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A cost-based model for integrating maintenance strategies in autonomous production control

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***Abstract* – Autonomous production control (APC) is able to deal with challenges, inter alia, high delivery accuracy, shorter planning horizons, increasing product and process complexity, and frequent changes. However, several state-of-the-art approaches do not consider maintenance factors contributing to operational and tactical decisions in production planning and control. The incomprehensiveness of the decision models and related decision support tools cause inefficiency in production planning and thus lead to a low acceptance in the manufacturing enterprises. To overcome this challenge, this paper presents a conceptual model for integrating different maintenance strategies in autonomous production control. The model provides relevant decision aspects and a cost function for a market-based approach.**

Keywords – Maintenance; Autonomous Production Control, Production Planning, Cyber Physical Systems, Industry 4.0

I. INTRODUCTION

In today's competitive market, manufacturing enterprises are faced with the challenge of achieving short delivery times and a high level of delivery capability despite ever-shorter planning horizons, a large number of external planning changes and increasing planning complexity [1]. This high degree of complexity in planning is no longer effectively and affordably manageable for humans [2]. On the one hand, there are high demands on flexibility and reaction times in planning and, on the other hand, high requirements regarding availability of production facilities, equipment and machines [3]. Considering the advancement towards Industry 4.0, autonomous production control represent suitable possibilities, especially approaches and methods, for increasing the degree of autonomy of a cyber physical production system (CPPS) while dealing with the aforementioned requirements [4]. The degree of autonomy of a CPPS describes the ability to plan, control and initiate actions autonomously [5]. However, these approaches are currently not yet limited to lab research and are not ready for industrial applications [6]. Most of the current approaches are based on idealised assumptions such as maximum availability (i.e. 95-98%) or do not take many decisive factors such as maintenance strategies into account. For example, the question such as "how the current state of a production plant can affect production control" is not taken into consideration [7]. Exactly these factors, as exemplified, are decisive for the acceptance and implementation maturity of autonomous approaches in industrial companies. Hence, the aim of the present work is to take a further step towards implementation maturity by integrating different maintenance strategies in APC.

II. MAINTENANCE IN AUTONOMOUS PRODUCTION CONTROL

Autonomous production control (APC) has the potential to deliver optimal and resource efficient processes as well as higher quality and variations of products than conventional, centralized decision-making systems [8] Adaptive, decentralised production control can reduce planning efforts [9], enable shorter reaction times in planning [10] and create greater planning flexibility [11]. To ensure high level of acceptance among operational planning staff, it is particularly important that the underlying models comprehensively take relevant factors of the production system into account and thus making robust decisions [12]. Current studies show that a large number of research activities are concerned with the development of approaches to autonomous production control [13]. However, few approaches deal with the integration of maintenance strategies in APC systems. For instance, Erol and Sihn (2017) presented a cloud based architecture for intelligent production planning and control considering maintenance [14]. Vallhagen et al. (2017) also presented a system and information infrastructure to enable optimized adaptive production control [15]. However, neither of these approaches explains which parts of maintenance should be considered and how they should be implemented in concrete terms. In the approach presented by Wang et al. (2018), the condition of production plants is automatically evaluated and thus the production sequence is intelligently adapted. System performance is improved by automatically evaluating the state of production systems and dynamically configuring processing paths for intelligent products and parts. While the implementation as decentralized production control is proposed, the work deals in detail with a three-machine problem and neglects the dependencies on a higher-level production planning [16].

In summary, it can be concluded that none of the identified approaches includes a systematic integration of different maintenance strategies into autonomous production control. However, if this aspect is not taken into account, these approaches remain largely unsuitable for industrial application, as no valid decisions can be made in the case of unplanned outages or planned maintenance, and thus ultimately the acceptance of such approaches by operational planning staff is not given.

III. RELEVANT ASPECTS FOR THE INTEGRATION OF MAINTENANCE IN APC

For the integration of maintenance into APC, an important step is to clarify which maintenance aspects are relevant for the integration decision. For this purpose, an expert survey has been conducted including professionals from industrial sectors, namely semiconductor production, metal processing industry, condition monitoring and automotive industry as well as national and international academic experts. The aim of this survey was to discuss the following question with the experts: "*How do you evaluate the individual aspects of maintenance with regard to their relevance for integration into production planning and control (PPC)?*" The first step was to discuss which aspects of Plant Maintenance (aka industrial maintenance) are generally important for PPC and for which area of PPC a specific aspect is relevant. Using the pair-wise comparison method, it was finally determined how relevant the individual aspects are for integration into the PPC. The results of this expert survey are presented in Figure 1. The essential aspects of maintenance are listed and evaluated with regard to their relevance for decision-making. A significant finding is that the relevance for the consideration of the individual aspects for the PPC strongly depends on the general operational conditions, especially the degree of automation, production type and flexibility in case of a plant failure. A closer look at the results shows that some aspects are particularly relevant for integration into APC, while other aspects may have a positive influence on the quality of decisions, but are not absolutely necessary for integration purpose. In addition, there are other aspects of Plant Maintenance which are particularly important for integration into medium- and long-term production planning.

Degree of Relevance	Symbol
very low relevance	○
low relevance	◔
medium relevance	◑
high relevance	◕
very high relevance	●

		Semiconductor	Metal Forming	Automotive	Condition Monitoring	Research National	Research National	Research International	Evaluation	
downtime & costs	*production control*	●	●	●	◕	●	●	●	●	Very High
repair time & costs	*production control*	◑	◕	●	◕	◑	●	●	◕	High
service time & costs	*production control*	◔	◕	●	◕	●	●	●	◕	High
availability of spare parts	*production control*	◑	◑	◑	●	◕	◕	●	◕	High
availability of maintenance personnel	*production control*	◕	◑	◑	◑	●	◕	●	◕	High
availability Qualification	*production control*	◕	◑	◑	◕	◕	◕	◕	◕	High
planned maintenance orders	*production control / production planning*	●	●	●	●	●	◑	◕	●	Very High
probability of failure	*production control / production planning*	◕	●	●	◑	◕	●	○	◕	High
condition of the system components	*production control / production planning*	●	◕	●	◕	●	◑	◑	◕	High
service intervals	*production planning*	●	◕	●	◕	●	◑	◑	◕	High
technical plant availability	*production planning*	●	●	◕	◕	◕	◑	◕	◕	High
maintenance quota	*production planning / production control*	◔	○	○	◔	◔	◔	◑	◔	Low
planned availability of spare parts	*spare parts management*	◕	◔	◔	●	◔	○	◕	◑	Medium
maintenance intensity	*production control*	◔	○	○	◔	◔	◔	◕	◔	Low
share of external services	*production control*	◑	○	◔	●	◔	○	○	◔	Low
labour cost share	*production control*	◔	○	◔	◔	○	○	◔	◔	Low
material cost share	*production control*	◑	○	○	◔	○	○	○	○	Very Low

Fig. 1. Aspects and their importance for APC integration into PPC system evaluated by various domain experts

IV. DEVELOPMENT OF A COST FUNCTION FOR AN INTEGRATED PLANNING

Different algorithms can be used to determine the order of the orders within the autonomous production control. Many of these algorithms use a cost function to prioritize or determine the production sequence. For example, when applying the market principle for APC, orders are allocated to individual production units based on a cost function. In this paper, a cost function for autonomous production control is developed using the market principle for autonomous production control as an example. Since different maintenance strategies make different demands on production control, but also allow for different information, it is advisable to use different cost functions for the different maintenance strategies. The cost functions are successively designed to build on each other, so that it is possible to use them in a production system that uses different maintenance strategies for the different assets and their components.

A. REACTIVE MAINTENANCE STRATEGY

The reactive maintenance strategy is characterized by the fact that the system components are operated until failure and therefore the failure probability and the associated costs are not relevant for decision-making. This is also reflected in the representation of the cost function of a production order under consideration of reactive maintenance (K_{RM} – cf. Equation 1). The cost function takes into account not only the sum of the fixed production costs (K_f), variable production costs (K_p), transport costs (K_t), as well as the current order load (Xp), and the number of transports (X_t), but also the maintenance cost ratio (K_m), The maintenance cost ratio describes the maintenance costs per production quantity produced. The maintenance costs under consideration include the costs for maintenance and repair of the various elements of the production system, the costs for spare parts stocking, and external service costs.

$$K_{RM} = \sum K_f + \sum K_v \times X_p + \sum K_t \times X_t + \sum K_m \times X_p \quad (1)$$

B. PERIODIC PREVENTIVE MAINTENANCE STRATEGY

In periodic preventive maintenance, measures are planned preventively either time-dependently, for example weekly, quarterly or annually, or load-dependently, for example after a certain number of operating hours or switching operations. Hence, the cost function of a production order, taking into account preventive maintenance (K_{PM} – cf. Equation 2). Also it takes into account the risk of an unplanned production downtime (R_{dtp}), costs in the event of a downtime event (K_{dt}), as well as any costs for contractual penalties due to schedule variances (K_P).
The costs in case of a downtime event are, for example, the lost contribution margin of the planned worklist in case of an unplanned downtime, as well as costs for repairs. These downtime costs are dependent on the current order load (Xp) as shown in Equation 3. The default risk in the case of periodic preventive maintenance (R_{dtp}), can be calculated based on historical failures. For this purpose, the probability density function fp(TSLF) is used for integration, where TSLF describes the time since last failure (equation). Normally, a normal distribution is assumed (equation 5]). While the normal distribution is calculated based on historical failures, the expected value is assumed by the MTBF (Mean Time Between Failure).

$$K_{PM} = \sum K_f + \sum K_v \times X_p + \sum K_t \times X_t + \sum K_m \times X_p + \sum K_{dt} \times R_{dtp} + \sum K_p \times R_{dtp} \quad (2)$$
$$K_{dt} = f(X_p) \quad (3)$$
$$R_{dtp} = \int_0^{TSLF} fp(TSLF) d_{TSFL} \quad (4)$$
$$fp(TSLF) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{TSLF-MTBF}{\sigma})^2} \quad (5)$$

C. CONDITION-BASED MAINTENANCE STRATEGY

The cost function of a production order under consideration of condition-based maintenance (K_{CM} – cf. Equation 6) corresponds largely to the cost function of preventive maintenance and also includes the risk of an unplanned production downtime (R_{dtc}) applying condition-based maintenance strategies. In this case, in which a maintenance task is planned depending on the actual condition of a component, (R_{dtc}) is calculated by a condition-based function fc at the respective time of the condition determination tc and the determined condition C at this time (equation 7). The determination of this function is usually based on empirical studies or on already known equations or manufacturer data. In many cases, especially if a complex empirical determination is not economical, it is sufficient to assign a fixed default risk R_{dtc} to defined states C based on empirical knowledge.

$$K_{CM} = \sum K_f + \sum K_v \times X_p + \sum K_t \times X_t + \sum K_m \times X_p + \sum K_{dt} \times R_{dtc} + \sum K_p \times R_{dtc} \quad (6)$$
$$R_{dtc} = fc(tc; C) \quad (7)$$

D. PREDICTIVE MAINTENANCE STRATEGY

In predictive maintenance (PdM), maintenance tasks are planned depending on prognosis of remaining useful life (RUL). The cost function of a production order, therefore, takes into account (K_{PdM} – cf. Equation 8), the risk of an unplanned production downtime (R_{drpdm}). The failure risk is calculated analogous to the condition-based maintenance by a function fp which is determined by the

RUL i.e. the remaining degree of wear and tear of the plant component (cf. Equation 9). This function must also be known or empirically determined.

$$K_{PdM} = \sum K_f + \sum K_v \times X_p + \sum K_t \times X_t + \sum K_m \times X_p + \sum K_{dt} \times R_{dtpdm} + \sum K_p \times R_{dtpdm} \quad (8)$$

$$R_{dtpdm} = fp(RUL) \quad (9)$$

$$RUL = e^{-\left(\frac{t}{T \times w_i}\right)^{\beta}} \quad (10)$$

In Equation 10, a determination of the RUL using a Weibull function is shown. Here, T represents the characteristic life, beta the shape parameter and w_i an influence factor to account for changing operating conditions of the Weibull function. In summary, Figure 2 shows the composition of the developed cost function depending on the applied maintenance strategy and visualizes the relationship between the individual cost factors

V. CONCEPTUAL MODEL FOR INTEGRATING MAINTENANCE STRATEGIES IN APC

The model for the integration of different maintenance strategies in APC is designed using three subsystems: i) a maintenance system, ii) a system for autonomous production control and iii) a system for production planning. In Figure 3, these subsystems and their interrelations are shown in detail. The system for autonomous production control maps the level for machine-to-machine (M2M) communication of the APC model. It regulates the real-time communication of the different elements of a production system with the aim of autonomously determining a production sequence based on the requirements of the production control system (the production orders) and the current framework conditions of the production system. To achieve this goal, real-time communication between different machine agents (MA), work piece agents (WPA) and resource agents (RA) is necessary (information flow A). An MA represents the different machines and plants of a production system. WPAs represent the open worklist within a production system. Depending on the production environment, an open worklist can be a concrete workpiece, production lot or any clearly identifiable portion of the production quantity. An RA represents further elements of a production system which are of interest for the task of production control. Depending on the production environment, these can be, for example, tools, workstations, measuring equipment, transport equipment and all other resources, which have a significant influence on the determination of the production sequence. The M2M communication between MA, WPA and RA takes place via a Message Transport System (MTS), which communicates between the elements of the production system and an Order Agent (OA) via an Agent Management System (AMS) and a Directory Facilitator (DF). The AMS manages the specific addresses of the individual agents (information flow B). In comparison, the DF manages the specific attributes and properties of each individual agent (information flow C). Examples of these attributes are the probability of failure, downtime costs, and repair and maintenance costs, which are communicated directly from the maintenance system to the DF (information flow D).

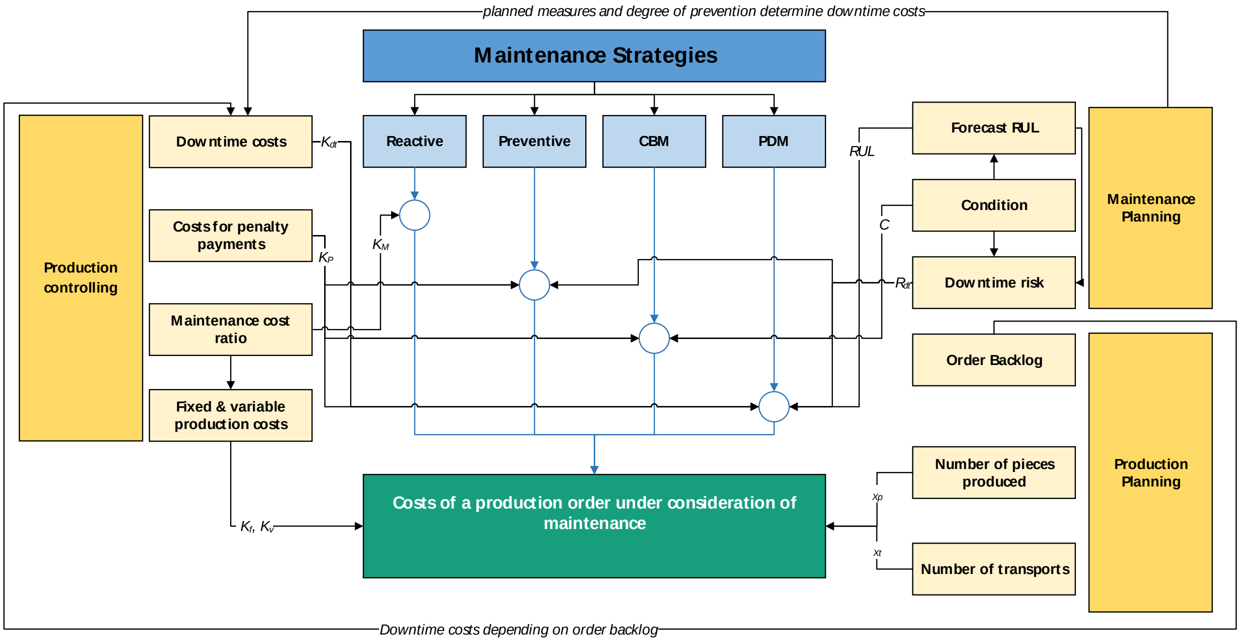

Fig. 1: Costs based production order under consideration of multiple maintenance strategies

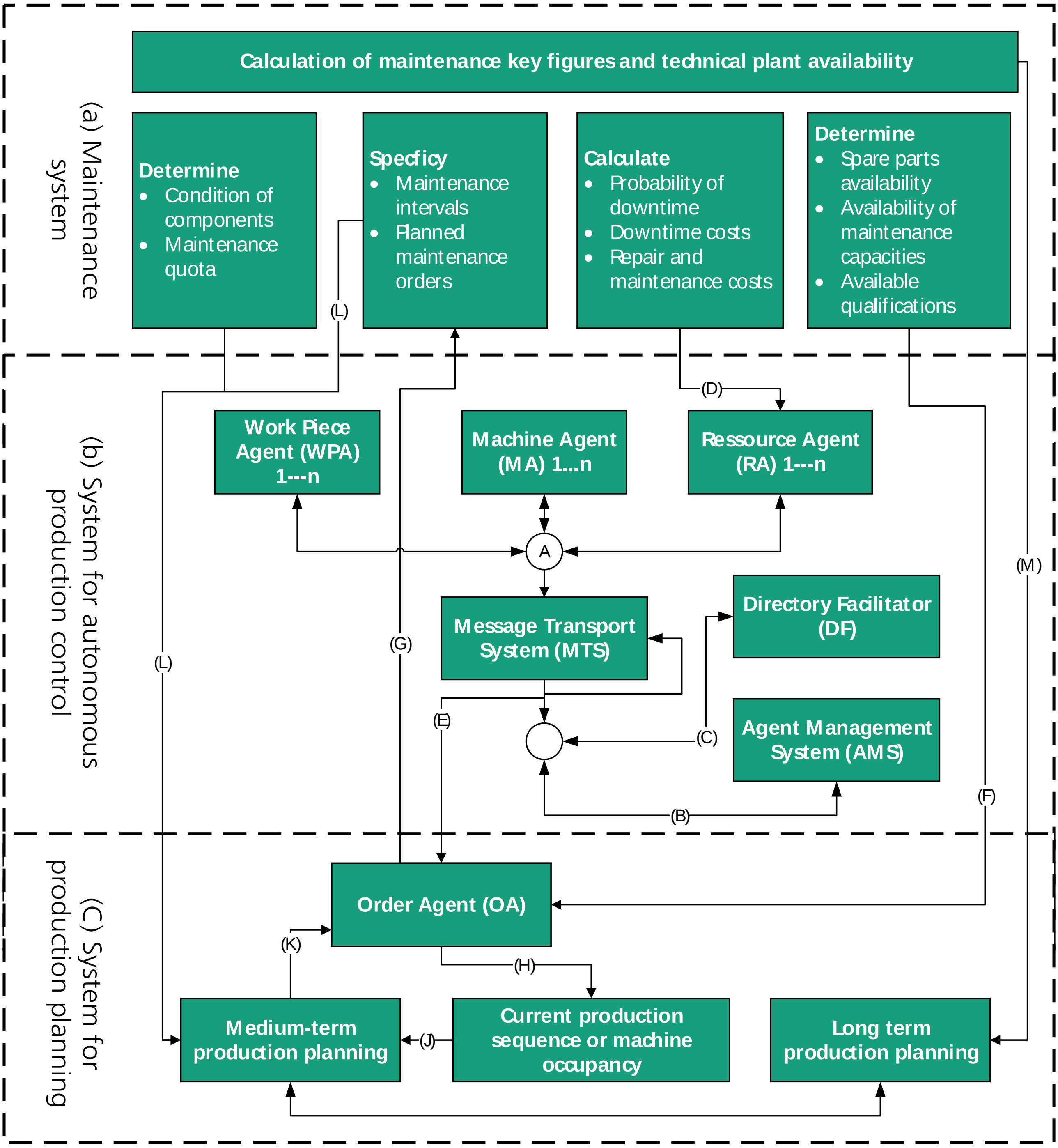

Fig. 2: Model for integrating maintenance strategies in APC

Further attributes describe, for example, the ability of an agent to determine which possible production steps can be carried out at the respective MA or which processing times result from this. The MTS distributes messages between the different agents and between agents and OA (information flow E). The MST transports information about the attributes and properties of the respective agents and production orders, which it receives from DF and OA. The MST transports this information from a specific address that it receives from AMS to another specific address that is also provided by AMS. The OA also receives information about spare parts availability, maintenance capacity availability, and available qualifications from the maintenance system (information flow F). With this information, taking into account the current production sequence, planned maintenance orders can be defined and confirmed to the maintenance system (information flow G). The operational control of these maintenance orders, as well as the control of production orders, takes place via communication between the various agents and DF and AMS using MTS. The central task of the system for APC is to determine the production sequence based on real-time M2M communication. Different scheduling models can be used to fulfil this task and to determine a sequential order for each of the different production orders provided by the OA. The production orders to be scheduled are typically created and managed by an ERP or MES system. In the present work, a "marketplace-based" model is used to illustrate the integration of the system for APC. In this case, the OA receives a demand in the form of a production order from an ERP or MES system. This demand is matched by a supply of capacities of the MAs and RAs representing the production capacities of the production system such as machine resources, work centre resources, tool resources or transport resources. The information necessary to describe the supply is provided to the OA by means of MST via the attributes of the production resources relevant for the production order in question, which are managed in the DF.

$$\mathrm{P} = \frac{1}{(t_i - t_e)} \times (t_c - t_i) \times K_{min} \qquad (11)$$

Using the information on supply and demand, OA is able to determine the priority of each production order (cf. Equation 11). The priority (P) is calculated by taking into account the desired completion date (t_c), the possible order start time (t_i), the order receipt time (t_e), and a priority factor (K_{min}). The OA can calculate the priority factor necessary to determine the priority using the information received from the MTS based on the information managed in the DF. To determine the priority factor, the cost function, presented in this paper, is used here.

$$p_{min} = \min[p(x)]\,; x > 0 < n_{MA} \quad (12)$$

Due to the structure of the underlying cost function, the priority of a manufacturing order increases the higher the costs of the manufacturing order and therefore the priority factor. Similarly, the greater the difference between the current time and the incoming order, the higher the priority. The higher the desired production duration of the worklist to be produced, the lower the priority of the underlying manufacturing order is calculated. Since it is usually assumed that both the variable production costs and the risk of an unplanned downtime differ between the different machines and plants of a production system, it is necessary to calculate the priority factor for the number of possible MA (n_{MA}), and then determine the minimum of the possible priority factors (p_{min}), (cf. Equation 12). Based on this minimum, the final step is to determine the sequence rank (N) of the production order to be produced on the assigned MA (cf. Equation 13) For this purpose, the priority rank (P(i)) of the individual available Production Orders (PA_n), is determined in order of the minimum priority.

$$\mathrm{N} = \mathrm{rank}\big(\mathrm{P(i)}\big) < \min\{PA_n\} \qquad (13)$$

Based on the sequence rank (N) and the lead time (t_{pt}), which the OA can determine using the information it receives from DF via the MTS and the current time (t_{act}), the OA can determine the estimated time of completion (t_N), (equation 14]) and communicate this together with the defined production sequence to the production planning system (information flow j). For example, the OA provides this information to an MES agent via the MST or an alternative interface.

$$t_N = t_{act} + \textstyle\sum_0^N t_{pt} \qquad (14)$$

VI. CONCLUSIONS AND OUTLOOK

In the present paper a novel model for integrating maintenance strategies in autonomous production control has been presented. Relevant decision aspects have been discussed and a cost function for an integrated planning using a market-based approach have been laid out. It is based on the key elements of a CPPS and their relations to establish a complete but fully, efficiently integrated component in PPC. As a next step the presented model needs to be implemented and evaluated. Since an implementation in a real time environment is yet hard to realize an implementation in a simulation environment using real production data is proposed.

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