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Condition-based Real-time Production Control for Smart Manufacturing Systems

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Abstract— **In this paper, we present condition-based real-time production control for smart manufacturing which is aimed at improving system performance by automatically assessing a production system's condition and dynamically configuring the processing routes for smart products and parts. A machine's degradation condition is defined in discrete states and modeled as a Markov chain. By taking into account machines' degradation and buffers' occupancy, an optimization problem is formulated to maximize the production rate using Markov Decision Processes. The effectiveness of the method has been demonstrated on a three-machine flexible production system. Traditionally, condition monitoring and production control are designed, developed, installed and managed separately by different domain experts. Hence, in this paper, the implementation challenges of condition-based production control are also discussed, with the existing and missing enabling standards identified and analyzed.**

I. INTRODUCTION

We are entering a new paradigm for manufacturing based on mass customization to meet today's consumers needs of highly customized, and even personalized products and services at the mass production cost. In the new era, manufacturing is demand driven. It requires the production system to be flexible, reconfigurable, and proactive to the changes in the market, supply chains and factories [1]. Real-time production control plays a crucial role in empowering smart machines, smart cells and smart production lines for the demand-driven mass-customization scenario [2]. Manufacturing assets are being equipped with self-diagnosis and self-improving capabilities to lower maintenance costs.

Traditionally, production control [3] and condition-based asset management [4] are in two separate manufacturing management and operation domains. The absence of a link between the two functional domains leads to either underutilized equipment or disrupted production due to machine failures.

Cndition-based production was proposed by unifying two concepts, asset condition management (ACM) [5] and real-time production control [6], to improve manufacturing system performance. ACM, comprised of manufacturing asset condition monitoring, health assessment and maintenance planning, is aimed at providing a reliability model for asset degradation prediction and management. Real-time production control tries to optimize production system performance under unexpected circumstances, such as order quantity changes, order priority changes, even part processing plan changes, as well as machine condition changes. Real-time production control demands quick decision making and continuous operation of machines. That forces a control mechanism that is proactive to resolve predicted deviations between planned and actual system response based on demand forecast and machine condition prediction.

Data acquisition and asset condition assessment are required to capture the degradation process. Data includes both process measurements and actuation decisions provided by control systems, with an increased availability of additional data from Internet of Things (IoT) devices and mobile devices. The latest artificial intelligence techniques utilize the diverse data sets and provide diagnostic and prognostic asset health assessment capabilities [7]. Data acquisition and asset condition assessment have been successfully applied to both discrete and continuous manufacturing, to monitor and manage rotary machines and machine tools. Autoregressive models, principal component analysis, support vector machine are frequently reported for machine fault detection and diagnosis and prognosis [8]. The use of an artificial neural network was reported for machine remaining useful life estimation [7]. Various statistical approaches are studied for data acquisition and data processing to support decision making [9]. Given that the degradation models are well understood, a stochastic model is developed to evaluate productivity [10] and proper controls on maintenance planning [11], [12]. However, the use of condition monitoring for production control is scarcely reported in practice, partly due to its complexity. Although the concept of condition-based production was actually proposed by an industry consortium as early as in 2005 [13], its use cases are not even considered in any of the same organization's pilot projects [14].

Over the last few years, there has been continuous acceleration in the Information Technology (IT) industry - a tremendous increase of embedded and cloud computing power, the emergence of the large volume of data from IoT devices and ever improved data analytics algorithms. Integrating new Information and Communication Technologies (ICT) into manufacturing environments triggers both researchers and practitioners to turn attention back to condition-based production control, or combined production and maintenance scheduling [15]. Lee and Ni [16] present a decision-making architecture to determine maintenance and product dispatching policies based on condition-monitoring information and the relationship between machine degradation and associated product quality. They use a Markov decision process for the long-term decision making and integer programming for

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the short-term decision making with a multi-product, multi-station system. Aramon et al. [17] propose integrated maintenance and production scheduling in a deteriorating multi-machine production system over multiple periods. However, existing methods applying ACM to production control are not flexible enough to extend models to more general production systems. The analysis and control of production systems are challenging partially due to the uncertainty in production systems such as machine reliability. A short-sighted control policy without considering the uncertainty may not improve a production system in long term. Besides, a gap exists between those methods and implementations. This paper provides a mathematical formulation of condition-based production problems and introduces a use case and method to illustrate how the optimization problem is formulated and solved. The effectiveness of the method has been demonstrated on a three-machine flexible production system. In addition, a model extension for larger scale system is discussed to shed light on how to deal with computational complexity and real time data streams.

Traditionally, asset management systems and production control systems are in two different domains. They are usually designed, developed, installed and managed separately by different domain experts. Hence, in this paper, implementation issues and related standards requirements are also studied to ease the application of our condition-based production (CBP) approach in practice.

The rest of the paper is organized as follows. Section II provides a general formulation of condition-based production control problem, considering order models, product models, production models and asset condition models. Section III uses a three-machine flexible production system to illustrate the formalized problem and proposes a decentralized solution based on Markov Decision Processes. Section IV discusses the implementation issues and related standards required to support the implementation of our approach. Section V summarizes the paper and prescribes the future work.

II. System descriptions and assumptions

A general formulation of the condition-based production control is introduced as a discrete-time Markov chain problem in this section. Discrete-time Markov chain is widely used in research on production systems with uncertainty, and it is practical and applicable to real-world production systems [18]. A production system consists of a network of machines and buffers. The production system produces parts of different types. Parts of the same type may choose different routes in the network to finish their required processes. A machine in the network may provide more than one processing function required by different types of parts. An example of a production system is shown in Fig. 1. Three types of parts can be processed in this example. There are two routing options for type A parts. Both machines m_3 and m_6 can finish the last process for a type A part. Each machine among machines m_4, m_5, and m_6 has more than one function. Machines m_4 and m_5 are able to process both type B parts and components for Part Type C. Similarly, type A parts and

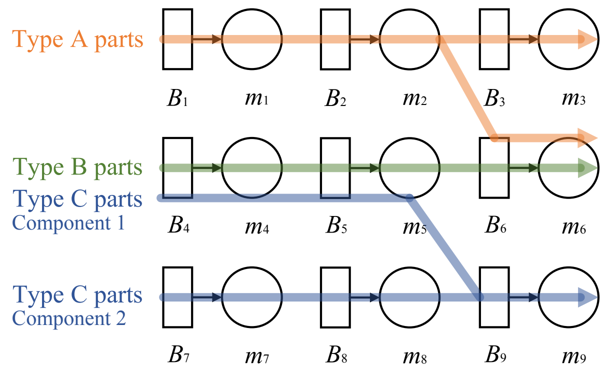


Fig. 1. Illustration of a customizable manufacturing system

type B parts share machine m_6. A type C part consists of two components, and they are assembled on machine m_9. Assumptions for a general flexible production system are formulated below.

(i) The production system can produce a total of J types of customized products. Part j, for $j = 1,\cdots,J$, has a total of K_j components.
(ii) The production system consists of M machines (denoted by machines $m_1, m_2, \cdots, m_M$) and H buffers (denoted by buffers $B_1, B_2, \cdots, B_H$).
(iii) All machines are synchronized with a constant processing time (cycle time), which is the time to process a part or a component.
(iv) The machines are classified into two categories: processing machines and assembly machines. The former can only work on one component at any time. The latter combines a certain number of different components into one part unit.
(v) Reliability models for machines are mutually independent. There are L degradation statuses for each machine. The statuses of machines are denoted by $s_1, s_2, \cdots, s_M$, respectively. For $i = 1,2,\cdots,M$, $s_i = l$ represents that machine m_i is in state l, where $l = 1,\cdots,L$. State 1 means a machine is down. The degradation of a machine is described as a discrete time Markov chain.
(vi) Buffer B_i has finite capacity N_i, for $i = 1,2,\cdots,H$.
(vii) The processing route of component k_j, for $j \in \{1,\cdots,J\}$ and $k \in \{1,\cdots,K_j\}$, follows a predefined machine sequence $s = (m_i) \in S_{j,k}$, where $S_{j,k}$ is the set of all valid sequences for component k_j.
(viii) Each part has its own due time and priority information. t_j^{due} denotes the due time for type j parts and $q_j = 1,2,\cdots$ denotes the priority, for $j = 1,\cdots,J$. A part with a smaller q_j has a higher priority for processing.

System performance is measured by production rate, work-in-process, and completion time.

- Production rate $PR_i^j(t)$: the expected number of units of type j parts processed by machine m_i per time unit in cycle t.
- Work-in-process $WIP_i^j(t)$: the expected number of units of type j parts in buffer B_i.
- Completion time CT_i^j: the expected total elapsed time

from start to finish processing the order for type j parts on machine m_i.

A higher production rate, lower work-in-process, and lower completion time are primary objectives pursued for the production system. Our goal is to achieve the objectives through condition-based production control. As the condition of all machines in a production system are being monitored, their degradation status can help select the best processing route for each component in real time to prevent unnecessary blockage. Analytical methods are required to evaluate production system performance and generate control policies applicable to decision making.

III. Modeling and control for three-machine flexible production systems

This section introduces a three-machine flexible production system to illustrate condition-based production. An optimization problem is formulated to obtain the optimal control policy that maximizes the production rate by considering machines' degradation and buffers' occupancy.

A. Model structure and settings

A three-machine flexible production system illustrates how analytical methods are used to evaluate a production system's performance and how real-time control policy can be obtained and applied to the system. The production system under study is shown in Fig. 2. The system under consideration contains three machines (m_1, m_2, and m_3) and two buffers (B_2 and B_3) to process three types of parts. The machine sequence set for type A parts, type B parts, and type C parts are $S_{A,1} = \{(m_1, m_2)\}$, $S_{B,1} = \{(m_1, m_3)\}$, and $S_{C,1} = \{(m_1, m_2), (m_1, m_3)\}$, respectively. The material flow of a type C part is not fixed. When a type C part finishes its process in machine m_1, a decision is required to assign the type part either buffer B_2 or B_3 depending on the states of the downstream buffers and machines. The health/condition states of the three machines are denoted by s_1, s_2, and s_3. For $i = 1,2,3$, $s_i = 1$ represents a down state of machine m_i, $s_i = 2$ represents that machine m_i is working but in a degraded reliability condition, and $s_i = 3$ represents that machine m_i is working in its best health condition. The degradation for a machine is described as a discrete time Markov chain. The transition matrix of the degradation of machine m_i is denoted by P^i.

$$P^i = \begin{bmatrix} p^i_{11} & p^i_{12} & p^i_{13} \\ p^i_{21} & p^i_{22} & p^i_{23} \\ p^i_{31} & p^i_{32} & p^i_{33} \end{bmatrix}, \tag{1}$$

where $p^i_{12} = p^i_{23} = p^i_{31} = 0$. If machine m_i is in its best condition, the probability that the machine degrades in the next cycle is p^i_{32} and the probability that the machine stays in the same status is p^i_{33}. For $s_i = 2$, the probability that the machine degrades to a worse state is p^i_{21}. When machine m_i is down, it will be repaired. The probability that its status is back to its best status in the next cycle is p^i_{13}, and the probability that it is still under repair in the next cycle is p^i_{11}. The transition diagram of the degradation is shown in

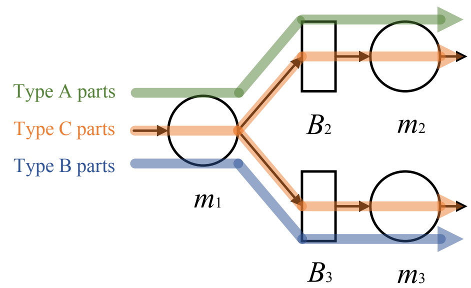


Fig. 2. A three-machine flexible production system

Fig. 3. Buffers B_2 and B_3 have finite capacity N_2 and N_3, respectively. The first-in-first-out policy is assumed regarding the buffer outflow process. Parts arrive at machine m_1 with a probability p_1, p_2 and p_3 for type A, type B and type C, respectively, where $\sum_{i=1}^{3} p_i = 1$. Machine m_1 is blocked during a time slot if at the beginning of the cycle, a) machine m_1 is functioning, b) the buffer to which machine m_1 is about to send the buffer is full, and c) the machine downstream from the full buffer is down. Machine m_1 is never starved. Machine m_i, for $i = 2,3$, is starved during a time slot if machine m_i is functioning, but with no parts in buffer B_i. Machines m_2 and m_3 are never blocked.

The state of the production system is defined as $(n_2, n_3, s_1, s_2, s_3, \alpha)$, where n_2 and n_3 denote the numbers of parts in buffers B_2 and B_3, respectively. s_1, s_2, and s_3 denote the state of machines m_1, m_2, and m_3, respectively. $\alpha = 1,2,3$ represents that the type of the part being processed by machine m_1, namely A, B, and C, respectively. $x(n_2, n_3, s_1, s_2, s_3, \alpha, t)$ defines the probability for state $(n_2, n_3, s_1, s_2, s_3, \alpha)$ at the beginning of cycle t.

The production rate $PR(t)$, defined as the expected number of parts produced by machines m_2 and m_3 in the t-th cycle, is used to measure the system performance. The production rate $PR(t)$ can be obtained in the following way:

$$\begin{aligned} PR(t) = & \sum_{n_2=1}^{N_2}\sum_{s_1=1}^{3}\sum_{s_2=2}^{3}\sum_{s_3=1}^{3}\sum_{\alpha=1}^{3} x(n_2,0,s_1,s_2,s_3,\alpha,t) \\ & + \sum_{n_3=1}^{N_3}\sum_{s_1=1}^{3}\sum_{s_2=1}^{3}\sum_{s_3=2}^{3}\sum_{\alpha=1}^{3} x(0,n_3,s_1,s_2,s_3,\alpha,t) \\ & + \sum_{n_2=1}^{N_2}\sum_{n_3=1}^{N_3}\sum_{s_1=1}^{3}\sum_{s_3=2}^{3}\sum_{\alpha=1}^{3} x(n_2,n_3,s_1,1,s_3,\alpha,t) \\ & + \sum_{n_2=1}^{N_2}\sum_{n_3=1}^{N_3}\sum_{s_1=1}^{3}\sum_{s_2=2}^{3}\sum_{\alpha=1}^{3} x(n_2,n_3,s_1,s_2,1,\alpha,t) \\ & + 2\sum_{n_2=1}^{N_2}\sum_{n_3=1}^{N_3}\sum_{s_1=1}^{3}\sum_{s_2=2}^{3}\sum_{s_3=2}^{3}\sum_{\alpha=1}^{3} x(n_2,n_3,s_1,s_2,s_3,\alpha,t). \end{aligned} \tag{2}$$

The summation of the first term and third term of the equation is the probability that machine m_2 produces a part and machine m_3 does not produce a part. The summation of the second term and fourth term of the equation is the probability that machine m_3 produces a part and machine m_2 does not produce a part. When neither buffer B_2 nor B_3 is empty and both machines m_2 and m_3 are functioning, two parts will be produced in the next cycle. Thus, the last term

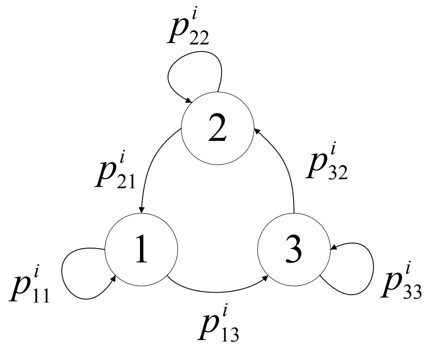


Fig. 3. Transition diagram of degradation for machine m_i, $i = 1,2,3$

is 2 times of the probability that two parts are produced by machines m_2 and m_3.

A binary variable $d_t(n_2,n_3,s_1,s_2,s_3,3)$ denotes the decision to assign type C parts to a specific machine. $d_t(n_2,n_3,s_1,s_2,s_3,3) = 0$ means that the type C part is assigned to machine m_2 when the state is $(n_2,n_3,s_1,s_2,s_3,3)$ in cycle t. $d_t(n_2,n_3,s_1,s_2,s_3,3) = 1$ means that the type C part is assigned to machine m_3 when the state is $(n_2,n_3,s_1,s_2,s_3,3)$ in cycle t. An optimization problem is formulated to maximize the production rate $PR(t)$ by finding the optimal control policy for $d_t(n_2,n_3,s_1,s_2,s_3,3)$.

B. Real-time control and performance evaluation

An infinite-horizon Markov Decision Process model is used to model the problem. Decision epochs are infinite. At each decision epoch, there are finite and discrete systems states. The action set at each decision epoch is $A_{(n_2,n_3,s_1,s_2,s_3,3)} = \{1,0\}$, for all $(n_2,n_3,s_1,s_2,s_3,3)$, and represents assigning a part to buffers B_2 and B_3, respectively. The production rate $PR(t)$ is the objective of the problem. Thus, the reward function is represented as

$$r(n_2,n_3,s_1,s_2,s_3,\alpha) = PR_{(n_2,n_3,s_1,s_2,s_3,\alpha)}, \tag{3}$$

for all $(n_2,n_3,s_1,s_2,s_3,\alpha)$. $PR_{(n_2,n_3,s_1,s_2,s_3,\alpha)}$ represents the number of parts to leave the system after the state $(n_2,n_3,s_1,s_2,s_3,\alpha)$. Let λ be the discount, y be the initial system state, and Y_t be the system state in cycle t. Then, the expected total discounted reward of policy π is

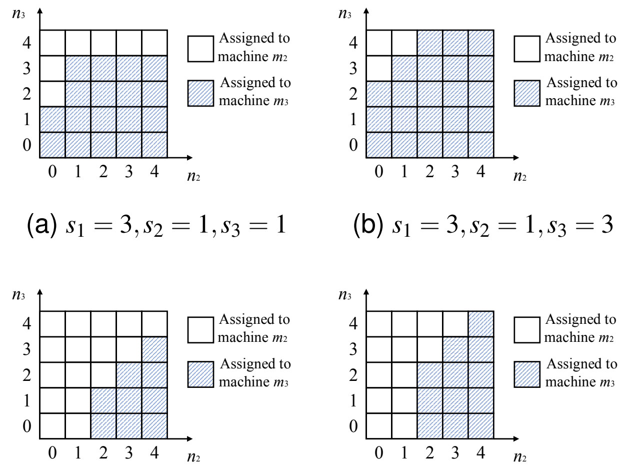
$$v_\lambda^\pi(y) = E_y^\pi\Big\{\sum_{t=1}^{\infty}\lambda^{t-1}r(Y_t)\Big\}. \tag{4}$$

The optimal policy is represented as

$$\pi^* = \arg\max_\pi E_y^\pi\Big\{\sum_{t=1}^{\infty}\lambda^{t-1}r(Y_t)\Big\}. \tag{5}$$

The states of the production system are discrete and the actions for each state are finite, so there exists an optimal deterministic stationary policy.

A case study is used to illustrate how the optimal control policy improves production rate. The parameters, determined artificially for the three-machine flexible production system as a demonstration, are given below.



(a) $s_1 = 3, s_2 = 1, s_3 = 1$ (b) $s_1 = 3, s_2 = 1, s_3 = 3$

(c) $s_1 = 3, s_2 = 3, s_3 = 1$ (d) $s_1 = 3, s_2 = 3, s_3 = 3$

Fig. 4. The optimal control policy for different machine status

$$N_2 = 4, N_3 = 4, p_1 = 0.2, p_2 = 0.05, p_3 = 0.75, \lambda = 0.95,$$

$$P^1 = \begin{bmatrix} 0.1 & 0 & 0.9 \\ 0.1 & 0.9 & 0 \\ 0 & 0.1 & 0.9 \end{bmatrix},$$

$$P^2 = \begin{bmatrix} 0.88 & 0 & 0.12 \\ 0.95 & 0.05 & 0 \\ 0 & 0.2 & 0.8 \end{bmatrix},$$

$$P^3 = \begin{bmatrix} 0.2 & 0 & 0.8 \\ 0.95 & 0.05 & 0 \\ 0 & 0.95 & 0.05 \end{bmatrix}.$$

Based on this setting, we apply the value iteration method to the Markov Decision Process model to obtain the optimal control policy. Part of the optimal control policy is presented in Fig. 4. It suggests that the optimal decision is to assign type C parts to a buffer with low occupancy, or a buffer next to a working machine. A detailed control policy can be obtained through this model. By following the machine-health-condition-based control policy generated from the model, the production system can have a higher production rate, which is validated through simulations.

The performance with the optimal control policy is compared with two benchmarking scenarios. In the first scenario, no real-time data is available, and a batch of type C parts is released to the production system with a fixed route, either following the sequence of machines m_1 and m_2 or the sequence of machines m_1 and m_3. In the second scenario, real-time data of buffer occupancy are available, but the machine status is not considered in the decision model. Type C parts are assigned to the buffer with a shorter queue between B_2 and B_3. The production system starts with both buffers empty and the three machines in their best conditions. The average production rate for the three different control policies from cycle 10 to cycle 50 is shown in Fig. 5. The performance of the proposed method and the shortest queue policy are much better than the policies that simply assign type C parts to a fixed machine. It suggests that production

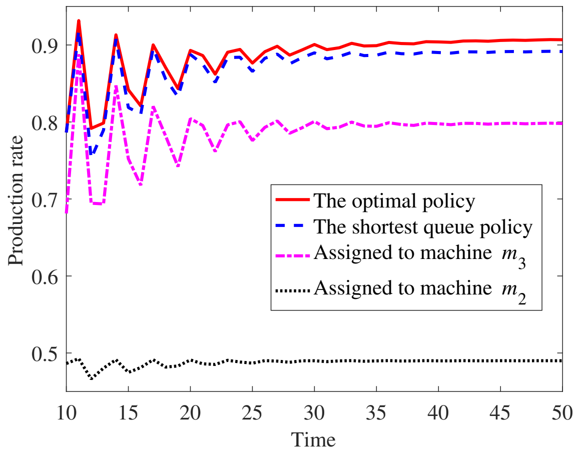


Fig. 5. The performance measures obtained by applying different control polices

systems supported by real-time information can fully utilize machines to achieve better performance. The performance measure from the optimal policy is slightly better than the shortest queue policy. It suggests that we can obtain a better control policy by taking more information, such as machines' degradation conditions, into consideration.

IV. Implementations Challenges and Standards Requirements for CBP

To implement the proposed method in industrial automation systems, it is critical to evaluate the integration needs between asset management systems and production control systems. Fig. 6 below shows a modified view of a condition-based production architecture based on Open O&M [13]. The connection of Automation and Control systems with their field bus sensors and transducers remains as is. Additional data from IoT and mobile devices is integrated through an Internet-based Automation and Control Bus. The bus also connects to Continuous Condition Monitoring (CCM) and Prognostics and Health Management (PHM) modules [19], [20]. CCM's primary functions include data-preprocessing, fault detection and asset health condition assessment. PHM runs fault diagnosis, asset remaining useful life prediction and predictive maintenance planning, and condition based production control.

When applying the proposed CBP, challenges have been discussed from the perspective of Operational Technology (OT) and IT integration [21]. Specifically, for the CBP implementation, the real time and safety requirements concern most practitioners. The integration of OT functions with IT functions through the Automation and Control bus using a service-oriented architecture has not been thoroughly studied and tested, and raise some concerns around performance and safety. Traditional manufacturing field system integrations are based on high frequency deterministic communications designed for small data exchange, for example, using field buses. The integration of IoT devices, mobile devices, and CCM/PHM modules usually need to accommodate a large amount of streaming data, while the communications between CCM/PHM modules and Automation and Control

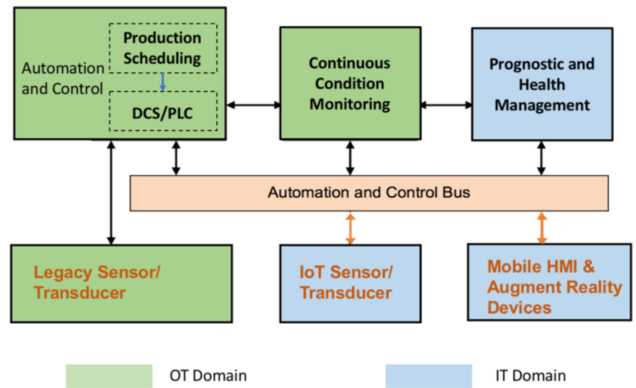


Fig. 6. Condition-based production architecture (adapted from [13])

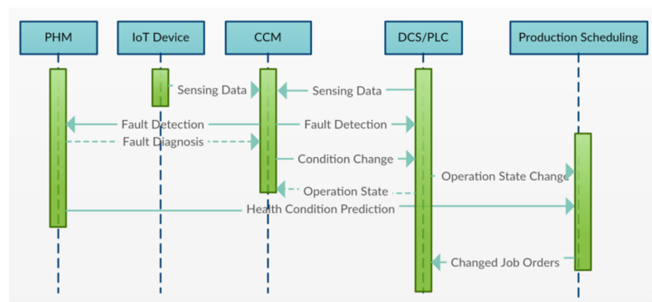


Fig. 7. Simplified sequence diagram for CBP

Systems are expected to be transactional (asynchronized). Neither the manufacturing industry nor standards development organizations have a mature solution to integrate asset management systems with production control systems. Safety issues are related to 1) the trustworthiness of the complex algorithms running inside PHM and 2) the computation efficiency of the real-time production scheduling algorithms. Learning-based PHM algorithms are essentially inductive reasoning which is seldom programmed to provide explanations on the learning results. Incorporating uncertain inputs into control loops definitely will worry operators and field engineers. Last but not the least, security issues are always a primary concern for the manufacturing industry, and will exist on until solutions with reinforced assurance are available.

Successful implementations of the proposed condition-based production control rests critically on standards. Three types of standards support CBP adoption:

(1) Common communication protocols and information models - Production systems and asset performance management systems adopt different communication and information models. Existing standards are developed by different consortiums or trade organizations. Field device integrations in automation and control domains are traditionally based on bus technology, such as Process Field Bus (PROFIBUS), Ethernet for Control Automation Technology (EtherCAT) and HART etc., which guarantee bi-directional communication determinism. Open Platform Communications Unified Architecture (OPC UA), evolved from Open Platform Communi-

cations Data Access (OPC DA), is considered the most relevant standard to integrate Distributed Control Systems/Programmable Logic Controller (DCS/PLC) with higher level functions, including production and job scheduling. IoT integration with CCM and PHM is more likely based on data sharing protocols, such as Message Queuing Telemetry Transport (MQTT) and Data Distribution Service for Real-Time Systems (DDS). General common information models for either production systems or asset management systems do not exist. The most general production system concept model is ISA 95 object model. In the machining industry, MTConnect provides an information model for operation monitoring, while Common Collaborative Object Model (CCOM) from MIMOSA is the most adopted information model for the process industry in asset management.

(2) Common service/message models - Fig. 7 shows a candidate sequence of the real time condition-based production control system. Each component in the CBP system provides certain services to realize real-time control and optimization. Services should be uniquely identified, with capability, capacity and performance accurately described for discovery, match and optimal composition. Currently, no shop floor manufacturing service modeling standards are available, neither are canonical message models for machine-to-machine communications.

(3) Safety and security - advanced analytics and artificial intelligence algorithms running in automation and control systems bring complexity to system decision making and raise safety concerns. IEC 61850 defines general Functional Safety of DCS and PLC control systems. But standards for artificial intelligence safety do not exist and are required to enable a trustworthy implementation of CCM, PHM and condition-based production control. Similarly, IEC 62443 defines security practice guidelines for industrial control systems, without specifications about how to integrate an OT system with an IT system as required by a CBP implementation.

V. Conclusion

We introduce a condition-based production control system for a smart manufacturing environment, where machines are flexible to perform various tasks and parts can be built with multiple route options. Real-time information on machines' degradation conditions and buffer occupancy are used to support condition-based real-time control. A flexible production system is adopted as a use case to illustrate how to evaluate system performance and generate a control policy through Markov Decision Processes. The implementation issues and related standards to support the implementation of our approach are discussed. The future work is to extend the decision model to a more general production network through aggregation methods [22].

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