




## Review

# A Critical Analysis of Job Shop Scheduling in Context of Industry 4.0

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**Abstract:** Scheduling plays a pivotal role in the competitiveness of a job shop facility. The traditional job shop scheduling problem (JSSP) is centralized or semi-distributed. With the advent of Industry 4.0, there has been a paradigm shift in the manufacturing industry from traditional scheduling to smart distributed scheduling (SDS). The implementation of Industry 4.0 results in increased flexibility, high product quality, short lead times, and customized production. Smart/intelligent manufacturing is an integral part of Industry 4.0. The intelligent manufacturing approach converts renewable and nonrenewable resources into intelligent objects capable of sensing, working, and acting in a smart environment to achieve effective scheduling. This paper aims to provide a comprehensive review of centralized and decentralized/distributed JSSP techniques in the context of the Industry 4.0 environment. Firstly, centralized JSSP models and problem-solving methods along with their advantages and limitations are discussed. Secondly, an overview of associated techniques used in the Industry 4.0 environment is presented. The third phase of this paper discusses the transition from traditional job shop scheduling to decentralized JSSP with the aid of the latest research trends in this domain. Finally, this paper highlights futuristic approaches in the JSSP research and application in light of the robustness of JSSP and the current pandemic situation.

**Keywords:** smart distributed system; job shop scheduling; Industry 4.0; smart factory; flexible job shop scheduling



**Citation:** Liaqat, R.A.; Hamid, S.; Warsi, S.S.; Khalid, A. A Critical Analysis of Job Shop Scheduling in Context of Industry 4.0. *Sustainability* **2021**, *13*, 7684. <https://doi.org/10.3390/su13147684>

Academic Editors: Aldona Kluczek, Bartłomiej Gładysz, Jacek Szymczyk and Patrycja Żegleń

Received: 31 May 2021

Accepted: 5 July 2021

Published: 9 July 2021

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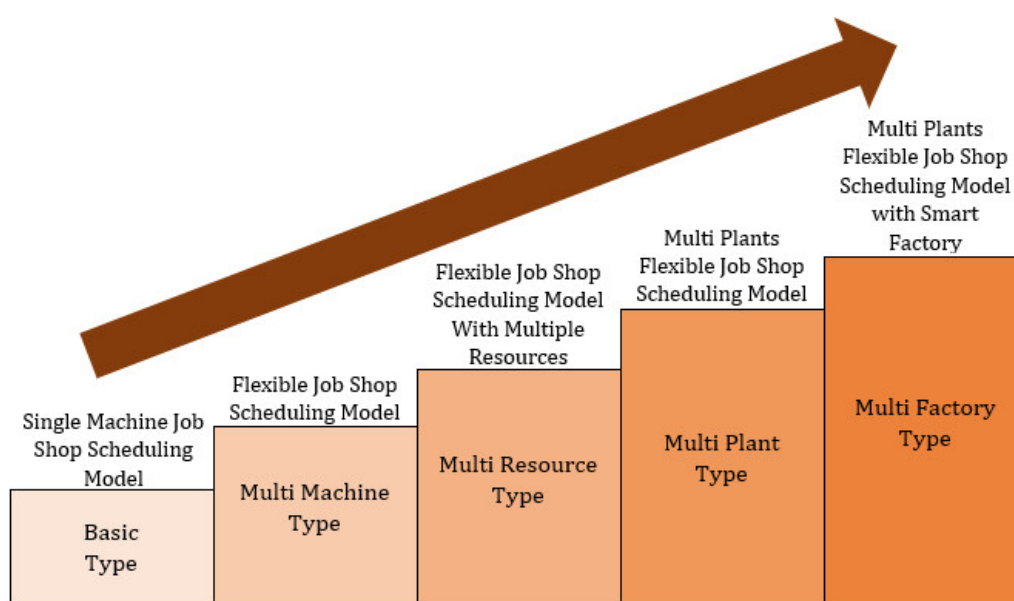
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## 1. Introduction

Scheduling plays a pivotal role in the production facility, as it maximizes the efficiency while minimizing various costs, lead time and cycle time, etc. Several studies have been conducted which analyzed the impact of the flow shop and job shop scheduling problem (JSSP) on manufacturing systems [1–3]. JSSP includes job operations with different machine sequences that have different processing times. The scheduling of machine operations can be done under various criteria; for instance, processing time, lead time, makespan, free float, or due dates, etc. [4]. Geyik & Cedimoglu (2004) [5] classified JSSP as an NP-hard optimization problem where different machines are assigned to various jobs while minimizing any of the applicable predefined criteria. Various algorithms and problem-solving techniques (such as first come first serve (FCFS), shortest processing time (SPT), earliest due date (EDD), etc.) have been developed and used over the years to solve JSSP [6–13]. However, as these optimization algorithms usually concentrate on centralized scheduling, these techniques are mainly focused on small-scale problems. While scaling up the problem, significant challenges arise in terms of computational time and cost [14,15]. Therefore, researchers and practitioners have gradually shifted their focus from traditional scheduling arrangement to smart-distributed scheduling (SDS) aided with technological pillars of the Industry 4.0 environment, such as Cyber-Physical Systems (CPS), Big data, Artificial Intelligence (AI), Internet of Things (IoTs), and Social, Mobile, Analytics, Cloud

computing (SMAC). The transition from traditional scheduling to SDS faces two major research challenges: the integration of conventional JSSP scheduling techniques with SDS, and the development of new problem-solving techniques required for SDS.

Various models for JSSP have been proposed for improving the operational efficiency of a job shop production facility. Figure 1 presents the classification of JSSP models with varying complexity based on the inclusion of various operational parameters. It is evident from Figure 1 that there is a drive toward the development of smart factories integrated with Industry 4.0. A detailed review of the literature reveals that several studies have reviewed the integration of JSSP with Industry 4.0. Chaudhry & Khan (2016) [16] performed an extensive review of literature from 1990 to 2014 and highlighted various techniques and approaches used to solve the JSSP problem. Their study argued the importance of flexible JSSP, especially in large-scale problems. The study also highlighted that the majority of the studies focused on algorithm development rather than solving real-world application problems. Parveen & Ullah (2010) [17] surveyed the literature to analyze the multi-objective scheduling in the context of flow shop and job shop scheduling environments. Their study highlighted the use of multi-criteria decision-making (MCDM) techniques along with mathematical optimization models to analyze the JSSP. A comprehensive review of job shop scheduling models, algorithms used for JSSPs, and the integration of techniques used in Industry 4.0 for solving JSSP were conducted by Zhang et al. [18]. Their study analyzed solving methods for various JSSPs in the Industry 4.0 environment.



**Figure 1.** Job shop Scheduling Models and Classifications.

However, the studies discussed above are limited to the generic literature review and have not focused on the emerging trend of robustness and smart scheduling. The review presented in this paper builds on the previous research and contributes by reviewing the up-to-date JSSPs and solving techniques to highlight their current usages and challenges for SDS in the context of Industry 4.0. The research also provides an outlook for the integration of job shop scheduling with the medical industry in wake of the current pandemic situation.

The paper proceeds as follows: Section 2 includes the research objectives of the study; Section 3 includes the review methodology; Section 4 presents the research design used for the comprehensive analysis of the published literature; Section 5 includes the detailed literature review of the articles based on existing models, methodologies, and their advantages along with the limitations of the centralized JSSP problem; Section 6 presents the analysis of decentralization techniques for solving JSSP problems that are used in the Industry 4.0 environment; Section 7 focuses on the analysis of the latest publications

on smart scheduling for JSSP; Section 8 presents the robustness in job shop scheduling integrated with Industry 4.0 environment in recent years; Section 9 includes the future research directions; Section 10 includes the conclusion of the study.

## 2. Research Objectives

Since the development of the first Job Shop Scheduling Problem (JSSP) [19], scheduling has been a research topic of interest amongst researchers and practitioners. JSSP is an NP-hard problem and extensive research has been done to solve its various classifications and complexities. However, there exist limited articles that comprehensively analyze different approaches developed by past researchers. Therefore, this study aims to examine the state-of-the-art literature available on JSSP for channeling it towards the Industry 4.0 implementation. In this regard, the following research questions have been addressed in this study:

- What is the existing research status of JSSP?
- How are JSSP models classified?
- What techniques/algorithms have been used for solving various JSSP classifications and what are their limitations?
- How JSSP can be integrated with the technological pillars of Industry 4.0?

## 3. Review Methodology

A systematic literature review-based study is conducted to address the above research questions. Peer-reviewed articles in ISI indexed journals in the context of JSSP (solving techniques/algorithms and integration of JSSP with Industry 4.0) are studied. Three selection criteria for the papers were considered, including (1) paper must be written in English; (2) paper must include the Job Shop Scheduling and Industry 4.0; (3) paper must include quantitative research methodology.

Published papers in international journals among electronic bibliographical sources including Scopus, Google Scholar, and Web of Science were searched by using a combination of different keywords.

In the first stage, keywords and sentence strings—‘Job Shop Scheduling’, ‘Flexible Job Shop Scheduling’, ‘Smart Factory’, ‘Job Shop Scheduling and Industry 4.0’—were employed to identify the relevant literature. The results obtained were then cross compared for possible overlap and checked for duplication.

The second stage of the process involved reviewing and screening the articles based on the above-stated criteria. This involved conducting an initial check with regard to the titles and keywords identified in the articles. From this, a total of 238 papers were identified. The third stage entailed reviewing the abstracts and conclusions of all 238 articles. This reduced the number of articles to 122.

## 4. Research Design

The research on scheduling in the context of Job Shop can be divided into two main categories: (1) problem modeling and (2) problem-solving techniques. JSSP is first classified based on model structures used in the literature. Characteristics of traditional JSSP model structures are analyzed in the context of Industry 4.0. Secondly, the classification and review of algorithms that are used for solving JSSP are done by taking into account both single and hybrid algorithms. Advantages and disadvantages, along with the limitations of the algorithms used in conventional scheduling are analyzed. The challenges of algorithms for using smart distributed scheduling are then highlighted. The driving forces such as IoT, deep learning, AI, cloud computing, and big data are analyzed for smart distributed scheduling. An analysis of the robustness of scheduling in the context of Industry 4.0 is also presented. Figure 2 presents the holistic framework of the research design for this study.

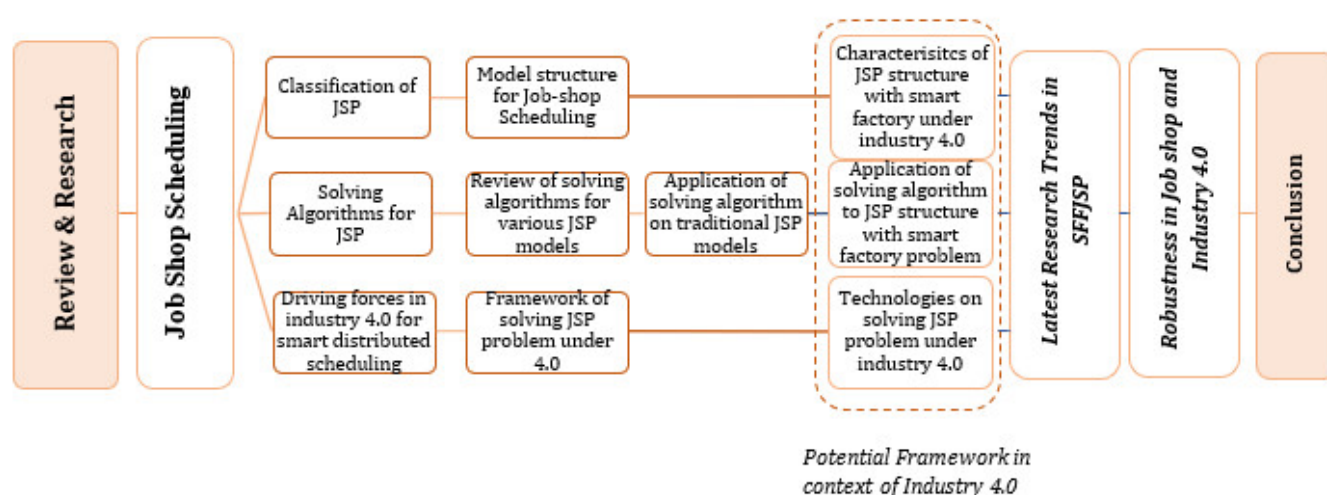


Figure 2. Research Design and Structure.

## 5. Literature Review

Johnson [19] did the pioneer work on scheduling by formulating the mathematical model with two machines. Garey et al. [20] classified JSSP with more than two machines as an NP-complete problem. The JSSP, as defined by Geyik & Cedimoglu [5], is a set of jobs  $J_i$ , where  $i = 1, 2, 3, \dots, n$  need to be scheduled on a set of machines  $M_j$ , where  $j = 1, 2, 3, \dots, m$  to minimize the makespan under some defined constraints. Some of the commonly used constraints are as follows Chen et al. [21]:

1. Each job will be assigned to different machines with a specified processing time;
2. Each machine can perform only one job at a moment;
3. The processing time of the job is fixed, and once the job is started it cannot be interrupted for each machining operation [22].

In advance scheduling techniques, the additional constraints such as machine capacity, labor productivity, resource availability, inventory, stock levels, and costs, etc., are also included [23].

### 5.1. Scheduling Model Structures

Scheduling can be done based on available resources, assigned jobs, and associated machines. Some review studies [24,25] on scheduling and model structures have analyzed diversified aspects of the scheduling models. The job shop scheduling models can be mainly classified into five types, i.e., performance measures, number of machines, production environment, resource constraint, and processing operations [26]. Based on the literature, JSSP was reclassified into five various types of structures as shown in Figure 3. The basic JSSP problem is an NP-hard problem with a specified operation on a specific machine/machining tool. It is an optimization problem employed to minimize the makespan, maximum lateness, and total weighted tardiness whilst achieving an optimum operation sequence. The Flexible Job Shop scheduling problem (FJSSP) tends to minimize expected makespan and balance the workloads on the selected machines for the optimized solution of an operation sequence [27]. In FJSSP, some or all the machines can be chosen by the algorithm for the desired solution [28]. Both JSSP and FJSSP are frequently used while implementing the algorithms. In Multi resource FJSSP, makespan, cost, and resource consumption are minimized by balancing the workloads [29]. It includes both renewable resources such as machinery and labor, etc., and non-renewable resources such as fuel and material. This type of problem is analyzed either by using disjunctive graphs or by developing the mathematical model [30]. In multi-plant-based FJSSP, multiple plants and transportation among them are also considered while minimizing makespan, costs, tardiness, and transportation distance [31]. This increases complexity and requires high computational power and time to achieve the optimized solution for the operation se-

quence with selected resources and plants. Due to its dynamic behavior, rescheduling is also required to achieve the optimum solution. The first four structures (i.e., basic type, multi-machine, multi-resource, and multi-plant) models are centralized scheduling models and are not effective for real-time dynamic changes [32]. As all four models are NP-hard problems, the incorporation of the actual dynamics results in increased cost, time and a long recovery period for disruptions in the manufacturing process. To incorporate the disruptions and stochastic environment related to orders, delivery times, machine breakdown, tool failure, and emergency events, etc., smart factory solutions are required in the future. In today's mass customization and adaptive manufacturing environment, there is a need for smart agents with the features of self-organization and decision making that should be used for scheduling the manufacturing processes. In a smart distributed scheduling problem, the problem is divided into small parallel sub-problems and solved separately either by using a mono or multi-objective approach, using the exact or approximate algorithm. The separated sub-problems simultaneously require less computational time rather than concentrated JSSP to achieve better results.

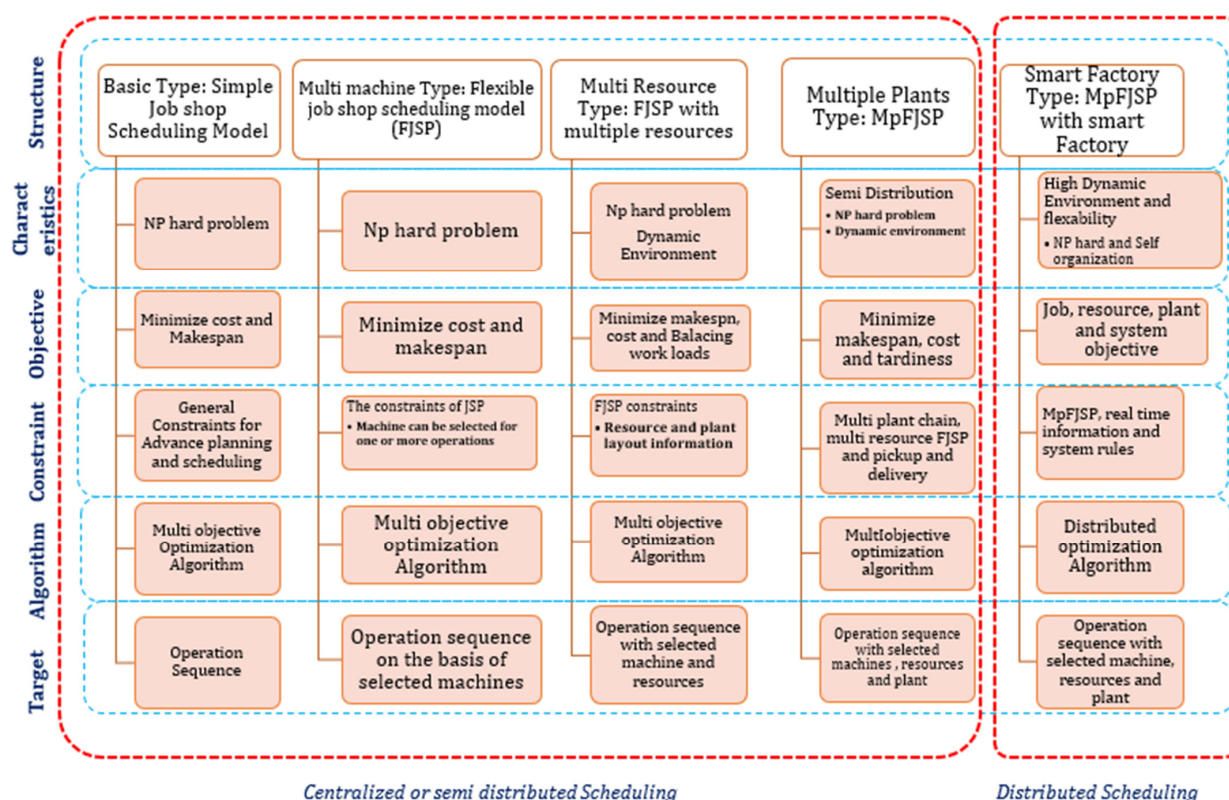


Figure 3. JSSP Structures.

## 5.2. Classification of Scheduling Algorithm

Various algorithms have been employed in the literature for solving JSSP. Both exact and approximate algorithms are classified, compared, and analyzed in various types of JSSP [33,34]. Tables 1 and 2 enlist some relevant research to classify the algorithms used in the JSSP problem.

JSSP can also be classified on the basis of machine tools, i.e., single and multi-machine shops. Various studies analysed the JSSP in the context of performance measures, i.e., cost, lead time, makespan, etc. Production environment also plays a pivotal role in JSSP. It is characterized as deterministic and stochastic. The addition of constraints and characteristics such as the number of plants, types of resources (i.e., renewable and nonrenewable) and type of operations would further classify the JSSP along with increasing the complexity and solution space of the problem.

**Table 1.** Exact Optimization Algorithms for JSSP.

Scheduling Algorithm	Study	Objective	Problem Type	Description
Efficient Rule Approach	[19]	Min. Makespan	2-Machines JSSP problem	• Rules-based on input data to find an exact optimized solution
	[35]	Min. Makespan	2-Machines JSSP problem	• Development of Longest remaining first Algorithm.
Mathematical Programming Approach	[36]	Min. Makespan	3-Machines JSSP problem	• Integer linear programming model to find a solution without loss of optimality
	[37]	Min. Makespan	2-Machines JSSP problem	• Mixed-integer linear programming with binary variables to solve large-scale scheduling problems.
Branch & Bound Method	[38–40]	Min. Makespan	3-Machines JSSP problem	• Branch and Bound heuristic approach to find an optimal solution [41].

**Table 2.** Approximate Optimization Algorithms for JSSP.

Scheduling Algorithm	Study	Objective	Problem Type	Description	
Constructive Method	Priority Dispatch Rule Method	[42]	Min. CPU Time & Makespan	10-Machines JSSP problem	• Priority rules are used to schedule the machining operations
	Insert Algorithms	[43,44]	Min. Makespan	5-Machines JSSP problem	• Construction of partial schedule incorporated with priority rule
	Bottleneck Based Heuristics Method	[45–48]	Min. CPU Time & Makespan	Multiple machines & jobs	• Subdivision of multiple machine problems
Artificial Intelligence <sup>1</sup>	Constraint Satisfaction Technique <sup>2</sup>	[49,50]	Min. CPU Time & Makespan	Multiple numbers of machines in JSSP	• Reduction in search space using value ordering heuristics
	Neurons Networks <sup>3</sup>	[51,52]	Min. Earliest Starting time & Makespan	Multiple machines JSSP problem	• Training & Testing input data [53,54].
	Expert System and Knowledge-based Method	[10,55]	Min. Makespan	Multiple Machines in JSSP problem	• Combination of priority rules, heuristics, and process information
	Fuzzy Logic	[56,57]	Min. CPU Time & Makespan	Large scale JSSP problem	• Solving uncertainties of the stochastic environment in JSSP [58].
Local Search Method	Simulated Annealing (SA), Genetic Local Search (GLS), Iterative Improvement (IM).	[59–61]	Min. CPU Time & Makespan	3-Machines JSSP problem	• Split search space into small packets for local and global optimal solutions [62], result in the increment of CPU time and cost [63]
Meta Heuristics Method <sup>4</sup>	Genetic Algorithm (GA) <sup>5</sup> , Tabu Search (TS) <sup>6</sup> , Ant colony Optimization (ACO) <sup>7</sup> , Fire fly Algorithm (FA) <sup>8</sup> , and Particle Swarm Optimization (PSO) <sup>9</sup> etc.	[6,7,9,29,64–70]	Min. CPU Time & Makespan	Multiple machines with multiple jobs	• Random number search technique used to solve large scale problems with large search space

<sup>1</sup>. AI is a field of computer science use for the development of programs that tends to replicate human intelligence [71]. <sup>2</sup>. The work of [72,73] can be used for understanding and detail review of constraint satisfaction techniques. <sup>3</sup>. Hybrid Approaches also used in neural networks (NNs) on the basis of three major factors: Arc weights, network structure and learning technique [74]. <sup>4</sup>. Recent trends show the use of hybrid approach(s) in the approximate optimization models to solve the FJSP (see for example: [64,75,76]). <sup>5</sup>. GA is a stochastic search algorithm that imitate the mechanics of natural selection and natural genetics [77]. <sup>6</sup>. TS is a multi-iterative method that store values from the previous iteration to gain the global optima. <sup>7</sup>. In ACO, the algorithm widely analyzes the search space by the set of agents called artificial ants to find the optimum solution. <sup>8</sup>. Real random numbers based on the global communication among the swarming particles are mainly used to find global optima. <sup>9</sup>. In PSO, the particles also referred as potential solutions move (fly) in the problem space while following the current global optima [78,79].

### 5.3. Characteristics, Limitations, and Challenges of Exact and Approximate Optimization Methods

As highlighted in Tables 1 and 2, optimization methods can be classified into exact and approximate solution approaches. The exact optimization method solves the optimization problem with an effort that grows polynomially with the problem size. It includes efficient rule approaches, mathematical programming approaches, branch definition methods, etc. For NP-hard problems such as JSSP, the exact approaches require exponential effort [80]. In contrast, the approximate optimization method used a dynamic environment with multiple dependent and independent variables. The approximate methods include constructive methods, artificial intelligence, local search, and meta-heuristic algorithms. Approximate methods do not guarantee finding optimal solutions. They are usually designed for a particular problem and tend to exploit problem-specific knowledge. Therefore, the performance of the problem can be often increased by increasing problem specificity and narrowing the application scope [81]. Figure 4 presents the characteristics, limitations, and challenges of optimization algorithms used for JSSP problems.

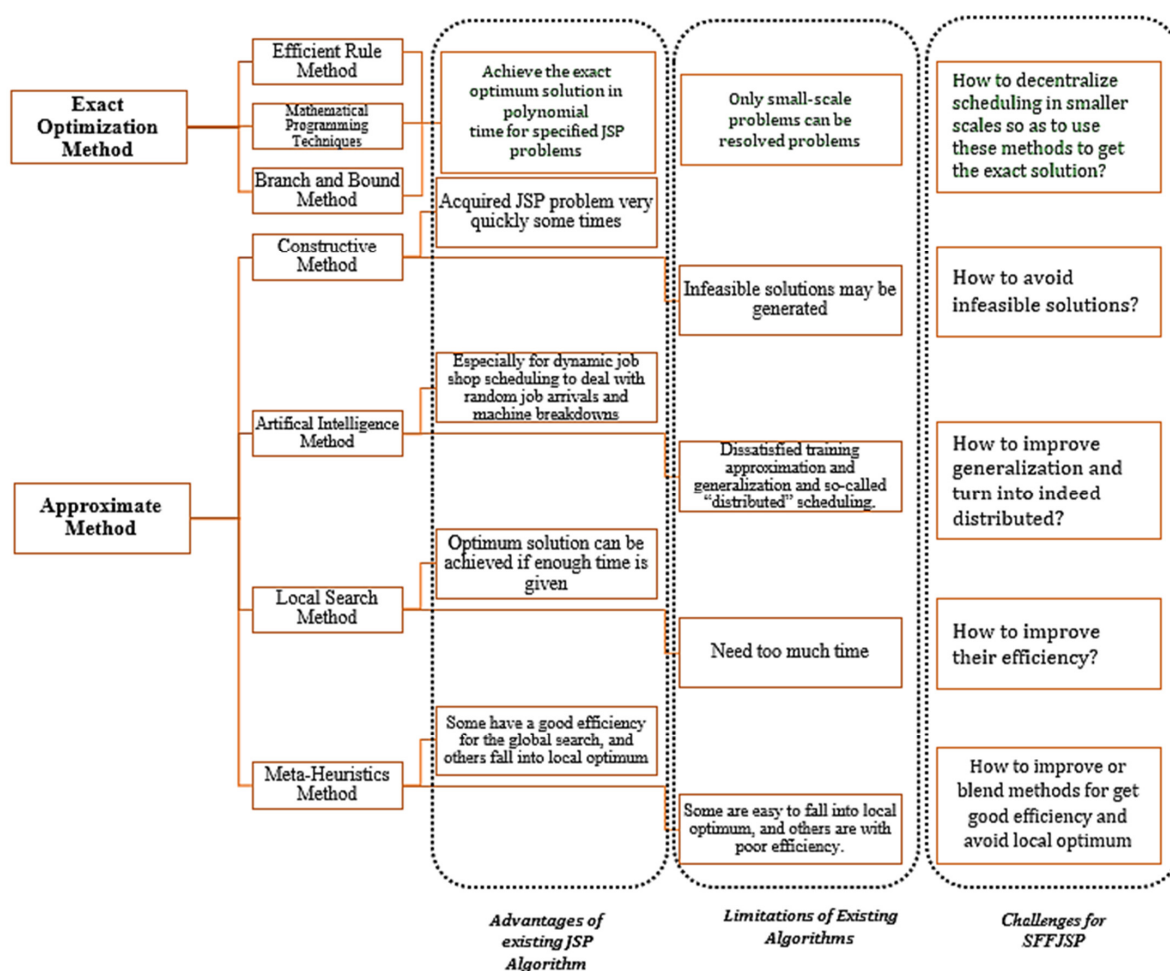


Figure 4. Characteristics and challenges of Optimization Algorithms in context of SFFJSP.

## 6. Decentralization

With decentralization taking over the manufacturing industry, flexible manufacturing systems have become a top priority which are smart as well as decentralized, and provide the opportunity to achieve autonomist manufacturing [82]. This approach is unlike the centralized and semi-centralized traditional JSSP. With Industry 4.0 making its shift towards smart manufacturing, the traditional JSSP application is expected to be utilizing smart scheduling along with optimization techniques. In the models based on the futuristic approach, the job, resource, system, and plant objectives are allotted to the smart agents.

These objectives act as the prime optimization objective for the smart agents for accessing smart distribution scheduling. Optimization through smart agents is based on distributed optimization algorithm feedback. The feedback is related to predefined parameters, system rules, and objectives. With this decentralized approach, Industry 4.0 has emerged as a pioneer in producing faster and easier operation schedules and sequences with predefined resources [83].

#### *6.1. Industry 4.0 Mainspring for Smart Distributed Scheduling*

The shift in the production processes to decentralization is obtained through the exchange of information among resources, plants, jobs, and machines [84]. The frequent exchange of information has brought various important aspects under research and implementation, such as: smart factories, cyber-physical systems, cloud computing, and Internet of Things. Artificial Intelligence utilization through deep learning has also emerged as an important solution for solving fast, self-decision problems for smart agents in job shop scheduling.

##### *6.1.1. Internet of Things (IoT)*

In the context of a job shop, Internet of Things (IoT) helps in connecting all the desired aspects of the manufacturing systems for the creation of big data [85]. The inclusion of IoT in the job shop scenario has made manufacturing smarter since it has made it more real through the use of real-time data and integration of network information of resources, tools, machines, and personals [86]. This has led to the optimization of the supply chain through improvisation of the production process, meeting demands, and performing jobs quickly.

##### *6.1.2. Cyber-Physical Systems (CPS)*

CPS merges the virtual world (computing stimulated process) and the real-world (physical process). Through this system, the physical process and parameters govern the scheduling through virtual models, where the embedded systems, control, and computing technologies govern production through optimized scheduling [87]. The futuristic CPS has become highly advanced and reduced computation and data storage by using advanced tools such as RFID, network gateways, and other tools. Such systems, contrary to traditional CPS, are highly efficient since data analysis is a distributed task, whereas, for the latter case, service agents are required for these tasks [88].

##### *6.1.3. Smart Factory*

Smart factories are based on CPS and IoT. In the smart factory concept, employing modules, CPS is more efficient as compared to IoT since it communicates among modules more effectively thus making decentralization possible in many aspects. The difference between traditional centralized job shop scheduling and smart decentralized job shop scheduling is the incorporation of the concept of a smart factory [89]. In a smart factory, a smart agent can decide the scheduling and its assignment based on its plan, choice, goals, current condition, and machining history. Therefore, flexible job shop scheduling models with multi-resources, multi-plants, transportation, and smart factory (SFFJSP) have emerged as a solution to scheduling problems [90].

##### *6.1.4. Cloud Computing*

Cloud computing has provided a structure for scheduling in manufacturing. It has provided a service and information sharing platform which has proved to be very fruitful for optimization during scheduling [91]. Cloud computing has enabled the incorporation of multi-plants, multi-suppliers, and multi-logistic providers in the scheduling of optimization procedures [92]. Cloud manufacturing has also eased parallel computing, which reduces the workload, enables distributed decisions for agents, and makes the solution of local problems possible through the use of computing power and big data [93,94].

### 6.1.5. Deep Learning

Deep learning, in recent years, has emerged as one of the mainstream subjects in machine learning and artificial intelligence. It applies nonlinear models of complex nature for the representation of the relationship between data [95]. It employs big data for the analysis and determination of end relationships between data. Deep learning applies the first come, first serve rule for scheduling in a job shop. The system, either randomly or by optimization, schedules the preliminary sorting. This sorting, with the deep learning technology, leads to self-determination for each job, whether it adjusts to the queue or not [96]. This practice covers two scenarios for each job. In the first scenario, each job judges the preliminary sorting against its delivery time and, if the delivery time is not met, then the job self-decides to override the sequence to achieve its target. In the second scenario, if the preliminary sorting guarantees the delivery time of the job, the job uses deep learning technology with autonomous decision-making for forecasting efficiency, cost, machine utilization, etc. Deep learning and improved learning techniques enable the system to predict failures. As a preventive measure, it enables the system to issue maintenance instructions, keep a record of machine maintenance, measures the jobs involved in the scheduling, and choose their process resources and orders in response. This self-decision process is realized when there is an information transfer among smart jobs and machines. Automated driving technology based on a combination of deep learning with incremental learning makes the logistics transport resourcing smart. Each vehicle and robot can perceive its environment in real-time, choose the shortest route, and avoid congestion dynamically [97]. This decision-making process is realized when there is an information transfer among smart jobs and smart multi-resources. This predictive model is constantly improved through deep learning and data-driven techniques, where data is obtained from the stimulated machining processes and the actual machining processes.

### 6.2. Implementation Steps of JSSP Structure with SFFJSP

The original centralized scheduling problem can be turned into smart agents-based problems. Framework for the solution of the JSSP problem under Industry 4.0 as summarized by Zhang et al. [18] is shown in Figure 5, and its related SFFJSP implementation is shown in Figure 6.

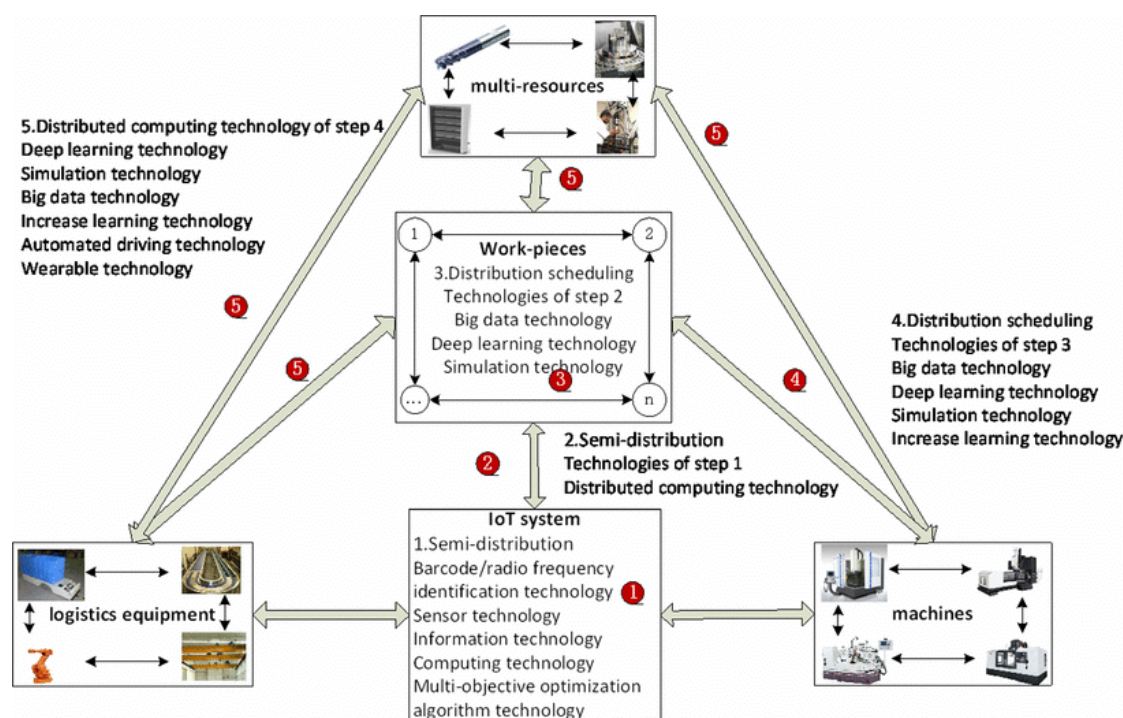


Figure 5. Key enabling technologies for JSSP under Industry 4.0 Reprinted from Zhang et al. (2019) [18].

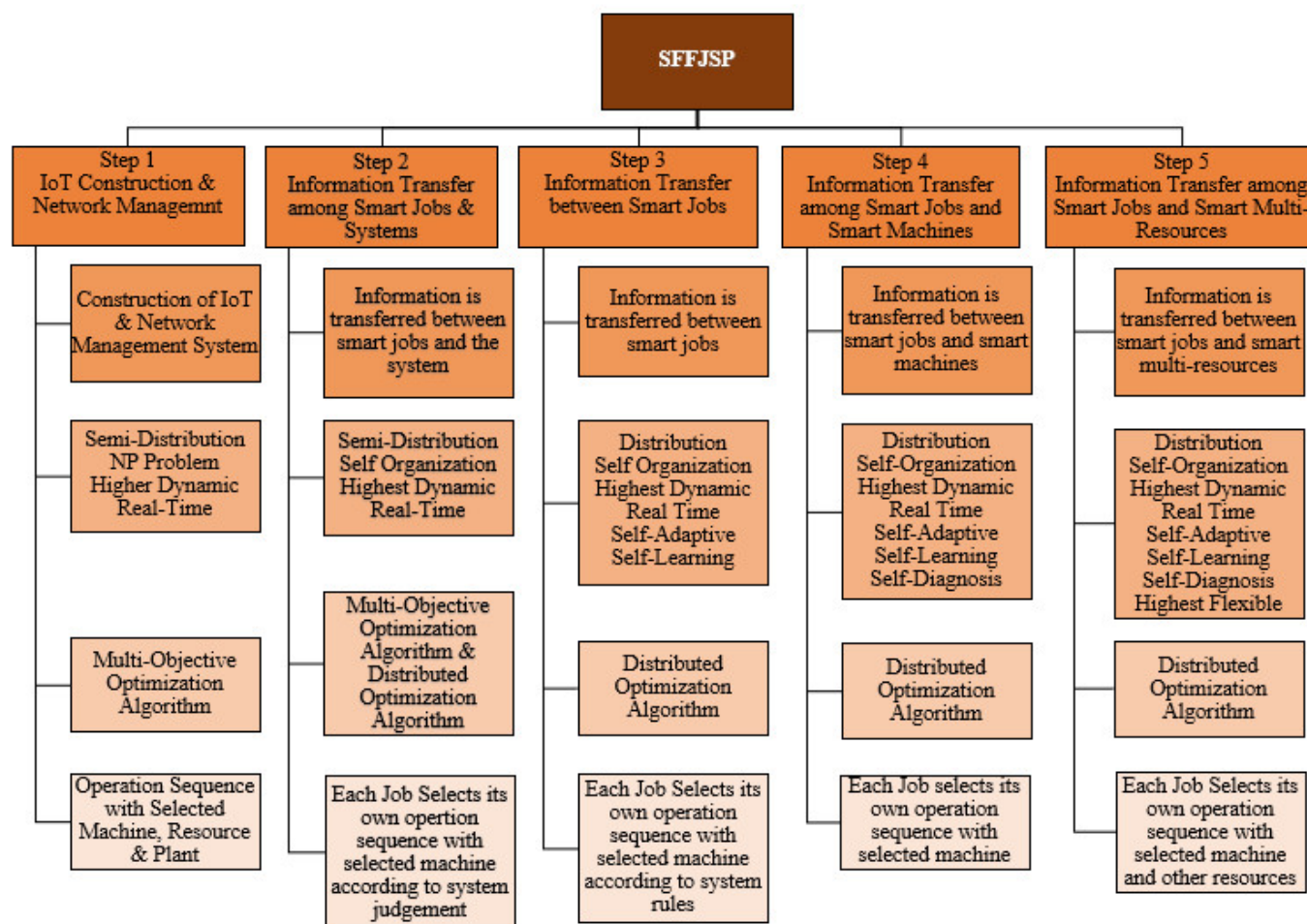


Figure 6. Steps of SFFJSP.

## 7. Latest Research Trends in SFFJSP

After the first industrial revolution, the concept of industry 1.0 emerged, which is mainly focused on a one-dimensional parameter (i.e., Product Demand). In industry 2.0, the manufacturing facilities focused on product volume and variety. In industry 3.0, the manufacturing facilities shifted from analog to digital controls while considering the three parameters (i.e., product demand, product variety, and product delivery time). Many industries are still undergoing these three revolutions. In Industry 4.0, the technological boom overlapped with all of the conventional approaches to manufacturing and attracted the focus of production managers, researchers, and various governments as well. Scheduling is the pivotal module of production management. Job shop scheduling is one of the most frequently used types of scheduling in manufacturing facilities. In recent years, various research has been conducted to analyze the integration and impacts of the Industry 4.0 environment on job shop scheduling.

### 7.1. Use of IoT

Leusin et al. [22] embedded MAS into CPS to solve complex dynamic JSSP. IoT is used in that model for extracting real-time data from the shop floor. The fluctuations in work in process (WIP) can be reduced by implementing the approach in the production environment. The conceptual framework proposed is based on a multi-agent system that can be used in numerous stochastic environments for achieving agility and high flexibility in the scheduling of jobs in the production facility.

### 7.2. Use of Genetic Algorithm

Niehues et al. [98] highlighted the importance of adaptive job shop control under a stochastic environment. The disruptions are included at each stage in the FMS, operated under the JSSP environment. The order shifting by scheduling the timeline is analyzed using a genetic algorithm by the development of a system that is capable of detecting the deviations with the help of location-based data acquisition (DAQ).

### 7.3. Decision Support System

Grieco et al. [99] presented the application of big data in the production facilities of Bottega Veneta. The job shop scheduling environment is analyzed based on the Decision Support System (DSS). The constraint and mixed-integer linear programming models incorporated with big data technology are used to provide insight for the production managers regarding delivery times and costs. Zhong et al. (2017) [100] did a comprehensive review of studies related to the applications of Intelligent Manufacturing Systems (IMS) on job shop scheduling.

### 7.4. Decentralization Outperformance

Mehrsai et al. [101] analyzed the JSSP problem under various considerations. It includes a centralized flow environment, FMS with multiple flow possibilities, decentralized sequencing of jobs with a central delivery system, decentralization for real-time data, and decentralization for real-time on-ground and historical data based on multiple agents. Their study concluded that the decentralization offered a substantiating result in JSSP.

### 7.5. Use of Semi Hierarchal Configuration

Guizzi et al. [102] evaluated the robustness of the JSSP by introducing a semi hierarchal configuration inspired by a cyber-physical system that will result in the combination of proactive and reactive approaches to JSSP. The system sub-divided the actual complex scheduling problem into three small problems. It is then solved at various stages, i.e., several jobs to be produced by the machine with Enterprise Resource Plan (ERP), the sequencing and routing of jobs with the help of CPs, and the identification of jobs at each stage with CPs.

### 7.6. Use of Heuristic Approaches

Sousa et al. [103] evaluated various heuristic approaches to find the optimal solution for makespan and total weighted tardiness. The Big Data technique is used with the help of various sensors at the facility which provide updated information. The Industry 4.0 environment, along with the conventional approximate method, is used for continuous scheduling of the operations in FMS. The study concluded that the shifting bottleneck algorithm outperformed various algorithms.

### 7.7. Maximizing Hamiltonian Function

Ivanov et al. [104] solved the multi-stage JSSP problem under FMS. The additional time-dependent processing speeds and machine availability constraints are used for evaluating job lateness and makespan using the optimal control method and maximized Hamiltonian function for a dynamic environment.

### 7.8. Use of CBJSP

Liu et al. [105] investigated the combined buffer job JSSP problem by formulating the mathematical model and solved using established heuristics techniques. The FJSSP instances are evaluated using the CBJSP. The results of the proposed methodology showed significant performance over the conventional methodology.

### 7.9. Use of RFID Based IoT

Ding & Jiang [106] provided insight for analyzing the data obtained by RFID-based production control. In their model, IoT facilities were used for extracting the data from the job shop. The three machines JSSP problem is solved using RFID-based IoT enabled smart JSSP. Their model intended to help the production manager to cope with the routine disruptions that occur in the production facility by incorporating smart factory technologies established under Industry 4.0.

### 7.10. Industry 4.0 in SFFJSP

Ahuett-Garza & Kurfess [107] highlighted the use of various techniques of Industry 4.0 for achieving the smart manufacturing environment. Applications of SFFJSP are analyzed in accordance with various applications to bring insight to the reader.

### 7.11. Use of Firefly Algorithm

Lunardi et al. [108] implemented the firefly algorithm using the mixed-integer linear programming (MILP) model to extract the smart solutions for FJSSP. Various instances of FJSSP are evaluated using the proposed methodology integrated with fixed and non-fixed availability constraints [109].

### 7.12. Use of Lagrange Relaxation Method

Yan et al. [110] estimated near-optimal schedules for large-scale JSSPs by developing tightened MILP with constraint & vertex conversion and vertex projection processes with the help of the Lagrange relaxation method. The convergence and complexity were reduced exponentially by the development of the decomposition and coordination method.

### 7.13. Use of AGVs

Heger & Voß [111] evaluated the mean flow time and mean tardiness of FJSSP based on various priority, routing, and dispatching rules. The multi-purpose autonomous guided vehicles (AGVs) are used in the model to estimate the complex manufacturing system. The study concluded that the use of AGVs in the model along with rules reduces the mean flow time up to 70%.

### 7.14. Use of HSTL

Dolgui et al. [112] analysed the JSSP by applying the optimal control techniques with the additional hybrid structure terminal logical (HSTL) constraints for optimizing multi-criteria, i.e., cost, delivery time, and makespan. In this model, both control and state variables are defined for a dynamic environment in the supply chain (i.e., multiple suppliers and multiple factories). Process structures are individually highlighted for various customer orders and manufacturing processes. The Flexible Manufacturing System (FMS) is used to execute the operations at multiple workstations.

### 7.15. Use of DSS with Big Data

Turker et al. [65] offered a framework that comprises of decision support system (DSS) equipped with big data, along with the frequently used dispatching rules such as shortest processing time, early due date, shortest slack time, etc., to increase the performance of job shop under dynamic scheduling. The schedule updates instantaneously based on the criticality of the queue of jobs waiting for the assignment of the workstation. Their study concluded that the contribution of big data fills the gap between theory and practice by considering the real-time dynamic behavior of jobs and machines.

### 7.16. Development of Standard Dataset

Weber et al. [113] made a major contribution by developing the standardized data set for the JSSP problem. The authors argued that the present data set contains uniformity to some extent and that there is a time of need to create a comprehensive random dataset that

can be used not only by operation research (OR) researchers but by production managers. In today's environment, where Industry 4.0 brings a solution to most of the problems that were not considered while analyzing the JSSP problem, the dataset for comprehensive analysis is needed.

#### 7.17. Use of Q-Learning Algorithm

Zhao et al. [114] proposed a Q-learning algorithm to solve the FJSSP by considering the machine failures. The Q-learning algorithm works on the preemptive strategy and evaluates the consequences of the selected solving approach by the agent. The agent-based approach is used to select the best priority rule that can be used at the instance for selecting the machines and operations when the machine failure occurs.

#### 7.18. Use of RRCF

Liu et al. [115] proposed an operator-based robust right coprime factorization (RRCF) approach to deal with demand fluctuations while maximizing the robustness of the system. The proposed RRCF stabilized the job shop by solving bottlenecks at each stage while considering constant demands and reducing work in process (WIP). To evaluate the effectiveness of (RRCF), the results are compared with the proportional-integral-derivative (PID) controller. Their study concluded that the proposed RRCF outperformed PID and showed low overshoots and more steady-state behavior.

### 8. Robustness in Job Shop and Industry 4.0

Robustness in the Job Shop environment has been viewed as a concern and a constraint in the past. However, it has been found that, among the robustness and energy efficiency, there exists a clear relationship and there is a tradeoff not only among robustness and makespan but also among energy efficiency and makespan [116]. It can be analyzed and incorporated in the scheduling problem if the processing times are modeled as fuzzy numbers and scheduling is performed through a Hybrid Genetic Algorithm which leads to minimized makespan [117].

Inclusion of additional measures in the robustness problem such as maximal machine workload and makespan objective functions along with uncertainty, when solved through Modified Multi-Objective Evolutionary Algorithm based on Decomposition (m-MOEA/D), leads to a better convergence to the problem as compared with the Multi-Objective Optimization Evolutionary Algorithms (MOEAs) for a Multi-Objective Stochastic Flexible Job Shop Scheduling Problem (MOFJSSP) [118].

Consideration of pre-defined/predicted disruptions in a JSSP for robustness indicated that small-scale problems give solutions through both the mathematical model and the branch and bound algorithm. For large-scale problems, the aforementioned methods were not found to be viable since the time to solution considerably increased. For large-scale problems, beam search algorithm and particle swarm optimization were found to be better performing. However, a single method could not be singled out for solving the scheduling problem, since each method outperformed the other in different scenarios [119].

Recent studies indicated the effects of robustness in the real time scenario of machine breakdowns. Robustness in the multi-objective optimization with the inclusion of machine breakdowns along with makespan leads to the development of meta-models which, when solved through MOEA, indicates a better convergence and diversity in Pareto solution sets as compared to the slack-based surrogate measures [120,121].

### 9. Future Research Agenda

The scope for research in JSSP in the context of Industry 4.0 is still largely untapped and its utility and viability in various applications is still to be explored further. Figure 7 presents the future research agenda of JSSP augmented with Industry 4.0.

- Incorporation of customized decision-making criteria for machine learning-based decentralized operating systems.

- Industry 4.0 also provides room for human-machine collaboration where smart machines can assist humans to achieve efficient solutions, as discussed in Berti et al. [122]. Moreover, involvement of human input in decision-making for efficient and sustainable decisions directed towards Industry 5.0 framework.
- Development of customized smart sensors for manufacturing performance criteria assurance and assessment.
- Development of specialized sensors and quality assurance procedures for decentralized JSSP for medical-grade manufacturing.
- Implementation of blockchain and distributed ledger technologies in a manufacturing environment for sharing and retrieving data of machines functions between agents.
- Determination of sustainability indices for decentralized JSSP.
- Implementation of sustainability indices and other decision-making criteria for application in decentralized JSSP focused on the concept of Industry 5.0 (fueled by Information Technology and Environmental Sustainability).

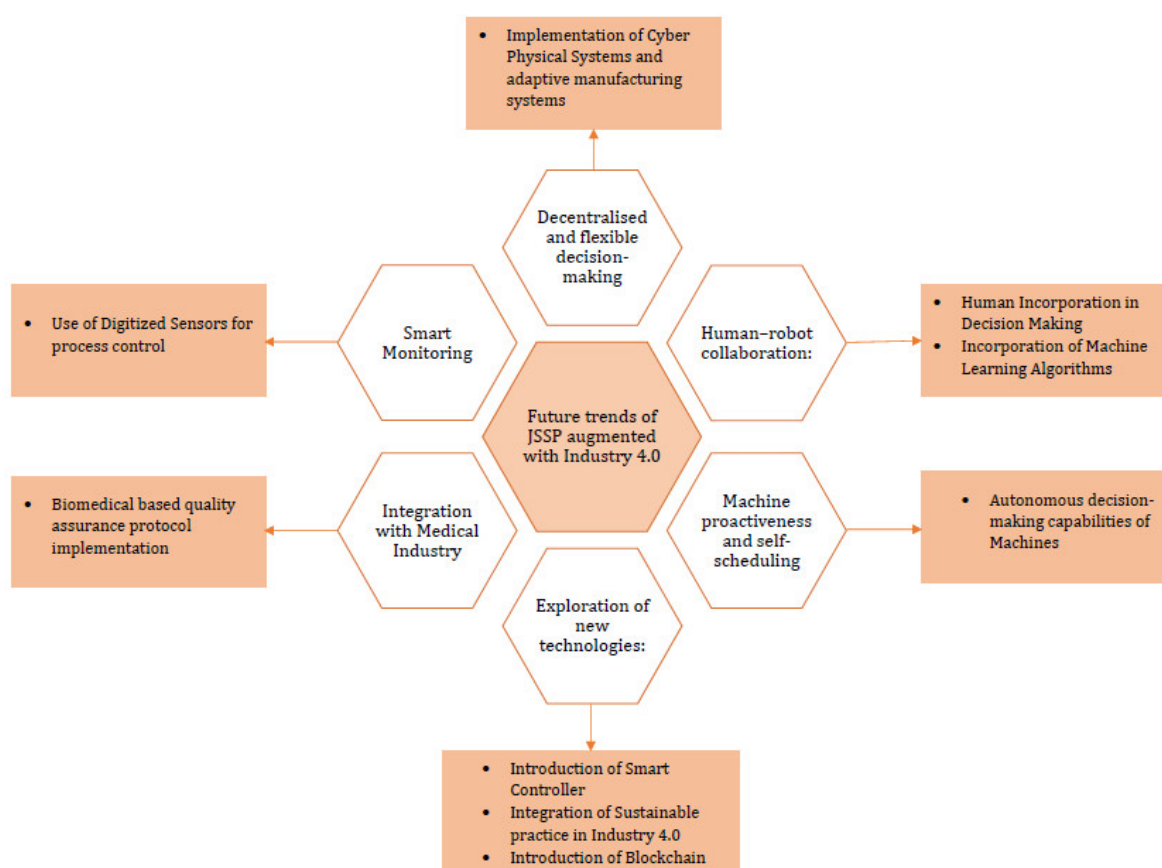


Figure 7. Dimensions of Future Research Perspectives.

## 10. Conclusions

In the first phase of this paper, the JSSP problem is summarized based on the structural framework and scheduling algorithms. Various studies are classified based on solving algorithms. The advantages and limitations of existing solving methods and challenges for the implementation in the Industry 4.0 environment are highlighted. In the second phase, the futuristic approaches to solving JSSP problems under Industry 4.0 environment are presented with their potential advantages. A framework is presented through which the original centralized scheduling problem can be turned into smart agents-based problems. In the third phase of this study, the latest studies from the year 2017–2021 are analyzed to provide an overview of the latest research trends in SFFJSP.

1. Integration of FJSSP with Industry 4.0 provides a conducive solution regarding computational time, makespan, tardiness, lateness, etc.
2. The latest research trends indicate that conventional JSSP is no more practical to study.
3. Multi machines, multi operations, multi resources with multiple factories and logistics centers should be incorporated in conventional JSSP to evaluate the actual dynamics of the system.
4. Currently, the research focus is on approximate algorithms rather than exact algorithms for solving JSSP and FJSSP. The global and local optimum solution is evaluated with the aid of multi-objective optimization techniques.
5. The metaheuristics approaches have acquired great popularity for solving the JSSP and FJSSP. Recent studies show that hybrid approaches are vastly used for solving JSSP under the Industry 4.0 environment.
6. The use of PID controllers, RFIDs, and barcodes has become a great source of integrating actual plant with its digital part.
7. Recent studies indicate the use of smart agents to determine the efficient sequencing of jobs while minimizing the complexity of JSSPs, is a competitive approach adopted by many scholars.
8. The merger of AI, CPS, deep learning, cloud computing, etc., in JSSPs has outperformed the conventional approaches of finding optimal solutions.

**Author Contributions:** R.A.L.: literature search and manuscript writing, editing. S.H.: literature search and manuscript writing. S.S.W.: content planning, reviewing and proof reading, manuscript editing. A.K.: content planning, reviewing, proof reading. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Not applicable.

**Conflicts of Interest:** The authors declare that there is no conflict of interest in the subject matter or materials discussed in this manuscript.

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