Review of Automated Inspection, Equipment Monitoring and Optimization of Manufacturing

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***Abstract*—Modern manufacturing has made huge progress in production efficiency. However, the status of the production equipment deteriorates during manufacturing, and their condition can then affect the quality of products and total production cost. When viable, maintenance, remanufacturing and replacement should be carried out for such equipment to reduce the total production cost. However, many processes, for example, inspection and manufacturing planning are carried out by a human. In the era of Industry 4.0, an automated production planning with automated condition monitoring, equipment inspection and maintenance planning is desired. In this article, the literature on related topics is reviewed. The state of the art in this study helps to improve the performance of production lines in manufacturing.**

Keywords—smart manufacturing, production planning, maintenance planning, automated inspection, diagnostic and prognostic, optimization, process control

I. Introduction

Production lines have improved the efficiency of manufacturing, however, the status of the production equipment deteriorates during high-efficiency mass production. The deterioration affects the quality of the products. Therefore, it is necessary to maintain the status of the equipment, which can be done by maintenance, remanufacturing or replacement of the tools. However, the normal maintenance interrupts the manufacturing schedule, so how to make an optimised total manufacturing plan is very important for modern production.

So far, there are many kinds of maintenance strategy: breakdown maintenance, time-based maintenance, PM (preventive maintenance), CBM (Condition-based Maintenance), TPM (Total Productive Maintenance) [1] and maintenance 4.0 [2]. The current maintenance inevitably interrupts the production, which is a waste of time and resource. The researchers are managing to improve the total production plan by optimizing the maintenance plan.

Inspection of the equipment and condition monitoring of the equipment is important to manufacturing. AS (Allocation Strategy) and PS (Parametric Strategy) are currently the main methods of inspection planning [3]. However, in the context of Industry 4.0, the method should be combined as the AS-PS method. With the development of sensing technology, the TCM (Tool Condition Monitoring) is more real-time and precise, the research trend nowadays is to fuse the sensor data to make an accurate evaluation of current state and prediction of the useful life of the equipment.

There are 2 main questions to be answered in this review article: how to monitor the status of the equipment optimally? How to make the maintenance plan without interrupting the production or at the least cost?

The reviewed research literature is searched in Scopus, ScienceDirect and ProQuest databases. Since the diagnostic and prognostic methods are limited to the development of sensors and heuristic algorithms, the Literature review of this part is limited from the 2000s to 2020. The key words ‘tool wear’ ‘manufacturing’ ‘diagnostic’ ‘prognostic’ are used to search for related literature in Scopus, ScienceDirect and ProQuest databases (see Fig. 1).

For optimisation of manufacturing processes, keywords ‘manufacturing optimisation’, ‘maintenance plan’, ‘quality inspection’ and ‘tool condition monitoring’ were used to find relevant journal articles. All the journals with the most impact indicator were searched. The number of literature in recent 30 years showed an increasing trend of this topic (see Fig. 2).

The article is organized like this: in section 2, the methods of tool condition monitoring are reviewed. Product quality inspection and inspection planning are reviewed in section 3. The methods of diagnostic and prognostic to determine the equipment state are introduced in section 4. The optimization

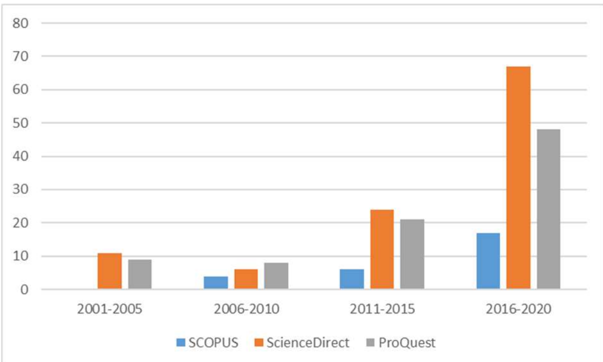

Fig. 1. The number of literature on tool wear diagnostic and prognostic in recent 20 years

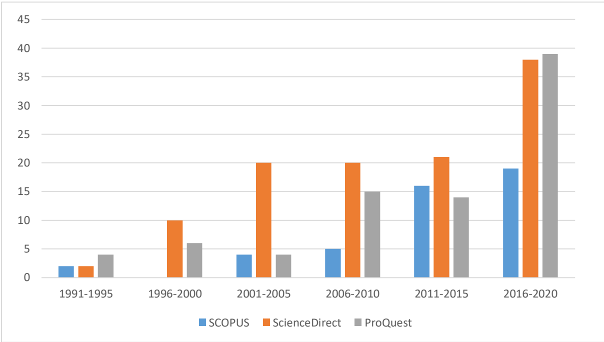

Fig. 2. The number of research literature on optimisation of manufacturing of recent 30 years

of the manufacturing process considering maintenance is reviewed in section 5. Section 6 draws the conclusion.

II. TOOL CONDITION MONITORING

To optimise the production planning according to the status of the tools, the status of the tools should be measured and predicted. There are two ways to monitor the status of the production equipment: monitoring of the tools directly (condition monitoring) or inspection of the produced parts. There is a confusion of the word 'inspection' in former literature, while 'inspection' is only used for products quality in this review, 'monitoring' is for the manufacturing tools.

The HSM (High-Speed Machining) is getting more attention due to its efficiency. The main issue in HSM is the tool wear [4]. Tool wear is also an important issue in other mass production. To diagnosis the tool wear and predict the tool's RUL (Remaining Useful Life), a method of tool condition monitoring (TCM) is required. The TCM help to (a) reduce the damages of the tools and parts; (b) improve productivity; (c) predict the tool wear. There are direct and indirect ways to monitor the tool wear, the indirect method means to disassemble the tools from the machine to measure.

Comparing to intelligent TCM, human operators are more subjective, flexible, but inaccurate [5]. With the development of sensors, the TCM became more and more automated. The common methods of TCM are acoustic emission (AE), temperature, vibration, current, power, force, computer vision, and other measurements.

After the 1990s, with the development of sensing technology, more research was approaching to fuse multi-measurement to make TCM. In the early 1990s, Tanaka et al. [6] introduced microphone into AE TCM. Choi et al. [7] introduced the AE method into on-line TCM. The AE was fused with cutting force. The tests showed that when the tool breakage happened, the AE went bigger. Sound pressure is used as well to monitor the tool wear [8]. Infrared pyrometer was used to measure the working interface temperature in [9]. Infrared thermography was also introduced in [10], which made the monitoring continuous. The fitting of acoustic and thermal measurement was used to monitor the tool wear in real-time [11]. After the 2000s, more researchers started to binding the force measurement TCM with more algorithms to modelling the tool wear. HMM(Hidden Markov Model) was used to track the progress of the tool wear [12]. The status of the tool wears was also classified by multiple modelling methods. Force measurement was combined with current measurement, used a neural-fuzzy network to identify the force with current measurement only to reduce the modelling uncertainty [13]. Real-time torque(Mz)-force(Fx, Fy, Fz,) measurement signal was used to train an ANN(Artificial Neural Network) to predict the flank wear of CNC (Computer Numerical Control) [14]. The model demonstrated good performance with a low error ratio. When the force indicates the static performance of the tool wear, the vibration demonstrates the dynamic characteristics of the tool wear [5]. Force and vibration measurements were carried out to collect data to train SW-ELM (Summation Wavelet-Extreme Learning Machine) models in high-speed milling CNC in [15]. Tool wear trend and RUL were estimated online in an efficient method. Martínez-Arellano et al. [16] used 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. The combination of the data of the sensors benefits the TCM. Besides, CV (Computer Vision), for example, laser sensors, thermography, is more used in the modern industry. The sensor fusion of CV and force measurement was used to predict the tool breakage, and to monitor the tool wear by training SOM (Self Organised Map) network [17]. A method combining CCD (Charge-coupled Device) camera with a microscope was introduced in [18]. The high-frequency noise was removed, the Laplacian method was used to detect the edge of the defect, however, the microscope is difficult to be used on-line. There is also an algorithm that estimates the depth of the defect by using one camera [19]. There is also 3D reconstruction method which building a 3D model to compare with the CAD (Computer-Aided Design) model of the tool [20]. White light interferometry was also introduced to TCM to measure the depth of the defects [21]. An automated CVTCM (computer vision-based tools condition monitoring) for the micro-milling system was introduced in [22], in which the filter filters the speckles and noises automatically, and the 3D carrier adjusts the position of the CCD, the lens and the light to make proper images automatically.

III. AUTOMATED PRODUCT QUALITY INSPECTION

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, so the inspection is also called "indirect TCM" because the status of the products has a relation with the condition of the tools.

In total production planning, there are two inspection factors to be considered: inspection planning and inspection method which are significant and challenging decision in quality control and cost plan of the whole production. Because after the inspection, the reasons for the defects are modified, the defected tools are replanned for maintenance, repair or replacement.

Inspection planning or inspection strategy (IS) research was started by Lindsay and Bishop [23]. The IS is classified into two approaches: allocation strategy (AS) and parametric strategy (PS) [3, 24],. While AS determines where to install the inspection devices, the PS plans the sample size to be inspected, the number of inspection repetitions, and the frequency of inspections. In automated inspection planning, AS-PS strategy should be proposed.

There are two directions of research for the inspection location. One is on computer vision, where to install the inspection sensors; and the other research is on where to implement inspection station on the production line. In this review, the focus is the latter one. The conventional linear cost function for inspection and rework was established in [23]. The total cost of the production line was modelled and the inspection stage is determined considering the minimizing of the total cost. The optimization functions to determine the inspection location, inspection capacity were built in [25]. The genetic algorithm was used to determine the location of inspection stations [26]. Genetic and simulated annealing algorithm were combined to allocate the inspection and minimize the total cost [27]. The fuzzy algorithm 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 [28].

While the bigger sample size guarantees the quality of the products, it increases the inspection time and cost. Barnett [29] 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 CMM (Coordinate Measuring Machine) which was common in manufacturing inspection [30]. Genetic algorithm was used to determine the sample size of each inspection in a multi-stage production line [31]. Dynamic programming was also used to dictate the optimal sample size and time interval of inspections [32]. Considering the sample size as a deciding factor in the inspection research, a dynamic solution using the simulated annealing algorithm was made to determine it [33].

There are many ways to implement the automated inspection: robot, measurement chamber [34]. The methods of inspection include tactile, optical and X-ray CT (Computed Tomography) (see Fig. 3).

IV. DEFECT DETECTION, IDENTIFICATION AND TOOLS EVALUATION

The results of TCM directly indicates the state of the tools, while the results of product inspection also have a positive relationship with the tool degradation. The detection of the defects helps evaluate the status of the tools, the total production plan is re-evaluated according to the integration of data.

According to [35], diagnosis and prognostic methods are included in the condition monitoring system. The diagnosis system is to estimate the current status of the production system, while the prognostic system is to estimate the root cause and the RUL of the tools. For the integrated condition monitoring system, there are two steps to realise: 1. Identify the defects in the products and the machines; 2. Estimate the status of the tools and predict the RUL of the tools.

After the defects are identified, the root causes should be found. Although there are many inspection stations on the production line, the products with 'in-built' defect or design defect slip through all the processes and degrades the tools [36]. 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. There are many methods to investigate the root cause of defects [37]: six sigma is a customer-focused methodology supported by a handful of methods and statistical techniques to reduce defects and eliminate waste from processes. It consists of DMAIC (Define, Measure, Analyze, Improve, Control) and DFSS (Design-For-Six-Sigma). A novel warrant cost reduction method was introduced in [38]: RCA (Root Cause Analysis). The RCA implemented FMEA (Failure Mode and Effects Analysis) to collect data and used BN (Bayesian Network) to elicit probabilistic inference for warranty failure, DTC (Detection-To-Correction) cycle time reductions are the benefit of RCA model. The RCA was used to improve the product quality, the conventional RCA case study showed an improvement, however, the RCA required much data, and it runs off-line [39]. While RMI (Root-cause Machine Identifier) was used to find the root cause for the defects online [40]. The data mining algorithm was used to identify the root reasons for the defects of products [41]. Dhafr et al. [42] 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 OLAP(Online Analytical Processing) management system to online monitor the defects and find the root cause and take actions for a jeans production line [43]. A weighted fuzzy algorithm was used to identify the root reason for the defects in the industry [44]. Brundage et al. [37] used machine learning Bayesian network algorithm to identify the root cause in a bottle opener manufacturing process.

The tool degradation and remaining useful life estimation are very important for the manufacturing planning since the tool degradation has impacts on the quality of products, and the RUL prediction of tools provides important information to help make the maintenance plan and avoid overstock of spare parts and to prevent fatal breakdown [45]. Kerr et al. [46] started to use computer vision to estimate the tool wear dimension, the RUL ended when the tool wear met the determined threshold. ANN was used to classify the tool wear [47], the conclusion was the Fy component of the cutting force can be neglected and Fz component increases when the tool wears increased. The fuzzy algorithm was introduced to fuse force, vibration and AE to estimate the tool wear condition [48]. The genetic algorithm assisted SVM (support vector machine) was used to fuse sensor data to diagnose the state of tools [49]. Three SVMs were used to classify the tools into sharp, workable, dull. GA was used to select useful features for the SVM classification. The tools were only classified for reuse, but the RUL was not estimated. A data-driven approach was introduced to estimate the RUL of the drilling machine [50]. Force and vibration sensors were used to monitor the condition of tools. The data features on the time domain and frequency domain were extracted. ABCPD (Adaptive Bayesian Change Point Detection) algorithm has been proposed to detect different machining stages. Ten algorithms were used to compare the effectiveness, the MLP (Multilayer Perception) outperformed others in terms of average RMSE (Root-mean-square Error). Mikołajczyk et al. [51] also used neural network combined with image processing tool to predict the tool life in manufacturing.

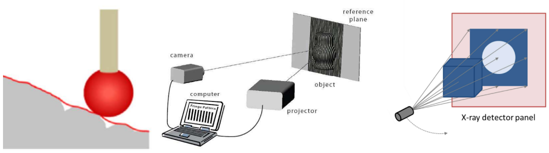

Fig. 3. Methods of quality inspection: (a). tactile; (b). optical; (c). X-ray

Meanwhile, there were few works of literature regarding the relation between products inspection and tool degradation estimation. Yeo et al. [52] used neural network to integrate the data of cutting chip surface reflectance and cutting forces as factors to estimate the tool wear. Neural network was also used to make a relation between product quality and tool wear [53]. The novel model can not only predict the tool wear but also predict the surface roughness. RLD (Remaining Life Distribution) was introduced into the spare part inventory to make the right decision for replacement [54]. An ANFIS model was established to predict the product surface roughness based on cutting force [55]. It can be also used to estimate the RUL of tools by the data of surface roughness combing with the cutting force. Hybrid deep learning (gated recurrent unit network) algorithm was used to predict the long-term tool wear and RUL in [56]. The training data came from the TCM system. An optimised SVM method was also used to estimate the RUL of tools by inspecting the product quality in real-time [35]. The relation between product quality and tool degradation was established. Then, the RUL of tools was estimated.

V. OPTIMIZATION OF MANUFACTURING PLANNING AND SCHEDULING

Production planning, maintenance scheduling and quality systems are the three functions of manufacturing systems with different goals defined on shared subjects [57]. The genetic algorithm and Tabu search algorithm have been used to find an optimised solution in the consideration of the total cost of production, inspection and maintenance. However, there were few research papers regarding this topic.

Ross [58] used a numerical approach to find the optimal maintenance policy to maintain a Markovian deteriorating production machine. The other approach, such as the rectifying sampling [59], is to sample the products to screen out the defective units [32]. Genetic algorithm was used to optimise maintenance scheduling by evaluating the tools life [60]. Hennequin et al. [61] introduced fuzzy algorithm to optimise the single-stage single machine manufacturing system. Nourelfath et al. [62] optimised a multi-state production system with PM planning. Pandey et al. [63] introduced a novel method to jointly optimise the maintenance scheduling, quality control and manufacturing planning. A block replacement method was introduced, the minimization of the cost per unit time of total schedule time was carried out. Zhu et al. [64] introduced a multi-component production maintenance scheduling based on the tool condition. A joint maintenance interval for all degraded equipment was introduced, and a component (machine) alert limit threshold was established. Li et al. [65] used TCM and on-line inspection to monitor the status of the production line. The TCM monitors the status of the machining tool by sensing the manufacturing processes, while the on-line product inspection also functions to confirm if the tools are working properly to avoid unrepairable damages on the workpiece (see Fig. 4). Lu and Zhou [66] used TCM, products inspection, and PM to schedule the production. For optimization, a cost-based improvement factor was introduced to rank the manufacturing system. Both the quality of products and the status of the manufacturing machines were monitored in the literature. In this literature, the tow triggers of preventive maintenance were used like former research, the quality of products and state of machines are both monitored in this case. Dong and Ye [67] introduced a joint-optimisation for the maintenance

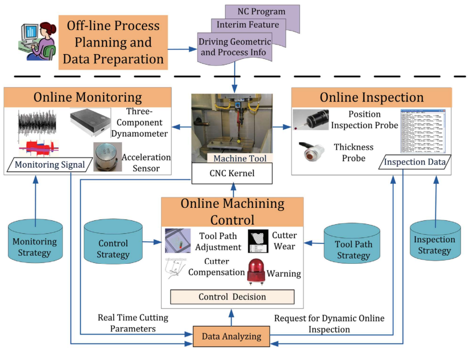

Fig. 4. Framework of the integrated monitoring system [65]

scheduling on green manufacturing. A novel synchronized scheduling and maintenance planning was introduced. However, the product quality and tool wear problems were not involved.

After the maintenance and manufacturing process are optimised, the manufacturing needs re-scheduling. For the manufacturing scheduling, many researchers were focusing on the multi-stage, multi-machine manufacturing considering maintenance. Maintenance is triggered when the predefined thresholds of the system condition are met. An integrated algorithm was introduced to optimise manufacturing planning [68]. A hybrid genetic algorithm was used to optimise the scheduling of flexible job shop manufacturing [69]. Hybrid GA was used to optimise the flow shop manufacturing with the consideration of CBM (Condition-based Maintenance) [70]. The degradation level of the production system was also evaluated. GA was also used to optimise the makespan and total completion time of the manufacturing [71]. BBO (biogeography-based optimization) and HSO (harmony search optimization) algorithm were used to optimise the FJSP (Flexible JobShop Problem) with the consideration of the degradation of the machine system [72].

VI. CONCLUSION

In this review, many current research and achievements have been evaluated in the aspects of inspection, condition monitoring, and integrated production & maintenance optimisation for the sake of cost reduction. It can be found that with the development of information technology, the evaluation of the manufacturing condition has been more accurate, as the RUL can be estimated. The quality of products can be inspected by various means, for example, computer vision, optical laser equipment and at the appropriate location. The researchers are pushing the improvement of manufacturing to Industry 4.0 era. However, there were only a small number of literature on the integration of TCM, inspection, maintenance, and production planning and scheduling.

As discussed, the TCM and product inspection can make up for each other: the TCM only monitors the state of equipment to prevent quality degradation of the products, meanwhile, the tool wear may be made by defected products. An optimised allocation of TCM and inspection can improve efficiency. The number of TCM and inspection equipment can be planned for the whole production line. Moreover, good integration of TCM and inspection can improve the design and reduce process defects of the product in return, consequently reduce the cost. Related research in this field should be considered and further studied in the future.

Different types of TCM and inspection methods have their 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 the products, the operation of production, the manufacturing condition and the total cost incurred. For certain context, the motion of inspection robot should also be researched.

Series, parallel, flexible job shop and other types of production can produce different kinds of problems. As the condition of the production components changes, the scheduling of manufacturing and maintenance is difficult. The human factor and possible delay of the maintenance increase the complexity of the problem. To balance this, the option to maintenance, remanufacturing or replacement can be based on the cost consideration.

Although the 'Industry 4.0' concept was introduced, the implementation of the concept has been rare in the literature. In Industry 4.0, all the information about the manufacturing system should be integrated, for example, the whole history of maintenance or repair, the logistic schedule, all the information and equipment should be connected with IoT (internet of things). The spare parts stock inventory, logistic plan, the maintenance, remanufacturing and replacement plan should share information to make sure the condition of equipment stay efficient. Then, Industry 4.0 can make manufacturing more efficient, cost-effective, and more environment friendly. Future research should focus on problems on these facets.

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