SUBJECT VARIABILITY AND THE EFFECT OF STRESS IN DISCRETE-EVENT SIMULATION

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ABSTRACT

This paper sets out to address the problem of representing the impact of variability in human characteristics and abilities on overall performance in military systems. It is argued that a key element of the impact is the interaction between individual characteristics and environmental stress. An approach to modelling the variation of multiple characteristics is put forward using factor analysis. An example is calculated using anthropometric data, and the application of the approach is demonstrated using the Integrated Performance Modelling Environment (IPME) to model the variation in performance of a Surface-to-Air Missile (SAM) operator subject to different levels of thermal stress. It is concluded that under stressful conditions up to one third of the subject population may find the task too demanding.

INTRODUCTION

This paper outlines the demands of modelling changes in human performance and variability in performance degradation due to both environmental factors and individual characteristics. The focus of the paper is on the problems of modelling human operators rather than modelling the behaviour of system components. A popular human factors approach to modelling performance is to use task analysis for the dissection of what the operator has to do, and then to simulate the system and operator elements together using task network modelling (Graine 1984; Hood et al. 1993). Examples of tools that use this approach are Micro Saint, a commercially available general-purpose discrete-event simulation tool, and the Improved Performance Research Integration Tool (IMPRINT) developed for the United States Army Research Laboratory for specialised workload and staffing analysis.

In parallel with the development of frameworks for analysing operator performance in systems, there has been an attempt to systematise understanding of cognitive and physical performance by defining taxonomies and other models (Farina and Wheaton 1971; Roth 1991). By relating the effect of a stressor to particular task types, it is possible to construct a concise mapping from environmental stress to task performance, and thus model performance degradation. This is the approach used in both IMPRINT and the Integrated Performance Modelling Environment (IPME), a Unix-based discrete-event simulation tool. The effects of stressors have been examined with respect to overall system performance, but variability of system performance due to individuals has not been typically included in an analysis. This paper argues that stressors and variability of individuals *combined* are an important component of the variability of system performance.

To establish a strategy for the representation of the effect of stressors and variability on human performance in a broad range of model frameworks, the following three issues need to be considered:

1. The phenomena we are trying to represent
2. How stressor effects and human performance are currently represented
3. How present methods can be developed in the future

THE NATURE OF THE PHENOMENA

The military context is noteworthy for the wide range of potential stressors to which personnel are exposed. A basic list of stressors, which aims to focus on the most important, contains 10 potential sources that should be considered (Belyavin 1999):

- Sleep loss fatigue/circadian effects and time on task
- Physical fatigue
- Thermal effects (thermal strain/dehydration/ discomfort)
- Visual environment
- Fear/Anxiety/Morale
- Task demand – workload
- Noise (continuous and impulse)
- Vibration
- Hypoxia (loss of oxygen in high flying fast jets)
- High G (fast jets only)

Before the effect of environmental stress or variability can be defined, it is necessary to define what the operator(s) have to do, and specify metrics through which performance can be quantified. In observational

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work, a task has customarily been defined as the smallest unit of operator activity with an observable output, and this definition has generally been retained in task network modelling. The metrics of task performance have then been defined usually as the time taken to undertake the specified task, and the accuracy with which the task has been executed.

This general approach has been employed in the modelling of human performance by identifying the *degradation factor* associated with the particular stressor, and applying it to the time taken to do the task. Variability has been modelled by making *time-to-perform* a stochastic variable. If suitable data are available, a similar approach has been used to estimate the effect on error, although the latter has proved more difficult in practice.

The stressors in the above primary list can be divided into two groups: those arising directly from the environment, such as heat, noise, vibration; and those arising from the context of the task, such as sleep loss, physical exertion or fear. The first group describe a direct change to the environmental conditions that influences human performance through a change in operator state. The second group includes stressors that are modified in a less direct manner, although their performance effects are also clearly mediated by a change in the state of the operator and may be moderated by individual traits.

Any description of the effect of both groups of stressors should at least recognise the change in the state of the operator implicit in the exposure to the stressful condition. Figure 1 shows how the sequence of cause and effect between environment change and performance change can be represented. Any change in the environment may be modified through the impact of individual characteristics at both stages of the process.

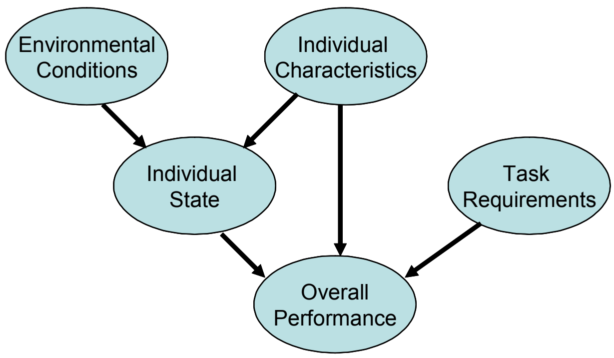

Figure 1: Sequence of Cause and Effect in Performance Changes

In the psychological literature, a similar approach to the analysis of the effect of stress on performance has been employed, although there is a tendency to identify a single state measure – arousal – rather than a multiplicity of state dimensions as the previous outline suggests. Whether a single state can be employed to cover all possible stressors remains to be tested rigorously. What the scientific evidence indicates is that a sound predictive model of human performance under stress should be considered as comprising two stages: first a model of operator state, and then a model relating state to task performance (Belyavin 1999). Both stages of this model may be subject to variability in individual characteristics. For example, change in body temperature in response to a change in thermal environment is affected both by clothing and individual body characteristics. Additionally, the operator's task performance as a result of having a high body temperature may be mediated by personality.

THE IMPLEMENTATION IN IPME

The approach represented diagrammatically in Figure 1 has been implemented in IPME. IPME is a discrete-event simulation system with a graphical modelling interface used to predict human performance. It is a Linux-based integrated environment of simulation and modelling tools for answering questions about systems that rely on human performance to succeed. IPME focuses on the human, the tasks that the human performs in support of a goal, the environment in which the human operates, the stressors that affect human performance, and interfacing with external simulations.

An IPME system model is composed of four component models: Environment, Crew, Performance Shaping and Task Network. The Environment, Crew, and Task Network models formally represent the cascade displayed in Figure 1. The Environment model represents the factors that control the physical, mission, threat, and crew environment. The Crew model represents the human operators in the system, including the operator characteristics, which include states, traits, and properties. States are changing operator characteristics such as temperature or fatigue. Traits are non-physical operator characteristics that remain constant during a simulation execution, such as fitness, cognitive ability, or personality. Properties describe an operator's physical characteristics, such as hands or eyes.

The Performance Shaping model contains functions that represent an operator's ability to perform a task, based on operator states and traits, and impact task time or probability of failure. The Task Network model represents the system processes, including those performed by human operators, and relates the environmental factors, performance shaping functions, and operator characteristics.

It has long been recognised that human performance of an individual task is subject to stochastic variation, and this has been captured in task network modelling frameworks through the variability of individual task performance. In practice this variability comprises two components: *intra*-individual variability (variability in individual performance from occasion to occasion) and *inter*-individual variability (variability between the performance of individuals within the target population) determined by individual characteristics. The second source of variability induces correlation between task performance for an individual for different tasks. Representing overall variability through independent variation of performance of different tasks does not reflect reality. The induced correlation is captured in the repeated measures model employed in statistical analysis.

A repeated measures model has been implemented in IPME to enable variability in system performance to be described. The Crew model has been modified to allow a sample of individual operator traits to be selected using a chosen joint distribution of operator traits. The remainder of the performance-shaping model has then been exploited to represent the impact of variation in traits on operator performance. As an example of the overall process, a preliminary model of the effect of variation in operator characteristics on performance under thermal stress has been implemented.

THE STATISTICAL MODEL

Before implementing the repeated measures model in IPME, an appropriate model of the distribution of the characteristics in the target population was first constructed. It is clearly necessary to consider multiple characteristics simultaneously, so a multivariate approach is essential. Although it is relatively simple to develop a sampling methodology for a single variable, it is considerably more difficult to achieve the same goal for a multivariate population, since potentially complex interdependencies between the variables must be accommodated.

A well-established approach to the problem of describing a complex multivariate population is to reduce the dimension of the relevant space to a small set of fundamental factors and to derive the values of all the measures from the reduced set of factors through simple functional relationships. If the fundamental factors are distributed independently, the sampling problem is reduced to that of sampling from a set of independent univariate populations. A key step in the argument is the construction of independent factors from a larger set of interdependent variables. This is achieved through linear transformation only in the case of the multivariate normal distribution, where all linear combinations of the variates are normally distributed.

A procedure that achieves the goal for unimodal distributions of characteristics is as follows:

1. Test a sample for multivariate normality.
2. If normality is rejected, seek power transformations of the variables to normality, using the maximum likelihood procedure of Box and Cox (1964).
3. Confirm multivariate normality for the transformed variables.
4. Calculate principal components of the transformed variables
5. Retain a minimum sufficient set of principal components
6. Confirm multivariate normality for the retained principal components
7. Derive the best relationship between the original variables and the principal components by inverting the transformations

ANTHROPOMETRIC CHARACTERISTICS

The procedure outlined in the previous section was applied to a set of three anthropometric variables used in the prediction of thermal strain: Body Weight (Wt), Height (Ht) and Mean Weighted Skinfold Thickness (MWST). These three measures are interrelated since both Ht and MWST affect Wt, and an approach to sampling the population must take account of the interdependencies.

The sample of data used in the analysis was drawn from the anthropometric study of aircrew characteristics conducted in the UK in 1973 (Bolton et al. 1973). As a first step, descriptive statistics were calculated for all three measures as shown in Table 1, and multivariate normality was tested using Mardia's (1970) measures of kurtosis and skewness. It was concluded that the population was non-normal and the initial variables should be transformed.

Table 1: Descriptive Statistics for Original Measures

Measure	Mean	Std. Dev.	Skew.	Kurt.
Ht (mm)	1774.0	62.34	0.050	3.159
Wt (Kg)	75.0	8.75	0.253	2.983
MWST (mm)	11.1	3.63	0.848	4.010

Power transformations of the measures were selected using the maximum likelihood procedure of Box and Cox (1964), and the following transformations were determined:

Ht No transform
Wt Square root transform
MWST Logarithmic transform

After confirming the normality of the transformed variables, principal components of the correlation matrix were calculated for the three-dimensional space. It was concluded that two components accounted for 94.1% of the variance. An orthogonal varimax rotation of the two components was calculated and the resultant components were standardised to unit standard deviation. The correlation matrix is displayed in Table

2, and the principal components are displayed in Table 3.

Table 2: Correlation Matrix Between Transformed Measures

	Ht	Wt
Wt	0.525	
MWST	-0.031	0.618

Table 3: Rotated Principal Components

	Factor 1 Loadings	Factor 2 Loadings
Ht	0.001	0.981
Wt	0.752	0.592
MWST	0.971	-0.078

The multivariate normality of the two-dimensional space was again checked using Mardia's skewness and kurtosis measures, and normality was not rejected. The best linear predictors of the transformed variables were then calculated and the formulae for reconstructing the original measures from the principal components derived. Constructing a sample from the tri-variate population is in this way reduced to generating a sample from a pair of independent normal variates in standard measure and applying the calculated relationships displayed in Table 4.

Table 4: Generation of Anthropometric data

Measure	Function
Ht	1774.5+0.08237*Fac1+61.138*Fac2
Wt	$0.1*(27.73+1.1987*Fac1+0.9434*Fac2)^2$
MWST	Exp(2.354+0.3135*Fac1-0.02517*Fac2)
Fac1 and Fac2 are independent normal variates	

In addition to the anthropometric data, there is evidence of individual variability in the metabolic cost of load carriage while walking. A good indication of the *expected* metabolic cost of movement while carrying load has been derived by Pandolf et al (1977). Recent work at QinetiQ indicates that there is individual variability about the expected value that can be described by a multiplier that is normally distributed about 1.0 with a standard deviation of approximately 0.09.

This model was implemented in IPME by generating two operator traits that were sampled independently, and deriving the values of the key traits from them using the relationships provided in Table 4. The scaling multiplier for metabolic cost of movement while carrying load was sampled as a third independent variable, and used to scale the metabolic cost of movement.

EXAMPLE SYSTEM

The system that was used to investigate this prototype statistical model was a model of a Surface-to-Air Missile (SAM) system that depends on optical detection and recognition of an incoming target. In the SAM model, it is assumed that there is a command centre that detects targets and passes them to a system operator in the field. The system operator then must detect and identify the incoming target before the target is engaged. The physical work rate associated with the system was assumed to be relatively low, so an artificial scenario was constructed in which it was assumed that the operator had to march briskly carrying a 20 Kg load for 30 minutes before a rapid series of engagements was commenced. It was then assumed that, if the system operator's core temperature exceeded 38.5° C, the operator would rest. Neither the system nor the scenario is based on real systems, but they provide a basis for illustrating how the variability of anthropometric data can be applied in IPME.

The complete system model was constructed from three components:

1. Target Client: a simple application that generates a series of targets for the SAM system
2. Thermal Client: a whole body thermophysiological model (Higenbottam and Belyavin 1998)
3. IPME System Model: a task network model describing the operation of the system.

The task network model includes the model of operator variability. Both the Target and Thermal applications are client applications to IPME, communicating with IPME via a TCP/IP sockets protocol.

The target client supplies target position and speed to the IPME simulation. IPME informs the target client of missile launch, enabling the target client to manage potential interception. The thermal model client supplies the current thermal state to IPME, and calculates water loss due to sweating. IPME supplies environmental conditions, the operator's clothing state, and the operator's current physical work rate to the thermal model. A diagram of this relationship is displayed in Figure 2.

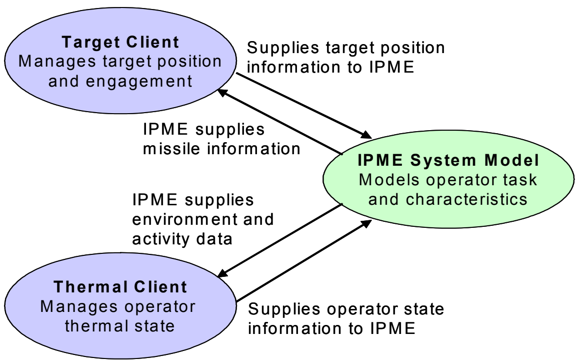

Figure 2: Relationship Between IPME and Client Applications

The task network model is displayed in Figure 3.

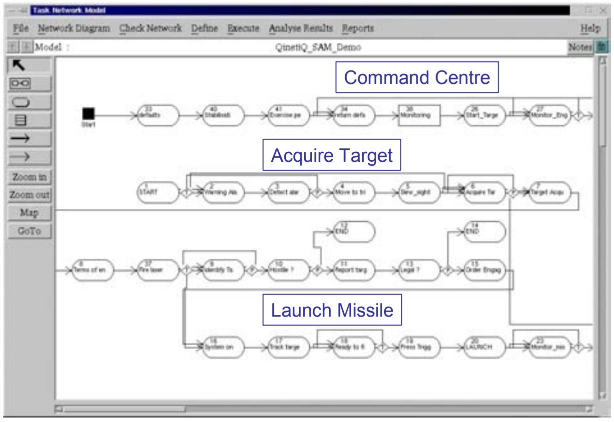

Figure 3: The SAM System Task Network Model

The system operator has to perform some physical activities to perform his or her task, as well as detecting and identifying incoming targets using an optical sight. To demonstrate the variability in system performance due to operator characteristics, a sample of 12 operators was generated based on the characteristics outlined in the previous section. Each operator was exposed to two conditions:

1. Dry bulb temp.: 26° C, Relative Humidity: 50%
2. Dry bulb temp.: 32° C, Relative Humidity: 50%

In both conditions the operator wore clothing with a thermal insulation of 1 clo. For the 30 minutes preceding the arrival of the targets, the operator walked briskly on level ground (1.75 metres sec^{-1}), carrying a load of 20Kg. While engaging the targets the operator was assumed to be working at a steady 50 Watts.

There are two routes through which the operator traits can impact performance. The direct effects of the operator traits will be on thermal strain in response to the environmental and clothing conditions. The main consequence will be the need for the operator to rest if his core temperature reaches 38.5°C. A number of smaller effects of thermal strain and dehydration on task performance were included as Performance Shaping Factors in the model. These were based on those described in Belyavin (2000), and it was anticipated that they would influence the precise timings of interceptions if and when they occurred.

The performance of the operator in successfully engaging targets was taken as the overall measure of effectiveness. In addition, core temperature, skin temperature and sweat loss were measured. Preliminary analysis of the results from this prototype model indicated that, under the less stressful condition, all engagements that could be achieved were successful. Under the more stressful conditions, 4 of the 12 subjects failed to complete the task, and thus failed to engage the last one or two targets. These subjects were the fattest and heaviest of the sample, and it would be anticipated that they would experience the largest thermal strain.

Under the less stressful condition, the mean core temperature reached 37.99°C at maximum, whereas, under the more demanding condition, the mean core temperature reached 38.45°C at maximum. This is consistent with the observation that all the operators continued to work in the first condition, but four stopped work in the second.

The precise timing of the interceptions varied from occasion to occasion but there was no evidence of an effect due to subject traits. It was concluded that in this particular example the "indirect" effects of thermal stress embodied in the Performance Shaping factors had relatively little impact on overall system performance.

FUTURE DEVELOPMENT

The model described in the previous section is simple and the effect of the varying characteristics on system performance is direct. However, even this relatively simple model embodies a number of critical concepts: the use of clients to describe additional processes, the cascade from environment to task performance, and the variability of individual characteristics. These underlying principles are reflected in the IPME architecture by design; however, these design principles may be applied in a broad range of architectures, such as those used in the construction of Computer Generated Forces or other discrete-event simulation engines.

Although the example discussed in this paper directly relates to dismounted soldiers and thermal stress, these same concepts may be applied to other stressors, such as physical fatigue, and other operator traits due to the general and extensible implementation in IPME.

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