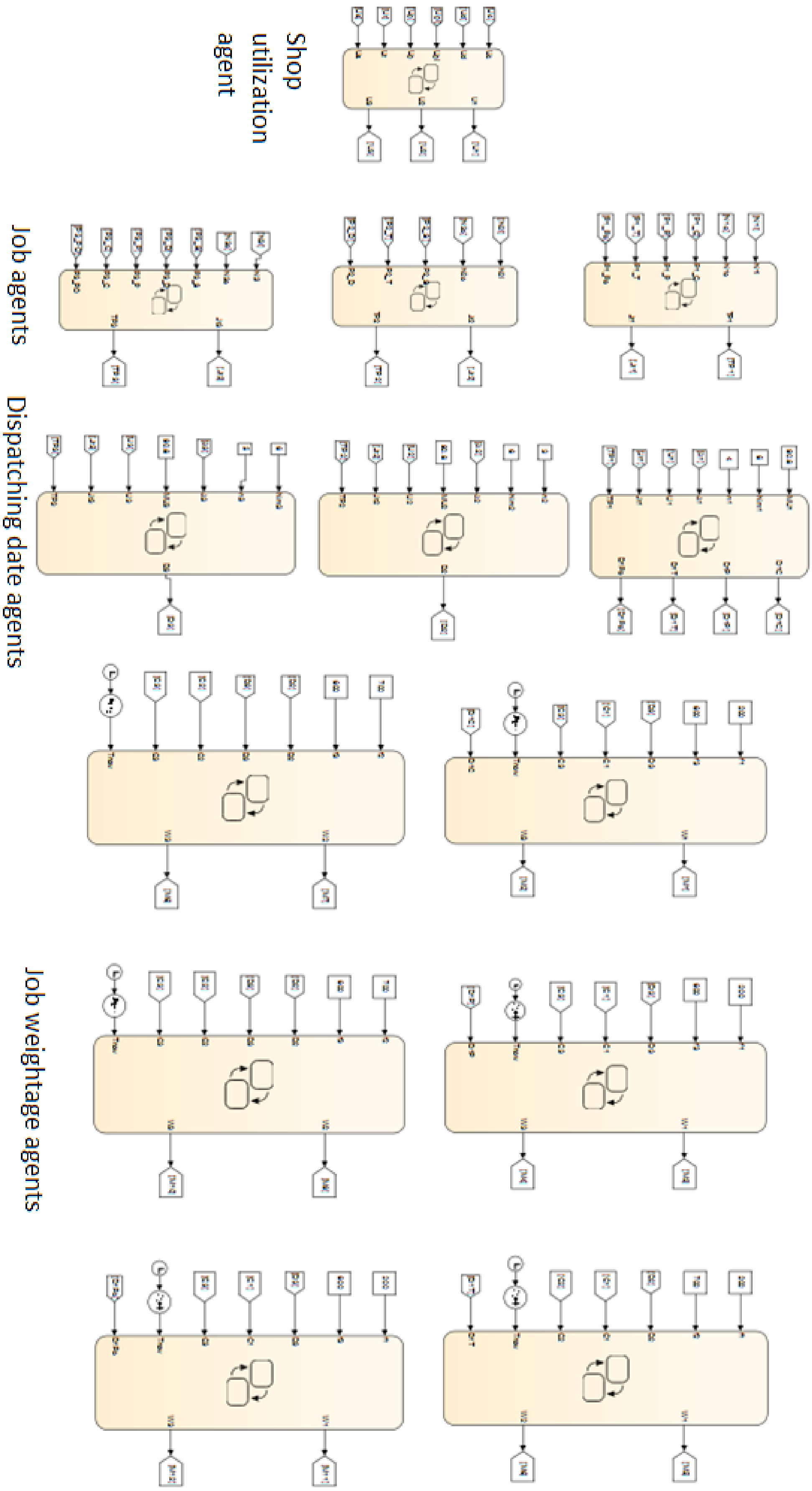

Figure 5.3: Stateflow model of agents

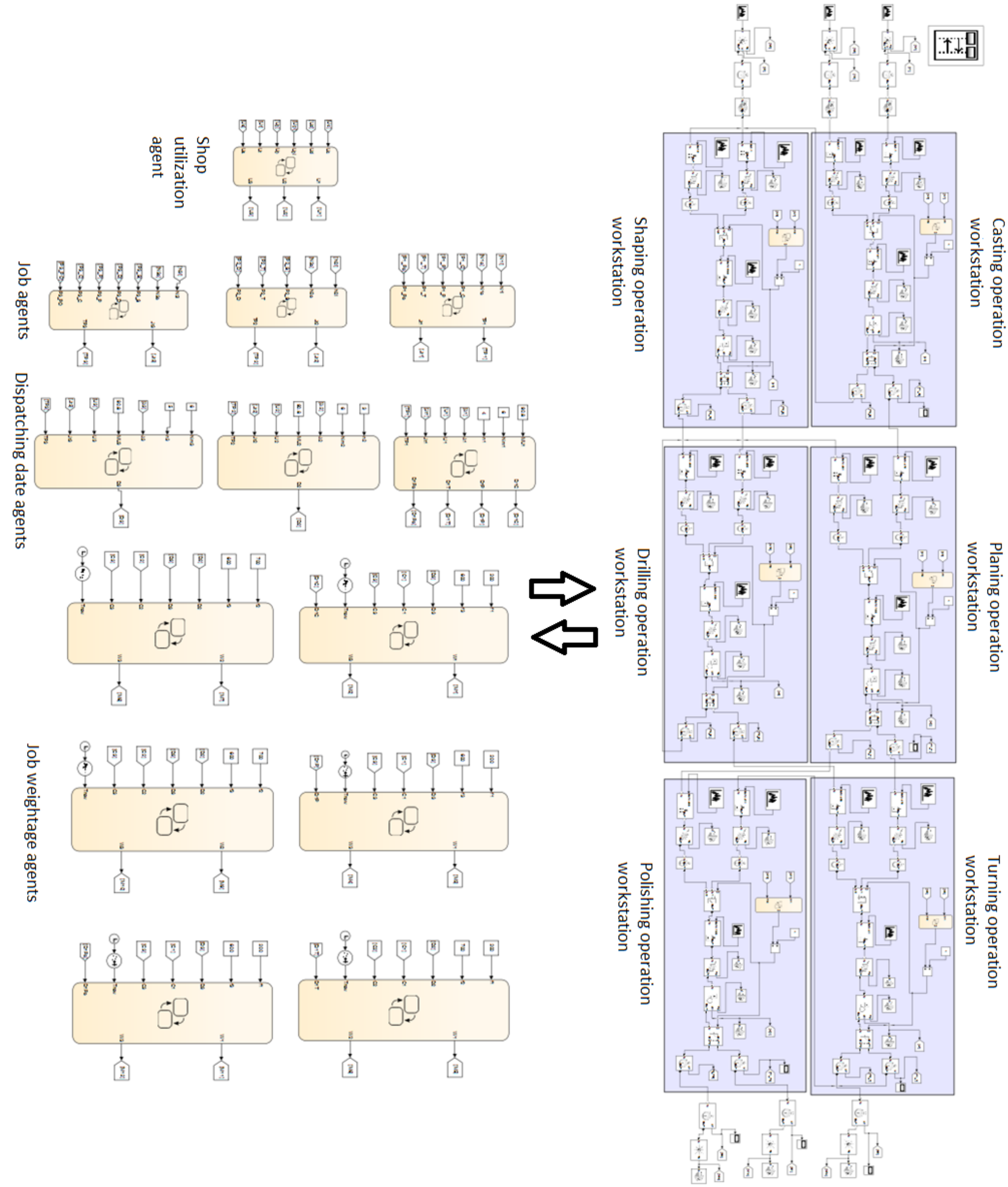

Figure 5.4: Interaction of agents with JMS

5.3.1 Interaction of agents with casting machine

The interaction of agents with casting machine is as shown in Figure 5.5 which also represents SimEvents model of casting operation. Here casting scheduling agent (CSA) takes decision on scheduling of jobs J1 and J3. This CSA facilitates real-time production schedule in casting process on the basis of job priority value using SimEvents blocks 'Input Switch' and 'Output Switch'.

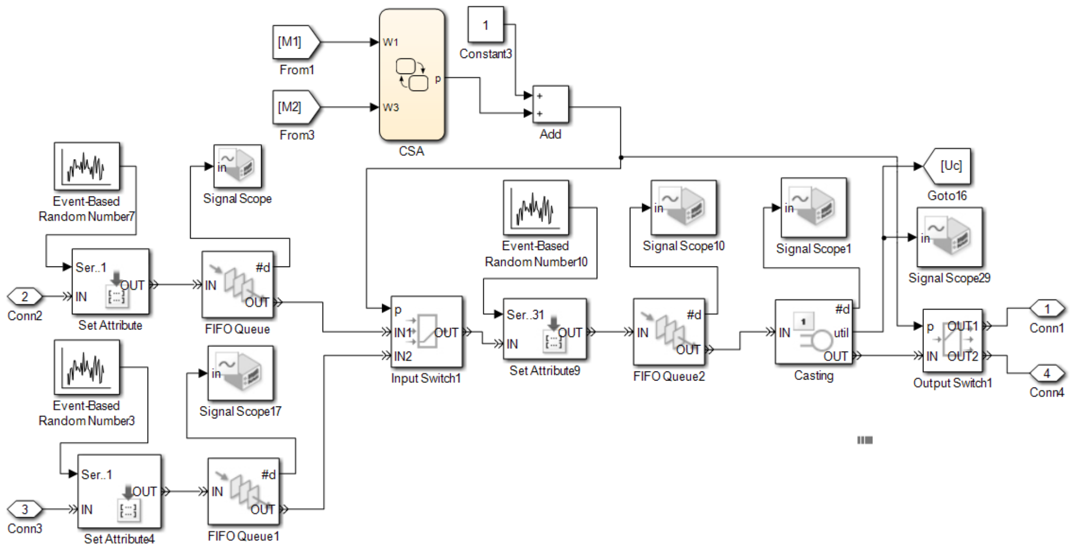

Figure 5.5: Interaction of agents with casting machine

5.3.2 Interaction of agents with planer

The interaction of agents with planer is shown in Figure 5.6 which also represents SimEvents model of planing operation. Here planing scheduling agent (PSA) takes decision on scheduling of jobs J1 and J3. This PSA facilitates real-time production schedule in planing operation on the basis of job priority value using SimEvents blocks 'Input Switch' and 'Output Switch'.

5.3.3 Interaction of agents with lathe machine

The interaction of agents with lathe machine is provided in Figure 5.7 which also represents SimEvents model of turning operation. Here turning scheduling agent (TSA) takes decision on scheduling of jobs J1 and J2. This TSA facilitates real-time production schedule in turning operation on the basis of job priority value using SimEvents blocks 'Input Switch' and 'Output Switch'.

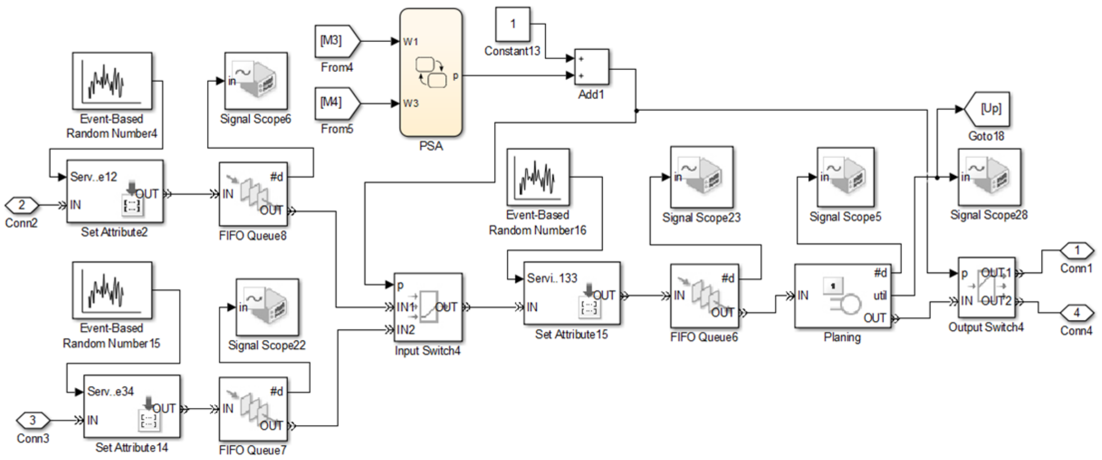

Figure 5.6: Interaction of agents with planer

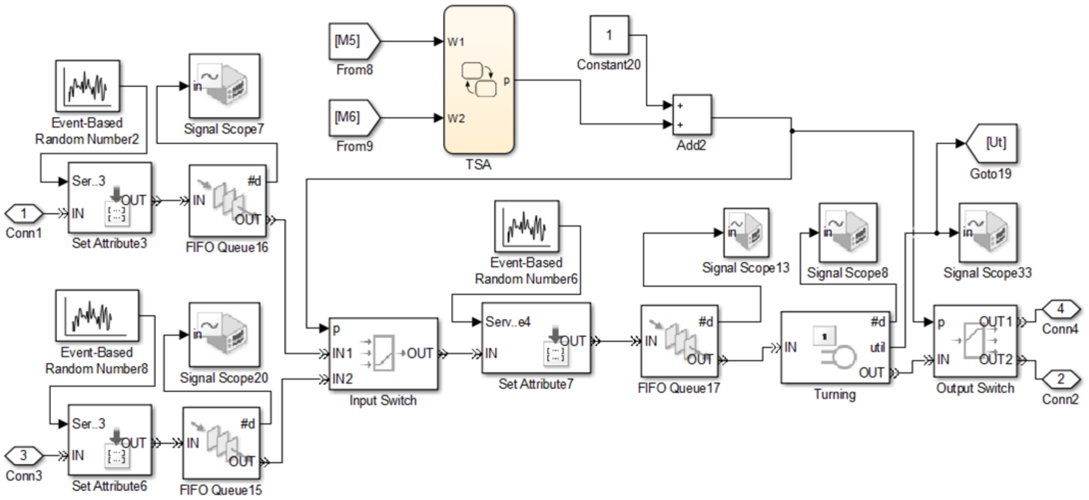

Figure 5.7: Interaction of agents with lathe machine

5.3.4 Interaction of agents with shaper

Figure 5.8 shows the interaction of agents with shaper which also represents SimEvents model of shaping operation. Here shaping scheduling agent (SSA) takes decision on scheduling of jobs J2 and J3. This SSA facilitates real-time production schedule during shaping operation on the basis of job priority value using SimEvents blocks ‘Input Switch’ and ‘Output Switch’.

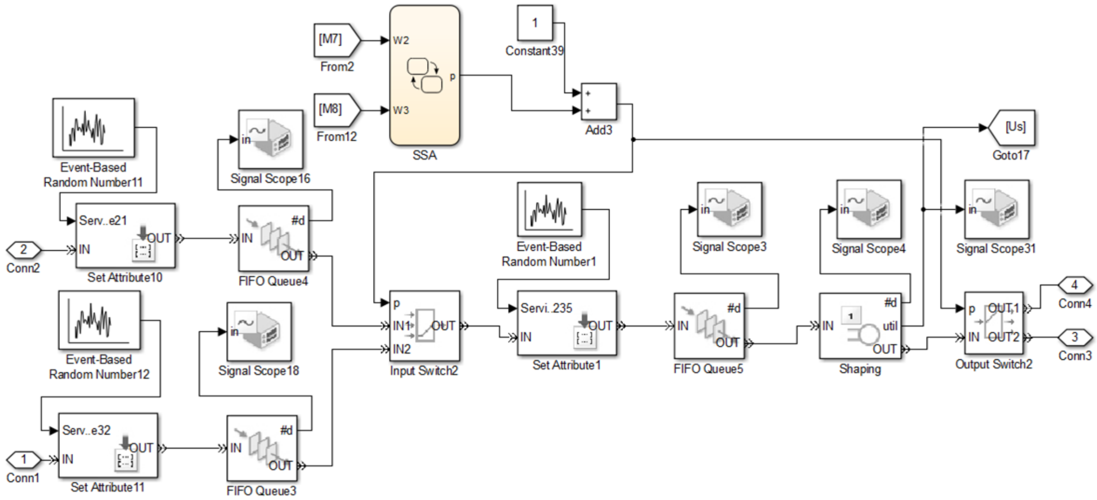

Figure 5.8: Interaction of agents with shaper

5.3.5 Interaction of agents with drilling machine

The interaction of agents with drilling machine is provided in Figure 5.9 which also represents SimEvents model of drilling operation. Here drilling scheduling agent (DSA) takes decision on scheduling of jobs J2 and J3. This DSA facilitates real-time production schedule in drilling operation on the basis of job priority value using SimEvents blocks 'Input Switch' and 'Output Switch'.

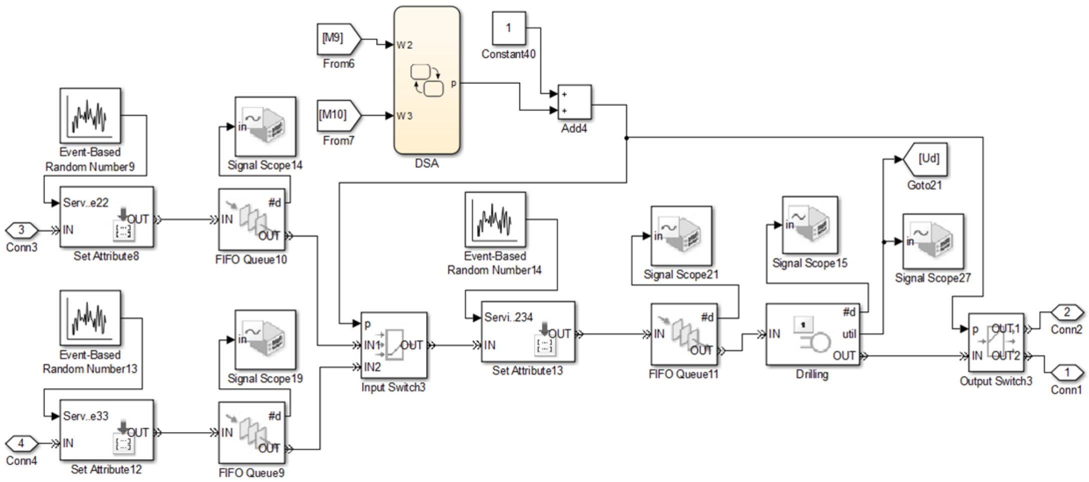

Figure 5.9: Interaction of agents with drilling machine

5.3.6 Interaction of agents with polishing machine

The interaction of agents with polishing machine is shown in Figure 5.10 which also represents SimEvents model of polishing operation. Here polishing scheduling agent (PoSA) takes decision on scheduling of jobs J1 and J3. This PoSA facilitates real-time production schedule in polishing operation on the basis of job priority value using SimEvents blocks 'Input Switch' and 'Output Switch'.

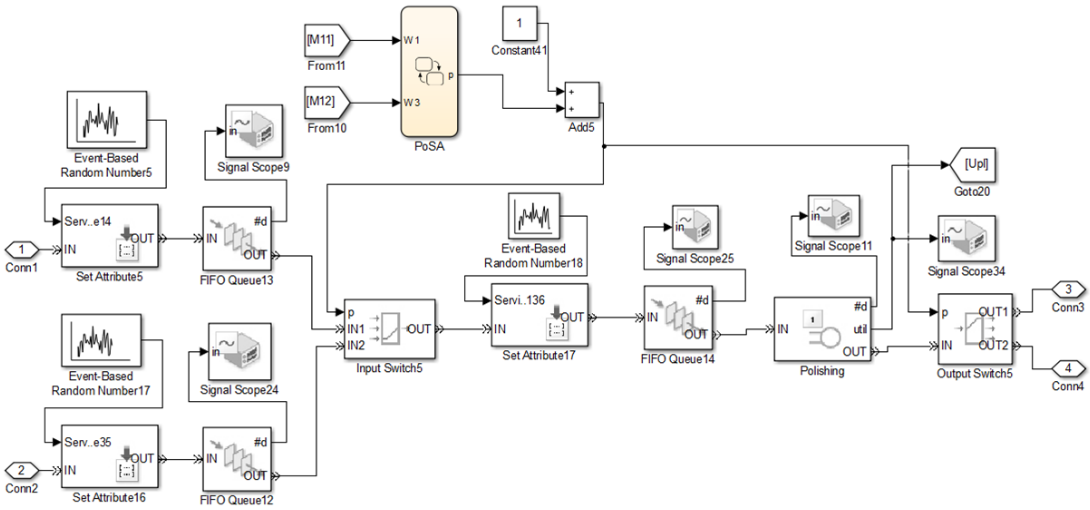

Figure 5.10: Interaction of agents with polishing machine

5.4 Simulation results and performance analysis

The SimEvents simulation tool with Stateflow function libraries (Abar et al., 2017) was used to simulate agent based job-shop manufacturing system (ABJMS) as well as to analyze the results and performance of ABJMS model. Manufacturing system data and basic rules for agent behavior were defined. The simulation runs for 15 days with 8 hours working shift i.e. 432000 seconds. In this simulation experiment, the fine values for late delivery of Jobs 1, 2 and 3 are considered as 1400, 600 and 400 rupees per unit part. The effect of different dispatching rules such as FIFO, LIFO, SPT and LPT are investigated here for the analysis. These are effective rules for job shop scheduling. There are many other dispatching rules which could be used but here the main focus is to analyze the performance measures of ABJMS model. The definitions and related formulas of various performance measures for JMS model are already discussed in chapter 3. The analysis of performance measures for ABJMS model using simulation results is given in the following subsections.

5.4.1 Mean flow time for ABJMS model

Simulation and graphical results of mean flow time (MFT) for ABJMS model are represented by Table 5.2 and Figure 5.11 respectively which provide the different combinations of three jobs with respect to four dispatching rules. The SPT rule has provided the best performance (smallest MFT values) for all the three jobs. While FIFO rule provides the worst performance (highest MFT values) for three jobs. In Table 5.2, zero value represents no part of respective job types is being produced. The following ranking is found in MFT performance measure.

For J1: FIFO <LPT <LIFO <SPT

For J2: FIFO <LIFO, SPT, LPT

For J3: FIFO <LIFO <SPT, LPT

Table 5.2: Simulation results of MFT (in seconds)

Jobs	FIFO	LIFO	SPT	LPT
J1	55204.69	20939.85	18961.18	20993.88
J2	15326.28	0	0	0
J3	61045.43	7860.91	0	0

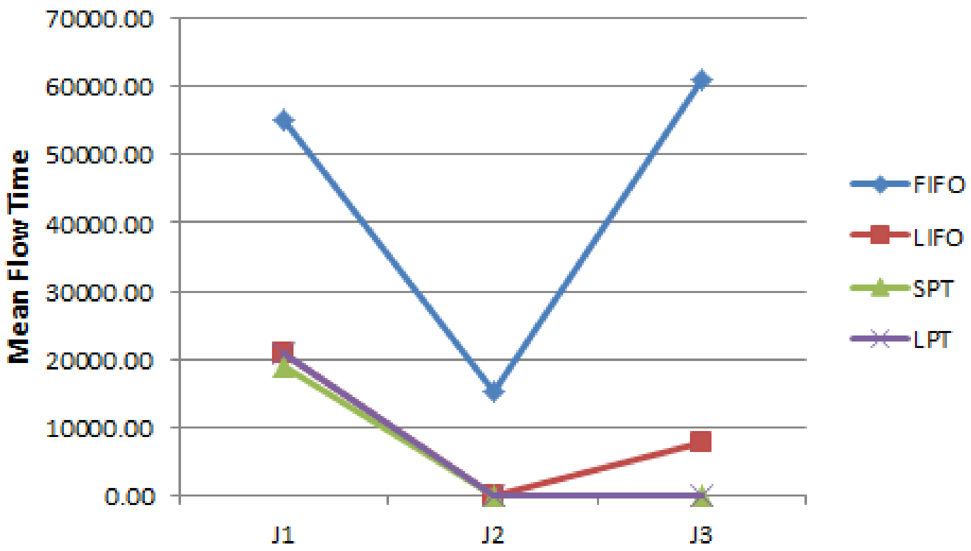

Figure 5.11: Mean Flow Time

5.4.2 Mean tardiness for ABJMS model

Simulation and graphical results of mean tardiness (MT) for ABJMS model are given in Table 5.3 and Figure 5.12 respectively. There are 12 different combinations of three jobs and four dispatching rules. In this simulation results of MT, FIFO rule has provided highest MT values for all three jobs. While MT values for all three jobs are lowest in SPT rule among all dispatching rules. Thus FIFO has shown lowest performance and SPT provides best performance. No part has been produced for J2 and J3 jobs in some dispatching rules which is represented by zero value in Table 5.3. The ranking of all four dispatching rules for MT performance measure is obtained as follows.

For J1: FIFO <LPT <LIFO <SPT.

For J2: FIFO <SPT, LIFO, LPT

For J3: FIFO <LIFO <SPT, LPT

Table 5.3: Simulation results of MT (in seconds)

Jobs	FIFO	LIFO	SPT	LPT
J1	267400.7	199180.5	194397.1	202119.9
J2	65092.34	0	0	0
J3	56050.17	154.14	0	0

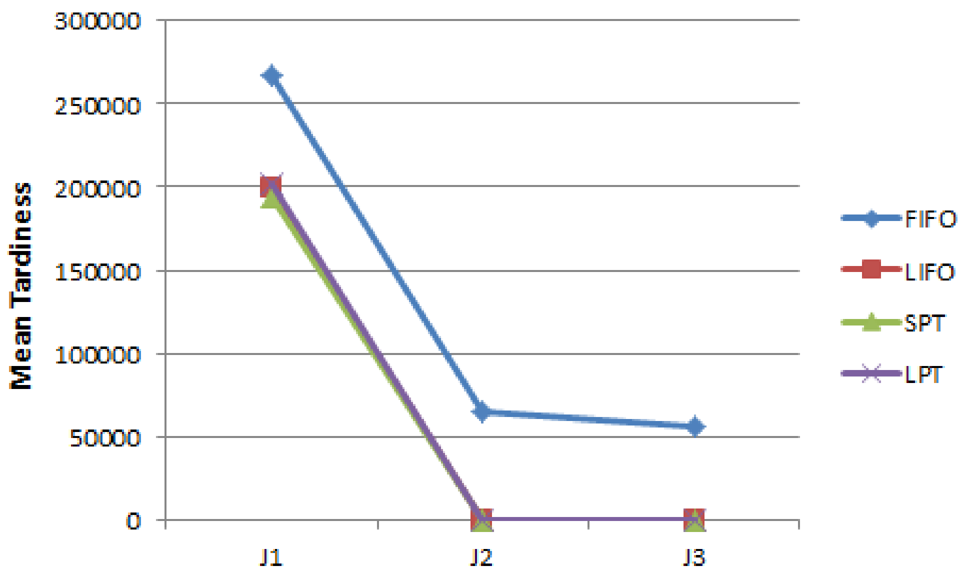

Figure 5.12: Mean Tardiness

5.4.3 Standard deviation of flow time for ABJMS model

Table 5.4 and Figure 5.13 represent the simulation and graphical results of standard deviation of flow time (SDFT) for ABJMS model. The simulation results of SDFT show that ABJMS model perform well in LPT dispatching rule and poor in FIFO rule for all three jobs. When adopting SPT rule, ABJMS model provides higher SDFT value for job type J1. Zero values of SDFT represent no part produced during simulation of ABJMS model. The performance wise ranking of four job dispatching rules for ABJMS model is obtained as follows.

For J1: FIFO <SPT <LIFO <LPT

For J2: FIFO <LIFO, SPT, LPT

For J3: FIFO <LIFO <SPT, LPT

Table 5.4: Simulation results of SDFT (in seconds)

Jobs	FIFO	LIFO	SPT	LPT
J1	27831.86	3598.29	4494.56	2881.45
J2	6297.31	0	0	0
J3	41850.33	1137.07	0	0

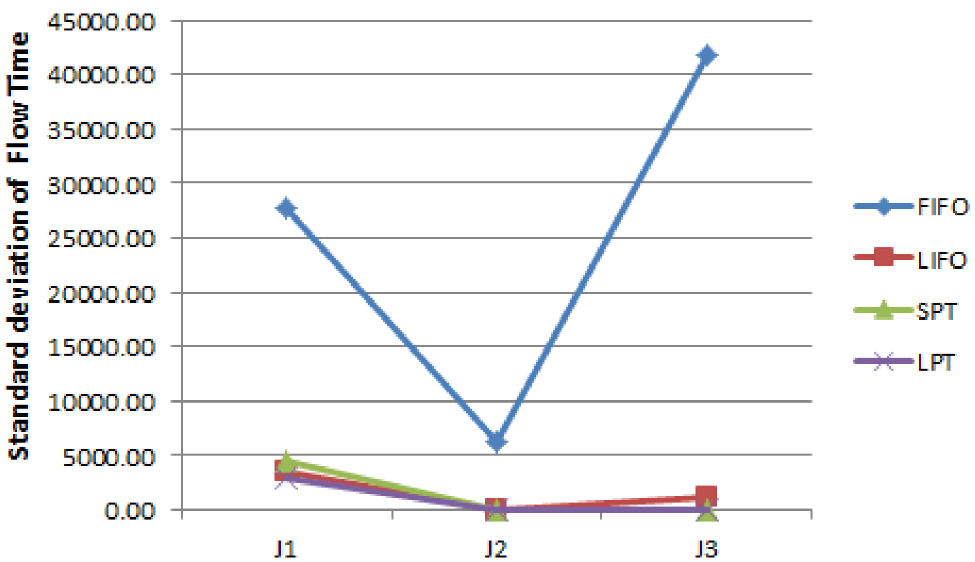

Figure 5.13: Standard Deviation of Flow Time

5.4.4 Standard deviation of tardiness for ABJMS model

Simulation and graphical results of standard deviation of tardiness (SDT) for ABJMS model are given in Table 5.5 and Figure 5.14. These simulation results represent the performance of ABJMS model in terms of SDT values for three jobs with respect to four dispatching rules. In SDT performance measure of ABJMS model, SPT rule provides highest SDT value for job J1 and hence worst in performance ranking. While FIFO rule gives lowest SDT value for job J1 and hence best in performance ranking. Thus performance wise ranking of all four dispatching rules for ABJMS model is found as follows.

For J1: SPT <LIFO <LPT <FIFO

For J2: FIFO <LIFO, SPT, LPT

For J3: FIFO <LIFO <SPT, LPT

Table 5.5: Simulation results of SDT (in seconds)

Jobs	FIFO	LIFO	SPT	LPT
J1	85184.66	124029.7	127046.6	121775
J2	30501.94	0	0	0
J3	40265.19	1100.75	0	0

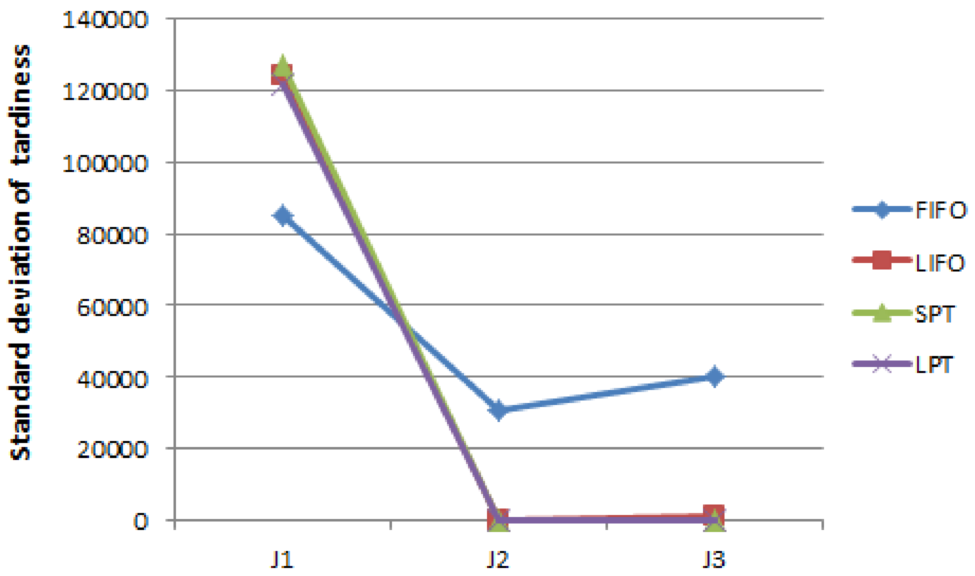

Figure 5.14: Standard Deviation of Tardiness

5.4.5 Production output for ABJMS model

Simulation and graphical results of production output (PO) for ABJMS model are provided in Table 5.6 and Figure 5.15. The simulation results represent the performance of ABJMS model in terms of PO values for three jobs with respect to four dispatching rules. In PO performance measure of ABJMS model, SPT rule provides highest production output for job J1 while no part production for jobs J2 and J3. The FIFO rule provides production output for all three jobs but lowest output for job J1. The performance ranking of dispatching rules for ABJMS model is given as follows.

For J1: FIFO <LPT <LIFO <SPT

For J2: LIFO, SPT, LPT <FIFO

For J3: SPT, LPT <LIFO <FIFO

Table 5.6: Simulation results of PO

Jobs	FIFO	LIFO	SPT	LPT
J1	1437	2042	2220	2004
J2	553	0	0	0
J3	153	1	0	0

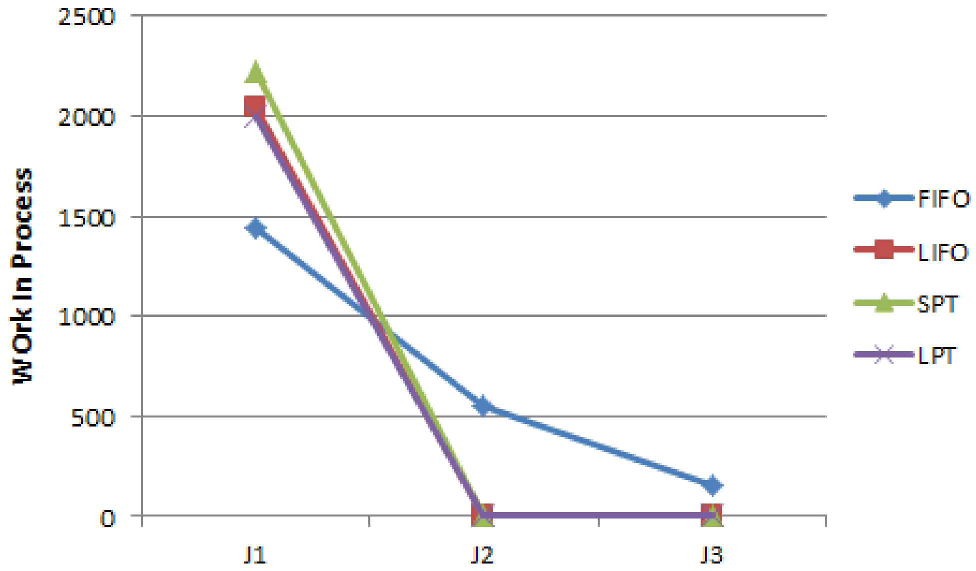

Figure 5.15: Production Output

5.4.6 Work-in-process for ABJMS model

Simulation and graphical results of WIP for ABJMS model are provided in Table 5.6 and Figure 5.16. In WIP performance measure, SPT rule has provided lowest value of WIP for job J1 and hence excellent performance in ranking. While FIFO rule has given lower WIP values for job J2 and J3 and hence better performance in ranking. LIFO, SPT and LPT rules provide 100% WIP values for job J2 while SPT and LPT rules provide 100% WIP values for job J3 as no part is produced of respective jobs during simulation. The performance ranking of four dispatching rules is obtained as follows.

For J1: FIFO <LIFO <LPT <SPT

For J2: LIFO, SPT, LPT <FIFO

For J3: SPT, LPT <LIFO <FIFO

Table 5.7: Simulation results of WIP (in %)

Jobs	FIFO	LIFO	SPT	LPT
J1	12.53	4.75	4.26	4.7
J2	50.49	100	100	100
J3	25.72	98.03	100	100

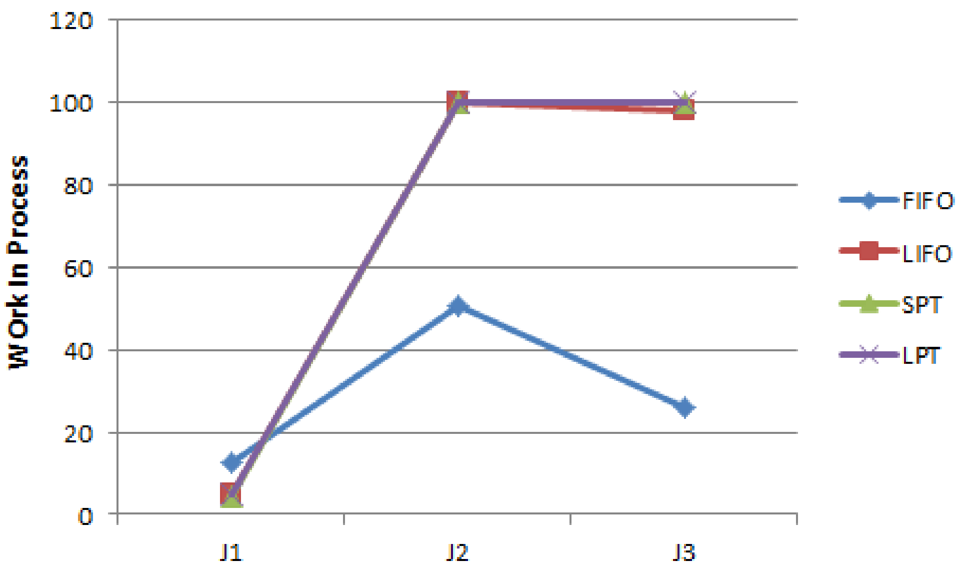

Figure 5.16: Work-In-Process

5.5 Evaluation of ABJMS model

5.5.1 Utilization and job arrival time

To test the behavior of ABJMS with respect to shop utilization, the utilization of each machine in the shop floor was examined with respect to job arrival time. The machine utilization is defined as the proportion of time that a machine is actually in operation. Its value can be calculated using following formula,

$$MU(\%) = \frac{OT}{TAT} \times 100 \tag{5.1}$$

Where MU is Machine Utilization; OT is Operating Time; TAT is Total Available Time.

No machine failure or maintenance was assumed during the simulation. Therefore maximum utilization of each of the machines can be 100% in the situation of over-utilization. Figure 5.17, Figure 5.18, Figure 5.19, Figure 5.20, Figure 5.21 and Figure 5.22 demonstrate the results of the experiment for utilization of casting machine, planer machine, lathe machine, shaper machine, drilling machine and polishing machine respectively.

One can immediately describe that the casting and shaper machines are over utilized from Figure 5.17 and Figure 5.20 for whole time period. As per Figure 5.18, the range of utilization for planer machine is approximate 14 - 39% in decreasing order which shows initially higher number of Job1 and Job3 were processed in planer machine that leads its more utilization in the beginning and as time passes job arrival rate also decreases which determines lower utilization. As inter-arrival time between the jobs increases, the utilization of each machine will decrease. In the beginning, very few jobs were processed in lathe machine as turning operation was the third operation of both Job1 and Job2. Therefore Figure 5.19 shows less utilization of lathe machine at the start but as time goes, the machine utilization was fluctuated from approximate 15% to 34%.

Drilling operation was the second operation of Job2 and third operation of Job3. In this simulation test, the job weightage value of Job2 and Job3 was less than Job1 which was calculated by JWAs using input values and conditions. Therefore, drilling machine was in operating mode for less time i.e. 12373 seconds which was obtained by Figure 5.21. The utilization of drilling machine also fluctuated from approximate 6% to 36% during simulation. Polishing operation was last operation

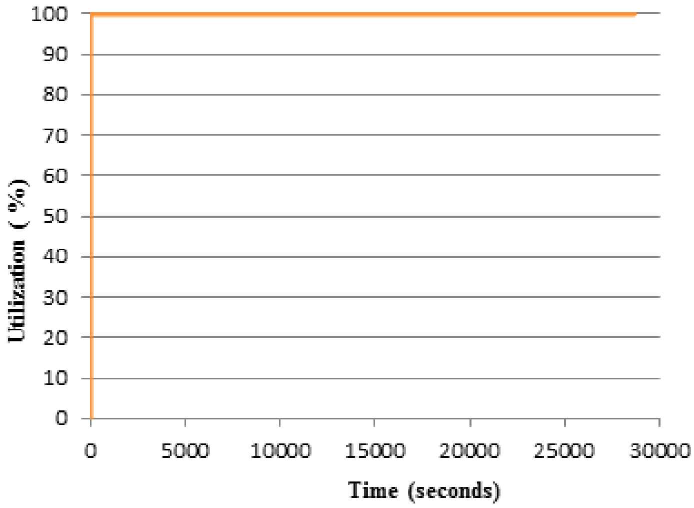

Figure 5.17: Utilization of casting machine

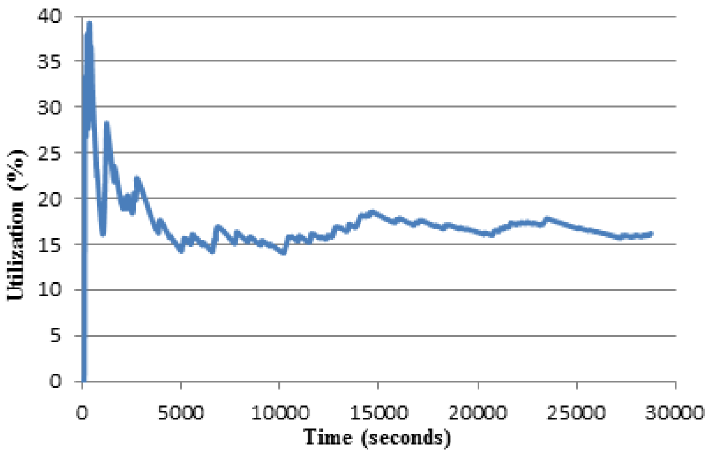

Figure 5.18: Utilization of planer machine

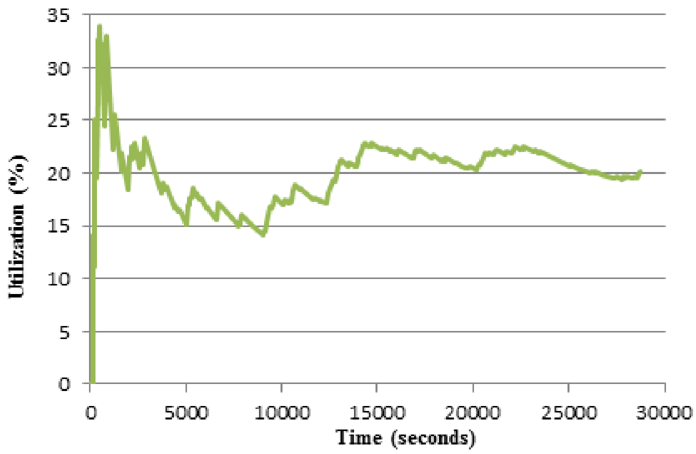

Figure 5.19: Utilization of lathe machine

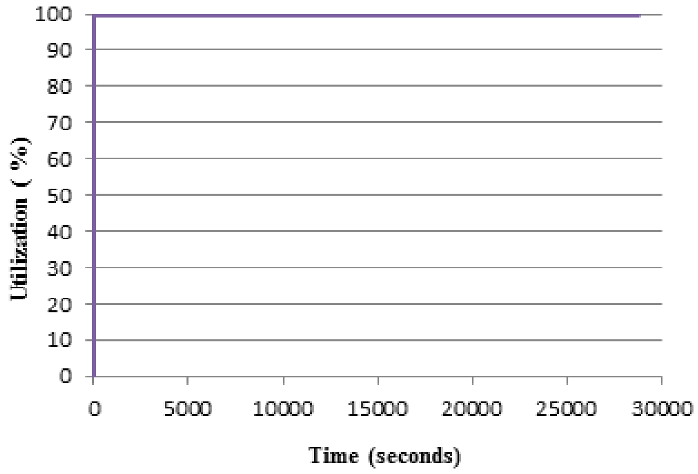

Figure 5.20: Utilization of shaper machine

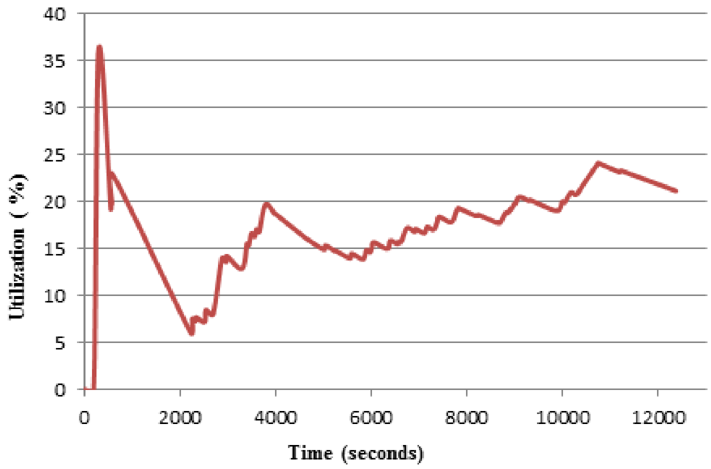

Figure 5.21: Utilization of drilling machine

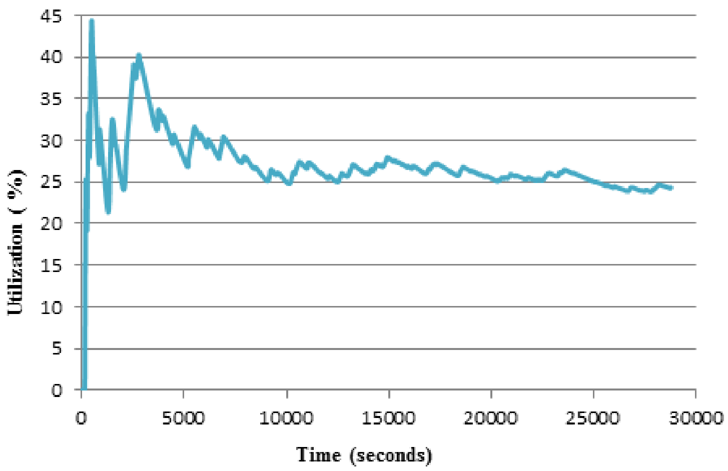

Figure 5.22: Utilization of polishing machine

of Job1 and Job3. Therefore, Figure 5.22 shows less utilization of polishing machine in the beginning i.e. 14% due to processing of few parts but as time passes, the machine utilization was increased and fluctuated in range from approximate 21% to 44%. The polishing machine was utilized for long time during the simulation as more number of parts for Job1 was produced. Hence, in under-capacity state, the utilization of all machines will be lower and it will be higher in over-capacity state. Thus, ABJMS has been evaluated through proper utilization of all machines in the shop floor.

5.5.2 Comparative evaluation of ABJMS and JMS model

The performance of ABJMS model with respect to JMS model is evaluated in terms of utilization of different resources (machines). Table 5.8 and Table 5.9 present the comparative evaluation of performance for ABJMS and JMS model in terms of maximum utilization and average utilization respectively. Maximum utilization is defined as the highest proportion of time at any instant that a machine is actually in operation over a scheduled working time. While average utilization is defined as the proportion of time on an average that a machine is actually in operation for scheduled working time.

Table 5.8: Performance evaluation in terms of "Maximum Utilization"

Resources	**JMS model**	**ABJMS model**	**Percentage increase**
Casting machine	100	100	0
Planer	29.12	39.23	34.72
Lathe machine	15.93	33.92	112.9
Shaper	100	100	0
Drilling machine	28.16	36.15	28.73
Polishing machine	24.58	44.28	80.14

Table 5.9: Performance evaluation in terms of "Average Utilization"

Resources	**JMS model**	**ABJMS model**	**Percentage increase**
Casting machine	100	100	0
Planer	16.46	17.54	6.56
Lathe machine	12.43	20.16	62.18
Shaper	100	100	0
Drilling machine	16.75	17.65	5.37
Polishing machine	17.81	27.30	53.28

The maximum and average utilization of casting and shaper machines in both models are 100% as both machines are busy in most of the time. Casting is the first operation for job 1 and job 3 while shaping is the first operation for job 2. Therefore these both machines are over-utilized. In case of planer machine, maximum utilization is increased by 34.72% and average utilization is increased by 6.56% for ABJMS model. Further the maximum and average utilization of Lathe machine is increased by 112.9% and 62.18% respectively for ABJMS model as compare to JMS model. In case of drilling machine, the maximum and average utilization is increased by 28.73% and 5.37% respectively for ABJMS model. While polishing machine is maximum and average utilized by 80.14% and 53.28% respectively in ABJMS model with respect to JMS model.

5.6 Chapter summary

This chapter has presented agent based simulation modeling approach for real-time production scheduling in JMS which consists of 10 steps. This novel approach used an integrated decision platform in Matlab environment which integrates SimEvents and Stateflow for developing agent based simulation model of JMS. This chapter analyzes the performance of ABJMS model using simulation results of various performance measures such as mean flow time, mean tardiness, standard deviation of flow time, standard deviation of tardiness, production output and WIP. Different dispatching rules such as FIFO, LIFO, SPT and LPT have been analyzed with respect to three jobs for ABJMS model. In most of the performance measures, ABJMS model with SPT rule perform well while FIFO rule provides lower performance. The evaluation of ABJMS model with respect to JMS model has also been discussed on the basis of maximum utilization and average utilization of different machines.

Chapter 6

Conclusion

The final chapter presents the conclusion of the thesis. The emphasis is on how this research has contributed to the body of research in agent based modeling considering real time behavior. The assumptions taken in this research work have been described in different chapters, wherever applicable. This chapter also presents potential areas for future research.

Section 6.1 describes managerial implications and Section 6.2 provides concluding discussion and significant findings of this study followed by highlighting limitations and future research opportunities in Section 6.3.

6.1 Managerial implications

This research work is highly relevant and timely, considering the recent developments in manufacturing due to the growth of Industry 4.0, Smart factories, Internet of Things (IoT), Artificial Intelligence etc. This study has proposed agent based architecture and developed agent based simulation model for job shop manufacturing system. Small and medium sized manufacturing industries such as sheet metal makers, gear, bearing and other automotive parts manufacturers etc. can be benefited from this research work. There are number of managerial implications of this research work which are described as below:

1. On the basis of literature review, a novel framework for implementing MAS in production scheduling was proposed. Any small and medium sized manufacturing industry can adopt this framework for applying the concept of MAS in its manufacturing system.

2. The case study considered in this research work is practical in the sense that it includes three jobs and six machine types job shop problem which enables the manufacturing firms to apply MAS concept in any problem size of JMS.

3. The proposed agent based architecture provides the information about the hierarchical arrangement of agents as per communication flow. This enables the SMEs to apply hierarchical architecture with functional agents using direct coordination mechanism in their JMSs.

4. This research work provides agent based solution for production scheduling problem in a JMS using SimEvents with Stateflow functions. This agent based simulation tool was dedicated to solve DES based problems. Hence this study enables the SMEs to take advantage of real time communication between agents through this agent based simulation tool for their discrete event problems.

6.2 Concluding discussion and significant contributions

In this research work, the literature review revealed that a number of key issues were responsible for the implementation of MAS in production scheduling problems. Several MAS platforms were also identified from different research works. The detailed explanation of each key issue was described in literature review chapter. The detailed understanding of each key issue had helped to build a conceptual framework for developing agent based model of a production scheduling system. It was observed that handling dynamic changes in manufacturing system is one of the critical issue and this has been addressed by the researchers in two ways; first, dynamic changes occur outside the system and second, it occur within the system. Additionally it was also observed that the researchers adopted analytical based traditional approaches with heuristic/ meta-heuristic techniques to solve job-shop scheduling problems in a large extent. Although some studies had considered simulation based approach for addressing this type of problems. Hence this study contributes to the related literature in this context and presents agent based simulation modeling approach to solve this complex type problem. Other than above observations, some major contributions are given below:

1. A novel framework for implementing MAS in production scheduling is proposed in this research work which is able to answer a number of important

questions related to modeling of agent based manufacturing system.

2. This study describes discrete event simulation modeling approach for developing discrete event model of JMS.

3. This study introduces dynamic changes within the manufacturing system through real time events.

4. This study presents a case study of three jobs and six machine types complex job-shop problem which is analyzed for testing agent based architecture.

5. Different agents are developed according to their functionality for considered job shop problem.

6. This study introduces agent based simulation modeling approach for real time production scheduling in JMS.

7. A new agent based simulation tool (SimEvents together with Stateflow Functions libraries) is explored in this study. This simulation tool is best suited for discrete event type problems. Here SimEvents is used for developing discrete event model of JMS and Stateflow functions libraries are used for developing agent based model of JMS.

8. This study analyzes the performance of ABJMS model using various performance measures. It also evaluates ABJMS model with respect to JMS model in terms of maximum utilization and average utilization of different machines.

6.3 Limitations and future research scope

This study contains some unique aspects like discrete event modeling and agent based simulation approach for production scheduling in JMS under dynamic changes which have significant potential for application in modern industry. Any such research aimed at meeting the academic requirements is bound to suffer from certain limitations. This study is not an exception as well. While deliberating various aspects related to the study reported in this thesis, a few points were noticed which could be identified as the limitations of the present research work, some of which are as follows. In this study, the prioritization of jobs is done on the basis of tardiness values of each job entity by respective JWA. While demand wise job priority rule might have been adopted for further scheduling of jobs. This study has attempted to give reliable results through simulation run of ABJMS model for a working shift of 8 hours. While the simulation experiments could have been run for a month or more than a month which could give more elaborative results.

In essence, this research has resulted in systematic and practical approaches for dealing with various issues in agent based architecture and ABJMS simulation model. Practically it has attempted to address the problem of production scheduling under dynamic changes in JMS that are of significant importance to the industry and also bridges the gaps identified from the literature. It is envisaged that this would open avenues for many more research studies in future. The future scope of the research can be summarized as follows.

1. This study considered three jobs and six machine types job shop problem in a manufacturing system and each machine type consists only one machine. More number of machines can be included in each machine type to make it more complex job shop problem.

2. This study can be extended with occurrence of machine breakdown or maintenance in the proposed ABJMS model.

3. Other job dispatching rules like earliest due date, slack per remaining process time, weighted shortest process time etc. can also be included for performance analysis of ABJMS model.

4. The dynamic behavior can be introduced in the ABJMS model from outside the manufacturing system simultaneously real time events occur within the system.

Appendix I

Input values used for simulation of JMS model

Input values used for job 1 using FIFO dispatching rule						
Ai	**Oi**	**FTi**	**Jti**	**Di**	**Ci**	**Ti**
0	199.23	199.23	225	28855.52	199.2335	0
11	717.31	706.31	224	28737.73	717.312	0
29	2408.40	2379.40	223	28626.93	2408.399	0
34	2617.42	2583.42	222	28503.14	2617.419	0
44	3470.58	3426.58	221	28384.35	3470.58	0
50	3612.95	3562.95	220	28261.55	3612.952	0
64	3943.02	3879.02	219	28146.76	3943.024	0
73	4967.13	4894.13	218	28026.96	4967.132	0
76	5552.33	5476.33	217	27901.17	5552.332	0
85	6152.20	6067.20	216	27781.37	6152.204	0
93	6291.42	6198.42	215	27660.58	6291.424	0
105	6757.41	6652.41	214	27543.79	6757.411	0
113	6795.71	6682.71	213	27422.99	6795.714	0
132	7320.69	7188.69	212	27313.2	7320.691	0
143	7669.46	7526.46	211	27195.4	7669.457	0
146	7979.92	7833.92	210	27069.61	7979.923	0
150	8346.68	8196.68	209	26944.81	8346.682	0
161	8962.72	8801.72	208	26827.02	8962.722	0
170	9148.03	8978.03	207	26707.23	9148.034	0
177	9171.06	8994.06	206	26585.43	9171.058	0
190	9639.81	9449.81	205	26469.64	9639.809	0
203	10331.85	10128.85	204	26353.84	10331.85	0
210	10978.37	10768.37	203	26232.05	10978.37	0
225	11046.42	10821.42	202	26118.25	11046.42	0
237	11359.72	11122.72	201	26001.46	11359.72	0
245	11817.28	11572.28	200	25880.67	11817.28	0
256	15097.76	14841.76	199	25762.87	15097.76	0
265	15403.44	15138.44	198	25643.08	15403.44	0
277	15529.61	15252.61	197	25526.28	15529.61	0
282	16791.56	16509.56	196	25402.49	16791.56	0
292	17178.00	16886.00	195	25283.69	17178	0
298	18125.73	17827.73	194	25160.9	18125.73	0
309	18638.83	18329.83	193	25043.1	18638.83	0
316	19424.92	19108.92	192	24921.31	19424.92	0
330	20715.37	20385.37	191	24806.52	20715.37	0
341	20858.77	20517.77	190	24688.72	20858.77	0
360	21053.02	20693.02	189	24578.93	21053.02	0
376	21777.11	21401.11	188	24466.13	21777.11	0
383	22476.87	22093.87	187	24344.34	22476.87	0
392	22626.44	22234.44	186	24224.54	22626.44	0
405	24175.64	23770.64	185	24108.75	24175.64	66.89
412	24926.68	24514.68	184	23986.96	24926.68	939.73
420	25347.01	24927.01	183	23866.16	25347.01	1480.85
426	25606.95	25180.95	182	23743.37	25606.95	1863.58
433	27145.33	26712.33	181	23621.57	27145.33	3523.75
445	27792.48	27347.48	180	23504.78	27792.48	4287.70
454	27912.25	27458.25	179	23384.98	27912.25	4527.27
461	28266.66	27805.66	178	23263.19	28266.66	5003.47
473	28314.22	27841.22	177	23146.4	28314.22	5167.82

Input values used for job 2 using FIFO dispatching rule						
Ai	Oi	FTi	Jti	Di	Ci	Ti
0.00	311.01	311.01	175	16891.86	311.01	0
6.00	699.62	693.62	174	16801.26	699.62	0
22.00	2417.17	2395.17	173	16720.66	2417.17	0
25.00	2961.62	2936.62	172	16627.07	2961.62	0
31.00	3396.69	3365.69	171	16536.47	3396.69	0
37.00	3666.66	3629.66	170	16445.88	3666.66	0
47.00	4008.65	3961.65	169	16359.28	4008.65	0
60.00	5062.24	5002.24	168	16275.69	5062.24	0
74.00	5585.16	5511.16	167	16193.09	5585.16	0
79.00	6144.84	6065.84	166	16101.49	6144.84	0
84.00	6411.14	6327.14	165	16009.90	6411.14	0
95.00	6722.87	6627.87	164	15924.30	6722.87	0
98.00	7034.45	6936.45	163	15830.71	7034.45	0
104.00	7413.83	7309.83	162	15740.11	7413.83	0
113.00	7818.50	7705.50	161	15652.51	7818.50	0
118.00	7983.69	7865.69	160	15560.92	7983.69	0
121.00	8375.07	8254.07	159	15467.32	8375.07	0
133.00	8850.09	8717.09	158	15382.73	8850.09	0
145.00	9102.48	8957.48	157	15298.13	9102.48	0
154.00	9159.44	9005.44	156	15210.54	9159.44	0
162.00	9991.30	9829.30	155	15121.94	9991.30	0
167.00	10470.09	10303.09	154	15030.34	10470.09	0
173.00	10987.20	10814.20	153	14939.75	10987.20	0
178.00	11114.85	10936.85	152	14848.15	11114.85	0
188.00	11229.66	11041.66	151	14761.56	11229.66	0
198.00	12673.50	12475.50	150	14674.96	12673.50	0
209.00	15108.20	14899.20	149	14589.37	15108.20	518.84
213.00	15425.20	15212.20	148	14496.77	15425.20	928.43
215.00	15791.51	15576.51	147	14402.17	15791.51	1389.33
226.00	16852.08	16626.08	146	14316.58	16852.08	2535.50
230.00	17319.93	17089.93	145	14223.98	17319.93	3095.95
240.00	18274.82	18034.82	144	14137.39	18274.82	4137.44
247.00	19266.02	19019.02	143	14047.79	19266.02	5218.23
254.00	20495.94	20241.94	142	13958.20	20495.94	6537.74
261.00	20737.44	20476.44	141	13868.60	20737.44	6868.84
269.00	20915.82	20646.82	140	13780.00	20915.82	7135.82
272.00	21057.69	20785.69	139	13686.41	21057.69	7371.29
280.00	21707.55	21427.55	138	13597.81	21707.55	8109.74
289.00	22505.84	22216.84	137	13510.22	22505.84	8995.62
290.00	23665.30	23375.30	136	13414.62	23665.30	10250.67
296.00	24494.07	24198.07	135	13324.03	24494.07	11170.04
303.00	25081.53	24778.53	134	13234.43	25081.53	11847.10
311.00	25535.05	25224.05	133	13145.83	25535.05	12389.21
322.00	25617.87	25295.87	132	13060.24	25617.87	12557.63
330.00	27463.63	27133.63	131	12971.64	27463.63	14491.99
331.00	27765.04	27434.04	130	12876.05	27765.04	14888.99
336.00	27984.17	27648.17	129	12784.45	27984.17	15199.72
344.00	28239.62	27895.62	128	12695.86	28239.62	15543.77
353.00	28335.88	27982.88	127	12608.26	28335.88	15727.62

Input values used for job 3 using FIFO dispatching rule						
Ai	**Oi**	**FTi**	**Jti**	**Di**	**Ci**	**Ti**
0.00	584.78	584.78	225	36359.40	584.78	0
6.00	2400.47	2394.47	224	36204.41	2400.47	0
16.00	2595.61	2579.61	223	36053.42	2595.61	0
22.00	3034.30	3012.30	222	35898.43	3034.30	0
31.00	3606.19	3575.19	221	35746.43	3606.19	0
39.00	3935.00	3896.00	220	35593.44	3935.00	0
47.00	4917.09	4870.09	219	35440.45	4917.09	0
56.00	5281.35	5225.35	218	35288.45	5281.35	0
64.00	6011.64	5947.64	217	35135.46	6011.64	0
73.00	6275.96	6202.96	216	34983.47	6275.96	0
83.00	6719.81	6636.81	215	34832.48	6719.81	0
91.00	6792.41	6701.41	214	34679.48	6792.41	0
104.00	7297.44	7193.44	213	34531.49	7297.44	0
110.00	7611.14	7501.14	212	34376.50	7611.14	0
119.00	7887.70	7768.70	211	34224.50	7887.70	0
124.00	8245.25	8121.25	210	34068.51	8245.25	0
130.00	8732.68	8602.68	209	33913.52	8732.68	0
140.00	9019.40	8879.40	208	33762.52	9019.40	0
147.00	9160.89	9013.89	207	33608.53	9160.89	0
155.00	9505.95	9350.95	206	33455.54	9505.95	0
161.00	10255.87	10094.87	205	33300.55	10255.87	0
167.00	10815.89	10648.89	204	33145.55	10815.89	0
170.00	10997.29	10827.29	203	32987.56	10997.29	0
177.00	11056.07	10879.07	202	32833.57	11056.07	0
184.00	11638.88	11454.88	201	32679.57	11638.88	0
194.00	15004.46	14810.46	200	32528.58	15004.46	0
203.00	15268.45	15065.45	199	32376.59	15268.45	0
215.00	15427.47	15212.47	198	32227.60	15427.47	0
225.00	16605.30	16380.30	197	32076.60	16605.30	0
229.00	17044.06	16815.06	196	31919.61	17044.06	0
237.00	17826.20	17589.20	195	31766.62	17826.20	0
244.00	18489.22	18245.22	194	31612.62	18489.22	0
247.00	19366.88	19119.88	193	31454.63	19366.88	0
250.00	20530.13	20280.13	192	31296.64	20530.13	0
260.00	20734.77	20474.77	191	31145.65	20734.77	0
268.00	20930.53	20662.53	190	30992.65	20930.53	0
274.00	21411.06	21137.06	189	30837.66	21411.06	0
279.00	22436.05	22157.05	188	30681.67	22436.05	0
284.00	22593.56	22309.56	187	30525.67	22593.56	0
293.00	24156.78	23863.78	186	30373.68	24156.78	0
300.00	24918.35	24618.35	185	30219.69	24918.35	0
311.00	25308.14	24997.14	184	30069.70	25308.14	0
315.00	25583.07	25268.07	183	29912.70	25583.07	0
325.00	26931.63	26606.63	182	29761.71	26931.63	0
332.00	27585.69	27253.69	181	29607.72	27585.69	0
340.00	27797.64	27457.64	180	29454.72	27797.64	0
347.00	28184.84	27837.84	179	29300.73	28184.84	0
355.00	28304.29	27949.29	178	29147.74	28304.29	0

Input values used for job 1 using SPT dispatching rule						
Ai	**Ei**	**FTi**	**Jti**	**Di**	**Ci**	**Ti**
0	200.00	200	296	27442.75	200	0
16	465.60	449.6	295	27365.62	465.6	0
22	604.20	582.2	294	27278.49	604.2	0
30	683.00	653	293	27193.36	683	0
41	1308.50	1267.5	292	27111.24	1308.5	0
49	1432.00	1383	291	27026.11	1432	0
60	1452.80	1392.8	290	26943.98	1452.8	0
69	1646.70	1577.7	289	26859.85	1646.7	0
76	1777.00	1701	288	26773.72	1777	0
91	1806.50	1715.5	287	26695.59	1806.5	0
96	1965.00	1869	286	26607.47	1965	0
103	2003.00	1900	285	26521.34	2003	0
108	2327.00	2219	284	26433.21	2327	0
121	2407.00	2286	283	26353.08	2407	0
127	2614.00	2487	282	26265.95	2614	0
134	2690.00	2556	281	26179.83	2690	0
146	2942.00	2796	280	26098.70	2942	0
157	3360.00	3203	279	26016.57	3360	0
163	3543.00	3380	278	25929.44	3543	0
175	3566.50	3391.5	277	25848.31	3566.5	0
183	3929.00	3746	276	25763.18	3929	0
191	4075.00	3884	275	25678.06	4075	0
197	4662.00	4465	274	25590.93	4662	0
206	4730.00	4524	273	25506.80	4730	0
213	5043.00	4830	272	25420.67	5043	0
227	5430.00	5203	271	25341.54	5430	0
239	5452.00	5213	270	25260.42	5452	0
249	5578.00	5329	269	25177.29	5578	0
258	5833.00	5575	268	25093.16	5833	0
266	6126.00	5860	267	25008.03	6126	0
283	6480.00	6197	266	24931.90	6480	0
288	6744.00	6456	265	24843.77	6744	0
296	6931.00	6635	264	24758.65	6931	0
305	7000.00	6695	263	24674.52	7000	0
317	7178.00	6861	262	24593.39	7178	0
330	7322.00	6992	261	24513.26	7322	0
343	7516.00	7173	260	24433.13	7516	0
352	8285.00	7933	259	24349.01	8285	0
362	8332.00	7970	258	24265.88	8332	0
374	8364.50	7990.5	257	24184.75	8364.5	0
380	8774.00	8394	256	24097.62	8774	0
384	8957.00	8573	255	24008.49	8957	0
392	9040.00	8648	254	23923.36	9040	0
402	9216.00	8814	253	23840.24	9216	0
408	9895.00	9487	252	23753.11	9895	0
419	10040.00	9621	251	23670.98	10040	0
428	10150.00	9722	250	23586.85	10150	0
434	10220.00	9786	249	23499.72	10220	0
446	10260.00	9814	248	23418.59	10260	0
449	10780.00	10331	247	23328.47	10780	0
461	10827.00	10366	246	23247.34	10827	0
471	11051.00	10580	245	23164.21	11051	0
479	11530.00	11051	244	23079.08	11530	0
487	11590.00	11103	243	22993.95	11590	0
497	12160.00	11663	242	22910.83	12160	0
503	12265.00	11762	241	22823.70	12265	0
513	12550.00	12037	240	22740.57	12550	0

515	13055.00	12540	239	22649.44	13055	0
526	13094.00	12568	238	22567.31	13094	0
538	13372.00	12834	237	22486.18	13372	0
552	13417.00	12865	236	22407.06	13417	0
555	13734.00	13179	235	22316.93	13734	0
568	13974.00	13406	234	22236.80	13974	0
578	14050.00	13472	233	22153.67	14050	0
584	14345.00	13761	232	22066.54	14345	0
597	14715.00	14118	231	21986.42	14715	0
612	14924.00	14312	230	21908.29	14924	0
623	15345.00	14722	229	21826.16	15345	0
630	15428.00	14798	228	21740.03	15428	0
641	15674.00	15033	227	21657.90	15674	0
648	16170.00	15522	226	21571.77	16170	0
655	16340.00	15685	225	21485.65	16340	0
663	16670.00	16007	224	21400.52	16670	0
673	16930.00	16257	223	21317.39	16930	0
682	17225.00	16543	222	21233.26	17225	0
690	17720.00	17030	221	21148.13	17720	0
701	17735.00	17034	220	21066.01	17735	0
709	18040.00	17331	219	20980.88	18040	0
713	18145.00	17432	218	20891.75	18145	0
721	18230.00	17509	217	20806.62	18230	0
731	18570.00	17839	216	20723.49	18570	0
742	18990.00	18248	215	20641.36	18990	0
755	19145.00	18390	214	20561.24	19145	0
765	19290.00	18525	213	20478.11	19290	0
771	19580.00	18809	212	20390.98	19580	0
781	20115.00	19334	211	20307.85	20115	0
791	20220.00	19429	210	20224.72	20220	0
800	20745.00	19945	209	20140.59	20745	604.41
810	21000.00	20190	208	20057.47	21000	942.53
821	21030.00	20209	207	19975.34	21030	1054.66
828	21350.00	20522	206	19889.21	21350	1460.79
835	21610.00	20775	205	19803.08	21610	1806.92
843	22010.00	21167	204	19717.95	22010	2292.05
850	22250.00	21400	203	19631.83	22250	2618.17
858	22365.00	21507	202	19546.70	22365	2818.30
868	22716.00	21848	201	19463.57	22716	3252.43
872	23210.00	22338	200	19374.44	23210	3835.56
882	23654.00	22772	199	19291.31	23654	4362.69
888	23783.00	22895	198	19204.18	23783	4578.82
895	24530.00	23635	197	19118.06	24530	5411.94
900	24542.00	23642	196	19029.93	24542	5512.07
907	24685.00	23778	195	18943.80	24685	5741.20
910	24865.00	23955	194	18853.67	24865	6011.33
918	25235.00	24317	193	18768.54	25235	6466.46
921	25445.00	24524	192	18678.42	25445	6766.58
930	25950.00	25020	191	18594.29	25950	7355.71
937	26360.00	25423	190	18508.16	26360	7851.84
947	26695.00	25748	189	18425.03	26695	8269.97
956	26746.00	25790	188	18340.90	26746	8405.10
966	27113.00	26147	187	18257.77	27113	8855.23
975	27413.00	26438	186	18173.65	27413	9239.35
985	27670.00	26685	185	18090.52	27670	9579.48
994	28070.00	27076	184	18006.39	28070	10063.61
1004	28355.00	27351	183	17923.26	28355	10431.74

Input values used for job 2 using SPT dispatching rule						
Ai	**Oi**	**FTi**	**Jti**	**Di**	**Ci**	**Ti**
0	311	311	246	17169.75	311	0
4	448	444	245	17103.91	448	0
17	613	596	244	17047.06	613	0
22	885	863	243	16982.22	885	0
29	1220	1191	242	16919.37	1220	0
36	1333.6	1297.6	241	16856.52	1333.6	0
46	1355	1309	240	16796.68	1355	0
55	1424	1369	239	16735.83	1424	0
58	1588.5	1530.5	238	16668.98	1588.5	0
64	1700	1636	237	16605.14	1700	0
68	1776.7	1708.7	236	16539.29	1776.7	0
71	1883.6	1812.6	235	16472.45	1883.6	0
75	2052.5	1977.5	234	16406.6	2052.5	0
82	2276	2194	233	16343.75	2276	0
89	2515.6	2426.6	232	16280.91	2515.6	0
96	2680	2584	231	16218.06	2680	0
100	3088	2988	230	16152.22	3088	0
105	3245.6	3140.6	229	16087.37	3245.6	0
111	3500	3389	228	16023.52	3500	0
119	3555	3436	227	15961.68	3555	0
126	3870	3744	226	15898.83	3870	0
134	4154	4020	225	15836.98	4154	0
142	4671	4529	224	15775.14	4671	0
150	4757	4607	223	15713.29	4757	0
155	4868.2	4713.2	221	15578.6	4868.2	0
165	5400	5235	220	15518.75	5400	0
168	5494	5326	219	15451.91	5494	0
170	5523.7	5353.7	218	15384.06	5523.7	0
174	5780	5606	217	15318.22	5780	0
179	6185	6006	216	15253.37	6185	0
184	6465	6281	215	15188.52	6465	0
191	6769	6578	214	15125.68	6769	0
202	6818	6616	213	15066.83	6818	0
211	6965	6754	212	15005.98	6965	0
220	7200	6980	211	14945.14	7200	0
231	7379	7148	210	14886.29	7379	0
236	7588.5	7352.5	209	14821.45	7588.5	0
243	8215	7972	208	14758.6	8215	0
249	8319.5	8070.5	207	14694.75	8319.5	0
254	8354	8100	206	14629.91	8354	0
260	8816	8556	205	14566.06	8816	0
266	8834.5	8568.5	204	14502.22	8834.5	0
270	8990	8720	203	14436.37	8990	0
279	9227	8948	202	14375.52	9227	0
286	9826.5	9540.5	201	14312.68	9826.5	0
290	9980	9690	200	14246.83	9980	0
296	10060	9764	199	14182.98	10060	0
305	10165	9860	198	14122.14	10165	0
309	10274	9965	197	14056.29	10274	0
314	10670	10356	196	13991.45	10670	0
319	10940	10621	195	13926.6	10940	0
325	11165	10840	194	13862.75	11165	0
329	11527	11198	193	13796.91	11527	0
333	11845	11512	192	13731.06	11845	0
336	12205	11869	191	13664.22	12205	0
346	12415	12069	190	13604.37	12415	0
354	12467	12113	189	13542.52	12467	0

360	13050	12690	188	13478.68	13050	0
366	13115	12749	187	13414.83	13115	0
375	13382	13007	186	13353.98	13382	28.02
384	13480	13096	185	13293.14	13480	186.86
388	13694	13306	184	13227.29	13694	466.71
394	13830	13436	183	13163.45	13830	666.55
399	13930	13531	182	13098.6	13930	831.40
405	14232	13827	181	13034.75	14232	1197.25
412	14715	14303	180	12971.91	14715	1743.09
419	14850	14431	179	12909.06	14850	1940.94
423	15320	14897	178	12843.22	15320	2476.78
431	15467	15036	177	12781.37	15467	2685.63
440	15863	15423	176	12720.52	15863	3142.48
447	16155	15708	175	12657.68	16155	3497.32
453	16312	15859	174	12593.83	16312	3718.17
464	16657	16193	173	12534.98	16657	4122.02
465	17130	16665	172	12466.14	17130	4663.86
468	17325	16857	171	12399.29	17325	4925.71
472	17670	17198	170	12333.45	17670	5336.55
484	17997	17513	169	12275.6	17997	5721.40
486	18120	17634	168	12207.75	18120	5912.25
497	18157	17660	167	12148.91	18157	6008.09
502	18236	17734	166	12084.06	18236	6151.94
510	18825	18315	165	12022.22	18825	6802.78
516	18996	18480	164	11958.37	18996	7037.63
522	19245	18723	163	11894.52	19245	7350.48
529	19304	18775	162	11831.68	19304	7472.32
535	19525	18990	161	11767.83	19525	7757.17
542	20090	19548	160	11704.98	20090	8385.02
548	20314	19766	159	11641.14	20314	8672.86
556	20790	20234	158	11579.29	20790	9210.71
563	20980	20417	157	11516.45	20980	9463.55
574	21035	20461	156	11457.6	21035	9577.40
580	21517	20937	155	11393.75	21517	10123.25
584	21642	21058	154	11327.91	21642	10314.09
593	21870	21277	153	11267.06	21870	10602.94
603	22130	21527	152	11207.22	22130	10922.78
614	22365	21751	151	11148.37	22365	11216.63
626	22714	22088	150	11090.52	22714	11623.48
632	23213	22581	149	11026.68	23213	12186.32
640	23717	23077	148	10964.83	23717	12752.17
652	23900	23248	147	10906.98	23900	12993.02
661	24518	23857	146	10846.14	24518	13671.86
667	24530	23863	145	10782.29	24530	13747.71
675	24750	24075	144	10720.45	24750	14029.55
687	24955	24268	143	10662.6	24955	14292.40
694	25258	24564	142	10599.75	25258	14658.25
700	25385	24685	141	10535.91	25385	14849.09
709	26100	25391	140	10475.06	26100	15624.94
717	26415	25698	139	10413.22	26415	16001.78
719	26747	26028	138	10345.37	26747	16401.63
730	26900	26170	137	10286.52	26900	16613.48
733	27090	26357	136	10219.68	27090	16870.32
736	27456	26720	135	10152.83	27456	17303.17
743	27755	27012	134	10089.98	27755	17665.02
750	28095	27345	133	10027.14	28095	18067.86
757	28400	27643	132	9964.292	28400	18435.71
765	28740	27975	131	9902.446	28740	18837.55

Input values used for job 3 using SPT dispatching rule						
Ai	**Oi**	**Fti**	**Jti**	**Di**	**Ci**	**Ti**
0.00	333.14	333.14	295	34477.03	333.14	0
13.00	596.19	583.19	294	34373.62	596.19	0
29.00	661.28	632.28	293	34273.21	661.28	0
37.00	872.54	835.54	292	34164.79	872.54	0
48.00	1315.58	1267.58	291	34059.38	1315.58	0
64.00	1439.80	1375.80	290	33958.97	1439.80	0
73.00	1502.82	1429.82	289	33851.56	1502.82	0
76.00	1675.45	1599.45	288	33738.15	1675.45	0
80.00	1790.99	1710.99	287	33625.74	1790.99	0
89.00	1841.12	1752.12	286	33518.33	1841.12	0
96.00	1968.18	1872.18	285	33408.92	1968.18	0
101.00	2040.78	1939.78	284	33297.51	2040.78	0
113.00	2348.43	2235.43	283	33193.10	2348.43	0
119.00	2469.15	2350.15	282	33082.69	2469.15	0
132.00	2683.58	2551.58	281	32979.28	2683.58	0
138.00	2840.98	2702.98	280	32868.87	2840.98	0
146.00	3128.16	2982.16	279	32760.46	3128.16	0
160.00	3414.88	3254.88	278	32658.05	3414.88	0
167.00	3553.68	3386.68	277	32548.64	3553.68	0
174.00	3795.02	3621.02	276	32439.23	3795.02	0
183.00	3999.69	3816.69	275	32331.82	3999.69	0
189.00	4499.37	4310.37	274	32221.41	4499.37	0
196.00	4680.76	4484.76	273	32112.00	4680.76	0
205.00	4739.55	4534.55	272	32004.59	4739.55	0
211.00	5252.02	5041.02	271	31894.18	5252.02	0
218.00	5436.18	5218.18	270	31784.77	5436.18	0
224.00	5572.08	5348.08	269	31674.36	5572.08	0
231.00	5588.28	5357.28	268	31564.95	5588.28	0
238.00	5940.07	5702.07	267	31455.54	5940.07	0
246.00	6378.84	6132.84	266	31347.13	6378.84	0
252.00	6517.52	6265.52	265	31236.72	6517.52	0
258.00	6771.58	6513.58	264	31126.31	6771.58	0
264.00	6954.27	6690.27	263	31015.90	6954.27	0
274.00	7054.80	6780.80	262	30909.49	7054.80	0
281.00	7198.05	6917.05	261	30800.08	7198.05	0
290.00	7348.33	7058.33	260	30692.67	7348.33	0
299.00	8089.62	7790.62	259	30585.26	8089.62	0
306.00	8307.79	8001.79	258	30475.85	8307.79	0
317.00	8358.02	8041.02	257	30370.44	8358.02	0
323.00	8771.33	8448.33	256	30260.03	8771.33	0
331.00	8948.65	8617.65	255	30151.62	8948.65	0
342.00	8992.58	8650.58	254	30046.21	8992.58	0
355.00	9192.04	8837.04	253	29942.79	9192.04	0
362.00	9681.58	9319.58	252	29833.38	9681.58	0
368.00	9898.74	9530.74	251	29722.97	9898.74	0
379.00	10046.64	9667.64	250	29617.56	10046.64	0
386.00	10181.52	9795.52	249	29508.15	10181.52	0
393.00	10258.80	9865.80	248	29398.74	10258.80	0
406.00	10663.15	10257.15	247	29295.33	10663.15	0
411.00	10804.41	10393.41	246	29183.92	10804.41	0
420.00	10995.71	10575.71	245	29076.51	10995.71	0
426.00	11514.70	11088.70	244	28966.10	11514.70	0
428.00	11567.68	11139.68	243	28851.69	11567.68	0
434.00	11991.17	11557.17	242	28741.28	11991.17	0
441.00	12257.16	11816.16	241	28631.87	12257.16	0
447.00	12371.50	11924.50	240	28521.46	12371.50	0
450.00	12863.82	12413.82	239	28408.05	12863.82	0

461.00	13056.63	12595.63	238	28302.64	13056.63	0
468.00	13256.26	12788.26	237	28193.23	13256.26	0
474.00	13377.63	12903.63	236	28082.82	13377.63	0
481.00	13430.86	12949.86	235	27973.41	13430.86	0
489.00	13763.82	13274.82	234	27865.00	13763.82	0
495.00	14008.04	13513.04	233	27754.59	14008.04	0
504.00	14174.40	13670.40	232	27647.18	14174.40	0
511.00	14411.75	13900.75	231	27537.77	14411.75	0
516.00	14905.87	14389.87	230	27426.36	14905.87	0
520.00	15271.04	14751.04	229	27313.95	15271.04	0
533.00	15426.99	14893.99	228	27210.54	15426.99	0
546.00	15505.17	14959.17	227	27107.13	15505.17	0
553.00	16028.79	15475.79	226	26997.72	16028.79	0
562.00	16307.56	15745.56	225	26890.31	16307.56	0
569.00	16497.18	15928.18	224	26780.90	16497.18	0
578.00	16752.60	16174.60	223	26673.49	16752.60	0
586.00	17015.80	16429.80	222	26565.08	17015.80	0
600.00	17391.10	16791.10	221	26462.67	17391.10	0
603.00	17731.54	17128.54	220	26349.26	17731.54	0
612.00	18001.03	17389.03	219	26241.85	18001.03	0
620.00	18111.05	17491.05	218	26133.44	18111.05	0
626.00	18230.41	17604.41	217	26023.03	18230.41	0
637.00	18555.91	17918.91	216	25917.62	18555.91	0
641.00	18983.25	18342.25	215	25805.21	18983.25	0
646.00	19095.29	18449.29	214	25693.79	19095.29	0
656.00	19188.84	18532.84	213	25587.38	19188.84	0
661.00	19530.51	18869.51	212	25475.97	19530.51	0
671.00	19909.85	19238.85	211	25369.56	19909.85	0
681.00	20180.29	19499.29	210	25263.15	20180.29	0
690.00	20575.25	19885.25	209	25155.74	20575.25	0
700.00	20773.99	20073.99	208	25049.33	20773.99	0
709.00	21013.45	20304.45	207	24941.92	21013.45	0
716.00	21145.78	20429.78	206	24832.51	21145.78	0
724.00	21593.23	20869.23	205	24724.10	21593.23	0
730.00	21812.60	21082.60	204	24613.69	21812.60	0
739.00	22010.58	21271.58	203	24506.28	22010.58	0
746.00	22275.79	21529.79	202	24396.87	22275.79	0
755.00	22593.92	21838.92	201	24289.46	22593.92	0
765.00	23086.38	22321.38	200	24183.05	23086.38	0
771.00	23628.40	22857.40	199	24072.64	23628.40	0
779.00	23738.00	22959.00	198	23964.23	23738.00	0
783.00	24299.38	23516.38	197	23851.82	24299.38	447.56
796.00	24533.72	23737.72	196	23748.41	24533.72	785.31
808.00	24615.23	23807.23	195	23644.00	24615.23	971.23
813.00	24716.63	23903.63	194	23532.59	24716.63	1184.04
823.00	24958.12	24135.12	193	23426.18	24958.12	1531.94
831.00	25236.49	24405.49	192	23317.77	25236.49	1918.72
843.00	25881.86	25038.86	191	23213.36	25881.86	2668.50
848.00	26106.60	25258.60	190	23101.95	26106.60	3004.65
855.00	26670.74	25815.74	189	22992.54	26670.74	3678.20
863.00	26712.65	25849.65	188	22884.13	26712.65	3828.52
870.00	26958.73	26088.73	187	22774.72	26958.73	4184.01
878.00	27252.61	26374.61	186	22666.31	27252.61	4586.30
887.00	27448.70	26561.70	185	22558.90	27448.70	4889.80
895.00	27994.98	27099.98	184	22450.49	27994.98	5544.49
898.00	28274.06	27376.06	183	22337.08	28274.06	5936.98

Input values used for job 1 using LIFO dispatching rule						
Ai	**Oi**	**FTi**	**Jti**	**Di**	**Ci**	**Ti**
0	157.64	157.6358	222	30418.62	157.64	0
10	1548.89	1538.887	221	30291.04	1548.89	0
17	3300.33	3283.332	220	30160.47	3300.33	0
25	3860.43	3835.435	219	30030.89	3860.43	0
36	4535.56	4499.565	218	29904.32	4535.56	0
47	4791.80	4744.798	217	29777.74	4791.80	0
53	5162.00	5108.998	216	29646.16	5162.00	0
66	5706.55	5640.548	215	29521.59	5706.55	0
71	5868.84	5797.841	214	29389.01	5868.84	0
84	5993.32	5909.32	213	29264.44	5993.32	0
89	6368.07	6279.072	212	29131.86	6368.07	0
100	6619.74	6519.741	211	29005.28	6619.74	0
112	7057.67	6945.668	210	28879.71	7057.67	0
115	7711.85	7596.852	209	28745.13	7711.85	0
128	8531.11	8403.107	208	28620.56	8531.11	0
133	8606.44	8473.439	207	28487.98	8606.44	0
142	8782.01	8640.013	206	28359.41	8782.01	0
154	9095.33	8941.335	205	28233.83	9095.33	0
160	9974.43	9814.431	204	28102.25	9974.43	0
164	10418.35	10254.35	203	27968.68	10418.35	0
182	10700.70	10518.7	202	27849.1	10700.70	0
190	10820.51	10630.51	201	27719.53	10820.51	0
196	11454.81	11258.81	200	27587.95	11454.81	0
202	12366.69	12164.69	199	27456.38	12366.69	0
209	13248.35	13039.35	198	27325.8	13248.35	0
214	13531.63	13317.63	197	27193.22	13531.63	0
224	15842.79	15618.79	196	27065.65	15842.79	0
230	16113.39	15883.39	195	26934.07	16113.39	0
240	16655.27	16415.27	194	26806.5	16655.27	0
247	17746.30	17499.3	193	26675.92	17746.30	0
259	19203.06	18944.06	192	26550.35	19203.06	0
266	19314.87	19048.87	191	26419.77	19314.87	0
278	19578.30	19300.3	190	26294.19	19578.30	0
285	19963.02	19678.02	189	26163.62	19963.02	0
292	20435.40	20143.4	188	26033.04	20435.40	0
304	21654.55	21350.55	187	25907.47	21654.55	0
313	22629.26	22316.26	186	25778.89	22629.26	0
325	23773.88	23448.88	185	25653.32	23773.88	0
340	23894.72	23554.72	184	25530.74	23894.72	0
350	24136.45	23786.45	183	25403.16	24136.45	0
363	25104.84	24741.84	182	25278.59	25104.84	0
368	25290.13	24922.13	181	25146.01	25290.13	144.12
381	26089.15	25708.15	180	25021.44	26089.15	1067.72
388	26129.59	25741.59	179	24890.86	26129.59	1238.73
398	26619.95	26221.95	178	24763.28	26619.95	1856.67
407	27435.57	27028.57	177	24634.71	27435.57	2800.87
414	27576.14	27162.14	176	24504.13	27576.14	3072.01
419	27782.94	27363.94	175	24371.56	27782.94	3411.38
434	27825.38	27391.38	174	24248.98	27825.38	3576.40
441	28293.59	27852.59	173	24118.41	28293.59	4175.19
451	28339.80	27888.8	172	23990.83	28339.80	4348.97
460	28788.06	28328.06	171	23862.25	28788.06	4925.80

Input values used for job 2 using LIFO dispatching rule						
Ai	**Oi**	**FTi**	**Jti**	**Di**	**Ci**	**Ti**
0	311.01	311.01	172	17734.87	311.01	0
9	1531.20	1522.20	171	17640.69	1531.20	0
16	3500.39	3484.39	170	17544.51	3500.39	0
22	4194.74	4172.74	169	17447.33	4194.74	0
27	4617.32	4590.32	168	17349.15	4617.32	0
34	4947.60	4913.60	167	17252.96	4947.60	0
42	5102.11	5060.11	166	17157.78	5102.11	0
50	5486.08	5436.08	165	17062.6	5486.08	0
54	5770.40	5716.40	164	16963.42	5770.40	0
62	5985.96	5923.96	163	16868.24	5985.96	0
66	6479.92	6413.92	162	16769.05	6479.92	0
73	6574.95	6501.95	161	16672.87	6574.95	0
79	7279.80	7200.80	160	16575.69	7279.80	0
89	8297.11	8208.11	159	16482.51	8297.11	0
98	8502.08	8404.08	158	16388.33	8502.08	0
107	8593.97	8486.97	157	16294.15	8593.97	0
111	8834.94	8723.94	156	16194.96	8834.94	0
119	9297.66	9178.66	155	16099.78	9297.66	0
124	10101.05	9977.05	154	16001.6	10101.05	0
130	10420.18	10290.18	153	15904.42	10420.18	0
137	10642.13	10505.13	152	15808.24	10642.13	0
144	10906.33	10762.33	151	15712.05	10906.33	0
150	12221.70	12071.70	150	15614.87	12221.70	0
158	12583.25	12425.25	149	15519.69	12583.25	0
162	13096.18	12934.18	148	15420.51	13096.18	0
170	15820.82	15650.82	147	15325.33	15820.82	495.49
178	15912.51	15734.51	146	15230.15	15912.51	682.37
185	16135.15	15950.15	145	15133.96	16135.15	1001.19
188	16736.22	16548.22	144	15033.78	16736.22	1702.44
198	17806.83	17608.83	143	14940.6	17806.83	2866.23
209	19188.76	18979.76	142	14848.42	19188.76	4340.34
219	19339.75	19120.75	141	14755.24	19339.75	4584.51
223	19847.82	19624.82	140	14656.05	19847.82	5191.77
227	19925.59	19698.59	139	14556.87	19925.59	5368.72
233	20457.47	20224.47	138	14459.69	20457.47	5997.78
238	22378.50	22140.50	137	14361.51	22378.50	8016.99
244	22835.55	22591.55	136	14264.33	22835.55	8571.23
246	23704.33	23458.33	135	14163.15	23704.33	9541.18
252	23895.87	23643.87	134	14065.96	23895.87	9829.91
262	24692.21	24430.21	133	13972.78	24692.21	10719.43
268	25151.29	24883.29	132	13875.6	25151.29	11275.69
271	25609.29	25338.29	131	13775.42	25609.29	11833.87
274	26098.57	25824.57	130	13675.24	26098.57	12423.33
286	26279.46	25993.46	129	13584.05	26279.46	12695.40
297	27129.79	26832.79	128	13491.87	27129.79	13637.92
303	27408.13	27105.13	127	13394.69	27408.13	14013.44
308	27672.94	27364.94	126	13296.51	27672.94	14376.43
319	27755.90	27436.90	125	13204.33	27755.90	14551.57
325	27884.00	27559.00	124	13107.15	27884.00	14776.85
331	28172.23	27841.23	123	13009.96	28172.23	15162.27
339	28661.84	28322.84	122	12914.78	28661.84	15747.05

Input values used for job 3 using LIFO dispatching rule						
Ai	Oi	Fti	Jti	Di	Ci	Ti
0.00	1343.09	1343.09	222	38313.27	1343.09	0
8.00	3292.40	3284.40	221	38149.30	3292.40	0
12.00	3840.98	3828.98	220	37981.33	3840.98	0
18.00	4265.45	4247.45	219	37815.36	4265.45	0
25.00	4785.04	4760.04	218	37650.39	4785.04	0
29.00	5153.97	5124.97	217	37482.42	5153.97	0
38.00	5693.57	5655.57	216	37319.45	5693.57	0
48.00	5756.59	5708.59	215	37157.48	5756.59	0
60.00	5897.58	5837.58	214	36997.52	5897.58	0
66.00	6352.61	6286.61	213	36831.55	6352.61	0
79.00	6582.14	6503.14	212	36672.58	6582.14	0
90.00	7054.37	6964.37	211	36511.61	7054.37	0
93.00	7690.68	7597.68	210	36342.64	7690.68	0
98.00	8472.79	8374.79	209	36175.67	8472.79	0
103.00	8600.67	8497.67	208	36008.70	8600.67	0
113.00	8703.27	8590.27	207	35846.73	8703.27	0
122.00	8927.42	8805.42	206	35683.76	8927.42	0
128.00	9857.48	9729.48	205	35517.79	9857.48	0
135.00	10385.61	10250.61	204	35352.82	10385.61	0
145.00	10587.25	10442.25	203	35190.85	10587.25	0
153.00	10776.84	10623.84	202	35026.88	10776.84	0
166.00	11323.85	11157.85	201	34867.91	11323.85	0
173.00	12301.61	12128.61	200	34702.94	12301.61	0
185.00	13007.52	12822.52	199	34542.97	13007.52	0
196.00	13364.06	13168.06	198	34382.00	13364.06	0
204.00	15726.35	15522.35	197	34218.03	15726.35	0
211.00	16094.23	15883.23	196	34053.06	16094.23	0
218.00	16566.69	16348.69	195	33888.09	16566.69	0
225.00	17573.81	17348.81	194	33723.12	17573.81	0
236.00	19100.46	18864.46	193	33562.15	19100.46	0
243.00	19241.23	18998.23	192	33397.18	19241.23	0
250.00	19342.42	19092.42	191	33232.21	19342.42	0
255.00	19908.22	19653.22	190	33065.24	19908.22	0
264.00	20347.93	20083.93	189	32902.27	20347.93	0
280.00	21565.16	21285.16	188	32746.30	21565.16	0
284.00	22531.59	22247.59	187	32578.33	22531.59	0
291.00	23496.19	23205.19	186	32413.36	23496.19	0
298.00	23858.88	23560.88	185	32248.39	23858.88	0
306.00	24126.30	23820.30	184	32084.42	24126.30	0
314.00	25097.86	24783.86	183	31920.45	25097.86	0
321.00	25281.80	24960.80	182	31755.48	25281.80	0
325.00	26052.21	25727.21	181	31587.52	26052.21	0
335.00	26116.53	25781.53	180	31425.55	26116.53	0
342.00	26449.33	26107.33	179	31260.58	26449.33	0
348.00	27247.91	26899.91	178	31094.61	27247.91	0
353.00	27440.73	27087.73	177	30927.64	27440.73	0
360.00	27720.53	27360.53	176	30762.67	27720.53	0
365.00	27820.57	27455.57	175	30595.70	27820.57	0
371.00	28176.27	27805.27	174	30429.73	28176.27	0
376.00	28315.87	27939.87	173	30262.76	28315.87	0
381.00	28763.14	28382.14	172	30095.79	28763.14	0

Input values used for job 1 using LPT dispatching rule						
Ai	**Oi**	**FTi**	**Jti**	**Di**	**Ci**	**Ti**
0	157.64	157.64	190	34729.33	157.64	0
16	1527.94	1511.94	189	34561.89	1527.94	0
22	4072.82	4050.82	188	34384.46	4072.82	0
30	4363.61	4333.61	187	34209.02	4363.61	0
41	5446.31	5405.31	186	34036.59	5446.31	0
49	6257.07	6208.07	185	33861.15	6257.07	0
60	7224.86	7164.86	184	33688.72	7224.86	0
69	8642.50	8573.50	183	33514.28	8642.50	0
76	9229.06	9153.06	182	33337.85	9229.06	0
91	9756.02	9665.02	181	33169.42	9756.02	0
96	10317.76	10221.76	180	32990.98	10317.76	0
103	10948.89	10845.89	179	32814.55	10948.89	0
108	11539.23	11431.23	178	32636.11	11539.23	0
121	12210.09	12089.09	177	32465.68	12210.09	0
127	12779.48	12652.48	176	32288.24	12779.48	0
134	13419.85	13285.85	175	32111.81	13419.85	0
146	14115.98	13969.98	174	31940.38	14115.98	0
157	15746.77	15589.77	173	31767.94	15746.77	0
163	16623.72	16460.72	172	31590.51	16623.72	0
175	16982.94	16807.94	171	31419.07	16982.94	0
183	17949.77	17766.77	170	31243.64	17949.77	0
191	18610.49	18419.49	169	31068.20	18610.49	0
197	19184.91	18987.91	168	30890.77	19184.91	0
206	19502.09	19296.09	167	30716.34	19502.09	0
213	20090.74	19877.74	166	30539.90	20090.74	0
227	21880.90	21653.90	165	30370.47	21880.90	0
239	24842.22	24603.22	164	30199.03	24842.22	0
249	26794.81	26545.81	163	30025.60	26794.81	0
258	27884.89	27626.89	162	29851.16	27884.89	0

Input values used for job 2 using LPT dispatching rule						
Ai	**Oi**	**FTi**	**Jti**	**Di**	**Ci**	**Ti**
0.00	311.01	311.01	140	19248.21	311.01	0
4.00	1510.25	1506.25	139	19114.63	1510.25	0
17.00	4130.58	4113.58	138	18990.05	4130.58	0
22.00	4657.09	4635.09	137	18857.48	4657.09	0
29.00	5356.86	5327.86	136	18726.90	5356.86	0
36.00	6329.55	6293.55	135	18596.33	6329.55	0
46.00	7254.90	7208.90	134	18468.75	7254.90	0
55.00	8744.86	8689.86	133	18340.18	8744.86	0
58.00	9267.78	9209.78	132	18205.60	9267.78	0
64.00	9748.66	9684.66	131	18074.02	9748.66	0
68.00	10359.14	10291.14	130	17940.45	10359.14	0
71.00	10921.82	10850.82	129	17805.87	10921.82	0
75.00	11647.46	11572.46	128	17672.30	11647.46	0
82.00	12340.28	12258.28	127	17541.72	12340.28	0
89.00	12940.40	12851.40	126	17411.15	12940.40	0
96.00	13423.62	13327.62	125	17280.57	13423.62	0
100.00	14143.00	14043.00	124	17146.99	14143.00	0
105.00	15634.14	15529.14	123	17014.42	15634.14	0
111.00	16578.17	16467.17	122	16882.84	16578.17	0
119.00	16984.77	16865.77	121	16753.27	16984.77	231.50
126.00	18253.35	18127.35	120	16622.69	18253.35	1630.66
134.00	18732.13	18598.13	119	16493.12	18732.13	2239.02
142.00	19193.74	19051.74	118	16363.54	19193.74	2830.20
150.00	19570.52	19420.52	117	16233.96	19570.52	3336.55
155.00	20354.40	20199.40	116	16101.39	20354.40	4253.01
165.00	24170.09	24005.09	115	15973.81	24170.09	8196.28
168.00	25373.12	25205.12	114	15839.24	25373.12	9533.88
170.00	27196.82	27026.82	113	15703.66	27196.82	11493.16
174.00	28358.11	28184.11	112	15570.08	28358.11	12788.03

Input values used for job 3 using LPT dispatching rule						
Ai	**Oi**	**FTi**	**Jti**	**Di**	**Ci**	**Ti**
0.00	847.38	847.38	189	43472.36	847.38	0
13.00	4064.90	4051.90	188	43256.07	4064.90	0
29.00	4344.15	4315.15	187	43042.78	4344.15	0
37.00	4927.06	4890.06	186	42821.48	4927.06	0
48.00	5972.35	5924.35	185	42603.19	5972.35	0
64.00	7079.08	7015.08	184	42389.90	7079.08	0
73.00	8592.46	8519.46	183	42169.61	8592.46	0
80.00	9024.17	8944.17	182	41947.31	9024.17	0
89.00	9648.40	9559.40	181	41727.02	9648.40	0
96.00	10120.78	10024.78	180	41504.73	10120.78	0
101.00	10899.47	10798.47	179	41280.43	10899.47	0
113.00	11392.04	11279.04	178	41063.14	11392.04	0
119.00	12188.91	12069.91	177	40839.85	12188.91	0
132.00	12660.29	12528.29	176	40623.56	12660.29	0
138.00	13233.64	13095.64	175	40400.26	13233.64	0
146.00	14037.23	13891.23	174	40178.97	14037.23	0
160.00	14955.65	14795.65	173	39963.68	14955.65	0
167.00	16291.01	16124.01	172	39741.38	16291.01	0
174.00	16845.82	16671.82	171	39519.09	16845.82	0
183.00	17694.03	17511.03	170	39298.80	17694.03	0
189.00	18566.82	18377.82	169	39075.51	18566.82	0
196.00	19053.96	18857.96	168	38853.21	19053.96	0
205.00	19203.83	18998.83	167	38632.92	19203.83	0
211.00	19833.17	19622.17	166	38409.63	19833.17	0
218.00	21713.34	21495.34	165	38187.33	21713.34	0
224.00	24762.44	24538.44	164	37964.04	24762.44	0
231.00	26775.64	26544.64	163	37741.75	26775.64	0
238.00	27796.31	27558.31	162	37519.45	27796.31	0

Appendix II

List of publications

International Journals

1. Om Ji Shukla, Gunjan Soni, Rajesh Kumar, Sujil A. (2018), "An agent based architecture for production scheduling in dynamic job-shop manufacturing system", at-Automatisierungstechnik 66(6), pp.492-502.

2. Om Ji Shukla, Abhijeet Joshi, Gunjan Soni, and Rajesh Kumar, (2018) "Analysis of critical drivers affecting implementation of agent technology in a manufacturing system", Journal of Industrial Engineering International, pp. 1-11.

3. Om Ji Shukla, Gunjan Soni, Rajesh Kumar,"Multi-agent based production scheduling in manufacturing systems: a literature review", Artificial Intelligence Review. (Under review)

4. Om Ji Shukla, Gunjan Soni, Rajesh Kumar, "SimEvents based discrete-event simulation modelling and statistical analysis for dynamic job-shop manufacturing system", Journal of Industrial and Production Engineering. (Under review)

International Conferences

1. Om Ji Shukla, Gunjan Soni, Rajesh Kumar, A. Sujil, and Surya Prakash. "An Agent-Based Simulation Modeling Approach for Dynamic Job-Shop

Manufacturing System". In Harmony Search and Nature Inspired Optimization Algorithms, pp. 751-760. Springer, Singapore, 2019.

2. Om Ji Shukla, Gunjan Soni, and Rajesh Kumar. "Simulation Modeling for Manufacturing System Application Using Simulink/SimEvents". In Soft Computing for Problem Solving, pp. 751-760. Springer, Singapore, 2019.

3. Om Ji Shukla, Gunjan Soni, and Rajesh Kumar, "Modeling and Simulation of Agents Structure for a Manufacturing System Using SimEvents". Ambient Communications and Computer Systems. Springer, Singapore, 2018. 381-391.

4. Om Ji Shukla, Vishnu Jangid, Man Mohan Siddh, Gunjan Soni and Rajesh Kumar. "Evaluating key factors of sustainable manufacturing in Indian automobile industries using Analytic Hierarchy Process (AHP)." In Advances in Mechanical, Industrial, Automation and Management Systems (AMIAMS), 2017 International Conference on, pp. 42-47. IEEE, 2017.

5. Om Ji Shukla, Gunjan Soni, Sujil A. and Rajesh Kumar, "Discrete event system framework for analysis and modeling of job shop scheduling system". In Advances in Computing, Communications and Informatics (ICACCI), 2016 International Conference on, pp. 2420-2424. IEEE, 2016.

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