Using a Systems Dynamics Model to Assess Skill Level Impact

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Abstract

Research activities have been performed to identify areas of complexity related to the product, process or operational tasks. The developed framework decouples the manufacturing complexity aspects using a systematic approach to decompose the problem into key impact factors. The result of this model provides insight into the system sensitivities when considering human characteristics. However, the model is a static model. Skill levels improve with experience and repetition. The actors within a system may have different levels of skills and knowledge, and how and where these resources are utilized within a system will impact inventory and throughput. As well, people have different learning characteristics. Both these static and dynamic elements impact the system performance. This research presents a systems dynamics model that contains production rules and rules to evaluate the impact of human skill level variations based on the complexity of a task / set of tasks. The impact of positioning a set of personnel with different skill levels on different positions in an assembly line is explored.

Keywords
Human performance, complexity, system dynamics, physical and cognitive performance modeling

1. Introduction
Humans have the widest range of physical and mental skill sets and dexterity of any creature. But humans are not “general purpose devices” capable of performing any and every task with equal skill and proficiency. Proficiency in any endeavour is obtained incrementally: skills are acquired by gradually increasing the complexity of the sub tasks, either physical or cognitive. A broad spectrum of diverse disciplines has presented theories, perspectives and insights with respect to human performance models. This includes, but is not limited to: psychology, sociology, engineering, computer science, biomechanics, and medicine. Human performance models focus on limited aspects of human performance such as models for learning, social behaviour, cognitive skills, motor skills, and man-machine systems. The particular models of interest for this research are those that combine human performance with system performance. In a man-machine environment, these models are used in system design, development and evaluation for military, air traffic control, process control and manufacturing applications [1]. The common thread for the above applications consists of the challenge to model performance in a dynamic, multi-tasking environment, as:

• tasks may overlap in time,
• there are conflicting demands,
• there are disparate activities and constant interruptions,
• there are variations of the task complexity, and
• there are multiple human / machine interdependencies and interactions.

The model presented in Section 3 targets the bullet points highlighted in bolded text. Human performance models may be designed to predict the outcome based on various inputs, or can describe performance results from existing data, as in the various models of the classic learning curve and variants as described by Yelle [2], which shown in Figure 1.
However, in modern society, people are utilizing tools with increasingly complex technology and learning is associated with decision making as well as developing physical dexterity. In almost every environment, the expectations are increased performance with reduced costs, so increased human-systems integration is probable. Therefore, human performance models are necessary to design systems that balance human needs and capabilities i.e., the physical system is designed around the people within the environment to augment the results of both the human and machine elements. With respect to the “man-machine” environment, this section presents an overview of human performance models in three broad categories: “physical” human performance models, “cognitive” human performance models, and human performance models using the “systems” approach, which complements the review performed by Pew [3].

1.1 “Physical” Human Performance Models
“Physical” human performance models consist of physiological and biodynamic models, which focus human physical characteristics such as physiological dimensions, capabilities and limitations. This leads into several areas of study, such as:

- Anthropometrics, which is the study of human body measurements;
- Biomechanics, which is the study of mechanical operation (motion and forces) of the human body; and
- Ergonomics, which is the study of work (“Latin: ergon = work, nomic = the study of”).

The modelling of dynamic human performance has been developed using control theory, extending the physical models from the spatial domain into the time domain. Mathematical models of human response range from simple, manual tracking tasks to complex, multivariable controls problems. Sub-models include perceptual, cognitive and motor activities, which lead to complex, dynamic interactions. The human operator is modelled as an information processing unit or a control/decision element in a closed loop system [4, 5] with sensory inputs and motor outputs. It is also assumed that the operators within the model are qualified, proficient, experienced experts; hence, the operator’s performance approximates the optimal qualities of an inanimate system performing the same function, but with “human” limitations or constraints with respect to the sensory inputs and response [4,5]. This type of modelling methodology is not appropriate for discrete tasks. Although these ergonomic and control theory models address how people interact with machinery and how to design the work envelop and controls for machines and vehicles, these models do not apply to computer systems. These models are based on tools, equipment and machinery that cannot be programmed (i.e., remain static throughout usage). A more complete human-system performance model addresses the interactions and issues of all the elements within a system, which includes human-computer interactions. Human Computer Interaction (HCI) theories combine the fields of software engineering, ergonomics, sociology, artificial intelligence and cognitive psychology to create a model to predict human performance that includes “mental work” [1,6,7] Cognitive psychology deals with how humans perceive their surroundings [8-14], and how humans react, think and plan. This area of research is not as mathematical or as precise as the physical performance models. A brief overview of human computer performance models is presented in the next section.
1.2 “Cognitive” Human Performance Models

There are several alternative theories to predict human performance in the field of Human Computer Interactions (HCI). The models have a generic architecture – visual input, physical output, memory and a problem-solving processor (Figure 2), and may consider decision making. Performance is measured for the amount of time to perform a discrete task. Performance varies from one person to another, and varies due to the difficulty of the task, the amount of repetitions of the task, the motor skills of the individual and so forth. These complex issues are addressed by reducing the human computer interactions into simplified actions and by using empirical models, and data from prototypes and experimental studies.

![Human Computer Interaction (HCI) model](image)

There has been much research with respect to the characteristics of human vision in the areas of physical reception, processing and interpretation. For human-computer interactions, the performance model for motor output focuses exclusively on limited hand/arm motions [8]. The typical model is a representation of Fitts’ Law [7, 8], which is a simple, empirical model of the amount of time required to make linear hand and arm movements. This model does not focus on accuracy, nor can it be used for other tasks such as using a joystick.

Researchers have determined that memory consists of three main subsystems: sensory memory, short-term or working memory and long-term memory. The two properties of concern are the memory size and the decay time – two variables very difficult to define and quantify, as there is no measurement for information content. Many experiments have concentrated on remembering letters. For this test, the results from Card et al. for sensory memory decay time and size are shown in Table 1:

<table>
<thead>
<tr>
<th>Sensory Memory</th>
<th>Decay Time</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual memory</td>
<td>200 [70 ~ 1000] msec</td>
<td>17 [7 ~ 17] letters</td>
</tr>
<tr>
<td>Auditory memory</td>
<td>1500 [900 ~ 3500] msec</td>
<td>5 [4.4 ~ 6.2] letters</td>
</tr>
</tbody>
</table>

Measuring the size of short term or working memory is difficult as it interacts with long-term memory. Short-term memory can be accessed rapidly but it decays rapidly. The capacity for working memory “chunks” (composite units of information) is limited (Miller’s 7 ± 2). There is no capacity limit for long-term memory and it takes longer to access information from long-term memory. There are three main processes associated with the operation of long-term memory:

- Encoding and Storage (requires repeated exposure or rehearsal in working memory)
- Forgetting (due to decay or interference)
- Retrieval (recall or recognition)

1.2.1 Uncertainty and Decision Making

The time to make a decision is related to the degree of uncertainty of the decision. Hence to predict the amount of time to make a simple decision $T_d$ is given by [7]:

$$T_d = I_c H$$

(1)
where $I_c = 150 \; [0\sim157]\; \text{msec/bit}$, and $c$ is an experimentally derived value, and $H$ = information-theoretic entropy (which was introduced by Claude Shannon in 1948 as a measure of information) [8].

$H$ can be used to determine the degree of uncertainty or as a measure of the rate of information acquisition.

The time it takes to make a decision or choose between alternatives for $n$ equally probable alternatives is given by Hick’s Law [7, 10, 11]:

$$H = \log_2 (n + 1) \quad (2)$$

or

$$H = \sum_{i=1}^{n} p_i \log(1/p_i + 1) \quad (3)$$

where $p_i$ = the probability of alternative $i$ for $n$ alternatives of unequal probability.

For a simple problem, humans do not linearly consider each alternative, but use a probability analysis to classify alternatives and to quickly pick the most viable solution. However, as the amount of alternatives increase, so does the time to make a decision.

The classical reference in the field of cognitive modelling in human-computer systems is “The Psychology of Human Computer Interaction” by Card et al. (1983) [6,7,9] in which the “Model Human Processor” is introduced. The model human processor views the user as composed of three processors (perceptual processor, cognitive processor, and the motor processor) and four memories (visual memory, auditory memory, short term memory and long term memory. This model was used to predict the typical time (and the range) with which users could perform computer tasks.

The perceptual processor contains the two sensory memories, and the cognitive processor contains the working and long-term memories. Each processor can operate separately, and operate in parallel (driving, reading signs and listening to the radio) or sequentially. The total task time is estimated by adding the mean time for each processing event. From Card et al, the total time required for human computer interaction is predicted by the simple equation:

$$T_{total} = n_c t_c + n_p t_p + n_m t_m \quad (4)$$

This has been expanded into Keystroke Level Model, which has been used to test text and graphics editors, and system utilities. The mental operations are far more complex than one simple linear variable, and one user’s methodology to obtain a goal will differ greatly from another user’s.

### 1.2.2 Human Performance Models

Card et al. [6,7] pioneered the GOMS model (Goals, Operators, Methods and Selection rules), which builds on the model human. The analysis of knowledge on how to perform the various tasks or the problem solving mechanisms is introduced with the GOMS model. GOMS provides a framework for modelling aspects of human cognition. Simply stated:

- Methods are used to achieve specific Goals.
- Methods are composed of Operators.
- Operators are specific tasks that are performed within a specific time period.
- More than one set of Methods can achieve the desired Goal; consequently, Selection rules are used to determine the appropriate Methods.

Once the task analysis is for a high level goal is completed, estimates of performance time are calculated based on the model human processor. This model of predicting human performance is based on a premise that human behaviour emulates a rational, information-processing system and that the cognitive activities are interpreted in terms of searching in a state space problem. In addition, the model can be used to predict the effects of errors on task performance as it can be assumed that recovering from an error involves similar GOMS components as the correct activities. It is time consuming to create a model for goals that contains a large set of tasks. GOMS is based on skill-rule behaviour, not knowledge behaviour. The model applies to skilled users, and does not address mental workload, fatigue, relearning, errors or system functionality. Interestingly, although Card et al. introduced the model human processor and the GOMS framework, the two concepts do not seem to have many direct, correlating associations.
Urbanic and Bacioiu

Rasmussen developed another keystone framework for cognitive tasks analysis for computer based information and process controls within a complex industrial environment [1, 6, 14]. This analysis is directed at optimizing human diagnosis and minimizing human errors by building systems that present relevant information in a clear, easily understandable format. The underlying principle of Rasmussen’s model is that human behaviour is a goal-oriented activity, and the decision-making stages are not sequential, but occur as in a stepladder in which stages can be bypassed based on training and experience. This model, as illustrated in Figure 3, complements the model human processor introduced by Card et al. The dashed arrows indicate where short cuts in the decision making process could occur based on the situation.

![Figure 3: Rasmussen’s step ladder model of decision making adapted from Neerincx [6]](image)

Rasmussen presented a three-tier framework of cognitive processes that complements process control tasks which is summarized in Figure 4:

- low level rigid tasks → autonomous → fast response time →
  - automatic (or below the conscious awareness) skill based actions
- medium level tasks → associative → moderate response time →
  - solutions to a situation is governed by rules or heuristics (if state x then action y), which is learned through training or experience
- high level tasks → cognitive → slow response time →
  - novel situation with no pre-established rules or procedures required knowledge based reasoning which focuses on the state, the goals, and initiates actions to achieve the goals

![Figure 4: Skills, Rules and Knowledge](image)

1.3 Cognitive Architectures

Several cognitive architectures have been proposed such as the Cognitive Complexity Theory (CCT), the State, Operator and Result (SOAR) and the Adaptive Control of Thought (ACT) cognitive architectures. These architectures
define how rules are interpreted, the conditions for execution, and so forth; however, the cognitive architectures
represent knowledge and information that is appropriate for problem solving tasks, but are not directly applicable for
perceptual and motor tasks (human I/O). Because of their initial assumptions, these models are limited in their range of
applicability. As well, these models focus on individuals at a “micro level”; consequently, they are too limited in scope –
the results of the models may not adequately reflect on the performance or functionality of the whole system [1, 6, 7].

To summarize, there are many human performance models that have been developed in several complementary
disciplines. These approaches provided a foundation into the development of a manufacturing complexity framework
that can be used to assess product, process, and operational complexity [15]. The model structure is shown in Figure 5,
and the operational complexity model is described briefly in the next section. However, this model is static. The
learning phenomenon is not captured, nor is there the ability to model performance variability, or a variable range of
skill sets. In order to capture these aspects, a systems dynamics (SD) model is built using a foundation from the
complexity model, which is described in section 4. The impact of varying levels of skills on the throughput is
investigated.

2. Complexity Model
As this research is an extension of previously described research, only a brief overview of the base complexity
model is presented here. Using a systems perspective, an adaptable framework for modeling and assessing product,
process, and operational complexity has been developed. The operational complexity model considers physical and
cognitive elements. A matrix consisting of tasks and attributes is developed (Table 2). The physical and cognitive
aspects that will impact the effort for that factor could be the environment (noise, heat, and vibration), the tool
characteristics (size, weight, and shape), the information processing, and/or the decision making. For a task set, the
specific subsets of physical and cognitive elements are determined. Based on the skill level of the personnel
involved with the task, a numerical value is assigned to attribute based on considering the skill level and effort
factors. The methodology that considers the relative efforts associated with each physical or cognitive attributes is
described in ElMaraghy & Urbanic, [15] and Urbanic, & Bacioiu, [16]. The skills-rules-knowledge model proposed
by Rasmussen is used as a basis for the evaluation method. This model is adaptable, and not mathematically
complicated. It must be noted that the same framework must be utilized for alternative scenario analyses.

The results related to the complexity evaluation can be graphed; therefore, the areas of complexity are readily
highlighted. This present model is static; whereas, learning and skills acquisition is not, and this needs to be
addressed. This model is a discrete model, and does not consider variations based on performance, or if personnel
with varying levels of skills and knowledge are working together or on the same system at different points in time.
This complexity model will provide insight into potential areas of complexity, but associating the operational
complexity characteristics into a stochastic dynamic model of a manufacturing system would allow for impact
assessment on performance while considering disturbances based on variable skill levels along with physical and
cognitive aspects. The human performance models described earlier have a time element in them, but are
cumbersome to work with; hence, a Systems Dynamics (SD) approach is employed in this research to consider
variable human performance characteristics (Figure 5). This is discussed in the next section.

Table 2: Assessment of the operational complexity for selected tasks

<table>
<thead>
<tr>
<th>TASK</th>
<th>Physical Elements: M = 3</th>
<th>Cognitive Elements: N = 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Reach</td>
<td>Dexterity</td>
</tr>
<tr>
<td>Task 1</td>
<td>aa</td>
<td>bb</td>
</tr>
<tr>
<td>Task N</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weighted factor values:</td>
<td>XX</td>
<td>YY</td>
</tr>
</tbody>
</table>
3. Systems Dynamics Approach

SD is a systems thinking methodology that provides insight related to the dynamics and response characteristics within a given system that can have stochastic, non-linear, and non-periodic behavior. The impact of interactions and the environment can be evaluated over a specified time window for varying scenarios and conditions. The systems perspective demonstrates that there are multiple levels of explanation in any complex situation, which need to be considered in a performance model. System dynamics is a set of conceptual tools that enables users to understand the structure and dynamics of complex systems, and supports decision making related to evolving, dynamic, complex environments [17]. These tools are applicable in many domains, and complement Discrete Event Simulation (DES) tools. DES models require a substantial amount of detailed data for developing fit distributions, and are typically leveraged for detailed design considerations, such as queue characteristics. SD is typically employed for decision making at the strategic level [18]. SD approaches will not model detailed aspects for a given system, but an understanding of the dynamics for complex systems can be gained. These models generally process data rapidly, so they can be operated interactively in real time with decision-makers. Consequently, these models could be used to compare high level design options, and then more in-depth analyses via DES could be used.

Therefore, an SD approach is developed that uses key physical and cognitive attributes employed in the operational complexity model. The dynamic model is built using Vensim®. The model has two major components: a traditional foundation model of the manufacturing line producing fuel systems (Figure 6) and, a human factors element integrated into the manufacturing system model. Attributes are included to provide a realistic model for production throughput that considers not only equipment variations, but variations in human performance. Using skilled and unskilled workers throughout a line, and the system interactions can be modeled (Figure 7). The overall system performance characteristics can be evaluated across a wide range of worker characteristics, and allow optimal personnel positioning for launches or evaluating system changes. This modeling approach is implemented using relationships, rules, and data flows. There are 103 rules and associated equations. Selected rules, dependencies and constraints are described in Table 3. The equation number references to the reference equation in the model. Using this model as a foundation, the impact of different personnel skill levels were assessed for three stations that had the highest complexity values when performing the static analysis. These stations are labeled <weighted average effort XXX> where XXX is the station with the high complexity value.

The model is calibrated using ‘highly skilled’ workers, which means that the task level factors are considered ‘low effort’, which is indicated by ‘All factors low’. The hourly line throughput rates were generated, which correlated well to the expected production rate of 26 pcs/hour. Analysis with medium skilled and low skilled work values is then performed, which corresponds to ‘All factors medium’ and ‘All factors high’ respectively, and the results are plotted in Figure 8. The production rates are impacted by the skill level of the personnel employed. The questions now to be answered are: what is the impact of having different skill levels of personnel on the three stations being investigated in this system, and can the placement of personnel with different skill levels impact the throughput based on their station assignment?

![Figure 5: System model overview with variable human performance characteristics](image-url)
Table 3: Subset of fuel tank processing line model rules

<table>
<thead>
<tr>
<th>Eq.</th>
<th>Rule</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>(001)</td>
<td>molding = mold capacity * capacity utilization</td>
<td>It accounts for changing capacity of the mold by either slowing down (&lt;1) or increasing the speed (&gt;1). Currently = 1</td>
</tr>
<tr>
<td>(002)</td>
<td>inspection = MAX (0, MIN (Inspection Conveyor / avg ct inspection , time ref insp / avg ct inspection))</td>
<td>The rate of production at the manufacturing cells is a positive value that is either the maximum the cell can produce. If the line is starved, the number of parts supplied by the previous station.</td>
</tr>
<tr>
<td>(019)</td>
<td>order rate = RANDOM NORMAL (20, 40, forecast level , 4, 100)</td>
<td>The actual order rate that is a stochastic function that follows a normal distribution centered around the forecast.</td>
</tr>
<tr>
<td>(049)</td>
<td>cognitive elements coefficient 0 = (decision making 0 + evaluation 0 + &quot;id &amp; interpret 0&quot;) / 3</td>
<td>The equation is combining the three elements that form the cognitive part of the human factors. It is an arithmetic average of the three.</td>
</tr>
<tr>
<td>(051)</td>
<td>cold scrap rate = MAX (0, RANDOM NORMAL (0.1, 0.34, avg cold scrap rate , 0.07, 100))</td>
<td>The rate of scrap produced at a particular station. It is a stochastic function (random normal in this case), centered around a value that represents the mean.</td>
</tr>
</tbody>
</table>
4. Assessment of the Impact of Skill Levels Using the Systems Dynamics Model

To investigate these questions, workers with various skill levels are moved from the inspection to the torque and test stations. In Figures 9 (a) and (b) the impact on throughput is shown. In Figure 9 (a), it is shown that moving unskilled personnel from one station impacts the throughput differently. Upon further perturbing the model, it was found that operator skill levels / complexity levels directly impacted blocked and starved conditions. Once a high level of operator competency is reached (high skill level or low complexity scenario), the system flow rates are the controlling factor, not the human interactions. Figure 9 (b) illustrates the impact of learning. As the skill levels improve on the test station, jumps in throughput are observed, again due to the interactions between the human element and this impact on the starved / bottleneck conditions. Personnel with significant differences in skill levels may be assigned to the three stations under consideration: the impact on the performance for this fuel tank processing line is shown in Figure 10.
6. Conclusions
Modeling human performance and this impact on a manufacturing system is challenging. Using a heuristic operational complexity model, work stations that have the highest operational complexity levels for a fuel tank processing line are identified. A SD model is generated for ‘what if scenario analyses’. A ‘human performance effort factor’ is included in this model at the critical work stations, and then perturbed to develop insights into whether personnel placement influenced throughput. Using this methodology along with a learning curve model can be used to plan an effective and realistic launch strategy based on the characteristics of the personnel involved in the system.

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