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MODELING OPERATOR PERFORMANCE CONFORMING QUALITY IN MANUFACTURING SYSTEMS

Andres G. Abad[1] and Jionghua (Judy) Jin[2]
University of Michigan, Ann Arbor, MI, USA
[1]agabad@umich.edu, [2]jhjin@umich.edu

1. Introduction

Mass customization appeared in the 1990's as a necessary production paradigm to satisfy an increase in the market demand's variability. Mixed model assembly systems were introduced to adopt mass customization schemes. One of the key requirements of a correct implementation of mixed model assembly systems is a high performance workforce [1], with special emphasis on assembly systems operator's performance.

Modeling of human operators' performance in an assembly environment is a particularly difficult task, mainly because the variables involved come from very different sources. Furthermore, a model that successfully characterizes operator's performance *must* include variables that are intrinsic and extrinsic to the operator.

In this work we will consider two intrinsic variables: the experience and time used to think before performing a task; and one extrinsic variable: the demand uncertainty.

Thinking time, denoted by τ , corresponds to the time that an operator at a workstation employs thinking during a production cycle. Production cycle is defined as the elapse of time needed at a workstation to process a unit. If we denote by CT the production cycle time and by CT_0 the operation time (defined as the minimum amount of time required to process a unit at the workstation), we obtain $CT = CT_0 + \tau$. Since we assume CT_0 to be fixed, we represent the thinking time by CT .

The demand uncertainty is the second variable considered in the model. Following the ideas proposed in [2], we will use the information entropy H_D corresponding to the uncertainty of the different possible tasks demanded at the workstation, to measure the mental workload imposed on the operator. Formally, if we let P_i^D denote the probability that product type i is demanded at a workstation and if we assume that each product type requires a different set of tasks to be performed at each workstation, then the uncertainty of the demand mix ratio is given by $H_D = -\sum_i P_i^D \log P_i^D$.

Lastly, we consider the operator's experience as the third variable. The operator's experience is denoted by L and refers to the improvement in an operator's performance gained from repetitive completion of a task. We will measure the operator's experience in terms of the cumulative number of units produced by the operator. Figure 1 (a) shows the structure of the proposed model.

The variables CT , H_D and L enter the model after being standardized, giving rise to the factors ρ_C , ρ_D and ρ_L , respectively. Explicitly, we have:

$$0 \le \rho_C = \frac{CT - CT_0}{CT_M - CT_0} \le 1;\ 0 \le 1 - \rho_D = \frac{H_D}{H_{D,M}} \le 1;\ 0 \le \rho_L = \frac{L}{L_M} \le 1$$

where CT_M , $H_{D,M}$ and L_M correspond to the maximum value for thinking time, demand uncertainty and experience, respectively. The value CT_M corresponds to the critical amount of time after which there is no marginal improvement in the operator's conforming quality. Similar interpretation is given to L_M . Furthermore, we impose that for $L > L_M$, we have $\rho_L = 1$. The maximum entropy value $H_{D,M}$ corresponds to the entropy of a random variable with equally likely outcomes [3].

The organization of the rest of this work is as follows. First, we propose a parametric model to characterize the effect of thinking time, demand uncertainty, and operator's experience on the operator's conforming quality. Then, we provide guidelines on designing an experiment to collect data to fit the model. After this, we show how to estimate the parameters in the model based on the data collected. We then discuss the effect of varying the cycle time of individual workstations in an assembly system consisting of two workstations in a serial layout. We finalize this work by giving the conclusions.

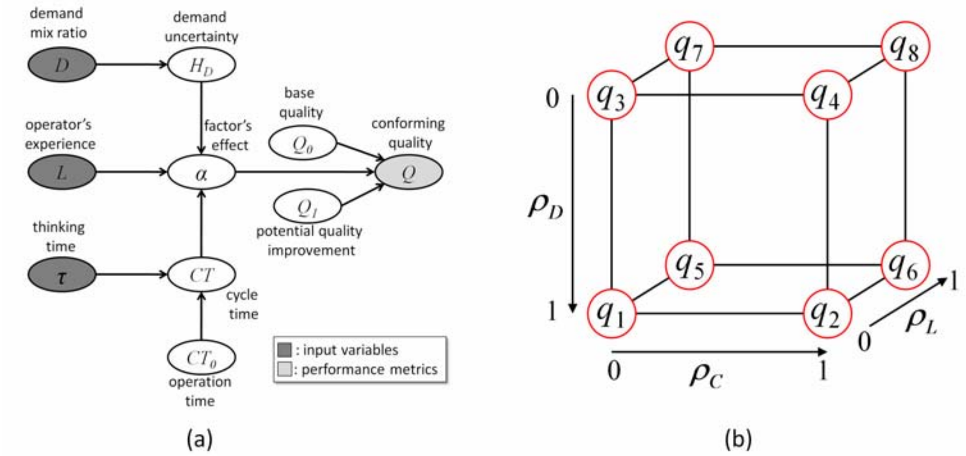

Figure 1: (a) Structure of proposed model; (b) Factorial cube

2. Proposed model

We model the process output conforming quality Q, as a function of the factors, ρ_C, ρ_D and ρ_L. Explicitly, the model adopts the following form

$$Q(\rho_C,\rho_D,\rho_L) = Q_0 + [1-\alpha(\rho_C,\rho_D,\rho_L)]Q_1$$

In this model, Q_0 is the process quality baseline, corresponding to the lowest conforming quality rate possible, while Q_1 corresponds to the maximum conforming quality improvement possible. In this way, $1-\alpha(\rho_C,\rho_D,\rho_L)$ characterizes the proportion of quality improvement achieved under specific level of the factors ρ_i's.

We require α to be convex and increasing on every factor ρ_i's. Additionally, for tractability purposes, we would like α to be continuous and differentiable over its domain. Furthermore, we would want the increments of α to be further attenuated as the value of the factors ρ_i's increase. In this work, we propose to use the following function for $\alpha(\rho_C,\rho_D,\rho_L)$, which satisfies all the requirements stated above,

$$\alpha(\rho_C,\rho_D,\rho_L) = e^{-\beta_C\rho_C-\beta_D(1-\rho_D)-\beta_L\rho_L}$$

subject to $-\beta_C\rho_C-\beta_D(1-\rho_D)-\beta_L\rho_L \le 0$, and thus $\beta_i \ge 0$, for $i = C,D,L$.

Since alpha is a convex increasing function and bounded in the factors domain, the function $Q(\rho_C,\rho_D,\rho_L)$ is convex and increasing on every factor ρ_i; lower and upper bounded by Q_0 and Q_0+Q_1, respectively.

The set of parameters β_C,β_D,β_L, associated with factors ρ_C,ρ_D,ρ_L respectively, account for the relative effect that increasing the corresponding factor by one unit has on the potential maximum process quality improvement Q_1. Because the factors ρ_i's are standardized, the relative effect of the factors can be compared in terms of the magnitude of their corresponding β_i's.

3. Calibrating the model parameters

In order to estimate the parameters β_i's we are required to obtain representative observations for each of the levels of the factors ρ_i's considered. Thus, designing an appropriate experiment requires some insights on the model. In this section we will provide practical guidelines for the collection of data and the subsequent fitting of the model.

Figure 1 (b) describes a full factorial design for the 3 different factors, where each point q_i corresponds to the observed conforming quality rate of a sample of fixed size obtained under the corresponding factor levels.

We can observe that points q_1, q_2, q_3 and q_4 are obtained from an inexperienced operator. After the number of cumulative units produced L has increased to its maximum L_M, we should conduct the experiment again, obtaining points q_5, q_6, q_7 and q_8. The question that arises now is how to determine the value of L_M. By definition we have that if $L' > L_M$, then $Q|_{L'} = Q|_{L_M}$, where we have written $Q|_x$ to represent the conforming quality rate observation taken from an operator with an experience of x cumulative units. As a consequence, we can assess L_M by considering a threshold $\varepsilon_L > 0$ associated with a magnitude $\Delta L > 0$, such that $Q|_{L_M} - Q|_{L_M+\Delta L} < \varepsilon_L$. Since $\beta_L \geq 0$, we must have $q_i \leq q_{i+4}$ for $i = 1,2,3,4$. Similarly, we require $q_i \leq q_{i+1}$ for $i = 1,3,5,7$ due to $\beta_C \geq 0$, and $q_i \leq q_{i+2}$ for $i = 1,2,5,6$ as a consequence of $\beta_D \geq 0$.

Let us now turn our attention to fitting the proposed model to the collected data. For fitting purposes, it would be convenient to have a linear model in the parameters β_i's. Towards that end, we propose the following transformation

$$\ln\left(\tfrac{Q_0+Q_1-Q}{Q_1}\right) = -\beta_C\rho_C - \beta_D(1-\rho_D) - \beta_L\rho_L \qquad (1)$$

Since $Q_0 + Q_1$ is the maximum achievable process quality (achieved when $\alpha = 1$) we can interpret the argument of the logarithm at the left hand of equation (1) as the percentage of the potential maximum quality improvement Q_1 still left to improve.

If we assume that the errors in the model enter in a multiplicative way, a linear regression analysis is well justified. However, in general it is difficult to determine how the errors enter the model ([4]). Thus, an analysis of the residuals after fitting the model is required. If the effect of the errors is not multiplicative, then non-linear regression techniques may be used to fit the model.

4. Thinking time allocation effect on conforming quality performance

When assigning thinking time to individual workstations in an assembly system, dependencies between the workstations arise. In particular, the amount of thinking time assigned to a workstation reduces the thinking time available for assignment to downstream workstations, if we assume that the total thinking time available is shared between the workstations. Furthermore, the demand uncertainty transferred from upstream workstations to downstream workstations increases as the percentage of nonconforming units transferred increases. These interactions can be analytically studied by considering their effect on the $\beta_i(k)$'s, where $\beta_i(k)$ corresponds to the coefficient of the i^{th} factor at the k^{th} workstation. In this section we discuss these interrelated effects in the context of an assembly system consisting of two workstations in a serial layout.

The production lead time LT corresponds to the required fixed amount of time elapsed from the moment when units enter the line as raw products to the moment when they leave the line as finished products. The time spent in transportation from a workstation to another workstation and the waiting time in buffers and stock points are not considered in the LT. In this way, the production lead time LT of an assembly line is given by the sum of the cycle times of every workstation. In the case of a two workstations line, the production lead time is given by $LT = CT(1) + CT(2)$. On the other hand, the overall conforming quality of the assembly line is given by $Q(L) = Q(1) \cdot Q(2)$. Since $Q(i)$ depends on $CT(i)$, then the overall effect on the line quality due to reducing the process cycle time of one workstations is not obvious.

We now study the effect that varying the cycle time of workstation 1 has on the overall conforming quality rate of the system. Here, we have assume that the models $Q(1)$ and $Q(2)$, corresponding to workstation 1 and workstation 2, respectively, are given by

$$Q(1) = Q_0(1) + Q_1(1) - (e^{-\beta_C(1)\rho_C(1) - \beta_D(1)(1-\rho_D(1)) - \beta_L(1)\rho_L(1)})Q_1(1)$$

$$Q(2) = Q_0(2) + Q_1(2) - (e^{-\beta_C(2)\rho_C(2) - \beta_D(2)(1-\rho_D(2)) - \beta_L(2)\rho_L(2)})Q_1(2)$$

1. Effect of increasing the production cycle time of workstation 1. An increase of $CT(1)$ by $\Delta_C(1)$ will increase $\rho_C(1)$ to $\rho_{C+\Delta_C}(1) = \rho_C(1) + \frac{\Delta_C(1)}{CT_M(1) - CT_0(1)}$ while increasing $Q(1)$ by $\Delta Q(1) = K(1)Q_1(1)(1 - e^{-\beta_C(1)\delta_C(1)})$ where $K(1) = e^{-\beta_C(1)\rho_C(1) - \beta_D(1)(1-\rho_D(1)) - \beta_L(1)\rho_L(1)}$ and $\delta_C(1) = \frac{\Delta_C(1)}{CT_M(1) - CT_0(1)}$.

2. Effect of increasing the production cycle time of workstation 1 at workstation 2. An increment of $CT(1)$ to $CT(1) + \Delta_C(1)$ will decrease $CT(2)$ to $CT(2) - \Delta_C(1)$ and consequently decreasing $\rho_C(2)$ to $\rho_{C+\Delta_C}(2) = \rho_C(2) - \frac{\Delta_C(1)}{CT_M(2) - CT_0(2)}$.

The analysis of the effect of increasing $CT(1)$ to $CT(1) + \Delta_C(1)$ on $Q(2)$ demands more consideration, since an increase of $Q(1)$ by $K(1)Q_1(1)(1 - e^{-\beta_C(1)\delta_C(1)})$ also affects the input demand entropy $H_D(2)$ at workstation 2. The input demand entropy at workstation 2, denoted by $H_D(2)$, is given by $H_D(2) = Q(1)H_D(1) + H_{Q(1)}$ where $H_{Q(1)} = -Q(1)\ln Q(1) - (1 - Q(1))\ln(1 - Q(1))$. Hence, an increase of $\Delta Q(1)$ in the process conforming quality at workstation 1 decreases the input entropy $H_D(2)$ at workstation 2, $H_D(2) = Q(1)H_D(1) + H_{Q(1)}$ by $\Delta_H(2) = H_D(1)\Delta Q(1) + H_{Q(1)+\Delta Q(1)} - H_{Q(1)}$

Overall, the decrease on $Q(2)$ by increasing the production cycle time at workstation 1 by $\Delta_C(1)$ can be computed as $\Delta Q(2) = K(2)Q_1(2)(e^{\beta_C(2)\delta_C(2) - \beta_D(2)\delta_D(2)} - 1)$ where $K(2) = e^{-\beta_C(2)\rho_C(2) - \beta_D(2)(1-\rho_D(2)) - \beta_L(2)\rho_L(2)}$, $\delta_C(2) = \frac{\Delta_C(1)}{CT_M(2) - CT_0(2)}$ and $\delta_D(2) = \frac{H_D(1)\Delta Q(1) + H_{Q(1)+\Delta Q(1)} - H_{Q(1)}}{H_M}$.

Finally, the effect on the overall line output quality $Q(L) = Q(1) \cdot Q(2)$ after increasing the cycle time of workstation 1 from $CT(1)$ to $CT(1) + \Delta_C(1)$ is

$$\Delta Q(L) = \Delta Q(1)Q(2) - \Delta Q(1)\Delta Q(2) - Q(1)\Delta Q(2) \qquad (2)$$

By use of equation (2) above we can maximize $Q(L)$ by finding the optimum $CT(1)$.

5. References

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