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A genetic algorithm for the multi-objective optimization of mixed-model assembly line based on the mental workload

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ABSTRACT

The increasing complexity of product varieties and productions leads to higher mental workload in the mixed-model assembly line (MMAL). Mental workload can improve product quality and guarantee the efficiency simultaneously. However, little research has been done on balancing the production quality and efficiency based on the effect of mental workload and complexity in the MMAL. This study aims to propose a mathematical model to formulate the multi-objective MMAL problem and the genetic algorithm is applied for problem solving due to the computational complexities. A numerical example is used to demonstrate the effectiveness of the proposed approach. The results show that incorporating the impact of mental workload on performance into account can make the rolled throughput yield (RTY) and efficiency balance when designing the MMAL. Moreover, we also verify that improving the experience of the operators can mitigate the impact of mental workload on the quality and efficiency.

1. Introduction

With the increase in market demand and fluctuation, the modern manufacturing company is driven to enhance the capability to provide high quality products within a wide range of product variety and short time-to-market delivery often experienced in the automobile assembly industry. Based on the process modular and just-in-time production mode, the mixed-model assembly line (MMAL) has been recognized as a major enabler to handle high product variety while simultaneously achieving quality in mass production and productivity (Rekiek et al., 2000). This kind of MMAL mainly consists of use of human operators for various assembly operations. However, diverse products and configurations not only lead to negative impacts on complex manual assembly processes, but also cause difficulties to the assembly process for the operators. In addition, these impacts can possibly lead to the occurrence of human errors and poor production performance, thus affecting product quality and productivity (Fisher and Ittner, 1999; MacDuffie et al., 1996).

The factors that affect operation errors are caused by choice complexity and the operator's mental state. On one hand, operators are confronted with increasing choice complexity during assembly operations, such as part choice, tool choice, fixture choice, and procedure choice. Choice complexity requires operators to use higher cognitive skills to finish the task successfully, which makes mental the workload much higher than single product assembly and therefore easily leads to more human errors. On the other hand, assembling complex products needs a large number of steps to be known, which further increases to the mental workload that operators face in a certain period of assembly time (Eklund, 1995). In U.S. manufacturing plants, human errors caused by improper manual action on average accounted for 40% of all errors, which were relevant to the level of the operators' skill (Vineyard et al., 1999). Based on the low usage of cognitive support and assembly operations that were performed by the operator's own experience, Fast-Berglund et al. (2013) indicated that choice complexity was positively correlated with assembly errors. Li et al. (2011) analyzed the human factors of each process in the piston production line and found that choice complexity and mental workload of operators were the main reasons for human operation errors. In addition, while the assembly product requires lot of complicate variants to be performed within a limited time span, the operators could become overloaded and incapable of performing all of the tasks, potentially leading to incorrect installation, and other incorrect operations. Furthermore, these incorrect operations may result in the deterioration of product quality, an increase in reassembly time, and a decrease in production rate (Benders and Morita, 2004).

The following studies have measured the complexity induced by product variety and assessed the impact of complexity on the performance in the MMAL. For example, Zhu et al. (2008) proposed

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information entropy to measure operator choice complexity and mentioned that the human errors can be reduced by making the module of many variants assembled in the latter station without violating the process principle. To assess the complexity of MMAL at an early design stage, Samy and ElMaraghy (2012) developed a structural classification coding scheme to measure assembly systems complexity including operation machines, material handling equipment and buffers equipment. Abad et al. (2011) proposed an integrated framework to analyze the impact of workstation assembly time, and the operators' experience and complexity on the assembly performance. In particular, the impacts of product quality and production throughput were evaluated based on the part mix ratio, operator' experience, and mental deliberation time. Zeltzer et al. (2013) also defined complexity at the workstation level and proposed a complexity measure for mixed-model assembly workstations to investigate the impact of complexity on production performance. Wang and Hu (2010) proposed a model of human reliability based on Weibull distribution by analyzing the impact of complexity on the reaction time and fatigue.

Level of mental workload plays a significant role in the modern production assembly lines. Both low and excessive workload levels result in poor operation performance of human operators (O'Hanlon, 1981; Young and Stanton, 2002). The optimal allocation of mental workload of operators could reduce human errors, improve system safety and increase quality and operator satisfaction (Moray, 1988). The operation cycle time at each station affects the mental workload and production performance. Liao (1998) presented the time pressure model to predict the metal workload as the basis of adjusting human workload. The tradeoff between operation speed and task accuracy has been presented how the production performance is influenced the available time for task operation (Plamondon and Alimi, 1997; Reed, 1973; Schouten and Bekker, 1967). Therefore, while the task time is abundant, the mental workload and human error are both reduced resulting in high assembly quality. However, little research has been done on bridging the gap between mental workload and production performance in the MMAL.

This paper aims to develop a mathematical model for solving multi-objective optimization problem by considering product quality and production efficiency in MMAL. In particular, a tradeoff between quality and efficiency can be achieved by considering mental workload and complexity during the operation of cycle time for each station. After the model construction, the genetic algorithm (GA) is applied to solve multi-objective optimization of mixed-model assembly line problems through allocating the mental workload and operation of cycle time for each station. Then a numerical case is conducted to demonstrate the effectiveness of proposed method.

The paper is organized as follows. In Section 2, the model of complexity for mixed-model assembly line is reviewed. Then a prediction model was constructed to predict operators' mental workload to avoid potential human errors and experimental results of mental workload. In Section 3, a multi-objective optimization model is formulated to balance the tradeoff between total product quality and production efficiency in consideration of the effect of mental workload. In Section 4, a numerical case is presented with numerical results from the proposed model for solving product quality and efficiency in MMAL. Finally, the conclusions and future work on this area are given in Section 5.

2. Mental workload in the mixed-model assembly line

2.1. Choice complexity model

The MMAL is consisted of a sequence of process stations based on the product structure and assembly order. Each product, which is represented by a product family architecture, has various features (F_t) and each feature has several variants (V_{st}). As shown in Fig. 1, one variant from its feature is selected for each process station in system level. For example, variant V_{12} from feature F_1 is selected for station 1, and variant V_{33} from feature F_3 is selected for station 3. In particular, the possible combinations of customized product are determined by the number of features and its variants. Typically, the number of feature is equal to the number of the process station.

Given one type of product mix is chosen in an MMAL. Then the operators at each station need to identify the variants of the product and determine the operation choices for the assembly instruction among lots of alternatives in the station level. In order to characterize the operation performance of making choice, Wang et al. (2011) proposed the information entropy to measure operator choice complexity which is defined as the average uncertainty in a random process. The choice complexity in the MMAL results from the choice of the right part, fixture, tool, and assembly procedure for each module variant. The part choice involves selecting the right part according to the order of customized product. According the partially completed assemblage, the fixture choice involves selecting the right fixture to be mounted on the selected part. The tool choice involves selecting the right tool based on the choices of part and fixture. The procedure choice involves selecting the right procedure by the prescribed assemble procedures such as part orientation and angle.

Let K_j be the total number of choice alternatives at station j. The choices needed in the kth activity of station j can be influenced by the variety added at the current station, as well as those of the upstream stations, which are called as "feed complexity" and "transfer complexity", respectively. L_j^k is the number of state of the kth activity at station j. A product process association matrix Δ_{ij}^k is defined to express the relationship between product variants and assembly process information. A vector $\mathbf{p}_i = \begin{bmatrix} p_{i1} & p_{i2} & \cdots & p_{iM_i} \end{bmatrix}$ represents the set of mix ratios of module variants at station i and M_i is the number of variant at module i. In the vector $\mathbf{q}_{ij}^k = \begin{bmatrix} q_1 & \cdots & q_t & \cdots & q_{L_j^k} \end{bmatrix}$, $t = 1, 2, \ldots, L_j^k$ is the probability of the kth activity being in state t at station j caused by the variants added at station i. The parameter α_j^k is the weights related to the task difficulty of the kth assembly activity at station j. The model of choice complexity (Cf_{c_j}) is defined as follows:

$$Cf_{c_j} = \sum_{k=1}^{K_j} \alpha_j^k \sum_{i=1}^{j} H_{ij}^k(\mathbf{q}_{ij}^k) \tag{1}$$

$$\text{Subject to} : H_{ij}^k(\mathbf{q}_{ij}^k) = -\sum_{t=1}^{L_j^k} q_t \log_2 q_t \quad t = 1, 2, \ldots, L_j^k \tag{2}$$

$$\mathbf{q}_{ij}^k = \mathbf{p}_i \Delta_{ij}^k \quad j = 1, 2, \ldots, n; \quad i \le j, k = 1, 2, \ldots, K_j \tag{3}$$

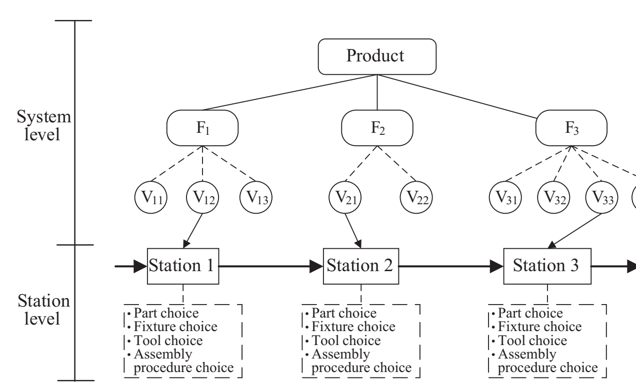

Fig. 1. Illustration of MMAL and the choice at one station (Zhu et al., 2008).