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Computational modelling of manufacturing choice complexity in a mixed-model assembly line

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Manufacturing systems have evolved to adopt a mixed-model assembly line enabling the production of high product variety. Although the mixed-model assembly system with semi-automation (i.e. human involvement) can offer a wide range of advantages, the system becomes very complex as variety increases. Further, while the complexity from different options can worsen the system performance, there is a lack of quantifiable models for manufacturing complexity in the literature. Thus, in this paper, we propose a novel method to quantify manufacturing choice complexity for the effective management of semi-automated systems in a mixed-model assembly line. Based on the concept of information entropy, our model considers both the options mix and the similarities between options. The proposed model, along with an illustrative case study, not only serves as a tool to quantitatively assess the impact of choice complexity on total system performance, but also provides an insight into how complexity can be mitigated without affecting the overall manufacturing throughput.

Keywords: manufacturing; mixed-model assembly line; choice complexity; similarity measure; information entropy

1. Introduction

In manufacturing contexts, increasing production variability while maintaining operation efficiency is an important issue in many industries. In the past, manufacturers provided the market with a few models that had long life cycles and a small variety of attributes. However, industries have recently faced several challenges driven by various factors, including the accelerated pace of technology development, the global wage difference and job skill shifts (John, Cannon, and Pouder 2001). To remain competitive, manufacturing organisations must offer a high product variety due to the increasing customer expectations along with technological advancement. For example, Wiendahl and Scholtissek (1994) have noted a 400% increase in the number of part variants from *n* 1975 to 1990.

Meanwhile, to fulfil customer requirements, manufacturers have resorted to mass customisation as the new manufacturing standard (Pine 1999). Mass customisation has become a key factor in maintaining or increasing market share since it offers a close match between customer preferences and offered products. It is widely thought that when a higher variety of models or options are offered, a competitive edge to companies can be guaranteed. On the other hand, manufacturing organisations are now facing an increase in manufacturing complexity due to the higher product variety. For example, around 64% of the respondents in a survey have identified the complexity resulting from managing variety as a significant cost driver in production by (Schleich, Schaffer, and Scavarda 2007).

In order to satisfy complex customer needs, manufacturing practitioners have opted for mixed-model assembly system and modular supply chains due to their reputation as major enablers for handling the increased variety. However, complexity inevitably arises in these systems. While the existence of complexity and its challenges are widely acknowledged, a formal quantification of manufacturing complexity is still a topic for discussion. In fact, complexity is often thought of as 'the state of having many different parts connected or related to each other in a complicated way' (Merriam-Webster 2016) with no systematic way to quantify it. In addition, there is no proper method to compare several manufacturing set-ups based on their respective complexities. Despite the clear lack of a common measure for manufacturing complexity, several studies have shown that a negative correlation between variety induced complexity and manufacturing performance exists (MacDuffie, Sethuraman, and Fisher 1996; Jenab and Liu 2010; Fisher and Ittner 1999). That is, there is a trade-off between additional advantages from a greater variety of options and the higher costs associated with complexity. Thus, from a decision-making standpoint, it is still a challenge to estimate the complexity

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trade-off since it is not only subjectively defined but also very vague due to lack of a constitutional measurement of variety-induced manufacturing complexity.

In the automotive industry, analysing manufacturing complexity is a reasonable way to ensure higher product variability, while maintaining production efficiency. Adding a model variant in a manufacturing system indeed increases the number of product components and the degree of their interaction. In addition, these conflicting aspects of complexity in the system incur additional direct and/or indirect costs for managing the manufacturing process and associated resources (Fisher and Ittner 1999). In other words, resource management and operations in the system are significantly affected by an increase in the system complexity, which should be properly managed and planned. For instance, adding to the variety in the assembly process may bring about changes in process plans, additional training for operators, different designs of tools (e.g. jigs and fixtures) and resource management. Thus, a cost-benefit scenario is typically studied to justify the variety introduced in the manufacturing line.

In spite of a recent advance in manufacturing automation, the role played by humans in the manufacturing system is still regarded a key factor in adaptable and flexible systems, such as in a mixed-model assembly line. In this paper, we define measures of complexity that reflect the underlying physics of the manual assembly process in the mixed-model system. Thus, the emphasis is placed on operator's choice complexity, which refers to the difficulties encountered by the operators when selecting the right component (e.g. tools, part, etc.,) from a number of options on the assembly line in manufacturing domains. The proposed measure integrates both the variety (i.e. option mix) and their respective similarities, which is expected to answer questions towards mechanisms between variety and complexity. Our proposed method also draws a clear and reasonable relationship linking the complexity metric to the manufacturing performance (e.g. cycle time). Once the complexity is measured in a representative quantifiable index that can be easily understood, a decision support system (DSS) for dynamic and effective manufacturing resource allocation will be suggested in our future work as a tool to mitigate overhead costs incurred by the complexities.

The remainder of this paper is organised as follows. In Section 2, we provide an overview of the existing literature. Section 3 provides complexity computation in the automotive manufacturing system. Next, Section 4 introduces an illustrative example accompanied by a description of an experiment that showcases the relationship between the proposed complexity measure and the reaction time. Finally, Section 5 concludes our paper and suggests future research directions.

2. Literature review

The study of complex systems represents a relatively novel approach which examines the relationships between parts, and how they relate to the collective behaviours of a system (Bar-Yam 2002). Meanwhile, the prevalent engineering viewpoint across systems is to reduce disturbance and variability in complex systems through automation. However, despite the recent advances in automation, human is still regarded as a key factor in maintaining higher adaptability and flexibility. Thus, technological expansion has been coupled with a need for effective and dynamic resource allocation methodologies in semi-automated systems (Shojafar et al. 2013, 2015).

The definition of complexity differs on a case by case basis and is considered to be subjective. Campbell (1988) suggests that complexity is often treated as (a) psychological experience, (b) an interaction between task and person characteristics and (c) a function of objective task characteristics. As a result, the notion of complexity is commonly conveyed using particular examples (Johnson 2009). While decision-makers agree upon the existence of complexity, the understanding of complexity and its characteristics is still limited (Johnson 2009).

The complexity in a manual assembly line is characterised by several factors, in which some of them are more impactful to the overall performance than others (Bergström and Karlsson 2013; Finnsgård and Wänström 2013). However, the assessment of the impact of complexity is often constrained by the ability to measure the complexity itself. Thus, Falck, Örtengren, and Rosenqvist (2014) and Falck et al. (2016) categorise the complexity in a manual assembly line into different levels based on several defined complexity parameters. Similarly, Zeltzer et al. (2013) propose a Likert scale measure of workstation complexity based on number of key variables identified to be the primary drivers of complexity. These researchers show that the high complexity in a manual assembly line often corresponds to the high likelihood of error. A similar relationship is also noted between the complexity and the time and the cost (Falck, Örtengren, and Rosenqvist 2012). In addition, Johansson et al. (2016) report a negative impact of high product variety on production quality. For the effective measuring of complexity in manufacturing systems, the information-based concepts (e.g. Shannon entropy) have been some of the most popular and commonly accepted theories used as a complexity measure. For instance, Matt (2012) demonstrates how axiomatic design principles can be used to control the effects of time-dependent complexity in manufacturing systems. Similarly, researchers have used the Shannon entropy to capture dynamic complexity of manufacturing systems, where all observable states of the manufacturing system are considered (Vrabic and Butala 2012; Smart, Calinescu, and Huaccho Huatuco 2013). In addition, Zeltzer, Aghezzaf, and Limère (2016) propose a complexity levelling method in which an entropic complexity measure is based on the variation of task cycle time. Also, using the entropy, Fujimoto and Ahmed (2001) propose a complexity measure for different stages of process planning, while ElMaraghy, Kuzgunkaya, and Urbanic (2005) demonstrate how the entropy function can be used in the quantification of complexity in machining process. Deshmukh, Talavage, and Barash (1998) define an entropic complexity measure for a part mix in job shop scheduling. While these efforts are worth lauding, the aforementioned studies of complexity measure pay little attention to the choice complexity from the human operators' perspectives, its relation to the varieties in models, and how it impacts overall performance in a mixed-model assembly line.

In this regard, recent researchers introduce models for the computation of operator choice complexity in a mixed-model assembly line (Zhu et al. 2008; Zhu 2009; Hu et al. 2008). These models adopt Hick's law, or the Hick–Hyman law, to model the cycle time as a function of complexity measured by information entropy. Hick's law is popularly used to describe the time it takes for a person to make a decision as a result of the possible choice (Hick 1952). However, the proposed choice complexity modelling relies heavily on the part mix ratio and puts less focus on the relationship and interdependency among the options that have been shown to be a significant factor in choice complexity (Irwin et al. 2012; Pankok et al. 2017). Hick's law considers the option mix as the primary determinant of reaction time in human-factor perspectives; however, recent studies have shown that not only the number of options, but also the similarity of options can significantly affect the operator's reaction time (Irwin et al. 2012; Hellier et al. 2010). For example, several cases exist, in which parts have been mistakenly taken for one another due to their close similarities.

Although the similarity of options in a mixed-model assembly line clearly impacts the choice complexity of the system operations and is detrimental to the total system performance, the formulation and analysis of the option similarity has received less attention from researchers to practitioners in the manufacturing industries. This is possibly due to its low perceived impact on the manufacturing performance in a mass-production environment. However, given the currently competitive manufacturing era, where the mass customisation is essential and can significantly increase the number of options at an unprecedented rate, both the option counts and the similarity of options have become important factors to be considered as they can affect human errors and workloads. In particular, the similarity of options has been given a lot of attention in some specific industries where human error can have a tremendously negative effect, to illustrate its consequences on reaction time and human errors. For example, several studies have been done in the pharmaceutical industry on the similarity of both the name and the container of drugs in a pharmacy (Irwin et al. 2012; Hellier et al. 2010). 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. Hellier et al. (2010) point out that the use of colour to differentiate the drugs can not only improve the accuracy but also reduce the search time of the target medication. Similar conclusions have been noted on the shape differentiation of the drugs, to some extents. Thus, in this paper, we propose a novel choice complexity model that incorporates both the option mix and their respective similarity.

3. Choice complexity model

The choice complexity particularly in a mixed-model assembly system is affected by several factors, some of which are more significant for operators than others. Recent studies show that increasing the number of options available for operators, including their respective similarities, can significantly affect the level of choice complexity (Zhu et al. 2008; Zhu 2009; Hu et al. 2008; Irwin et al. 2012; Hellier et al. 2010). While quantifying the number of options is straightforward, measuring the similarity of options is both complex and subjective. Thus, in the next subsection, we propose a similarity measure in a mixed-model assembly line. Later, we develop a novel choice complexity model that integrates both the option mix and its respective similarity.

3.1 *Similarity measure in semantics*

While the definition of complexity can be customised to serve a given need, in the abstract sense, complexity is based on visual structures perception (Stanowski 2011). For example, before an assembly process, an operator will receive a command requesting him or her to select a specific part from a pool of available options. As in the abstract sense, the complexity of selection will increase based on perceptions of visual structures. Research has shown that, once the command is received, the operator's memory retrieval cue can become less effective when the command stimuli are associated with multiple items in the memory (Surprenant and Neath 2009; Watkins and Watkins 1975). That is, the more similar the options, the more ambiguous an operator will become when responding to the stimuli. The similarity effect on an operator's selection also depends on the brain activation, which is more or less category-based (Kreiman, Koch, and Fried 2000).

There is little to no existing research on the similarities of options in a mixed-model assembly, although psychologists have long attempted to formalise similarity measures (Nosofsky 1992). The current formalisation of similarity measures has relied heavily on knowledge representation, where the similarity between two objects is typically based on the semantic similarity. Here, objects are represented using the description of their properties (Zhang and Lu 2004) Thus, the commonalities and differences between two semantic representations of objects can be taken as one indicator for similarity (Nosofsky 1992). That is, the more commonalities and the less differences, the higher the similarity. One of the well-known similarity measures built based on the commonalities and differences between two semantic representations is the feature-based similarity measure. In the feature-based similarity measure, the similarity between two particular objects A and B, $s(A, B)$, can be formulated as a function between their common and distinct features as shown in Equation (1) (Tversky 1977).

$$s(A,B) = F(A \cap B, A - B, B - A) \tag{1}$$

Equation (1) shows the feature-based similarity measuring model based on a set-theoretic knowledge representation (Figure 1(a)). These features correspond to components with concrete or abstract properties of the object. Thus, objects can be represented as a linear combination of an unstructured set of features as shown in Figure 1(b).

Although the feature-based similarity measuring model can, due to its simplicity, be easily adopted as the part mix similarity measure for the mixed-model assembly line, its inability to incorporate partial match in the model becomes a serious drawback. For example, based on the feature-based similarity measuring model, the similarity between objects 1 and 2 in Figure 1(b) can be said to be equal to the similarity between objects 1 and 3 despite the better colour similarity in the former pair. Thus, to fill the loophole of a feature-based similarity measure, it is possible to express the similarity as a function of distance between an object's respective properties. In this case, object properties will be represented in the form of dimensions with ordered values. In this context, the geometric model can be used in analogy to spatial distance. Due to its superior performance, we utilise this approach in our study.

Geometric measure is based on the concept of multidimensional vector spaces, based on which objects or concepts are modelled and their spatial distance indicates the semantic similarity (Groenen 2005). The geometric model uses what's called multidimensional scaling (MDS), which is a method that represents the measurement of similarities (or dissimilarities) as a distance between points of a low-dimensional multidimensional space among pairs of objects

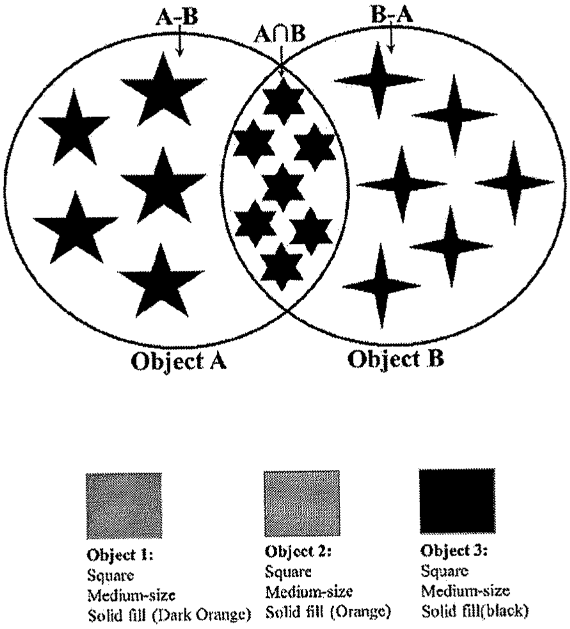

Figure 1. (a) Feature-based similarity measuring model in set-theoretic operations, (b) Object representation via an unstructured set of features.

(Groenen 2005). Once the dimensions are set and represented, the semantic distance between objects a and b denoted as $d(a,b)$ can be formulated as a function of total compound weighted distance of all their properties. We note that the distance obtained is spatial distance, which is also known as the Minkowski distance measure (Equation (2)).

$$d(a,b) = \left[\sum_{i=1}^{n} |\varepsilon_i(x_{ai} - x_{bi})|^r\right]^{1/r} \tag{2}$$

where x_{ai} is the value of dimension i for stimulus a, x_{bi} is the value of dimension/feature i for stimulus b, ε_i is the weight assigned to dimension/feature i as a functional reflection of the salience or prominence of the various dimensions and r determines the measured distance ($r = 1$ results in city-block distance and $r = 2$ results in Euclidian distance).

In this equation, it is important to acknowledge the difference in the object properties. For example, while some properties can be geometrically comparable (e.g. volume, etc.), other properties that are difficult to measure can present a bigger challenge (e.g. complex shapes, etc.). Thus, object properties with a measurement challenge can be presented as features with Boolean values (i.e. true or false). In this paper, we represent objects using a combination of dimensions with ordered values as well as features that hold for that specific object, in which features can be considered as a special case of the dimension with only Boolean values. In particular, the distance between two objects based on a given feature can be obtained as shown in Equation (3).

$$|x_{ai} - x_{bi}| = \begin{cases} 0 & \text{if both a and } b \text{ possess feature } x_i \\ 1 & \text{otherwise} \end{cases} \tag{3}$$

where x_{ai} and x_{bi} denote feature x_i of object a and b, respectively.

Next, after the semantic distance between objects a and b, $d(a,b)$, is obtained, it is converted to the similarity measure using Equation (4), where the similarity is an exponential decay function of distance (Pashler and Medin 2004).

$$s(a,b) = e^{-c.d(a,b)} \tag{4}$$

where $s(a, b)$ is the similarity between object a and b, and c is the general sensitivity parameter.

Note that for N number of options, there exist a $N \times N$ distance matrix whose entry d_{ij}, $1 \le i,j \le N$, satisfies the following metric's properties:

- $d_{ij} = 0$ for all $i = j$,
- All the off-diagonal entries are positive, such that $d_{ij} > 0$ if $i \neq j$,
- The matrix is a symmetric matrix, such that $d_{ij} = d_{ji}$ and
- For any i and j, $d_{ij} \le d_{ik} + d_{kj}$ for all k (the triangle inequality).

Here, d_{ij} denotes the distance between option i and j, (See Equation (2)).

Recall that the representation often describes elementary characteristics, such as the shape, the colour, the texture. While each visual properties of simple objects can be listed, the description of complex objects presents more challenges. Notice, however, how the similarity measure is heavily reliant on the representation of the discriminatory features, regardless of the part complexity. For example, a weighted colour difference can be used for similarity measure of two very complex parts whose only difference resides in their colour. Also, complex visual features can be automatically extracted and represented as feature vectors using several well-known algorithms often utilised in the field of computer vision (Zhang and Lu 2004). In fact, recent research in neuroscience has shown that object recognition in primates is done in a manner similar to that used by feature descriptors algorithms used in machine learning, such as Scale-Invariant Feature Transform (Tanaka 1997; Lowe 2004). Thus, visual attributes are regarded as points in a multidimensional feature space, where the distance between extracted feature points (see Equation (2) for distance measure) reflects feature similarity.

3.2 *Similarity in a mixed-model assembly line*

In a mixed-model assembly line environment, before each task, an operator receives a stimulus requesting him or her to select a specific part from a pool of alternative options. Typically, the choice process involves two successive steps. First, the operator receives a stimulus, after which he/she proceeds to select the corresponding option. Note that often, at the station level, an assembly task may involve several sequential choices (i.e. part choice, fixture choice, tool choice, etc.). Let $k = 1, 2, \ldots, K$ denotes a choice activity at a given station, where K is the maximum number of sequential choices on the station. It follows that for each station i, we can define two random variables X_i^k and Y_i^k describing the outcome of targeted variant (per stimulus) and the actual operator's choice, respectively. Note that both X_i^k and Y_i^k are defined on the same sample space $\Omega_i^k = \{v_{ij}^k | j = 1, 2, \ldots, \mathrm{N}\}$, where v_{ij}^k denotes the jth variant and N is the total number of possible alternatives (parts/tool/fixture, etc.) that could be chosen in kth choice activity at the station i. In this context, $\mathrm{p}_{X_i^k}(v_{ij}^k)$ denotes the probability that v_{ij}^k is the target part/tool in a given task (i.e. $p_{X_i^k}(v_{ij}^k) = P(X_i^k = v_{ij}^k)$). On the other hand, $p_{Y_i^k}(v_{ij}^k)$ denotes the probability that variant v_{ij}^k is the actual operator's choice in the given task. Once the targeted option is identified, the visual differentiation of options can be done based on their respective physical features, such as shape, colour, size. That is, the operator's effectiveness will depend on several factors, including the available options and their similarities to the target variant. Thus, for each target variant v_{ij}^k, there is an associated perceived similarity level that differs from one target variant to another. Let $\Theta = \{\Theta_{v_{it}^k} | t = 1, 2, \ldots, N\}$, where $\Theta_{v_{it}^k}$ is the overall level of perceived similarity associated to target variant v_{it}^k. That is, Θ maps a given target variant to the sum of the pairwise similarities between the target variant and each alternative option as shown in Equation (5)

$$\Theta_{v_{it}^k} = \sum_{\mathrm{j}}^{\mathrm{N}} \left(\mathrm{s}\left(v_{it}^k, v_{ij}^k\right) | X_i^k = v_{it}^k \right) \tag{5}$$

where N is the total number of variants, $s\left(v_{it}^k, v_{ij}^k\right)$ is the similarity between variant v_{it}^k, and v_{ij}^k

Based on Equation (4), the distance matrix can be transformed into a similarity matrix S as shown in Equation (6), where $s_{qp} = s\left(v_{iq}^k, v_{ip}^k\right); s_{qp} \in [0, 1]; 1 \leq q, p \leq N$.

$$S = \begin{bmatrix} s_{11} & \cdots & s_{N1} \\ \vdots & \ddots & \vdots \\ s_{N1} & \cdots & s_{NN} \end{bmatrix} \tag{6}$$

The level of the perceived similarity associated to the target variant $\Theta_{v_{it}^k}$, from Equation (5) can be extracted from the similarity matrix S as follows (Equation (7)).

$$\Theta_{v_{it}^k} = \sum_j^N (s_{jt} | X_i^k = v_{it}^k) \tag{7}$$

According to Equation (7), v_{it}^k is the target option, and the overall level of activated similarity is simply the sum of the pairwise similarities between v_{it}^k and every other available option, which is equivalent to the summation of tth row of the similarity matrix S.

3.3 *Incorporating similarity measure in a complexity model*

Originally used as a measure of uncertainty, the information entropy, or so-called Shannon entropy, has been widely adopted as a measure of complexity in several manufacturing processes (Efthymiou et al. 2016). After a comprehensive justification on the use of entropy as a measure of choice complexity, (Zhu et al. 2008) proposed the entropic measure of choice complexity as follow:

$$C = \alpha(a + bH), \alpha > 0 \tag{8}$$

where α is the weight of the choice, a and b are ergonomics constants, and H is the information entropy associated to the operator's choice.

The information entropy H quantifies the expected value of the information contained in a message and can be regarded as an average unpredictability of a random variable (Shannon 2001, 1951). In an uncertain environment, such as a mixed-model assembly line, an operator shall make the right part selection from several options to be assembled within the limited allocated time to ensure the working flow for a specific task. Considering that an assembly task often involves several sequential choices at the station level (i.e. part choice, fixture choice, tool choice, etc.), based on the Equation (8), the total choice complexity at the station level can be expressed as follow:

$$C_i = \sum_{k=1}^{K} \alpha_i^k \left(a_i^k + b_i^k H_i^k\right), \; k = 1, 2, \ldots K \tag{9}$$

where k denotes the sequential choice activity comprised in the assembly operations at station i.

Since α, a and b are constants, the choice complexity can be assessed by evaluating the information entropy H. Recall that, first the target option is revealed (per stimulus), then an actual choice is made accordingly. As stated earlier, the selection task. First, the operator receives a stimulus, after which he/she proceeds to select the right option. In terms of information entropy, the successive juxtaposition of information is equivalent to the overall information entropy contained in variables $X_i^k Y_i^k$ with joint distribution $p_{X_i^k Y_i^k}$ Thus, H_i^k from Equation (9) can obtained as follows (Equation (10)):

$$H_i^k = H(X_i^k Y_i^k) = H(X_i^k|Y_i^k) + H(X_i^k) \tag{10}$$

Here, $H(X_i^k)$ is the average information gained by acquiring the targeted variant (per stimulus), while $H(X_i^k|Y_i^k)$ denotes the average information required for selection of the part after the acquisition of the stimulus. Individually both $H(X_i^k)$ and $H(X_i^k|Y_i^k)$can be obtained using Equations (11) and (12), respectively.

$$H(X_i^k) = -\sum_{j=1}^{N} p_{X_i^k}(v_{ij}^k)\log_2 p_{X_i^k}(v_{ij}^k) \tag{11}$$

$$H(Y_i^k|X_i^k) = -\sum_{j=1}^{N}\sum_{t=1}^{N} p_{X_i^k}\left(v_{ij}^k\right) p_{Y_i^k|X_i^k}\left(v_{ij}^k|v_{it}^k\right)\log_2 p_{Y_i^k|X_i^k}\left(v_{ij}^k|v_{it}^k\right) \tag{12}$$

The term $p_{Y_i^k|X_i^k}\left(v_{ij}^k|v_{it}^k\right)$ in the above equations denotes the probability that the operator will select v_{ij}^k, after he or she receives the stimulus requesting to select v_{it}^k. Based on the fuzzy logical model of perception, Luce (2008) suggests that the probability of selecting part 'a' when 'b' is requested, denoted by $P_{a|b}$, can be calculated using Equation (13).

$$P_{a|b} = \frac{s(a,b)}{\sum_{l \in N} s(l,b)} \tag{13}$$

where s (a, b) is the similarity between part a and b and N is the set of all available alternatives.

Thus, based on Equations (7) and (13), $p_{Y_i^k|X_i^k}\left(v_{ij}^k|v_{it}^k\right)$ can be obtained using Equation (14)

$$p_{Y_i^k|X_i^k}\left(v_{ij}^k|v_{it}^k\right) = \frac{s(v_{ij}^k, v_{it}^k)}{\sum_{l \in N} s(v_{il}^k, v_{it}^k)} = \frac{s_{jt}}{\Theta_{v_{it}^k}} \tag{14}$$

Next, Equation (10) can be extended as follows (Equation (15)).

$$H(X_i^k Y_i^k) = -\sum_{j=1}^{N}\sum_{t=1}^{N} p_{X_i^k}\left(v_{ij}^k\right)\frac{s_{jt}}{\Theta_{v_{it}^k}}\log_2\frac{s_{jt}}{\Theta_{v_{it}^k}} - \sum_{i=1}^{N} p_{X_i^k}(v_{ij}^k)\log_2 p_{X_i^k}(v_{ij}^k) \tag{15}$$

The probability $p_{X_i^k}\left(v_{ij}^k\right)$ that a given variant is to be requested in a given product assembly is proportional to the ratio of the said variant and the total number of possible alternative variants. Thus, the probability $p_{X_i^k}\left(v_{ij}^k\right)$ is equivalent to the demand in percentage of the jth variant (i.e. $\sum_j p_{X_i^k}\left(v_{ij}^k\right) = 1, \forall_k$). We note that once the operator acquires the target (e.g. $X_i^k = v_{ij}^k$), the remaining complexity is equivalent to $H\left(Y_i^k|X_i^k = v_{it}^k\right)$ and can be obtained as follows (Equation (16)).

$$H\left(Y_i^k|X_i^k = v_{it}^k\right) = -\sum_{j=1}^{N} p_{Y_i^k|X_i^k}\left(v_{ij}^k|v_{it}^k\right)\log_2 p_{Y_i^k|X_i^k}\left(v_{ij}^k|v_{it}^k\right) = -\sum_{j=1}^{N}\frac{s_{jt}}{\Theta_{v_{it}^k}}\log_2\frac{s_{jt}}{\Theta_{v_{it}^k}} \tag{16}$$

Using Jensen Inequality, it can be shown that the information entropy, $H\left(Y_i^k|X_i^k = v_{it}^k\right)$ will be maximised when all options are visually identical (*i.e.*, $\sum_{j=1}^{N}\frac{s_{jt}}{\Theta_{v_{it}^k}} = \frac{1}{N}, \forall_t$). Thus, each part/tool has equal probability to be selected by an operator. Equation (17) thus follows.

$$H\left(Y_i^k|X_i^k = v_{it}^k\right) \leq -log_2\frac{1}{N} \tag{17}$$

4. Illustrative case study

4.1 *Screw choice complexity*

We provide a case study for the screw choice complexity in this section. A sequence of assembly process typically involves a selection of proper screws. We note that the proposed complexity model presented earlier is not necessarily limited to the mixed-model assembly line. In fact, the choice complexity does exist in many other manual assembly settings in which operator's task involves the 'search' and the 'selection' of an appropriate component Ma (2014). Also, several cases exist in which a company may choose a strategy to deliver product to be assembled by customer(s) at the destination to reduce inventory and transportation costs. However, although the package often includes an instruction and an assembly guideline, it can be challenging and time-consuming for customer(s) to match each component to its right position. Similar to the mixed-model assembly, one of the challenges is that the assembly involves a large number of parts, some of which are very similar and difficult to differentiate. Screws are especially some of the common parts causing an ambiguity to customer(s)/operators. In this illustrative example of screw choice complexity, we consider a set of screws to illustrate option similarity and variant as shown in Figure 2 (Screws *A*–*K*).

In this example, each screw can be represented using five dimensions: thickness, colour, length, head shape and screw drive type. We use the similarity measure explained in Section 3 to generate the distance matrix and the resulting similarity matrix. We note that the overall dimension matrix is a weighted summation of all individual dimension-based similarity matrices (See Equation (2)). For example, the distance matrix that is based on colour dimension is illustrated for all 11 screws (i.e. A … K) in Table 1. Each entry m_{ij} of Table 1 is a pairwise colour distance between option i and j. We note that $m_{ij} = 0$ for all $i = j$ implies that the colours are identical. The colour distance is measured using the most recently updated colour difference, known as CIEDE2000, proposed by the International Commission on Illumination (CIE). Compared to other colour difference measure (e.g. CIE76, CIE94, etc.), CIEDE2000 is deemed to be perceptually uniform throughout the colour space; thus, fits well as a colour difference measure. Similar to any colour difference measures, CIEDE2000 allows a quantified examination of colour comparison that formerly could only be described with adjectives. For more details on CIEDE2000 and how it is computed, see Luo, Cui, and Rigg (2001). The matrix distance based on head shape as well as screw type was obtained using Equation (3). We note that other distance matrices based on other dimensions can be quantitatively calculated in a more-or-less similar way.

Next, the overall distance matrix can be calculated using Equation (2) and the values are shown in Table 2. As stated earlier, the overall dimension matrix is a weighted summation of all individual dimension-based similarity matrices

For a better visualisation, we then used the MDS algorithm and the graphical result was obtained. As shown in Figure 3(a), options J and K are identical, while option G is closely similar to the pair J–K. On the other hand, options A and B are very dissimilar from all other options. By simply looking at the MDS plot, one can confidently argue that option F or H is more likely to cause a higher choice complexity than options A and B (all things being equal). In this example, each option is equally likely to be requested as the target option at any time. That is, $p_{X_i^k}(v_{ij}^k) = \frac{1}{N}$, where N is the total number of options. Figure 3(b) presents the contribution of each variety of screw to the overall complexity of the system. It can be observed how the options in the crowded area in Figure 3(a) are the major contributor to the complexity. This is because the similarity of options is one of the underlying factors of choice complexity.

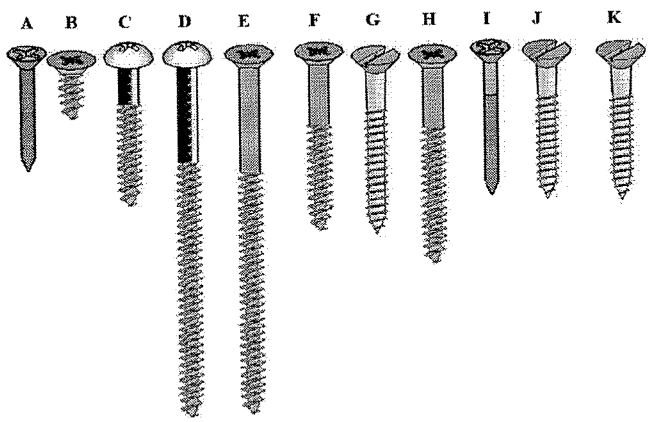

Figure 2. A set of screws and their variety.

Table 1. Distance matrix based on colour dimension (CIEDE2000).

	A	B	C	D	E	F	G	H	I	J	K
A	0.00	21.94	30.97	30.97	21.94	21.94	42.08	21.94	25.77	42.08	42.08
B	21.94	0.00	9.50	9.50	0.00	0.00	27.61	0.00	6.74	27.61	27.61
C	30.97	9.50	0.00	0.00	9.50	9.50	25.59	9.50	7.66	25.59	25.59
D	30.97	9.50	0.00	0.00	9.50	9.50	25.59	9.50	7.66	25.59	25.59
E	21.94	0.00	9.50	9.50	0.00	0.00	27.61	0.00	6.74	27.61	27.61
F	21.94	0.00	9.50	9.50	0.00	0.00	27.61	0.00	6.74	27.61	27.61
G	42.08	27.61	25.59	25.59	27.61	27.61	0.00	27.61	33.27	0.00	0.00
H	21.94	0.00	9.50	9.50	0.00	0.00	27.61	0.00	6.74	27.61	27.61
I	25.77	6.74	7.66	7.66	6.74	6.74	33.27	6.74	0.00	33.27	33.27
J	42.08	27.61	25.59	25.59	27.61	27.61	0.00	27.61	33.27	0.00	0.00
K	42.08	27.61	25.59	25.59	27.61	27.61	0.00	27.61	33.27	0.00	0.00

Table 2. Overall distance matrix considering all dimensions.

	A	B	C	D	E	F	G	H	I	J	K
A	0.00	0.63	0.66	0.82	0.54	0.40	0.74	0.42	0.17	0.72	0.72
B	0.63	0.00	0.59	0.75	0.46	0.32	0.94	0.35	0.57	0.92	0.92
C	0.66	0.59	0.00	0.16	0.45	0.31	0.86	0.33	0.51	0.84	0.84
D	0.82	0.75	0.16	0.00	0.28	0.42	0.98	0.40	0.67	1.00	1.00
E	0.54	0.46	0.45	0.28	0.00	0.14	0.76	0.12	0.43	0.78	0.78
F	0.40	0.32	0.31	0.42	0.14	0.00	0.62	0.02	0.29	0.64	0.64
G	0.74	0.94	0.86	0.98	0.76	0.62	0.00	0.64	0.67	0.02	0.02
H	0.42	0.35	0.33	0.40	0.12	0.02	0.64	0.00	0.32	0.66	0.66
I	0.17	0.57	0.51	0.67	0.43	0.29	0.67	0.32	0.00	0.65	0.65
J	0.72	0.92	0.84	1.00	0.78	0.64	0.02	0.66	0.65	0.00	0.00
K	0.72	0.92	0.84	1.00	0.78	0.64	0.02	0.66	0.65	0.00	0.00

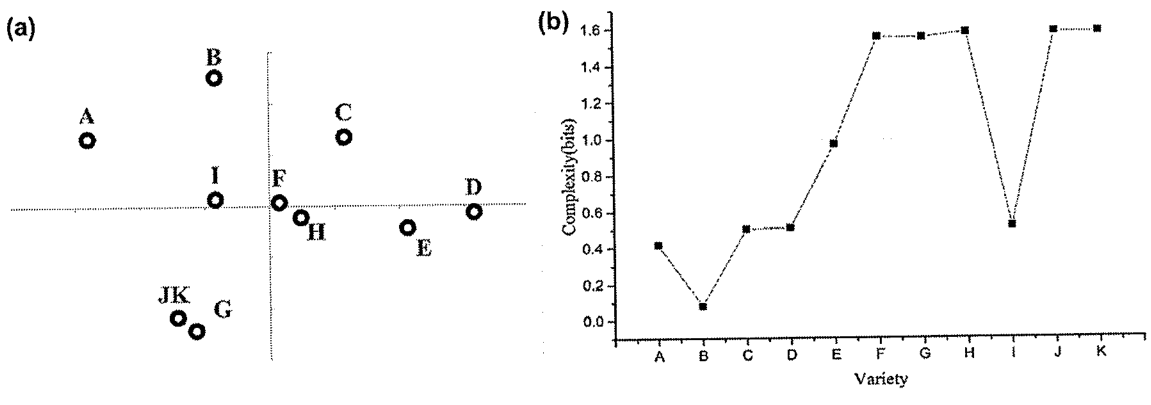

Figure 3. (a) Option similarity plot based on MDS, (b) The expected complexity of each option.

Next, Figure 4(a) presents the complexity when each variety of screw is sequentially added into the system. In the figure, the graphical cumulative complexity in bits is plotted against the screw variety as obtained using Equations (15). We note the different rates of increase in the cumulative complexity when each new screw variety is added. Thus, it is interesting to see how removing or adding some options can improve or worsen the choice complexity. However, in the proposed model, the similarity is by no means the sole major factor determining the level of choice complexity in a mixed-model assembly line in our study. In fact, the level of complexity is also affected by the demand share of every

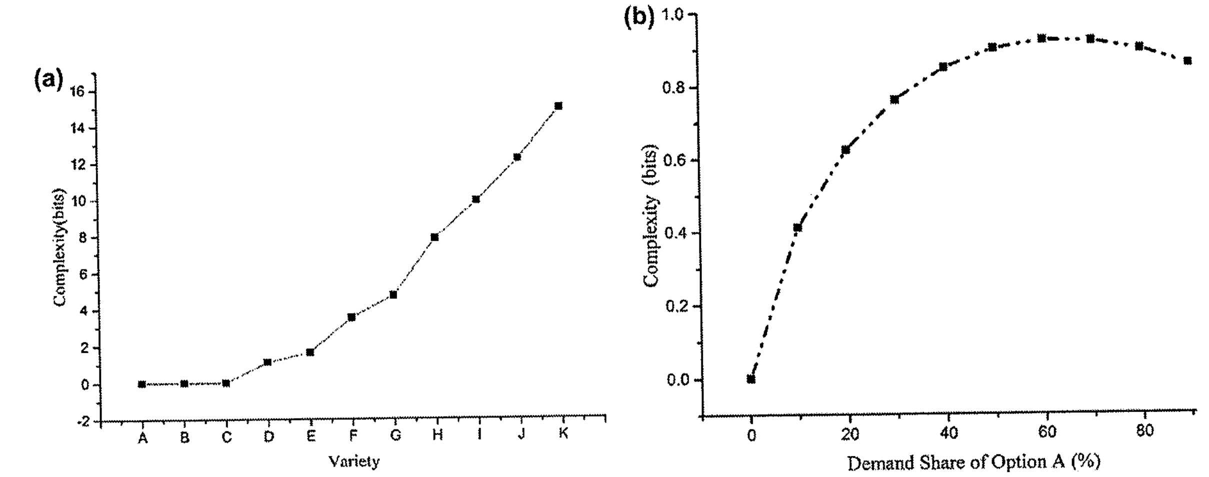

Figure 4. (a) A graphical cumulative complexity against variety, (b) Option A's complexity contribution as its demand share varies.

option in the system $p_{X_i^k}(v_{ij}^k)$. Considering an increase in the demand share of option A, for example, its contribution to the level of choice complexity varies as shown in Figure 4(b). It can be observed how its contribution starts from 0 bits when the demand share is 0. Then, it continuously increases and starts to fall once the demand gets very high. This is because, when the demand share of v_i is close to zero (i.e. $p_{X_i^k}\left(v_{ij}^k\right) \cong 0$), the operator is more likely to ignore part. v_i.Similarly, as the demand share approaches 100, the operator is more likely to ignore other options since he /she can correctly guess the next target option.

We further conducted a sensitivity analysis to see how adding or removing a particular option can affect the overall complexity. For example, by not introducing the F variety (option), the overall choice complexity $(H(Y_i^k X_i^k)$ is found to reduce from 14.94 to 11.55 bits. A 22.65% drop is found despite holding 9.09% of the demand share $(i.e., p_{X_i^k}(v_{ij}^k) = \frac{1}{N})$. On the other hand, option B is found to be the lowest contributor to the complexity at the station. Thus, removing option B only reduces the overall complexity from 14.94 bits to 14.17 bits, which is only 0.51% decrease in the overall complexity, despite equaling the market share of variety F.

It is clear that the complexity measure can offer an insight on how the complexity can be mitigated through various process, such as modularisation. Once the major contributors of the complexity are identified, a detailed cost-benefit scenario can be used to decide the most appropriate solution for a decision-maker. The solution may include moving some tasks to a different station, discontinuing or reducing the volume of products responsible for high complexity, introduction of an error proofing system, designing optimal modules that ensure an acceptable level of complexity, etc. (Cheldelin and Ishii 2004; Elmaraghy, Nada, and ElMaraghy 2008).

4.2 *Choice complexity and reaction time*

This subsection illustrates the choice complexity and the impact from reaction time. We note that a detailed relationship linking the proposed complexity measure to a formal performance metric is in our future work. However, we briefly give a glimpse of what an entropic measure of manufacturing complexity implies in terms of traditional practical performance metrics (i.e. cycle time, etc.) in this subsection. Based on Hick's law (Hick 1952; Hyman 1953), the average reaction time (RT) can be approximately formulated as a linear function of the information entropy conveyed by the stimulus (Equation (16)).

$$RT = C_i \tag{18}$$

where C_i is station level complexity obtained using Equation (8).

According to Equation (18), as the complexity increases, the uncertainty also increases and the part selection generally takes additional time due to the slower reaction time of the operator. Thus, we intend to analyse a relationship between complexity and reaction time. The use of information entropy for modelling the manufacturing complexity in a mixed- model assembly line is relatively novel; it can be seen that the few existing works use the option mix as the sole parameter in entropy computations. In the following toy example, we show that the proposed entropic measure can be used to predict the reaction time, which can provide an insight into the expected cycle time. We also illustrate that the proposed model that integrates both the option mix and similarity performs a better job compared to the existing entropic measure of choice complexity that simply relies on the part mix.

4.2.1 *An experimentation overview*

To verify the relationship between the proposed complexity measure and the reaction time, we conducted an experiment, in which an operator receives stimuli instructing him or her to perform a given task following certain guidelines. Practically, the form of these stimuli varies from one instance to another. For example, the operator may receive the instructions that include a coded name or an image of the part to be assembled with the mainframe. In this experiment, the stimulus is given in the form of an image. Once the operator receives the stimulus, he or she must click on the matching option according to the guidelines. An example of the stimulus and the pool of options in the form of Lego images are shown in Figure 5. We then pay more attention to the effectiveness of the stimulus-option matching process.

In this experiment, the operator (subject) is requested to select the matching image, after which the next matching command appears. The task begins when the stimulus is displayed on top of the options and finishes when the subject clicks on one of the options. Once the subject clicks on one of the options, the experiment proceeds by displaying the next stimulus. As stated in Equation (5), the target option at any time, t, is an element of the set of all options. Thus, a stimulus is uniformly selected from the set of all available options in this experiment. We vary the number of options with six levels (i.e. 2, 4, 8, 12, 16 and 20) as shown in Table 3. For each level, both the length in centimetres and colour in Red-Green-Blue (RGB value) are randomly generated with three levels from a uniform distribution with specified minimum and maximum values. Thus, there are 18 experimental trials in the study in total. The experiment was run on a desktop with a 21-inch monitor and a total of 10 subjects participate in the experiment.

4.2.2 *Feature selection and complexity measure*

In order to properly measure the similarity of objects, discriminatory features should be selected based on the semantic representation of the objects. The representation of each feature should also be independent. That is, the degree that each feature or pair of features shares between two objects affecting the similarity should not be dependent on other shared features. In addition, the feature set should also be sufficiently rich and representative.

In the above experiment, the discriminatory features chosen in the study are the length and the colour of the Lego images. The CIEDE2000 is used as a quantitative measure of difference between colours, whereas the length in centimetres is used to measure the size feature. As noted in an earlier section, the CIEDE2000 is popularly used to replace visual subjective judgments of colour difference by instrumental objective measurements. For each pair of objects, the similarity is obtained using Equation (4) and the resulting complexity is computed using Equation (8).

4.2.3 *Result and discussion*

In this experiment, the average reaction time in seconds, RT, follows the Hyman–Hick's law, which can be shown to be linearly dependent on the information entropy representing the complexity (Figure 6). However, when we conducted a regression analysis to see how closely the data fits the regression line, the prediction power from using the traditional Hick–Hyman's law as the primary determinant of the reaction time (i.e. based on option counts and their respective demand share) is relatively low ($R^2 = 0.48$) (Figure 6(a)). We next conducted a similar analysis using the proposed complexity measure based on the modified information entropy from Equation (13). The graphical analysis between the

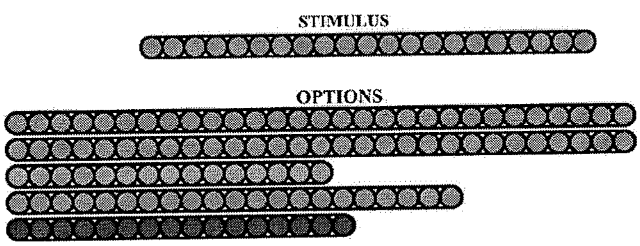

Figure 5. The reaction time experiment with stimulus and matching task.

Table 3. Experimental study based on length and colour.

Number of options	Length(cm) Min	Length(cm) Max	Colours (RGB) Min	Colours (RGB) Max
2	4	16	0	250
2	8	12	50	150
2	8	10	50	100
4	4	16	0	250
4	8	12	50	150
4	8	10	50	100
8	4	16	0	250
8	8	12	50	150
8	8	10	50	100
12	4	16	0	250
12	8	12	50	150
12	10	12	50	100
16	4	16	0	250
16	8	12	50	150
16	8	10	50	100
20	4	16	0	250
20	8	12	50	150
20	8	10	50	100

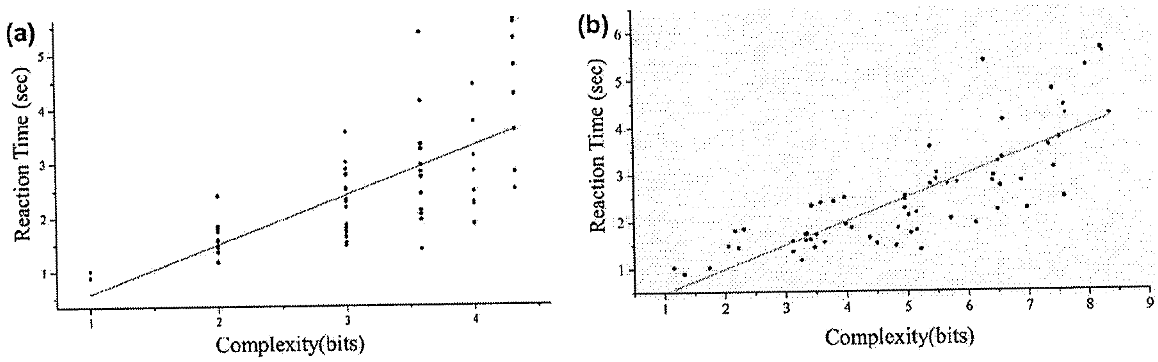

Figure 6. (a) Reaction time as a function of the traditional complexity measure, (b) Reaction time as a function of the proposed complexity measure.

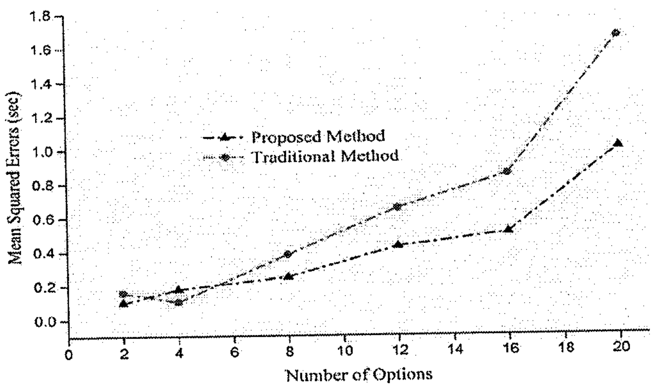

Figure 7. Comparison of MSE between the traditional and proposed complexity models.

modified information entropy and the reaction time is shown in Figure 6(b). A regression analysis shows an improvement in the prediction power by over 34% ($R^2 = 0.64$), which is considered relatively high for human experimentation.

We next compared the traditional method and the proposed complexity measure using the mean square error (MSE) as shown in Figure 7. The traditional method tends to become volatile when the number of options goes up. Thus, although the advantage of the proposed model over the traditional one may seem to be minimal for the cases with a low number of options, there is a clear trade-off such that the gap grows larger when the number of options increases representing a higher complexity. In particular, when we increase the number of options from 4 to 14, the MSE increases more than seven times (7.2 times) when using the traditional method compared to less than two times (1.8 times) when using the proposed complexity model.

5. Conclusion and future research

As mass customisation is becoming a new norm in manufacturing systems, the number of distinct options in mixed-model assembly line has been growing at an unprecedented rate, inducing complexity in the business. Additionally, due to flexible market demands, demand changes are also imminent in manufacturing systems. However, there is a lack of quantifiable methods to account for manufacturing complexity. In this paper, we presented a novel method to compute manufacturing choice complexity, incorporating option counts and option similarity based on the well-known information entropy model. The proposed model not only has the ability to compute the overall complexity of the system, but can also track the contribution of each specific option or station to the overall system complexity. We conducted an experimental design to verify the impact of the similarity of options and reaction time to the overall complexity. Then, we further compared our proposed complexity measure with the traditional complexity that did not explicitly discuss the similarity of options and found that our model is more effective.

Our proposed complexity model can be used as a tool to investigate how the system performance will look if a given set of policies were to be implemented. For example, it offers a decision-maker the ability to hypothetically add a number of options, after which an analytical result can be obtained. Thus, the model can be used to assess various scenarios and their respective effects on the overall complexity and reliability of the system. For example, to help an operator have less of a workload in terms of the decisions he/she must make, a company typically utilises a system in which parts are delivered to the assembly line in a precise build sequence. Thus, parts associated with the highest level of complexity can be determined and included in the system using the proposed model. In addition to the computation of the system complexity, it can be shown that with a fixed option count, both the similarity and proximity level can be adjusted to mitigate the system complexity.

The proposed complexity model with an experimental study, while practical, could be further understood with more experimentations accounting for operator experience, stimulus sequence, etc. In addition, cost and time impacts on a decision-maker should be further explored. Thus, future research directions include a justification study of how the addition of a new variation has impacts on the overall company performance in terms of the cost-benefit analysis. On one hand, if customers base their purchasing decisions on specific features, the increased complexity can be compensated by the increased sales. On the other hand, additional costs associated with the increased complexity may be unwarranted with lower demand. In addition, as the cost associated with system reconfiguration can depend on system flexibility, a study on the flexibility of a mixed-model assembly line and its relationship to overall system complexity, as well as to mitigation approaches, will be central to our future work. Last but not least, although the screw part is illustrated in our study, more complex parts could be further investigated in the future to see the impact and trend of complexity measure.

Disclosure statement

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