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Analytical Modeling of Human Choice Complexity in a Mixed Model Assembly Line Using Machine Learning-Based Human in the Loop Simulation

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ABSTRACT Despite the recent advances in manufacturing automation, the role of human involvement in manufacturing systems is still regarded as a key factor in maintaining higher adaptability and flexibility. In general, however, modeling of human operators in manufacturing system design still considers human as a physical resource represented in statistical terms. In this paper, we propose a human in the loop (HIL) approach to investigate the operator's choice complexity in a mixed model assembly line. The HIL simulation allows humans to become a core component of the simulation, therefore influencing the outcome in a way that is often impossible to reproduce via traditional simulation methods. At the initial stage, we identify the significant features affecting the choice complexity. The selected features are in turn used to build a regression model, in which human reaction time with regard to different degree of choice complexity serves as a response variable used to train and test the model. The proposed method, along with an illustrative case study, not only serves as a tool to quantitatively assess and predict the impact of choice complexity on operator's effectiveness, but also provides an insight into how complexity can be mitigated without affecting the overall manufacturing throughput.

INDEX TERMS Manufacturing, mixed model assembly line (MMAL), choice complexity, machine learning, information entropy.

I. INTRODUCTION

In the past, manufacturers had provided the market with a few models that had few attributes and long life cycles. Today, the increasing customer sophistication and expectations along with the accelerated pace of technology development have led to a much more complex market [1]. Manufacturing organizations are now expected to offer a high product variety to remain competitive. As a result, the number of part variants registered a 400% increase between the year 1975 and 1990 [2].

Meanwhile, the mixed-model assembly system and modular supply chains have been adopted in order to handle the increased variation [3]. By offering a range of models, companies have gained a competitive edge. However, as the variety increased, manufacturing performance worsened due to the complexity from creating and handling multiple product models [4], [5].

This means that there exists a tradeoff between additional advantages from a greater variety of options and higher costs associated with manufacturing complexity. However, from a decision-making standpoint, it is still a challenge to estimate the tradeoff since it is not only subjectively defined but also very vague due to lack of constitutional measurement of manufacturing complexity.

Thus, analyzing the complexity of manufacturing is a promising way of ensuring higher product variability, while simultaneously maintaining the production efficiency. This paper proposes a machine learning methodology in which various features of choice complexity are not only identified, but also used in assessing and predicting the dynamics of operator's performance. The paper focuses on operator's choice complexity; since, in spite of advances made in manufacturing automation, human is still regarded as a key factor in adaptable and flexible manufacturing systems such as MMAL. Here, choice complexity (CCO) 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. The operator's performance is expressed as function of the time it takes to select the right component; which, according to research, diminishes as the number of options increases [6], [7].

As in most complex systems in which closed-form analytical solution is nonexistent, simulation has become a powerful tool in the analysis of complex manufacturing systems. Thanks to the technological advances in the new ''smart manufacturing'' era, simulations analysis has hit its strides. However, the existing progress and research on smart manufacturing put little emphasis on human, the essential component of a smart factory, while focusing, instead, on the higher level artificial intelligence in factory environments [8], [9].

Furthermore, due to the dynamics of human behaviors, modelling or simulating human performance via traditional methods is often hard. In fact, the statistical estimations of the human role fall short in several human-involved systems [10]. We aim to simulate and analyze the CCO and its underlying effects, by incorporating a real human (human-in-the-loop) in the overall assembly simulation in a manner that accurately represents the core physical aspect of choice complexity. Furthermore, using the human in loop simulation (HIL) platform, we build and train a machine learning model, to not only assess possible features affecting the operator's performance in an MMAL, but also through prediction, to potentially be used for allocating accurate dynamic cycle time in accordance with the task complexity. The proposed methodology provides an in-depth analysis of CCO, and gives a hint how on how to effectively encapsulate human component in smart manufacturing settings.

II. RELATED WORKS

A. MANUFACTURING COMPLEXITY

The study of complex systems represents a collective scientific effort that investigates how interaction between parts give rise to the overall behaviors of a system [11], [12]. Recent progress in the study of complexity has made it possible to systematically characterize a wide range of complex systems [12], [13]. Due to heterogeneous characteristics of different complex systems, the scientific notion of complexity has been traditionally conveyed using particular examples [14].

In this regard, recent researchers introduced models for the computation of operator choice complexity in a mixed model assembly [6], [7]. These models adopt Hick's law, later known as the Hick-Hyman law, to model the cycle time as a function of complexity measured by information entropy. Hick's law has been popularly used to describe the time it takes for a person to make a decision as a result of the number of possible choices [15]. However, Hick's choice complexity modeling relies heavily on the part mix ratio and pay little attention on other factors such as the relationship and interdependency among the options that have been shown to be an important factor in choice complexity [16].

From MMAL perspective, before an assembly process, an operator receives a command requesting him or her to select a specific part from a pool of available options. 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 [17], [18]. For example, the more similar the options, the more ambiguous it becomes to the operator 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 [19]. Thus, [20] proposed an entropic choice complexity model that considers both part mixes and their respective similarity. The model, however, ignores the effect of task sequence on the operators' effectiveness [21]. Despite these research attempts, there is still no validated model that explicitly explains the nature of choice complexity in MMAL and its underlying effects on system performance.

B. MODELING AND SIMULATION OF HUMAN-INVOLVEMENT IN MANUFACTURING SYSTEMS

Simulation, specifically the discrete event simulation (DES), plays a major role in analyzing the manufacturing complexity. Simulation allows the testing and analysis of a new resource policy before actual implementation, deployment, or gathering information and knowledge without disturbing the actual system [22]. Thanks to advances in computing, the simulation in manufacturing has had several progresses in recent history.

The success of the simulation is based upon the advances in the representation of several aspects of the manufacturing in computable terms (i.e., conceptual model) [23]. For example, computer simulations have represented different technological aspects of manufacturing systems (e.g., machines, conveyors) with deterministic and stochastic data. However, the traditional approach, which is based on simple discrete event-based specifications, often fails to represent the details of the relationship between the performance of a person and his or her working environments, which is regarded a key modeling attribute in human-machine co-working environments [10]. In fact, human variation is the cause of a significant percentage of the discrepancy between simulation predictions and real world performance. This presents a problem when modelling systems that involve highly manual work contents such as a MMAL.

While several aspects of manufacturing complexity can be modeled, and analyzed, the choice complexity presents a greater challenge due to several human factors involved. This is why few researchers opted to incorporate human models in DES for simulating various aspects of manufacturing processes [10]. Because of the complexity of human actions, the existing human models are often oversimplified and only built for specific purposes (e.g., military, etc.). For example, [10] included a human performance model that only considers both the age and experience to simulate the manufacturing assembly production. Similarly, due to technological advances in 3D representation, several researchers have successfully opted for digital human models (DHM) to increase the accuracy of various simulation of manufacturing assembly process, particularly with regards to human factors [24]. However, the study also points out the need for several needed improvements to bridge the gap that still exist between DHM and real human operators [24], [25]

Although human models, including DHM do a better job compared to most other discrete event simulations, there is no ideal human performance model yet that encloses all the relevant human factors from a manufacturing point of view. In this regard, studies have noted a surge in number of researchers and practitioners embracing the virtual simulation as the new norm of simulation of human-centered systems [26]. Virtual simulation has many advantages, including the ability to provide adaptable virtual replication of physical systems that would otherwise be overly expensive, sometimes even impossible to explore [27]. Whereas the majority of virtual simulation focus on practice and testing user's knowledge using interactive scenarios and environments to reflect real-life situations [28]; in this paper, we propose machine-learning-based HIL simulation in which a non-immersive virtual choice simulation is used to accurately represent and analyze the CCO and predicts its impact on manufacturing performance.

III. HUMAN IN THE LOOP MACHINE LEARNING

A. MACHINE LEARNING IN MANUFACTURING SYSTEMS

Through the advancement of technology, manufacturing industry has become capable of collecting a wide range of data in different format and quality [29]. As the available data grow, practitioners have relied on machine learning to create new ways to support decision-making or to improve the system automatically. The goal of certain machine learning techniques is to detect patterns or regularities that describe vital relations, necessary to understand or improve the system [30], [31]. As a field that originated from the study of pattern recognition and computational learning theory in artificial intelligence and expert system, machine learning explores construction of algorithms that can learn from historical relationships and trends in the data to make data-driven predictions or uncover hidden critical insights needed to produce reliable, repeatable decision [32], [33].

Machine learning has been successfully utilized in process optimization, monitoring, control applications, and predictive maintenance in different manufacturing industries [34], [35], [36]. Whereas the majority application of machine learning concept has often been limited to optimization of sequencing or line balancing problems, machine learning has, sometimes, been applied to predict the task duration of a wide range of manufacturing processes. For example, [37] used support vector regression to predict the life of cutting tools. Similarly, in [38] various regressions models have been proposed to predict the factory cycle time based on historical data. However, little has been researched in quantified modeling and analysis of CCO under flexible manufacturing environments. In fact, the role of human involvement in the aforementioned research is either minimal, or considered as a physical resource expressed in statistical terms, which may not hold in reality, given the dynamism of human operators, especially in a complex MMAL.

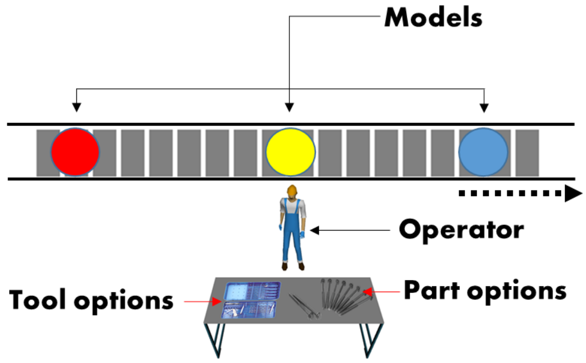

FIGURE 1. Choice Complexity in a mixed-model assembly line. Once an operator receives the stimulus, he/she proceed on selecting the right part from several options available.

B. HIL MACHINE LEARNING IN MMAL

Planning and training assembly operations during the early stages of product design can ensure that a product is manufactured in the most efficient way. Thus, manufacturers rely on simulation results for insights necessary for adequate planning before further expenditure is made.

However, due to the dynamics of human behavior, it is often impossible to accurately simulate the choice complexity in a mixed model assembly via the traditional simulation methods. Thus, we use the HIL to reproduce the assembly problem by embedding a real human in the system to accurately reproduce the physical facet of choice complexity. As opposed to simply considering human as a physical resource represented in statistical terms, in this type of simulation, a human is always part of the simulation, thus, affects the outcome of the simulation in such a way that it would be almost impossible to reproduce without him/her [39]. In other words, HIL readily identifies the problems and requirements that may not be easily identified by other means of simulation.

As shown in Fig. 1, in a MMAL environment, the operator receives, before each task, the stimuli instructing him or her to perform a given task following certain guidelines. Practically, the form of the stimuli varies from one instance to another. For example, the operator may receive instructions that include a coded name or an image of the part to be assembled with the mainframe. Once the command is received, the operator starts by selecting the right part from a pool of available options, after which he/she proceeds with the assembly. In this paper, the proposed approach is accompanied by an illustrative example, in which a human subject is requested to identify the right part in similar fashion as in the real physical assembly line.

The proposed method mirrors the actual physical setups that characterizes the choice complexity in a MMAL. After selecting the features of choice complexity, we build and train

FIGURE 2. Screw Selection task. The subject click on a specific screw according to the stimulus.

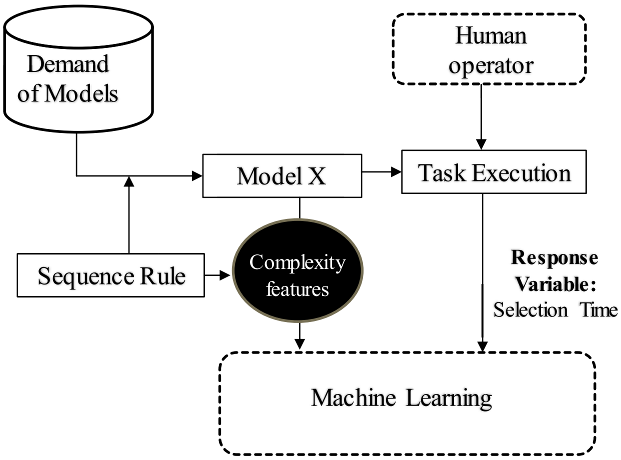

FIGURE 3. Human in the loop machine learning in a MMAL.

a machine learning model based on the operator's selection time as depicted in Fig.3, which will be discussed further in the next sections.

IV. FEATURES AND CHARACTERISTICS OF CHOICE COMPLEXITY IN MMAL

A. SIMULATION OF CHOICE COMPLEXITY IN MMAL

The mixed model assembly lines often consist of multiple stations arranged along some kind of a transportation system, e.g., a conveyor belt, which is carrying workpieces from one station to another. Operators move along the workpiece carrying out distinct tasks, most of which require the "*selection of the right part*" according to the model at hand. Recall that "operator's choice complexity" refers to the difficulty that operators face when selecting the right component from a number of options. That is, a more complex choice is

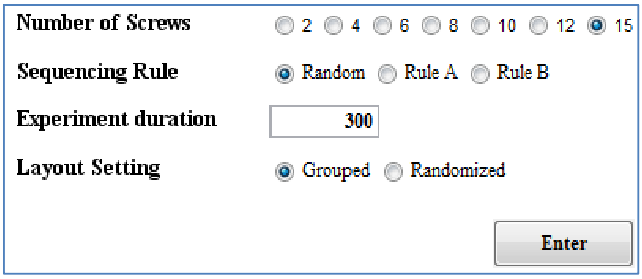

FIGURE 4. User interface of the experiment.

more likely to take longer time to make, or results in an erroneous part selection. The selection process involves a visual search, which, according to [40], is "a type of perceptual task requiring attention that typically involves an active scan of the visual environment for a particular object or feature (the target) among other objects or features (the distractors)".Therefore, options can be visually differentiated on the basis of their respective physical features, such as shape, color, size, and position. The effectiveness of the visual search depends on several factors, some of which are more significant than others. The major factors include the number of alternatives or distractors and their similarities to the target object, the sequence and frequency of target and proximity, grouping and orientation [20],[40]–[42].

For further understanding, let us take an example, in which an operator is required to pick up the right screw to be used according to the stimulus. Each available screw has a distinctive corresponding model variety, in which it is to be used. As in most visual search experiments, subjects are asked to detect a target object upon receiving a command. That is, once the stimulus is received, the subject goes on to select the right screw according to the instructions. The selection is done by clicking on the corresponding part, after which a feedback is given to signal that the choice has been recorded (See Fig.2).

Subjects were asked to detect a particular target screw presented among the irrelevant non-targets. Here, six human subjects were involved in this illustrative example. Three major simulation parameters were considered: namely, the number of screws, the sequence rule and the layout settings. As shown in Fig.4, seven distinct numbers of screws, three sequencing rules and two layout settings were used in the simulation for a total of 41 distinct experimental setups. The experiment was run at a randomized order; that is, before each subject began the selection task, levels were set according to a predefined random order. The experiment lasted approximately 40 minutes consisting of at least 10 distinct factors' combination for each subject. The duration of each individual trial varied for each combination of factors' levels depending on the number of screws involved, ranging from 60 seconds for two screws to 300 seconds in the case of 15 screws.

B. FEATURES OF OPERATOR's CHOICE COMPLEXITY

Several factors deemed to be affecting the operator's choice complexity are considered in this simulation. As shown

TABLE 1. List of collected data in MMAL.

Attributes	Attributes ID(s)
Number of options (screws)	1
Sequence rule	2
Physical arrangement (Layout)	3
Position data*	4, 22-36
Similarity data**	5, 7-21
Entropy	6
Variation in Similarity matrix	38
Reaction time	39

in Table 1, on each selection task, we collected a total of 39 raw variables, ranging from the number of options to operator's reaction time. The position data include distance between the two consecutively requested target screws (i.e., attribute 4) and the row of position matrix corresponding to the requested option (i.e., how far apart any given option is to the targeted option).

The similarity data include the similarity level as obtained in (3) (i.e., attribute 5), and the row of the similarity matrix corresponding to the requested option (how similar any given option is to the targeted option). The entropy refers to a complexity measure as proposed in [6], while the variation in similarity matrix refers to the standard deviation of the row of the similarity matrix corresponding to the requested option. Note that the collected data may contain variables that are either redundant or irrelevant, thus can be ignored without losing much information. Hence, it is important to select a subset of relevant features (predictors) to be used in model construction. A successful feature selection not only makes it easier to interpret, but also to reduce the training time and the variation [43].

For selection of features, researchers have shown the importance of selecting subsets of variables that together have good predictive power, as opposed to simply ranking variables according to their individual predictive power [44]. Thus, we use the wrapper method which evaluates selected subsets of variables in terms of their overall prediction power. Using greedy forward algorithm we select subsets of features to be evaluated under a specific criterion (i.e., RMSE) [44]. Eleven algorithms representing an array of popular machine learning (i.e., Linear Regression, Regression Trees, Regression Rules, Instance-Based Learning Algorithms, and Support Vector Machines) were used for the evaluation. Fig.5 shows how frequently a given feature was deemed necessary in the prediction of time of selection. In the next section, we will discuss three of the more complex selected features of choice complexity in a mixed model assembly line and the form in which they were collected in this illustrative example.

1) SIMILARITY OF VARIANTS

Researchers have argued that an increase in the similarity of choice alternatives leads to longer decision time, due to inefficient memory retrieval [17], [18].

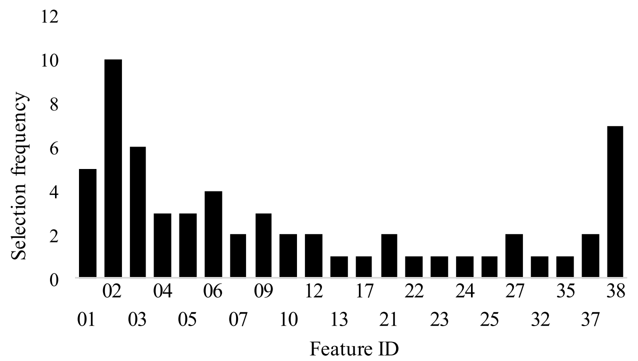

FIGURE 5. Selected features.

The current formalization of similarity measures has relied heavily on knowledge representation, where the similarity between two objects is typically based on the semantic similarity. Knowledge representation allows a better understanding of the complexity or the ambiguity caused by stimuli, since some semantic memory data structures store and use lexical information in a way similar to how humans store and use lexical information [45]. Semantically, objects can be represented using the description of their properties. That is, 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 [46]. In this context, the semantic distance can be used as an analogy to spatial distance.

Geometric based semantic distance measure is based on the notion of multi-dimensional vector spaces. Objects or concepts are modelled within a multi-dimensional space and their spatial distance indicates the semantic similarity. The geometric model uses multi-dimensional scaling (MDS), which is a method of representing the measurement of similarities (or dissimilarities) as a distance between points of a low-dimensional multidimensional space among pairs of objects [46]. 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 the Euclidian spatial distance as shown in (1).

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

where x_{ai} is the value of dimension i for stimulus a x_{bi} is the value of dimension i for stimulus b, ε_i is the weight assigned to dimension i as a functional reflection of the salience or prominence of the various dimensions. By default, we set ε_i to 1, that is, each dimension is equally important.

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

TABLE 2. Similarity matrix of screws.

	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15
s1	1.0000	0.1353	0.0183	0.0067	0.0009	0.0001	0.0041	0.0498	0.0183	0.0067	0.0025	0.0041	0.0015	0.0002	0.0025
s2	0.1353	1.0000	0.1353	0.0498	0.0067	0.0009	0.0302	0.0498	0.1353	0.0498	0.0183	0.0302	0.0111	0.0015	0.0183
s3	0.0183	0.1353	1.0000	0.3679	0.0498	0.0067	0.2231	0.0067	0.0183	0.0498	0.1353	0.0041	0.0111	0.0111	0.0025
s4	0.0067	0.0498	0.3679	1.0000	0.1353	0.0183	0.0821	0.0025	0.0067	0.0183	0.0498	0.0015	0.0041	0.0302	0.0009
s5	0.0009	0.0067	0.0498	0.1353	1.0000	0.1353	0.0111	0.0003	0.0009	0.0025	0.0067	0.0002	0.0006	0.0041	0.0001
s6	0.0001	0.0009	0.0067	0.0183	0.1353	1.0000	0.0015	0.0000	0.0001	0.0003	0.0009	0.0000	0.0001	0.0006	0.0000
s7	0.0041	0.0302	0.2231	0.0821	0.0111	0.0015	1.0000	0.0015	0.0041	0.0111	0.0302	0.0183	0.0498	0.0498	0.0006
s8	0.0498	0.0498	0.0067	0.0025	0.0003	0.0000	0.0015	1.0000	0.3679	0.1353	0.0498	0.0821	0.0302	0.0041	0.0015
s9	0.0183	0.1353	0.0183	0.0067	0.0009	0.0001	0.0041	0.3679	1.0000	0.3679	0.1353	0.2231	0.0821	0.0111	0.0183
s10	0.0067	0.0498	0.0498	0.0183	0.0025	0.0003	0.0111	0.1353	0.3679	1.0000	0.3679	0.0821	0.2231	0.0302	0.0067
s11	0.0025	0.0183	0.1353	0.0498	0.0067	0.0009	0.0302	0.0498	0.1353	0.3679	1.0000	0.0302	0.0821	0.0821	0.0025
s12	0.0041	0.0302	0.0041	0.0015	0.0002	0.0000	0.0183	0.0821	0.2231	0.0821	0.0302	1.0000	0.3679	0.0498	0.0183
s13	0.0015	0.0111	0.0111	0.0041	0.0006	0.0001	0.0498	0.0302	0.0821	0.2231	0.0821	0.3679	1.0000	0.1353	0.0015
s14	0.0002	0.0015	0.0111	0.0302	0.0041	0.0006	0.0498	0.0041	0.0111	0.0302	0.0821	0.0498	0.1353	1.0000	0.0002
s15	0.0183	0.1353	0.0183	0.0067	0.0009	0.0001	0.0041	0.0498	0.1353	0.0498	0.0183	0.0302	0.0111	0.0015	1.0000

properties with a measurement challenge can .be presented as features with Boolean values (i.e., true or false). In this paper, we represent objects by using a combination of dimensions with ordered values and Boolean values. Here Boolean values represent features that hold or not for that specific object. In this particular case, the distance between two objects based on a given feature can be obtained as shown in (2).

$$|x_{ai} - x_{bi}| = \begin{cases} 0 & \textit{if both a and b possess feature } x_i \\ 1 & \textit{otherwise} \end{cases} \tag{2}$$

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 by using (4), where the similarity is an exponential decay function of distance expressed as follow [47]:

$$s(a, b) = e^{-c.d(a,b)} \tag{3}$$

where $s(a, b)$ is the similarity between object a and b; 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}, $1 \leq i, j \leq N$, 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, $d_{ij} \leq d_{ik} + d_{kj}$ *for all* k *(the triangle inequality)*

Here, d_{ij} denotes the distance between option i and j, as seen in (1).

It follows that the level of similarity corresponding to a given target variant (v_t) can be obtained as follow:

$$S(v_t) = \sum_{i}^{N} s\left(v_t, v_i\right) = \sum_{i}^{N} \left(s\left(v_j, v_i\right) \mid v_j = v_t\right) \tag{4}$$

where N is the total number of variants, n is the number of dimensions, t is the target variant, $s\left(v_j, v_i\right)$ is the similarity between variant i and j computed as shown in (3).

In our illustrative example, we represent each screw using three dimensions: thickness, length, and head shape. The overall similarity matrix is shown in Table 2.

2) SEQUENCE RULE

The MMAL is an assembly line system, in which various models of a common base product are manufactured in intermixed sequences. In a mixed-model assembly line, assembly sequence planning plays a crucial role in a successful assembly procedure, and a good sequence often saves time and cost [48]. In fact, other than line balancing problems, the mixed-model assembly lines give rise to a short-term sequencing problem. Therefore, within a planning horizon, the production sequence ought to ensure an efficient workflow. Sequencing is central to effectiveness of the assembly process because different sequencing rules or constraints are set to ensure that the line do not present a work overload, or the works are well balanced throughout the stations. The sequencing rules often specify how many models should contain a specific option out of a given successive models. Thus, based on the predefined rules, the sequencing problem can be formulated as a constraint satisfaction problem.

Assembly sequencing in this illustration can be defined as a three-tuple, (V, S, r) where

- $V = \{v_1, .., v_{15}\}$ is the set of different variants (screw);
- $S = \{S_1, .., S_n\}$ is the set of different subsequences; $S_k = \{p_{k1}, .., p_{km}\}$ where p_{kj} denotes a position j in subsequence k, and m is the number of variants in the subsequence
- $r : V \times S_k \rightarrow$ æ$\{0, 1\}$; that is, if variant v_i is to be part of assembly at p_{kj} then $r_{v_i p_{kj}} = 1$; $r_{v_i p_{kj}} = 0$, otherwise.

Assuming that the objective is to minimize the choice complexity, a good sequence not only fulfils the constraint but also minimizes the uncertainties in the choice process by promoting a correct anticipation. Since there are three different classes, all variants are partitioned into 3 subsets (i.e., per head shape) where V $= \bigcup_{i=1}^{3} V_i$. The subsets are as follows:

- $V_1 = \{v_1, v_4, v_6, v_8, v_{12}, v_{14}, v_{15}\}$

- $V_2 = \{v_2, v_5, v_7, v_9, v_{10}, v_{11}, v_{13}\}$
- $V_3 = \{v_3\}$

We consider three types of sequence in this illustrative example. The first sequence rule (i.e., Rule A) can be described using the following constraint

$$\sum_{j}^{2} r_{v_i p_{kj}} < 2, \quad v_i \in V \tag{5}$$

Constraints in equation (5) mean that the same variant shall not be requested successively in any sequence. In other words, the constraint imposes that, for any subsequence of two consecutive model on the line, at most one of them may require v_i, for any $v_i \in V$. The constraints of the second sequence rule (i.e., Rule B) are as follows:

$$\sum_{v_i \in V_t} \sum_{j}^{5} r_{v_i p_{kj}} \leq 2, \quad t = 1, 2, 3 \tag{6}$$

$$\sum_{v_i \in V_t} \sum_{j}^{2} r_{v_i p_{kj}} < 2, \quad t = 1, 2, 3 \tag{7}$$

Constraints in equation (6) mean that in any sequence of 5, at most two screws from any partition shall be included. That is, for any subsequence of 5 consecutive products on the line, at most 2 of them may require screw v_i from the same group V_k for all k. The constraints in equation (7) imply that two variants from the same group or partition shall not be requested successively in any sequence. The final sequence rule is simply a random sequence in which the stimuli are randomly generated from a uniform distribution to ensure an equal probability for all the screws. That is, each variant is equally likely to be requested at any position of any given sequence.

The objective function in the sequencing problem is often minimizing the labor utilization or the spreading of material demand [49]. For example, the solution to a sequencing problem can ensure that models responsible for high station times alternate with less work-intensive ones. In this illustrative example, the objective is to minimize the time it takes to respond to the stimulus requesting to select a given screw. Here, the goal is to minimize the operator's visual search space. Let $x_{p_{kj}}$ be the position of screw requested at p_{kj}, thus our objective function is as follows:

$$min \sum \left| x_{p_{kj}} - x_{p_{kj+1}} \right| \tag{8}$$

Note that we assume that the positions of screws are fixed.

3) PHYSICAL ARRANGEMENT

According to [50], location information is one of the most important factors in ubiquitous computing. In this example, the positions of screws are fixed before each experimental run. Two setups are used: first; the screws are arranged according to their visual features. That is, we place screws from each subset (i.e., V1, V2& V3) closely together. In the second setup, screws are randomly positioned regardless of their features because the theory of grouping states that humans naturally perceive objects as organized patterns and objects. For example, parts that are similar and close to each other tend to be grouped since their attributes are perceived as related [42]. Note that the distance between any two closely positioned screws is equal for both setups.

C. RESULT & DISCUSSION

1) MACHINE LEARNING AND PREDICTION OF SELECTION TIME

A perfect prediction of the operator's selection time is unattainable; however, the proposed method fairly mimics the actual physical setups that define the choice complexity in a mixed model. Hence, in accordance with the features of choice complexity, we built several machine learning algorithms and trained them by using the human in loop search time. As stated earlier, we select representative algorithms from some of the popular machine learning technique namely: linear regression, regression trees, regression rules, instance-based learning algorithms, and support vector machines.

a: LINEAR REGRESSION

We fit the regression model using the least squares. Based on the result in Table 3, the performance of linear regression on our dataset is extremely poor.

b: REGRESSION TREES

Regression trees are binary decision trees with numerical values at the leaf nodes: In this analysis, we use random forest to predict the operator's reaction time. The forests studied here consist of using randomly selected inputs or combinations of inputs at each node to grow each tree. The number of features the random forest is allowed to try in a given individual tree was set to the first integer less than log2M+1, where M is the number of features. We put no limitation on the maximum number of trees [51].

c: REGRESSION RULES

Here we use the decision table with default mapping to the majority class, where a stepwise selection is used to find good attribute combinations for the decision table [52].

d: INSTANCE-BASED LEARNING ALGORITHMS (IBL)

IBL are learning algorithms that compares new problem instances with instances seen in training, and stored in memory. That is, they construct hypotheses directly from the training instances themselves. Here we use k-nearest neighbor (K-NN) regression as exemplar IBL algorithm. K-NN is a non-parametric method that assign weight to the contributions of the neighbors, to ensure that the nearer neighbors are more emphasized. Using a cross validation, four nearest neighbors were obtained to be optimal. The Euclidian distance was used to compute the distance between neighbors [53].

TABLE 3. Comparison of regression algorithms.

Test options	Regression Algorithm	Correlation Coefficient	MAE	RMSE
10fold Cross-Validation	SVM	0.8405	0.2562	0.3625
	Decision Table	0.8327	0.2406	0.3674
	Random Forest	0.9101	0.1832	0.2827
	K-NN	0.7917	0.2792	0.4119
	Linear Regression	-0.0461	16.4838	371.492
70/30 split	SVM	0.8434	0.2614	0.4114
	Decision Table	0.8358	0.2553	0.4138
	Random Forest	0.9172	0.1977	0.3236
	K-NN	0.784	0.3193	0.4743
	Linear Regression	0.5597	0.3406	0.7369
Leave 1 out Cross-Validation	SVM	0.8326	0.2637	0.3704
	Decision Table	0.8445	0.2369	0.3551
	Random Forest	0.909	0.1846	0.2834
	K-NN	0.798	0.2757	0.4067
	Linear Regression	-0.0474	16.7196	368.4111

The random forest algorithm outperforms the rest of the algorithms in the prediction of the operator's selection time.

e: SUPPORT VECTOR MACHINE

We used the sequential minimal optimization algorithm to implement the SVM with Gaussian kernels. After a thorough grid search, the SVM parameters, namely, C parameter, RBF Sigma and Epsilon were set to 0.7024, 0.9045, and 0.0702 respectively [54].

Three testing methods were used to assess the accuracy of each machine learning. First, seventy percent of the data were used for training while the remaining 30 was used for testing the regression models. Second, a 10fold and leave one out cross validation were also used for training and testing. The time to build each model varied from less than 0.1sec for KNN and decision table to approximately one second for random forest and SVM. We compared the regression models based on the three metrics; namely, the coefficient of correlation, the mean absolute error (MAE) and the root mean squared error (RMSE).

Table 3 shows the selected regression models and their respective performance according to the three metrics. The maximum coefficient of correlation reaches as high as 90% implying a high correlation between the actual and the predicted values. Decision tree appears to be the better fit for this particular problem where random forest outperforms other algorithms in all categories, regardless of the testing methods. That is, the Random forest present both the highest coefficient of correlation, the lowest MAE and RMSE. Notice how all the three testing methods have very similar results. To some extent, the results shown in table 3 corroborates the notion of human in the loop machine learning simulation. That is, while the standard for a good machine learning model varies

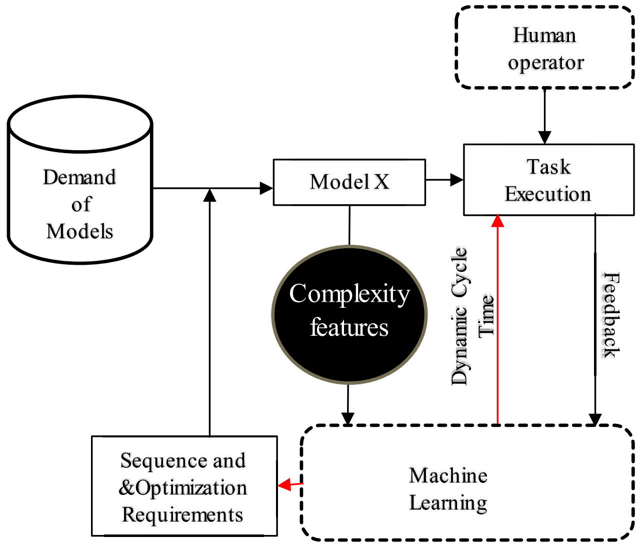

FIGURE 6. Incorporation of machine learning into a MMAL.

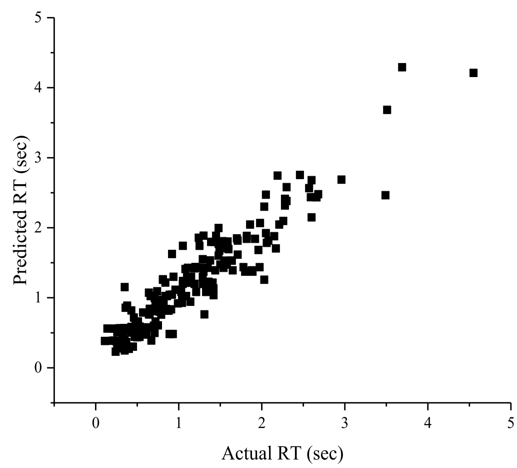

FIGURE 7. Comparison of Actual selection time (tested) vs. Predicted selection time (simulated) obtained using random forest regression algorithm.

depending on the prediction goal, one can argue that even the least accurate predication on the list still offer significant insights on the factors affecting the choice complexity and their implication on the service time. The results in Table 3 are confirmed in Fig. 7 that shows the comparison between predicted selection times (per random forest) along with the real selection times.

2) HUMAN-INVOLVED SYSTEM CONTROL AND SIMULATION

Using the proposed method, the operator's task can be broken down into subtasks that include part selection whose service time can be obtained by following the steps in Fig. 6. Thus, the operator becomes a part of the simulation until the simulation parameters are accurately extracted. The training ends when the threshold RMSE or accuracy rate is consistently reached. This means that the model is reliable enough to be used independently in predicting the operator's performance to be included in simulating the overall assembly line.

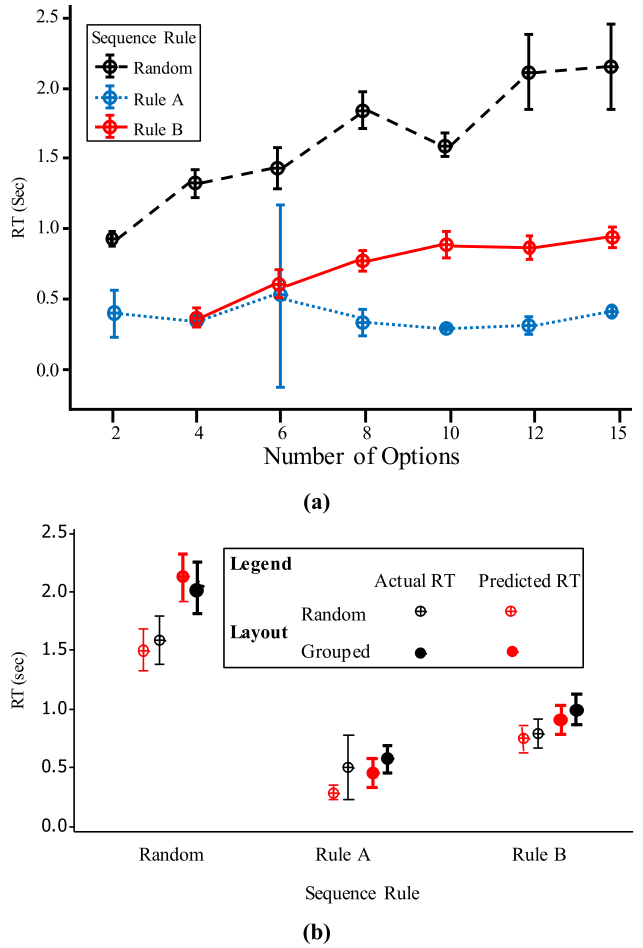

FIGURE 8. Changes in the mean of the actual reaction time (RT) caused by various parameter changes. In (a), as the number of alternative choices grow, the changes in the selection time depend heavily on the sequencing rule. Here, (b) show the combined effect of sequence rule and the layout setting on both the actual and predicted reaction time (selection time). We use random forest regression algorithm for the prediction selection time.

The inclusion of a real human in the simulation improves the accuracy and reliability of the simulation prediction, particularly regarding the operator's service time. Human involvement in the loop also provides more room for testing and optimizing the number of assembly line policies. As shown in Fig.8, changes in key factors improve the choice complexity in a mixed model assembly. Thus, it is possible to reduce the time required to make a choice by optimizing the sequence, the layout, or to reduce the number of options. Furthermore, Smart manufacturing boosts sensing technologies capable of capturing a wide range of data necessary for advanced analysis of manufacturing operations. (e.g., sequences, task data, etc.) [55]. That is, the imminent adoption of smart manufacturing in the future will give rise to several possible applications of machine learning in a wide range of human-involved manufacturing processes in which the proposed framework can be applied accordingly.

Each model commands a different level of complexity. Thus, in a flexible manufacturing environment, the proposed methodology can be of assistance in analyzing and optimizing the task sequence. Also, the predicted reaction time, can be used to allocate dynamic cycle time for tasks according to their complexities. For example, Fig 6 summarizes how machine learning algorithms can be incorporated into the overall assembly as follow:

- The human operator's performance logs serve as response variable (Feedback) used to train and continuously improve the machine learning algorithm
- The trained algorithm is used to predict the cycle time based on the complexity of the scheduled task.
- The scheduling and sequencing algorithm incorporates the machine learning data to ensure that the chosen sequence is associated with low complexity level.

V. CONCLUSION

One of the problems that emerges from increased varieties in a mixed assembly line is the choice complexity. Adding a model variants in a manufacturing system increases the number of product components, the resources needed to manage the interactions of these components. These aspects of complexity in the system incur additional direct and/or indirect costs for managing the manufacturing process and associated resources. As the number of options grow, operators inefficiently require more time to make accurate decisions. Different parameters have been shown to improve or worsen the choice complexity.

In this paper, we proposed a simulation framework in which various parameters of choice complexity are tested to assess the overall effect on operators' effectiveness. We select the features of choice complexity and build a regression model where human reaction time is the response variable used for training and testing the model. The model, along with an illustrative case study, serves as both a tool to evaluate the impact of choice complexity on operator's effectiveness, and provides insight on how to approach the choice complexity without necessarily affecting the overall manufacturing throughput.

Although the primary research objective was attained, there was some unavoidable limitations. For instance, while the screw selection experiment illustrates the overall proposed framework, it is arguable that the system is too simple to showcase every aspect of human in the loop machine learning simulation framework. Also, due to the subjective nature of human operators and the small sample size of human subjects involved in the experiment, the simulation results cannot be generalized; instead, the experiment should serve as exemplary template of the proposed simulation framework. Despite the limitations, the proposed model is valuable tool in the pursuit of an effective modeling and simulation of human-centered complex systems.

Although the proposed simulation framework is limited to the simulation of choice complexity in a mixed model assembly line, the same schematic may be applied in real-time simulation of most human involved systems, especially with the technological advances in data collection, e.g., sensors.

Thus, the proposed model provides an example of how one can effectively incorporate human component in the smart manufacturing environments.

We admit that the illustrative example used in this paper is not identical to the real manufacturing assembly line. However, it still captures the underlying source of complexity in the choice making. Thus, this method is further expected to be duplicated in a real assembly line with the right resources. In our future work, we plan to investigate the feasibility and scalability of the proposed model in real and complex manufacturing assembly lines, including an expansion of the model to include the overall assembly system simulation.

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