Towards Smart Remanufacturing and Maintenance of Machinery - Review of Automated Inspection, Condition Monitoring and Production Optimisation

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Abstract—Modern manufacturing has made huge progress in production efficiency. However, the status of machinery in production line deteriorates during production, subsequently, their condition can affect the quality of products, and also leads to unexpected failure and consequent disturbance to the production. In order to address this problem, smart remanufacturing and maintenance should be carried out for machinery. Current remanufacturing and maintenance are largely carried out by inefficient manual process and also lack smart tools to understand the impact of remanufacturing and maintenance to the current production. To go towards smart remanufacturing and maintenance in the era of Industry 4.0, automated inspection, condition monitoring and integrated optimisation of production and maintenance planning is necessary. In this article, the prior research on these topics was reviewed. Articles from peer-reviewed academic journals with high impact factors were found by using the related keywords and studied according to their research topics. It is found that the automated product inspection and tool condition monitoring have been studied, but they were not much integrated for the optimisation of production and maintenance planning. The integration of automated product inspection, tool condition monitoring, and optimisation of production and maintenance planning is a potential future research direction. This potential research can not only help to improve performance, but also reduce cost and waste of production, remanufacturing and maintenance.

Keywords — Industry 4.0, smart manufacturing, smart remanufacturing, automated inspection, condition monitoring, maintenance planning, production planning, diagnostic and prognostic, optimisation

I. INTRODUCTION

Production lines have improved the efficiency of manufacturing, however, the status of production equipment deteriorates during high-efficiency mass production. The deterioration affects the quality of products, and it will incur additional cost and resources to manufacturers unless being handled correctly. Therefore, it is necessary to maintain the status of production machinery, which can be done by remanufacturing and maintenance. However, the remanufacturing and maintenance are generally not efficient because they are carried out largely by manual process. In addition, remanufacturing and maintenance will disturb the production schedules inevitably, so smart remanufacturing and maintenance are needed in the era of Industry 4.0 to improve the efficiency and support optimised production planning.

For direct monitoring of the tool condition, many non-destructive testing (NDT) methods are used, and the abnormal features of equipment are under monitoring, for example, using the measurement of acoustic emission and vibration. With the development of sensor technology, the accuracy of tool condition monitoring (TCM) is increasing. Moreover, some researchers are focusing on automated detection and identification of defects in products. In some cases, TCM cannot detect the flaw of machinery, but the quality of products can indicate the status of tools. In the research of products inspection, allocation strategy (AS) and parametric strategy (PS) are currently the main approaches of inspection planning [1]. However, in the context of Industry 4.0, the methods should be combined as the AS-PS, since both location and parameter help improve the effectiveness of inspection. The research trend nowadays is not only to implement the suitable methods of inspection, but also fuse the sensor data to make an accurate evaluation of current state and prediction of the useful life of equipment.

After the defects are detected, the equipment system should be evaluated, and the root reason should be found out. The decision of remanufacturing and maintenance should be made accordingly. Since remanufacturing and maintenance interrupt production, they should be planned to save cost and improve efficiency. So far, end-of-life (EOL) and active remanufacturing are two main types of remanufacturing [2, 3]. While EOL achieves the biggest value of components, active remanufacturing takes actions before the cores are broken. Similarly, there are many kinds of maintenance strategy: breakdown maintenance, time-based maintenance, preventive maintenance (PM), condition-based maintenance (CBM), total productive maintenance (TPM) [4]. Current remanufacturing and maintenance methods inevitably disturb production, which is a waste of time and resources. Maintenance 4.0 [5], on the other hand, uses all the real-time data in the internet of things (IoT) to continuously monitor the system. Maintenance planning is updated to minimise the planned downtime and resource waste.

The real-time planning of maintenance influences production scheduling, so the integrated production scheduling is necessary. Two approaches can be used to achieve integrated production planning: model-based and data-driven. In industry 4.0, production planning should be real-time and data-fusion-based. With the development of the metaheuristic algorithms, hybrid methods of optimisation on planning are also developed. Since the structure of production is various, more specific studies have been carried out by researchers.

This review aims to survey the state of the art of automated inspection, condition monitoring, and production planning optimisation based on remanufacturing and maintenance. The research trends on these topics were studied. To achieve the aim, the relevant research literature was searched in the most comprehensive databases, Scopus, ScienceDirect and ProQuest. Since the automated inspection and condition monitoring methods are related to the development of sensor
technology and metaheuristic algorithms, the literature on this topic is searched from 2000 to 2020. Because automated inspection and condition monitoring are included in the research topic of diagnostic and prognostic (DP) of production system. The search terms “production”, “tool wear”, “diagnostic” and “prognostic” were used to search for related literature in each database. For the optimisation of production and maintenance planning based on automated inspection and condition monitoring, the search terms “production optimisation”, “maintenance plan”, “quality inspection” and “tool condition monitoring” were used to find relevant journal articles.

For all the reviewed literature, only research articles in peer-reviewed academic journals were considered. All the journals with the most impact indicator, for example, Journal of Manufacturing Systems, International Journal of Production Research, were searched. After the collection of articles, the cleansing was implemented by reading all the articles. The articles, which included the keywords, but with different topics, or not related to engineering and manufacturing, were excluded from the searched results. Fig. 2 and Fig. 1 show the distribution of the final article numbers during different periods. Since the timespan of the searched literature is large, the number was analysed in every 5 years.

The number of papers showed an increasing trend of publishing on the research topic on automated inspection, condition monitoring, and optimisation of production and maintenance. As shown in the figures, although many research articles focused on DP of production system, fewer researchers are studying the integrated optimisation of production and maintenance planning based on automated inspection and TCM. The number of literature is increasing in recent years since the topic has drawn researchers’ attention, but the total number is still small comparing to the conventional optimisation of production planning. Moreover, no review has considered all the topics.

There are two main questions to be answered in this review article: how to evaluate the status of the equipment in an autonomous way; how to make the remanufacturing and maintenance plan guaranteeing continuous production at the least cost. The state of the art on related topics was reviewed in this study. The research trends were also predicted in this research area. The rest of the paper is organised as follows: the automated methods of product inspection is reviewed in section 2. The methods of automated tool condition monitoring are reviewed in section 3. Based on the product quality and tool condition, the methods evaluating the equipment status are reviewed in section 4. The optimisation of production scheduling considering remanufacturing and maintenance planning is reviewed in section 5. The discussions and conclusion are drawn in the last section.

II. AUTOMATED INSPECTION OF PRODUCT QUALITY

The produced parts are inspected in the production line to guarantee quality. Meanwhile, the quality of products, for example, the surface roughness has a positive relationship with the state of tools [6], the inspection can be used as indirect TCM.

There are two factors to consider in the planning of inspection: inspection plan and inspection method. They are significant factors and challenging decisions in quality control and cost plan of the whole production process.

Inspection plan or inspection strategy (IS) research was started by Lindsay and Bishop to solve the optimisation problem of inspection cost [7]. The IS research is classified into two approaches nowadays: allocation strategy (AS) and parametric strategy (PS) [1, 8]. While AS determines where to install the inspection devices, PS plans the sample size to be inspected, the number of inspection repetitions, and the frequency of inspections. In automated inspection planning, hybrid AS-PS strategy should be proposed.

There are two directions of research on the inspection location. One is on where to install inspection sensors using computer vision, which is not investigated in this study. The other research is on where to set inspection station on the production line. The conventional method is to determine the location by optimising total cost and maintaining quality. Linear cost function for inspection and rework was established in [7]. The total cost of production line was modelled and the inspection stage is determined considering the minimisation of total cost. The optimisation functions to determine the inspection location, inspection capacity were built in [9]. The genetic algorithm (GA) was used to determine the location of inspection stations [10]. GA and simulated annealing (SA) algorithm were combined to allocate the inspection and minimize the total cost in [11]. The fuzzy logic was also used to calculate the number of inspection points and Hammersley’s algorithm to determine the locations of measuring points for the feature-based inspection planning [12].

While bigger sample size guarantees the reliability of inspection, it increases the inspection time and cost. Barnett [13] started the research on the economic sample size choice for inspection. Hammerly sequence and a stratified sampling method were used to determine the sample size in coordinate.
measuring machine inspection [14]. GA was used to
determine the sample size of each inspection in a multi-stage
production line [15]. Dynamic programming was also used to
dictate the optimal sample size and time interval of inspections
[16]. A dynamic solution using SA was made to decide the
sample size and acceptance limit by the system itself in a
multistage production process [17].

The methods of inspection include tactile, optical and X-
ray computed tomography (see Fig. 3). There are many ways
to implement automated inspection: computed tomography
(CT) and ultrasonic testing (UT) using industrial robot arms,
in-line installed eddy current, laser and computer vision
sensors, and X-ray measurement chamber [18]. The
automated inspection techniques can help maintain the quality
of products, subsequently, the condition of equipment can be
evaluated and identified by combining inspection system and
TCM.

III. AUTOMATED TOOL CONDITION MONITORING

The high-speed machining (HSM) is getting more
attention due to its efficiency, however, tool wear is the main
issue in HSM, as well as in other mass production [19]. Tool
condition monitoring (TCM) is a direct method to diagnose
tool wear and predict tool’s breakage. TCM helps to (a) reduce
the damages of the tools and parts; (b) improve productivity;
(c) predict the tool wear. NDT methods, such as acoustic
emission (AE), temperature, vibration, current, power, force,
computer vision, and other measurements, are used as TCM
methods.

TCM was normally implemented manually. Comparing to
autonomous method, human operators are more subjective,
flexible, but inaccurate [20]. With the development of sensor
technology, more research approaches to fuse multi-sensor
measurements and makes TCM more real-time and flexible.
In the early 1990s, Tanaka et al. [21] introduced microphone
into AE method of TCM. Choi et al. [22] introduced AE
method into on-line TCM. In their study, AE was set to be a
trigger to measure the cutting force which indicates the tool
breakage when a significant drop happens. The system can
recognise the potential breakage in 0.02 second. Sound
pressure was used to monitor the tool wear [23], as it is
significantly positive relative to the cutting force. Infrared
pyrometer was also used to measure the working interface
temperature continuously [24, 25]. The fitting of acoustic and
thermal measurement was used to monitor the tool wear in
real-time [26]. The combination of various TCM methods
prevents the errors made by external factors and makes the
monitoring more reliable. After the 2000s, more researchers
started to combine force measurement TCM with algorithms
to model tool wear, which makes tool wear process more
predictable. Hidden Markov model (HMM) algorithm was
used to track the progress of tool wear [27]. It was proved that
tool condition can be monitored using bargraph HMM method,
and predicted using multiple modelling HMM method.
Cutting force and power signal were used as monitoring
parameters. Force measurement can be also combined with
current measurement using a neural-fuzzy network which
identifies the force with current measurement to reduce
modeling uncertainty [28]. Real-time torque ($M_t$) and forces
($F_{nx}, F_{ny}, F_{nz}$) measurement signals were used to train an
artificial neural network (ANN) to predict flank wear of the
tools on computer numerical control (CNC) [29]. The model
 demonstrated good performance with a low error ratio. While
the force indicates the static performance of the tool wear, the
vibration demonstrates the dynamic characteristics of the tool
wear [20]. Force and vibration measurements were carried out
to collect data to train summation wavelet-extreme learning
machine models in high-speed milling CNC [30]. Tool wear
trend and remaining useful life (RUL) were estimated online
in an efficient method. Martínez-Arellano et al. [31] combined
vibration measurement, force measurement, acoustic emission
and a microscope to monitor the tool wear, with the help of
deep learning algorithm which was trained by the sensor data,
the tool wear condition was classified. Combining the deep
learning and the Gramian angular summation fields (GASF)
signal imaging techniques, the complexity of computation is
simplified, and the accuracy of classified tool wear is over
90%. The sensor fusion of CV and force measurement was
used to monitor the tool wear, and predict the tool breakage
by training self organised map network [32]. The method is
easy to implement online, the system was validated online in
experimental environment. Besides, laser sensors, infrared
thermography, and more visual monitoring techniques are
used in the modern TCM.

As reviewed, the automated TCM can be implemented by
using automated sensor techniques, and automated data
processing can be used to classify the defects of production
equipment. Multi-sensor data fusion is used to eliminate the
uncertain signal error caused by single-sensor measurement.
Computer vision and other advanced visual methods help
improve the reliability of TCM. Algorithms are introduced to
help improve the accuracy of the classification of defects.
However, some defects can not be detected by TCM in time,
the inspection of products, indirectly, can help predict the
deterioration of the equipment.

IV. DEFECT DETECTION, IDENTIFICATION AND TOOLS
EVALUATION

The results of TCM directly indicates the state of tools, the
results of product inspection also have a positive relationship
with the tool degradation. The two processes can be combined
to detect and predict defects in the system. The detection of
defects helps evaluate the status of tools, maintenance
decision can be made according to the status of system and the
root cause analysis.

The detection and prediction of the system are defined as
diagnostic and prognostic (DP) in production. DP is normally
included in TCM system [6], but there are also studies
showing the inspection of product helps DP in the evaluation
of production system. The diagnostic system is to estimate the
current status of the production system, while the prognostic
system is to analyse the root cause and predict RUL of tools.

There are few works of literature regarding the relation
between product inspection and tool wear. Predictive neural
network was used to not only predict the surface roughness,
but also evaluate tool wear [33]. The data of surface roughness
of products and the tool flank wear under certain turning
condition was collected to train the neural network. The
surface roughness and tool wear can be predicted in other cutting conditions within the training range. Yeo et al. [34] used neural network to integrate the data of cutting chip surface reflectance and cutting forces to estimate the tool wear. An adaptive neuro-fuzzy inference system model was established to estimate RUL of tools by using the data of surface roughness combining with the cutting force [35]. The model can be also used to predict product surface roughness based on the cutting force. An optimised support vector machine (SVM) method was also used to estimate RUL of tools by inspecting the product quality in real-time [6]. The relation between product quality and tool degradation was established, subsequently, RUL of tools was estimated. The identification of defects can be implemented by comparison with CAD model of the tools. When the nominal CAD model is not available, some feature identification algorithms, for example, iterative closest point algorithm [36], can help solve the problem. Comparing with the identification of defects, the root cause of defects is more interested to the researchers.

The root causes of the tool deterioration should be found out after the defects are identified. Although there are many inspection stations on the production line, the products with in-built defect or design defect slip through all these processes and degrades the tools [37]. Some defects affect the appearance of the products, while others have an impact on the components (tools) on the production line. So when the defects are detected, the root cause of the defects should be found out. There are many methods to investigate the root cause of defects [38], for example, six sigma is a customer-focused methodology supported by a handful of methods and statistical techniques to reduce defects and eliminate waste from processes. A novel warrant cost reduction method was introduced in [39]: root cause analysis (RCA). The RCA implemented failure mode and effects analysis (FMEA) to collect data and used Bayesian network to elicit probabilistic inference for warranty failure, detection-to-correction cycle time reductions are the benefit of RCA model. Root cause analysis was used to help identify defects, make maintenance planning, and improve the quality of product [40]. The conventional RCA case study showed an improvement, however, the RCA required much data, and it runs off-line [41]. Root-cause machine identifier (RMI), on the other hand, was used to find the root cause for the defects online [42]. The data mining algorithm was used to identify the root reasons for the defects of products [43]. Dhafr et al. [44] introduced a statistical method to identify the root cause of defects by the probability map of the process. The data mining method was also used to establish a hybrid online analytical processing management system to online monitor the defects and find the root cause and take actions for the production line [45]. Besides the root cause, the RUL estimation of the tools is also important for production planning.

The tool degradation has an impact on the quality of products, the RUL prediction of tools provides important information to help make the remanufacturing and maintenance plan and avoid overstock of spare parts and to prevent fatal breakdown [46]. Remaining life distribution (RLD) was introduced into the spare part inventory to make the right decision for replacement [47]. A data-driven approach was introduced to estimate the RUL of a drilling machine [48]. Force and vibration sensors were used to monitor the condition of tools. The data features on the time domain and frequency domain were extracted. Adaptive Bayesian change point detection algorithm was proposed to process data and detect different machining stages. Ten machine learning algorithms were compared for the effectiveness, the multilayer perception algorithm outperformed others in terms of average root-mean-square error. Kerr et al. [49] started to use computer vision to estimate the tool wear dimension, RUL ended when the tool wear met the determined threshold. Mikolajczyk et al. [50] also used neural network combined with image processing tool to predict tool life in production. A hybrid deep learning gated recurrent unit network algorithm was used to predict the long-term tool wear and RUL [51]. The training data came from the AE, cutting force and vibration measurement of TCM system. The experiments showed that the proposed method outperformed other deep learning algorithms.

DP in production is an integrated process. Many works of literature focused on one facet of the problem, i.e., using only TCM or inspection to predict RUL or analyse the root causes, however, only a few previous papers included all facets of the problem. The DP integrating TCM and product inspection should be studied.

V. OPTIMISATION OF PRODUCTION PLANNING AND SCHEDULING

Production planning, maintenance and quality systems are the three key functions of production systems [52]. The potential future research direction is to model these topics simultaneously. There have been few studies regarding this direction, while current research studies the topics individually. For maintenance planning, numerical approach was used to find the optimal maintenance policy to maintain a Markovian deteriorating modelled production machine [53]. The rectifying sampling was used to sample the products to screen out the defective units [54], these two conventional methods are usually carried out jointly to improve the maintenance planning [16], GA was used to optimise maintenance scheduling by evaluating the degradation of tools [55]. The expense of maintenance and the gain of production were set as the cost function. GA was also used to optimise a multi-state production system with cyclical PM planning [56]. The inter-dependence between production and maintenance planning was taken into consideration. Zhu et al. [57] established a numerical model of a multi-component production maintenance scheduling method based on the tool condition. Prior research was integrated to introduce a joint maintenance interval for all degraded equipment, and a component alert limit threshold was established.

Some prior research has integrated DP or maintenance to maintain the quality of products and improve production planning. Hennequin et al. [58] optimised the single-stage single machine production system by establishing a fuzzy model of human factors in maintenance. Pandey et al. [59] introduced a novel method to jointly optimise maintenance scheduling, quality control and production planning. A block replacement method was introduced, the minimisation of the cost per unit time of total schedule time was carried out. However, only three batches of jobs were considered, metaheuristic algorithms can be used when the job batches are more than three. The Tabu search algorithm was used to find an optimised solution in the consideration of total cost of production, inspection and maintenance in a multi-machine multi-product system [52]. Li et al. [60] used TCM and on-line inspection to monitor the status of production line to improve the production processes. TCM monitored the status of machining tool, while on-line product inspection was used...
to evaluate if the tools are working properly to avoid unrepairable damages on workpieces, however, maintenance planning was not considered (see Fig. 4). Lu and Zhou [61] used TCM, products inspection, and PM to schedule the whole production. For process optimisation, a cost-based improvement factor was introduced to rank the subsystems of production. Both the quality of products and the status of production machines were monitored in the study. The low level of equipment states was used to trigger preventive maintenance. Maintenance can be scheduled by the proposed method, the quality and reliability of product were maintained. Dong and Ye [62] introduced a novel synchronized planning of production and maintenance. The joint-optimisation aims at green manufacturing. However, only the product quality was inspected to plan the maintenance.

The production needs re-scheduling, as the production and maintenance processes have been optimised. The production scheduling problem includes assigning jobs on machines and determining the sequence of jobs [63]. For production scheduling, more researchers are currently focusing on the multi-stage, multi-machine, multi-product production considering maintenance scheduling. Maintenance is triggered when the predefined thresholds of the system condition are met. It is shown that GA has the advantage to optimise the makespan and total completion time of the production for the simple production system [64]. Although simple metaheuristic algorithms have a high degree of randomness to solve various problems, a hybrid algorithm has the advantages, for example, a wider exploration of the solution space but a faster convergence, to optimise complex production planning problems [65]. For example, a hybrid genetic algorithm combining local search was used to optimise the scheduling of flexible job shop production [66]. The algorithm used partial representation method to shorten the chromosome length, the phenotype crossover and mutation were used to strengthen the inheritability of the method. Moreover, the local search is used to improve the algorithm in a balanced way. Similarly, a hybrid algorithm of GA and SA was also used to optimise the flow shop production with the consideration of CBM [67]. SA helped the crossover and mutation processes in GA. The degradation level of production system was also evaluated in this method. Most recently, a simulation-based optimisation (SBO) algorithm combining biogeography-based optimisation and harmony search optimisation was used to optimise the flexible production planning for the simple production system [64]. Although the researchers are pushing the improvement of production to Industry 4.0, there were only a small number of data of logistics, the data of planning and scheduling of production and maintenance. Moreover, most of the research focused on the cost reduction, while the consumption of time and resource, the impact on environmental were not considered.

In this review, current research has been studied in the areas of tool condition monitoring, product inspection, and integrated optimisation of production and maintenance (see Table 1). In the product inspection process, algorithms were used to evaluate the location of inspection and the number of inspection stations. With the development of sensor technology, the reliability of inspection can be higher. In cooperation with TCM, the integration of inspection and condition monitoring system can be used to diagnose and prognose the status of system. However, inspection errors are usually ignored in the prior researches of DP system. The root cause of the defects in products should also be analysed. The complex problems, for example, the efficient inspection planning for FJSP, should be studied in future research.

For TCM, sensor fusion and the use of metaheuristic algorithms have been implemented to improve the effectiveness of monitoring. However, the methods of TCM are still not efficient, more research should focus on how to realise real-time integration of TCM and inspection system to identify the defects, and implement real-time production planning. An optimised data process should be also considered to improve efficiency. More efficient algorithms with small computation complexity should be studied to make the measurement real-time. Good integration of TCM and inspection can help investigate the root cause of defects, improve the design and reduce defects of the product due to improper processes, consequently, total production cost can be reduced. RUL should be estimated, the production planning can be updated based on this value. With the on-line DP system, the evaluation of production system can be realised autonomously. More reliable data fusion algorithms should be introduced to make a more effective DP model.

Many articles studied hybrid algorithms to make scheduling of production based on the need for preventive maintenance. The effectiveness of the algorithms is satisfactory according to the literature, however, more efficient scheduling method is needed to realise the on-line scheduling purpose. In the era of Industry 4.0, more data of production, such as inventory and storage, the data of logistics, should be fused in the autonomous scheduling system. Although the researchers are pushing the improvement of production to Industry 4.0, there were only a small number of literature on the integration of automated inspection, TCM, and the planning and scheduling of production and maintenance. Moreover, most of the research focused on the cost reduction, while the consumption of time and resource, the impact on environmental were not considered.

As reviewed, product inspection and TCM can compensate each other in DP: TCM monitors the state of equipment to prevent quality degradation of the products, meanwhile, the tool wear may be made by defected products or designs. An optimised allocation and equipment selection of inspection and TCM can improve effectiveness. Different types of inspection and TCM methods have unique features, the selection of appropriate sensors and data fusion algorithm is another problem to be solved. Sensor selection should be
made based on the shape of products, the operation of production, the production condition and the total cost incurred. For particular production scenarios, the motion of inspection robot should also be studied. Data from different sensors should be trained to fuse to build algorithms to detect defects in production machinery.

Series, parallel, flexible job shop and other types of production system can produce different kinds of planning problems. As the condition of the production components changes, the scheduling of production, remanufacturing, and maintenance is difficult. The human factor and possible delay of the remanufacturing and maintenance increase the complexity of the problem. To balance this, the option to remanufacturing, maintenance or replacement can be made based on the cost consideration. The study on effective metaheuristic algorithms should be continued to find an adaptive algorithm for the integrated planning purpose.

Although the Industry 4.0 concept has been introduced, the smart remanufacturing and maintenance based on automated inspection, condition monitoring, and optimisation of production and maintenance planning is rare in the literature. In Industry 4.0, all the information of production system should be integrated, for example, the whole history of maintenance and repair, the logistic schedule, all the information and equipment should be connected to IoT. The spare parts stock inventory, logistic plan, the remanufacturing and maintenance plan should share information to guarantee the condition of equipment stay effective. The relationship of the stakeholders in production are transformed from a linear to a networked multi-level one. Subsequently, Industry 4.0 can make production more efficient, cost-effective, and more environment friendly. This is a new research area requiring more study in future.

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Table I. Overview of Research Directions and Representative Literature

| Products Inspection | TCM | Optimisation of Production and Maintenance |
|---------------------|-----|------------------------------------------|
| Research fields     |     |                                          |
| Tactile, optical,  | AE, | CBM, PM, TPM                            |
| X-ray, computer     | force, vibration measurement           |
| vision              | Metaheuristic algorithm model          |
| AS-PS planning      |     |                                          |
| Root cause analysis |     |                                          |
| RUL estimation      |     |                                          |
| Trends              |     |                                          |
| Automated inspection| Sensor fusion | Hybrid algorithm                  |
|                     | Integrated DP |                           |
|                     |     | FJSP with maintenance                   |
| Li et al., 2015 [63]| √   | Without root cause analysis             |
| Rahmati et al., 2018|     | Without RUL estimation                  |
| Jain and Lad, 2019  | √   | Without production scheduling           |
| Vogel et al., 2019  | √   | Without production scheduling           |
| Lu and Zhou, 2019   | √   | Without root cause analysis and RUL     |
| Proposed Research Direction | √ | √ | √ | √ |
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