Available online at www.sciencedirect.com
ScienceDirect
Procedia CIRP 67 (2018) 558 – 562
www.elsevier.com/locate/procedia

11th CIRP Conference on Intelligent Computation in Manufacturing Engineering - CIRP ICME '17

Product-specific process time estimation from incomplete point of production data for mass customization

Satoshi Nagahara[a,*], Youichi Nonaka[a]

[a]Production Systems Research Dept., Research & Development Group, Hitachi, Ltd., 292 Yoshida-cho, Totsuka-ku, Yokohama-shi, Kanagawa-ken, 244-0817, Japan

* Corresponding author. Tel.: +81-50-3135-2057; fax: +81-50-3135-3412. *E-mail address:* satoshi.nagahara.eb@hitachi.com

Abstract

To realize cyber-physical production system on mass customization, process time estimation of each product is critically important. However, actual process time is often unobvious because POP (Point of Production) data is incomplete for operational reasons for example process start/end time of multiple products are registered simultaneously. Therefore, new work combination analysis method was developed. In this method, process time is modeled by product-specific value and model parameters are identified through correlation analysis between total work time and worked products combination in arbitrary time period. This method has been applied to real process of custom-made electronic device production.

Peer-review under responsibility of the scientific committee of the 11th CIRP Conference on Intelligent Computation in Manufacturing Engineering

Keywords: Manufacturing; Mass custimization; Point of production data; Process time estimation

1. Introduction

With expanding of global supply chain network and diverging of customer requirements, production systems are required to have capabilities to produce various kinds of product [1]. In such situation, mass customization, that is a concept of production systems which produce engineering-to-order customized products within a cost comparable to mass production, has attracted attentions [2]. In order to realize mass customization, there are some challenges to be tackled [3] e.g. appropriate definition of product solution space, automation of engineering tasks, efficient production through utilization of flexible and reconfigurable production systems, accurate quotation of cost and lead time, etc. For these challenges, process time estimation of each product is critically important because the estimates are used in various ways [4]. In a production phase, the estimates are used for production system configuration, resource planning and production scheduling [5]. In a design phase, the estimates are utilized to evaluate certain product design from the perspective of production efficiency. Therefore, the effectiveness of production and the accuracy of cost and lead time quotation is highly depend on the accuracy of process time estimation. Additionally, in order to correspond with various kinds of product, process time estimation based on product characteristics is required.

There is some literatures regard to process time estimation for multiple products. There are two different approaches. One is a deductive approach represented by Predetermined Time Standards (PTS) method. In PTS method, standard times for worker or machine actions, such as moving, screwing, welding, etc., are determined beforehand and a process of each product is defined as a series of actions. Then, the process time is estimated by the sum of the standard time of each action. In [6], a process time estimation method based on Standard Operation Unit (SOU) which is a series of actions and a part of process was proposed. However, since maintenance of standard time data and definition of action series for each product are time-consuming tasks, it is often difficult to steadily use this method in practice. Especially in mass customization, the effort for maintaining them for various products becomes enormous.

Peer-review under responsibility of the scientific committee of the 11th CIRP Conference on Intelligent Computation in Manufacturing Engineering
doi:10.1016/j.procir.2017.12.260

Another approach is an inductive approach. In this approach, statistical model of process time is derived from actual process time data and process characteristic values. In [7], Meiden et. al. proposed a process time modeling method using machine learning and data mining for semiconductor products. In the method proposed in [4], each process is described as a combination of tasks, and then process time is estimated through regression between actual process time and the combination of tasks. Although these statistical modeling methods are useful for process time estimation, there are problems with collecting actual process time data. In many cases, actual process time is calculated as a period between process start and end time contained in Point Of Production (POP) data. However, the period between the start and end time is not definite “process time” but “ownership time” including time other than process time, e.g. waiting, set-up. Additionally, especially in mass customization, since production processes are often hard to be automated due to various kinds of products, the acquisition of POP data is also manual, resulting in incompleteness of POP data. In some cases, workers forget the registration of the start time. And workers often register the start/end time of multiple products at the same time. Actually, in a certain assembly line, the data in which start time is not lacked and start time differs from end time are less than half of the total data. In such cases, the actual process time data cannot be directly obtained from POP data. There are few existing studies targeting incomplete POP data. In [8], Karnok et. al. presented a method that determines routing and process time from incomplete POP data. In their method, the process time data which start and end time is not overlapped with that of other processes is assumed as correct data and utilized to identify process time model. However, this assumption is not always valid in actual cases because the start time data is often lacked or registered simultaneously with the end time data.

In order to solve the difficulties mentioned above, we propose a novel method for process time estimation. In this method, based on the premise that the actual process time data cannot be acquired from POP data, only end time data and total working time data are utilized for the estimation. The remaining contents of this paper are as follows. In section 2, the detail of the proposed method is described and some statistical analysis methods are compared through computational experiments. Application results to real processes of custom-made electronic device production are presented in Section 3, and the paper closes with conclusions in Section 4.

2. Process time estimation from incomplete POP data

2.1. Overview of the proposed method

A schematic view of this method is shown in Fig. 1. Here, $\hat{y}$ and $\boldsymbol{x}$ represents an estimated process time and a vector of product characteristic values, e.g. product size, weight, number of parts, etc., respectively. f represents a function of process time estimation model. In this method, we assume that the sum of process time is approximately equal to total working time in arbitrary period. According to this assumption,

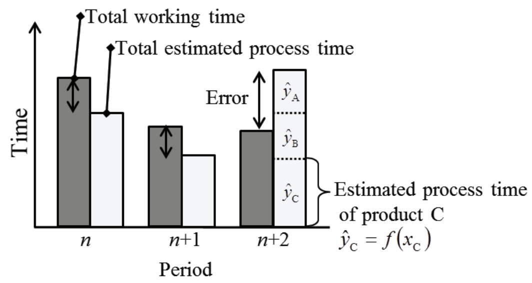

Fig. 1. Schematic view of the proposed method.

if the process time of each product is estimated accurately, the error between sum of process time and total working time becomes small. Therefore, process time can be estimated through the minimization of error between sum of estimated process time and total working time.

If we assume that f is a linear function, the estimated process time of product i and the sum of estimated process time in period j can be expressed by following equations, respectively.

$$\hat{y}_i = f\left(\boldsymbol{x}_i\right) = a_1 x_{i,1} + a_2 x_{i,2} + \cdots + a_M x_{i,M} \tag{1}$$

$$\sum_{i \in P_j} \hat{y}_i = a_1 \sum_{i \in P_j} x_{i,1} + a_2 \sum_{i \in P_j} x_{i,2} + \cdots + a_M \sum_{i \in P_j} x_{i,M} \tag{2}$$

Here, M is the number of product characteristics values. And, P_j and N_j represents a group of products and the number of products completed in period j, respectively. Let,

$$\hat{Y}_j = \frac{1}{N_j} \sum_{i \in P_j} \hat{y}_i \quad , \quad X_{j,k} = \frac{1}{N_j} \sum_{i \in P_j} x_{i,k} \tag{3}$$

Then, the sum of estimated process time can be rewritten as follows.

$$\hat{Y}_j = a_1 X_{j,1} + a_2 X_{j,2} + \cdots + a_M X_{j,M} \tag{4}$$

Therefore, if Y_j is the total working time divided by N_j in period j, the identification problem for the coefficient vector $\boldsymbol{a}$ can be expressed as follows.

$$\hat{\boldsymbol{Y}} = \boldsymbol{X} \cdot \boldsymbol{a} \tag{5}$$

$$\hat{\boldsymbol{a}} = \underset{\boldsymbol{a}}{\arg\min} \left\| \boldsymbol{Y} - \hat{\boldsymbol{Y}} \right\| \tag{6}$$

Here, $\boldsymbol{X}$ is a matrix with $X_{j,k}$ as each element. $\boldsymbol{Y}$ and $\hat{\boldsymbol{Y}}$ are vectors with y_i and $\hat{y}_i$ as each element respectively. Eq. (5) and (6) can be solved by multiple regression methods, e.g. least squares method. As described above, the process time of each product can be estimated through the minimization of the error between the sum of estimated process time and total work time.