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Computation of Manufacturing Complexity in a Mixed Model Assembly

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Abstract

Manufacturing systems have evolved to adopt a mixed-model assembly systems in order to enable the production of high product variety. Mixed-model assembly systems offers a wide range of advantages, however, as variety increases, the system becomes very complex, thus worsening the system performance. This paper proposes a novel method for complexity quantification in a mixed model assembly line. The model uses the information entropy and considers both the options count as well as the relationship among options. The resulting measure not only serves an input in the assessment of the impact of the complexity on the system performance, specifically on human error; but also provides an insight on how the complexity can be mitigated without affecting the overall manufacturing throughput.

Keywords
Manufacturing, Assembly line, Complexity, Entropy

1. Introduction

In the past, vehicle manufacturers had provided the market with a few models that had a small variety of attributes and long life cycles. However, diverse customer needs have led to mass customization as the new manufacturing standard (Pine, 1999). Manufacturing organizations must now offer a high product variety to remain competitive as they are facing increasing customer sophistication and fast-paced technological developments in the market. The mass customization have become a key factor for maintaining or increasing the market share since it offers a close match of customer preferences and offered products. On the other hand, organizations face increasing manufacturing complexity due to high product variety. It is regarded that, when a higher variety of models or options are offered, a competitive edge to companies can be guaranteed. In reality, however, the additional complexity which results from creating and handling variety has been identified as an important cost driver in production by 64% of the respondents in a survey(Schleich et al., 2007). In order to satisfy complex customer needs, a mixed-model assembly systems and modular supply chains have been recognized as major enablers to handle the increased variety.

Based on the study in the automotive industry, it is regarded that there exists a negative correlation between complexity and manufacturing performance (MacDuffie et al., 1996). Thus, a cost-benefit scenario must be studied in order to justify the variety introduced in the manufacturing line. In the automotive industry, analyzing manufacturing complexity has to be a promising way to ensure higher product variability while maintaining production efficiency. Although the interpretation and analysis of manufacturing complexity is costly and time-consuming due to the lack of constitutional measurement of the complexity, it is still necessary and intriguing in that many advantages can be guaranteed by the investigation of the manufacturing complexity. Adding a model variant in a manufacturing system undoubtedly increase the number of product components, the extent of interactions to manage between these components, and the degree of product novelty. These conflicting aspects of complexity in the system incur additional indirect costs for managing the manufacturing process and associated resources. In other word, the increased number of resource managements and operations in the system significantly affect the increment of the system complexity. For instance, adding one more variety in the assembly process may bring about changes in process plans, additional training for operators, different designs of tools, jigs, and fixtures, and resource managements. In order to analyze the manufacturing complexity, it is necessary to have an explicit cost-conversion system that translates manufacturing complexity in the context of production efficiency and cost. Once the complexity is measured in a representative quantifiable index, a decision support system for dynamic and effective manufacturing resource allocation can be suggested to mitigate overhead costs incurred by the complexities.

2. Background

The variation in products contributes to the assembly process complication and, in turn, impacts the operational efficiency of mixed model assembly system(MacDuffie et al., 1996). As a result, several research have attempted to establish an analytical relationship between product varieties and system performance (Zhu et al., 2007; Hu et al., 2008; Zhu, 2009; Wang and Hu, 2010). It has been shown that the increase in the product variations rises the complexity of the system, thus measuring the system complexity is supposed to be the starting point of the performance analysis in the complex manufacturing systems. Frizelle and Woodcock (Frizelle and Woodcock, 1995) suggested that two types of complexities in supply chain: structural complexity and operational complexity. The former is associated with the variety embedded in the static system while the latter is with the uncertainties of the dynamic system. As a measure of uncertainty contained in a message, the entropy, also known as Shannon entropy, has been one of the most popular and commonly accepted theory used as a complexity measure(Shannon, 1951; Shannon, 2001). Therefore, generally speaking, the more ambiguous the information, the higher the complexity. For example, (Deshmukh et al., 1998)defined an entropic complexity measure for part mix in job shop scheduling. Using the entropy, Fujimoto et al. (Fujimoto and Ahmed, 2001) proposed the complexity measure of different stages of process planning. ElMaraghy et al. (ElMaraghy et al., 2005) proposed and demonstrated how the entropy function can be used in the quantification of complexity in machining process.

3. Complexity and option counts (Entropy)

Shannon entropy, quantifies the expected value of the information contained in a message and can be regarded as average unpredictability in a random variable(Shannon, 1951; Shannon, 2001). According to Shannon, the entropy (H) of a discrete random variable X with possible values $\{x_i, x_2, .., x_n\}$ and probability mass function $P(X)$, is obtained as follow:

$$H(X) = -\sum_i P(x_i)I(x_i) = -\sum_i P(x_i)log_b P(x_i) \quad (1)$$

I is the information content of X and b the base of the algorithm. The selection of b value determines the unit of measurement of information content in random variable X; b= 2 is one of the most common value where the information content stored in X is measured in bit(s). In manufacturing, specifically the assembly line, the uncertainties depend on a wide range of factors. For example, in a mixed model assembly, an operator should select the right part (from several options) to assemble within a limited time offered to that specific task while ensuring the optimality of the flow. As the number of variety increases, the uncertainty increases and the part selection generally take additional time due a slower reaction time. While there is a good number of theories that attempt to map the complexity and reaction time, Hick's law is one of the most (if not the most) well known. According to Hick's law, also known as Hick-Hyman's law(Hick, 1952; Hyman, 1953), the average reaction time is approximately a linear function of the complexity as measured by the information entropy conveyed by the stimulus (Shannon, 2001). Let Y^i be a random variable that takes on the values $y_1^i, y_2^i, \dots, y_j^i, \dots, y_N^i$ with corresponding probability $p(y_1^i), p(y_2^i), \dots, p(y_j^i), \dots, p(y_N^i)$. In this context, y_j^i denotes part/tool j at station i while $p(y_j^i)$ denotes the probability that part/tool j at station i is to be selected for the upcoming task. To this end, the entropy as a measure of complexity of a mixed-model assembly line can be expressed as follows:

$$H(Y) = \sum_i H(Y^i) = -\sum_{i=1}^{S} \sum_{j=1}^{N} p(y_j^i) log_2 p(y_j^i) \quad (2)$$

According to Hick's law, the reaction time R of a given selection is as follow:

$$R = a + bH(Y) \quad (3)$$

In the equation, a and b are ergonomic parameters while $H(Y)$ is the entropy of the system.

4. Complexity and option similarity

In the manufacturing systems, human participations are critical in the operation processes, the role of human in decision making and task performing is regarded as a major factor when evaluating the overall performance of the system. In this regard, the manufacturing complexity in automated processes may be relatively easy to be solved by resource investments (e.g., more robots, more spaces, higher speed), while human-induced complexity are not easily resolved due to the complex cognitive processes in human decision making.

Hick's law considers the option counts as the primary determinant of the reaction time in human factors perspectives; however, several research have shown that not only the number of options but also the similarity of options significantly affect the operator's reaction time(Hellier et al., 2010; Irwin et al., 2012). In other word, the uncertainty or ambiguity can as well be affected by several other parameters such as the similarity of options at hand.

Traditionally, the similarity of options in a mixed model assembly has received less to no attention from researcher in the manufacturing industry. This is possibly due to of its low perceived impact on manufacturing performance in traditional mass-production environments. However, given the current manufacturing era in which the customization can increase the number of options at an unprecedented rate, the similarity of options has become a factor worthy of consideration due to the impact on human error. In fact, in some industry where human error is of tremendous negative effect, the similarity of options have been given lots of attentions to showcase its effects on reaction time and human error. For example, in pharmaceutical industry, several research have been done on the similarity of both the name or the container of drugs in pharmacy. Assuming a close proximity, it has been shown that the selection of a target medication within several similarly named medications increases the difficulty of the visual search for the target (Irwin et al., 2012). Hellier et al.(Hellier et al., 2010) showed that the use of color to differentiate the drugs, not only improved the accuracy but also the search time of the target medication. Similar conclusion has been noted on the shape differentiation with more or less amplitude.

4.1 Knowledge Representation

Before the assembly process, an operator receives a command requesting to select a specific part from a pool of available options. The command creates or activates knowledge required for the task. It has been shown that the brain activation is more or less category-based (Kreiman et al., 2000). Once the command is received, research has shown that the operator's memory retrieval cue can become less effective once the command stimuli becomes associated with multiple items in memory(Watkins and Watkins, 1975; Surprenant and Neath, 2009). Knowledge representation plays an important role in understanding the complexity or the ambiguity caused by the stimuli. In various field, especially in natural language processing (NLP), the knowledge representation has been the focus of many research. Whereas different representations received success in specific applications, the attention has been placed on models of semantic memory data structures that may store and use lexical information in a ways similar to humans (Duch et al., 2008).

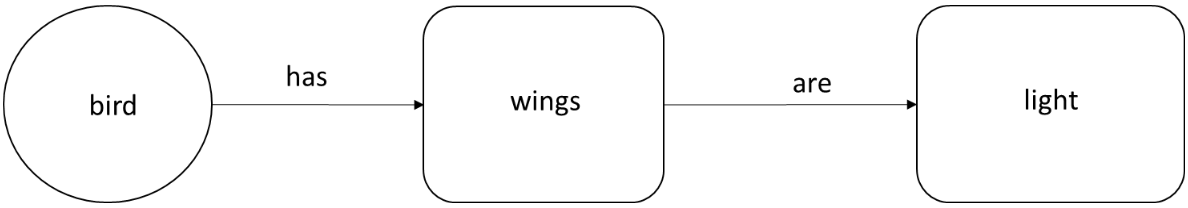

Figure 1: Knowledge representation

The reference to the NLP is somehow adequate since in most assembly line, the stimulus comes in a natural language form or other closely related form. According to(Duch et al., 2008), using semantic network to express knowledge is somehow not only natural to humans but also reflect more or less some brain association. One of the existing representation method is to refer to a word meaning using three main parameters: object, relation type and feature (see Figure 1) (Szymański and Duch, 2012).

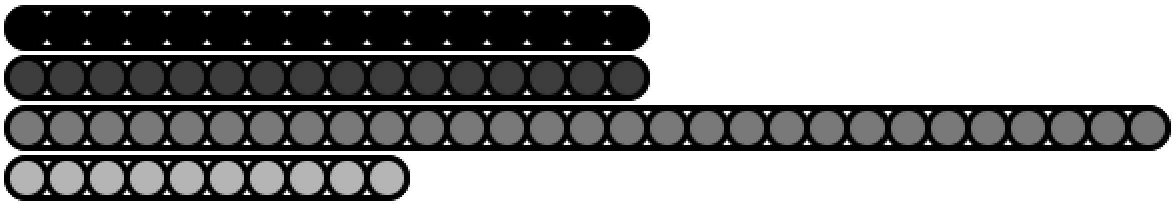

Figure 2: Four different lego parts (technical beams)

Similarly to a word meaning, a part can be represented or be distinguished from another by its category or its features. For example, the Lego beams in **Error! Reference source not found.** can be differentiated based on their two main underlying features: length and color. Multiple objects can be associated due to a wide range of reasons such as being in same category or having similarities in their features(Kreiman et al., 2000). According to communication theory, multiple schemes are said to be orthogonal when an ideal receiver can completely reject unwanted signals from the desired signal using different basis functions. Similarly, assuming a feature can be represented in a form of vector, in this paper, two features are considered orthogonal if the commonality or the confusion level between the two features is almost non-existent. Note that the confusion level can be represented as the projection of one feature to one another as shown in **Error! Reference source not found.**.

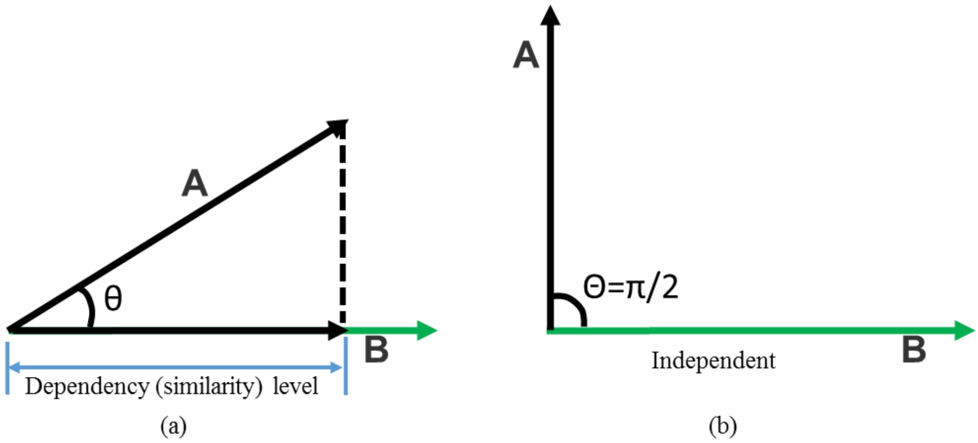

Figure 3: Representation of options dependancy. In (a)option A and B have a high livel of simularity while in (b) the similarity in A and B is non-existent.

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4.2 Complexity computation

As stated earlier, before each selection, the operator receives a stimuli requesting to select a specific part from a pool of available options. To this regard, the visual differentiation of options is done based on their respective physical features such as shape, color, size, etc. Once the command is received, the operators' effectiveness will depend on the available options and their similarities to the target option (Watkins and Watkins, 1975; Usher et al., 2002; Surprenant and Neath, 2009; Schneider and Anderson, 2011). For each option $j, j = 1,2, \dots, N$; where N is the number of available options, the magnitude of ambiguity rises with the similarity level of options' features to that of the target option. For each selection, a number of discriminatory features can be selected on which to base the visual differentiation of options. Let's $f_i, i = 1,2, \dots, F$; where F is the number of discriminatory features. For a given target option at time t, each feature f_i on the targeted option, denoted as O_t^{fi}, the associated level of similarity activated can be represented as:

$$\Psi\left(O_t^{f_i}\right) = [a_{1k}^{f_i}, a_{2,k}^{f_i}, \dots, a_{Nk}^{f_i}][O_1^{f_i}, O_2^{f_i}, \dots, O_N^{f_i}]^T \tag{4}$$

In equation (4), $[a_{1k}^{f_i}, a_{2,k}^{f_i}, \dots, a_{Nk}^{f_i}]$ is row entry of similarity matrix A^{f_i}corresponding to $O_t^{f_i}$. In other word, the taget option at time t is $O_k^{f_i}$ with k=0,1,..N. Note that for each feature f_i, the target option at time t, ($O_t^{f_i}$)is an element of $\left\{O_1^{f_i}, O_2^{f_i}, \dots, O_N^{f_i}\right\}$; in other words, $O_t^{f_i} \in \left\{O_1^{f_i}, O_2^{f_i}, \dots, O_N^{f_i}\right\}$. Also, since every option has to be requested at some point in time, the following follows:

$$\bigcup_{t=1}^{\infty} O_t^{f_i} = \left\{O_1^{f_i}, O_2^{f_i}, \dots, O_N^{f_i}\right\} \tag{5}$$

Thus, by taking into account every possible target option, equation (4) can be extended as:

$$\begin{bmatrix} \Psi(O_1^{f_i}) \\ \vdots \\ \Psi(O_N^{f_i}) \end{bmatrix} = \begin{bmatrix} a_{11}^{f_i} & \cdots & a_{N1}^{f_i} \\ \vdots & \ddots & \vdots \\ a_{1N}^{f_i} & \dots & a_{NN}^{f_i} \end{bmatrix} \begin{bmatrix} O_1^{f_i} \\ \vdots \\ O_N^{f_i} \end{bmatrix} \tag{6}$$

In this equation, $A^{f_i} = \begin{bmatrix} a_{11}^{f_i} & \cdots & a_{N1}^{f_i} \\ \vdots & \ddots & \vdots \\ a_{1N}^{f_i} & \dots & a_{NN}^{f_i} \end{bmatrix}$ is the similarity matrix which is equivalent to a projection matrix in geometric representation. **Error! Reference source not found.** shows the graphical representation of Equation (4). The overall dependancy or similarity level also known as reingularity in axiomatic design theory, can be obtained as:

$$R = \prod_{\substack{i=1,n-1 \\ j=1+i,n}} \left(1 - \frac{\left(\sum_{k=1}^{n} A_{ki}^2 A_{kj}^2\right)^2}{\left(\sum_{k=1}^{n} A_{ki}^2\right)\left(\sum_{k=1}^{n} A_{kj}^2\right)}\right)^{1/2} \tag{7}$$

As noted earlier, in this paper, both the option counts and similarity level are considered in the complexity computation. To this regard, the similarity level plays as weighting factor in the entropy computation. In other word, the overall complexity C can be expressed as follow:

$$C = \prod_{\substack{i=1,n-1 \\ j=1+i,n}} \left(1 - \frac{\left(\sum_{k=1}^{n} (A_{ki}^{f_i})^2 (A_{kj}^{f_i})^2\right)^2}{\left(\sum_{k=1}^{n} A_{ki}^2\right)\left(\sum_{k=1}^{n} A_{kj}^2\right)}\right)^{1/2} \left(-\sum_i P(x_i) log_b P(x_i)\right) \tag{6}$$

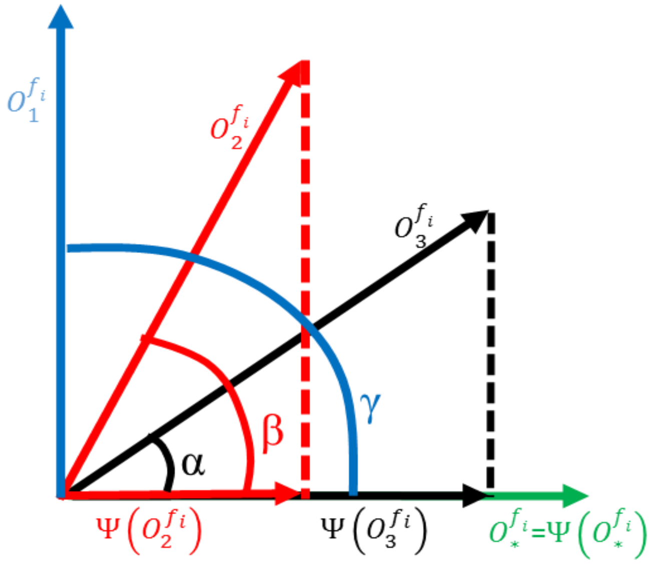

Figure 4: Geometric representation of option similiraties and complexity

5. Conclusion

Mass customization is becoming a new norm in the manufacturing system; as a result, the number of distinct options in a mixed model assembly line has been growing at an unprecedented rate. This paper introduces a novel method to compute the system complexity using the information entropy. The proposed model not only has the ability to compute the overall complexity of the system, it can also track the contribution of each specific option or station to the overall system complexity. Due to flexible market demands, changes are imminent in the manufacturing system. To this end, this model can be a tool that provides a glimpse of how the system performance would look like if a given set of policies were to take place. For example, the model offers to a decision maker the ability to hypothetically add a number of options after which an analytical results can be obtained. Thus, before committing to a given policy; e.g. introducing a new option in the assembly line, this model can be used to assess various scenario and their respective effect on the overall complexity and reliability.

In a modern manufacturing system, JIT (Just in Time) has become the norm for several operations in the manufacturing system. Company can now utilize a system in which parts are delivered to the assembly line in the precise build sequence, thus giving the operator less decisions to make. The aforementioned time inventory system has the ability to greatly reduce the complexity vis-à-vis to the human operator. While not all parts can be accommodated into the JIT system, using the proposed model, parts associated with the highest level of complexity can be determined and included in the automated system.

In additional to the computation of the system complexity and reliability, it can be shown that some system can be reconfigured to reduce system overall reliability. With a fixed options counts, both the similarity and proximity level can be adjusted to mitigate the system complexity. Note that any attempt to reconfigure the system may result in an overhead cost. Addition of new variety must be justified though positive impact on the company overall performance. In one hand, additional cost associated to the increased complexity may be unwarranted for variety with lower demand. On the other hand, if consumers based their purchasing decision on specific features, the increased complexity is compensated by the increased sales(MacDuffie et al., 1996).
Thus after validating our proposed model, in our future work we will attempt to establish a relationship between system complexity and overhead cost. Also, the cost associated to system reconfiguration can be partially dependent on the system flexibility. To this regard, a study on the flexibility of mixed-model assembly line and its relationship to the overall system complexity and its mitigation will be central to our future work.

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