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Online-scheduling using past and real-time data. An assessment by discrete event simulation using exponential smoothing

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ABSTRACT

Often deviations occur in the execution of a production schedule because prediction of productivity is unrealistic. Therefore, researchers have shown huge interest in understanding and modelling productivity factors to consider them in planning and design of manufacturing systems. In contrast, this paper examines how productivity can be considered in online-scheduling using past and real-time data and which effect this has on the overall system performance. The discrete event simulation exemplarily considering human productivity factors shows promising results but also the need for more complex forecasting methods Future work will also consider other factors such as tool wear and disturbances.

Introduction

The advances in ICT and their increasing application in manufacturing, currently summarised under the terms of Cyber-Physical systems (CPS) [1], Cyber-physical production systems (CPPS) [2] and Big Data [3], have inter alia two effects on future manufacturing systems: Original planning tasks such as scheduling are carried out increasingly online and more real-time data of the current manufacturing process are available for manufacturing control [4,5].

Often deviations occur in the execution of a production schedule because prediction of productivity is unrealistic [6]. Errors occur due to multiple reasons such as technical, organisational or personal ones. For instance, model builders tend to assume that workers operate at an identic and constant rate throughout the day [7]. Therefore, researchers have shown huge interest in understanding and modelling productivity factors to consider them in planning and design of manufacturing systems [8–13]. In the context of the described development towards CPPS, we put forward two hypotheses in this paper:

– Productivity factors can be considered not only in planning and design but also in real-time control of manufacturing systems. This increases the performance of the manufacturing system.
– In contrast to most research done, we hypothesise that it is not necessary to have valid models of productivity factors for online-scheduling. While huge effort would have to be spent on empirical studies to validate these models of productivity factors, this paper is based on the thesis that these factors can be considered adequately using exponential smoothing of past and current data from the manufacturing process.

This paper firstly describes the current development towards CPPS (Section “Cyber-physical (production) systems and big data”). Afterwards, the factors determining human productivity and their consideration in planning/control approaches are presented (Section “Factors of human productivity and their consideration”), as they are exemplarily used in the following examinations. Thereafter, Section “Approach for considering past data online in manufacturing control” presents an approach based on simple exponential smoothing to consider forecasted processing times due to productivity variability in manufacturing control. Section “Experimental setup” contains the setup and Section “Results” the results of a case study, which tests the hypotheses using discrete event simulation.

Background

Cyber-physical (production) systems and big data

According to Lee [1], CPS are “integrations of computation and physical processes. Embedded computers and networks monitor

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and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa". CPS have sensors to collect, process and evaluate data, actuators to react to changes in their environment and are able to interact with other CPS in real-time [14]. The implementation of CPS in factories is referred to as smart factory or Cyber-physical production system (CPPS) [14]. CPPS rely on the developments in computer science, information and communication technologies and manufacturing science and technology [2]. They consist of autonomous and cooperative elements and sub-systems, which interact with each other in situation dependent ways, from machine level up to production and logistics networks [2]. Implementing multiple CPS in factories creates huge amount of data which must be processed and analysed. In this context also the term "big data" is used inflationary in current publications. Several definitions exist, which have in common, that large and complex data volumes are captured, communicated, aggregated, stored, and analysed [3].

For this paper, two consequences of this development concerning production planning and control are highlighted: with more and more CPS in factories, also original planning tasks such as scheduling will be carried out increasingly online and more real-time data of the current manufacturing process are available for manufacturing control [4]. Due to more real-time data, more factors can be considered in decision making. As the human is the most important part of CPPS [15], it is particularly promising to consider human productivity factors in manufacturing control. Therefore, this paper exemplarily considers only human productivity factors in the later simulation runs.

Factors of human productivity and their consideration

Multiple factors determine human productivity in manufacturing systems. Accordingly, there are numerous survey papers dealing with collections and quantifications of human productivity factors, e.g., [7,16–20]. The survey of Baines et al. [7] shall be highlighted at this point, because it offers a framework weighting and categorising productivity factors based on an extensive literature review. Baines et al. [7] differentiate three categories comprising 65 potential factors: individual factors such as experience and commitment, physical factors such as the noise level and organisational factors like shift patterns and work team organisation. Furthermore, productivity factors can be distinguished into low and high level factors. Low level factors represent basic physiological mechanisms such as the daily biological rhythm which are relatively simple and thus, particularly suited for mathematical models [8]. In contrast, high-level factors comprise complex interactions and psychological mechanisms such as the impact of job satisfaction on productivity, which are difficult to implement in simulation models [8].

Considering the list of 65 productivity factors of Baines et al. [7], it can be stated that literature pays significantly different attention to certain factors. Some have been more in the focus of research than others. For instance, the influence of learning effects on productivity has been scientifically examined since the 1930s with Wright [21] often named as pioneer in this field. The surveys of Biskup [16] and Teyarachakul et al. [13] give an overview on multiple approaches considering and/or modelling learning effects and resulting learning curves. Another aspect that is often considered is the circadian rhythm. This cycle represents a typical pattern of human productivity fluctuation depending on day time [22]. It is common knowledge, that the adaption of a human's working speed to the circadian rhythm has a positive effect on human condition [23]. For example, Branton [24] finds a relevant correlation between the time of day according to the circadian rhythm and the occurrence of accidents. Piper and Vachon [25] considers besides the effects of overtime and reduced motivation due to layoffs also the circadian rhythm in aggregate planning using a linear programming approach. Glonegger and Reinhart [9] consider the circadian rhythm in planning of synchronized assembly lines.

Besides, many papers focus on creating valid models of human productivity factors. For example, Neumann and Medbo [12] examine how to consider the effect of an operator's autonomy and capacity in discrete event simulations. Mason et al. [11] also focus on the issue, how to represent the variation of human productivity in discrete event simulations using probability density functions. Kiassat et al. [10] use models of both machine-related and human-related factors in the context of an intervention method to reduce human-related machine failures.

The papers of this overview have in common that human productivity factors are modelled and/or considered in planning and design of manufacturing processes or in production planning to create a schedule before execution (offline-scheduling). The focus of this paper is not to model certain human factors most realistic for planning or design purposes, but to examine whether productivity factors can be considered in online-scheduling without having valid models of these productivity factors. We use the exponential smoothing technique for this purpose, which is explained in the next section in the course of the presentation of our approach.

Approach for considering past data online in manufacturing control

Learning from past data for future decisions requires the application of methods of forecasting. Literature offers multiple methods such as simple/multiple or dynamic regression, autoregressive integrated moving average (ARIMA) models or advanced methods such as neuronal network models [26]. In this paper, we use the simple exponential smoothing (SES) method. This method was chosen for two reasons: first, it requires short computational effort, which is advantageous for real-time control. And second, it

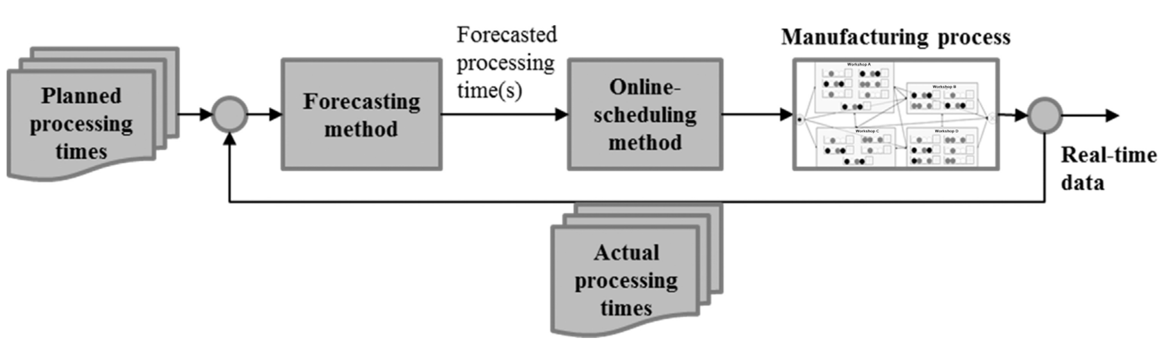

Fig. 1. Basic approach.

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