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Man-Machine Integration Design and Analysis System (MIDAS) Task Loading Model (TLM) Experimental and Software Detailed Design Report

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(NASA-CR-177640) MAN-MACHINE INTEGRATION DESIGN AND ANALYSIS SYSTEM (MIDAS) TASK LOADING MODEL (TLM) EXPERIMENTAL AND SOFTWARE DETAILED DESIGN REPORT (Sterling Software) 75 p

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PREFACE

This is the Experimental and Software Detailed Design Report for the prototype Task Loading Model (TLM) developed as part of the Man-Machine Integration Design and Analysis System, as implemented and tested in Phase VI of the Army-NASA Aircrew/Aircraft Integration (A3I) Program. The A3I Program is a joint Army and NASA exploratory development effort to advance the capabilities and use of computational representations of human performance and behavior in the design, synthesis, and analysis of manned systems. The MIDAS TLM computationally models the demands designs impose on operators to aid engineers in the conceptual design of aircraft crewstations. This report describes TLM and the results of a series of experiments which were run this phase to test its capabilities as a predictive task demand modeling tool. Specifically, it includes discussions of: the inputs and outputs of the TLM; the theories underlying it; the results of the test experiments; the use of the TLM as both standalone tool and part of a complete human operator simulation; and a brief introduction to the TLM software design.

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1.0 INTRODUCTION

Task Load Prediction is a critical aspect of design; It is a construct related to performance measures and subjective workload ratings that may help spot design defects. Figure 1 depicts how the construct of task load relates to workload and performance from the MIDAS modeling perspective.

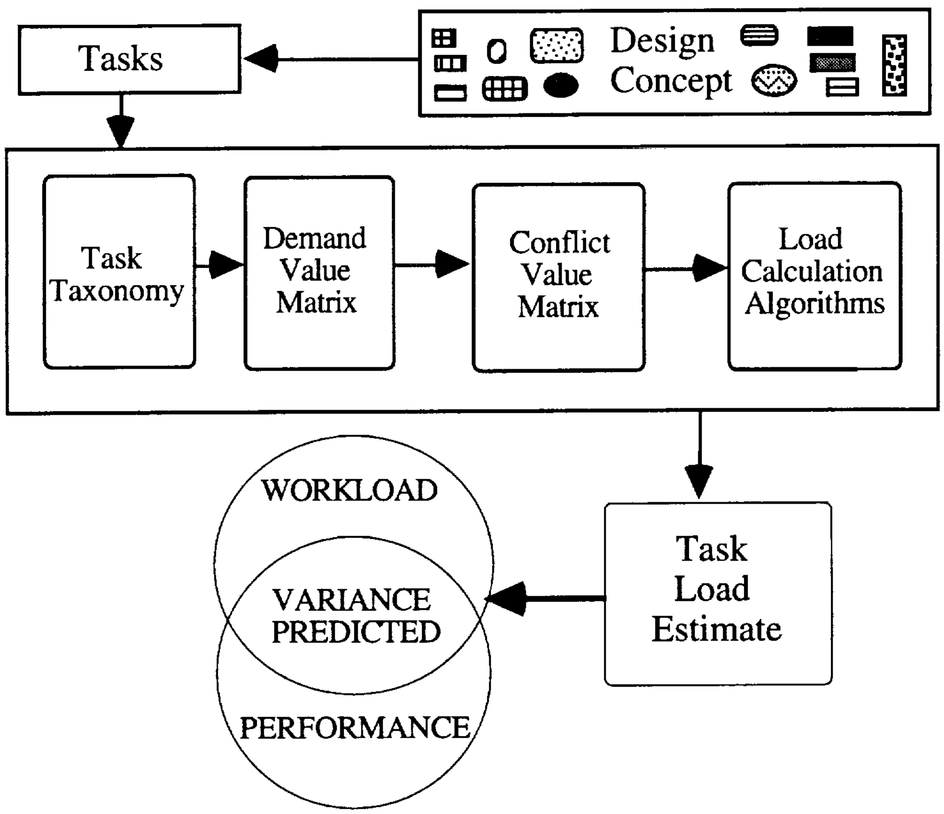


Figure 1-1: An overview of MIDAS Task Load Modeling

The MIDAS Task Loading Model computationally models the demands designs impose on operators to aid engineers in the conceptual design of aircraft crewstations.

- Load = Task Load = % resources required to meet demands.
- Loads modeled on four dimensions: Visual, Auditory, Cognitive, Motor.

1.1 Identification of Report

This reports details the TLM Experimental results conducted to test the TLM as a predictive task demand modeling tool.

1.2 Scope of Report

This report describes all of the aspects of the TLM. It describes the following in detail:

- The inputs and outputs of the TLM.

- The theories underlying the TLM.
- The experimental results from testing the TLM.
- Its use as a standalone and simulation modeling tool.
- A brief introduction to the TLM software design.

The readers of this report should have knowledge of human performance modeling techniques, human information processing theories, and some experience designing and analyzing experiments.

Refer to the MIDAS Software detailed design document for a complete report on the implementation of the TLM (Banda, C., Bushnell, D., Chen, S., Chiu, A., Neukom, C., Nishimura, S., Pisanich, G., Prevost, M., Shankar, R., Staveland, L., & Smith, G., 1991).

1.3 Objectives of Report

Readers will learn the following:

- How the TLM classifies task attributes.
- How the TLM represents imposed task demands and conflicts.
- How the TLM calculates the task load estimates.
- How well TLM task load estimates correlate with empirical performance and workload data.

2.0 TLM OVERVIEW

2.1 Goal of TLM

The overall goal of the MIDAS-TLM is to predict the information processing demands on each of four psychological dimensions that activities associated with a conceptual system design impose on the system's operator. The demands are used to calculate an estimate of task loading, allowing the system's designers to evaluate how a conceptual design affects information processing demands. The four dimensions are Visual, Auditory, Cognitive, Motor, abbreviated as VACM throughout this report.

Tasks and activities are used interchangeably in this report. They represent a low level procedure, operator movement, decision process or task that satisfies a goal.

2.2 Scope of TLM

The MIDAS-TLM expands the previously used MIDAS loading model to include an evaluation of the loads that are placed on pilots interacting with a given design within the context of a series of flight activities or tasks that are generated during a simulated flight. The TLM is an extension of computational workload modeling and simulation efforts by Wickens (1984), McCracken & Aldrich (1984), North & Riley (1989).

2.2.1 TLM as a Simulation Tool

The TLM computationally links with other MIDAS workstation tools and models that render a conceptual crewstation design and analyze the design for the activities required to operate it. The analyst classifies the activities using the TLM's task attributes and the MIDAS simulation changes the attributes to match the run time context. Estimated loads are calculated from the run time classifications.

2.2.2 TLM as a Standalone Tool

The TLM can be combined with a CAD tool and mission and task analysis tool to render a conceptual crewstation design and analyze the design for the activities required to operate it. The analyst classifies the activities using the TLM's task attributes. Estimated loads are calculated from the analyst classifications.

2.3 Definition of Task Loading

Task loading is defined as the aircrew's or operators' capabilities to perceive and process the information imposed on their perceptual, cognitive and motor systems by activity demands. This definition is based on the assertion of information processing which holds that human performance can be objectively and quantitatively described with information processing structures in conjunction with the mental processes that act on those structures (Wickens & Flach, 1988; Lachman, Lachman & Butterfield, 1979; Kantowitz & Roediger, 1980; Posner, 1986: Chase, 1986). This assertion leads to the following assumptions that form the basis of the TLM taxonomy, and the demand and conflict structures.

1. A structure is a symbolic representation of information.
2. A process is a manipulation of that representation.
3. A limited set of structures and processes represents the necessary task attributes for sufficiently estimating loads.

4. The structures and processes require resources to function.
5. The resources are attention, memory, and time.
6. Demands represent the percentage of the resources required for task performance.
7. Conflicts represent the imposition of similar demands required for concurrent task performance.

The demands are rank-ordered according to resource use. The task load estimates are calculated from the demands.

These demand values represent the relative magnitudes of the demands imposed on the person performing the activity(s). The magnitudes are anchored to a 100 point scale to differentiate load values among activities relative to other tasks, not to an absolute scale. Therefore, high load values represent potentially high demands. Potentially, because the demands are relative among tasks. If the average demands are low, then peaks may represent more demands, but may not represent high demands.

2.4 Definition of TLM Model

The model is an output, normative, bottom-up, multi-task model of imposed task demands. It is an output model because it generates the loading values after being fed a task description. It is normative because it assumes that the aircrews or system operators are highly skilled and motivated, and would perform in a manner that is rational and consistent with the information available, and with the constraints, risks and objectives that exist. It is bottom-up because it generates the values based on rank orderings of the interactions and combinations of basic perceptual, cognitive, and motor activities. In this sense, it also has some process and prescription characteristics, because the basic activities can be diagnostic of the problems in the conceptual designs (indicated by high loading values). It is a multi-task model because it evaluates the loading of a variety of tasks performed concurrently as well as serially.

2.5 Structure of TLM

Figure 2-1 graphically depicts the structural overview of the TLM. The top half of the graphic depicts the models functional structure, the bottom half depicts the computational structure. Both the functional structure and computational structure are depicted in three dimensions. The x-axis depicts processing from input to output. The y-axis depicts model attributes, either functional or computational. The z-axis depicts the tasks relevant to the analysis.

In the top half of Figure 2-1, the model's functional structure, the x-axis depicts the stages of information processing from the start to finish of a task, in which the stimuli are mapped to a response. The three stages are input modality (auditory and visual), central processing (response selection), and output modality (either verbal or manual response execution). The y-axis depicts both the demand values and the conflict values assigned to each dimension for each of the three stages. Visual and Auditory are in the input modality stage, Cognitive is in the response selection stage, and Motor is in the response execution stage. The demand values are partially listed. The conflict values (also partially listed) are depicted for the attributes of each task (shown in the z-axis) associated with each stage: reading multiple gauges are shown as separate tasks for the visual dimension. Choosing between the best responses given the different gauge readings is shown in the processing stage. Executing the correct movement is shown in the response execution stage.

The bottom half of Figure 2-1 shows how the TLM computationally represents the top half. The x-axis depicts in three steps how the TLM estimates loads from the analysts classification of the stimuli (input) to the estimates of demands and conflicts (processing) to the estimated load values for each dimension (output). The analyst classifies the stimuli of the tasks depicted in the Z-axis using the attribute taxonomy partially depicted in the y-axis. Table 2-1 lists the full taxonomy. This input determines the applicable demands and which demands conflict, which are algorithmically processed. The resulting load estimates for single or concurrent tasks can be output to any display or interface.

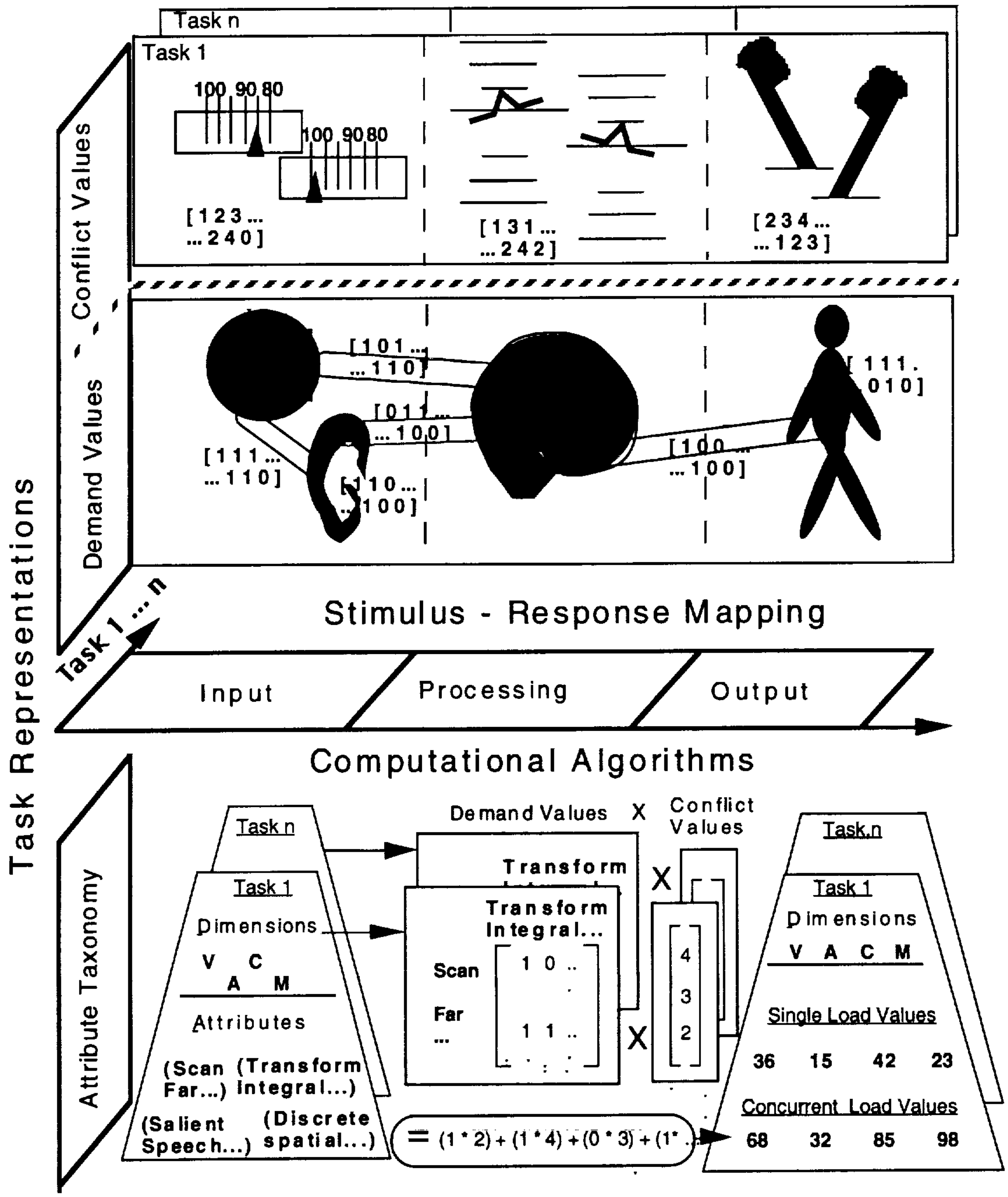


Figure 2-1. The structural design of the TLM.

2.6 Generation of Task Load Values

Generating load estimates requires three steps: classifying a task, listing the demand and conflict values referenced by the classification, and then calculating the load estimates from the lists of demand and conflict values. In step 1, an analyst classifies tasks, using a taxonomy of perceptual, cognitive and motor attributes (Table 2-1). The taxonomy parses imposed task demands into four dimensions; each dimension is parsed into sets of binary task attributes (only one member of a pair per task). Based on a literature review, the memory, attention, and time demands and conflicts between attributes in this taxonomy were rank ordered. Note that in the TLM the rankings do not change across tasks or task contexts.

Table 2-1: Taxonomy of Visual, Auditory, Cognitive and Motor Classifications.

Visual	Auditory	Cognitive	Motor
near visual	orient	direct	verbal
far visual	discriminate	transformation	spatial
scan	signal	single choice	near
fixate	speech	multiple choice	far
signal-ratio	signal-ratio	verbal	discrete
noise-ratio	noise-ratio	spatial	continuous
salient	temporal-location	separable	gross
masked	physical-location	integral	fine
static		planned	
dynamic		unplanned	

In step 2, the TLM creates lists of demand and conflict values from matrices of demand and conflict values using the classifications as matrix accessors. In step 3, the TLM algorithms are applied to the lists to generate load estimates for each VACM dimension.

2.7 Strengths of the TLM

First, and most importantly, the individual task demand values do not need to be specified—they are derived by the model. This frees a designer from having to specify the task demand values for each new set of tasks required to simulate a design. However, these values can be tailored to a testing environment by re-coding demand and conflict matrices before being used.

Second, by classifying a task, a designer/analyst makes explicit the information required and the kind of processing involved in performing a flight task.

Third, the conflict matrices explicitly predict conflicts between the demands required to perform the flight task..

Fourth, the classifications are context sensitive because they are adjusted to match the run time context. The classification of one task can influence the classification of another task.

Fifth, this approach allow for the loads a design imposes on an operator to be estimated during the conceptual design of the aircraft cockpit (or other complex system). These predictions normally occur late in the design phase after the requisite system mockups are built.

2.8 Limitations Of the TLM

1) In general, the TLM and MIDAS are dependent on the quantity and quality of the simulation state information encoded by analysts using MIDAS to build and simulate design scenarios. As a result, the simulation state information that determines imposed loads represents a subset of the possible state information that changes as the simulation progresses. Currently, this information adjusts only the Visual and Cognitive dimensions.

There were two reasons for this: One, MIDAS lacks a model of audition that can generate information useful to the TLM, and two, MIDAS lacks an operator continuous manual control model that can generate the appropriate psycho-motor information.

2) All VACM load values are relative. Do not treat them as absolutes. Values exceeding 100 mean little unless compared to all the activities in the overall load trace, and should be compared to additional simulation state information to determine the load drivers.

3) The weakness in this modeling approach lies in its testing requirements. This model uses complex classifications and algorithms to generate loading values that are difficult and time consuming to validate.

The values have only been tested four times: once in an experiment, and three times by retrofitting TLM predictions to empirical data: the first data were from an experiment conducted by Sarno and Wickens (1991), the second and third sets of data were from experiments conducted by Andre (1993). A fifth test currently underway uses an instrument flight simulator

2.9 Future Directions

A final experiment, described in section 7.0 is currently being conducted. However, no further extensions to the TLM are planned as part of the MIDAS program.

3.0 DETAILS OF VACM TAXONOMY

3.1 Generating Classifications

The taxonomy in Table 2-1 lists the attributes used to classify activities; as the table shows it is composed of four dimensions, each consisting a set of paired attributes. One attribute from each pair of attributes from each dimension can be used to classify an activity. However, one attribute from every pair does not have to be selected. Only those attributes that are relevant to the activity being classified are required. The definitions of the attributes used to determine relevancy are listed in section 3.3 (brief definitions) and 3.4 (detailed definitions).

The attributes selected from each dimension constitute the classification for an activity. The selected attributes are assigned a unique number within a dimension (numbers are re-used between dimensions). Within a dimension the numbers increase from 1 to n, where 1 is assigned to the first member of the first attribute pair, and *n* equals the number assigned to the second member of the last pair. Table 2, next page, lists the numbers assigned to the attributes.

The numbers assigned to each activity are represented as a nested list - a list of four sub-lists

For example, ((1 3 5 7 9)(2 4)(1 4 5 8 10)(2 4 6))).

The list of numbers assigned to an activity are passed as arguments to the TLM algorithms; the numbers index the task demand values and the conflict values that feed into algorithms that calculate the load values on each dimension for every activity or set of activities.

3.2 The Taxonomy Spreadsheet

Table 3-1 shows a taxonomic spreadsheet that can be used to manually classify each task or task combination. Task names are written in the spaces at the top of each column. The names of each attribute are listed in the left column, one attribute per row. To classify a task, the analyst uses available knowledge of task procedures and equipment to select one attribute from each pair of attributes listed. The number to the right of the attribute name is entered into the cells along that attribute's row, only in the columns that correspond to the tasks being classified. All of the numbers in a column become the classification list for the task listed at the top of the column. The lists of numbers become the row and column accessors to the matrices of demands and conflicts.

Table 3-1: The VACM full taxonomic classification spreadsheet.

	ELEMENTS		TASKS										
VISUAL	near	1											
	far	2											
	scan	3											
	fixate	4											
	signal - ratio	5											
	noise - ratio	6											
	salient	7											
	masked	8											
	static	9											
	dynamic	10											
AUDITORY	orient	1											
	discriminate	2											
	signal	3											
	speech	4											
	signal - ratio	5											
	noise - ratio	6											
	temporal loc	7											
	physical loc	8											
COGNITIVE	direct	1											
	transform	2											
	single choice	3											
	multiple choice	4											
	verbal	5											
	spatial	6											
	separable	7											
	integral	8											
	planned	9											
	unplanned	10											
MOTOR	verbal	1											
	spatial	2											
	near	3											
	far	4											
	discrete	5											
	continuous	6											
	gross	7											
	fine	8											

3.3 Brief Definitions Of The Taxonomic Attributes.

VISUAL-DIMENSION

NEAR:	Near visual field classification.
FAR:	Far visual field classification.
SCAN:	Fixating multiple stimuli.
FIXATE:	Fixating single stimuli.
SIGNAL-RATIO:	Greater stimulus signal.
NOISE-RATIO:	Greater noise signal.
SALIENT:	Strong stimulus signal.
MASKED:	Weak stimulus signal.
STATIC:	Stationary stimulus.
DYNAMIC:	Moving stimulus.

AUDITORY-DIMENSION

ORIENT:	Locate stimulus.
DISCRIMINATE:	Identify stimulus.
SIGNAL:	Non-verbal stimulus.
SPEECH:	Verbal stimulus.
SIGNAL-RATIO:	Greater stimulus signal.
NOISE-RATIO:	Greater noise signal.
TEMPORAL-LOCATION:	Localize stimulus in time.
PHYSICAL-LOCATION:	Localize stimulus in space.

COGNITIVE-DIMENSION

DIRECT:	Unprocessed stimulus mapped directly to a response.
TRANSFORM:	Stimulus needs processing to map to response.
SINGLE-CHOICE:	Stimulus requires processing.
MULTIPLE-CHOICE:	Stimulus requires complex processing.
VERBAL:	Stimulus is verbally encoded.
SPATIAL:	Stimulus is spatially encoded.
SEPARABLE:	Stimulus is uni-dimensional.
INTEGRAL:	Stimulus is multi-dimensional.
PLANNED:	Stimulus requires processing that maps to current situation.
UNPLANNED:	Stimulus requires processing that maps to different situation.

MOTOR-DIMENSION

VERBAL:	Verbal response required.
SPATIAL:	Spatial response required.
NEAR:	Input device close to effector.
FAR:	Input device not close to effector.
DISCRETE:	Short duration responses.
CONTINUOUS:	Long duration responses.
GROSS:	Large tolerances or motion in motor control.
FINE:	Narrow tolerances or small range of motion in motor control.

3.4 Detailed Definitions Of The Taxonomic Attributes.

Visual: Each visual taxonomic classifier (ie., scan, fixate, near, far) is a visual, perceptual attribute, usually referred to as a visual attribute, or just attribute. The attributes in the visual dimension characterize the information that is present in the optic array that is pertinent to the activity. This information is referred to as the visual stimuli, and the attributes classify the different aspects of the optic array.

Near versus Far: Defining *near-visual* as the visual stimuli in the cockpit and *far-visual* as the visual stimuli outside of the cockpit divides the spatial location of the stimuli in the optic array into two course-distinctions. The stimuli in the cockpit can be divided into quadrants (left, right, front, and back) to make finer distinctions between the locations. Transitions within a quadrant are classified as near, and transitions between quadrants are classified as far. The stimuli outside the cockpit can be divided in a similar fashion with classifications dependent on viewing distance instead of cockpit quadrant.

Scan versus Fixate: Classifying an activity as *scan* or *fixate* depends on the information acquisition process on the part of the pilot. In other words, the optic array may be sampled once or multiple times to acquire the stimulus or stimuli (a piece of equipment or object in the terrain). If multiple sampling occurs, then scan applies. Multiple sampling can occur within a display as well as across a display. If single sampling, fixate applies. Scan and Fixate are dependent on the level of activity decomposition (the extent of the detail of the activity definition). A multiple sampling can be a fixate if the information source, such as a HUD, is treated as a uni-dimensional source (a single stimuli), as in perceive HUD. However, if the activity is to interpret HUD, then scan applies because the pilot may have to individually sample each symbol on the HUD, treating each as a separate source of information (separate stimuli) that has to be sequentially fixated on to determine the status of the aircraft. The level of detail depends on the analytical questions asked.

Signal-to-Noise Ratio: These attributes classify only the energetic strength of the stimulus; they do not classify the operators knowledge of the stimulus, which helps set the operators thresholds for perceiving the stimulus. Accordingly, these attributes are not traditional measures of intelligibility or signal detection; however, these attributes capture more in the traditional sense when they are used to classify activities in conjunction with attributes in the cognitive dimension. Basically, the *Signal-to-Noise Ratio* attributes account for the imposed demands relating to whether the stimulus is discriminable: if it is, what the chance is of identifying it and if it is not, what the chance is of detecting it. The more discriminable the stimulus, the greater the signal to noise ratio, and conversely, the less discriminable the stimulus, the greater the noise to signal ratio.

Salient versus Masked: These attributes classify the objective, physical discriminibility of the stimuli, not the cognitive discriminibility. Cognitive salience is assumed if the object is physically discriminable (results of the simulation must be analyzed for the presence or absence of cognitive salience). Salience depends on the discriminibility of the stimuli with regard to the time-of-day, contrast, legibility, font size, display clutter, glare, spatial position (hard-to-see position in the cockpit), occlusion, weather conditions, movement, strength of perceptual grouping (possibly measured by the stimuli's coherence to gestalt principles), and other stimuli. If it's a night scenario, the displays may be *salient* due to cockpit lighting or *masked* due to incompatibility with night vision systems, and the external (far) visual stimuli may be masked due to darkness or salient if viewed through night vision systems. Conversely, in a daytime scenario external stimuli may be salient, or masked if there is fog. Internal (near/cockpit) stimuli may be masked due to glare, or they may be salient if glare is not a factor or if glare shields are used. If a display uses the proper font size, and with adequate contrast in daylight conditions providing legible display symbols, the visual stimuli would probably be salient. This classification depends on the simulated internal and external environmental conditions.

Static versus Dynamic: *Static* and *Dynamic* are fairly straight-forward attributes. A visual stimulus is static if it is stationary, if there is movement involved it is dynamic. It only becomes complicated if, for example, the compass rose of a horizontal situation display is moving, but the whole display is viewed as a static unit, and the individual display attributes (such as the moving compass rose) aren't the visual stimuli of interest.

Auditory: The auditory attributes are treated similarly to the visual attributes. Each auditory taxonomic classifier (ie., orient, discriminate) is an auditory, perceptual attribute, referred to as an auditory attribute, or just attribute. The attributes in the auditory dimension characterize the information that is present in the aural array that is pertinent to the activity. This information will be referred to as the auditory stimuli, and these attributes classify the different aspects of the aural array.

Orient versus Discriminate: *Orient* and *Discriminate* are attributes that classify the extent to which a pilot must process the aural stimuli. Orient refers to simply detecting or being alerted to the direction of a sound and or the general nature of the stimuli. Discriminate refers to identifying the stimuli by pinpointing the location in space, recognizing or recalling the specific kind of signal, and discriminating between different signals based on the direction, kind (e.g., frequency, amplitude, pitch), or temporal properties (simultaneous occurrence to cause grouping, or sequential occurrence to inhibit grouping and cause serial processing).

Signal versus Speech: *Signal* and *Speech* classify the type of aural stimulus. Signal is any kind of non-linguistic (non-verbal) stimulus. Speech is any kind of linguistic stimulus (machine generated, recorded or spoken).

Signal-to-Noise Ratio: These attributes classify only the energetic strength of the stimulus; they do not classify the operators knowledge of the stimulus, which help set the operators thresholds for perceiving the stimulus. Accordingly these attributes are not traditional measures of intelligibility or signal detection; however, these attributes capture more in the traditional sense when they are used to classify activities in conjunction with attributes in the cognitive dimension. Basically, the attributes account for the imposed demands relating to whether the stimulus is discriminable: if it is, what the chance is of identifying it and if it is not, what the chance is of detecting it. The more discriminable the stimulus, the greater the signal to noise ratio; conversely, the less discriminable the stimulus, the greater the noise to signal ratio.

Temporal Location versus Physical Location: These attributes classify the proximity and distribution of the stimulus in time and space. *Temporal location* captures whether the auditory stimulus is temporally proximal or temporally distant. *Physical location* captures whether the stimulus is physically proximal or distant from either ear. It also captures its direction.

Cognitive: The cognitive attributes classify the kind and extent of mental processing that is brought to bear on the stimuli. These attributes represent processes that act on the stimuli that have been filtered through the visual and auditory input modalities. These processes map the stimulus to the appropriate response(s). Activities should be subjected to a cognitive task analysis or a similar analytic activity in order to determine the activity details sufficient to assign a cognitive classification. Conversely, the definitions of the cognitive attributes also can be used to guide the analyst.

Direct versus Transformation: These attributes classify the stimulus-response mapping requirements. If the stimulus automatically evokes a response, a *direct* classification applies. If the stimulus needs to be modified or changed, a *transformation* classification applies. Automatic mappings may be activities, such as flight control under nominal conditions, in which changes in the aircraft's attitude are rapidly compensated, without interfering with another activity. If the flight control activity occurs in a severe thunderstorm, it could be classified as transformation since the stimulus (visual or haptic information) may at that time require extensive attention (an indicator of processing) to efficiently compensate for changes in attitude or changes in latitude. Transformations can be rotating visual input, recall or recognition of information to identify the stimulus, re-coding a visual image into an appropriate mental image (transforming infrared to normal "television view"), pattern recognition, computations, triangulations and other transformations. The stimulus may be hard to classify using direct and transformation definitions without the analyst specifying what information is required and how it will be used to perform the activities (i.e. a cognitive task analysis).

Single Choice versus Multiple Choice: These attributes roughly classify the amount of processing required. Essentially, *Single Choice* refers to one transformation or decision. It is the "easy" level, or least amount of processing required. If the activity is classified as a direct activity (see previous paragraph - direct versus transformation), then Single Choice is not used in the classification because direct assumes no choice - it is an automatic stimulus-response mapping process. If more than one transformation of the stimulus, or a lot of memory access, or more than one decision is required, the classification is *Multiple Choice.*

Verbal versus Spatial: These two attributes classify the form of the mental code in which the stimulus is received or processed. If the stimulus is linguistic, a *verbal* classification applies (digital information, alpha-numeric characters, symbols with linguistic or syntactic meaning). If the stimulus is not verbal, it's *spatial* - probably the most straightforward way to define it, since verbal is the more constrained and manageable set. Spatial stimuli can be symbols referring to spatial locations, symbols that indicate appropriate responses (pitch ladders), and analogue indicators of state information (airspeed indicators, pointers on the compass). Some things have both components, such as airspeed and compass displays. However, one or both classifications may be used depending on the activity. Reading airspeed would be verbal, checking for trend information - increase/decrease - would be spatial. In the general case, activities requiring specific state information probably are verbal, and those activities requiring trend, or rough estimates, probably are spatial.

Separable versus Integral : These two attributes classify the relatedness of the visual stimuli. Relatedness is defined with respect to function. The *integral* stimuli are related; *separable* stimuli are unrelated. The degree of relatedness depends on the functional nature of the stimuli and are defined in relation to the activity, display or environment, or relationships among the stimuli (e.g., color). The stimuli may be inherently related (similarities inherent to the stimuli, such as color or form), or they may be related by design principle or functionality (different forms but similar function, as in the HUD). In either case, related stimuli can be similar displays, similar symbols used in displays, similar environmental objects, similar display fonts, and similar colors or color codes. Unrelated stimuli are just the opposite: dissimilar displays, symbols, etc.

Planned versus unplanned: These two classifiers pertain to attentional shifts associated with expected and unexpected events. If a stimulus is expected, attention can be primed for the onset of the stimulus and can be readily shifted to the stimulus without cost. The shift can occur in conjunction with attention focused on the current stimulus or attention can be rapidly shifted between the current and expected stimulus without interfering with the processing of the current stimulus. If the stimulus is unexpected, the attentional shift can incur a cost and interfere with either or both the current and unexpected stimuli. The interference can be in the form of reordering the stimuli for processing, restructuring the type of processing, or slow memory access. It can cause processing to go from an automatized or perceptual-response mode to an inferential, controlled, or "deeper" processing mode (i.e. pattern recognition to problem solving).

Motor: Each motor taxonomic classifier (e.g., verbal, spatial, gross, fine) is a motor-response attribute. The attributes in the motor dimension characterize the action that is required to generate a response to a stimulus or set of stimuli (an activity or set of activities). These actions will be referred to as the motor responses. The attributes classify the different aspects of a response(s). The motor attribute definitions are more straightforward than the others since they classify objective, observable behaviors: the specific types of movements, but not the physical effectors of movement. The specific types of movements the motor attributes classify can vary in degree, requiring classifications based on context

Verbal versus Spatial: These attributes classify the specific type of response. If the response is spoken, it's *verbal.* If the response is manual, it's *spatial.*

Near versus Far: These attributes classify the extent of the reach required to generate a response. If no reach is required or the reach is very-short, it's *near.* If the required reach is longer than very-short, it's *far.* Since these attributes represent a binary classification of a short-long continuum, near represents hands on the stick/collective, far represents a reach to the panel or from one side of the panel to the other. The point is to grossly differentiate between reaches that take less time versus more time. These attributes are used only with a spatial response, a near/far verbal distinction is meaningless

Discrete versus Continuous: These attributes differentiate between responses requiring a single movement or multiple movements. If one movement is required, it's *discrete.* If more than one movement, or the same movement over a length of time is required, it's *continuous.* For example, flipping a switch on the collective/cyclic or a panel is discrete, operating the collective or cyclic is continuous. Some movements, such as using a multi-function display, may be either discrete or continuous depending on the number of movements. A strict classification would limit one key punch for a discrete classification, but practically, a couple of quick key punches could be considered discrete. Extensive key punching would be continuous. The operating definition is the total time the movement must be maintained, short time periods as opposed to long ones.

Gross versus Fine: These attributes differentiate between two coarse levels of motor control, and gain of a control movement. If a movement requires very slight motor control inputs, it's *fine.* If a movement requires large motor inputs, it's *gross.* For example, a high gain system would be fine and a low gain system would be gross. Using a coolie hat with the OORT for target acquisition or low level flight control would be fine motor control, whereas NOE flight control or using the flight controls and the HUD to acquire a target with the reticle would be gross motor control.

4.0 TASK DEMAND AND CONFLICT MATRICES

This section lists the task attribute demand and conflict matrices and their values. Subsets of the values from each of these matrices are used to calculate the load values for single and concurrent tasks. In all the matrices that follow, the labels at the top of each column are abbreviations of the attribute names for the relevant dimension, For within-dimension matrices the letters match the names in the left column. For between-dimension matrices, the letters match the attribute names for the dimension listed at the begining of the row.

4.1 Matrices of Task demand Values: Tables 4-1 to 4-8.

Table 4-1: Visual Demand Values .

Visual Dimension	NR	Ne	Fa	Sc	Fi	SR	NR	Sa	Ma	St	Dy
Null Row	0										
Near	0	1									
Far	0	0	1								
Scan	0	1	0	1							
Fixate	0	0	1	0	1						
Signal Ratio	0	0	0	0	0	1					
Noise Ratio	0	1	1	1	1	0	1				
Salient	0	0	0	0	0	1	1	1			
Masked	0	1	1	1	1	1	1	0	1		
Static	0	0	1	0	0	0	1	1	0	1	
Dynamic	0	1	0	1	1	0	1	1	0	0	1

Table 4-2: Auditory Demand Values

Auditory Dimension	Nr	Or	Di	Si	Sp	Sr	Nr	Tl	Pl
Null Row	0								
Orient	0	1							
Discriminate	0	0	1						
Signal	0	0	1	1					
Speech	0	0	1	0	1				
Signal Ratio	0	0	0	0	0	1			
Noise Ratio	0	1	1	1	1	0	1		
Temporal Location	0	1	1	1	1	0	1	1	
Physical Location	0	0	1	0	0	0	1	0	1

Table 4-3: Cognitive Demand Values

Cognitive Dimension	Nr	Di	Tr	SC	MC	Ve	Sp	Se	In	Pl	Un
Null Row	0										
Direct	0	1									
Transformation	0	0	1								
Single Choice	0	0	1	1							
Multiple Choice	0	0	1	0	1						
Verbal	0	0	1	0	1	1					
Spatial	0	0	1	0	1	0	1				
Separable	0	0	1	0	1	0	1	1			
Integral	0	0	1	1	0	1	0	1	1		
Planned	0	1	0	0	0	0	0	0	0	1	
Unplanned	0	0	1	1	1	1	1	1	1	0	1

Table 4-4: Motor Demand Values.

(For this dimension, numbers are added to the abbreviations listed at the top to indicate which fingers are used, and correspond to the numbers of the fingers listed in the left columns.)

Motor Dimension	Nr	Ve	Sp	Ne	Fa	Di	Co	Gr	Fi	M	H	N E	LE	R E	B E	N H	R H	
Null Row	0																	
Verbal	0	1																
Spatial	0	0	1															
Near	0	0	1	1														
Far	0	1	1	0	1													
Discrete	0	0	1	1	1	1												
Continuous	0	1	0	0	0	0	1											
Gross	0	0	1	1	0	0	1	1										
Fine	0	0	1	0	1	1	0	0	1									
Mouth	0	1	1	1	1	1	1	1	1	1								
Head	0	1	1	1	1	1	1	1	1	1	1							
No Eyes	0	1	1	1	1	1	1	1	1	1	1	1						
Left Eye	0	1	1	1	1	1	1	1	1	1	1	1	1					
Right Eye	0	1	1	1	1	1	1	1	1	1	1	1	1	1				
Both Eyes	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1			
No Hands	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
Left Hand	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	

Table 4-4 continued: Motor Demand Values.

Motor Dimension	R H	B H	0L F	LT	1L F	2L F	3L F	4L F	0R F	R T	1R F	2R F	3R F	4R F	N Ft	L Ft	R Ft	B Ft
Right Hand	0																	
Both Hands	0	1																
No Left Fingers	0	1	1															
Left Thumb	0	1	1	1														
1st Left Finger	0	1	1	1	1													
2nd Left Finger	0	1	1	1	1	1												
3rd Left Finger	0	1	1	1	1	1	1											
4th Left Finger	0	1	1	1	1	1	1	1										
No Right Fingers	0	1	1	1	1	1	1	1	1									
Right Thumb	0	1	1	1	1	1	1	1	1	1								
1st Right Finger	0	1	1	1	1	1	1	1	1	1	1							
2nd Right Finger	0	1	1	1	1	1	1	1	1	1	1	1						
3rd Right Finger	0	1	1	1	1	1	1	1	1	1	1	1	1					
4th Right Finger	0	1	1	1	1	1	1	1	1	1	1	1	1	1				
No Feet	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1			
Left Foot	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
Right Foot	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
Both Feet	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 4-5: Visual-Auditory Demand Values.

Auditory / Visual	Nr	Or	Di	Si	Sp	Sr	Nr	Tl	Pl
Null Row	0	0	0	0	0	0	0	0	0
Near	0	0	1	0	1	0	1	1	0
Far	0	0	1	1	1	0	1	1	0
Scan	0	0	1	0	0	0	1	0	0
Fixate	0	0	1	1	1	0	1	1	1
Signal Ratio	0	0	1	0	0	0	1	0	0
Noise Ratio	0	0	1	1	1	0	1	1	1
Salient	0	0	1	0	0	0	1	0	0
Masked	0	0	1	1	1	0	1	1	1
Static	0	0	1	0	0	0	1	0	0
Dynamic	0	0	1	1	1	0	1	1	1

Table 4-6: Visual-Cognitive Demand Values

Cognitive / Visual	Nr	Di	Tr	SC	MC	Ve	Sp	Se	In	Pl	Un
Null Row	0	0	0	0	0	0	0	0	0	0	0
Near	0	0	1	0	1	0	0	0	0	0	1
Far	0	0	1	0	1	1	1	1	1	0	1
Scan	0	0	1	0	0	0	0	0	1	0	1
Fixate	0	0	1	1	1	1	1	1	0	0	1
Signal Ratio	0	0	1	0	1	0	0	1	1	0	1
Noise Ratio	0	0	1	0	1	1	1	0	0	0	1
Salient	0	0	1	0	1	0	0	1	1	0	1
Masked	0	0	1	0	1	1	1	0	0	0	1
Static	0	0	1	0	1	0	1	1	0	0	1
Dynamic	0	0	1	0	1	0	1	0	1	0	1

Table 4-7: Auditory-Cognitive Demand Values .

Cognitive / Auditory	Nr	Di	Tr	SC	MC	Ve	Sp	Se	In	Pl	Un
Null Row	0	0	0	0	0	0	0	0	0	0	0
Orient	0	0	1	0	0	0	1	1	1	1	1
Discriminate	0	0	1	0	1	1	1	1	1	1	1
Signal	0	0	1	0	1	0	1	1	1	1	1
Speech	0	0	1	0	0	1	1	1	1	1	1
Signal Ratio	0	0	1	0	0	0	0	1	1	1	1
Noise Ratio	0	0	1	1	1	1	1	1	1	1	1
Temporal Location	0	0	1	0	1	0	1	1	1	1	1
Physical Location	0	0	1	0	1	1	0	1	1	1	1

Table 4-8: Motor-Cognitive Demand Values .

(For this dimension, numbers are added to the abbreviations listed at the top to indicate which fingers are used, and correspond to the numbers of the fingers listed in the left columns.)

Motor Cognitive	Nr	Ve	Sp	Ne	Fr	Di	Co	Gr	Fi	M	H	EN	EL	ER	EB	H N
Null Row	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Direct	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
Transformation	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Single Choice	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
Multiple Choice	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Verbal	0	0	1	0	1	0	0	1	1	1	1	1	1	1	1	1
Spatial	0	1	0	0	1	1	0	1	1	1	1	1	1	1	1	1
Separable	0	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1
Integral	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	1
Planned	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
Unplanned	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Motor Cognitive	Nr	HL	HR	BH	NL F	LT	1L F	2L F	3L F	4L F	NR F	RT	1R F	2R F	3R F	4R F
Null Row	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Direct	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Transformation	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Single Choice	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Multiple Choice	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Verbal	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Spatial	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Separable	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Integral	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Planned	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Unplanned	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Motor Cognitive	Nr	NF	LF	RF	BF
Null Row	0	0	0	0	0
Direct	0	1	1	1	1
Transformation	0	1	1	1	1
Single Choice	0	1	1	1	1
Multiple Choice	0	1	1	1	1
Verbal	0	1	1	1	1
Spatial	0	1	1	1	1
Separable	0	1	1	1	1
Integral	0	1	1	1	1
Planned	0	1	1	1	1
Unplanned	0	1	1	1	1

4.2 Matrices of Task Conflict Values: Tables 4-9 to 4-16.

Table 4-9: Visual Conflict Values .

Visual Dimension	Nr	Ne	Fa	Sc	Fi	Sr	Nr	Sa	Ma	St	Dy
Null Row	0										
Near	0	1									
Far	0	10	2								
Scan	0	1	3	1							
Fixate	0	2	4	10	10						
Signal Ratio	0	1	3	2	1	1					
Noise Ratio	0	2	4	4	3	2	3				
Salient	0	1	3	2	1	1	2	1			
Masked	0	2	4	4	3	3	4	2	3		
Static	0	1	2	1	2	1	2	2	3	1	
Dynamic	0	4	3	3	4	3	4	1	4	2	3

Table 4-10: Auditory Conflict Values

Auditory Dimension	Nr	Or	Di	Si	Sp	Sr	Nr	Tl	Pl
Null Row	0								
Orient	0	1							
Discriminate	0	2	3						
Signal	0	1	2	1					
Speech	0	3	4	3	2				
Signal Ratio	0	1	2	1	2	1			
Noise Ratio	0	3	4	3	4	2	3		
Temporal Location	0	1	3	1	2	1	2	1	
Physical Location	0	2	3	3	4	3	4	3	2

Table 4-11: Cognitive Conflict Values

Cognitive Dimension	Nr	Di	Tr	SC	MC	Ve	Sp	Se	In	Pl	Un
Null Row	0										
Direct	0	1									
Transformation	0	2	3								
Single Choice	0	1	3	1							
Multiple Choice	0	2	4	2	3						
Verbal	0	2	4	2	3	3					
Spatial	0	1	3	1	4	1	2				
Separable	0	1	3	1	2	1	2	1			
Integral	0	2	4	3	4	3	4	2	3		
Planned	0	1	3	1	2	2	1	1	2	1	
Unplanned	0	2	4	3	4	4	3	3	4	2	3

Table 4-12: Motor Conflict Values.

Motor Dimension	Nr	Ve	Sp	Ne	Fa	Di	Co	Gr	Fi	M	H	N E	LE	R E	B E	N H	R H
Null Row	0																
Verbal	0	10															
Spatial	0	1	2														
Near	0	1	2	1													
Far	0	3	4	3	2												
Discrete	0	1	2	1	2	3											
Continuous	0	3	4	3	4	1	2										
Gross	0	1	4	1	3	3	4	1									
Fine	0	2	3	2	4	1	2	2	3								
Mouth	0	1	1	1	1	1	1	1	1	10							
Head	0	1	1	1	1	1	1	1	1	1	10						
No Eyes	0	1	1	1	1	1	1	1	1	1	1	0					
Left Eye	0	1	1	1	1	1	1	1	1	1	1	1	10				
Right Eye	0	1	1	1	1	1	1	1	1	1	1	1	1	10			
Both Eyes	0	1	1	1	1	1	1	1	1	1	1	1	1	1	10		
No Hands	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	
Left Hand	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10

Table 4-12 continued: Motor Conflict Values.

Motor Dimension	R H	B H	0L F	LT	1L F	2L F	3L F	4L F	0R F	R T	1R F	2R F	3R F	4R F	N Ft	L Ft	R Ft	B Ft
Right Hand	0																	
Both Hands	0	10																
No LFt Finger	0	1	0															
Left Thumb	0	1	1	10														
1st LFt Finger	0	1	1	1	10													
2nd LFt Finger	0	1	1	1	1	10												
3rd LFt Finger	0	1	1	1	1	1	10											
4th LFt Finger	0	1	1	1	1	1	1	10										
No Rt Finger	0	1	1	1	1	1	1	1	0									
Right Thumb	0	1	1	1	1	1	1	1	1	10								
1st Rt Finger	0	1	1	1	1	1	1	1	1	1	10							
2nd Rt Finger	0	1	1	1	1	1	1	1	1	1	1	10						
3rd Rt Finger	0	1	1	1	1	1	1	1	1	1	1	1	10					
4th Rt Finger	0	1	1	1	1	1	1	1	1	1	1	1	1	10				
No Feet	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0			
Left Foot	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10		
Right Foot	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10	
Both Feet	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10

Table 4-13: Visual-Auditory Conflict Values.

Auditory / Visual	Nr	Or	Di	Si	Sp	Sr	Nr	Tl	Pl
Null Row	0	0	0	0	0	0	0	0	0
Near	0	10	2	1	2	1	3	1	2
Far	0	3	4	3	4	2	4	3	4
Scan	0	1	3	3	4	3	4	2	3
Fixate	0	2	4	1	2	1	2	1	4
Signal Ratio	0	1	3	1	2	1	2	1	2
Noise Ratio	0	2	4	3	4	3	4	3	4
Salient	0	1	3	1	2	1	2	1	2
Masked	0	2	4	3	4	3	4	3	4
Static	0	1	2	1	2	1	3	1	2
Dynamic	0	3	4	3	4	2	4	3	4

Table 4-14: Visual-Cognitive Conflict Values

Cognitive / Visual	Nr	Di	Tr	Sc	Mc	Ve	Sp	S	I	Pl	Un
Null Row	0	0	0	0	0	0	0	0	0	0	0
Near	0	1	3	1	3	1	2	1	2	1	3
Far	0	2	4	2	4	4	3	3	4	2	4
Scan	0	1	3	2	4	3	4	3	2	2	4
Fixate	0	2	4	1	3	1	2	1	3	1	4
Signal Ratio	0	1	3	1	2	1	2	1	2	1	3
Noise Ratio	0	2	4	3	4	3	4	3	4	2	4
Salient	0	1	3	1	2	1	2	1	2	1	3
Masked	0	2	4	3	4	4	3	3	4	2	4
Static	0	1	3	1	3	2	1	1	2	2	4
Dynamic	0	2	4	2	4	4	3	3	4	1	3

Table 4-15: Auditory-Cognitive Conflict Values .

Cognitive / Auditory	Nr	Di	Tr	Sc	Mc	Ve	Sp	S	I	Pl	Un
Null Row	0	0	0	0	0	0	0	0	0	0	0
Orient	0	1	3	1	3	1	2	1	2	1	3
Discriminate	0	2	4	2	4	3	4	3	4	2	4
Signal	0	1	3	1	4	1	2	1	4	1	3
Speech	0	2	4	2	3	4	3	2	3	2	4
Signal Ratio	0	1	3	1	2	1	2	1	2	1	3
Noise Ratio	0	2	4	3	4	3	4	3	4	2	4
Temporal Location	0	1	3	1	3	1	3	1	3	1	3
Physical Location	0	2	4	2	4	2	4	2	4	2	4

Table 4-16: Motor-Cognitive Conflict Values .

Motor / Cognitive	Nr	Ve	Sp	Ne	Fr	Di	Co	Gr	Fi	M	H	EN	EL	ER	EB	HN
Null Row	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Direct	0	1	2	1	2	1	2	1	2	1	1	1	1	1	1	1
Transformation	0	3	4	3	4	3	4	3	4	1	1	1	1	1	1	1
Single Choice	0	1	2	1	2	1	2	1	2	1	1	1	1	1	1	1
Multiple Choice	0	3	4	3	4	2	2	2	3	1	1	1	1	1	1	1
Verbal	0	4	2	1	2	1	2	1	2	1	1	1	1	1	1	1
Spatial	0	1	3	3	4	3	4	4	3	1	1	1	1	1	1	1
Separable	0	4	3	3	4	1	3	3	2	1	1	1	1	1	1	1
Integral	0	2	1	1	2	4	2	4	1	1	1	1	1	1	1	1
Planned	0	1	2	1	2	1	2	2	1	1	1	1	1	1	1	1
Unplanned	0	3	4	3	4	3	4	4	3	1	1	1	1	1	1	1

Motor / Cognitive	Nr	HL	HR	BH	NLF	LT	1LF	2LF	3LF	4LF	NRF	RT	1RF	2RF	3RF	4RF
Null Row	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Direct	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Transformation	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Single Choice	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Multiple Choice	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Verbal	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Spatial	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Separable	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Integral	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Planned	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Unplanned	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Motor / Cognitive	Nr	NF	LF	RF	BF
Null Row	0	0	0	0	0
Direct	0	1	1	1	1
Transformation	0	1	1	1	1
Single Choice	0	1	1	1	1
Multiple Choice	0	1	1	1	1
Verbal	0	1	1	1	1
Spatial	0	1	1	1	1
Separable	0	1	1	1	1
Integral	0	1	1	1	1
Planned	0	1	1	1	1
Unplanned	0	1	1	1	1

5.0 THE TASK LOADING MODEL CALCULATION ALGORITHMS

The VACM classifications determine which activity demand and conflict values are passed to the load calculation algorithm; This algorithm was derived from one developed by North & Riley (1989) and by Wickens & Andre (1989). It multiplies the appropriate demand and conflict values, summing their products to generate the load estimates for each dimension: L_V, L_A, L_C, and L_M.

5.1 The Algorithm's Factors

The load calculation algorithm pairs respective attributes of two index lists to select demand values from each of the conflict matrices. Three factors comprise this algorithm: VACM Index Integration, Activity Demand Integration and the Matrix Combining algorithm.

5.1.1 VACM Index Selection

VACM Index Integration integrates indices across tasks to determine which classification indices are paired to access their associated activity demand and conflict values. The 4 VACM sets of classification indices for each task combine within and across tasks to form the pairs of indices that act as the row and column indices to each of the demand and conflict matrices. This algorithm computes all the possible pairs of indices between two sets of classification indices.

For example,

The visual set for task one	maps to	visual set for task two.
(1 3 5)	maps to	(2 4 6)

The mapping forms 18 pairs of matrix reference lists;

(1 2), (1 4), (1 6), (3, 2), (3, 4), (3, 6, (5 2), (5 4, (5 6) and
(2, 1), (2, 3), (2, 5), (4, 1), (4, 3), (4, 5), (6, 1), (6, 3), (6, 5)

to calculate the load value for the interactions within the visual dimension across tasks.

This procedure repeats to calculate each of the four within dimension load values and each of the four between dimension load values that are averaged to calculate the VACM load values for each task and set of tasks.

5.1.2 VACM Index Integration

VACM Index Integration either integrates index lists across tasks to prevent task order effects, or it keeps the index lists separate. Integral sacrifices conficts to reduce the order effects. Separable represents all conflicts, but at the price of potentially biasing load estimates due to the order the tasks are passed to the algorithms..

For example,

The visual set for task one	maps to	visual set for task two.
(1 3 5)	maps to	(2 4 6)

The mapping forms one classification list — (1 2 3 4 5 6).

5.1.3 Activity Demand and Conflict Integration

Activity Demand Integration combines the activity demand values by multiplying the demand values in each subset selected from each matrix.

The product algorithm multiplies the demand values to penalize activity(s) to the extent that the interacting attributes have high mutual conflicts (Wickens & Andre, 1989). Multiplying high demands adds more to the resulting load values than multiplying low demands.

5.1.4 Matrix Combining Algorithms

Average across within and between matrices for each dimension.

5.2 Assumptions Underlying the Algorithms

Three assumptions were made to ensure that the algorithm was mathematically fair across the order of attributes.

1) A set consists of four values that defines a unique relationship between the rank orders of two pairs of attributes (two pairs of indices). The order of the values is dependent on the interactions among the two pairs, and only one value from the set enters into the algorithms.

2) The values used in the Activity Demand Integration factor are cross-multiplied, they do not have a unique relationship among each other and are, therefore, independent of order.

3) The values from each set are independent, therefore, the algorithms of the first factor insure that any one value is not given extra weight.

5.3 VACM Index Integration Algorithm for Calculating each Matrix Load

There are two distinct cases for calculating each matrix load: (1) Single Activities and (2) Multiple, Concurrent Activities. First, the pairs of indices are computed. Then the indices are used to access the demand values in the demand and conflict value matrices; the demand values are then mulitplied by its respective conflict value representing the conflict penalty. The Activity Demand Integration is represented by $(d_{tki}d_{uki})\ (c_{tki}c_{uki})$ in the equation below.

$$M_L = \sum_{t=1}^{s-1} \prod_{u=t+1}^{s} \prod_{k=1}^{n} \prod_{i=1}^{l} (d_{tki}d_{uki})\ (c_{tki}c_{uki})$$

d_{tki} = indices to the rows in the demand matrices
d_{uki} = indices to the columns in the demand matrices
c_{tki} = indices to the rows in the conflict matrices
c_{uki} = indices to the columns in the conflict matrices
s = number of concurrent activities
n = number of rows
l = number of columns
t, u = activity indices

5.4 Matrix Combing Algorithms to Calculate each VACM load

The final load value for each dimension is computed by averaging the within-matrix value with the appropriate between-matrix values. Appropriateness depends on which dimensions interact.

Information is assumed to be processed serially across stages. Consequently, the visual and auditory dimensions (the input modalities) interact with the central processing dimension (cognitive dimension) since they feed in the information and operate concurrently. The central processing dimension interacts with motor performance (the motor dimension) since it determines and monitors the course of action. There is no direct interaction between motor and vision or auditory. These interactions occur indirectly via cognition.

5.4.1 Visual Dimension

$$L_V = V_{cw} + \left[(VA_{bw} + VC_{bw}) / 2\right]$$

V_{cw} = loading value for the visual within-matrix
VA_{bw} = loading values for the visual-auditory between-matrix
VC_{bw} = loading values for the visual-cognitive between-matrix

5.4.2 Auditory Dimension

$$L_A = A_{cw} + \left[(VA_{bw} + AC_{bw}) / 2\right]$$

A_{cw} = loading value for the auditory within-matrix
VA_{bw} = loading values for the visual-auditory between-matrix
AC_{bw} = loading values for the auditory-cognitive between-matrix

5.4.3 Cognitive Dimension

$$L_C = C_{cw} + \left[(AC_{bw} + VC_{bw} + CM_{bw}) / 3\right]$$

C_{cw} = loading value for the cognitive within-matrix
AC_{bw} = loading values for the auditory-auditory between-matrix
VC_{bw} = loading values for the visual-cognitive between-matrix
CM_{bw} = loading values for the cognitive-motor between-matrix

5.4.4 Motor Dimension

$$L_M = M_{cw} + CM_{bw}$$

M_{cw} = loading value for the motor within-matrix
CM_{bw} = loading values for the cognitive-motor between-matrix

6.0 TLM VALIDATION PARAMETERS

The following sections list and discuss the parameters tested to validate the TLM.

6.1 TLM Base Experimental Design

Figure 6-1 shows the factors comprising the base design of the TLM that was implemented and tested. The TLM was tested by correlating load estimates for experimental conditions with the empirical data for those conditions. These factors are the same as shown in Figure 1-1, the overview of the TLM.

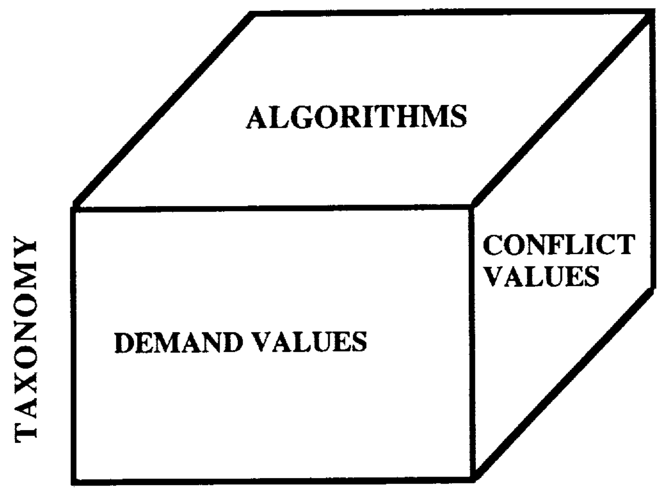


Figure 6-1: TLM Base Design

6.2 Experimental Design Parameters

Figure 6-2 shows the parameters that were varied for each of the factors in the basic design, which are discussed in the following sections.

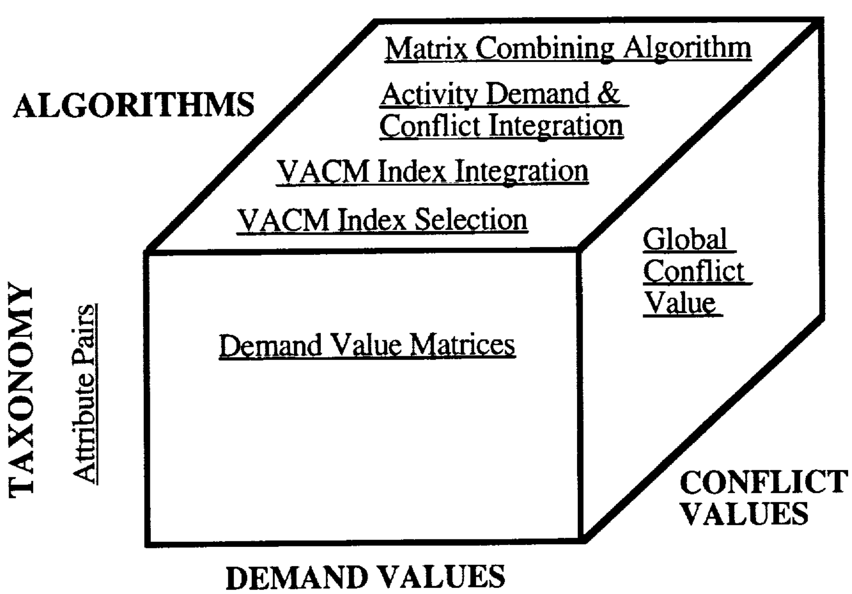


Figure 6-2: TLM Base Design Parameters

6.2.1 Taxonomy

The taxonomy is comprised of sets of binary task classification attributes for each of the four VACM dimensions.

6.2.2 Demand Values

Demand Values are sets of rank-ordered demands

6.2.2.1 Demand Matrices

Demand matrices are matrices of the ranks assigned to the task attributes. These values represent the demands impacting an operator during task performance.

6.2.2.2 Demand Matrix Values

The values in the demand matrices vary across task attributes represent varying magnitudes in demand.

6.2.3 Conflict Values

6.2.3.1 Global Conflict Values

Conflict values are the penalties assigned to the interacting demands that conflict during task performance. All demands are multiplied by a single global conflict value that represents the amount of conflicting resources. As the number of conflicts increase across tasks, the penalties increase.

6.2.4 Algorithms

6.2.4.1 VACM Index Selection

This factor determines how the task attribute index pairs that index the matrices of demand and conflict values are selected from the lists of task classifications.

6.2.4.2 VACM Index Integration

This factor determines how the task attribute lists are combined across tasks.

6.2.4.3 Activity Demand and Conflict Integration

This factor determines the type of calculations used in the equations that combine the demand conflict values.

6.2.4.4 Matrix Combining Algorithm

This factor determines how the values from the calculations for the within and between matrices are combined across dimensions.

6.3 Experimental Variations of the Design Parameters

Questions arose while developing the TLM. The questions led to variations in the design that needed experimental verification. Figure 6-3 lists the variations.

6.3.1 Taxonomy

6.3.1.1 Full Set: Table 3-1

Attribute Pairs per dimension:	5	4	5	4

Visual: near/far, scan/fixate, s-n ratio, salient/masked, static/dynamic
Auditory: orient/discriminate, signal/speech, s-n ratio, temporal/physical location
Cognitive: direct/transform, single/multiple choice, verbal/spatial, separable/integral, planned/unplanned
Motor: verbal/spatial, near/far, discrete/continuous, gross/fine

Use Table 3-2 to classify activities using this full set of attributes.

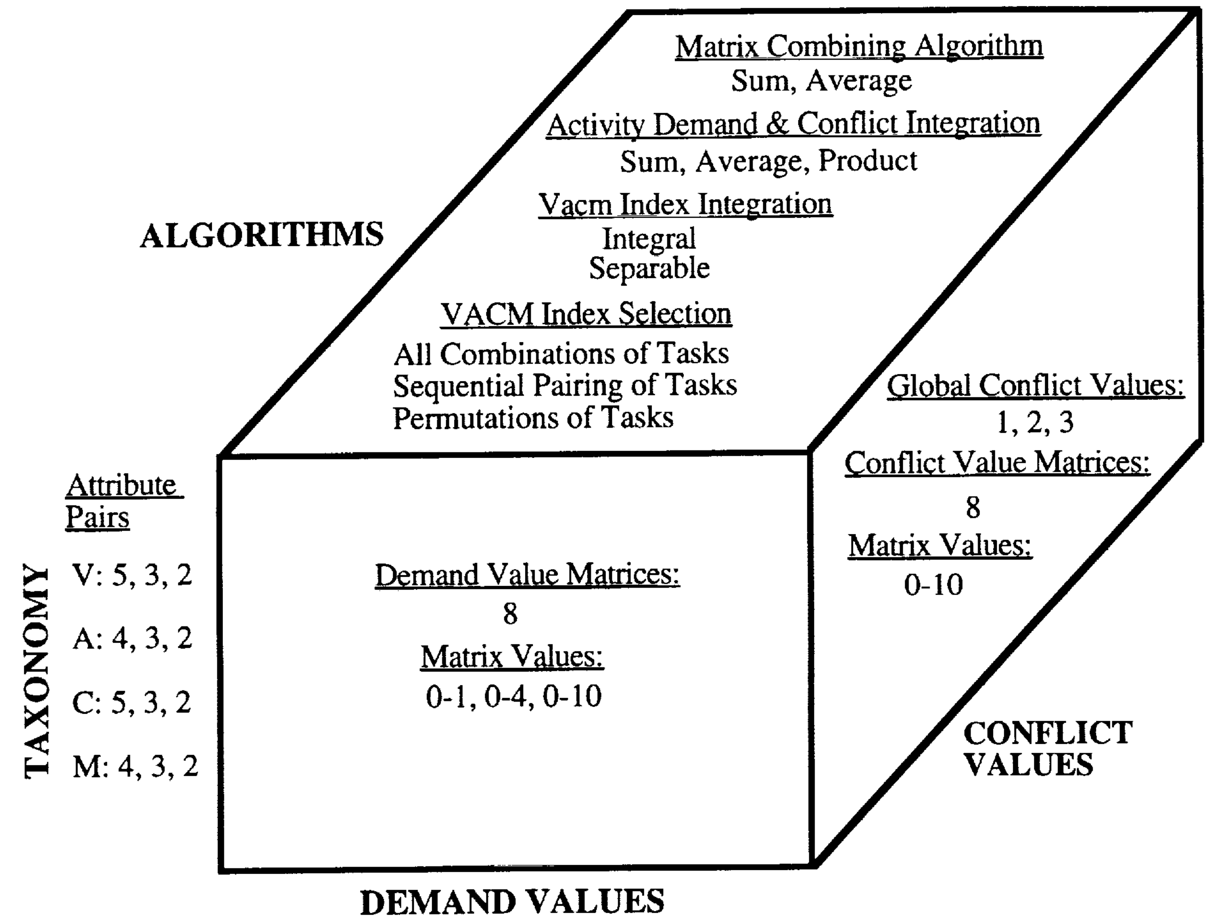


Figure 6-3: Variations in the Design Parameters That Were Tested

6.3.1.2 3 Pair Set: Table 6-1

Attribute Pairs per dimension:	3	3	3	3

Visual: near/far, scan/fixate, salient/masked
Auditory: orient/discriminate, signal/speech, temporal/physical location
Cognitive: direct/transform, single/multiple choice, planned/unplanned
Motor: verbal/spatial, discrete/continuous, gross/fine

Use Table 6-1 to classify activities using this full set of attributes.

Table 6-1: 3 pair taxonomic classification set spreadsheet.

	ELEMENTS		TASKS										
VISUAL	near	1											
	far	2											
	scan	3											
	fixate	4											
	salient	7											
	masked	8											
AUDITORY	orient	1											
	discriminate	2											
	signal	3											
	speech	4											
	temporal loc	7											
	physical loc	8											
COGNITIVE	direct	1											
	transform	2											
	single choice	3											
	multiple choice	4											
	planned	9											
	unplanned	10											
MOTOR	verbal	1											
	spatial	2											
	discrete	5											
	continuous	6											
	gross	7											
	fine	8											

Table 6-3: 3 pair taxonomic classification set spreadsheet.

	ELEMENTS / TASKS												
VISUAL													
	scan	3											
	fixate	4											
	salient	7											
	masked	8											
AUDITORY													
	orient	1											
	discriminate	2											
	temporal loc	7											
	physical loc	8											
COGNITIVE													
	direct	1											
	transform	2											
	single choice	3											
	multiple choice	4											
MOTOR													
	verbal	1											
	spatial	2											
	discrete	5											
	continuous	6											

6.3.1.3 2 Pair Set: Table 6-2

Attribute Pairs per dimension:	2	2	2	2

Visual:	scan/fixate, salient/masked
Auditory:	orient/discriminate, temporal/physical location
Cognitive:	direct/transform, single/multiple choice
Motor:	verbal/spatial, discrete/continuous

Use Table 6-2 to classify activities using this full set of attributes.

6.3.2 Demand Values

6.3.2.1 Demand Matrices

Eight: Four within-dimension and four between-dimension matrices.

Demand matrices are matrices of the ranks assigned to the task attributes. These values represent the demands impacting an operator during task performance.

6.3.2.2 Demand Matrix Values

Range: 0-1, 0-4, or 0-10

The test here is that a wider range of values better represent varying magnitudes in demand. Based on this assumption, the 0-1 range should correlate least well, the 0-4 range should correlate better, and the 0-10 range should correlate best.

However, Wickens' research, suggests that a binary set of demand values, Range 0-1, will add more systematic than random variance and correlate better than wider ranges, because they will only add more random than systematic variance.

6.3.3 Conflict Values

6.3.3.1 Global Conflict Values

Values: 1, 2, or 3

This factor globally increases the penalty value for conflicts among activities as the number of activities increases, irrespective of the type of conflict.

6.3.3.2 Conflict Matrices

Eight: Four within-dimension and four between-dimension matrices.

Conflict matrices are matrices of the penalties assigned to interacting task attributes that conflict during task performance. The number of matrices that best represent the set of weights must equal the number of demand matrices, since each demand matrix must have an associated set of weights. Visual-motor and auditory-motor weights won't be assigned if they do not have associated demand matrices.

6.3.3.3 Conflict Matrix Values

Range: 0-10

Multiplying demand values by conflict values specific to the conflicting demands represents conflicting resources between all tasks better than multiplying all demands by a single conflict value that represents the amount of conflicting resources.

6.3.4 Algorithms

6.3.4.1 VACM Index Selection:

Three algorithms were tested to determine how the task attribute index pairs should be selected from the lists of task classification indices entered into the task classification spreadsheets.

<u>All combinations across tasks</u>: Separately selects from each concurrent task all of the possible pairwise combinations among the classification lists for each task. This does not capture conflicts between tasks.

<u>Sequential pairings across tasks</u>: Separately selects from each concurrent task the sequential pairs from the classification lists for each task. This is the simplest case for combining the activity demand and conflict values. This does not capture conflicts between tasks. The order of the tasks does not affect the load estimates, because the estimates are calculated for each task and then summed across tasks.

<u>Permutations across tasks</u>: Selects the possible pairwise permutations between the classification lists of concurrent tasks. This captures conflicts between tasks. The order of the tasks does not affect the load estimates, because the permutations capture both of the orders possible for matrix reference.

6.3.4.2 VACM Index Integration

Two algorithms were tested to determine how the task attribute lists should be combined across tasks: Integral and Separable.

Integral: One classification list for each dimension is created by taking the union of each dimension's lists across all of the tasks. Pairs of indices are selected from each of the four integrated lists.

Separable: The classifications lists for each dimension are kept separate across tasks. Pairs of indices are selected from all of the lists.

6.3.4.3 Activity Demand and Conflict Integration

Operand: Sum, Average or Product

This factor determines the operand applied to the demand and conflict values for each within- and between-dimension matrix.

6.3.4.4 Matrix Combining Algorithms

Operand: Sum or Average

Sums or Averages across the load estimates for the within- and between-dimension matrices to calculate the load for each VACM dimension.

6.4 Final Design Parameters

Figure 6-4 lists the final design parameters discussed in the previous sections.

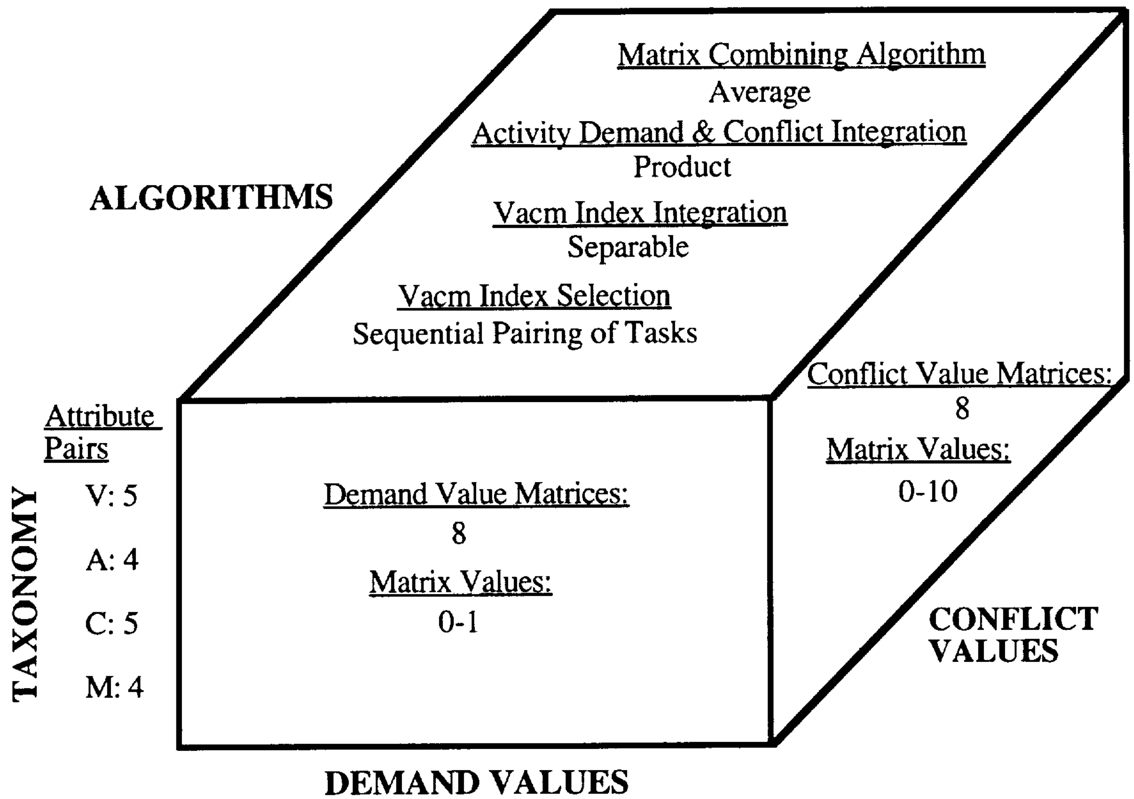


Figure 6-4: TLM Final Design Parameters

7.0 SUMMARY OF VALIDATION TESTS

Based on results from 4 tests, the TLM parameters that best model the data have been integrated into MIDAS. This section summarizes the results. A detailed discussion of the results is presented with the data in the next section.

The TLM's parameters were tested in two separate analyses of data from four experiments. In the first analysis, all of the parameters were tested. In the second analysis, a subset of the parameters were tested that included some changes based on the results of the first analysis. In the second analysis, the data from experiment 1 were not modeled again because the data were too variable to be reliable.

7.1 First Analysis of All Parametric Variations

All of the parameters that were varied were tested by fitting the TLM load estimates for conditions from four experiments to the results of those experiments.

Table 7-1:Parameters Tested

Taxonomy Taxonomy Attribute Pairs	**Demand Values** Demand Value Matrices Matrix Values
Conflict Values Global Conflict Values Conflict Value Matrices Matrix Values	**Algorithms** VACM Index Selection VACM Index Integration Activity Demand & Conflict Integration Matrix Combining Algorithms

All of the variations are not listed here because Figure 6-3 lists them. The variations resulted in 324 different load estimates for each condition that were generated from 324 different sets of parameters: each set contained one variation of each parameter from each factor listed above.

NOTE: Three variations listed in Figure 6-3 were not used in the first analysis, because they were added as a result of the first analysis. They are VACM Index Selection: Permutations Across Tasks, Conflict Values: Conflict Value Matrices, and Matrix Values.

7.1.1 Test 1: A rough look at the activity integration factor: using integral vs separable parameters with a full classification set to predict workload in a military helicopter environment.

This test only generated two sets of load estimates.

Table 7-2: Parameters and Variations Tested

Demand Values: Demand Value Matrices: 8 Matrix Values: 0-4	**Algorithms:** VACM Index Selection: All Combinations Within Tasks VACM Index Integration Integral Separable Activity Demand & Conflict Integration: Product Matrix Combining Algorithm Average

Results indicated that predicted loads were sensitive to how activity classification indices represent activity conflicts. Load estimates generated from separate dual task classifications correlated marginally higher than from integrated (the union of all classifications) dual task classifications (Tables 7-3 & 7-4). This was felt to result from the fact that more conflicts were captured using dual classifications than were captured using integrated classifications. Conflicts were represented by multiplying demand values together; multiplying larger demand values implicitly factored in a conflict penalty.

Table 7-3:

Correlations between the paired comparison data from the attack and scout pilots and the MIDAS TLM predicted task loads (V=Visual, A=Auditory, C=Cognitive, M=Motor, Avg=Average Of VACM Values, Sc=Separable Classifications, Ic=Integral Classifications, *=Significant at the 0.01 level)

	V	A	C	M	Avg
Attack					
Single tasks	0.5782	-0.3958	0.3677	0.1780	0.4024
Dual tasks - SC	0.3682	-0.5966	-0.1092	0.3537	-0.4105
Dual tasks - CC	0.3036	-0.3826	-0.2192	-0.1006	-0.0682
Scout					
Single tasks	0.6077*	-0.4363	0.6401*	0.5402*	0.5831*
Dual tasks - SC	0.0329	0.0106	0.5424	0.2325	0.4123
Dual tasks - CC	-0.1465	-0.2069	0.0519	0.4227	-0.1232

Table 7-4:

Correlations between the workload ratings from the Attack and Scout pilots and the MIDAS TLM predicted task loads (V=Visual, A=Auditory, C=Cognitive, M=Motor, Avg=Average of VACM values, SC=Separable Classifications, IC=Integral Classifications, *=significant at the 0.01 level)

	V	A	C	M	Avg
Attack					
Single tasks	0.5859*	-0.3595	0.4814	0.1868	0.4780
Dual tasks - SC	-0.0208	-0.0836	0.4336	0.0992	0.1431
Dual Tasks - IC	-0.0993	-0.2849	0.2262	0.4851	-0.1059
Scout					
Single tasks	0.4582	-0.3440	0.6789*	0.5432	0.5324
Dual tasks - SC	-0.1999	0.1028	0.7079*	0.1484	0.4719
Dual tasks - IC	-0.007	0.1049	0.3344	0.4631	0.1455

Since this experiment indicated that capturing conflicts in addition to demands was important, conflict and conflict values were separated from the demand values to explicitly try to capture their effect. Consequently, tests 2, 3, and 4 represent conflicts as a separate Conflict Value Factor.

Another finding was that the dual task classifications were confounded with order; The order of classification lists among the tasks determines the row and column values for referencing the demand and conflict matrices. This order effect potentially can affect the load estimates because some interactions are not captured that may be important.

Because of the order effect and the fact that the marginal correlations may have stemmed from methodological problems in data collection, integrated classifications were used to generate load estimates for tests 2, 3 and 4 for the first analysis. However, the Integral and Separable variations were tested in the second analysis.

7.1.2 Test 2: Correlating predictions between the TLM, and the TLAP, VACP and W/Index workload models in a multiple task setting.

Table 7-5 lists all the parameters and variations in test 2 that were compared to the data from Experiment 2. (These were also tested against data from Experiments 3 and 4.)

Table 7-5
Parameters and Variations Tested

Taxonomy	Algorithms:
Taxonomy Attribute Pairs:	VACM Index Selection:
Full set	All Combinations of Tasks
3 Pair Set	Sequential Pairing of Tasks
2 Pair Set	VACM Index Integration:
	Integral
Demand Values:	Activity Demand & Conflict Integration:
Demand Value Matrices:	Sum
8	Average
Matrix Values:	Product
0-1	Matrix Combining Algorithm:
0-4	Sum
0-10	Average
Conflict Values:	
Conflict Value Matrices:	
8	
Matrix Values:	
0-10	

7.1.2.3 Task Conditions

The tasks used in this experiment were coded and classified according to the TLM Taxonomy, and used to predict the task demands imposed on the operator by the 17 task conditions. These predictions will then be correlated to the data used in the Sarno and Wickens (1991) study.

Task Conditions:
1) Tracking task
2) Monitoring task
3) Decision tasks
    1) visual or auditory presentation
    2) spatial or verbal cognition
    3) easy or hard conditions
    4) key press or voice responding

7.1.2.4 Subtasks

These conditions were evaluated using a task analysis to determine the list of subtasks the subjects had performed (Sarno & Wickens, 1991; pp 24-25). Seven subtasks were delineated and were assigned demands for each of the workload components in the three different models: TLAP, VACP and W/INDEX. These models were then used to make predictions for each of the sixteen multiple task conditions using the appropriate combinations of the seven subtasks. Product moment correlations were calculated between these predictions and the mean tracking decrements for each condition.

The seven subtasks used are

Tracking	Visual Processing	Spatial Cognition	Manual Responding
	Speech Processing	Verbal Cognition	Voice Responding

7.1.2.5 Contrasting the TLM with TLAP, VACP, and W/INDEX

Sarno & Wickens (1991) reported that their decision task data demonstrated little variance in performance as a result of multiple task interference. Therefore, they calculated percent tracking decrement scores for each of the 16 conditions based on decomposing the conditions into their respective subtasks, listed above. These tracking decrements were used to fit the predictions from the workload models. The TLM predicted loads for each of the 16 decision tasks paired with the tracking task. The TLM predictions used the same procedure to generate predictions that the workload models used (see section 9-11). The W/INDEX, VACP, and TLAP all produced one load estimate, so the individual TLM VACM load estimates were averaged for a comparable comparison. However, the mean VACM value showed the same patterns of results, although the correlations were lower than its component load estimates. Therefore, the component VACM values were graphed because they are more diagnostic, and because the TLM was designed to produce estimates along each dimension.

7.1.2.6 Results

The numbers on the x-axis of figures 7-1 to 7-5 correspond to the different algorithms used to calculate TLM load predictions; They are composed of the different combinations of parameters listed in Table 7-5. Table 7-6 maps the parameters to algorithm number only for the Full-set of taxonomic classifiers, because the same parameteric combinations repeat for the other sets of attribute pairs.

7.1.2.6.1 Taxonomy Factor

Figures 7-1 and 7-2 show the same patterns of correlations between the TLM load estimates and the Tracking decrement scores for the full-set and 2-pair set of taxonomic classifiers. Figures 7-3, 7-4 and 7-5 show the same patterns of correlations between the TLM and the TLAP, VACP and W/INDEX models. These patterns were the same for the 3-pair set of taxonomic classifiers, so these data weren't displayed. These patterns clearly show that the different levels of task attribute detail used to classify the tasks didn't have an effect. Parsimony would suggest rejecting the full-set and the 3-pair set. However, the full set of task attributes was kept as a final parameter because 1) It allows for more detailed classifications, which can potentially account for more conflicts among tasks and because the Full-set is currently in use, and 2) This factor wasn't sufficiently tested in this analysis, because the experimental conditions didn't methodically manipulate the level of task attribute detail. The final test (Experiment 5) examines the level of task detail required more thoroughly. If the results from this next test show no difference, then the number of task attributes TLM uses should be reduced.

7.1.2.6.2 Demand Value Factor

The three redundant patterns Figures 7-1 and 7-2 show results from the three Matrix Demand Value parameters, Matrix Values 0-10, 0-4, or 0-1. These patterns correspond to algorithms 1-18, 19-36, and 37-54 as shown in Table 7-6. Since the three patterns are the same, two of the Matrix Values can be rejected. For parsimony, 0-4 and 0-10 were rejected. The workload data shown in Figures 7-3, 7-4 and 7-5 clearly show the same patterns.

Table 7-6: The combinations of parameters tested that correspond to the Algorithm Type number list on the x-axis of Figures 7-1 to 7-5.

Algorithm Type #	Taxonomy	Matrix Demand Value	Activity Index Selection	Activity Demand & Conflict Integration	Conflict Penalty Value
1-3	Full Set	0-10	Combination	Average	1, 2, 3
4-6				Sum	1, 2, 3
7-9				Product	1, 2, 3
10-12			Sequential	Average	1, 2, 3
13-15				Sum	1, 2, 3
16-18				Product	1, 2, 3
19-21		0-4	Combination	Average	1, 2, 3
22-24				Sum	1, 2, 3
25-27				Product	1, 2, 3
28-30			Sequential	Average	1, 2, 3
31-33				Sum	1, 2, 3
34-36				Product	1, 2, 3
37-39		0-1	Combination	Average	1, 2, 3
40-42				Sum	1, 2, 3
43-45				Product	1, 2, 3
46-48			Sequential	Average	1, 2, 3
49-51				Sum	1, 2, 3
52-54				Product	1, 2, 3

7.1.2.6.3 Conflict Value Factor

In this first analysis, only the global conflict value parameter was used. Figures 7-1 to 7-5 show that increasing the value of the global conflict penalty generally increases the correlations. This can be seen by examining the algorithms in sets of three, e.g., 1-3, 4-6, ... 52-54. These triples map to conflict values of 1, 2 and 3 respectively. In most cases, the correlations increase as the conflict values increase, although the amount of increase varies widely across algorithms. The consistently higher correlations associated with higher values indicates that the conflict values can substantially affect the load estimates, often increasing the correlation coefficient by 0.2, except for algorithms 16-18. In these cases, the coefficients jump substantially from conflict values of 1 to 2, up to 0.7. They remain the same from 2-3 indicating that conflicts aren't discriminated further using a global increase.

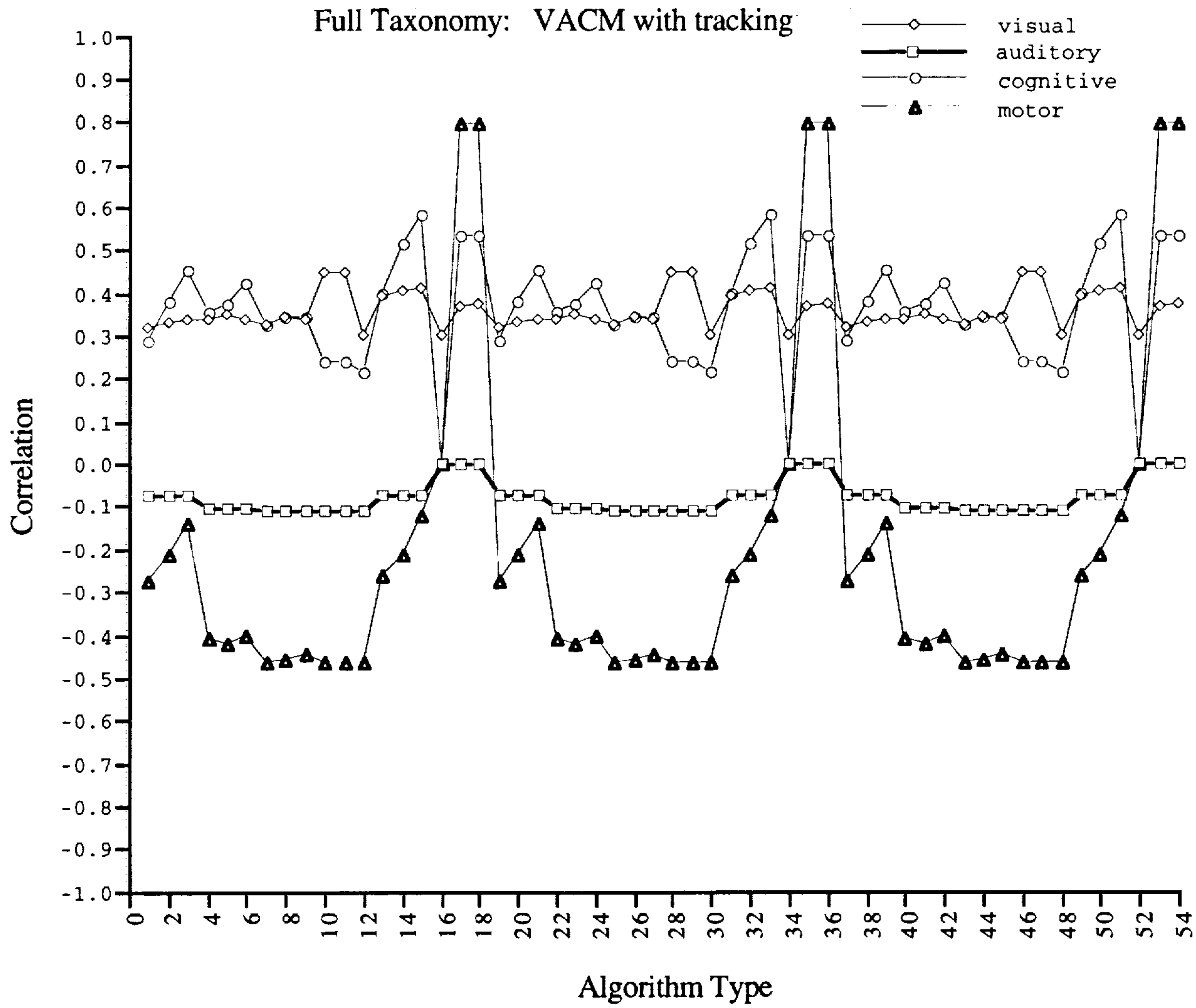


Figure 7-1: Correlations of TLM Load Predictions with percent tracking decrement scores using the full set of task attribute classifiers.

These results show that conflict values 1 and 2 can be rejected, using only a global value of 3. However, this approach can also be modified to try and increase the correlations by making the values more diagnostic. This approach was selected, but not applied to all the algorithms because of the repetitive effects. Choosing a more diagnostic approach was selected for testing in the second analysis because the results show the impact from penalizing conflicts, even when the penalties are applied indiscriminately to conflicts between demands, i.e., irrespective of the type of demands. Algorithm 18 was selected because it has the highest correlations, and because it didn't increase from values 2 to 3 implying a ceiling effect that could be mitigated using more diagnostic approach.

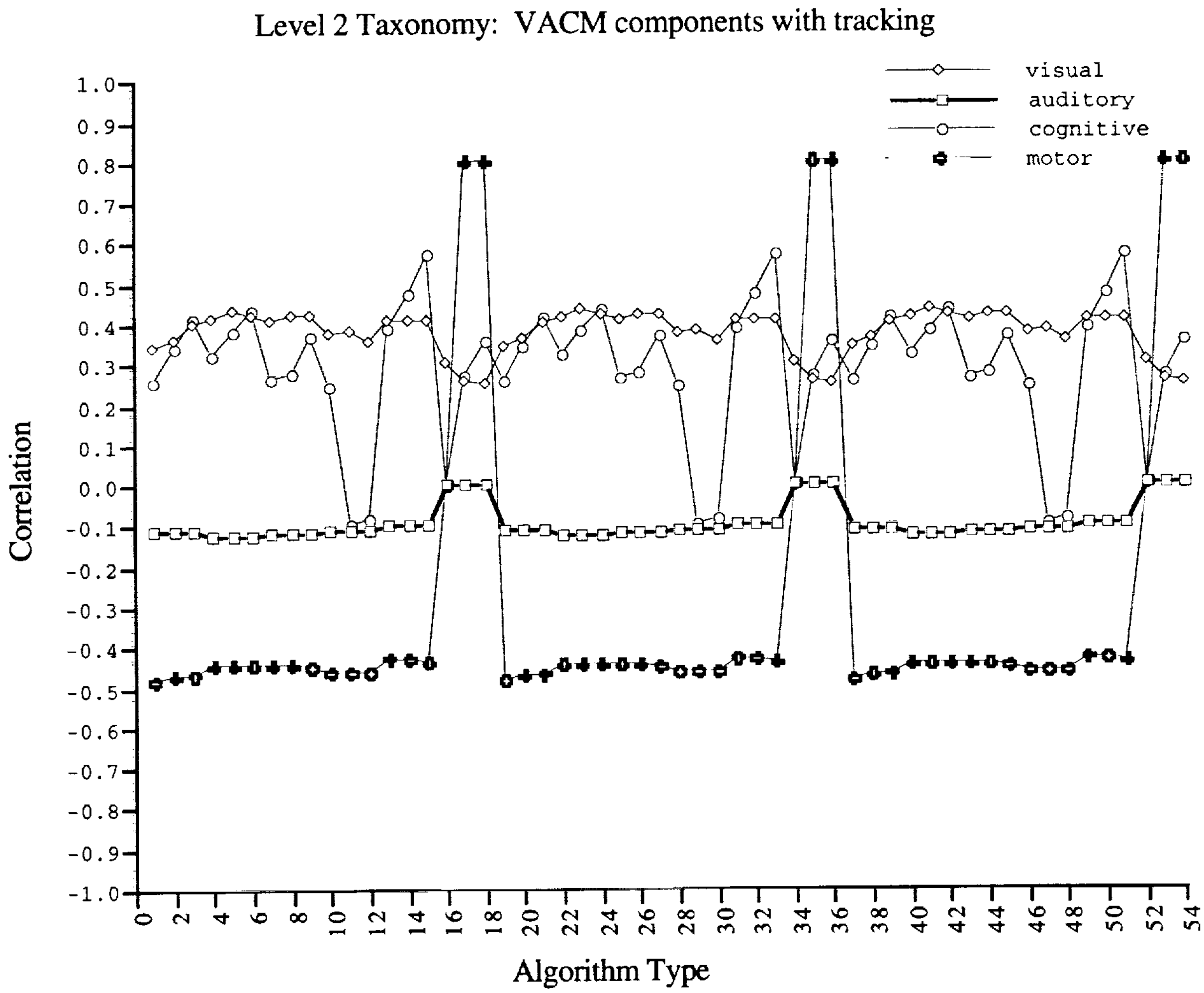


Figure 7-2: Correlations of TLM Load Predictions with percent tracking decrement scores using the set of task attribute classifiers reduced to two attribute pairs for each dimension

7.1.2.6.4 Algorithm Factor

7.1.2.6.4.1 Algorithm Index Selection

This parameter was varied by manipulating the way pairs of indices are formed. The Figures show that Algorithms 1-9, forming index pairs from all possible combinations of classification lists that are integrated across tasks, correlated less well than Sequential Selection, Algorithms 10-18. These patterns were repeated for the rest of the algorithms. This is a surprise because combinations capture all possible conflicts between demands, whereas sequential pairing does not. In fact sequential pairing captures only a small number of the conflicts. This suggests that capturing all possible conflicts adds noise past a certain point. The addition of conflicts past this point could add noise because relevant and irrelevant conflicts aren't distinguished. The best representation of conflicts then is not the total of them, but a set of important ones. In this light, combinations add to many relevant and/or irrelevant conflicts, while sequential pairing adds to few.

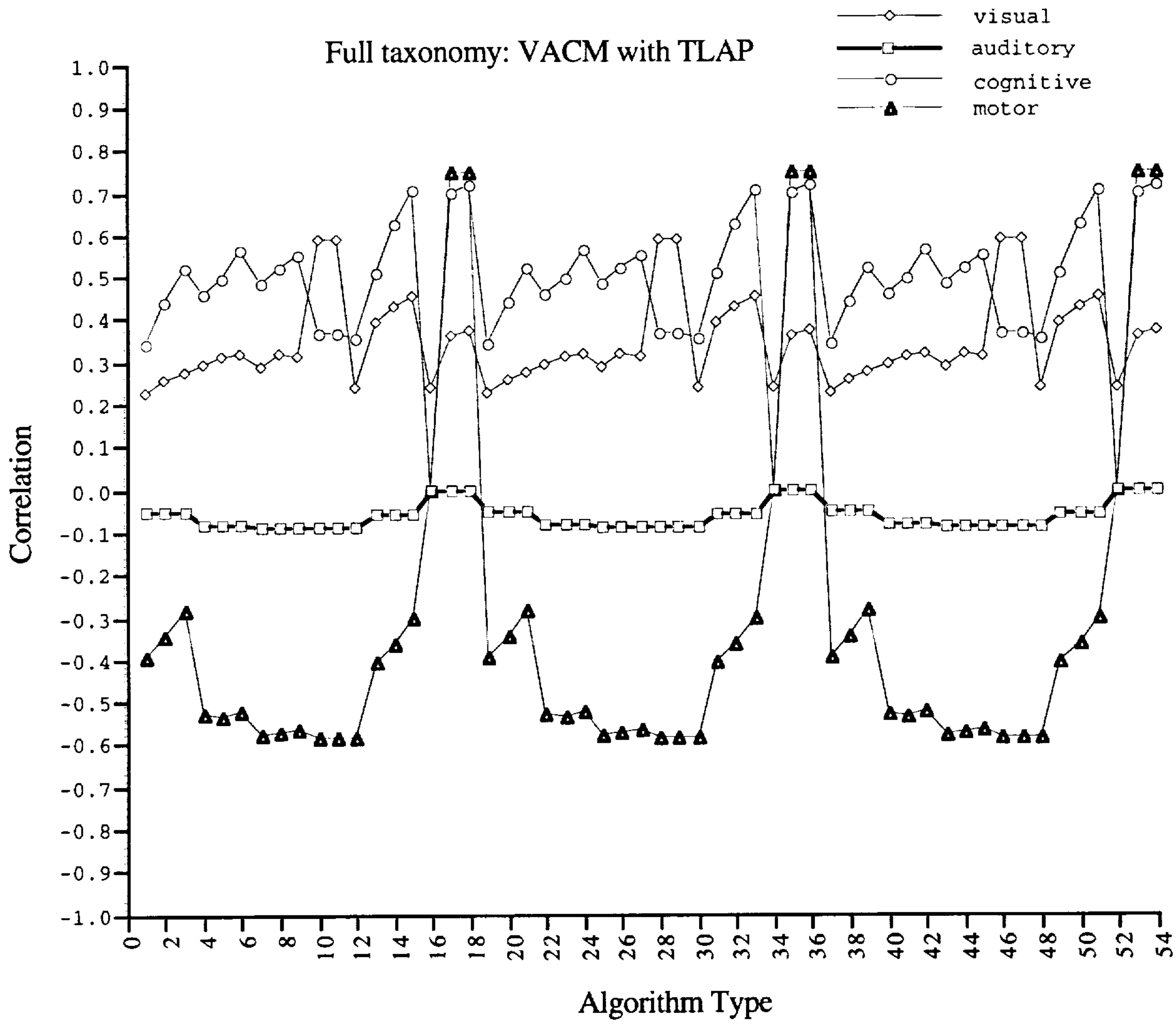


Figure 7-3 Correlations of TLM Load estimates with TLAP estimates using the full set of task attribute classifiers.

The first analysis could not distinguish between relevant or irrelevant conflicts because the index lists were integrated before the pairs were formed. This completely confounded the different types of conflicts among demands between tasks. This finding supports the results from Test one, which indicated that lists of indices that were integrated across tasks correlated less well than separated lists. Since the integrated lists were chosen for this first analysis to mitigate a possible order effect in the light of the marginal correlations from Test 1, a different approach was chosen for analysis two that uses separable classification lists that account for any order of tasks. This approach uses permutations of classification lists across tasks, which avoids order effects and also differentiates between relevant and irrelevant conflicts between task demands.

7.1.2.6.4.2 Activity Demand and Conflict Integration

This parameter determines whether the products of the demands and the conflict values are averaged, summed or multiplied. The Figures show that the average correlates least well, and that the product correlates best. The sum correlations are highest for Sequential Index Selection. Though not as high as the product, they were sufficiently high to retain for the second analysis.

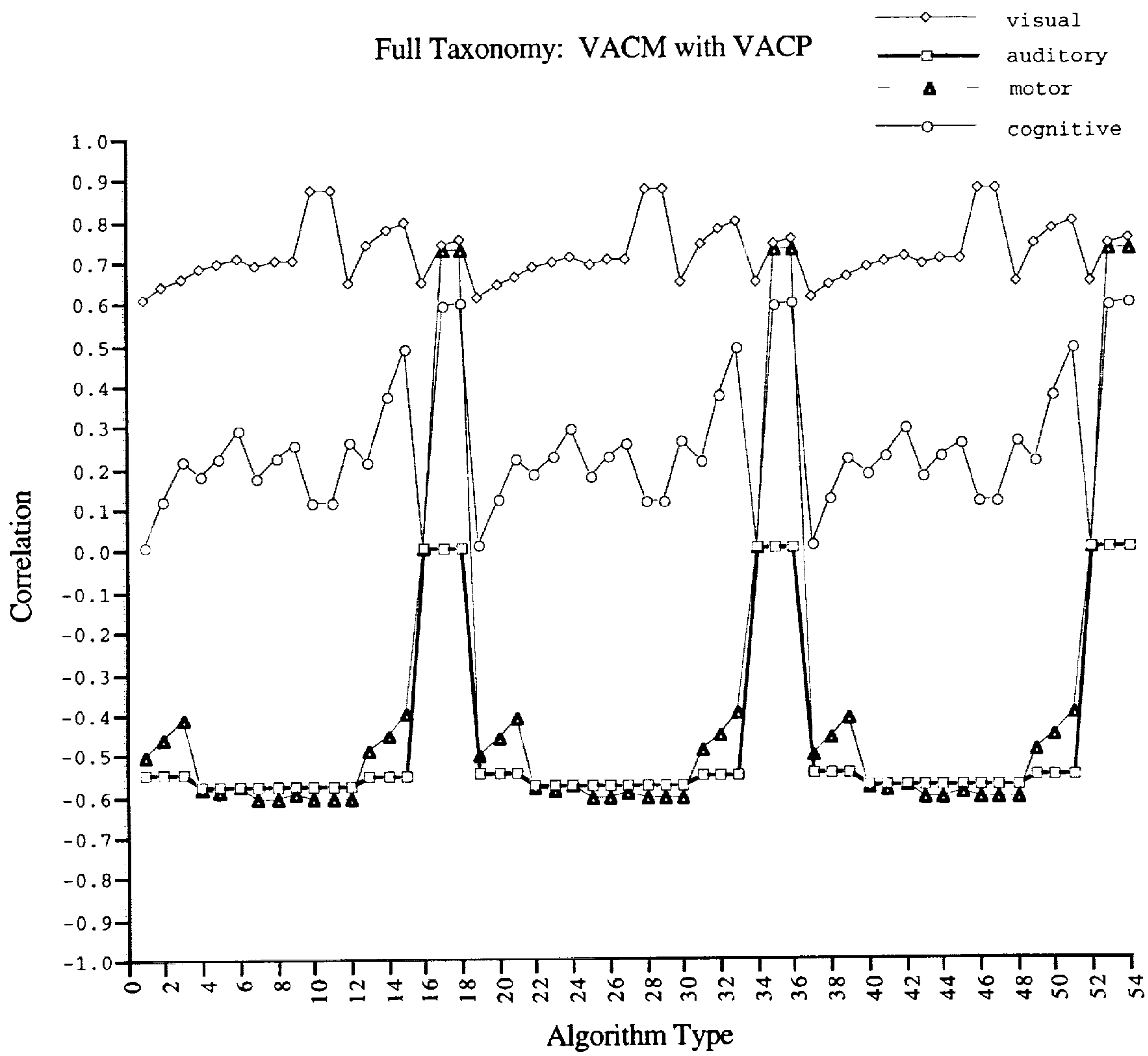


Figure 7-4 Correlations of TLM Load estimates with VACP estimates using the full set of task attribute classifiers.

7.1.2.6.4.3 Matrix Combing Algorithms

This parameter determines how the values that are calculated for each of the within- and between-matrices using the Activity Demand and Conflict Integration parameter are combined. They were either summed or averaged. There was no difference between the two, so the Average was chosen.

7.1.2.6.5 Correlation coefficient comparisons between the Models

The figures indicate algorithm type 18 generates the highest correlation. It uses the full taxonomic set of task attribute classifiers, task demand values ranging from 0 to 10, the summation and product algorithms, and a conflict penalty value of 3.

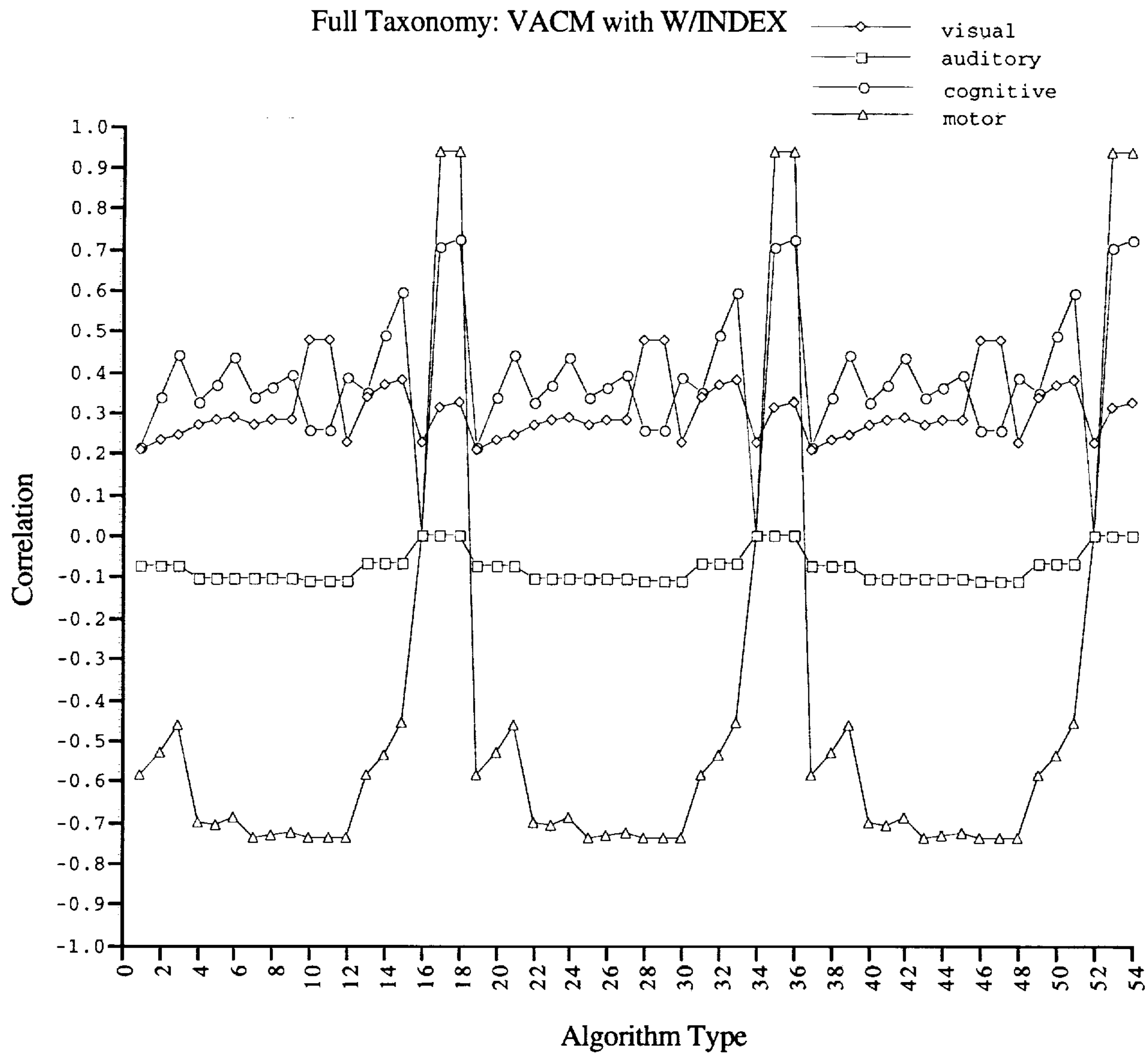


Figure 7-5 Correlations of TLM Load estimates with W/INDEX estimates using the full set of task attribute classifiers.

Table 7-7 lists the correlations between the load values predicted using #18, the predictions from the other models and the tracking decrement scores. It shows that the TLM overall load estimate correlates with tracking decrement scores at least as well as the TLAP and VACP models, but less well than W/INDEX. The TLAP, VACP and W/INDEX models only produced one load estimate in this experiment, so the TLM VACM load estimates were averaged for a comparable comparison. This overall load estimate is listed in the row titles TLM Overall Load.

However, the coefficients for the individual VACM dimensions are more diagnostic, and need to be considered. The highest correlations are found between for the cognitive and motor dimensions. This finding supports the diagnostic claim. The tracking decrement scores were for concurrent tracking and decision tasks that theoretically should impose more demands on motor and cognitive processes than on visual and auditory processes. Despite the fact that the decision tasks manipulated the auditory and visual modalities, TLM estimates did not correlate along these dimensions. Since only the VACP model has component estimates and they weren't reported, component comparisons between models can't be made.

Table 7-7:
Correlations between the various model predictions and tracking decrement scores. TLM predictions are for New Algorithms 1 - 6.
n=16, df=14, p<.10 = .426, p<.05 = .497, p<.01 = .623

Model	Tracking	TLAP	VACP	W/INDEX	W/INDEX NC
TLAP	.6725				
VACP	.7053	.8306			
W/INDEX	.8573	.8423	.8244		
W/INDEX NC: No spatial or verbal Code	.8301	.8645	.8800	.9747	
TLM Overall Load (mean VACM)	.7166	.7939	.9852	.8180	.8689
Visual	.3761	.4367	.7902	.3594	.4426
Auditory	.0	.0	.0	.0	.0
Cognitive	.6764	.8334	.9475	.8204	.8674
Motor	.7829	.7728	.7330	.9476	.9345

7.1.2.7 Summary of Test 2

In summary, the parameters can be classified as sensitive or insensitive to the experimental conditions (Table 7-8). The sets of algorithms were reduced to one that generated load estimates that correlated fairly well with the tracking decrement scores and with the other models' predictions.

Table 7-8:
Test 2 Results

Insensitive Parameters	Sensitive Parameters
Algorithms: Matrix Combining algorithms	**Algorithms:** VACM Index Selection
Taxonomy	Activity Demand & Conflict Integration
Taxonomy Attribute Pairs	**Conflict Values**
Demand Values Demand Value Matrices	Global Conflict Values

7.1.3 Tests 3 and 4: Predicting Attention effects using TLM in a multi-task windowing environment.

Tests 3 and 4 were conducted on data from two experiments that used a low fidelity multi-task simulation that investigated the effects of cue specificity on task preparation and performance (Andre and Heers, 1993). Both experiments were designed and presented using Window/PANES: Workload/PerformANcE Simulation (Andre & Heers, 1993).

The first experiment manipulated type of cue, either specific, general or no-cue. The second experiment manipulated difficulty level along with type of cue. The TLM was used to generate load estimates only for the different cue manipulations in both experiments, not for the difficulty manipulations. The TLM does not explicitly represent levels of difficulty. It implicitly represents difficulty as a function of the interacting task attributes, some of which impose more demands than others. (Experiment 5 was designed to test whether implicitly representing different levels of difficulty suffices.)

Since the second experiment was an extension of the first experiment, both will be discussed together. The TLM comparisons will state which data set is being modeled.

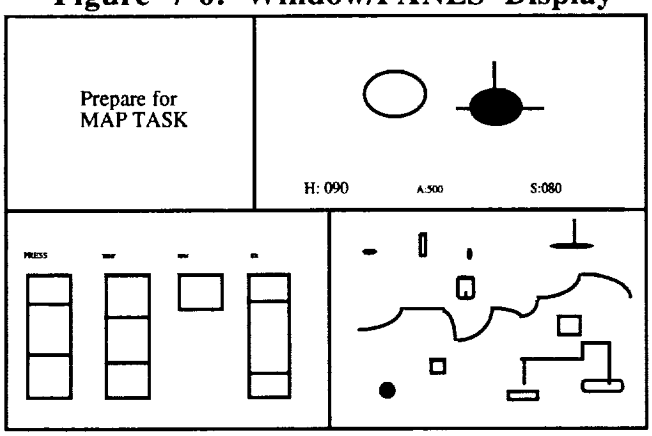
7.1.3.1 TLM Parameters Tested

The parameters tested against the Window/PANES data, tests 3 and 4, were the same as those tested against the Sarno & Wickens (1991) data, test 2 (Table 7-5). The results were very similar to those found in test 2. The results are discussed in the same order, but no figures will be presented, just tables of correlation coefficients.

7.1.3.2 Experimental Tasks and Conditions

The Window/PANES software presents a color display with four quadrants (Figure 7-6). The upper left quadrant displays alphanumeric messages and presented task questions and cue messages. The upper right quadrant displays the target and ownship symbols for the primary compensatory tracking task and includes digital heading, altitude, and speed indicators at the bottom , which were used in the flight path estimation task. The indicators changed value throughout the trial to reflect the ownships current position in each of the axes. The lower left quadrant displayed one digital and three analog gauges that were used for the gauge reference task. Finally, the lower right quadrant displayed a static top-down map composed of a variety of colored symbols that were used for the map orientation task.

Figure 7-6: Window/PANES Display



<u>Tracking Task</u>: Subjects performed a continuous compensatory tracking task throughout the entire trial. This Primary task was periodically time-shared with one of four secondary tasks: call sign, flight path estimation gauge reference and map orientation.

<u>Call Sign</u>: Subjects memorized a four-item alphanumeric string at the beginning of each trial for later recognition. Each time the message displayed an alphanumeric string, subjects had to decided if the string was identical to YES, or different from NO, the memorized string.

<u>Flight Path Estimation</u>: Subjects answered yes/no about their current heading or altitude relative to a specified heading or altitude by consulting the two indicators at the bottom of the tracking window. Questions pertained to either one axis or the other, never both.

<u>Gauge Reference</u>: Subjects answered yes/no to questions about the status of the red/safe zones of one or more of the gauges. The four gauges periodically changed values between their safe and upper and lower red zones. From the onset of the gauge question, the gauges were stabilized during the remainder of the task response interval to allow subjects to unambiguously assess their values.

<u>Map Orientation</u>: Subjects answered yes/no questions regarding the relative left/right locations of two specified map features. Subjects were instructed to view the map window as a static map which they were traveling across from left to right. To correctly, answer the question, subjects needed to locate the two items and assume the correct left-to-right orientation before judging their relative locations.

Cue Information: Specific cues informed the subject of the type of task about too ccur; General cues informed the subject only that a task was about to occur; or No Cues were given.

7.1.3.3 Results

Thee correlations listed in the tables that follow were generated by separately correlating TLM predictions with the performance data (collapsed across subjects) for the four different tasks (n = 4). The correlations were generated separately for the cue and no-cue conditions (four tasks per condition). The performance data correlated with TLM predictions for Andre & Heers' first experiment were rt and rms scores. For the second experiment, rt and rms performance data were used as well as four subjective measures: a visual load score (vl), a cognitive load score (cl), an overall workload score (ow), and a rank ordering of the difficulty of the tasks (rank).

7.1.3.3.1 Taxonomy Factor

This factor was not tested.

7.1.3.3.2 Demand Value Factor

The three redundant patterns found in Figures 7-1 to 7-5 resulting from the three Matrix Demand Value parameters, Matrix Values 0-10, 0-4, or 0-1 also were found in tests 3 and 4. These patterns clearly show in the correlations listed in Table 7-9. This table only show results for the cue conditions for both Andre & Heer's (1993) experiments, but the same results were found for no-cue conditions as well. This supports rejecting Matrix Values 0-4 and 0-10. Because of the low n, no significant correlations were found even though the correlations are high for the visual and cognitive dimensions.

Table 7-9: Window/PANES 1 Cue Conditions (Val = Matrix Value, Alg = Algorithm).
n=4, df=2, $p<.10 = .900$, $p<.05 = .950$, $p<.01 = .990$

Val	Alg	DV	vis	aud	cog	mot	ow
0-10	17	rms	.233	0	.364	0	.269
		rt	.768	0	.882	0	.802
	18	rms	.269	0	.378	0	.287
		rt	.802	0	.892	0	.818
0-4	35	rms	.233	0	.364	0	.269
		rt	.768	0	.882	0	.802
	36	rms	.269	0	.378	0	.287
		rt	.802	0	.892	0	.818
0-1	53	rms	.233	0	.364	0	.269
		rt	.768	0	.882	0	.802
	54	rms	.269	0	.378	0	.287
		rt	.802	0	.892	0	.818

7.1.3.3.3 Conflict Value Factor

Again only the global conflict value was used. Table 7-9 shows fairly similar correlations for algorithms 17 and 18, which used conflict values of 2 and 3 respectively. Not shown is algorithm 16, which had very low correlations. These results mirror those from test 2.

7.1.3.3.4 Algorithm Factor

The correlations of each of the algorithms with the Window/PANES data sets were high only for the 6 algorithms listed in the algorithm column in Table 7-8. This finding also mirrors the findings from test 2. These 6 algorithms use the parameters discussed in the following sections (also listed in Table 7-8).

7.1.3.3.4.1 Algorithm Index Selection

Sequential Pairing correlated highest.

7.1.3.3.4.2 Activity Demand and Conflict Integration

The Product of the demand values multiplied by their respective conflict values correlated highest.

7.1.3.3.4.3 Matrix Combing Algorithms

Little if any difference was found between summing and averaging.

7.1.3.4 Goodness of Fit

Tables 7-10 and 7-11 below show the TLM estimates correlate fairly highly with the rt's from the first and second Window/PANES experiments, but only for the cued conditions. The estimates show very high negative correlations with Window/PANES 1 No Cue conditions (Table 7-12) and not at all for Window/PANES 2 No Cue conditions (Table 7-13). Why this occurred is not at all clear. For all four tables, n=4, df=2, p<.10 = .900, p<.05 = .950, p<.01 = .990.

Table 7-10:
Window/PANES 1 Cue Conditions (Val = Matrix Value, Alg = Algorithm).

Val	Alg	DV	vis	aud	cog	mot	ow
0-10	18	rms	.269	0	.378	0	.287
		rt	.802	0	.892	0	.818

Table 7-11:
Window/PANES 2 Cue Conditions (Val = Matrix Value, Alg = Algorithm).

Val	Alg	DV	vis	aud	cog	mot	ow
0-10	18	rms	.589	0	.487	0	.574
		rt	.829	0	.760	0	.821

Table 7-12:
Window/PANES 1 No Cue Conditions (Val = Matrix Value, Alg = Algorithm).

Val	Alg	DV	vis	aud	cog	mot	ow
0-10	18	rms	-.981	0	-.989	-.993	-.989
		rt	-.712	0	-.747	-.775	-.746

Table 7-13:
Window/PANES 2 No Cue Conditions (Val = Matrix Value, Alg = Algorithm).

Val	Alg	DV	vis	aud	cog	mot	ow
0-10	18	rms	.084	0	.059	.039	.061
		rt	-.074	0	-.121	-.160	-.119

7.2 Second Test of All Parametric Variations

This second analysis only tested variations in four parameters of the Algorithm and Conflict Value factors. The first analysis indicated that these parameters were worthy of investigation (Table 7-14). The parameters are VACM Index Selection: Permutations Across Tasks; VACM Index Integration: Separable; Activity Demand & Conflict Integration: Sum and Product ; and Conflict Values: Conflict Value Matrices, and Matrix Values.

Table 7-14:
Parameters and Variations Tested

Conflict Values:	Algorithms:
Conflict Value Matrices: 8 Matrix Values: 0-10	VACM Index Selection: All Combinations of Tasks Sequential Pairing of Tasks Permutations of Tasks VACM Index Integration: Separable Activity Demand & Conflict Integration: Sum Product

All of these algorithms use the separable index integration algorithm. Task classification lists are not combined before the index pairs are formed. All index pairs are selected from the individual lists from all concurrent tasks. They also use the 0-1 Demand Matrix Values and the Full-set of task attribute pairs.

These variations resulted in 6 different load estimates for each condition that were generated from 6 different sets of parameters Table 7-15. These load estimates were re-correlated in tests 5 - 8 against the same four empirical data sets used in tests 1 - 4.

Table 7-15:
The combinations of parameters tested that correspond to the Algorithm number in Tables 7-16 to 7-20.

Algorithm Type #	Matrix Demand Value	Matrix Conflict Value	Activity Index Selection	Activity Index Integration	Activity Demand Integration
1	0-1	0-4	Combination	Separable	Sum
2	0-1	0-4		Separable	Product
3	0-1	0-4	Sequential	Separable	Sum
4	0-1	0-4		Separable	Product
5	0-1	0-4	Permutation	Separable	Sum
6	0-1	0-4		Separable	Product

7.2.1 Test 5: A rough look at the activity integration factor: using integral vs separable parameters with a full classification set to predict workload in a military helicopter environment.

This data set was not re-analyzed.

7.2.2 Test 6: Correlating predictions between the TLM, and the TLAP, VACP and W/Index workload models in a multiple task setting using the new algorithms.

The results shown in Table 7-16 indicate that algorithms 1 and 6 show the highest correlations across all models and tracking decrement scores. Comparing these coefficients to those in Table 7-7 shows that motor correlations increased for algorithms 1 and 6, cognitive correlations increased for algorithm six; some significant auditory correlations occurred; Visual correlations decreased somewhat, and only significantly correlate with VACP estimates. Based on this test, algorithm 6 appears best; it has the highest correlations and the most significant ones.

Table 7-16: Correlations between the workload models and tracking decrement scores for the 6 new algorithms.

n=16, df=14, $p<.10$ = .426, $p<.05$ = .497, $p<.01$ = .623

Alg	model	vis	aud	cog	mot	ow
	tlap	.434	-.002	.747	.832	.770
	vacp	.752	-.467	.534	.666	.571
1	pwdx	.359	.031	.696	.875	.741
	ncwdx	.431	-.056	.683	.848	.722
	track	.405	-.001	.639	.839	.707
	tlap	.272	-.083	.27	-.393	-.04
	vacp	.671	-.568	-.054	-.480	-.332
2	pwdx	.249	-.083	.145	-.553	-.186
	ncwdx	.317	-.177	.07	-.582	-.257
	track	.286	-.094	.245	-.278	.017
	tlap	.315	-.047	.479	.275	.421
	vacp	.660	-.545	.21	.078	.18
3	pwdx	.275	-.07	.345	.136	.287
	ncwdx	.344	-.158	.327	.125	.269
	track	.352	-.085	.459	.409	.460
	tlap	.302	-.041	.446	.318	.396
	vacp	.623	-.541	.162	.12	.124
4	pwdx	.264	-.068	.316	.183	.268
	ncwdx	.328	-.155	.296	.176	.246
	track	.354	-.085	.435	.446	.437
	tlap	.335	-.047	.714	.482	.628
	vacp	.696	-.540	.461	.275	.371
5	pwdx	.292	-.059	.645	.432	.553
	ncwdx	.364	-.147	.622	.385	.517
	track	.355	-.072	.632	.605	.622
	tlap	.35	-.091	.861	.806	.874
	vacp	.683	-.581	.822	.735	.831
6	pwdx	.323	-.109	.941	.965	.982
	ncwdx	.372	-.204	.941	.945	.969
	track	.354	-.109	.753	.839	.841

7.2.3 Tests 7 and 8: Predicting Attention effects using TLM in a multi-task windowing environment using the new algorithms.

Tests 7 and 8 show that algorithms 1 and 6 result in the highest correlations, with more significant correlations than the other algorithms (Tables 7-17 to 7-20), but only with rt, not with rms (same as the first analyses). Table 7-17 shows rt significantly correlating with visual and cognitive dimensions, but low correlations with the motor dimension despite the presence of the tracking task. Its possible that the tracking task was simply not hard enough. This is plausible since Andre & Heers (1993) reported that the type of cue showed no main of effect for tracking error in experiment 1; The tracking task was not difficult enough to benefit from cueing. Tables 7-18 and 7-19 support this, with little change in the degree of correlation or the number of significant ones. Although, Table 7-19 shows that algorithms 3 and 4, the permutation algorithms, correlate better relative to the cue condition.

Andre and Heers (1993) reported a main effect of task; Subjects data indicated that the tasks varied in difficulty. However, the data analyzed in this study were collapsed across tasks, so they could not be individually analyzed.

Comparing these results to those obtained in the first analysis (Tables 7-10 to 7-13) shows mixed results. Tables 7-19 and 7-20 show high though non-significant correlations with the visual and cognitive dimensions only for the cued conditions in both experiments. Table 7-20 shows high, and significant correlations between rt and the cognitive dimension in algorithms 1, 5, and 6; a single high, significant correlation with the visual dimension for algorithm 4; and cognitive and overall load for rms. Its hard to interpret the rms correlations because there are so few. However, algorithms 1 and 6 consistently correlate the highest.

Table 7-20 shows significant correlations only between the visual dimension and rt and between the visual dimension and visual workload report. These showed for algorithms 1, 2, 5, and 6, with algorithm 6 recording the highest correlations again.

Table 7-17: TLM load estimates correlated with Window/PANES 1 data collapsed across cue and no-cue conditions

n=8, df=6, p<.10 = .622, p<.05 = **.707**, p<.01 = **.834.**

Alg	model	vis	aud	cog	mot	ow
1	rms	.464	0	.511	.342	.51
	rt	**.799**	0	.545	.178	.624
2	rms	.311	0	.378	0	.25
	rt	.687	0	.381	0	.429
3	rms	.687	0	.527	.431	.622
	rt	**.865**	0	.343	.129	.524
4	rms	**.723**	0	.57	.364	.664
	rt	**.90**	0	.384	.054	.58
5	rms	.485	0	.519	.314	.503
	rt	**.816**	0	.547	.175	.634
6	rms	.382	0	.57	.208	.434
	rt	**.748**	0	**.710**	.136	.685

Table 7-18: TLM load estimates correlated with Window/PANES 1 data for no-cue conditions

n=4, df=2, p<.10 = .900, p<.05 = **.950**, p<.01 = **.990**

Alg	Model	vis	aud	cog	mot	ow
1	rms	.503	0	.800	.453	.683
	rt	.879	0	**.998**	.158	**.971**
2	rms	.388	0	.667	0	0
	rt	.801	0	.865	0	0
3	rms	.689	0	.566	.325	.717
	rt	**.966**	0	.455	-.027	.774
4	rms	.698	0	.593	.181	.730
	rt	**.965**	0	.499	-.192	.791
5	rms	.525	0	.795	.383	.668
	rt	.890	0	**.998**	.198	**.967**
6	rms	.492	0	.738	0	.584
	rt	.866	0	**.983**	0	.920

Unfortunately, comparisons can't be made with correlations found for Window/PANES 2 data in the first analysis, because the first analysis separated cue from non-cue conditions, while the second analysis collapsed across them. This was due to an oversight of the experimenter.

Table 7-19: TLM load estimates correlated with Window/PANES 1 data for cue conditions

n=4, df=2, p<.10 = .900, p<.05 = **.950**, p<.01 = **.990**

Algorithm	Model	Visual	Auditory	Cognitive	Motor	Overll Workload
1	**rms**	.346	0	.759	.774	.593
	rt	.831	0	**.993**	.244	**.951**
2	**rms**	.195	0	0	0	.195
	rt	.728	0	0	0	.728
3	**rms**	.714	0	**.958**	.672	**.994**
	rt	.947	0	.528	.075	.784
4	**rms**	.752	0	**.969**	.558	**.987**
	rt	**.950**	0	.557	-.055	.824
5	**rms**	.372	0	.801	.670	.555
	rt	.850	0	**.992**	.201	.949
6	**rms**	.155	0	.586	0	.169
	rt	.638	0	**.951**	0	.571

7.2.4 Summary of the Second Analysis

Since there was some doubt about whether algorithm 1 or 6 was better, a regression analysis was conducted in hopes that the two could be differentiated based on r-squared values adjusted for collinearity among the predictor variables. In these analyses, the VACM estimates were regressed on the empirical data in each experiment.

7.3 Regression Analysis

7.3.1 Test 9: Regressing on Sarno & Wickens tracking decrement scores

Table 7-21 shows that algorithms 1 and 6 have very similar adjusted r-squared values. Consequently, to decide between the two, the regression coefficients were analyzed (Table 7-22). This shows that each of the coefficients' contribution to r-squared is about the same, a little higher for algorithm 6 in fact, but the 2 tailed significance test indicates that only two are significant for algorithm 1, while three are significant for algorithm 6. Consequently, though 6 may do better, the difference will probably be slight.

Table 7-20: TLM load estimates correlated with Window/PANES 2 data collapsed across cue and no-cue conditions. n=8, df=6, p<.10 = .622, p<.05 = .707, p<.01 = **.834**

Algorithm	model	Visual	Auditory	Cognitive	Motor	Overall Workload
	rms	.516	0	.163	-.18	.255
	rt	**.905**	0	.489	.003	.61
1	**cl**	.157	0	-.139	-.256	-.061
	vl	**.867**	0	.423	-.069	.547
	o w	.41	0	.001	-.258	.111
	rank	.396	0	-.008	-.258	.1
	rms	.619	0	.034	0	.398
	rt	**.875**	0	.263	0	.545
2	**cl**	.296	0	-.169	0	.171
	vl	**.838**	0	.184	0	.484
	o w	.529	0	-.1	0	.305
	rank	.516	0	-.104	0	.298
	rms	.57	0	-.042	-.214	.132
	rt	.809	0	.066	-.188	.289
3	**cl**	-.24	0	-.475	-.531	-.457
	vl	.778	0	.009	-.241	.235
	o w	.015	0	-.437	-.564	-.35
	rank	0	0	-.44	-.563	-.358
	rms	.611	0	-.002	-.27	.193
	rt	.824	0	.087	-.252	.336
4	**cl**	-.293	0	-.525	-.494	-.492
	vl	.801	0	.034	-.307	.288
	o w	-.026	0	-.474	-.55	-.367
	rank	-.043	0	-.479	-.548	-.375
	rms	.533	0	.158	-.184	.271
	rt	**.914**	0	.479	.013	.623
5	**cl**	.134	0	-.157	-.226	-.053
	vl	**.878**	0	.413	-.061	.56
	o w	.392	0	-.019	-.227	.122
	rank	.377	0	-.028	-.228	.112
	rms	.535	0	.375	-.201	.433
	rt	**.928**	0	.706	.082	.827
6	**cl**	.292	0	-.088	0	.199
	vl	**.893**	0	.651	0	.773
	o w	.543	0	.117	0	.42
	rank	.529	0	.105	0	.408

Table 7-21: R-values of the VACM load estimates regressed on the tracking decrement scores from the Sarno & Wickens study

t	1	2	3	4	5	6
r-sq	0.854	0.774	0.269	0.274	0.702	0.837
r	0.924	0.880	0.519	0.523	0.837	0.914
adj r-sq	0.801	0.692	0.004	0.010	0.593	0.777
res ms	207.134	320.959	1039.53	1033.29	424.013	231.926
st err est	14.392	17.915	32.241	32.144	20.591	15.229
f-stat	16.1	9.45	1.02	1.04	6.48	14.1
num df	4	4	4	4	4	4
den df	11	11	11	11	11	11
signf	0.000	0.001	0.440	0.430	0.006	0.000

Table 7-22: Regression Coefficients of the VACM load estimates regressed on the tracking decrement scores from the Sarno & Wickens study

Name	Reg Coeff	St Error	St Coeff	T-Stat	2tailsig	Tolerance	Cont to R-Sq
Intercept	-36.352	18.041	-1.12	-2.0	0.06		
visual	1.9805	2.9397	0.39	0.6	0.51	0.03769	0.0060
auditory	1.1922	3.1398	0.22	0.3	0.71	0.03669	0.0019
cognitive	-3.7583	1.8004	-1.08	-2.0	0.06	0.04927	0.0576
motor	10.289	1.8861	1.65	5.4	0.00	0.14441	0.3935
Intercept	-45.477	19.663	-1.40	-2.3	0.04		
visual	101.35	37.534	0.80	2.7	0.02	0.16844	0.1079
auditory	89.730	54.777	0.42	1.6	0.13	0.22368	0.0397
cognitive	-46.464	25.471	-0.63	-1.8	0.09	0.12225	0.0492
motor	81.059	19.757	1.28	4.1	0.00	0.15109	0.2492

7.3.2 Test 10: Regressing on Window/PANES 1 Data

The selection of the best algorithm is more straightforward for Window/PANES 1 data. Table 7-23 indicates that 3 and 6 are good, with 3 being slightly better. Since these are for rms scores, which didn't correlate well with TLM load estimates, more weight should be given to the rt results. Table 7-24 shows that 6 accounts for nearly all the variance, with 3 a close second. These results support algorithm 6 as a good algorithm.

Table 7-23: VACM load estimates regressed on Window/PANES 1 rms collapsed across cue and no-cue conditions

	1	2	3	4	5	6
r-sq	0.407	0.159	0.832	0.538	0.578	0.815
r	0.638	0.399	0.912	0.733	0.760	0.902
adj r-sq	-0.03	-0.17	0.707	0.191	0.261	0.676
res ms	27.14	30.77	7.662	21.14	19.31	8.455
st err est	5.210	5.547	2.768	4.598	4.394	2.907
f-stat	0.92	0.48	6.63	1.55	1.83	5.89
num df	3	2	3	3	3	3
den df	4	5	4	4	4	4
signf	0.509	0.647	0.049	0.331	0.282	0.059

Table 7-24: VACM load estimates regressed on Window/PANES 1 rt collapsed across cue and no-cue conditions

	1	2	3	4	5	6
r-sq	0.720	0.471	0.985	0.916	0.777	0.997
r	0.848	0.686	0.992	0.957	0.881	0.998
adj r-sq	0.510	0.260	0.973	0.854	0.610	0.994
res ms	915284.8	1382230.8	48615.42	272340.42	727516.6	9643.13
st err est	956.705	1175.68	220.489	521.862	852.945	98.199
f-stat	3.43	2.23	88.3	14.6	4.66	450.91
num df	3	2	3	3	3	3
den df	4	5	4	4	4	4
signf	0.132	0.202	0.000	0.012	0.085	0.000

7.3.3 Test 11: Regressing on Window/PANES 2 Data

The selection of the best algorithm is not as clear for Window/PANES 2 data. Table 7-25 indicates that 3, 4, 5 and 6 are good predictors of rt. Three and 4 were about the same for rms, but this table was left out because the TLM load estimates were not good predictors overall the algorithms.

Table 7-26 shows that 3 accounts for all the variance when predicting subjects' Visual Workload reports, with 4, 6 and 5 closely following. These results support algorithm 3 and 6 as good predictors for both of the Window/Panes' experimental data sets. However, since 1 and 6 were good for predicting the tracking decrement scores for the Sarno & Wickens data, 6 seems to be the best predictor over all of the tests.

Table 7-25: VACM load estimates regressed on Window/PANES 2 rt collapsed across cue and no-cue conditions

	1	2	3	4	5	6
r-sq	0.966	0.789	0.998	0.985	0.978	0.979
r	0.983	0.888	0.999	0.992	0.989	0.989
adj r-sq	0.915	0.648	0.995	0.964	0.945	0.948
res ms	229037.4	955473.5	11050.71	97850.87	148598.9	140681.5
st err est	478.578	977.483	105.122	312.811	385.485	375.075
f-stat	19.1	5.62	409.6	45.6	29.8	31.5
num df	3	2	3	3	3	3
den df	2	3	2	2	2	2
signf	0.050	0.096	0.002	0.021	0.032	0.030

Table 7-26: VACM load estimates regressed on Window/PANES 2 Visual Workload Report collapsed across cue and no-cue conditions

	1	2	3	4	5	6
r-sq	0.949	0.751	1	0.997	0.967	0.976
r	0.974	0.866	1	0.998	0.983	0.988
adj r-sq	0.873	0.585	1	0.993	0.917	0.941
res ms	21.491	70.510		1.0434	13.968	9.9030
st err est	4.6359	8.3970		1.0215	3.7375	3.1469
f-stat	12.5	4.53		271.1	19.6	27.9
num df	3	2	3	3	3	3
den df	2	3	2	2	2	2
signf	0.074	0.123		0.003	0.048	0.034

7.4 Final Analysis

Based on these results of the first and second analyses and the regression analyses, the parameters were reduced to a final set (Figure 6-4, Table 7-27), and will be tested in a final experiment to be conducted in 1994.

7.5 Experiment 5: Predicting timesharing of tracking with modality and stage specific decision tasks in Instrusim using TLM.

7.5.1 Objective

The objective of the final experiment is to test which clash pairs capture modality and dimension specific interactions.

To test this, the experimental tasks need to reflect specific interactions across perceptual modalities and processing stages. The following design was created to fit this need. This experiment is currently being run using a simulation testing environment called Instrusim, developed by Dr. Tony Andre at Ames Research Center.

7.5.2 Design

Figure 7-7 depicts the design of this final experiment. The bottom two-thirds of the figure depict the different difficulty levels of the primary task pointing to different levels of the secondary tasks. The secondary tasks are broken down into their modality and dimension specific components in the bottom half of the figure. The top half lists the dependent measures, with the circle-arrow graphics delineating the data collection points.

The design incorporates the following assumptions:

1) Conflicts drive meaningful load values.

Therefore, the tasks should distinguish between Conflict driven and Demand driven effects.

2) The task classifications probably interact with the load calculation algorithms, i.e., the loads might be a function of the number of attributes, not the type of attributes.

Therefore, the tracking and decision tasks should have the same or different attributes representing conflicts or no conflicts. If the algorithm and classifications don't interact, then loads should distinguish between tasks irrespective of the number of attributes used to classify the tasks.

7.6 Summary of Validation of All Tests

Table 7-27:
Final Parameters and Variations

Taxonomy Attribute Pairs: Full set **Demand Values** Demand Value Matrices: 8 Matrix Values: 0-1	**Conflict Values** Conflict Value Matrices: 8 Matrix Values: 0-10 **Algorithms** VACM Index Selection: Sequential Pairing of Tasks VACM Index Integration: Separable Activity Demand & Conflict Integration: Product Matrix Combining Algorithms: Average

Eleven tests were conducted using four different experimental data sets to validate the TLM, with one final experiment currently being planned for this winter. This last experiment will be the final effort on the part of the A3I project. Further validation will only take place by other researchers.

Table 7-8 lists the factors and parameters currently incorporated into the TLM. These were selected based on the results of the 11 tests. The results were fairly consistent across all the tests, allowing the final set of parameters to be selected with a fair degree of confidence.

These parameters are surprising, particularly the Algorithms. Permutations of tasks would seem better than Sequential Pairing because Sequential Pairing misses conflicts. Further, permutations would seem better than Combinations because Combinations is sensitive to order effects. The driving factor seems to be that Permutations adds noise by virtue of its capturing all conflicts. The Conflict Value Matrices are a good addition to the TLM, because penalties are specialized on the type of task, which adequately represents the conflicts. Apparently though, the sheer number of conflicts accounted for by the Permutation of tasks still reduces the distinction between relevant and irrelvant tasks that conflict matrices add.

7.6.1 Taxonomy

Selecting the set of Taxonomic attribute pairs to classify tasks was not as clear-cut. This factor was only studied in test two of the first analysis: correlating TLM load estimates against those generated by three other workload models in a dual task setting (Sarno & Wickens, 1991). The correlations of the TLM load estimates with the other models' estimates and with tracking decrement scores indicated that the patterns of correlations across the three different sets of attribute pairs (Full, 3-Pair, and 2-Pair) were sufficiently similar that one could be confidently selected. There were some differences, but they did not appear strong enough to indicate a trend of any kind. Using parsimony as the only criterion would dictate selecting the 2-Pair set. However, the theory behind the task attribute classifiers suggests that a more detailed task representation should capture more task variance, resulting in better predictions. Since this factor was not studied in all tests, parsimony may not be the best, sole criterion in this case. On the practical side, using fewer attributes results in timelines that reflect very little difference in tasks across a mission scenario. This reduces the ability of the analyst to view task behavior and to understand what the operator is doing. Therefore, the Full Set of Taxonomic attributes was selected as a sufficient way to represent the attributes important to task performance.

7.6.2 Demand Values

All of the tests unequivocally indicated that binary Demand Matrix Values (0 to 1) were sufficient to capture the appropriate task demands. The two other value sets, 0-4 and 0-10, showed the exact same patterns as the binary value set. Even though the TLM was initially designed for the 0-4 set, parsimony dictates using binary values in the absence of other differentiating criterion.

7.6.3 Conflict Values

Testing the Conflict Value Factor in the first analysis showed that using global penalty values that were insensitive to the type of conflicting demands did not capture conflicts as well as using matrices of conflict values that were specialized on the type of conflict. The global values manipulation indicated that capturing conflicts using different values was necessary, as indicated by the poor correlations using a conflict value of 1 versus values of 2 or 3. The mixed results for values of 2 or 3 indicated that in some cases this further differentiation helped but was not sufficient. Therefore, the second analysis used values that were completely specified by the type of the conflict in order to resolve the mixed results, which they did. The correlations were higher and there were more significant correlations across all the tests in the second analysis (tests 5-11). Consequently, matrices of conflict values that ranged from 0 to 10 were selected as the best way to penalize conflicting demands.

7.6.3 Algorithms

The results of testing the Algorithm's Factor from both the first and second analyses clearly indicated which parameters should be selected with the exception of the VACM Index Selection parameter.

The Matrix Combining Algorithm did not differentiate between summing or averaging, so averaging was selected because the it was the current implementation.

In the first analysis, the Activity Demand and Conflict Integration Algorithm did not differentiate between summing or averaging the product of each demand and conflict value, but did between summing the product and multiplying the product, Consequently, both summing and multiplying were tested further in the second analysis, which indicated that the product correlated better with the data sets.

The VACM Index Integration Algorithm results were clear across the tests in the two analyses, keep the VACM classification indices separate; In the first analysis, integrating the classifications before selecting the index pairs that access the appropriate demand and conflict values lost important distinctions between the demands and conflicts; In the second analysis, keeping the classifications separate while selecting the index pairs captured the relevant conflicts and demands.

The VACM Index Selection Algorithm produced the least clear results of the Algorithm parameters across analyses. All of the correlations were lower in the first analysis than in the second because of integrating the classifications, but sequentially pairing classification indices generated load estimates that correlated higher than using all of the combinations of indices (permutations of indices were not selected in the first analysis). All of the correlations were higher in the second analysis than in the first because of separating the classifications. Permutations of indices were tested against the others, but correlated less well than either all combinations or sequential pairing. Regression analyses conducted in the second analysis indicated that sequential pairing of indices produced individual VACM load estimates that captured more variance than those generated using all combinations. This means that representing demands and conflicts is a trade-off. A more accurate and detailed representation is better up to a point, in which the sheer number of the types of demands and conflicts represented overshadows the more important ones. Beyond this point, adding details of the demands and conflicts adds error variance and reduces the correlations. Sequential pairing seems to best represent this trade-off, sacrificing some of the detail of the less important distinctions for fewer, more important ones.

It is possible that this trade-off in detail interacts with the number of taxonomic attributes used to classify tasks. However, this trade-off was not tested, so currently it remains an open question. However, it will be tested in the final experiment sometime in early 1994.

7.6 Conclusion

Based on these results, the current implementation of the TLM uses 4 to 5 pairs of task attributes per dimension to classify tasks. These classifications determine which binary demands apply, and which conflict penalties between 0 and 10 apply. The sequential pairing algorithm determines which demands conflict and therefore which conflict penalty values will be multiplied to the conflicting demands. Eight load estimates (products of the demand-conflict products) are calculated from 16 matrices (eight demand and eight conflict). Four load estimates represent the combined demands and conflicts within each VACM dimension, and four represent the combined demands and conflicts between the Visual-Auditory, Visual-Cognitive, Auditory-Cognitive, and Cognitive-Motor dimensions. These eight load estimates are re-scaled using a log transformation and then averaged across the dimensions. The results are load estimates of the Visual, Auditory, Cognitive, and Motor loads that would be imposed on an operator of the design in question.

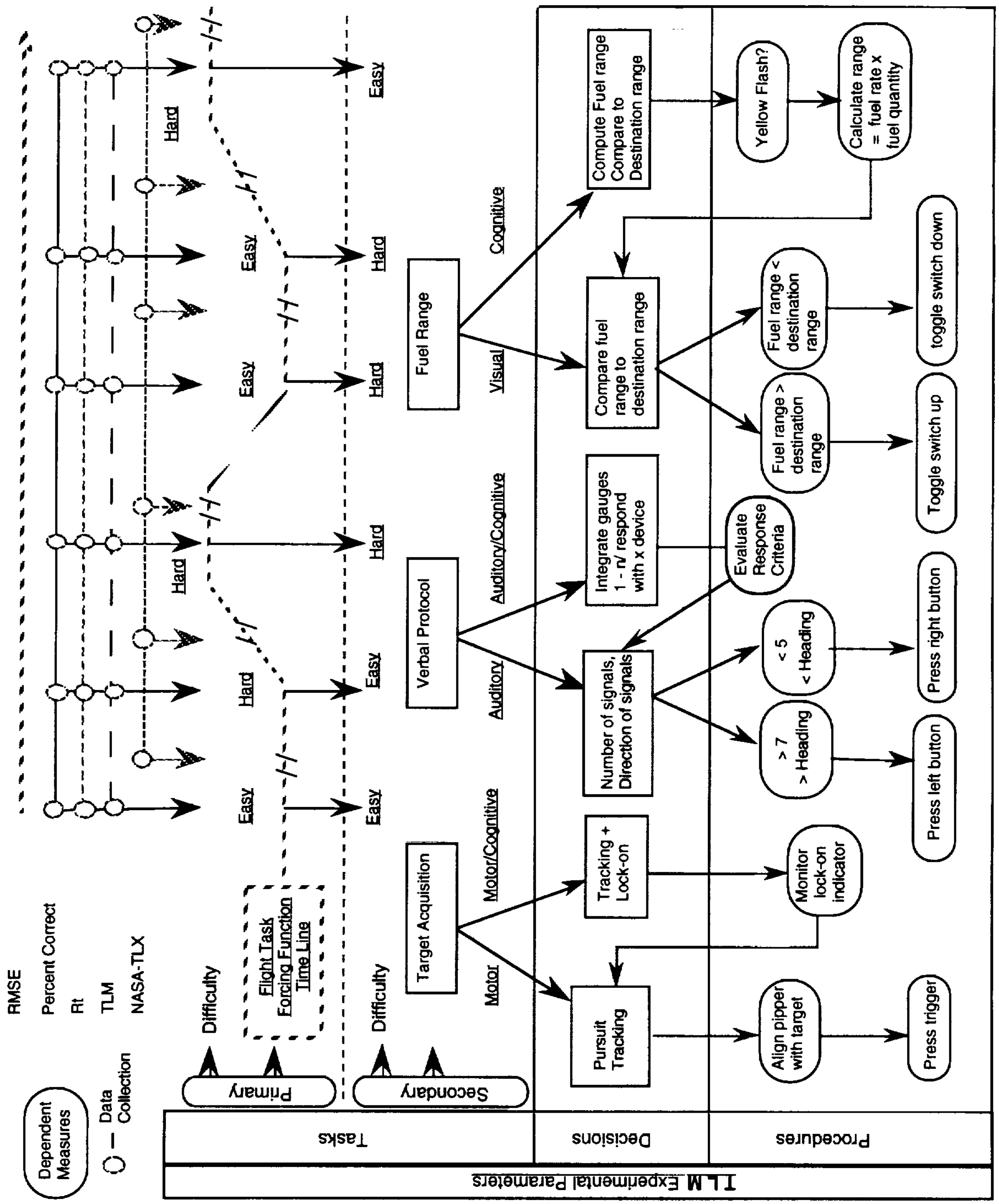


Figure 7-7: Design of the final TLM experiment

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9.0 ABBREVIATIONS AND ACRONYMS

AC_{bw}	Auditory-Cognitive between matrix.
A_{cw}	Auditory within matrix.
CAD	Computer Aided Design.
C_{cw}	Cognitive within matrix.
C_{tki}	Indices To The Rows In The Conflict Matrices
C_{uki}	Indices To The Columns In The Conflict Matrices
D_{tki}	Indices To The Rows In The Demand Matrices
D_{uki}	Indices To The Columns In The Demand Matrices
M_L	Equation for calculating loads using the integral, summation algorithm.
CM_{bw}	Cognitive-Motor between matrix.
L_a	Auditory load value.
L_c	Cognitive load value.
L_m	Motor load value.
L_v	Visual load value·
M_{cw}	Motor load value.
M_L	Matrix load value
MIDAS	Man-Machine Design and Analysis System.
TLM	Task Load Model.
TLAP	Timeline Analysis Procedure.
VA_{bw}	Visual-Auditory between-matrix.
VACM	Visual Auditory Cognitive Motor.
VACP	Visual Auditory Cognitive Psycho-Motor.
VC_{bw}	Visual-Cognitive between-matrix·
V_{cw}	Visual within-matrix.·
W/INDEX	Workload Index
Window/PANES	Workload/PerformANcE Simulation

10.0 GLOSSARY

Additional-Cost
: An unknown function or constant that accounts for the obtained increases in the magnitude of workload predicted by an averaging model.

Separable Permutation Algorithm
: An algorithm that sums the pairwise products of all possible combinations of elements within each activity and then sums these products across all concurrent activities

Attention
: A mental control mechanism that guides, focuses, or elaborates the acquisition and processing of information.

Auditory
: A modality of perception involving aural stimuli.

Auditory-Cognitive
: The interaction of aural perceiving and central processing mechanisms.

Auditory-Visual
: The interaction of aural perceiving and visual perceiving.

Averaging Model
: A model that predicts retrospective workload ratings by averaging the difficulty of the events or stimuli that are experienced.

Behavioral State
: A description of the attributes and values that constitute a specific pattern of human performance.

Best-Fitting Model
: A model that best describes the obtained patterns of human performance or behavioral states.

Between-Matrix
: A two dimensional matrix of values that represents the demands incurred on the human information processing system from the interaction of information processing mechanisms in different stages.

Cognitive
: The central processing stage composed of at least the attentional, transformational, and memory mechanisms and processes that act on perceived information and which prepare the information processing system to generate a response to stimuli if necessary.

Cognitive-Motor
: The interaction of central processing mechanisms and motor response mechanisms.

Conflict Matrix
: A two dimensional matrix of values that represents the demands and conflicts among the structural and procedural psychological attributes that describe an activity.

Conflict Value
: A specific value that represents the interaction between two structural or procedural psychological attributes classifying an activity.

Dimension
: A top level set of structural or procedural psychological attributes that corresponds to a specific stage of information processing. This is the level at which load-values are assigned to an activity.

Element
A bottom level structural or procedural psychological attribute that is used to classify an activity.

Event Based
A simulation that progresses according to changes in state variables that represent specific events that occur in the environment or behavior of the operator.

Genera 8.1
The Symbolics Lisp operating system.

Human Information Processing
The human mental activities and structures that represent and manipulate information symbolically, and which enable humans to perceive and respond to changes in external (environmental) or internal (mental) states.

Human Performance Model
A quantitative (analytic or computer-based) representation or description of all or parts of human operators or maintainers of complex, dynamic systems.

Invariant Property
A characteristic of the information processing system that does not change as a function of the information extracted from the perceptual array.

Load Balancing Strategy
A behavioral change in an operator as a function of the imposed visual, auditory, cognitive and motor loads imposed by performing an activity. The effect of the behavioral change is a regression to the mean workload (reduction of peak loads) of the pertinent activities with regard to allotted time.

Load Value
A value that represents the amount of psychological resources required to perform an activity relative to performing another activity or set of activities.

Memory
The psychological mechanisms that maintain information over time.

Mental Workload
An evaluation about the difficulty of ongoing experiences and the impact of those experiences on the physical and mental states of an operator. The evaluation is a function of the collection of attributes, that may or may not be relevant, controlling the evaluations or behavior that depend on the circumstances and design of a given activity(s) and the a priori bias of the operator.

Motor
The effector mechanisms of the human body.

Multiplicative Algorithm
An algorithm that sums all the possible combinations of pairwise products of elements within and between all concurrent activities.

Object-Oriented Programming
Programming languages that represent data structures as objects with attributes and values.

Normative Model
A model that predicts how an operator should perform by assuming rational operator behavior.

Phase IV
The period of research and development on MIDAS from the small offsite in March 1989 to the end of demos in July 1990.

Phase V
The period of research and development on MIDAS from the large offsite in November 1990 to the end of demos in June 1992.

Physical System
The design of the system hardware and software.

Process
A specific information processing mechanism that manipulates information symbolically.

Resource
The attentional, physical and memory capabilities of an operator.

Scheduling Model
The software configuration item that sequences the order of the simulated activities.

Serial Constraints
The imposed order of interactions between the dimensions used in the TLM.

Simulation Executive
The software configuration item used to control the simulation by controlling the flow of execution of the rest of MIDAS' software configuration items.

Software Component
A component of a software architectural unit/item used to implement a specific model or tool within MIDAS.

Structure
A specific information processing mechanism that represents information symbolically.

Summing Model
A model that predicts retrospective workload ratings by summing the difficulty of the events or stimuli that are experienced.

Activity Decomposition Model
The software configuration item that decomposes high level goals into the simulated activities.

Task Loading Model
The software configuration item that predicts the visual, auditory, cognitive, and motor loads that the simulated activities impose on the operator of the system.

Tick Based
A simulation that progresses according to changes in state variables that represent specific events that occur in the environment or behavior of the operator.

User Interface
The commands and displays that an analyst or user of MIDAS uses to interact with MIDAS.

Variant Property
A characteristic of the information processing system that changes as a function of the information extracted from the perceptual array.

Visual
A modality of perception involving visual stimuli.

Visual-Cognitive
The interaction of visual perceiving and central processing mechanisms.

Within-Matrix
A two dimensional matrix of values that represents the demands incurred on the human

information processing system from the interaction of information processing mechanisms within the same stage.

REPORT DOCUMENTATION PAGE

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Man-Machine Integration Design and Analysis System (MIDAS) Task Loading Model (TLM) Experimental and Software Detailed Design Report

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13. ABSTRACT *(Maximum 200 words)*

This is the experimental and software detailed design report for the prototype Task Loading Model (TLM) developed as part of the Man-Machine Integration Design and Analysis System (MIDAS), as implemented and tested in Phase VI of the Army-NASA Aircrew/Aircraft Integration (A^3I) Program. The A^3I Program is a joint Army and NASA exploratory development effort to advance the capabilities and use of computational representations of human performance and behavior in the design, synthesis, and analysis of manned systems. The MIDAS TLM computationally models the demands designs impose on operators to aid engineers in the conceptual design of aircraft crewstations. This report describes TLM and the results of a series of experiments which were run this phase to test its capabilities as a predictive task demand modeling tool. Specifically, it includes discussions of: the inputs and outputs of the TLM; the theories underlying it; the results of the test experiments; the use of the TLM as both a stand-alone tool and part of a complete human operator simulation; and a brief introduction to the TLM software design.

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