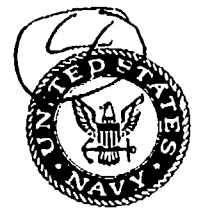


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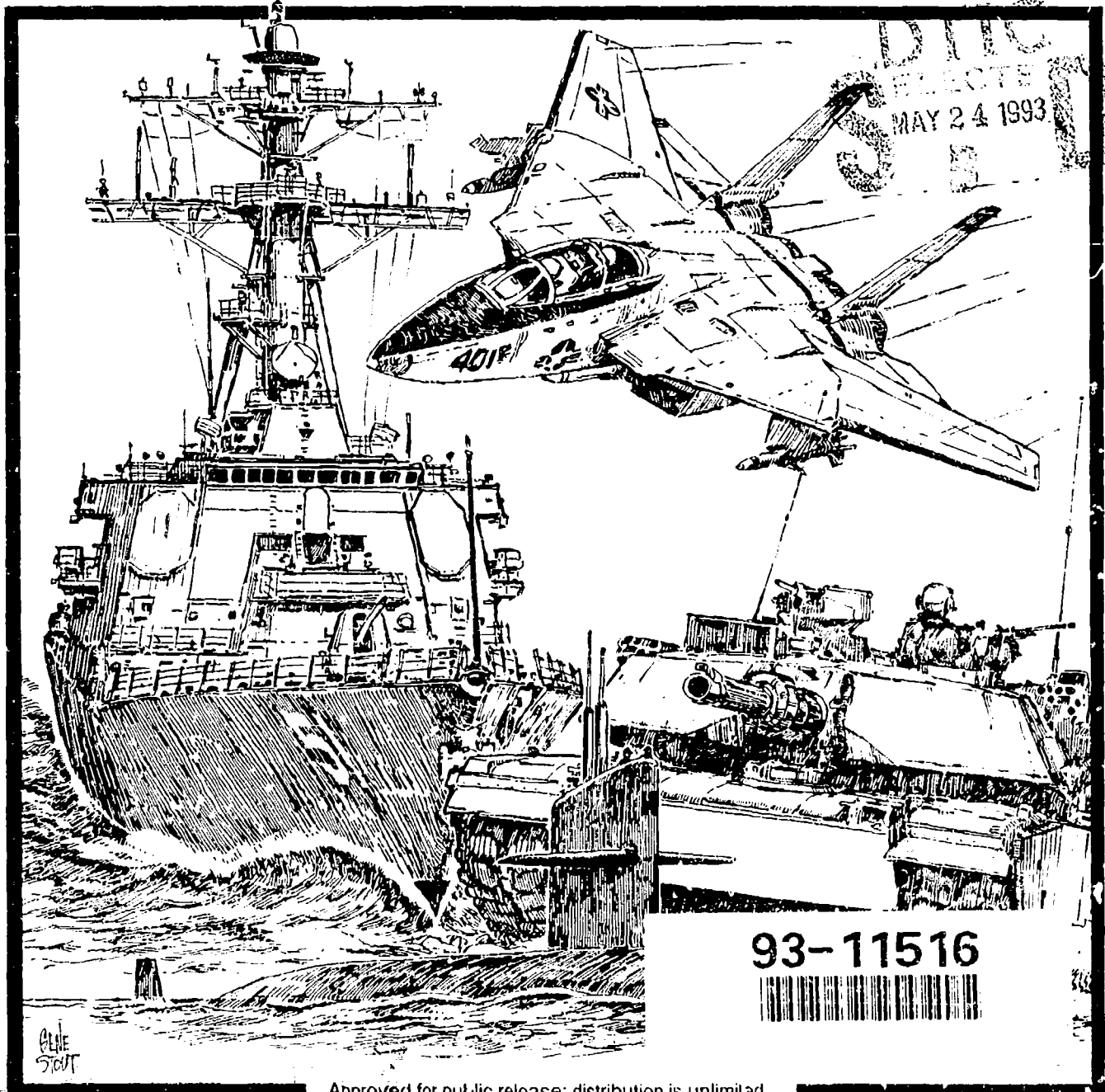
Navy Personnel Research and Development Center

San Diego, California 92152-7250

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April 1993

Independent Research and Independent Exploratory Development FY92 Annual Report



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Administrative Information

This report documents the activities and accomplishments of the Independent Research (IR, 0601152N) and Independent Exploratory Development (IED, 0602936N) programs at the Navy Personnel Research and Development Center for FY92. In addition to technical presentations, program administrative information is provided. For further information, contact the IR/IED Program Coordinator, Dr. William E. Montague, Autovon 553-7849 or any of the Principal Investigators.

**Independent Research and Independent
Exploratory Development Programs:
FY92 Annual Report**

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**Navy Personnel Research and Development Center
San Diego, California 92152-7250**

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Independent Research and Independent Exploratory Development Programs: FY92 Annual Report

Introduction

The Technical Director encourages scientists and engineers at the Navy Personnel Research and Development Center (NPRDC) to generate new and innovative proposals to promote scientific and technological growth in the organization and the development of knowledge and technology of interest to the Navy. Support for this is provided by discretionary funding furnished by the Independent Research (IR) and Independent Exploratory Development (IED) programs of the Office of Naval Research. These programs support initial research and development of interest to the Navy with emphasis on the NPRDC mission areas of the acquisition, training, and effective utilization of personnel.

Funds are provided to the Technical Directors of Navy Laboratories to support innovative and promising research and development outside the procedures required under normal funding authorization. The funds are to encourage creative efforts important to mission accomplishment. They enable promising researchers to spend a portion of their time on examining the feasibility of self-generated new ideas and scientific advances. They can provide an important and rapid test of promising new technology and can help fill gaps in the research and development program. This may involve preliminary work on speculative solutions too risky to be funded from existing programs.

The funds also serve as means to maintain and increase the necessary technology base skill levels and build in-house expertise in areas likely to become important in the future. These programs contribute to the scientific base for future improvements in the manpower, personnel, and training system technology and provide coupling to university and industrial research communities.

The FY92 IR/IED programs began with a call for proposals in June 1991. Technical reviews were provided by supervisors and scientific consultants and six IR and three IED projects were funded. This report documents the results and accomplishments of these projects. Dr. William E. Montague administers the IR

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and IED programs, coordinating project selection, reporting, and reviewing to assure an innovative and productive program of science and technology.

Tables 1 and 2 list the projects active during FY92 and those supported in FY93. Two papers, one IR and one IED, chosen by the Technical Director as "Best Papers of 1992" are presented. Subsequent pages, which were written by the principal investigators of each project, contain brief reports of research progress during FY92.

Table 1
Independent Research
Work Units for FYs 92 and 93
(PE 0601152N)

Work Unit	Title	Principal Investigator	Internal Code	Telephone (619) 55 or DSN 55	FY Funding (K)	
					92	93
0601152N.R0001.01 ^a	Brain mechanisms and cognition: Advanced signal processing using the wavelet	Trejo	13	37711	42.2	40.0
0601152N.R0001.05	Responses on computer surveys	Rosenfeld	01E	37658	0.0	45.0
0601152N.R0001.09	Feedback in computer-based training	Cowen	13	37698	2.0	0.0
0601152N.R0001.10	Neural networks as an alternative to regression	Wilkins Dickieson	13	37618 39270	55.0	0.0
0601152N.R0001.11	Neural network modeling of skill acquisition	Gollub Dickieson	13	37849 39270	13.0	0.0
0601152N.R0001.12	Individual differences in information acquisition and processing	Morrison	12	39256	30.0	55.0
0601152N.R0001.13	Cognitive resources, performance feedback, and decision processes in a simulated work environment	Tatum	16	37955	48.0	44.0
0601152N.R0001.14	Long-term retention of information and skills learned in school	Ellis	13	39273	0.0	30.0

^aAdditional matching funds obtained from the Office of Naval Research.

Table 2

**Independent Exploratory Development
Work Units for FYs 92 and 93
(PE 0602936N)**

Work Unit	Title	Principal Investigator	Internal Code	Telephone (619) 55 or DSN 55	FY Funding (K)	
					92	93
0602936N.RV36I27.01	Linking biodata and personality	Booth-Kewley	01E	39251	27.0	0.0
0602936N.RV36I27.03	Enlisted requirements model	Krass Thompson	11	37895 37925	50.0	45.0
0602936N.RV36I27.08	Evaluation of alternative prediction models for dichotomous criteria	Sands	12	39266	0.0	90.0
0602936N.RV36I27.09	A goodness of fit (GOF) test of minority vs. majority exclusion rates	Folchi	12	37750	0.0	40.0
0602936N.RV36I27.13	Cognitive and motivational effects of employee involvement interventions	Sheposh	16	37947	29.0	25.0

Independent Research Best Paper

Best Paper Nomination Rationale

Research Merit

Recently, Navy scientists have begun to apply a long history of laboratory-based research to the enhancement of human performance in real-world tasks. One exciting possibility is to use brain-potential monitoring of performance in radar, sonar, air traffic control, and aviation. Enhancing and sustaining human performance in these and other critical occupations may avoid costly human errors and save lives.

For many years, scientists have known that electrical recordings of event-related brain potentials known as ERPs have distinct features that obey lawful relationships to perceptual, cognitive, and motor aspects of performance. The description of these relationships was made possible by the technique of signal averaging, which increases the reliability of ERP measures. The size and latency of ERP peaks such as the P300 were observed to covary with aspects of human performance. However, signal averaging sacrifices accuracy in the measurement of when the ERPs occur. This is due to the requirement for averaging many single ERPs, which occur at different times, resulting in an average ERP that is representative of a relatively long time interval but not very useful in real-time/real-world applications.

This research examined ways of measuring ERPs within time intervals that are short enough to be useful for real-time applications. It uses a signal processing innovation known as the wavelet transform for short-interval analysis of the relationships between ERPs and human performance.

Research Approach/Plan/Focus/Coordination

ERPs are scalp-recorded, time-varying, electrical signals produced by the activity of millions of neurons involved in processing task-relevant events, such as the sudden appearance of a symbol on a radar screen. At short latency (e.g., soon after the symbol appears) neurons in the primary visual cortex respond with a brief wave of excitation. This wave propagates to secondary visual areas and then to association areas where slower, longer-latency waves of excitation reflect

decision-making processes. Finally, the excitation may be relayed to motor neurons which produce even longer-latency waves that control the hand with which the radar operator responds to the symbol. Thus, the ERP for this event is a complex mixture of brief and slow waves, each with its own latency (onset time), time course, and associated brain regions. Because the voltage of ERPs at the scalp is tiny—a few millionths of a volt—signal averaging is used to cancel superimposed electroencephalographic (EEG) voltages, which may be a hundred times larger than an ERP.

The wavelet transform of an ERP provides a record of ERP energy at different times and scales. It does this by producing a set of filtered time series at different scales. The late slow waves associated with decision processes may appear at different scales than the short-latency waves associated with sensory perception. Wavelets are also good at keeping track of when the waves occur. One way to think of this process is that it “unmixes” the waves that constitute an ERP, yielding a compact representation of important ERP features.

Pre-existing data from a radar signal detection task collected from Navy technicians at NPRDC were used to investigate the power of wavelets for describing real-time relationships between ERPs and performance. First, short-term signal averages of ERP and signal detection performance data were created. The goal was to predict the performance time series from the ERP data at 30-second intervals. Prior research had shown that while long-term averages (several minutes) showed strong ERP-performance relationships, it was not possible to predict performance using 30-second long intervals with traditional peak-measurement techniques. The current research showed that by representing the short-term ERP averages with the coefficients of the wavelet transform, it was possible to demonstrate reliable ERP-performance relationships at 30-second intervals. The research also showed that wavelets were superior in this regard to principal components analysis, another signal processing transform used in ERP research.

This research would not have been possible without the collaboration of Dr. Mark Shensa of the Naval Command, Control and Ocean Surveillance Center, Research and Development, Test, and Evaluation Division, San Diego. Dr. Shensa developed powerful computer programs for applying wavelet transforms to large volumes of ERP data. More importantly, however, he contributed to the long process of

selecting the type of wavelets and parameters of the transforms that would be most appropriate for ERP data and to the evaluation of their effectiveness. Additional funding and support for this research was provided by Dr. Joel Davis, Dr. Terry Allard, and Dr. Donald Polk of the Office of Naval Research. This research is currently in its second year of funding and is expected to continue through FY94.

Difficulty of Problem Addressed

The analysis and interpretation of subtle and complex relationships between brain activity and behavior continues to challenge the scientific and engineering community. In particular, the challenges of real-time/real-world tasks, where strict laboratory controls are not possible, leads to irregularity in the data acquired. New and powerful methods such as wavelet transforms will make the brain-behavior problem more tractable by increasing the information that can be extracted from ERP recordings.

Originality of Approach

While there have been two other independent attempts to use wavelets for ERP analysis, this is the first effort in which wavelet transforms were used to analyze the relationship between ERPs and human performance. In particular, no other effort has examined the application of wavelet transforms to the extraction of ERP features useful for real-time/real-world human performance prediction.

Potential Impact on Navy/Center Needs

Human error is a major cause of accidents in Navy operations. Through improved assessment and prediction of human performance, human error could be reduced. The Navy and NPRDC in particular, are continuing the investigation of ERP and EEG methods for enhancing human performance. However, ERP methods need to be improved for application to real-world problems. This research has identified an approach based on wavelet transforms that may have immediate impact on the way ERP data are processed for real-world applications.

Probability of Achieving Impact on Naval Needs

For the analysis and interpretation of ERP signals, it is very likely that methods such as the wavelet transform developed at NPRDC will be used in monitoring systems or in the physiologically enhanced human interfaces of the future. Other methods will compete with this approach, including neural networks and other signal processing transforms. There may never be a single method of choice; instead the methods may be problem-dependent. Nevertheless, this approach increases the repertoire of analytical innovations for real-world applications as well as for ERP research.

Brain Mechanisms and Cognition: Advanced Signal Analysis Using the Wavelet Transform

Leonard J. Trejo

Abstract

Basic research relating event-related potentials (ERPs) to aspects of human cognition, such as perceptual sensitivity, attention, and memory has spurred renewed interest in physiological methods for the assessment of human performance. One focus area has been the development of models which use ERP measures for on-line assessment of cognitive states that are related to the quality of human performance. The ERP measures used have included amplitudes and latencies of peaks in the ERP as well as factors derived using principal components analysis (PCA) or discriminant analysis. While models based on such measures explain significant proportions of variance in human performance, their generality may be limited and the development costs may be high. This report introduces a novel approach to ERP measurement based on a recent signal processing innovation called the wavelet transform. The discrete wavelet transform (DWT) was compared to PCA for representation of ERP data in linear models developed to predict a general measure of human signal detection performance. Models developed using DWT measures succeeded in predicting signal detection performance with half as many free parameters as comparable PCA-based models and were relatively more resistant to model degradation due to overfitting. Finally, the DWT models provided evidence that a pattern of low-frequency activity (1 to 3.5 Hz) occurring at specific times and scalp locations is a reliable correlate of human signal detection performance.

Introduction

Studies have shown that simple linear models may significantly explain and predict human performance using measures of ERPs elicited by stimuli presented in the context of a task (Trejo, Lewis, & Kramer, 1991; Trejo & Kramer, 1992). These models use, as predictors, measures such as the amplitude and latency of ERP components (e.g., N1, P300). Other studies have used more comprehensive measures such as factors derived from principal components analysis and discriminant functions (Humphrey,

Sirevaag, Kramer, & Mecklinger, 1990). However, the models work reasonably well only when they have been adapted to the individual subject, taking into account the temporal and topographic uniqueness of the ERP. Even then, the models suffer from a limited ability to generalize to new data. Finally, the cost of developing and adapting such models for individuals is high, requiring many hours of expert analysis and interpretation of ERP waveforms.

Non-linear models for ERP data, such as neural networks, may be an improvement over linear models (DasGupta, Hohenberger, Trejo, and Mazzara, 1990; Ryan-Jones & Lewis, 1991). However, when these models have been based on traditional ERP measures, such as the sampled ERP time points or the amplitude of ERP components, the improvement in correlation between ERP measures and human performance provided by a neural network has been small, typically about ten percent (Venturini, Lytton, and Sejnowski, 1992). Transformations of the ERP data prior to neural network analysis, such as the fast Fourier transform (FFT), may provide a small additional improvement of neural network models (DasGupta, Hohenberger, Trejo, & Kaylani, 1990). However, the FFT is not very well suited for transient signal representation; it is more appropriate for continuous signals, such as sine waves.

The wavelet transform provides for powerful and economical representation of arbitrary signals and is particularly well-suited for analysis of transients with time-varying spectra, such as the ERP (Tuteur, 1989). Discrete wavelet transforms (DWT) represent signals as coefficients in a time-frequency plane where the number of coefficients (resolution) in time decreases with frequency.¹ Each level of the transform corresponds to one octave of signal bandwidth beginning with the highest frequencies. Both the bandwidth and the number of coefficients are halved with each successively lower octave. Although it is not strictly correct to speak of the bandwidths of the octaves in Hz (due to aliasing effects), this familiar unit will be used to make the following simple illustration. For a one-second long EEG signal with a bandwidth of 32 Hz and 64 time points, the first octave of the DWT would represent frequencies in the range from 16 to 32 Hz with 32 coefficients. The next octave down

¹More precisely, the DWT represents signals in a time-scale plane, where scale is related to—but not identical with—frequency. The concept of scale comes from the dilation of a “mother wavelet” in the time domain. Each dilation is a doubling of the wavelet length in the time domain which results in a halving of the bandwidth in the frequency domain.

would represent frequencies of 8 to 16 Hz with 16 coefficients. Successively lower bandwidths and numbers of coefficients would be 4-8 Hz/8, 2-4 Hz/4, 1-2 Hz/2, 0-1 Hz/1. A single additional coefficient would represent the DC level, for a total of 64 coefficients. As with the discrete Fourier transform, the DWT is invertible, allowing for reconstruction of the original signal. An important feature of the DWT, however, is that the coefficients at any level are a series that measures energy within the bandwidth of that level as a function of time. For this reason it is of interest to study signals within the DWT representation and use the DWT coefficients of brain signals directly in modeling cognitive or behavioral data.

In this study, the effect of transforming ERP data using the discrete wavelet transform (DWT) (Shensa, 1991) was compared with a more traditional approach based on principal components analysis (PCA). The comparison determined which transformation (DWT or PCA) provided a more efficient and valid reduction of the ERP data for use in developing linear models of human signal detection performance. Linear models were chosen because they are the simplest to compute and as such may serve as the first step in comparing the effectiveness of the two types of measures. The signal detection task was chosen because the ERP data from this task have been extensively analyzed and described in previous work with linear models based on peak and latency measures of ERP components (Trejo et al. 1991; Trejo & Kramer, 1992).

Method

In an earlier study (Trejo et al., 1991), ERP data were acquired in a signal detection task from eight male, Navy technicians experienced in the operation of display systems. Each technician was trained to a stable level of performance and tested in multiple blocks of 50-72 trials each on two separate days. Blocks were separated by 1-minute rest intervals. About 1000 trials were performed by each subject. Inter-trial intervals were of random duration with a mean of 3 sec and a range of 1 sec. The entire experiment was computer-controlled and performed with a 19-inch color CRT display.

Triangular symbols subtending 42 minutes of arc and three different luminance contrasts (.17, .33, or .53) were presented parafoveally at a constant eccentricity of 2 degrees visual angle. One symbol was designated as the target, the other as the

non-target. On some blocks, targets contained a central dot whereas the non-targets did not. However, the association of symbols to targets was alternated between blocks to prevent the development of automatic processing. A single symbol was presented per trial, at a randomly selected position on a 2-degree annulus. Fixation was monitored with an infrared eye tracking device. Subjects were required to classify the symbols as targets or non-targets using button presses and then to indicate their subjective confidence on a 3-point scale using a 3-button mouse. Performance was measured as a linear composite of speed, accuracy, and confidence. A single measure, PF1, was derived using factor analysis of the performance data for all subjects and validated within subjects. PF1 varied continuously, being high for fast, accurate, and confident responses and low for slow, inaccurate, and unconfident responses. The computational formula for PF1 was

$$PF1 = .33 \text{ Accuracy} + .53 \text{ Confidence} - .51 \text{ Reaction Time}$$

using standard scores for accuracy, confidence, and reaction time based on the mean and variance of their distributions across all subjects.

ERP data were recorded from midline frontal, central, and parietal electrodes (Fz, Cz, and Pz; Jasper, 1958), referred to average mastoids, filtered digitally to a bandpass of .1 to 25 Hz, and decimated to a final sampling rate of 50 Hz. The prestimulus baseline (200 ms) was adjusted to zero to remove any DC offset. Vertical and horizontal electrooculograms (EOG) were also recorded. Across subjects, a total of 8184 ERPs were recorded. Epochs containing artifacts were rejected and EOG-contaminated epochs were corrected (Gratton, Coles, & Donchin, 1983). Furthermore, any trial in which no detection response or confidence rating was made by a subject was excluded along with the corresponding ERP.

Within each block of trials, a running-mean ERP was computed for each trial. Each running-mean ERP was the average of the ERPs over a window that included the current trial plus the 9 preceding trials for a maximum of 10 trials per average. Within this 10-trial window, a minimum of 7 artifact-free ERPs were required to compute the running-mean ERP. If fewer than 7 were available, the running mean for that trial was excluded. Thus each running mean was based on at least 7 but no more than 10 artifact-free ERPs. This 10-trial window corresponds to about 30 sec of task time. The PF1 scores for each trial were also

averaged using the same running-mean window applied to the ERP data and excluding PF1 scores for trials in which ERPs were rejected.

Prior to analysis, the running-mean ERPs were clipped to extend from time zero (stimulus onset time) to 1500 msec post-stimulus, for a total of 75 time points. Sample running-mean ERPs (prior to application of rejection criteria) for one subject from one block of 50 trials are shown in Figure 1. Over the course of the block, complex changes in the shape of the ERP are evident.

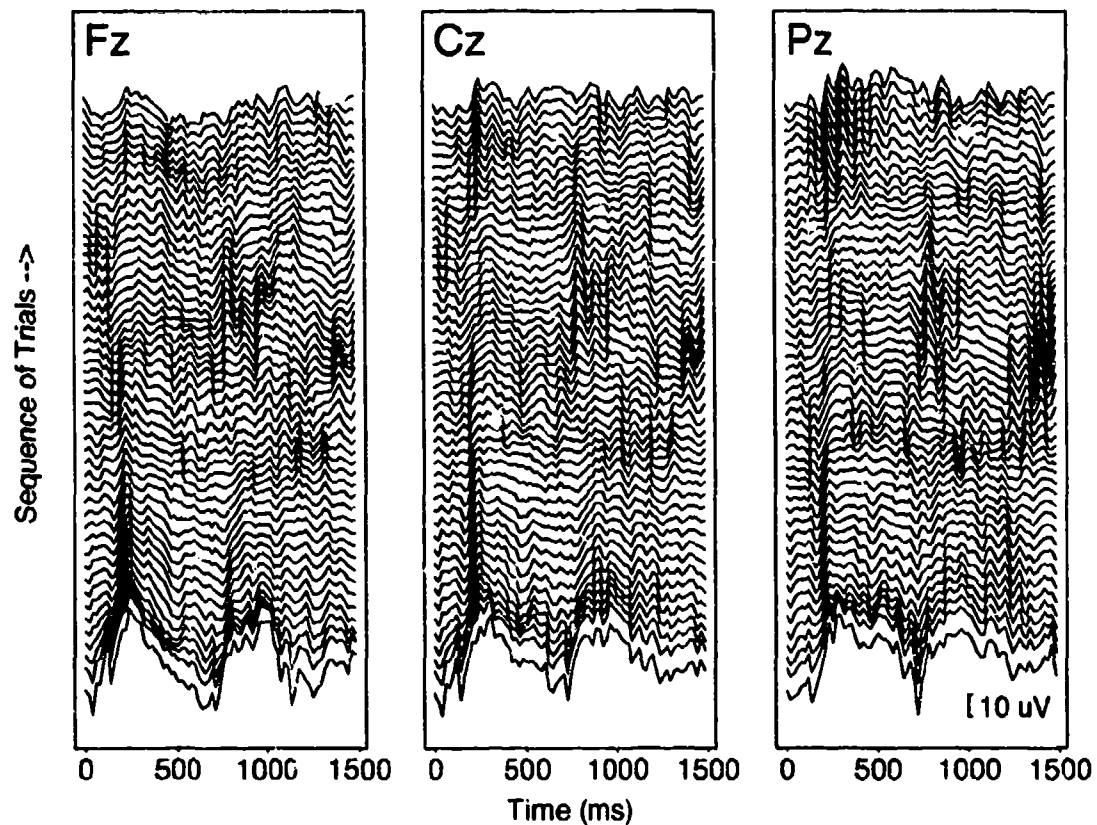


Figure 1. Running-mean ERPs at sites Fz, Cz, and Pz for subject 2 in the first block of 50 trials. Zero on the abscissa represents the stimulus onset (appearance of the display symbol used for the signal detection task). The ordinate represents scalp voltage at each electrode site; positive is up. The running-mean ERPs for successive trials of the block are stacked vertically from bottom to top (lowest is first).

The running-mean ERP data set was split into a screening sample for building models and a calibration sample for cross-validation of the models. For each subject, odd-numbered blocks of trials were assigned to the screening sample, and even blocks were assigned to the calibration sample. After all trial-rejection criteria were satisfied, 2765 running-mean ERPs remained in the screening sample and 2829 remained in the calibration sample.

A multiple-electrode (Fz, Cz, Pz) covariance-based PCA was performed on the running-mean ERP data. Each observation consisted of the 75 time points for each electrode for a total of 225 variables per observation. The BMDP program 4M (Dixon, 1988) was used for the calculations, using no rotation and extracting all factors with an eigenvalue greater than 1. One hundred and thirty-six factors were extracted, accounting for 99.45% of the variance in the data. The decay of the eigenvalues was roughly exponential, with the first 10 factors accounting for 70.96% of the variance in the data. Factor scores were computed for each running-mean ERP and stored for model development.

The DWT (Daubechies, 1990, 1992; Shensa, 1991) was computed using the same ERP data as in the PCA. A Daubechies analyzing wavelet (Daubechies, 1990) was used to compute the DWT over four octaves of the bandwidth of the EEG data. The length of the filters used for this wavelet was 20 points. This results in very smooth signal expansions in the wavelet transform. The octave boundaries and center frequencies in Hz were as follows:

Octave	Bandwidth	Center Frequency
1	10.5 - 25.0	16.2
2	4.42 - 10.5	6.82
3	1.86 - 4.42	2.87
4	0.78 - 1.86	1.20

The transform was offset to center the coefficients of the transform within the ERP epoch and avoid using the edges, yielding a total of 70 coefficients per transform (very low frequency octaves and the DC term were excluded). The number of coefficients was approximately halved with each increasing octave after decimation. For octaves 1-4, the respective numbers

of coefficients were 37, 19, 9, and 5. The real values of the DWT were stored for model development. No further transformations, such as power computations, were performed.

Linear regression models for predicting performance (PF1), from either the PCA factor scores or from the DWT coefficients of the running-mean ERPs, were developed using a stepwise approach (BMDP program 2R). A criterion F-ratio of 4.00 was used to control the entry of predictor variables into a model. The F-ratio to remove a variable from a model was 3.99, resulting in a forward-stepping algorithm. The performance of each model was assessed by examining the coefficient of determination, r^2 , as a function of the number of predictors entered (r^2 is the square of the multiple correlation coefficient between the data and the model predictions and also measures the proportion of variance accounted for by the model when the sample size is adequate and distributional assumptions are met).

Using the criteria described above, 90 factors of the PCA entered into models predicting PF1, and 92 coefficients of the DWT entered into models predicting PF1 (Figure 2). The r^2 increased for the PCA models in a fairly smooth, negatively accelerated fashion from a minimum of .07 for a single factor model to a maximum of .58 using 90 factors as predictors. The r^2 for the DWT model based on a single coefficient was .12, nearly double that of the PCA model based on a single factor. The increase in r^2 for the DWT models was almost linear for models using up to four coefficients as predictors; beyond that, further increases occurred in a piece-wise linear fashion reaching a maximum of .62 using 92 predictors. The greatest difference in r^2 between the DWT and PCA models (.11) also occurred with four predictors.

Prior experience has shown that models using more than 10 predictors have limited generality and are difficult to interpret. For this reason cross-validation of the PCA and DWT models was performed with no more than 20 predictors. The models developed using the screening sample were applied in turn to the PCA scores and DWT coefficients of the calibration sample. As for the screening sample, performance of the models for the calibration sample was assessed using r^2 (Figure 3). In addition, the significance of r^2 was assessed using a F-ratio test (Edwards, 1976). This test used an adjusted number of degrees of freedom for the denominator, to allow for the serial correlation in the data introduced by computing the running means of the ERPs. In effect, the number of degrees of freedom was divided by 10, to allow for the 10-trial cycle length of the

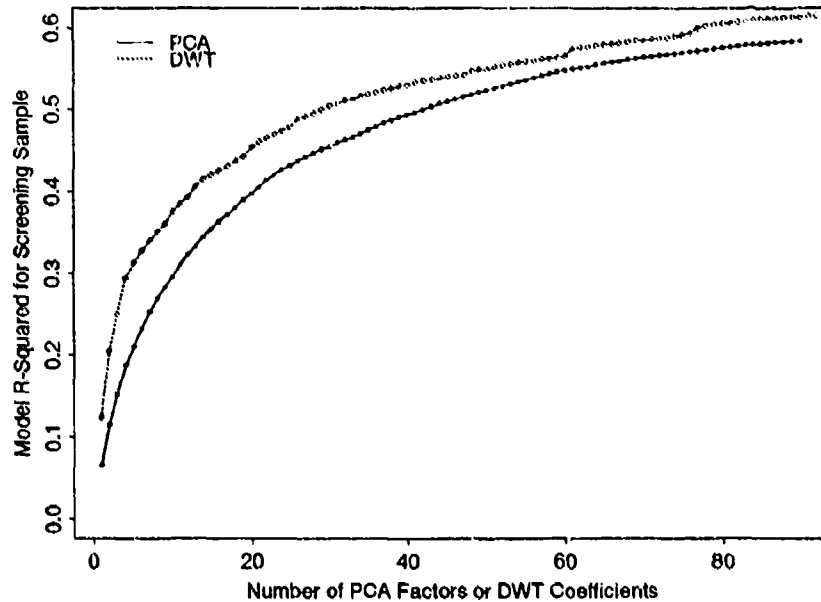


Figure 2. Coefficients of determination (r^2 or variance accounted for) for PCA and DWT models developed to predict task performance (PF1) for eight subjects in a signal detection task. Models were based on a screening sample of running-mean ERP and PF1 data, drawn from odd-numbered blocks of trials. Models are assessed by the r^2 as a function of the number of predictors entering into the model. Only models in which predictors met a criterion F-ratio of 4.0 to enter (3.99 to remove) are shown.

running-mean window. A conservative significance level of .001 was chosen, given the large number of models computed. The contour of r^2 values at this significance level appears as a dot-dashed line in Figure 3.

All of the PCA and DWT models tested explained significant proportions of variance in the calibration data set. For the PCA models, r^2 rose gradually from a nearly insignificant level to a maximum of .22 using 10 predictors. The equation for the 10-predictor PCA model was

$$\begin{aligned}
 \text{PF1} = & .11 \text{ Factor2} - .10 \text{ Factor4} + .13 \text{ Factor5} - .05 \text{ Factor8} \\
 & - .09 \text{ Factor9} + .08 \text{ Factor11} - .06 \text{ Factor15} \\
 & - .08 \text{ Factor43} + .07 \text{ Factor47} - .07 \text{ Factor68} + .02
 \end{aligned}$$

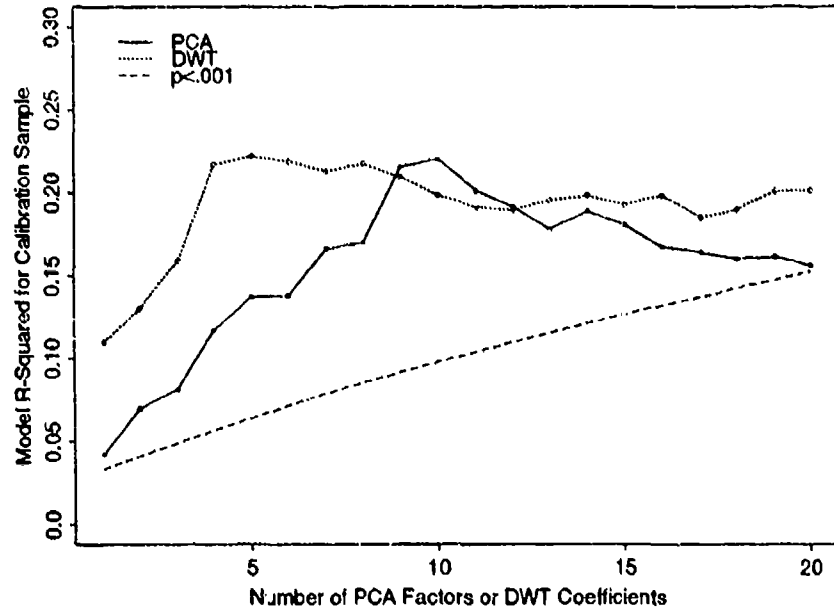


Figure 3. Coefficients of determination (r^2 or variance accounted for) for the first 20 PCA and DWT models of Figure 2, cross-validated using running-mean ERP and PF1 data from a calibration set of data drawn from even-numbered blocks of trials. The dot-dashed line indicates the contour of r^2 values significant using an F-ratio test at the $p < .001$ level where the numerator degrees of freedom depends on the number of predictors and the denominator degrees of freedom is one-tenth of the sample size. Values above this contour are significant.

where the factors are indexed according to the proportion of variance accounted for in the running-mean ERP data. The factor accounting for the greatest variance in the ERP data (Factor 1) did not enter the model. Five of the first 10 factors (Factors 2, 4, 5, 8, and 9) entered the model. Respectively, these factors accounted for proportions of variance in the ERP data of .12, .031, .0283, .0184, and .0169, or a total of .21 (21%). The entry of many of the factors in the 10-predictor model is surprising, given the small amount of variance in the ERP data that they account for. For example, Factors 11, 15, 43, 47, and 68 accounted for proportions of variance equal to .014, .01, .0022, .0019, and .0011, respectively, or a total of .0292 (under three percent).

Among the DWT models, the r^2 for a single predictor (.11) was well above that of the corresponding single-factor PCA model (.04) and rose to a maximum of .22 using five predictors. The best single-predictor model was based on coefficient CzS3T22, with a regression coefficient of -.03 and an intercept of .02. Beyond five predictors, the r^2 for the DWT models declined gradually, and leveled off after about 10 predictors, showing no further improvement. As for the screening sample data, the greatest difference in r^2 between the DWT and PCA calibration sample models (.10) occurred with four predictors.

The equation of the best five-predictor DWT model selected by the stepwise regression algorithm was

$$\text{PF1} = -0.03 * \text{FzS3T6} + 0.04 * \text{FzS3T22} + 0.06 * \text{CzS3T6} \\ - 0.01 * \text{CzS3T22} - 0.05 * \text{PzS3T6} - 0.17$$

where each coefficient is coded by electrode (Fz, Cz, Pz), octave (S1, S2, S3, S4) and time point (T0, T1, . . . , TN). Actual latencies of the time points are obtained by multiplying the time index by 20 msec, the sampling period. It is clear that a single octave, number 3, is most important for predicting task performance. This octave mainly reflects the time course of energy within the bandwidth of .078 to 1.86 Hz, which overlaps the range of the delta band of the EEG (1- 3.5 Hz) and will include some influence from low-frequency ERP components such as the P300 and slow waves. Two time intervals are indicated across electrodes: point 6 at Fz, Cz, and Pz (120 ms), and point 22 at Fz and Pz (440 ms). Frontal and parietal energy (Fz, Pz) in scale 3 at 120 msec is inversely related to PF1 as shown by the negative regression coefficients, whereas central activity (Cz) is positively related to PF1. Central and parietal energy (Cz, Pz) in scale 3 is inversely related to PF1 at 440 ms.

One potential problem with the wavelet analysis performed here stems from the length of Daubechies filters used (20 points). These filters had lengths over one fourth the length of the signals (75 points). While these filters produce smooth wavelet transforms, they also increase the "support" of the transforms in the time domain. This means that the transforms are extrapolated in time before and after the interval of the signal. It also means that, with respect to the filter length, the signal is short in duration and appears to be a brief impulse at larger scales. A possible complication from this is that time resolution for signal features at the larger scales may be imprecise.

It is possible to decrease the support of the wavelet transform at the expense of smoothness by using shorter filters. To test the effects of shorter filters, the current data were partially re-analyzed using Daubechies filters of 4 points in length. With these filters, the support of the transform is reasonable at all four of the scales analyzed and time resolution of signal features at the larger scales is more precise than with the 20-point filters.

Not surprisingly, the most important single predictor was located at electrode Cz and scale 3, as for the best single-predictor model based on 20-point filters. However, the wavelet coefficient in the 4-point filter model, CzS3T15, was at the 15th time point or a latency of 300 msec. This lies 120 msec earlier than the scale 3 coefficient in the best single-predictor model based on the 20-point filters (CzS3T22). The regression coefficient for this model was .03, with an intercept of -.16. The cross-validation r^2 for this model was .15, which is higher than the corresponding 20-point filter model.

Discussion

Both PCA and DWT methods yielded regression models that significantly explained signal detection performance in a 30 sec running window and generalized to novel data. Both methods also performed better than a traditional peak amplitude and latency analysis of the running-mean ERP data. For comparison, the best stepwise linear regression model developed using predictors drawn from a set of 96 multi-electrode amplitude and latency measures of the ERP on the same data set yielded an r^2 of .28 for the screening sample and failed to significantly cross-validate on the calibration sample (Trejo & Kramer, 1992; peak amplitude- and latency-based models did cross-validate when adapted to the ERP waveforms of individual subjects).

The DWT models were clearly superior to the PCA models when based on a small number of predictors. Twice as many PCA factors were required to explain the same amount of variance in the data as DWT models based on 5 coefficients. In cross-validation, no clear advantage of the PCA models was evident with any number up to 20 predictors. The PCA models showed evidence of over-fitting the data when more than 10 predictors were used, as shown by the decline in r^2 for the calibration sample for models using 10 to 20 predictors. In contrast, the DWT models suffered relatively small decreases in r^2 when using more than 5 coefficients.

Single-predictor models for the DWT based on 4-point filters were compared to the 20-point filters used initially to determine the sensitivity of the location estimates to filter length. The net effect of using shorter filters to compute the wavelet transform changed the location estimate, but not the electrode or scale estimates of the best single predictor model, and increased in cross-validation r^2 . The higher cross-validation r^2 for the 4-point filter model than the 20-point filter model was unexpected. However, this result suggests that more precise temporal localization of features in the wavelet transform may provide more robust representation of the ERP or EEG features associated with task performance.

PCA is known to produce factors that resemble the shape and time course of ERP components. The information provided by the DWT is somewhat different. For example, the 5-predictor DWT model indicated that a pattern of energy at specific latencies in the ERP—confined to the bandwidth associated with P300, slow waves, and EEG delta band activity—was correlated with signal detection performance across a sample of eight subjects. It is well known that P300 and slow waves correlate with the allocation of cognitive resources during task performance. However, it is not clear that the wavelet coefficients included in the regression models reflect traditional measures of these ERP components. Comparisons of ERPs reconstructed from the DWT coefficients and the average ERP waveforms will be required to express the coefficients in terms of familiar ERP peaks.

Conclusions

For ERP-based on-line assessment of cognitive states related to human performance, generality of the predictive models, ease of model development, and speed of computation are critical factors. The cost of computing the DWT is trivial when compared to deriving a PCA solution, which involves inverting and diagonalizing a large covariance matrix. Even more time is required for peak and latency analyses, which depend on expert human interpretation of the waveforms.

The results described here show that the DWT can provide an efficient representation of ERP data suitable for performance-prediction models. Furthermore, the DWT-based models tested here exhibited good generalization and were relatively insensitive to the detrimental effects of over-fitting seen with

PCA models. This result, together with the linear rise in r^2 for the DWT models (Figure 2) suggest that the DWT coefficients measure sources of variance in the ERP that are independent of each other, but still correlated with task performance. Although such independence of predictors is also the goal of PCA, it appears that the DWT more closely achieved this goal with the ERP and task performance data considered.

The DWT may also provide new insight into the physiological bases of cognitive states associated with different performance levels in display monitoring tasks. By indicating the time and frequency of energy in the ERP related to task performance, references to specific ERP or EEG generators may be indicated, as shown by the dominant presence of slow waves and delta-band activity in the 5-predictor DWT model of signal detection performance.

Recommendations

While these results are encouraging, interpretation of the DWT models must be expanded. Through inversion of the DWT, it is possible to reconstruct the time course of the energy indicated by a specific model. In addition, other wavelet transforms may provide a finer analysis of the time-frequency distribution of the ERP. For example, wavelet transforms using multiple "voices" per octave, such as the Morlet wavelets or wavelet packets, provide much finer resolution than that afforded by the DWT method used in this study. Future work should examine the reconstructed time course and scalp distribution of the patterns indicated by DWT or other wavelet models and relate these to known physiological generators. In addition, data from other kinds of tasks should be analyzed and the development of models for individual subjects should be also explored. Finally, the value of using wavelet coefficients of ERPs instead of time-domain data in non-linear classification problems, such as those based on neural networks should also be assessed.

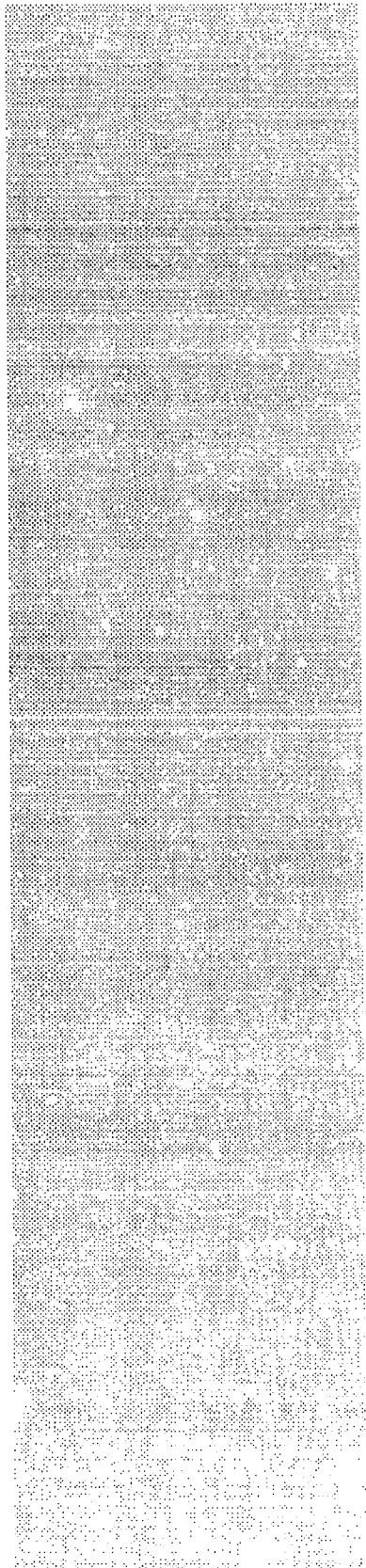
Presentation

Trejo, L. J. (1993, February). *Pattern recognition neural networks for human event-related potentials (ERP): A comparison of feature extraction methods*. Paper presented at the Artificial Neural Network Conference, San Diego.

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**Independent Exploratory
Development
Best Project**

Best Project Nomination Rationale

Originality/Technical Merit

Public and private organizations are expending significant resources in adopting Total Quality Leadership (TQL) as a system to improve organizational performance. Little empirical research however has been conducted on the effect that TQL has on the individual employee despite the fact that substantial demands are placed on the individual to apply TQL in the work place. Theoretically, TQL, if conducted properly, should provide empowering experiences to the individual employee. That is, individuals are more directly involved in planning, decision making, and execution of the conduct of their work without oversight. No published research has addressed this issue. The present study collected information about the involvement and acceptance of TQL and level of employee empowerment was the first step to fill this void.

Research Approach/Plan/Focus/Coordination

The present study, which is in its final year, was conducted at two U.S. Navy engineering facilities. A survey instrument, which was used as the primary means of data collection included the following content areas: general organizational climate, job motivating potential, empowerment, and acceptance of and involvement in TQL. Three hundred and sixty-eight randomly selected employees across all organizational levels from one site and all 73 employees from a second site participated in the survey. First year survey results revealed that empowerment was significantly related to demographics such as supervisory level, education, and age, with greater empowerment associated with higher levels of all three. These findings combined with additional analyses of the second year results suggest that TQL and empowerment have a reciprocal effect on each other.

Difficulty of Problem Addressed

A major difficulty in studying the effects of TQL is that in most organizations TQL is still at a formative stage and has not been fully integrated into the way work is conducted. The fact that TQL is not fully integrated in the organizations surveyed posed

a problem in this study. Because TQL is at the beginning stages it is difficult to ascertain the direct effects it has on the individual and work units. This difficulty was anticipated and was one reason for a planned three year longitudinal assessment of this research issue. As TQL becomes more firmly rooted over time, the causal linkages between TQL and empowerment will be discernible.

Potential Impact on Navy/Center Needs

At present there is a Navy-wide implementation of TQL. However, there is a paucity of empirical evaluation in this area, particularly with respect to acceptance and use of TQL and its effect on individual employees. The results of this exploratory research provide useful information as to the kind of employees who would be receptive to and involved in TQL as well as the benefits TQL may have for the individual. This information can then be used in refining the implementation process.

Productivity

This effort was highly productive. Milestones of the research have been met on time. Two papers were presented at the Military Testing Association (MTA) conference and other papers are in progress or planned. The survey results have also had practical consequences. They have been presented to the two sites involved in the study and have been used to make changes in site organization and in TQL implementation.

Appropriateness of IED Support

The implementation of TQL has shown it to be an uneven, difficult, and extended process. The primary reason for implementation focuses on effects on the organization, not the individuals. As a result, support for longitudinal evaluation of effects on individuals has not come from normal research funding. The survey technique under development in this project reveals the interrelationship of organizational and individual factors and will refine TQL implementation procedures. Therefore, IED support was provided to accomplish an important unfunded, novel technology goal.

An Examination of Cognitive and Motivational Effects of Employee Interventions

John P. Sheposh, Mark Rosenthal, Cynthia B. Heller, and David Dickason

Abstract

This project examined the interrelationship of organizational characteristics, employee involvement in and acceptance of TQL, and employee empowerment. Two U.S. Navy engineering facilities served as the sites at which survey administrations were conducted. First year survey results revealed that empowerment was significantly related to demographics such as supervisory level, education, and age, with greater empowerment associated with higher levels of all three. Employees who scored high on empowerment reported greater communication, cooperation, openness, and opportunities for creativity within the organization than employees who scored low on empowerment. In addition, high empowered employees reported more involvement in and greater personal acceptance of TQL. These findings combined with additional analyses from second year results suggest that TQL and empowerment have a reciprocal effect on each other.

Background

Public and private sector organizations are showing continuing interest in adopting total quality as a system to improve organizational performance. This is evident from the Navy-wide implementation of TQL. TQL programs are characterized by the following: a focus on systemic rather than individual causes of poor quality, the use of statistical evidence as the basis for quality improvement actions and for the assessment of their impact, an emphasis on intra- and interdepartmental communication in solving and preventing problems, and removal of defects through process improvement rather than through inspection (Deming, 1982). Full-scale adoption of these principles involves a major change in the organization's orientation toward the way work is conducted, including the reduction of sectionalism, the adoption of participatory management, and the use of a cross-functional approach to solve problems (Ishikawa, 1985). Thus TQL is far from a cosmetic fix. It requires a fundamental change in the way work is conducted and the way an organization operates.

Considering the nature of the changes prescribed by a quality improvement intervention (e.g., required training, changes in work procedures) and the effort required of individual workers to enact these changes, it is extremely important to examine the way in which the quality program affects the individual employee. The emphasis in selling these programs, understandably, is on the advantages they give the organization. Solely focusing on the benefits to the organization (e.g., profitability, higher productivity, and improved client satisfaction), however, may create some serious difficulties in selling quality improvement programs to employees (cf. Guaspari, 1987). By only stressing organizational benefits, the employee may perceive that he/she is being asked to change, to work harder, to be more closely monitored, and to achieve goals of increasing difficulty without personal rewards. This may seriously compromise the implementation effort. It follows that research on the effects of quality programs on the individual would be beneficial to the assessment and implementation of such quality programs.

TQL, when properly implemented, should alter a person's job in significant ways (e.g., collection and reporting of data, focus on process, increased interaction with supervisors, coworkers, and management, increased responsibility, and more precise and frequent job feedback). Ideally, these changes provide workers the opportunity to participate in decision making and enhance personal reliance, a sense of autonomy and control which theoretically should lead to heightened intrinsic motivation and empowerment (Conger & Kanungo, 1988).

The major focus of this study is on the relationship between TQL and the concept of empowerment. An adaptation of Tyman's conceptualization of empowerment (Tyman, 1988) was used as the basis for operationalizing empowerment. According to Tyman, a person's cognitive style (e.g., the tendency to attribute success to one's self) in combination with his/her situational assessments (e.g., assessment of one's competence, impact and progress on the job) directly influence performance, job satisfaction, and job stress. Situational assessments are the psychological components of empowerment, and cognitive styles represent critical intrapersonal processes influencing situational assessments. Antecedent conditions and practices that affect empowerment were also included in the examination of empowerment. According to Conger and Kanungo (1988) such factors as the meaningfulness of tasks, task variety, and organizational communication affect empowerment.

The present study, which covers two years of a three year project, was conducted at two U.S. Navy engineering facilities. This study (1) assessed the level of empowerment among employees; (2) determined the extent to which certain contextual factors identified by Conger and Kanungo (1988) are related to empowerment (e.g., do differentially empowered employees perceive specific organizational and individual factors differently?); and (3) assessed differences in perceptions of factors relating to the implementation and use of TQL among differentially empowered employees.

In addition, a proposed model was tested to determine the overall pattern of relationships among TQL, empowerment, and organizational characteristics. The model presented in Figure 1 posits that: (1) specific TQL-related impediments and organizational climate factors influence the degree to which TQL is successfully implemented and practiced; (2) the status of TQL in terms of implementation and use is expected to affect properties of individual jobs and employees' perceptions of their jobs; and (3) these effects will influence the level of job satisfaction and perceived stress.

The second year survey administration afforded the opportunity to conduct a longitudinal assessment of the relationship between employee involvement with TQL and the level of empowerment. A longitudinal assessment of the relationship helps to establish whether early involvement in TQL leads to heightened intrinsic motivation and empowerment.

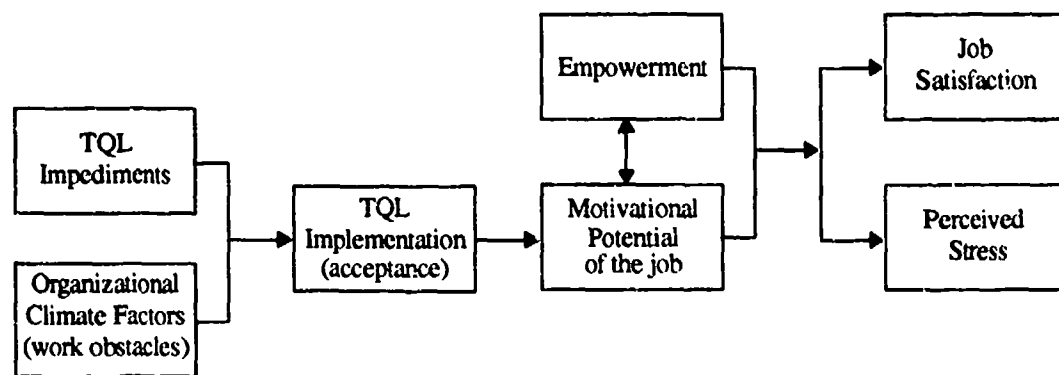


Figure 1. Proposed model.

Method and Procedures

Overview

To assess the relationships among empowerment, selected organizational characteristics, and involvement in and acceptance of TQL, a survey instrument was devised and given at two U.S. Navy engineering facilities. The TQL effort at these sites, which was initiated approximately two years earlier, was still in the process of being integrated into the overall organizational work processes. The workforce at each site is predominantly technical. Approximately 40% of the workforce is comprised of scientists and engineers, 30% logisticians and administrators, 20% technicians, and 10% clerical.

Materials

The survey instrument used as a primary means of data collection, included questions on: (1) general organizational climate characteristics such as openness, communication, and cooperation (Gordon & Cummins, 1979; Klauss & Bass, 1982); (2) constraints on the immediate work situation (Peters & O'Conner, 1980), task preparation, relevant information, materials and supplies; (3) perceived relationship between rewards and performance; (4) perceived involvement and recognition in the conduct of work, which is an indicator of the integration of employees into the workings of the organization (Hatvany & Pucik, 1982); (5) motivating potential of ones' job based on specific job characteristics (Hackman & Oldham, 1980); (6) empowerment, which included an assessment of cognitive styles (e.g., attributing success) and situational assessments (e.g., competence, impact) (Tyman, 1988); (7) job satisfaction (Young, Reidel, & Sheposh, 1979); (8) job stress (e.g., lack of recognition, work overload, and lack of career progress); (9) involvement and participation in TQL activities; (10) impediments to the successful implementation and operation of TQL (e.g., fear, lack of adequate training, lack of support); and (11) personal and organizational acceptance of TQL.

The groupings of the items for each of these areas were confirmed by means of factor analyses using varimax rotation. All non-TQL items employed a 7-point scale ranging from 1: "Strongly Disagree" to 7: "Strongly Agree." TQL-related items

used a 7-point scale ranging from 1: "Not At All" to 7: "A Very Great Extent." In addition, survey respondents were invited to provide written comments on the issues addressed in the survey.

Subjects

Three hundred and sixty-eight randomly selected employees (approximately 15% of the workforce) across all organizational levels were selected from one site and all 73 employees from the second site participated in the survey. Using the upper and lower limits of the standard error of the mean derived from the survey results of the empowerment scores for the total sample, three equal sized groups differing on relative measures of empowerment were formed. For purposes of reporting, the groups will be referred to as "Low", "Medium", and "High" with the understanding that these titles are somewhat of a misnomer—a majority of even the "Low" group indicated empowerment scores above the scaled mid-point of 4.

Results

Results from the first survey administration revealed an overall mean of 5.57 (SD=.865) on a 7-point scale for empowerment across the two sites. The sample of respondents in general perceived themselves as highly empowered. Chi-square analyses were conducted on each demographic variable from the questionnaire to determine its relationship to reported empowerment. These analyses revealed that age ($X^2(14, N=336) = 24.24, p < .05$) and level of education ($X^2(16, N=336) = 35.27, p < .005$) were related to empowerment. Older workers were more likely to report higher levels of empowerment than younger workers. More specifically, while 41% of workers over 40 reported empowerment scores falling within the High group only 24% of workers under age 40 fell into this category. A significant X^2 was also obtained for education level. Those reporting the most empowerment tended to be employees with some college and accompanying technical training or employees having earned a graduate degree. These findings indicate that for those positions which require a college degree, individuals with only a bachelor's degree felt the least empowered. Similarly, for positions that do not require a bachelor's degree, individuals with less education were less empowered. In addition, when empowerment was analyzed in comparison to supervisory level, it was found that over 75% of the supervisors who responded to

the questionnaire reported moderate to high levels of empowerment. Sixty-two percent of nonsupervisory employees reported moderate to high empowerment scores. A chi-square analysis indicated that in comparison to nonsupervisory employees, a significantly higher proportion of supervisors fell into the High group relative to the other empowerment groups ($X^2(1, N=181) = 4.46, p < .05$). Among the remaining demographic variables (e.g., gender, ethnicity, length at present paygrade, etc.), none was significantly related to empowerment.

A series of one-way analyses of variance was also performed to assess the differences in employees' perceptions on selected organizational factors across the differentially empowered groups (see Table 1). As can be seen in Table 1, employees in the High group reported more favorable perceptions of their organization and their jobs than those in either the Medium or Low groups. Particularly impressive were the differences

Table 1
Mean Responses to Organizational and Individual Job Factors across Groups

	Empowerment			F Ratio ^a
	Low	Medium	High	
Overall Organizational Climate	3.77 ^b	4.22	4.81	22.58
Communication	3.69	4.32	4.87	24.88
Openness	3.66	4.09	4.72	14.86
Cooperation	3.36	3.51	3.87	3.29
Customer Orientation	4.40	4.72	5.22	12.11
Creativity	3.90	4.61	5.27	22.88
Performance Appraisal	4.00	4.71	5.18	22.37
Lack of Control Over Work	3.95 ^c	3.65	2.88	24.30
Lack of Sufficient Support	3.64 ^c	3.25	2.74	14.48
Motivating Potential of the Job (MPS) ^d	97.17	152.78	220.34	112.68
Job Satisfaction	4.46	5.42	6.15	53.55
Job Stress	4.36 ^c	3.99	3.42	20.37

^aAll F values are significant at the $p < .0001$ level, except for "Cooperation" for which the F value is significant at the $p < .05$ level.

^bThe higher the value, the more positive the response.

^cThe lower the value, the more positive the response.

^dMPS = $\frac{[\text{Skill Variety} + \text{Task Identity} + \text{Task Significance}] \times [\text{Autonomy}] \times [\text{Feedback}]}{3}$.

Scores can range from 1 to 343.

obtained for the motivating potential scores (MPS) of one's job. The most highly empowered employees were clearly more positive on this index than less empowered employees. Furthermore, these employees expressed greater job satisfaction and less job stress than workers in the Medium or Low groups.

Table 2 represents responses concerning TQL-related factors across the three groups. Employees in the High group were more personally involved in TQL implementation, reported higher personal acceptance, and perceived greater organizational acceptance of TQL. In addition, they saw factors potentially impeding the successful implementation of TQL as less severe than employees in the Medium or Low groups.

A path analysis was conducted to examine the sequential relationship of the organizational, TQL, and empowerment variables. The pattern obtained (see Figure 2) was generally consistent with the proposed model depicted in Figure 1 with some modification. Organizational characteristics and TQL impediments are significantly related to TQL acceptance and involvement. TQL acceptance and involvement have an impact on empowerment and the motivating properties of ones' job, and these variables in turn affected the level of reported job satisfaction and stress. In contrast to the proposed model,

Table 2
Mean Responses to TQL Factors across Groups

	Empowerment			F Ratio ^a
	Low	Medium	High	
Organizational Acceptance	3.46 ^b	4.05	4.34	13.46
Personal Acceptance	4.46	4.98	5.21	5.69
TQL Involvement	3.84	4.31	4.83	8.25
Impediments to Implementation	3.73 ^c	3.38	3.18	6.09
Fear	2.98 ^c	2.43	2.35	7.53
Lack of Knowledge	4.48 ^c	3.89	3.55	7.11
Lack of Support	4.27 ^c	3.85	3.43	7.05

^aAll F values significant at the $p < .005$ level.

^bThe higher the value, the more positive the response.

^cImpediments to Implementation mean is the sum of the three factors listed underneath. The lower the value, the more positive the response.

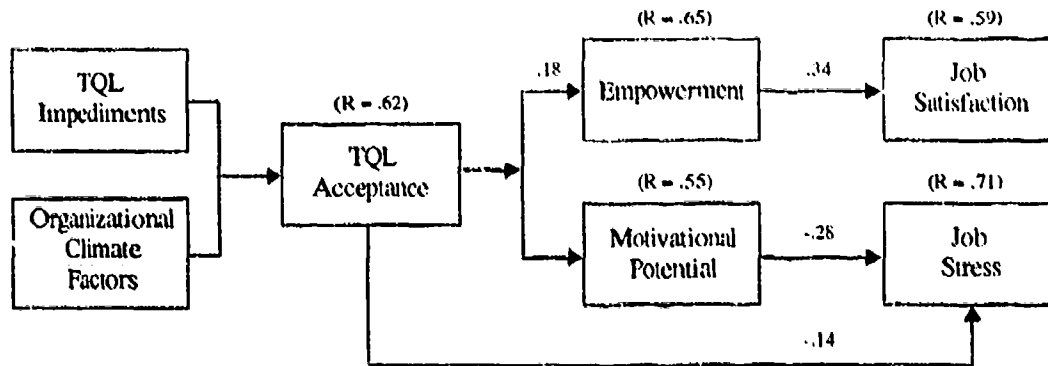


Figure 2. Model based on path analyses.

empowerment is significantly related to job satisfaction but not to job stress while the motivating potential of the job is significantly linked solely to job stress. It appears that the proposed model successfully captures the interrelationships that emerged from the first year survey administration.

A cross-lagged correlational analysis was performed on TQL involvement and empowerment for the two time periods (see Figure 3). As can be seen from the pattern of correlations, TQL involvement and empowerment were fairly stable over time. The cross-lagged correlation for TQL involvement at Time 1 with empowerment at Time 2 was statistically significant. However, the cross-lagged correlation for empowerment at Time 1 with TQL involvement at Time 2 was also significant. The expected larger correlation for TQL at Time 1 with empowerment at Time 2 was not supported, therefore, no clear causal link between these variables could be established.

Summary and Conclusions

The current findings have implications for research and practice and provide strong theoretical support for the cognitive model of empowerment. The results show that the application of the cognitive model of empowerment as conceptualized by Thomas and Velthouse (1990) and Tymon (1988) successfully differentiated individuals' perceptions of relevant organizational factors. The most highly empowered employees differed from less empowered employees on a number of perceived organizational and job dimensions. These include some of the conditions proposed by Conger and Kanungo (1988) identified

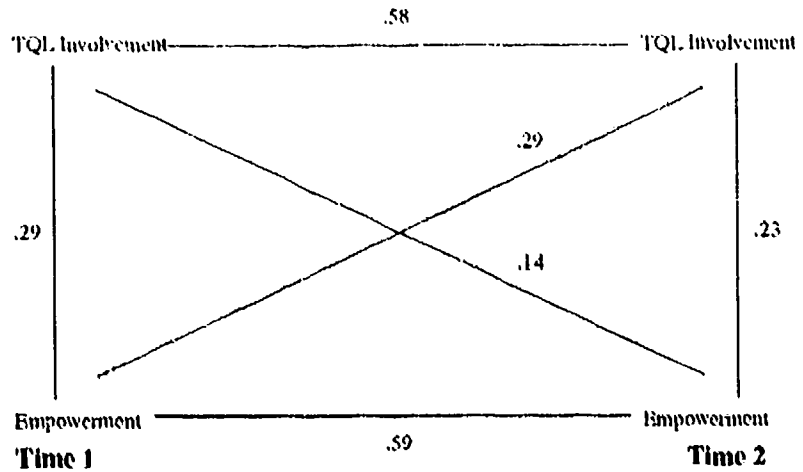


Figure 3. Correlation of TQL Involvement and Empowerment in Time 1 and Time 2

as fostering empowerment. Of particular interest was the differential response to TQL based on empowerment. Employees in the High group were favorably disposed and more involved in the implementation of TQL. Consistent with the cognitive theory of empowerment it would appear that individuals who see themselves as having higher competency levels are more willing to be involved in such efforts as TQL.

One implication from the results based on the path analysis (see Figure 2), is that implementation demands and the organization characteristics must be addressed for TQL to be fully adopted. Early identification of the degree to which organization characteristics are compatible with the proposed change and implementation process is important. In addition, subsequent formative evaluations designed to periodically assess the compatibility between organizational characteristics and change features should be conducted.

It was expected that TQL involvement would lead to higher levels of empowerment. The results from the longitudinal assessment raise questions about the causal relationship of these two variables. It appears that each variable has a reciprocal influence on the other over time. Higher involved TQL individuals reported higher subsequent levels of empowerment and the converse was also true. This suggests that these factors act upon each other in a synergistic fashion. One factor that must be considered when interpreting these results is that the TQL site

efforts were in a formative stage. The causal effect between these variables would be more clear if the TQL effort was fully integrated into the organization.

The results of this experimental study established a link between empowerment and TQL factors. A longitudinal analysis of the model over three years to incorporate all variables is planned. From a theoretical perspective these results would provide a fuller understanding of the reciprocal causal relationships of all the relevant variables. Furthermore, from an applied perspective, such an analysis would help DoD organizations understand more clearly the TQL implementation process.

Publications

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Independent Research Progress Reports

An Exploratory Examination of Artificial Neural Networks as an Alternative to Linear Regression

Jan Dickieson and Charles Wilkins

Abstract

The Navy bases many decisions on predictions of the future performance of personnel. These predictions are most commonly made using some type of linear-regression based method. This means that not all available information (e.g., nonlinear relationships) are used in making predictions. Artificial Neural Network (ANN) technology, on the other hand, allows the creation of prediction models which do take into account nonlinear relationships. This study was designed to explore the feasibility of applying neural network technology to a typical Navy problem; specifically, predicting premature attrition from the U.S. Naval Academy (USNA). USNA attrition data were used to predict premature attrition using both standard linear regression and six alternative predictive ANN models. Under a variety of conditions, it was found that the predictive efficacy of the ANN models was superior to that of linear regression, leading to the conclusion that ANN models merit additional research.

Background and Problem

Everyday in the Navy, important decisions are made about a wide variety of personnel issues based, in part, upon the prediction of future performance. For example, applicants are accepted or rejected, "A" school graduates are given one of many possible job assignments, and some Navy personnel are promoted over others. To the degree that these predictions are less valid than possible, the decisions based upon these predictions may have an adverse impact for both the Navy and the personnel involved.

The most common statistical method used to predict performance is multiple linear regression, which is simple to use. This works well when the data used to make the predictions (predictors) are related linearly to what is being predicted (the criterion) such as SAT scores and subsequent academic

performance. However, simple linear regression-based procedures cannot account for any nonlinear relationships between predictors and criteria. For example, as the level of stress increases from very low to moderate levels, job performance will often improve; however, too much stress will lead to a decline in job performance. Simple linear regression cannot model a nonlinear relationship between stress and job performance. One possible solution is to use nonlinear regression techniques. Unfortunately, these typically require *a priori* specification of a model of the nonlinear relationship. Unless the form of the nonlinearity is well understood, choosing a reasonable nonlinear model is difficult.

In recent years, new techniques have been developed in which computers "learn" the relationships between a set of variables, without needing *a priori* information about the relationships (Rumelhart & McClelland, 1986). These techniques, called Artificial Neural Networks (ANNs), have been applied to a wide variety of problems such as controlling robotic arm movement (Martinetz & Schulten, 1990), modeling the spelling ability of brain-damaged persons (Olson & Caramazza, 1988), and examining artificial intelligence problems such as learning to play backgammon (Tesauro, 1990).

An ANN learns relationships through the process of training. This consists of showing the ANN a set of predictor scores along with the correct criterion score. The ANN makes its prediction about the criterion from the predictor scores, and then compares this prediction with the correct value. The network then makes adjustments and the process is repeated with another piece of data. At some point the ANN is judged to have "learned" the relationships, and training is terminated.

Although a great deal of research on ANNs has been undertaken recently, very little of this research has examined the efficacy of using neural networks for prediction. Recently, a number of researchers have proved that ANNs (at least theoretically) can model essentially any function (linear or nonlinear) under a wide variety of conditions (Hecht-Nielsen, 1990; Hornik, Stinchcombe, & White, 1990). However, ANNs are iterative techniques which require that the user make certain decisions (e.g., choosing the best neural network configuration, deciding when to terminate the learning process, and encoding the input data). Since these decisions affect how the ANNs model the data, it is not clear that they will, in actual practice, lead to better predictive efficacy than linear regression.

Most of the recent research on ANNs has examined predictive problems in which the predictors and criterion have been deterministically related. In other words, each set of predictors has only one correct criterion value. This makes it easy to determine when the ANN has learned the relationships sufficiently well to terminate the training process. On the other hand, the prediction problems with which we are concerned have predictors and criteria which are probabilistically related to each other. The fact that two persons with exactly the same set of predictor scores might have different criterion scores makes this prediction problem fundamentally different from those in which neural networks are typically used. Therefore, the rules for deciding when to terminate training (called stopping rules) which have been developed for ANNs do not apply.

This research examined some of these practical issues in the context of a serious Navy problem; namely, premature voluntary attrition from the USNA. The USNA, one of the Navy's most important resources for recruiting and training top quality officers, is an expensive resource. A 4-year course of study costs approximately \$153,000 per person (GAO, 1991). When a USNA midshipman attrites prematurely, the money invested in his or her training has been essentially wasted. In light of reduced operating budgets, it is important to study ways in which attrition can be reduced, since even a small reduction could lead to substantial savings. For example, approximately 150 of the original 1354 midshipmen in the class of 1989 attrited voluntarily. Reducing this loss by as little as 10% could have saved up to \$1.2 million dollars for that class.

Objective

The objective of this work was to explore, empirically, the advantages and disadvantages of using ANNs as an alternative to linear regression techniques for Navy prediction problems. Specifically, this study examined whether or not the prediction of premature voluntary attrition from the USNA could be improved. The study was intended to determine if ANNs show sufficient promise to warrant additional research into how to apply ANNs to Navy personnel and manpower problems. It was also hoped that this initial study would help find promising paths for such future research.

Approach

This study developed prediction models using both linear regression and ANNs and compared their predictive efficacy. The study used data from USNA classes of 1984, 1988 and 1989, which will be referred to as Class I, Class II, and Class III respectively.

Prediction models for both methods were developed using the seven predictors that the USNA currently employs to evaluate candidates. These predictor variables are Scholastic Aptitude Test (SAT) verbal scores, SAT quantitative scores, rank in high-school class, recommendations from high-school teachers and administrators, extracurricular activity score, technical interest score, and career interest score (Wahrenbrock & Neumann, 1989). These predictors are used because they have a strong linear relationship with criteria of interest to the USNA: academic performance, military performance, choice of major, and, the criterion of interest in this study, voluntary attrition. One of the possible benefits of using ANNs instead of linear regression would be the ability to take advantage of nonlinear relationships. There may well be predictor variables nonlinearly related to the above criteria. However, since ANNs are an untested technology for this type of problem, before we can search for new variables which are related to attrition in a nonlinear fashion, we must demonstrate that ANNs predict attrition as well as linear regression when using variables that are related to attrition in a linear manner. Thus, these seven variables represent an appropriate initial comparison between linear regression and ANNs.

The first part of this study consisted of calculating a linear regression equation using Class I data and the same stepwise procedure with the same software currently used by the USNA. This regression equation was then cross-validated with data from Class III, which was independent of Class I. The next portion of the study consisted of developing six ANNs of varying characteristics (see Table 1) with which to compare the regression results. The procedure for the ANN portion of the study was more complicated than for the linear regression. Since ANNs are trained with an iterative procedure, there is no simple way to determine when training should be stopped when using the probabilistic type of data examined in this study. Therefore, a two-phase cross-validation paradigm was developed to determine the stopping criterion (Phase 1) and to then employ this stopping criterion on a completely independent second

Table 1**Neural Network's Characteristics**

Network	Architecture	Inputs	Hidden Layer 1	Hidden Layer 2	Outputs
1	Backpropagation	7	14	0	1
2	Backpropagation	7	7	0	1
3	Functional Link	7	7	0	1
4	Functional Link	7	4	3	1
5	Backpropagation	7	21	0	1
6	Backpropagation	7	2	0	1

cross-validation data set (Phase 2). In the Phase 1 cross-validation, each ANN was trained on data from Class I in increments of 10,000 iterations. The ANNs were then cross-validated on Class II data at each iteration increment (e.g., after 10,000 iterations, 20,000, etc.). These results were used to determine the number of iterations for training during Phase 2, in which the network was cross-validated with data from Class III, which was independent of both Classes I and II.

The results of the two-phase cross-validation can be used to find several stopping criteria. Two of the most promising criteria were examined in this study: Criterion A is the number of iterations which provides the maximum cross-validation correlation coefficient for Class II data. Criterion B is the midpoint of the range of iterations for which ANN provides a higher cross-validation correlation coefficient than linear regression. Criterion B is a rougher estimate of the optimal stopping criterion, but one which is expected to be more robust than criterion A to idiosyncracies within the original training data from Class I.

Results

Stepwise multiple linear regression was conducted on the data in Class I using SPSSX (the Statistical Package for the Social Sciences). The resultant regression equation was then used to predict attrition for Class III. The correlation between predicted attrition and actual attrition was then calculated for Class III. Because attrition is a dichotomous variable, with only a small

percentage of people actually attriting, the correlation coefficients are small. The correlation in this case was found to be .0561. This served as a baseline for comparisons with ANNs.

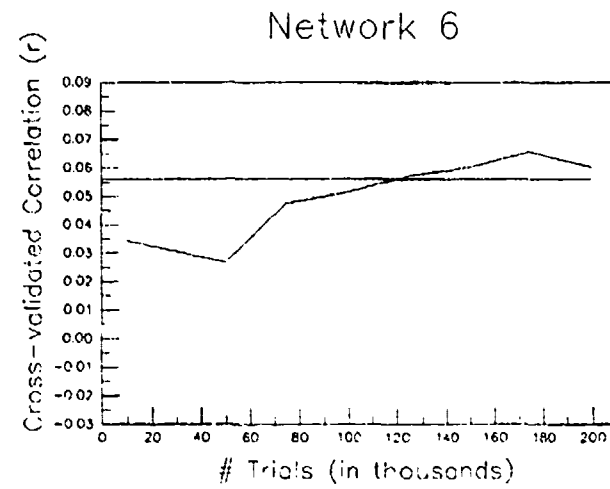
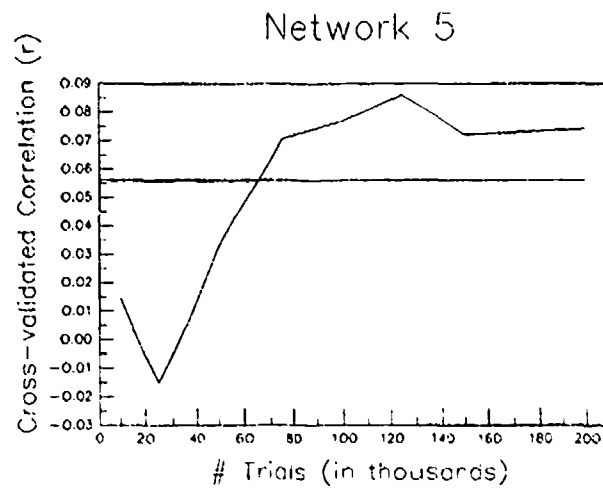
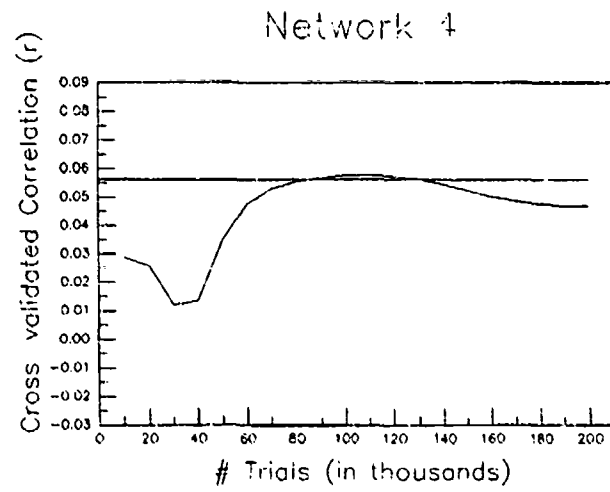
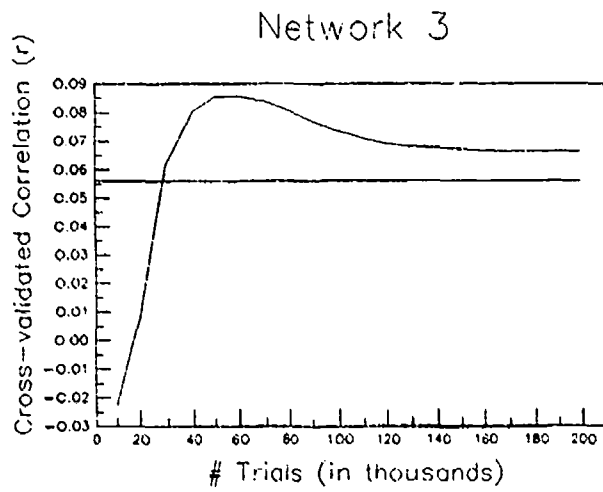
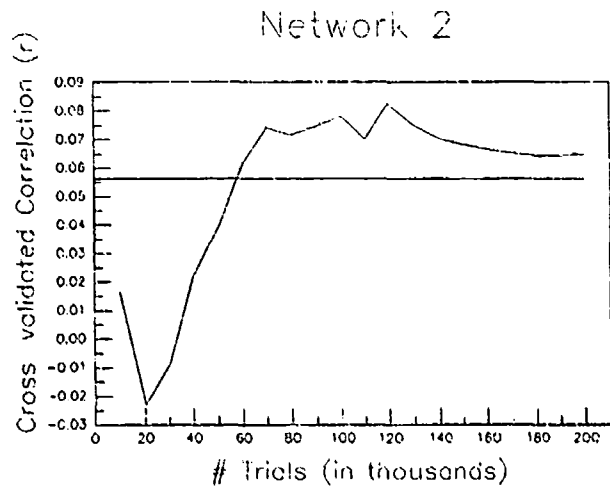
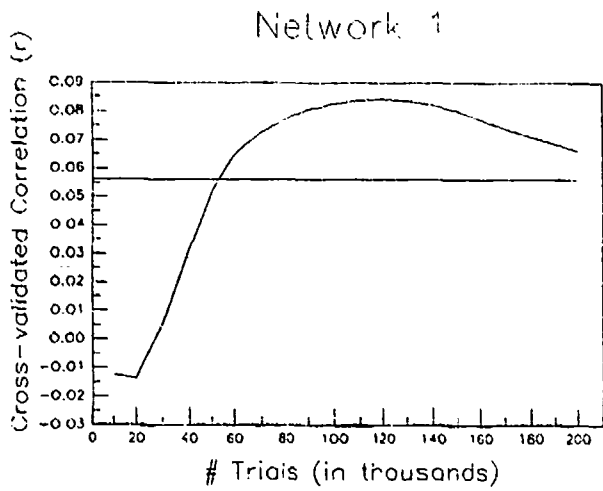
The ANNs were trained and tested in increments of 10,000, up to 200,000 iterations. The correlation between predicted attrition and actual attrition was calculated for each increment. The broad range of stopping values for which the ANNs had higher correlations than linear regression are shown in Figure 1.

The two-phase cross-validation paradigm was used to observe how well information about Class II could be used to choose a stopping criterion for Class III. Criteria A and B were calculated for each of the six networks and used to calculate the cross-validated correlations for Class III. For all six networks, both Criteria A and B yielded correlations higher than those provided by linear regression (See Table 2).

Discussion and Conclusion

The results of this study indicate that ANNs show great promise as an alternative method to linear regression for prediction. For the USNA attrition data, the predictive efficacy of ANNs was as high and indeed often higher than the predictive efficacy of simple linear regression. This is encouraging since ANNs can accommodate nonlinear relationships between the input and output data.

The main drawback to ANNs is their complexity. In particular, the iterative nature of the learning mechanism makes them more difficult to use than linear regression. Also, if trained for too many or too few iterations, their performance is suboptimal. Unfortunately, most previous ANN research has focused only on deterministic problems where any given input vector was always mapped to a single output value. The methods which have been used in such research for determining when to halt training are essentially measures of when the ANN has learned all of the input-output patterns to a sufficient degree. These methods are not applicable to probabilistic problems, such as the one examined in this study, since the ANNs can never learn all of the input-output patterns.



Note. The horizontal line represents the correlation for linear regression.

Figure 1. Cross-validated correlation coefficient for Class III for varying stopping criteria.

Table 2

Class III Cross-validated Correlation Coefficients

Network	Regression	NN-Criterion A	NN-Criterion B
1	.0561	.0846	.0806
2	.0561	.0806	.0762
3	.0561	.0854	.0858
4	.0561	.0577	.0577
5	.0561	.0860	.0769
6	.0561	.0657	.0657

Development of the two-phase cross-validation paradigm shows great promise as a method for determining when to stop training for probabilistic problems. This study certainly indicates that further research is warranted.

Future Efforts

Preliminary research has shown neural network technology to be a potentially powerful method for improving prediction for a number of issues of importance to the Navy. One of the primary areas of research planned for further study is an examination of other predictor variables. Predictors which have strong, but nonlinear, relationships with attrition would improve the ability of ANNs to predict attrition, since ANNs are capable of modeling such nonlinearities. On the other hand, such variables would not be very helpful to linear regression. Since the linear regression model was used to select the current predictors, there is good reason to believe that appropriate nonlinear predictors can be found.

It is also important for future research to expand the number and types of neural network models examined, since only a few different neural networks were included in this study. Further research on how to choose the best configuration of ANNs would be very useful. Research in these areas is currently underway at NPRDC.

Finally, it would also be important at some point to compare ANN methodology with a variety of nonlinear statistical techniques, as well as with various algorithms being developed at NPRDC that search large databases for relationships (e.g., TETRAD).

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Artificial Neural Networks and Training

Jan Dickieson and Lew Gollub

Abstract

The development of effective training methods requires predicting how the trainee will respond to the training procedure. At present, only qualitative models and intuitions can guide the training developer. A quantitative model of human behavior, as it changes through training, would facilitate the development of optimal training methods and materials by providing a platform for rapidly pretesting procedures prior to a more costly field test. This project used neural network analysis techniques to develop a model of the acquisition of some aspects of a Navy training task (Air Intercept Controller). The model will then serve as the basis for predicting the effects of changes in training conditions.

Rationale

The primary goal was to develop an artificial neural network (ANN) model of learning and performance on a Navy relevant task. Such a model can then be used to predict the effects of changes in training conditions with the long-term goal of developing a model that can predict the effects of novel combinations of training parameters.

Artificial neural networks are a recently developed method for modeling complex systems. A great variety of processes have already been modeled with this approach. The diversity of applications indicates the flexibility of the approach.

Progress

We continued to review the published literature for applications of ANNs to learning and performance. Because ANNs have not been applied to skill learning situations, a thorough review of related studies on simple classical and operant conditioning was undertaken to examine points of similarity and difference from skill learning.

Reductions in FY92 project funding after the first quarter resulted in suspending the research until funds are available.

Individual Differences in Information Acquisition and Processing Style

Robert F. Morrison

Abstract

A decision making model depicting perception's effect on judgment and choice and its interaction with information plus the effect of information on judgment is incomplete without the inclusion of individual differences among the decision-makers. Individual characteristics guide the way that a problem is perceived and analyzed and the type of information that is acquired and used in making a choice. In this research, the effect of decision-maker's individual characteristics (e.g., cognitive style, cognitive ability, cognitive strategy, motivation level, past experiences, self-efficacy, adaptability, and time horizon) on information acquisition and processing and decision making are analyzed using an actual career decision making experience. The research subjects are officer candidates from two Naval accession programs who are between 4 months and 3 years away from choosing the community into which they want to be commissioned.

Background

Dynamic decision making (DDM) is characterized by the following: A sequence of decisions is made over time, primarily as a consequence of previous decisions but, possibly, independently; information and alternatives available for later decisions may be contingent upon the results of earlier decisions; and the implications of any one decision extend far into the future. While DDM is probably the most relevant process for individual and organization decision-makers, it is also the most complex topic in decision-making, especially since the decision-maker and environment constantly interact and adjust to each other. Because it is complex, this decision-making task is the least understood of all such tasks, and the relevant research is preliminary and exploratory (Stevenson, Busemeyer, & Naylor, 1990).

Decision-making tasks that represent DDM range from corporate strategic planning to career planning. Both examples take place over a long time span and have no clear, optimal

outcome. A model depicting perception's effect on judgment and choice and its interaction with information plus the effect of information on judgment provides very good guidance for thinking about what a DDM process might look like. However, such a model is not complete. Individual characteristics of the decision-maker direct and guide the way that a problem is perceived and analyzed and the type of information that is acquired and used in making a choice. In each instance, the time horizon (Stevenson, Bussemeyer, & Naylor, 1990) of decision-makers is a constraint along with their ability to adapt to the constant changes in the environment (Payne, Bettman, & Johnson, 1990). Some other biases that limit effective DDM are overconfidence, recency, availability (Russo & Schoemaker, 1990), anxiety (Fuqua & Newman, 1989), gender (Thompson, Mann, & Harris, 1981; cited in Robertson, 1985), motivation (e.g., interests), past experiences, self-efficacy, and perceptions of the decision task and its environment as well as the cognitive characteristics that are typical in research on cognitive processes. All of these individual differences may describe the decision-makers using different decision styles (e.g., Phillips, Paziienza, & Ferrin, 1984) in DDM situations.

A factor that effects not only the perceptions of information and the judgments of alternatives but also the intensity with which the decision-maker becomes involved in the decision problem is motivation. At extreme levels of motivation (Driver, Brousseau, & Hunsacker, 1990), individuals may perceive little need to be involved in the decision making process.

The experience that the decision-maker has had will partially determine the approach that is taken to acquire and process information and make judgments. Some characteristics of experience that may have differential effects on the DDM process are recency and relevance. The impact of past experience on the effectiveness of the decision making process is not all direct. A major portion of its effect operates via the decision-maker's feeling of self-efficacy (Morrison & Brantner, 1992) which facilitates the optimal use of the decision-maker's cognitive resources.

In this research, Kogan's (1976) taxonomy was used as a theoretical framework to classify and measure three cognitive aspects of decision-makers' predispositional behavior. The taxonomy has three components: cognitive styles, cognitive abilities, and cognitive strategies. Cognitive style is defined as "the characteristic, self-consistent mode of functioning which

individuals show in their perception and intellectual activities" (Simon, 1960). While there are a large number of cognitive style descriptors (e.g., Messick, 1976; Robertson, 1985), nearly all can be grouped into two categories that can be described either as analytic, logical, linear, detail-oriented, and focused or as intuitive, heuristic, impulsive, global, and free-wheeling.

One approach to defining constructs that describe cognitive style has been developed by Driver and his colleagues (Driver et al., 1990). Their paradigm is developed around two dimensions, information use and focus and outlines two types of cognitive styles, operating and role. This concept of cognitive style assumes that people differ markedly in the amount of information that they acquire and process in their decisions. The second dimension in this paradigm is focus, i.e., whether the decision-maker focuses on one (unifocus) or more (multifocus) possible solutions to a problem. The person's operating style is the cognitive approach to decision making that is adopted naturally when the individual is least self-conscious or self-aware. The person's role style is the style that is used when conscious of the need to create a favorable impression.

A second major approach to defining cognitive style was initiated by Jung (1971) who introduced two bipolar psychological properties, sensing (detail-types) and intuiting (global-types), to describe how clients perceived information. The global-type individual takes a macro perspective and processes information from the top (macro) down into more micro detail. Detail-type persons use a micro perspective, i.e., starting with detailed bits of information at the bottom (micro) and working upward toward the more global concepts.

Cognitive ability represents the situational- or domain-specific-dimension of cognition concerning itself with (1) the content of cognition and (2) how cognition operates and in what form (Messick, 1976). However, when applied, theoretically domain-specific measures of cognitive processing demonstrate significant general cognitive ability (Marshalek, Lohman, & Snow, 1983). Until measures of cognitive ability are developed by merging psychometrics and cognitive psychology, an adequate set of measures of domain-specific cognitive abilities will probably not be available (Carroll, 1992). To date only the Paper Formboard, a predictor of processing speed and accuracy, has been subjected to the appropriate developmental steps.

A cognitive strategy is an interaction between an individual's cognitive styles and his/her cognitive abilities. Therefore, cognitive strategies are partly affected by task requirements, situational constraints, and the individual's amount of knowledge (Shields, 1984) and partly by the individual's way of thinking. Using ambiguity of information as a characteristic of the decision problem and/or the situation, the behavior of decision-makers can be scaled according to how they cope with the situation.

Problem

Many potential users avoid computer-based decision aids. This behavior may occur because the users' decision styles are not compatible with the one(s) assumed when the decision aids were developed. When decision-makers avoid the use of decision aids, they may take much longer to make decisions and the decisions may be poorer than if they had used the aids. Thus, it would be useful if computer-based decision aids could be made as adaptable to different styles of effective decision-making as possible.

The development of computer-based decision aids, e.g., Surface Warfare Officer Bulletin Board (Bureau of Naval Personnel, 1991), appears to have been initiated under the assumption that all potential users are homogeneous in the manner with which they process information while making decisions (Osborn, 1990). Research in noncomputer-aided circumstances (Phillips et al, 1984) indicates that there may be multiple approaches to making decisions, and it has been posited that some of the styles are successful but others are not. Some decision styles can be modified for a short time via training. However, the effect may not last and not all styles are modifiable through training. It would appear to be more efficient to adapt the design of computer-based decision aids so that such aids can be used by individuals applying more than one decision style. This research can help establish the knowledge required to make computer-based decision aids more usable by a wider variety of decision-makers.

This research (1) identified the various schema that individuals with different decision-making styles use to acquire and process information in DDM situations and (2) developed a preliminary model of individual differences that identifies individuals that use different approaches to DDM under different circumstances.

Method

A sample of 1,800 USNA and Naval Reserve Officer Training Corps program midshipmen from each of the four college years will be research subjects. Their DDM task will be to select the Naval occupational community in which they will be commissioned upon graduation. An adaptive computer-based decision aid will assist them by collecting data on their decision behavior (e.g., any changes in their decisions as they interact with their environment, the quantity of information that they obtain, the number of alternatives that they judge, and the depth of information used in making such judgments). In addition, individual differences data will be collected separately using paper-and-pencil or computer-administered questionnaires. Some of the individual differences measures are being developed for use in this research and others (e.g., Myers-Briggs Type Inventory and Paper Formboard) will be obtained from publishers. The primary analytical technique will be structural equation modeling.

Progress

The basic literature search has been completed and the key individual differences variables identified and placed in a theoretical DDM model. Each of the relevant hypotheses has been developed and the research design formulated. A schematic of the adaptive computer-based decision aid has been prepared for programming. Individual differences measures are being developed for pilot testing. Pilot testing of the decision aid is planned for July 1993 with fall data collection scheduled for September-October 1993.

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Cognitive Resources, Performance Feedback, and Decision Processes in a Simulated Work Environment

B. Charles Tatum and Delbert M. Nebeker

Abstract

The Organizational Systems Simulation Laboratory (OSSLAB) is a facility that addresses the need for empirical data on many critical organizational issues important to the Department of the Navy. To date, the OSSLAB's value has been primarily in the exploratory development phase of research and development. The studies have addressed research problems that make an easy transition into field applications. These studies have been driven by sound organizational theory, but the intent has not been explicitly to test theoretical constructs or to increase fundamental knowledge and understanding in organizational science. Over the years, however, the OSSLAB has become a more sophisticated tool for the study of organizational issues. The present study investigated some fundamental processes in human information processing, decision making, and motivation.

Background Rationale

Kanfer and Ackerman (1989) used an information processing framework to integrate the constructs of motivation and ability. The basic approach draws heavily on the notion of cognitive resources (e.g., Kahneman, 1973; Norman & Bobrow, 1975), and how the same task at different stages of acquisition requires different amounts of a person's cognitive resources. In a key-entry task, such as the one used in the OSSLAB, the cognitive demands of the task would also depend on the phase of skill acquisition (Ackerman, 1988, Ackerman, 1992; Anderson, 1982, 1983). For example, during the early phase of learning a key-entry task, the operator would require extensive cognitive resources to perform the task. Later phases in the learning process would require fewer cognitive resources, and would make these resources available to perform other cognitively demanding aspects of the task (e.g., use performance feedback to reach assigned goals, develop and implement process improvements).

The basic framework of Kanfer and Ackerman's (1989) model also has implications for decision making processes. It follows from the model that when a person is trying to reach a goal, the decision processes involved in selecting and using the available performance feedback will depend on the phase of skill acquisition. Beach and Mitchell (1978) argue that one of the factors that influences decision processes is the cognitive demands placed on the person. Beach and Mitchell outlined a continuum of decision styles that ranged from analytic (e.g., formal algorithms, subjective expected utility analysis, cognitive algebra) to non-analytic (e.g., simplifying heuristics, superficial thinking, habit) depending upon various contingencies in the task, the person, and the environment. One of the contingencies controlling whether a person adopts an analytic or a non-analytic style, according to Beach and Mitchell, is the cognitive demand placed on the decision-maker. If, as suggested by Kanfer and Ackerman, the early stages of skill acquisition require greater cognitive resources, we would expect that strategy selection during this early phase should be characterized by the use of non-analytic decision processes. Contrariwise, strategy selection in the later phases would involve a more analytic decision process.

Primary Objective

This research investigated the relationship between cognitive resources and the decision processes involved in the selection and use of feedback information. Workers performing a task very often seek information about how they are performing, especially if there is an explicit goal they are attempting to reach. We propose that seeking and using feedback will be heavily influenced by the cognitive demands of the task. To test this proposition, we manipulated the cognitive demands placed on the workers in three ways:

1. **Qualitative Work Load:** One group of workers was required to reach three simultaneous work goals (high demand condition), while another group was required to pursue only a single goal (low demand condition).
2. **Quantitative Work Load:** One group of workers was assigned a very difficult goal (high demand), while another group was assigned an easy goal (low demand).

3. **Phase of Skill Acquisition:** Early phases of learning the key-entry task would require more cognitive resources (high demand), while later phases would require fewer cognitive resources (low demand).

Given these manipulations of cognitive demand, we tested three hypotheses:

1. The amount of feedback information requested will be inversely related to the level of cognitive demands placed on the worker. That is, workers in the low demand conditions will seek more feedback than workers in the high demand conditions.

2. The type of information the worker requests will depend on the level of cognitive demand. Specifically, workers in the low demand conditions will seek more complex, diagnostic feedback than workers in the high demand conditions.

3. The decision style the worker uses in selecting feedback will differ depending on the cognitive demand. Workers in the high demand conditions will use a simplified decision style relative to workers in the low demand conditions.

Approach

Thirty-seven employees were hired to work on a data-entry task in a simulated work environment (the OSSLAB). The employees worked ten days (Monday through Friday for two weeks) in four-hour shifts. The task involved entering information from scientific references into a computerized database. On the first day the employees were trained and allowed to practice the task. On the second day, the workers were divided into four experimental groups: (1) Low Quantitative Work Load/Low Qualitative Work Load, (2) Low Quantitative Work/High Qualitative Work Load, (3) High Quantitative Work Load/Low Qualitative Work Load, (4) High Quantitative Work Load/High Qualitative Work Load. Each group was told that from the second day until the final day (day 10) of the work assignment, they should try to reach certain performance goals and that they would receive computerized feedback reports indicating their progress toward these goals. Those individuals assigned a low quantitative work load were assigned performance goals that were easy to achieve (as determined by the results of an earlier pilot study). Those individuals assigned a high quantitative work load were assigned performance goals that were difficult to achieve. The people assigned a low

qualitative work-load were asked to reach a single performance goal that consisted of a composite measure of their keystroke rate, accuracy, and time usage. The people assigned a high qualitative work-load were asked to reach three separate performance goals: one for keystroke rate, a second for accuracy, and a third for time usage.

The workers were given unlimited access to on-line feedback reports so they could monitor their own progress toward the assigned goals. These reports provided information on all relevant dimensions of performance (i.e., the workers received reports on their keystroke rate, the accuracy of the data they entered, how efficiently they used their time, and a composite measure of these three). The reports also provided different levels of diagnostic information. For example, one report delivered very little diagnostic information, but did provide a general evaluation of how well the worker was performing. By contrast, another report displayed more specific information that the worker could use to diagnosis causes of good or poor performance. We recorded which reports the workers used, as well as how often they selected a given report and how much time they spent viewing a report.

At the end of each day, the workers completed a survey that asked many work-related questions such as how they liked the job, whether they were experiencing any stress, how much social support they received, and so on. On several other occasions during their two week assignment, the workers were also given paper-and-pencil exercises to complete. One of these exercises was the Driver Decision Style Exercise (Driver, 1974) that assessed the workers primary decision making style. The exercise categorizes people into one of five decision styles that range from decisive (a style in which decisions are made by considering few options and using little information) to integrative (a style that considers many options and uses much information). The Driver Decision Style Exercise was administered twice (once on day 3 and again on day 9) to determine whether any changes in decision style occurred over the two week work assignment.

Results

The study results fall into three general areas, each of which are portrayed in Figures 1-3. Figure 1 shows the relationship between feedback seeking and cognitive demands. As predicted, the workers in the low demand conditions (i.e., those assigned a single, easy goal) requested more feedback reports than those in the high demand condition (i.e., those assigned three difficult goals). We expected that over time the demands on the workers in the high demand conditions would diminish and they would increase the frequency of their requests. As shown in Figure 1, there was only a slight rise in requests for these workers. Perhaps if the study had been conducted for a few more days we would have seen an upswing in their desire for feedback information in the high demand groups.

Figure 2 shows the relationship between the diagnostic value of the reports and the level of cognitive demand. Contrary to our hypotheses, there is little evidence that workers in the low demand condition request more diagnostic information than workers in the high demand conditions. Figure 2 seems to show that the workers in the low demand conditions request more feedback information of all types, and this pattern does not change significantly over time. Again, had the study been conducted for a longer duration, we might have seen differences in the type of information requests made in the low and high demand conditions.

Figure 3 shows the relationship between decision style and cognitive demand. This figure shows the extent to which the workers in the two demand conditions adopted a decisive decision style (i.e., a style that considers few options and relies on minimal information). The hypothesis we tested was that workers in the high demand condition would be more likely to use this simplified style. Although initially the high demand workers were *less* likely than the low demand workers to use this style, they were *more* likely to discard the style as time passed. Apparently, as the cognitive demands diminished over time, the high demand workers were more inclined to adopt other, more integrative, decision styles.

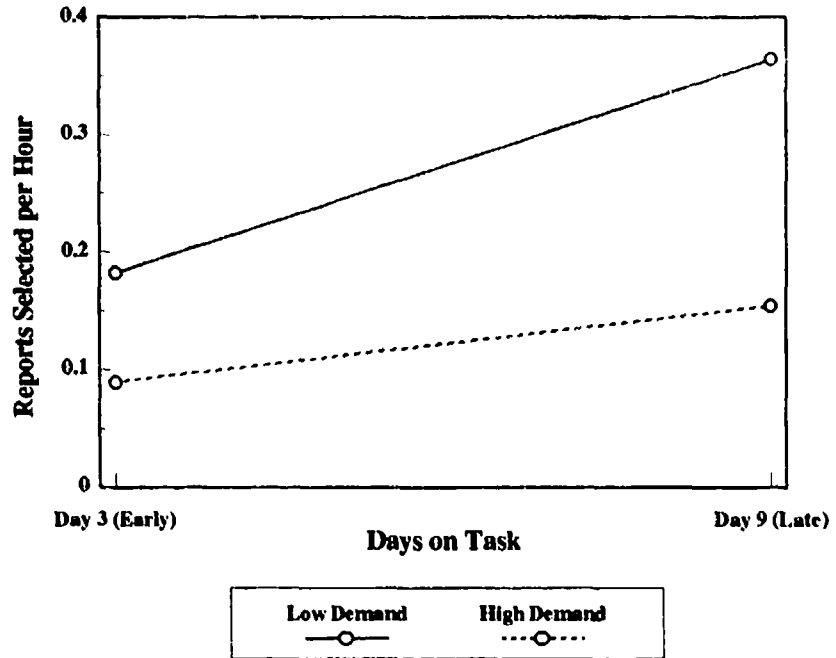


Figure 1. Report selection across days as a function of low and high cognitive demand.

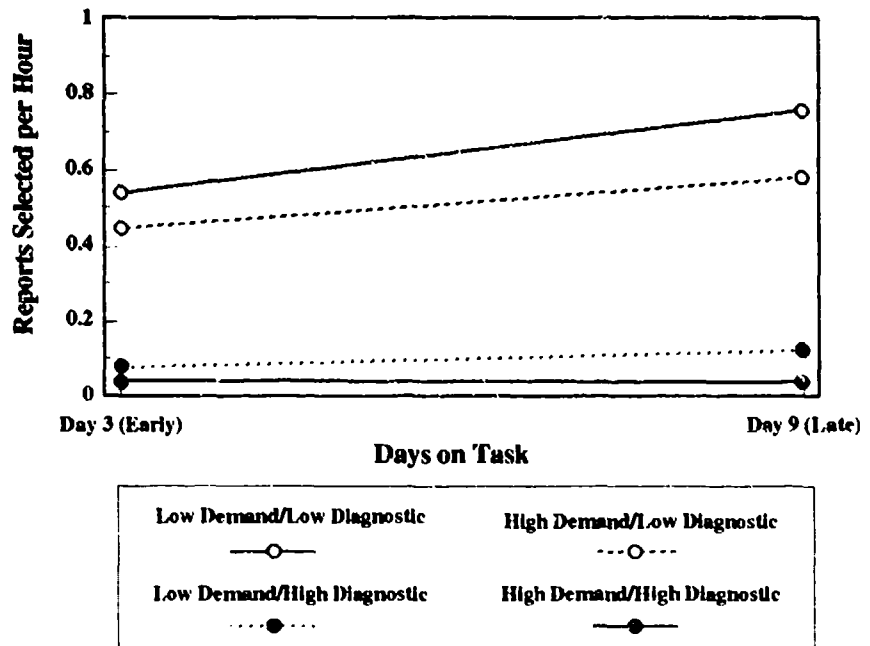


Figure 2. Report selection across days as a function of low and high cognitive demand and diagnostic level of report.

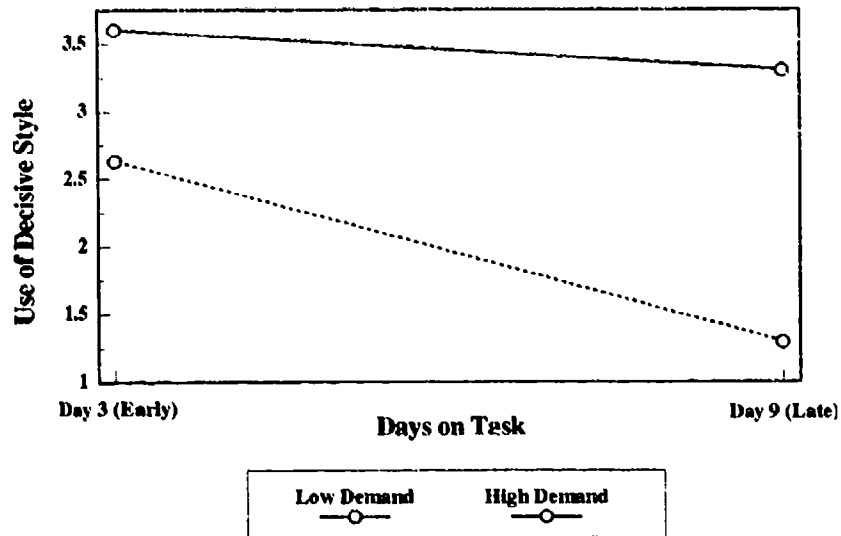


Figure 3. Use of decisive style across days as a function of low and high cognitive demand.

Discussion and Expected Benefit

The study investigated the relationship between cognitive resources, performance feedback, and decision processes. The results show that people seek performance feedback in the pursuit of their assigned goals. Moreover, the extent to which they seek feedback information depends on the cognitive demands of the task. If the task places heavy demands on their cognitive resources, they are less inclined to seek feedback. Further, the results show that as the cognitive demands diminish over time, there is a corresponding reduction in the use of a decisive, simplified decision style. These are important findings in any attempt to understand the relationship between cognitive processes and organizational behavior.

Workers and managers alike are called upon daily to make decisions about their jobs and co-workers. It is important to the understanding of work behavior to know how these decisions are made and what factors influence these decisions. The present study is especially relevant because it examines cognitive and decision processes in the context of goal setting and feedback. The literature consistently shows that goal setting and feedback are powerful motivators in the workplace (Locke & Latham, 1990). Making the link between the cognitive processes that

underlie both decision making and motivation is a critical first step in understanding organizational behavior and human information processing. Organizational changes of the magnitude achieved by gainsharing or total quality, rest on a foundation of basic scientific knowledge in the areas of organizational behavior, work motivation, and information processing. The benefits of this scientific and technical knowledge are already being seen in improved efficiency and effectiveness in the Navy, DoD, and the private sector.

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The Role of Feedback in Computer-Based Training: Follow-On Work

Michael Cowen

Abstract

Current research in computer-based training (CBT) provides little guidance as to when feedback should be provided and how to design feedback content. In the initial, base effort, an experimental CBT on how to operate a military phone system was administered to 80 Navy students. The lesson was presented individually on a microcomputer and consisted of an introduction, a practice, and a posttest. During practice, each treatment group received one of four types of feedback. The computer provided feedback either immediately following an error or at the end of the button-pushing of the to-be-learned sequence. Feedback was the correct response or a wrong indication. All the CBT treatment groups outperformed a no-treatment control group. The treatment group who received delayed feedback performed significantly better on the posttest than those who received immediate feedback. A second study extended the base effort.

Progress

Segments of the CBT developed for the base effort were revised so that the practice time would be increased during the CBT with immediate feedback and decreased during the CBT with delayed feedback. Practice time during CBT with immediate feedback was increased by requiring the subjects in this condition to practice each task twice. Practice time during CBT with delayed feedback was decreased by showing these subjects how to do a task before they practice a task.

Other features of CBT with delayed feedback were also modified to decrease practice time. These included not forcing subjects to start at the beginning of the task each time they wanted to redo a step (an "erase last entry" feature was implemented) and the use of only correct response feedback. In the base effort it was found that the delayed condition with confirmatory feedback used significantly more practice time

than the delayed condition with correct response feedback. It should be noted that these two groups performed about the same on the post-test.

In total, the follow-on study tested five conditions: three immediate correct response feedback groups and two delayed correct response feedback groups. The immediate feedback conditions consisted of (1) a condition identical to the immediate correct response feedback treatment used in the base effort, (2) a condition identical to the first with the addition of having these subjects shown how to do a task before they practiced a task, and (3) a condition identical to the first using two practice trials. The delayed feedback conditions consisted of (4) a condition identical to the delayed correct response feedback treatment used in the base effort with the addition of the "erase last entry" feature, and (5) a condition identical to the fourth with the addition of having these subjects shown how to do a task before they practiced a task. Also, the follow-on study added a second administration of the post-test 24 hours after the experimental CBT.

The revised experimental CBT was administered to 110 Navy students awaiting instruction at sonar technician "A" school. The results of the follow-on study are similar to the results of the first study. Those who received delayed feedback significantly outperformed those who received immediate feedback. Specifically, the delayed correct response feedback group (i.e., Condition 4) significantly outperformed the immediate correct response feedback group (e.g., Condition 1) on both administrations of the performance test. However, the advantage found for delaying the feedback was greatly reduced when the immediate feedback subjects were provided another practice trial (i.e., Condition 3). Showing the subjects how to do a task before they practiced a task (e.g., Conditions 2 and 5) did not impact the effect of delaying the feedback.

Implications

An instructional simulation of ways to operate a phone system was developed without showing the user an engineering model. The users learned ways to activate features by discovering syntax and semantics of the phone's entry panel. Users interacted with the simulation of the electronic device by pressing buttons and receiving feedback. The CBT was most effective when it provided two practice trials with immediate

feedback or one practice trial with delayed feedback. The strong performance effect for the delayed feedback groups suggests that users may have formed hypotheses about button syntax or semantics. Users may have guessed the steps initially, but would have had to account for the feedback to advance to the next task.

Expected Benefit

This research suggests that CBT for a digitally controlled device should be designed to allow users to discover the syntax and semantics of its entry panel. This approach offers learners a challenging and exciting environment where they must actively respond. This study reviewed ways users learn how to operate digitally controlled equipment and made a considerable step toward designing a practical system for training users. For a digitally controlled device of reasonable complexity, a low-cost simulation was implemented. Therefore, with appropriate attention to implementation, this computer-based instructional system could impact personnel performance.

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**Independent Exploratory
Development**

Progress Reports

Biodata and Personality: Are They Related?

Stephanie Booth-Kewley and Marie D. Thomas

Abstract

Despite the demonstrated utility of biodata, little research has been directed towards increasing our theoretical understanding of biodata. Many of the biodata factors that researchers have extracted from biodata instruments seem to have clear linkages to personality. This study examined the relationship of broad personality constructs to validated biodata measures in a sample of Navy personnel. A sample of male Navy recruits ($N = 484$) completed the Owens Biographical Questionnaire (BQ), the Armed Services Applicant Profile (ASAP), the NEO Personality Inventory, and measures of self-esteem and self-efficacy. Only modest correlations were found between the personality variables and the biodata scales. The mean correlation was .16 for the BQ and .15 for the ASAP. It was concluded that the biodata instruments show minimal overlap with personality dimensions. Possible reasons for the lack of associations are discussed.

Background

Biographical information, or biodata, is being used with increasing frequency in personnel selection. Past research indicates that biodata measures are capable of predicting a variety of important criteria, such as occupational choice, academic performance, job performance, and tenure and adjustment to the military (Owens, 1976; Hough, 1987). Despite the demonstrated utility of biodata, little research has been directed towards increasing our theoretical understanding of biodata. The need for some theoretical framework for biodata has been pointed out by numerous researchers (e.g., Hough, 1987; Russell, Mattson, Devlin, & Atwater, 1990).

A number of biodata researchers (e.g., Ghiselli, 1966; Mumford & Collins, 1987) have drawn a sharp distinction between biodata measures and personality or temperament measures. However, as was pointed out by Mael (1991), "Many items termed 'biodata' are indistinguishable from the types of self-report items found in temperament and attitude measures" (p. 764). Moreover, many of the biodata factors that researchers have

extracted from biodata instruments seem to have clear linkages to personality. For example, factor analysis of biodata has revealed factors that measure social participation; these seem to overlap conceptually with the widely studied personality construct of Extraversion. Similarly, in some biodata instruments, factors measuring drive, ambition, or achievement motivation have been identified; these seem conceptually similar to the personality construct of Conscientiousness.

Given recent research in organizational psychology suggesting that broad personality variables translate into important organizational outcomes (George, 1989; Staw, Bell, & Clausen, 1986; Barrick & Mount, 1991), and given that the relationship between biodata and personality has not received much research attention, research is needed to determine the degree of association between personality and biodata.

Recent advances in personality measurement research indicate the existence of five major, robust dimensions of personality (Costa & McCrae, 1985; Digman, 1990). These dimensions are Extraversion, Neuroticism, Agreeableness, Conscientiousness, and Openness to Experience. Two additional personality variables—self-esteem and self-efficacy—were also included in the present study because we thought that they might be related to biodata.

Objective

The present study examined the relationship of broad personality constructs to validated biodata measures in a sample of Navy personnel.

Method

Subjects

The subjects were 484 male U.S. Navy recruits completing basic training in San Diego. The sample was made up of 68% nonHispanic whites, 13% blacks, 12% Hispanics, 4% Asians, and 3% "other" race/ethnic groups. The subjects ranged in age from 17 to 33.

Measures

Owens Biographical Questionnaire. The Owens Biographical Questionnaire (BQ) is a widely used, 118-item biodata instrument. It assesses diverse areas of an individual's background, such as academic achievement, social activities, sports participation, and temperamental attributes such as sensitivity to criticism and social confidence. Factor analysis of the BQ indicates the existence of 13 male (and 15 female) factors. The male factors are as follows: (1) Warmth of parental relationship, (2) Intellectualism, (3) Academic achievement (4) Social introversion, (5) Scientific interest, (6) Socioeconomic status, (7) Aggressiveness/independence (verbal), (8) Parental control vs. freedom, (9) Positive academic attitude, (10) Sibling friction, (11) Religious activity, (12) Athletic interest, (13) Social desirability. For the present data, the coefficient alphas of the BQ factors ranged from .54 to .84, with a median of .73.

Armed Services Applicant Profile. The 50-item Armed Services Applicant Profile (ASAP) was designed to tap background dimensions that might predict an individual's propensity to adapt well to the military. Like the BQ, the ASAP measures diverse areas of a person's background, including academic attitude, delinquency, athletic interest, and work history. The ASAP has adequate criterion validity and is reasonably resistant to faking (Trent, 1993).

Although factor analysis was not used to develop the ASAP, principal components analysis of this measure indicates the following six factors (Trent, 1993): (1) School achievement, (2) Delinquency, (3) Work ethic, (4) Independence, (5) Social adaptation, (6) Physical involvement. In the present data, the coefficient alphas of the ASAP factors ranged from .35 to .64.

NEO Personality Inventory. The 118-item NEO Personality Inventory (NEO-PI; Costa & McCrae, 1985) is a widely used personality inventory developed to measure the "Big Five" personality dimensions: Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness. The NEO-PI scales have adequate internal consistency, test-retest reliability, and validity (Costa & McCrae, 1985). The coefficient alphas of the five scales ranged from .72 to .90 for the present sample.

Rosenberg Self-Esteem Scale. The Rosenberg Self-Esteem Scale (Rosenberg, 1965) is a widely used, 10-item measure of self-esteem. This scale has adequate internal consistency, test-retest reliability, and validity (Rosenberg, 1965). For the present sample, the scale had a coefficient alpha of .85.

Self-Efficacy Scale. The 17-item General Self-Efficacy scale developed by Sherer et al. (1982) was used to measure self-efficacy. The General Self-Efficacy scale has adequate internal consistency and construct validity (Sherer et al., 1982). The coefficient alpha for the present sample was .90.

Procedure

Besides completing the biodata and personality measures, respondents also provided their age, race/ethnicity, education, and marital status. Subjects were administered the questionnaires in groups of 10 to 60, as a scheduled part of Navy basic training.

Results

Correlation coefficients were computed between the seven personality variables and the 13 BQ factors. These results are presented in Table 1. As the table shows, most of the personality-BQ correlations were of modest size, with a mean correlation of only .16. However, because a fairly large sample was used, most of the correlations (66%) were statistically significant ($p < .05$).

The largest personality-BQ association was the correlation of -.63 between Neuroticism and the BQ Social Desirability factor. Although Owens and Schoenfeldt (1979) labeled this factor Social Desirability, its strong inverse association with Neuroticism, coupled with its item content suggest that "Positive Adjustment" would be a more accurate label. This same BQ factor (Social Desirability or Positive Adjustment) also correlated substantially with the personality dimensions Self-Efficacy ($r = .47$) and Self-Esteem ($r = .48$). Aside from these three correlations, there was only one other personality-BQ correlation that exceeded .40: this was the correlation between Openness to Experience and the BQ factor Aggressiveness/Independence ($r = .46$). Individuals high on Openness to Experience tended to be verbally aggressive, independent, and unconventional.

Table 1
Correlations Between Personality Variables and BQ Factors

	Neuroticism	Extra- Version	Conscien- tiousness	Agreeable- ness	Openness	Self- Efficacy	Self- Esteem
F1	-.12	.21	.16	.21	-.07	.21	.25
F2	-.20	.07	.05	.05	.13	.09	.06
F3	-.27	.23	.33	.09	.09	.33	.25
F4	.12	-.39	-.04	.09	.02	-.12	-.20
F5	-.19	.14	.19	.15	.22	.25	.17
F6	-.15	.17	.02	-.08	.10	.14	.21
F7	-.04	.32	.17	.09	.46	.24	.19
F8	.06	.04	-.05	-.09	.02	-.02	-.04
F9	-.21	.15	.25	.31	.08	.26	.13
F10	.14	.04	.02	-.03	-.02	-.03	-.08
F11	.06	-.10	-.04	.12	-.08	-.05	-.13
F12	-.17	.29	.21	.04	-.03	.26	.22
F13	-.63	.08	.27	.22	.03	.47	.48

Note. Correlations of .09 and above are significant at the .05 level; correlations of .12 and above are significant at the .01 level. F1 = Warmth of Parental Relationship. F2 = Intellectualism. F3 = Academic Achievement. F4 = Social Introversion. F5 = Scientific Interest. F6 = Socioeconomic Status. F7 = Aggressiveness/Independence. F8 = Parental Control vs. Freedom. F9 = Positive Academic Attitude. F10 = Sibling Friction. F11 = Religious Activity. F12 = Athletic Interest. F13 = Social Desirability.

Correlation coefficients were computed between the personality variables and the ASAP factors; these are shown in Table 2. As was found for the BQ, the ASAP factors had only modest correlations with the personality dimensions, with a mean correlation of .15. Again, due to the large sample size, most of the correlations (62%) were statistically significant. The personality-ASAP correlations were of a magnitude similar to the personality-BQ correlations, with mean correlations of .15 and .16, respectively.

Because the ASAP factors had somewhat lower coefficient alphas than the BQ factors, all personality-biodata correlations were corrected for unreliability of the biodata factors to permit a more accurate comparison. The coefficient alphas of the biodata factors were used in making the corrections. Although the correction for unreliability increased the personality-biodata

Table 2
Correlations Between Personality Variables and ASAP Factors

	Neuroticism	Extra- Version	Conscien- tiousness	Agreeable- ness	Openness	Self- Efficacy	Self- Esteem
School Achievement	-.23	.20	.24	.20	.08	.29	.24
Delinquency	-.27	.07	.29	.29	-.06	.21	.15
Work Ethic	-.11	.16	.11	.05	.07	.18	.13
Independence	.00	.08	.03	.09	-.06	-.01	-.03
Social Adaptation	-.10	-.21	-.07	.07	-.05	-.09	-.04
Physical Involvement	-.28	.25	.26	.16	.01	.33	.29

Note. Correlations of .09 and above are significant at the .05 level; correlations of .12 and above are significant at the .01 level.

correlations, the overall effect was minimal (the corrected correlations are not shown). Correcting for unreliability raised the mean correlation for the BQ from .16 to .19 and the mean correlation for the ASAP from .15 to .22. The overall pattern of results remained essentially unchanged: neither biodata instrument related strongly to personality.

Discussion

Our prediction that there would be substantial associations between biodata and personality was not confirmed. For both biodata instruments, overlap with the personality dimensions was minimal. These findings were surprising, given that the BQ and, to a lesser degree, the ASAP, contain a number of items resembling those typically found on personality scales, and given that both measures contain factors (e.g., Social Introversion on the BQ and Work Ethic on the ASAP) that seem related to personality.

The reasons for the lack of substantial associations between the biodata and personality measures are not clear. It may be that the particular personality constructs that we chose to measure in this study are not the ones that relate the most strongly to biodata. It is also possible that biodata and personality are truly distinct content domains. Research in which a large number of diverse

personality constructs are measured in conjunction with biodata is needed before we can conclude that biodata and personality are truly separate domains.

The fact remains that many items that are referred to as biodata are, as Mael (1991) pointed out, indistinguishable from items that appear in personality and temperament measures. Yet it is often claimed that because they assess factual, objective information, biodata instruments are less subject to distortion and social desirability effects and have other related advantages compared to "softer" self-report measures, such as personality scales (e.g., Owens, 1976; Stokes, Mumford, & Owens, 1989). To the degree that biodata measures are made up of nonfactual, subjective items, they are similar to personality measures, and the claims of their greater objectivity and associated advantages seem unfounded. We suggest that biodata researchers more clearly establish the boundaries of the biodata domain, either by limiting the domain to content that is truly biographical (i.e., items that assess discrete, objective past behaviors or objective characteristics of the person) or by explicitly broadening the biodata domain so that "softer" items assessing personality, feelings, attitudes, likes, and preferences are included.

Presentation

Booth-Kewley, S., & Thomas, M. D. (1992, October). *Personality and biodata: Is there a relationship?* Paper presented at the meeting of the Military Testing Association, Del Mar, CA.

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Optimal Enlisted Requisition Model

Iosif Krass and Ted Thompson

Abstract

We have created an optimization model, which directly incorporates personnel unit readiness into the assignment process. The model belongs to a class of optimization problems known as *networks with side constraints*. Due to the large dimensions of the problem, we were unable to solve it with available optimization packages. We developed a heuristic algorithm that provides a feasible solution to the readiness problem and adapted the Linear-Quadratic Penalty algorithm to provide an optimal solution. With the above approach, we solved the full scale readiness problem for the Navy using a CRAY computer. We continued work to develop algorithms which would allow nearly optimal solution using available IBM 4341/12 computers.

Background

To maximize personnel readiness in its ships, aircraft squadrons, and shore units, the Navy attempts to "place the right sailors, in the right jobs, with the right skills, at the right time." When matching people to available jobs, assignment decision-makers, known as detailers, are expected to obey a complex set of rules and adhere to fluctuating policies. One very important policy for the assignment process is unit personnel readiness. However, currently, due to complexity in calculation, the assignment process does not explicitly optimize unit personnel readiness. Instead, individual combat units are monitored by a central personnel management office; and problems, such as personnel shortages, are addressed when identified. Even for one combat unit maximizing unit personnel readiness requires interaction between detailers of different assignment communities; the problem becomes much more complicated when the global objective is to maximize unit personnel readiness for all combat units.

The Navy maintains over 900 combat units. Each combat unit must report its personnel readiness. A unit's readiness is based on manning within its missions. Manning is defined as the percentage of manpower requirements filled by on-board

personnel. Each mission has a readiness measure (M-rating). The readiness measure for the entire unit, the C-rating, is equal to the minimum M-rating among the missions within the unit. A mission for a unit requires personnel with different attributes to support operational capabilities. Personnel are characterized by skill (ratings and Navy Enlisted Classifications) and experience (paygrades). A shortage of essential personnel degrades a mission. The large number of units, missions, and personnel to be matched make maximizing readiness a complex decision-making problem. Other researchers have studied the military personnel assignment problem and suggested models and solution techniques. However, no one has yet tried to incorporate the personnel readiness objective.

Approach

In our research we created an optimization model, which directly incorporates personnel unit readiness into the assignment process. The model belongs to a class of optimization problems known as *networks with side constraints*. The presence of network structure in mathematical programming models can greatly speed up the solution process through the use of specialized optimization techniques and data structures which have been developed over the past two decades. However, additional non-network constraints complicate the task. These constraints drastically diminish the advantages offered by the network structure. In such cases, the operations research analyst is compelled to design special solution techniques that will exploit the network structure and thus provide access to network optimization tools. One such specialized algorithm, the Linear-Quadratic Penalty (LQP) algorithm, has been used to solve very large planning models for the Military Airlift Command with *multicommodity network flow* structure, a special case of the network with side constraints model.

The personnel readiness problem has not been previously addressed in the Operations Research literature. Due to the large dimensions of the problem we were not able to solve it with available optimization packages. The model was formulated as a network with side constraints problem. A complicated formulation that attempts to minimize the number of side constraints was used. A formulation with approximately 17000 nodes, 36000 arcs and 3700 side constraints resulted. We

developed a heuristic algorithm that provides a feasible solution to the readiness problem and adapted the LQP algorithm to provide an optimal solution.

Results

With the above approach we were able to solve the full scale readiness problem for the Navy using a CRAY computer (Krass, Thompson, Pinar, & Zenios, in press). However, because the personnel readiness problem needs to be solved operationally and simultaneously with some other complicated problems (such as fleet balancing and school scheduling problems), we continued work to develop algorithms which will allow us to get nearly optimal solution using available IBM 4341/12 computers. This research also was successful. The corresponding algorithm, based on an optimization program of Professor Kennington and a "fan" approximated network, was built and tested. Results are presented in a paper (Krass, & Thompson, in preparation). Results will also be presented at the Organizational Research Society of America/The Institute of Management Sciences Joint National conferences in San Francisco and Chicago.

References

- Krass, I., Thompson, T., Pinar, M. C., & Zenios, S. A. (in press). A large-scale model to maximize Navy unit personnel readiness. *Management Science*.
- Krass, I., & Thompson, T. (in preparation). "Fair share" problem and approximated network with application to Navy unit personnel readiness.

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