DEVELOPMENT AND VALIDATION OF A METHODOLOGY FOR COMPREHENSIVE PERFORMANCE ASSESSMENT OF COMPLEX TASKS

by

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(ABSTRACT)

A new task analysis methodology was developed to provide objective information on complex tasks. A complex task was broken down into observable elements and unobservable elements that were inferred to have taken place in support of the observable actions. Subject matter experts (SMEs) were used to assist in this breakdown. Additionally, guidelines for specifying the level of detail in the task analysis breakdown were developed to help objectify the analysis. A simulation model framework then was built of the task elements. Personnel proficient in the task were observed during work, and objective data on their observable actions were collected. These data then were used to provide numeric input to a simulation model. The simulation was run, and the results of the model of performance compared to the observed performance data. The model was altered at that point to reflect lessons learned during data collection. The process yielded a model that accurately reflects human performance on the task. Variations on the model based on a conceptual understanding of operator's strategies also correlated well with observed performance, indicating the value of the methodology for building an understanding of the motivations critical to successful task performance.

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LIST OF ABBREVIATIONS

AN/SLQ-32A(V) DCC	Display Control Console
ASMD	Anti Ship Missile Defense
CIC	Combat Information Center
DR	Data Reduction
DX	Data Extraction
EFX	Emitter File Index
EW	Electronic Warfare
EWOBT	Electronic Warfare Onboard Trainer
FAB	Fast Action Button
FSG	Friendly-Surface-Guidance
GEF	Global Emitter File
HAG	Hostile-Air-Guidance
HAH	Hostile-Air-Homing
HAS	Hostile-Air-Search
LANTFLT	U.S. Navy Atlantic Fleet
NAS	Neutral-Air-Search
OTD	Operator Training Device
OTE	Operator Training Equipment
PACFLT	U.S. Navy Pacific Fleet
SEQ FAB	SEQUENCE Fast Action Button
SIG SEL FAB	SIGNAL SELECT Fast Action Button
SME	Subject Matter Experts
SSM	Surface-to-Surface Missile
Virginia Tech	Virginia Polytechnic Institute and State University

INTRODUCTION

Objective analysis of complex tasks has been a key focus of the field of human factors engineering. Methods of task analysis have been used to determine human performance in a descriptive way; these results have led to redesign of task sequences, training systems, and equipment to better match the capabilities of human operators. With the advent of sophisticated computer systems, the ability to create detailed simulations of human performance is now possible. These simulations can be used to objectify the task analysis process, yielding information that can be used to describe, assess, and predict performance. Simulation has been used in other fields to understand complex random processes and now can be applied to human performance.

Simulation is a natural outgrowth of a progression of increasingly objective complex task analysis techniques. Frank and Lillian Gilbreth began with creation of task analysis tools such as simultaneous motion charts in the early part of this century. Later, other tools were developed that increased the objectivity of task analysis techniques, such as the operational sequence diagram which is useful for describing person-machine interactions. Also, predetermined time systems were developed in an attempt to quantify the time for specific motions included in task taxonomies (Fleishman and Quaintance, 1984). Building simulation models of complex tasks goes a step farther by using time distributions instead of fixed values, and by quantifying decision points and associated probabilities along the way. This last area has the additional benefit of enabling "backwards" analysis, whereby more can be learned about the task activities through the process of modeling them.

A new task analysis methodology was developed to provide objective information on complex tasks. A complex task was broken down into observable elements and unobservable elements that were inferred to have taken place in support of the observable actions. Subject matter experts (SMEs) were used to assist in this breakdown. Additionally, guidelines for specifying the level of detail in the task analysis breakdown were developed to help objectify the analysis. A simulation model framework then was built of the task elements. Personnel proficient in the task were observed during work, and objective data on their observable actions were collected. These data then were used to provide numeric input to a simulation model. The simulation was run, and the results of the model of performance were compared to the observed performance data. The model was altered at that point to reflect lessons learned during data collection. The process yielded a model that accurately reflects human performance on the task.

This task analysis process has yielded information at each step that is useful in describing the task of interest. The initial model framework was used to describe various possible task sequences based on decisions the personnel made towards successful task completion. Data collected during observations of personnel performing the task were analyzed with inferential statistics to attempt to determine the causes behind the decisions that lead to these different task completion strategies. Descriptive statistics of the strategies used could lead to improved training methods that emphasize the benefits of different strategies in the different situations that are modeled. Finally, the complete, accurate model may be used to assess performance by a particular person in a particular situation as compared to the predicted norm, and could also be used to predict the effect of changes in the task sequence.

Purpose

The purpose of this work was to show that this variant on traditional task analysis methodology (hereafter referred to as the "Performance Assessment Methodology" or PAM), which is based on observable events and actions and inferred decisions, can be used to describe, assess, and predict performance of personnel on a complex task. The task sequences were described through observation of personnel and interviews with SMEs. A simulation model framework was constructed based on these task sequences and, in conjunction with a set of guidelines, developed to aid in the specification of the level of detail for the task analysis. A laboratory study was conducted to confirm the task sequences and collect objective data that was included in a simulation model. Strategies personnel use in completing the task are described. The completed simulation model's summary human performance results are compared with summary observed results to validate the methodology. The validated simulation model is then used to develop performance norms under different task environments. The validated model is also used to provide norms and other information on strategies personnel use, to demonstrate the utility of the methodology in providing more detailed information on human performance than is currently feasible with other task analysis techniques.

Background

The task selected for use in developing and validating the task analysis and simulation methodology is part of the job of the operators of the U.S. Navy's AN/SLQ-32(V) Electronic Warfare console (for background on this piece of equipment, see Appendix A). This task was chosen because the Virginia Tech Displays & Controls Laboratory is engaged in ongoing work with this system as part of the Navy's Shipboard Assessment of Required Proficiency (SHARP) program. The AN/SLQ-32(V) is a model system for analysis of complex tasks. The AN/SLQ-32(V) is a passive radar receiver; that is, it detects radar signals in the environment surrounding a ship and attempts to interpret the source of those signals. The Display and Control Console (DCC) presents this information to the operator by placing a symbol indicative of a particular type of radar emitter on a polar display. The console provides numeric information on the electronic parameters of each signal detected and provides an audio signal based on the radar signal received that operators can use to aid in their recognition of the emitter. Operators must recognize and monitor emitters detected by the console to do their job of protecting the ship.

Related Literature

This section provides a selected history of complex task analysis. Beginning with the origins of task analysis at the start of this century, complex task analysis has gone through a progression of techniques including "scientific management", time and motion studies, process charts, hierarchical task analysis, and finally progressing to cognitive user models and stochastic modeling techniques. At the end of the section, logical guidelines for the PAM that have come out of this background are stated.

Origins of task analysis. Frank and Lillian Gilbreth and Frederick Taylor (see Gies, 1991) are credited with beginning the study of task analysis. The Gilbreths contributed the idea of charting the motions of a worker to help determine ways to increase productivity (Gilbreth and Gilbreth, 1921 as referenced in Kirwan and Ainsworth, 1991). Simultaneous motion charts were a particularly useful method developed by the couple as a way of acknowledging the interaction between the two hands during manual tasks. Further, each item in one of these charts was termed a "therblig", and postulated to have a reliable duration and repeatability for a variety of tasks. This was a precursor to task taxonomy systems. Taylor's main contributions to task analysis were firstly his coining of the term, and secondly his establishment of methods for time and motion study. These methods were later expanded upon by others.

Task analysis does not have a very firm definition. One useful definition is "Task analysis... is the process of critically examining task factors -- the operator's resources, constraints and preferences -- in order to establish how these influence human operations in the attainment of system goals." (Kirwan and Ainsworth, 1991).

Sampling techniques. A precursor to the use of detailed computer data collection techniques was activity sampling, or work sampling (Heiland and Richardson, 1957). In this type of technique, a worker's activities are cataloged and then sampled at regular intervals. After a set time period, analysis of the data collected can begin to describe relative frequencies of work behaviors. Problems with this technique include lack of rationality in choosing a sampling frequency and a cataloging level of detail. Additionally, there is not necessarily a relation between frequency of an activity and its criticality.

A sampling technique quite different than regular work sampling is the critical incident technique (Meister, 1985; Singleton, 1974). This technique was pioneered during WWII, as investigations were conducted on airplane crashes (Fitts and Jones, 1947 as referenced by Kirwan and Ainsworth, 1991). The critical incident technique involves surveying workers about incidents or accidents with a system to identify points of concern. This technique can quickly determine problem areas, but cannot always pinpoint their causes.

Task taxonomies. Attempts have been made to develop task taxonomies that can be applied to any complex task. Recent work includes that of Hogan, Raza, Metz, and Driskell (1986), who detailed a taxonomy that can classify team tasks. Shingledecker, Crabtree, and Eggemeier (1985) reported development of the CTS taxonomy, which they said is a step toward development of "...efficient, standardized human factors measurement technologies which are based on the state-of-the-art in human performance theory and experimental methodology." The also noted that because understanding of human performance is far from complete, that "...batteries such as the CTS should never be considered as final or static technologies."

Charting. Charting techniques were pioneered by the Gilbreths, but have been greatly expanded and modified since that time (Kirwan and Ainsworth, 1991). In addition to the early process and simultaneous motion charts, functional flow charts and informational flow charts have added a great deal to this method. These type of charts include decision points, typically with boolean operators to describe choices a worker has in completing the task. Symbols for these charts include rectangles and ovals for actions and diamonds and circles for decisions (Kadota, 1982).

A particular method of charting that includes the state of the system as well as operator actions is the operational sequence diagram (OSD). This type of charting method, also known as "Job process charts" (Tainsh, 1985) is useful in systems where the machinery has a variety of responses to operator actions depending on its state. This is the case with many modern complex electronic systems.

Hierarchical task analysis (HTA). This technique, an extension to qualitative charting techniques, allows varying levels of detail in task decomposition to be used depending on need (Kirwan and Ainsworth, 1991). HTA is also an inferential method, in that it provides a view of tasks as pertaining to goals of the system. It can include other task analysis methods, particularly types of charts. The technique involves three major terms, "goals", "tasks", and "operations". These are defined as desired states of the system, methods for attaining those states, and units of behavior that can be defined in "terms of its objective", respectively (Kirwan and Ainsworth, 1991).

Kirwan and Ainsworth (1991) begin to attack the problem of the necessary level of detail or "stopping rule" for hierarchical task analysis with the "PxC" rule. P refers to the probability of inadequate task performance, and C to the cost or consequences of inadequate performance. If the product of these variables is unacceptable, than the task needs to be described at that level of detail. Unfortunately, all of the quantities in this relation are qualitative, and thus do not provide objective rules for specifying a level of detail for analysis.

Task analysis guidelines and simulation. Although task analysis techniques are a fundamental part of applied human factors work, little research has been conducted on objective guidelines for their implementation, particularly for use in simulation. There is a need for standardization in the task analysis techniques used in simulation models. In particular, there is considerable variability in the level of detail included in the description of models and in the links which are established between the models and the individual tasks described by them (Shingledecker et al., 1985). Most authors take the view that task analysis involves a certain level of judgment in deciding what level of detail should be examined.

Meister (1971) highlighted the problem involved in task analysis. This problem is the particular level of detail that the task should describe. He said that the particular level of task description is arbitrary and judgmental, and that precise rules for this breakdown cannot be specified. He noted that the methodology is largely a trial-and-error process.

Griffith and Stewart (1991) used task analysis techniques to provide input to a MicroSAINT simulation model. "The level of system decomposition... depends on the particular problem. The system can be defined in as detailed or gross a level as desired and *common sense* on the part of the modeler is usually sufficient for determining this level." (Griffith and Stewart 1991; emphasis added).

Siegel and Wolf (1969) discussed the building of simulation models from task analysis. They recommended that subtasks in a model correspond to "natural" behavioral units. These behaviors are "usually" single operator actions that take "several seconds to a few minutes." These requirements are remarkably general.

Another approach has been to develop criteria that tasks must meet for measurement. Vreuls, Obermayer, Wooldridge, and Kelly (1985) have developed a criterion for what they term a "measurement segment" which "generally correspond[s]" to a task element. They mention performance must be "lawful," and the segment must have an unambiguously defined beginning and end. The use of "lawful" in this work is not defined explicitly.

The Perception-Decision-Action model (AGARD, 1989) (see Figure 1) is useful for analyzing complex tasks. In this model, the human gets input from the environment through perception of events, makes a decision on how to respond to the environment, and proceeds to take some action. This model will be referred to hereafter as the Event-Decision-Action model, because our focus is on observable events rather than perception of those events.

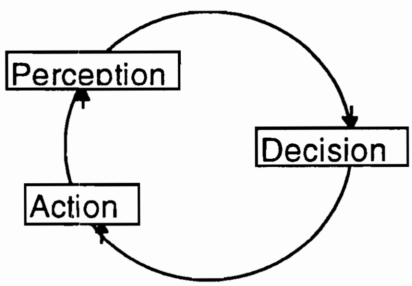


Figure 1. *Perception-decision-action model.*

In summary, task analysis techniques are descriptive and not designed for implementation in an objective way in simulation models that can describe, predict, and assess performance. A new method has been developed to guide practitioners in the creation of task networks that are the basis of the simulation model.

<u>Guidelines</u>. To objectify the technique of task analysis, the method of guidelines for task description holds promise for modeling work. Guidelines can be developed for specifying the appropriate level for simulation models, based on the Event-Decision-Action model:

- Subtasks must begin with measurable events and end with measurable actions,
- The number of decision options may be large, but must be finite,
- The number of subtasks to be modeled for a particular task must be practical in scope,

- The level of detail should be one more than what events and actions are measurable; that is, for each measurable event, action, or decision a set of sub-events, actions or decision parameters should be included in the analysis.

This set of guidelines provides for an objectively verifiable model. The subtasks can be measured from defined beginning and end points. A finite number of decision options allows for finite probabilities for choosing among options. A level of detail one deeper than that which is measurable allows for inferences about the cognitive processes leading to the actions that are measured.

PRELIMINARY ANALYSIS OF THE TASK OF INTEREST

This section reviews task analysis work done on the functional recognition task of the AN/SLQ-32(V) operator. This analysis was conducted utilizing the guidelines developed and delineated at the close of the previous section.

The most important part of the recognition process in AN/SLQ-32(V) operation is that of functional recognition, where the operator determines the purpose of the emitting radar. This task of functional recognition of emitting radars is that which was analyzed with the new methodology. This task was chosen because it is complex, in that it has many possible strategies for completion, and that it has many task elements that can be objectively measured through data collection from the console's user interface computer subsystem.

The duties of an AN/SLQ-32(V) operator encompass many activities, such as operating the display console, performing system maintenance, and conducting non-EW shipboard assignments. The functional recognition task under investigation in this work is one aspect of the operation of the AN/SLQ-32(V) display console. This task is an essential element of the operator's primary objective to maintain a high level of situational awareness about the emitter environment surrounding the vessel.

The functional recognition task begins when the AN/SLQ-32(V) signals a new or updated emitter event. The onset of an event signal is associated with an auditory alert, which may occur while the operator is idle or taking console actions with other emitters. For the purposes of this work, the functional recognition task does not include the events involved in attending to other emitters. Rather, the beginning of the task is defined as the onset of an emitter event, which may involve a new emitter detected by the AN/SLQ-32(V) system or a change of parameters (i.e., scan type) for a previously detected emitter.

EW operators place an emitter into close control following an emitter event (i.e., detection of a new emitter or a parameter change for an existing emitter). With the emitter in close control, the AN/SLQ-32(V) provides a tabular listing of the emitter's parameters on the display screen, as well as a graphical icon of the emitter based on the system's interpretation of the emitter threat level and bearing position. Operators use several alternate manual actions (or so-called task action sequences) to place emitters into close control: enter the emitter track or EFX number, HOOK the emitter with a stiff-stick input device, press the SEQUENCE Fast Action Button (FAB) multiple times to sequence to the emitter, or press the SEQUENCE FAB once if the emitter event is the highest priority alert. Additionally, if the emitter parameters change while it is in close control, the operator must press the SEQUENCE FAB to update the close control parameter listing.

To functionally recognize an emitter, operators may choose to view the close control parameters, to listen to the signal on the AN/SLQ-32(V) speaker by depressing the SIGNAL SELECT FAB, to view an ULQ-16 spectrum analyzer to examine the emitter signal properties closely, or use some combination of these information sources. The operator also relies on intelligence information, his own experience, and verbal information from the EW supervisor to anticipate the potential emitters in the ship's environment. Regardless of the task sequence taken, the functional recognition decision process can be monitored through the observable actions made by the operator.

Operators initiate a verbal report of the emitter following its functional recognition, especially if the emitter threatens the ship or battle group. Although the EW community does not rely on a standard verbal report format for most emitter types (except for a hostile missile), it is possible to define several essential elements of information that need to be announced in the EW report. As listed in Table 1, the essential components of the verbal report are radar function (i.e., guidance, search, homing), platform (i.e., air, surface), and owner (i.e., friendly, neutral, hostile). The EW operator's verbal reports can include some or all of the essential elements of information and they may use various synonyms (and ship-specific language) to reference emitter characteristics, either explicitly or implicitly. For example, a report with the statement "missile" is understood to reference the Hostile and Air specifiers; a report of "Comair" is understood to reference the Neutral, Air, and Search specifiers.

TABLE 1

Essential Elements of Information for Functional Recognition Reports

Essential Element of Information	Generic Specifies	Example uses and description
Function	Guidance	fire control, weapon control, acquisition, illumination, tracking
	Search	navigation, surveillance, early warning, reconnaissance
	Homing	missile
Platform	Air	Commercial Air
	Surface	SPG-62, Surface Guidance
	Subsurface	Hostile Sub
Owner	Friendly	Friendly Air Search
	Neutral	Commercial Air
	Hostile	Hostile Surface Search

Three main emitters of interest to the AN/SLQ-32(V) operator are the FSG, NAS, and HAH emitters. The NAS emitter is usually associated with commercial air traffic. The FSG is typically associated with friendly targeting radars for weapons systems, such as the PHALANX. The HAH refers to an anti-ship missile. EW operators are highly sensitive to the HAH emitter, and are trained to report them quickly. EW operators have a much decreased sense of urgency about the NAS and FSG emitters, and are trained to only report these emitters in the context of providing requested environmental information.

EW operators rely on different information sources to determine the essential elements of information for a functional recognition decision. Moreover, they often ascertain the individual elements of information in a sequential manner (see Figure 2). For example, EW operators may infer the Function component of a recognition decision from the emitter parameters displayed on the AN/SLQ-32(V) screen or auditory speaker. This information, in turn, may be used to define the Platform component or, perhaps, a specific signal identification (emitter identification is considered a more detailed decision than functional recognition). From the Function and Platform components (or the specific emitter identification), the EW operators may infer the Owner component of the decision since certain radars are used by specific countries. Operators may also view an emitter's bearing drift on the polar display (e.g., missiles drift faster than surface ships), rely on their knowledge of the emitter environment, or call upon the EW supervisor to provide supporting information to ascertain parts of the functional decision.

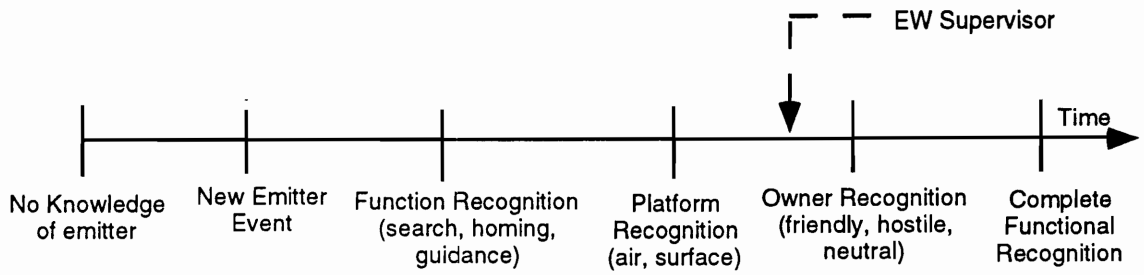


Figure 2. *Sequential steps in functional recognition decisions.*

Task Network

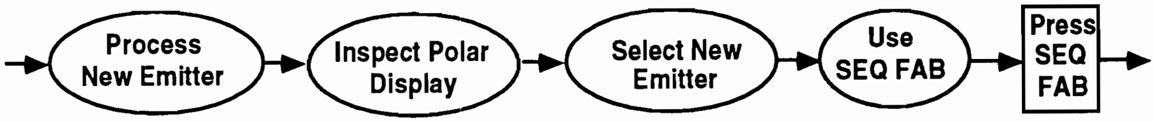
The EW task of functional recognition of emitters follows a prescribed set of events, decisions, and actions; albeit, the task sequences are complex and executed rapidly among other actions supporting the AN/SLQ-32(V) operator's main objective of maintaining situational awareness. Therefore, a task network model was developed to describe and evaluate the operator's performance in the functional recognition task. A task network model is an extensible tool of human factors engineering, used to organize the task activities in complex operator-machine systems. The task network model was used as the framework for the simulation model that was developed. This task network model was developed based on the task analysis guidelines proposed at the close of the previous chapter.

Task network models codify a task into sequences of observable elements (i.e., events, decisions, actions). The task elements are represented as ***nodes***, while the temporal sequences used to perform the elements are represented as ***links***. For example, the task element of repeatedly pressing a FAB is represented graphically as a node (i.e., labeled Press SEQ FAB) and a loopback link (i.e., repeat node X times).

Although operator decisions are not observable directly, these intrinsic task elements can be represented in the network model. For example, consider the non-observable task element of analyzing the auditory signal produced by an emitter. To execute this intrinsic task element, the operator must bring an emitter into close control using either the SEQUENCE FAB or by entering an EFX number and then must depress the SIGNAL SELECT FAB. Thus, at least one observable event precedes the operator's intrinsic efforts to evaluate the auditory signal and, therefore, the observable event can be used to mark the beginning of the non-observable task element. Likewise, the operator must press the SEQUENCE FAB or HOOK FAB or make a verbal report once the auditory analysis has been completed. Once again, another observable event can be used to mark the end of the non-observable event. The grouping of non-observable events between directly measurable ones affords an approach to represent and monitor intrinsic task steps.

The task network model for functional recognition decisions consists of many uses of three sub-network models (Figures 3, 4, and 5). These sub-network models were developed to attempt to describe the sub-tasks involved in the functional recognition task, and are based on information from SMEs and observations of console operators, as well as previous work done with the AN/SLQ-32(V) (Moscovic, 1992). The temporal sequence of events in the sub-network models is indicated by arrows. The task sub-network models include nodes thought to be required for the depiction of work flow. These nodes represent model-related decisions made by the EW operator, such as "Listen to signal" (Figure 5). These models were developed to show one more level of detail than can be objectively measured, fulfilling a guideline for level of detail stated at the end of Chapter 1.

The sub-network in Figure 3 shows the inferred cognitive steps and the physical step necessary to use the SEQUENCE (SEQ) FAB to bring an emitter into close control. The operator inspects the display to find the new emitter, visually selects it, decides to use the SEQ FAB, and then presses the FAB.



Place Unknown Emitter in Close Control with SEQ FAB

Figure 3. *SEQ FAB sub-network model.*

The sub-network in Figure 4 shows the inferred cognitive steps and the physical steps necessary to use the HOOK FAB to bring an emitter into close control. The operator inspects the display to find the new emitter, visually selects it, decides to use the stiff stick, the hand is moved to the stick, the stick is used to position the cursor on the correct bearing line for the emitter, and the HOOK FAB is pressed. Note that the use of the Stiff Stick is shown as an un-measured event; this was because that motion was not output from the system, not because that was a cognitive event. The use of the Stiff Stick was inferred because data on it could not be collected with the used data collection techniques.

Place Unknown Emitter in Close Control with Hook FAB

Figure 4. *HOOK FAB sub-network model.*

The sub-network in Figure 5 illustrates the task elements of using the SIGNAL SELECT (SIG SEL) FAB to aid in the process of functionally recognizing an emitter in close control. This task segment begins when the operator decides to listen to the signal. The operator then presses the SIG SEL FAB, and begins the functional recognition decision process by listening to the emitter signal. He may simultaneously inspect an oscilloscope or frequency analyzer (ULQ-16) and view the emitter parameters to aid in the decision process. Note that it is not necessary, just typical (and recommended by SMEs), to listen to the signal to functionally recognize the emitter.

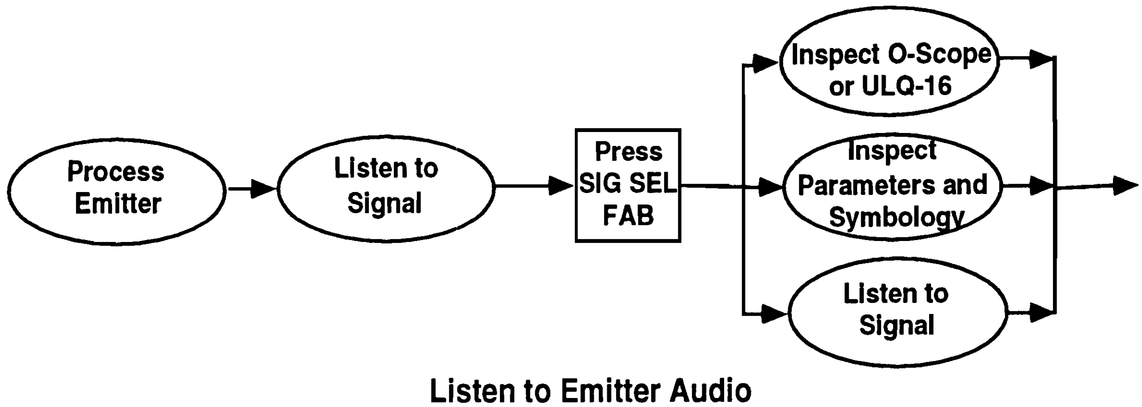


Figure 5. *SIG SEL sub-network model.*

The full task of functional recognition requires some of these subtasks for completion, depending on the particular emitter of interest, the environment, and possibly other factors such as operator preference. Because the subtasks change the state of the console, the state of the system must be part of the task network model (this is a similarity between the task network model and another task analysis tool, the Operational Sequence Diagram). The full task network model shows different system states in each node, and completion of the task proceeds from each node to one of several other nodes by the use of the actions described in the sub-network models. The full task network model is shown in Figure 6. Table 2 shows an analysis of which actions connect which nodes in the network model.

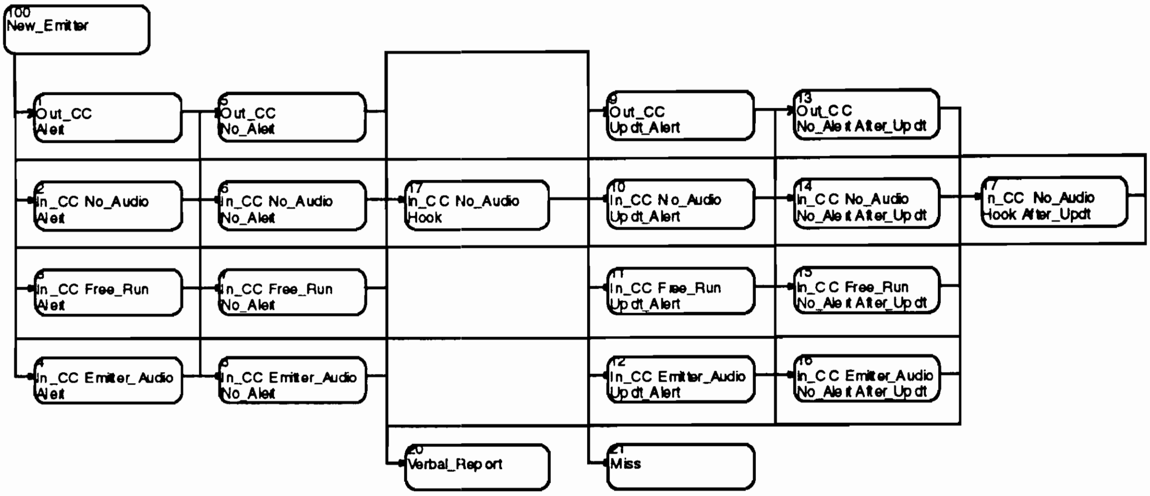


Figure 6. *Task network model of the functional recognition task.*

TABLE 2

Connections through the Task Network Model

From	Use of	Goes to
100	SEQ	6
	Hook	2
1	SEQ	6
	Hook	2
2	SEQ	6
	Hook	1
	SIG SEL	3
	Report	20, 21
3	SEQ	6
	Hook	1
	SIG SEL	4
4	SEQ	6
	Hook	1
	SIG SEL	3
5	SEQ	6
	Hook	17
	Update Alert	9
	Report	20, 21
6	SEQ	5
	SIG SEL	7
	Update Alert	10
	Report	20, 21
7	SEQ	5
	SIG SEL	8
	Update Alert	11
	Report	20, 21
8	SIG SEL	7
	Update Alert	12
	Report	20, 21
9	SEQ	14
	Hook	10
10	SEQ	14
	Hook	9
	SIG SEL	11

From	Use of	Goes to
	Report	20, 21
11	SEQ	14
	Hook	9
	SIG SEL	12
	Report	20, 21
12	SEQ	14
	Hook	9
	SIG SEL	11
	Report	20, 21
13	SEQ	14
	Hook	18
	Report	20, 21
14	SEQ	13
	SIG SEL	15
	Report	20, 21
15	SEQ	13
	SIG SEL	16
	Report	20, 21
16	SEQ	13
	SIG SEL	15
	Report	20, 21
17	SEQ	5
	SIG SEL	7
	Update Alert	10
	Report	20, 21
18	SEQ	13
	SIG SEL	15
	Report	20, 21

Only one action sub-network can be used at a time to proceed to another node in the network model. For example, from the "In_CC No_Audio No_Alert" node, the operator could use the HOOK FAB sub-network, or use the SEQ FAB sub-network; however, the operator could not enter two or more sub-networks simultaneously.

Certain nodes in the full task network model are particular to the flow of the functional recognition task. The "Update Alert" action is one taken by the system, not the operator; it occurs if the parameters of the emitter of interest change while the emitter is under scrutiny. The "Report" action is the giving of the verbal report by the operator.

The task network model of the full functional recognition task begins with the onset of a new emitter alert (node 100). The following nodes are identified by the state of the system: In_CC and Out_CC mean that the emitter of interest is in close control or out of close control, respectively. Note that the sub-networks of either using the SEQ FAB or HOOK FAB (Figures 3 and 4) are required to bring an emitter into close control, but they differ in that the auditory alert signaling the onset of a new emitter is not canceled by use of the HOOK FAB. Thus, another identifier of the system state is Alert or No_Alert. When the emitter alert occurs, the operator can perform other tasks or may attend immediately to the emitter event. If the operator chooses to attend to the emitter alert, he can bring the emitter into close control using one of two main strategies (corresponding to the sub-networks in Figures 3 and 4). The operator can press the SEQ FAB or use the stiff-stick and press the HOOK FAB. According to system documentation, the operator could also manually enter the emitter's EFX number or Track number, but SMEs report that these actions are very rare, and these actions were not observed during data collection conducted for model verification. A different kind of alert is generated if the emitter changes parameters after initially appearing; this is the Update Alert (Updt_Alert). It is interesting that, according to the system documentation, a SEQ FAB usage will clear the alert of the emitter sequenced to, but a HOOK FAB usage to bring that same emitter into close control will not clear that alert. In the task network model, nodes were added to reflect the system state where the emitter could be in close control but still have an alert pending.

Not all emitters undergo parameter changes. A scan or parameter change occurs for example when a radar implements a different scan or power pattern (paradigm). Scan paradigms are employed for different purposes, such as a circular pattern for search or navigation and a steady pattern for targeting. Missile and fire control radars can appear initially to the AN/SLQ-32(V) system with a sectional or circular scan and then change to a steady scan after acquiring a target. If a parameter change does occur, this is reflected in the system state as described previously concerning Update Emitter.

If the operator decides to listen to an emitter, he can use the SIG SEL FAB on an emitter that is in close control. The first usage of the FAB will bring the emitter into "Free Run" mode, where all signals on that bearing are sent to the headset, and the operator must distinguish the signal of interest. A second press of the FAB activates system electronics that attempt to isolate the signal of interest and present only that to the operator. The task network model has separate nodes for both these types of system state.

Task Completion Strategies (Pathways). EW operators can use different task completion strategies to functionally recognize an emitter. All of these strategies require the operator to place the emitter into close control, albeit through different task sequences. Four primary task sequences (strategies) have been identified and they are designated as: SEQ, HOOK, SEQ-SIG, and HOOK-SIG. These strategies are illustrated in Figures 7a-d. The four strategies can be used by EW operators for functionally recognizing an emitter that has just appeared in the AN/SLQ-32(V) or for an emitter that has recently changed its parameters or scan. Thus, eight different strategy pathways through the task network model can be defined.

The SEQ strategy path is the most common strategy for functionally recognizing emitters. Upon system receipt of an emitter signal, the operator visually identifies the new emitter on the polar display and brings it into close control by pressing the SEQUENCE FAB. The operator then functionally recognizes the emitter by comparing its displayed close control parameters to his/her knowledge of common radars. The operator then verbally reports the emitter. Variations on this strategy include pressing the SEQUENCE FAB multiple times to bring an emitter that was not the most recently received one into close control and pressing the SEQUENCE FAB in a latter portion of the task to update the parameters after a scan change.

The HOOK strategy path is often used when many new emitters appear simultaneously. The operator visually inspects the polar display and moves the cursor with the stiff-stick to the most salient emitter. The operator presses the HOOK FAB to bring the emitter into close control and inspects the emitter's parameters. The operator then functionally recognizes the emitter and makes a verbal report similar to the strategy in the SEQ path. Variations on this task include pressing the HOOK FAB multiple times to bring into close control one of many emitters on a bearing line and, using the SEQUENCE FAB in a latter portion of the task, to update the emitters parameters after a scan change.

The SEQSIG strategy path is similar to the SEQ strategy, except that the SIGNAL SELECT FAB is pressed once after the emitter is in close control. The operator then listens to the signal while making the functional recognition decision. The HOOKSIG strategy path is similar to the HOOK strategy, with additional use of the SIGNAL SELECT FAB as described the SEQSIG strategy. Variations in these two strategies involve the additional uses of the HOOK, SEQUENCE, and SIGNAL SELECT FABs.

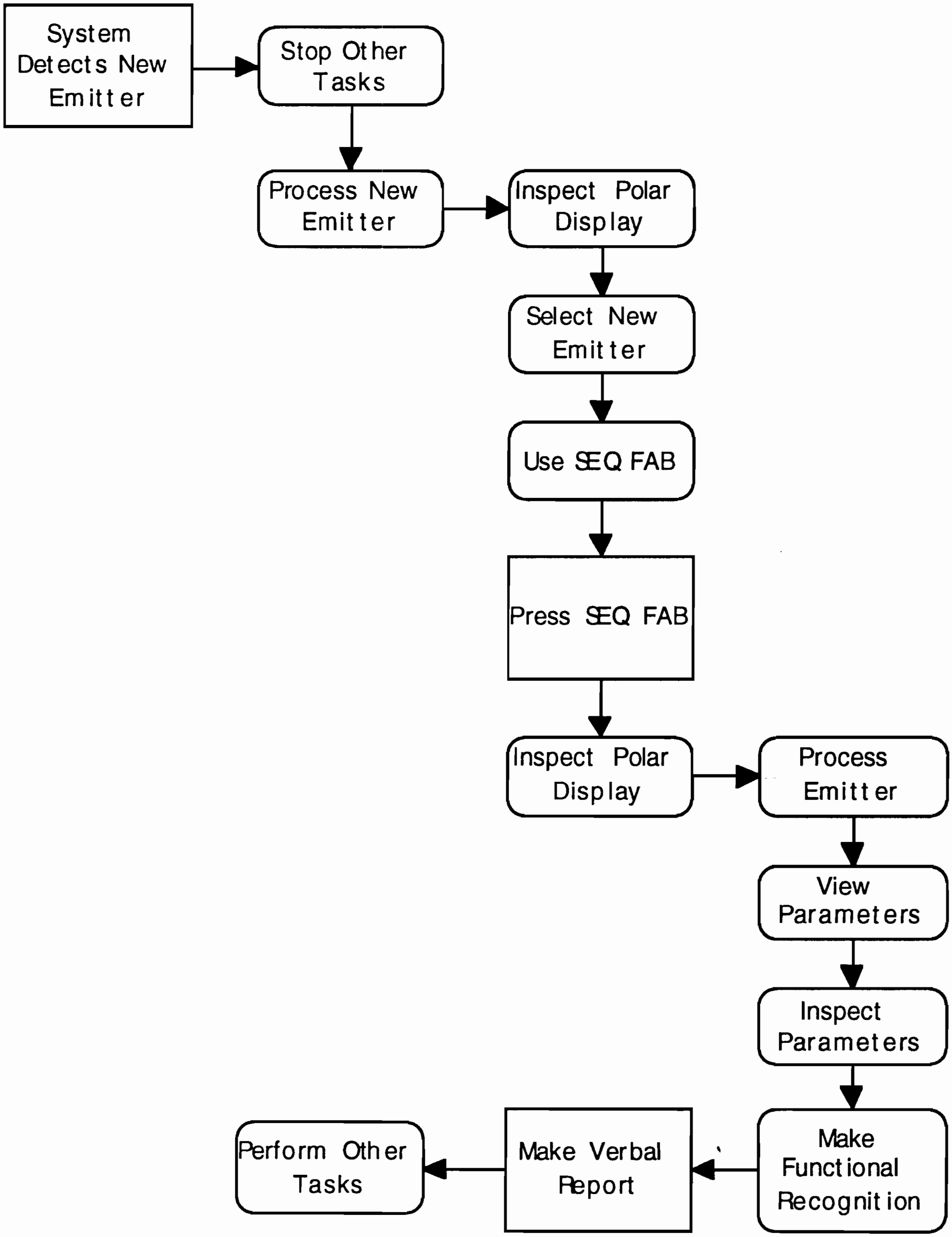


Figure 7a. *SEQ pathway for completion of functional recognition decisions.*

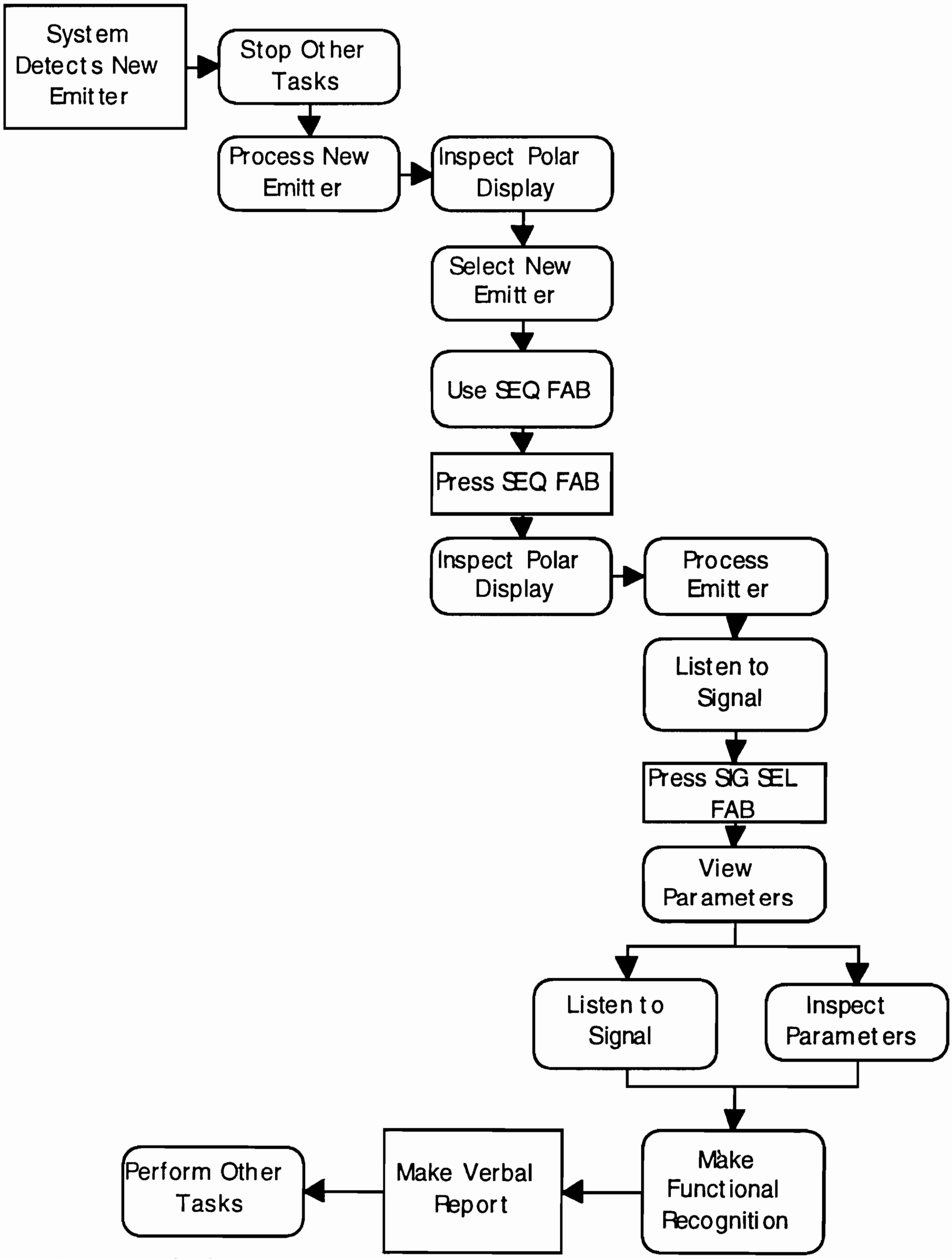


Figure 7b. *SEQ-SIG pathway for completion of functional recognition decisions.*

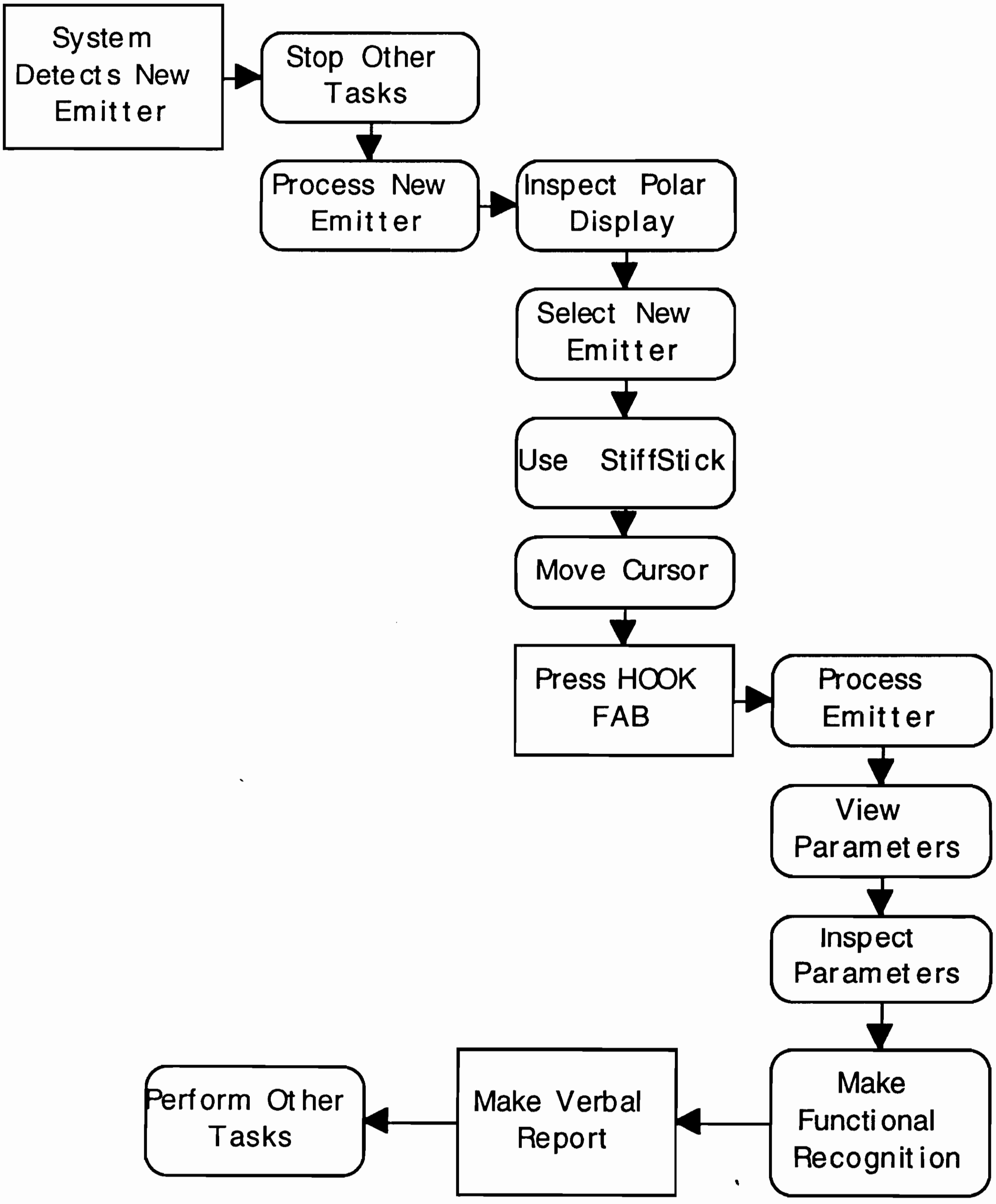


Figure 7c. *HOOK pathway for completion of functional recognition decisions.*

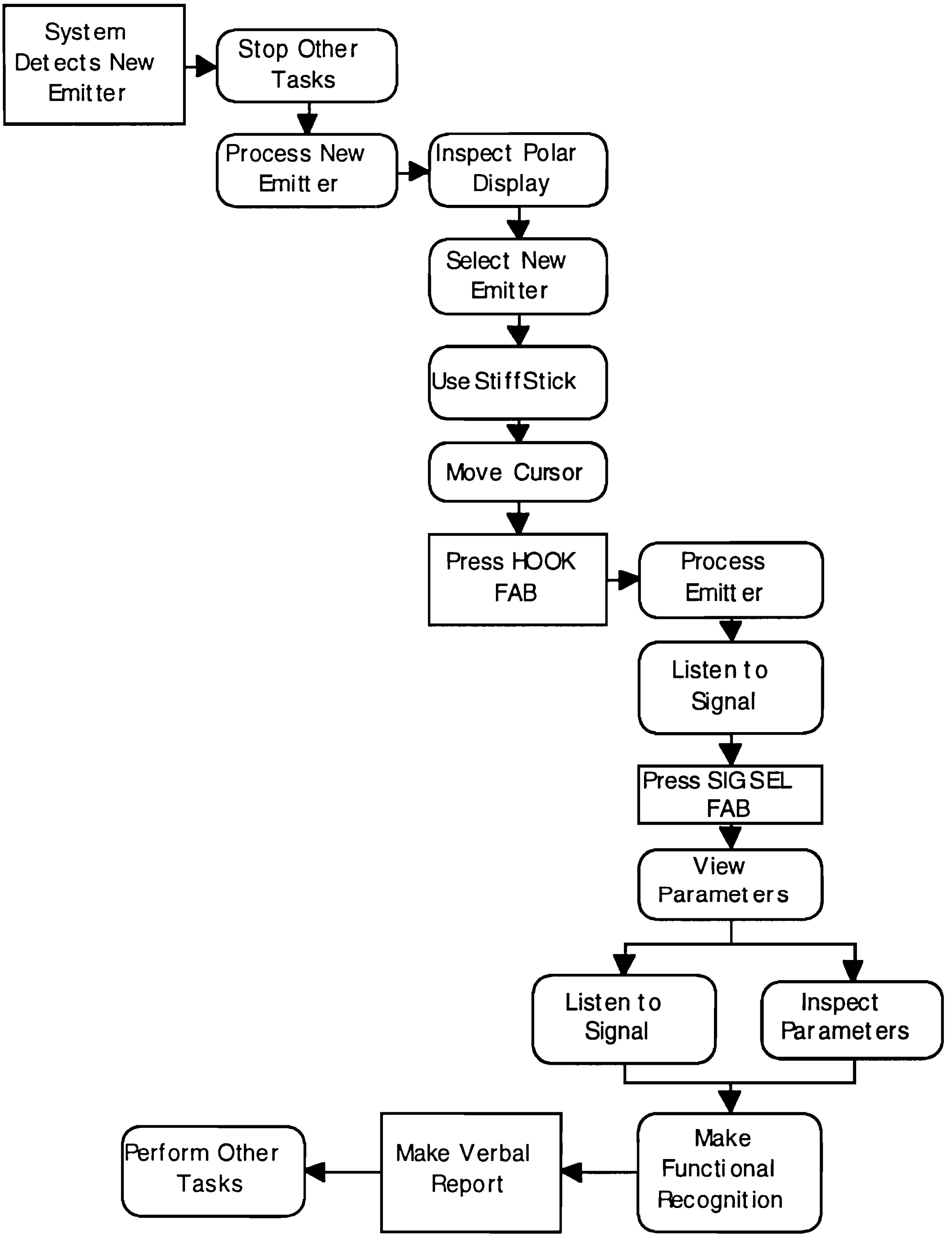


Figure 7d. *HOOK-SIG pathway for completion of functional recognition decisions.*

A descriptive analysis of pathways used by the EW operators was performed on the data collected during the validation study. The pathway descriptions used in the analysis are listed in Table 3.

TABLE 3

Description of Paths

Path #	Description
1	Sequence to Emitter
2	Hook Emitter
3	Sequence and Signal Select Emitter
4	Hook and Signal Select Emitter
5	Sequence to Emitter after a parameter change
6	Hook Emitter after a parameter change
7	Sequence and Signal Select Emitter after a parameter change
8	Hook and Signal Select Emitter after a parameter change

MicroSAINT Model

MicroSAINT is a computer programming environment used to construct network simulations (Micro Analysis and Design, 1990). MicroSAINT models consist of network nodes and links that can be described with transition probabilities (i.e., statistical averages, standard deviations, and distributional properties) and flow control information particular to given conditions (i.e. parameters or factors). Because MicroSAINT models can be executed on a computer to simulate the flow of network events, they allow examination and prediction of network performance under various circumstances.

MicroSAINT was chosen as a development environment for the model of the functional recognition task because of its flexibility, as well as Virginia Tech's experience with it. MicroSAINT allows specification of decision probabilities between nodes, as well as time distributions. Further, in anticipation of future work, MicroSAINT has the capability of using equations to specify any of these items, rather than fixed values. Lastly, the program offers several distributional choices.

Based on the task network model shown in Figure 6 and the sub-networks in Figures 3, 4, and 5 above, a MicroSAINT model for the EW operator task of functionally recognizing emitters was constructed. The MicroSAINT program can implement all aspects of the task network models described earlier, including various strategies to place emitters into close control.

The task model was developed by identifying the task events that can be monitored objectively through Data Extraction (DX) capabilities of the AN/SLQ-32(V) system or external devices (e.g., microphones, video cameras). The major events include system detection of a new emitter; system detection of a scan or parameter change; SEQUENCE, HOOK, and SIGNAL SELECT FAB presses by the operator; and issuing a verbal report. The detection of a new emitter or an emitter parameter change serve as measurable reference points for the beginning of the task model.

Gamma distributions were used in each measurable operator action node in the model, because they are best suited for task element movement times on the AN/SLQ-32(V) (MicroSAINT, 1990; Moscovic, 1991). Gamma distributions describe random variables that have a relatively fixed variability below the mean, but have larger variability above the mean. The distribution is skewed such that the positive tail is extended much farther than the negative tail. For our task elements, this distribution reflects true time variation: operators have a limited capability to perform better than the mean because physical actions take a finite, positive amount of time; however, an operator can always perform worse than the mean. For example, if the mean time to press a key on a typewriter is 3 seconds, it may be impossible to press that key faster than 1 second. It is certainly possible that it could take 20 seconds to press the same key because of distractions or other factors. For the SLQ-32 operator, distractions were often seen to cause this type of delay during experimental data collection.

Data. Time data collected from DX and video analysis of experimental data were sorted by condition (emitter Type, Density of the operational environment) and by task element. Each task element corresponded to a measurable operator action node in the MicroSAINT model that was constructed. Not all nodes in the model were represented; a time value for a particular node indicated the time from the last observable action node along a flow path to that node. Note that task element data were averaged over (and standard deviation calculated for) only those cases where the element could be measured; for example, if the operator did not use the signal select FAB during processing of an emitter, that task element time for a Signal Select node was not included in the calculations.

Population. Data were collected for the various nodes in the model from a laboratory study with OTEs (actual fleet versions of the console, with the exception of external antennae). The two main sources for data were the videotapes of each session with the OTEs and the data extraction file associated with each session of the OTEs. The data extraction (DX) files provided the information for populating all nodes in the MicroSAINT model except that of verbal report; this node was populated with information from video tape analysis.

DX data was collected through use of a PC-compatible computer connected to the AN/SLQ-32(V). This data collection method enabled embedded monitoring of operator performance. All relevant keystrokes made by the operator during a session were recorded into the DX file, along with the time of their occurrence and the state of the system.

Means and standard deviations were calculated for all task element times during successful functional recognitions of emitters. Probabilities for choosing particular paths from a specific decision node (including misses) were determined from proportions of task elements performed along that particular path as opposed to other paths stemming from that decision node. Probabilities were calculated for "missed" emitters by determination of each possible miss path and proportion of misses observed in experimental data collection that followed each path. These probabilities for particular paths through the model were not associated with distributions; MicroSAINT does not possess that capability.

Means and standard deviations for task element times and decision point probabilities also were calculated and tabulated for particular conditions (Density, emitter Type). For low-probability task elements (e.g., Enter EFX) and flow paths, too few data points caused the resulting analysis to report zero standard deviations and zero probabilities for certain task element times and flow paths. The task network model does not contain some of these paths (such as Enter EFX, as described previously), nor does the MicroSAINT model.

Simulation. After appropriate probabilities for decision points, and mean times and standard deviations for task element times, were determined and placed in the model, the model was run for sufficient emitters for each condition combination to match the amount of data collected in the validation study. The specific numbers on this analysis are presented in the RESULTS section of this document.

VALIDATION STUDY

The PAM required several steps for validation. A general validation was conducted with the intent to show overall correlation between summary results of the model and aggregate results of the functional recognition task. A more detailed validation was conducted by comparing results of the model for specific strategies (pathways through the model) operators took to aggregate values for the strategies observed in the laboratory. Lastly, the model was refined to show the variance of predicted results and to show how the methodology was used to develop information not normally available through task analysis. The laboratory data were used to categorize the performance of operators into Proficiency Level categories and then results of the model within categories were compared to observed data from operators in the laboratory according to those categories. The model was accepted because the criterion for the PAM of 75% of variance in the observed data predicted by the simulation was met, as shown through correlation between predicted data and laboratory data. Specific numbers for these analyses are presented in the RESULTS section of this document.

This section of the work describes the laboratory validation study undertaken to validate the PAM. In this study, U.S. Navy personnel experienced in the operation of the AN/SLQ-32(V) participated in data collection sessions lasting two weeks. During the sessions, sailors operated two AN/SLQ-32(V) OTEs and their functional recognition performance was monitored and recorded using computer DX techniques. The data were evaluated statistically using Virginia Tech's Proficiency Assessment Device (SHARP PAD) software, which was developed to aid in determining overall performance trends and to refine the simulation model for EW operators performing the functional recognition task.

Procedure

The validation study was conducted in Virginia Tech's Electronic Warfare Area Test Center (EWATC) over a period of two weeks. One week of data collection prior to collection for use in the proposed methodology was used as a pilot study to allow final modifications to the test equipment, procedures, and the task network model. The actual data collection took place during two weeks following this pilot week.

Eight individuals participated in the study during each of the three weeks (24 total participants), although data were only collected on the participants from the second and third weeks. These individuals were U.S. Navy sailors who were stationed on active duty billets in the Atlantic and Pacific Fleets. All participants were qualified AN/SLQ-32(V) operators; however, their AN/SLQ-32(V) operational experience ranged from a few months to several years. All participants were selected for this study by senior EW personnel assisting the project.

The EW operators of the system were of varying experience levels. Some operators were within a year of graduating from apprenticeship school. Other operators had served in the Persian Gulf conflict. No operators were chiefs, but some were 1st class enlisted personnel. No operators had not attained 3rd class rating.

The EW operators were highly stimulated for the shore-based testing. Visiting a university campus provided a level of excitement not found in peacetime steaming aboard ship or at a naval base. Their motivation levels were more varied, and depended on their desire to add to the performance data store, their sense of duty, their age, and other factors.

During each week of testing, eight sailors were grouped into four two-person teams consisting of an EW operator and a supervisor. Each team received nine emitter scenarios, lasting four hours each (36 total hours per team). The emitter scenarios were presented in separate test sessions throughout the week. Table 4 shows the weekly test schedule used for the EW teams.

TABLE 4

Weekly Schedule of Test Sessions for Four Teams

Time	Monday	Tuesday	Day Wednesday	Thursday	Friday
0600-1000	Team 1	Team 1	Team 1	Team 1	Team 1
	Team 2	Team 2	Team 2	Team 2	Team 2
1015-1415	Team 3	Team 3	Team 3	Team 3	Team 3
	Team 4	Team 4	Team 4	Team 4	Team 4
1430-1830	Team 1	Team 1	Team 1	Team 1	
	Team 2	Team 2	Team 2	Team 2	
1845-2245	Team 3	Team 3	Team 3	Team 3	
	Team 4	Team 4	Team 4	Team 4	

At the beginning of each week, the EW teams received an intelligence briefing about all scenarios to be completed. Electronic Order of Battle (EOB), Watch Turn-Over, and Signal Intercept Log documents were provided to the EW teams prior to each test. The EW teams were allowed to ask questions to clarify the test procedures and scenario details prior to initiating their work. AN/SLQ-32A(V) on-line libraries were not provided for the scenarios although the EW teams were allowed to construct on-line libraries during the test sessions (only a few on-line libraries were actually constructed by any EW teams during the testing; they did not feel it was useful in the testing time allotted).

During the test session, tactical queries from a Tactical Action Officer (TAO) were simulated by Virginia Tech staff through the use of scripted dialogues written by EW SMEs. The so-called "tipper" scripts were rehearsed by Virginia Tech staff prior to the study to establish a high level of realism.

EWATC Facility

Virginia Tech's EWATC facility is a secure area housing two self-contained and isolated work areas. Each work area contains an AN/SLQ-32(V) OTE, interfaced to an EW On Board Trainer (EWOBT) and an IBM/PC-type desktop computer. The EWOBT executes emitter scenarios to stimulate the AN/SLQ-32(V) OTE, while the IBM/PC desktop computer controls the PC/DX hardware and software. Additionally, the EWATC work areas contain a world chart and dual clocks for Greenwich Mean Time (GMT) and local time calculations. The relevant environmental controls in the EWATC are presented below.

Noise. The ambient noise in the EWATC stems primarily from the test equipment (e.g., AN/SLQ-32A(V) OTE, EWOBT, various desktop computer systems used for data collection). The audible sound levels from this equipment were maintained in the range of 68-78 dBA.

Illumination. The ambient illumination in the EWATC is provided by overhead fluorescent lights. The light fixtures consist of blue-colored filters to simulate shipboard EW module settings. The ambient illumination level was maintained in the range of 200-500 lux.

Shock and Vibration. The EWATC is a stand-alone structure placed on concrete flooring. There was no noticeable vibration to the EWATC flooring from the test equipment or the surrounding environment during the study.

Air Temperature and Humidity. The EWATC facility has two air conditioner units, one located in each test room. Room temperature was maintained in the range of 70-80 degrees F during the study.

Ventilation. The EWATC air conditioner units provided adequate ventilation during the test sessions.

Toxic or Hazardous Substances. The participants were not be exposed to any toxic or hazardous substances during the test.

Design

The validation study was designed to provide time and accuracy data on the EW operator's functional recognition decisions under operationally relevant conditions. The conditions were defined by combinations of three variables: emitter density, emitter type, and time-on-watch, as shown in Figure 8. Each EW team received a total of nine unique conditions (3 emitter density levels X 3 emitter types), one condition per emitter scenario. The time-on-watch variable was assessed during data analysis, as explained later in this document.

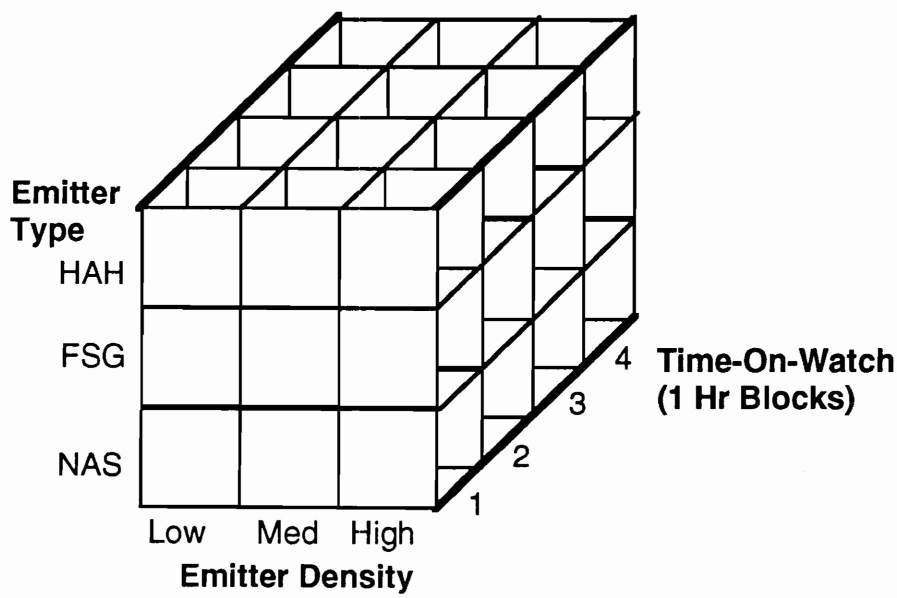


Figure 8. *Experiment design matrix for the validation study.*

Emitter density levels were defined by a panel of EW SMEs from LANTFLT and PACFLT to replicate actual levels found during afloat operations. Emitter density was a within-subjects variable with three levels: low, medium, and high (see Table 5). The density levels were defined by two parameters: total number of emltters detected by the AN/SLQ-32A(V) and the pacing of emitter events (i.e., a new emitter or emitter parameter change alert).

TABLE 5

Emitter Density Levels Used in Validation Study

Density	Number of Emitters	Pace	Number of emitters of interest per hour
Low	1-25	1-4 per four minutes	3
Medium	26-50	1-4 per two minutes	6
High	51-75	1-4 per minute	9

Emitter type was a within-subjects variable with three levels: Hostile-Air-Homing (HAH), Friendly-Surface-Guidance (FSG), and Neutral-Air-Search (NAS). HAH emitters represented high threat emitters, such as missiles; FSG emitters represented non-hostile shipboard weapon systems; and NAS emitters represented non-combatant airborne emitters, such as navigational systems.

Time-on-watch was a within-subjects variable with four levels. Specifically, the length of each emitter scenario (i.e., one scenario for each combination of emitter density and emitter type) was four hours, and the functional recognition data were analyzed across the four hour-long blocks.

RESULTS

Data Analysis

The validation approach for the PAM began with general study and proceeded to detailed analyses. General analyses began with ANOVAs to describe the laboratory data. Next, additional variables were derived from the laboratory data for use in later detailed analyses. A general correlation was made between the summary results of the model and aggregate results of the functional recognition task in the laboratory. Detailed analyses followed, including correlations between predicted and observed functional recognition times based on first, original variables from the validation study design, and second, based on re-castings of the model and re-apportioning of the laboratory data from the derived variables just mentioned.

The data analyses consisted of three steps:

> (1) The effects of the model parameter variables (Emitter Type and Emitter Density) on performance were analyzed. The complete functional recognition performance for each type of emitter of interest in each density condition and in each hour time block was analyzed inferentially with ANOVAs on each dependent measure (including the Greenhouse-Geisser correction to deal with heterogeneity of covariance). Graphs with error bars showing standard error of the mean and Newman-Keuls tests were performed on the significant effects.
>
> (2) Two new variables, EW team "Proficiency Level" and task strategy ("Path") were derived from the laboratory data to enable comparisons with similar derivations from the simulation model.
>
> The laboratory performance data were used to descriptively compare EW team performance. Accuracy and number of reports made by operators were compared. A histogram of the overall functional recognition time data was used to develop ranges of Proficiency Levels for the EW teams. The EW teams were categorized into these ranges, and descriptive statistics were calculated.

The data on each step of the functional recognition process measured with the SHARP PAD DX software were manipulated as described in the latter part of the section of this document concerning model population, and was used to develop the variable "Path" for each emitter of interest; descriptive statistics on percentages for each condition of paths/strategies used were calculated.

(3) The DX data were used to fill out the framework of the simulation model (to "populate" the model). The simulation model was run and its results for complete functional recognition times were paired with the actual observed values during the validation study to determine the predictiveness of the model. The results of the model as run with parameters of Emitter Type and Emitter Density were compared with the results from the laboratory data for those conditions. Lastly, results from variations on the model created using the new variables of EW team Proficiency Level and Path were compared to the performance results on these variables from the laboratory data to test the extensibility of the model.

ANOVAs for Functional Recognition Time and Accuracy

Table 6 shows the ANOVA summary table for functional recognition time. The main effect of Emitter Type was significant ($\alpha = 0.10$). The interaction of Emitter Type and Hour on Watch also was significant ($\alpha = 0.10$). No other ANOVA effects were statistically significant.

TABLE 6

ANOVA Summary Table for Functional Recognition Time

Source	df	MS	F	G-G* epsilon	G-G* corrected p-values
Subjects	7				
Emitter Type	2	53729.34	7.82	0.5699	**0.0212**
Emitter Type * Subject	14	6872.30			
Emitter Density	2	8599.87	0.90	0.6185	0.3931
Emitter Density * Subject	14	9602.59			
Time Block	3	7560.74	2.08	0.6619	0.1624
Time Block * Subject	21	3636.51			
Type * Density	4	5212.66	1.11	0.4465	0.3520
Type * Density * Subject	28	4680.27			
Type * Time Block	6	7130.17	3.27	0.3569	**0.0638**
Type * Time Block * Subject	42	2183.76			
Density * Time Block	6	3682.03	1.20	0.4393	0.3331
Density * Time Block * Subject	42	3064.64			
Type * Density * Time Block	12	6585.95	2.25	0.2717	0.1061
Type * Density * Time Block * Subject	84	2932.26			
Total	287				

* G-G: Greenhouse-Geiser

Figure 9 shows the main effect of Emitter Type on functional recognition time. A *post hoc* Newman-Keuls test indicates that functional recognition times are longer for the FSG and NAS emitters as compared with HAH emitters ($p < 0.10$). On average, the HAH emitters were functionally recognized about 2.82 times faster than FSG and NAS emitters (i.e., 22 versus 61 seconds).

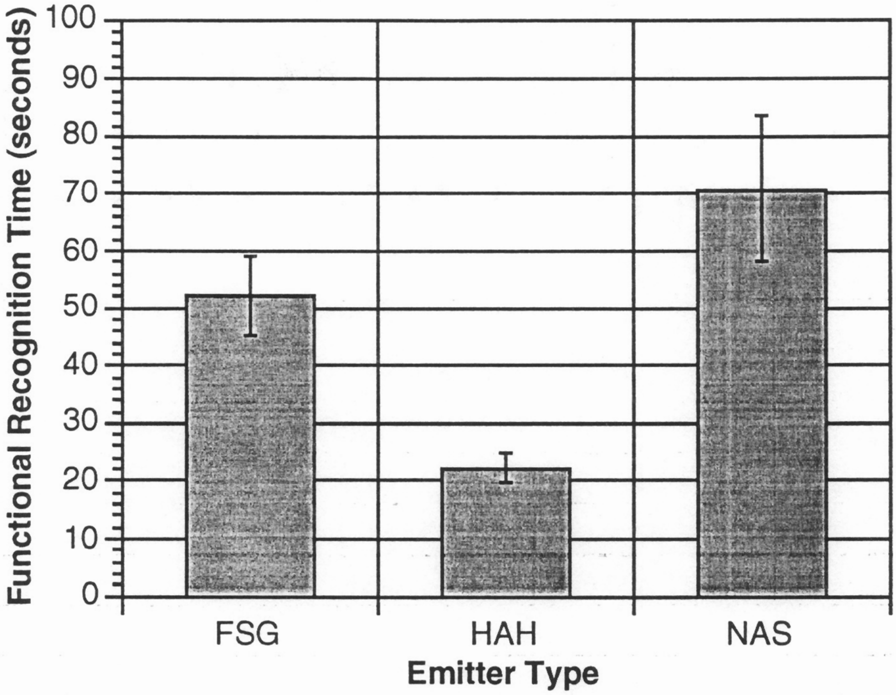


Figure 9. *Main effect of emitter type on functional recognition time.*
(Error bars indicate +/- 1 standard error of the mean units)

Figure 10 shows the two-factor interaction effect of Emitter Type and Time-on-Watch on functional recognition time. A *post hoc* simple effects test, followed by Newman-Keuls (N-K) tests, indicate that functional recognition times are longer for NAS emitters than HAH emitters in the fourth hour, FSG emitters than NAS emitters in the second hour, FSG emitters in the second hour than FSG emitters in other hours, and NAS emitters than HAH emitters in the first hour ($p < 0.10$). The simple effects test is shown in Table 7 and the subsequent N-K tests are shown in Table 8.

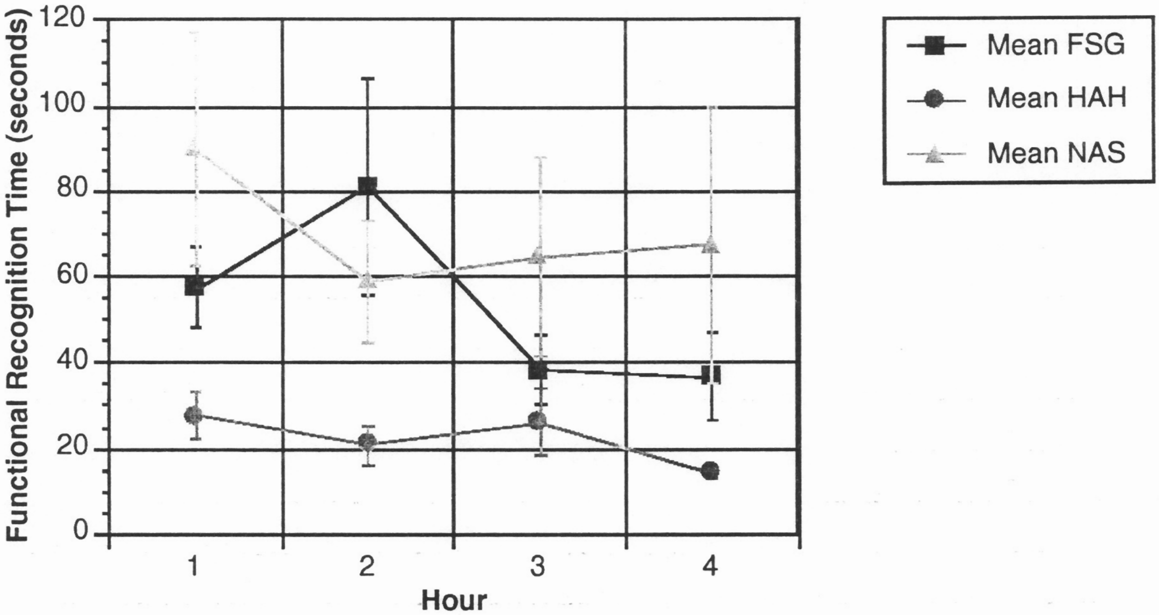


Figure 10. *Interaction of Emitter Type and Hour on Watch on functional recognition time.* (Error bars indicate +/- 1 standard error of the mean)

TABLE 7

Simple Effects test on the Interaction of Emitter Type * Hour on Watch on Functional Recognition Time.

Main Effect	at Level of	MSeffect	MSerror	F	p
Type	1st Hour	24798.362	2183.765	11.356	**0.001**
Type	2nd Hour	28792.455	2183.765	13.185	**0.001**
Type	3rd Hour	8394.618	2183.765	3.844	**0.029**
Type	4th Hour	13134.398	2183.765	6.015	**0.005**
Hour	FSG	14456.015	2183.765	6.620	**0.001**
Hour	NAS	6365.310	2183.765	2.915	**0.045**
Hour	HAH	999.743	2183.765	0.458	0.713

TABLE 8

Newman-Keuls tests on the Interaction of Emitter Type * Hour on Watch on Functional Recognition Time.

Main Effect	at Level of	Level of Effect	Means			
Type	1st Hour			57.624	91.281	
		HAH	27.016	30.608*	64.265*	
		FSG	57.624		33.657*	
		NAS	91.281			
	2nd Hour			55.075	90.058	
		HAH	20.786	34.289*	69.272*	
		NAS	55.075		34.983*	
		FSG	90.058			
	3rd Hour			38.120	63.153	
		HAH	26.567	11.553	36.586*	
		FSG	38.120		25.033*	
		NAS	63.153			
	4th Hour			37.980	59.594	
		HAH	13.195	24.785*	46.399*	
		FSG	37.980		21.614	
		NAS	59.954			
Hour	FSG			38.120	57.624	90.058
		4th Hour	37.980	0.140	19.644	52.078*
		3rd Hour	38.120		19.504	51.938*
		1st Hour	57.624			32.434*
		2nd Hour	90.058			
	NAS			59.954	63.153	91.281
		2nd Hour	55.075	4.879	8.078	36.206*
		4th Hour	59.954		3.199	31.327*
		3rd Hour	63.153			28.128*
		1st Hour	91.281			

* indicates p<0.10

Functional Recognition Accuracy

The analysis of functional recognition accuracy depends on two factors. First, as defined in this work, functional recognition accuracy refers to the correctness of a verbal report given by the EW operator. Thus, functional recognition accuracy analysis considered only those emitters that the EW operator verbally announced. Second, because the verbal report consisted of three components (i.e., emitter function, platform, and owner), the functional recognition accuracy analysis considered the correctness of each part of the verbal reports.

Percent of total reports. Table 9 shows the ANOVA findings for the percent of verbal reports given during the validation study. The percent of reports is defined as the total number of reports on emitters-of-interest given during a trial (i.e., watch period) divided by the total number of emitters-of-interest presented during the trial. For example, under a test of HAH emitters in a high density condition, an operator who verbally reported one-half of the HAH emitters received a 50 percent score.

The main effects of Emitter Type and Emitter Density on the percent of verbal reports were significant ($\alpha = 0.10$). No other ANOVA effects were statistically significant.

TABLE 9

ANOVA Summary Table for Percent of Functional Recognition Reports Given

Source	df	MS	F	G-G* epsilon	G-G* corrected p-values
Subjects	7				
Emitter Type	2	2.72	13.70	0.9368	**0.0007**
Emitter Type * Subject	14	0.20			
Emitter Density	2	0.56	4.94	0.9927	**0.0242**
Emitter Density * Subject	14	0.11			
Time Block	3	0.07	1.77	0.7718	0.1989
Time Block * Subject	21	0.04			
Type * Density	4	0.14	1.50	0.6480	0.2504
Type * Density * Subject	28	0.09			
Type * Time Block	6	0.12	2.28	0.3639	0.1328
Type * Time Block * Subject	42	0.05			
Density * Time Block	6	0.06	1.09	0.5923	0.3799
Density * Time Block * Subject	42	0.05			
Type * Density * Time Block	12	0.04	1.23	0.3197	0.3200
Type * Density * Time Block * Subject	84	0.03			
Total	287				

Figure 11 shows the main effect of Emitter Type on the percent of functional recognition reports given by the EW operators. A *post hoc* Newman-Keuls test indicates the percentage of FSG and NAS verbal reports is smaller than that for HAH emitters ($p <$ 0.10). The percent of emitter reports for HAH emitters was about 1.63 times higher than FSG and NAS emitters (i.e., 75 versus 46 percent).

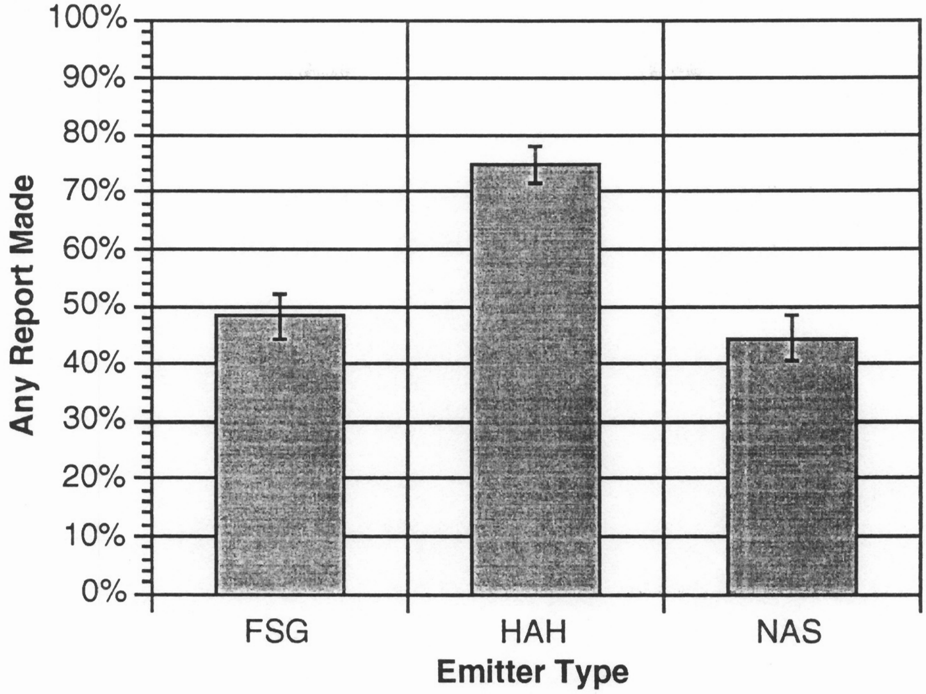


Figure 11. *Main effect of emitter type on percent of verbal reports made by EW operators.* (Error bars indicate +/- 1 standard error of the mean units)

Figure 12 shows the main effect of Emitter Density on the percent of functional recognition reports given by the EW operators. A *post hoc* Newman-Keuls test indicates the percent of verbal reports under the High and Medium density conditions is smaller than that for Low density condition ($p < 0.10$). The percent of emitter reports given under the Low density condition was about 1.07 times higher than Medium and High density conditions (i.e., 61 versus 57 percent).

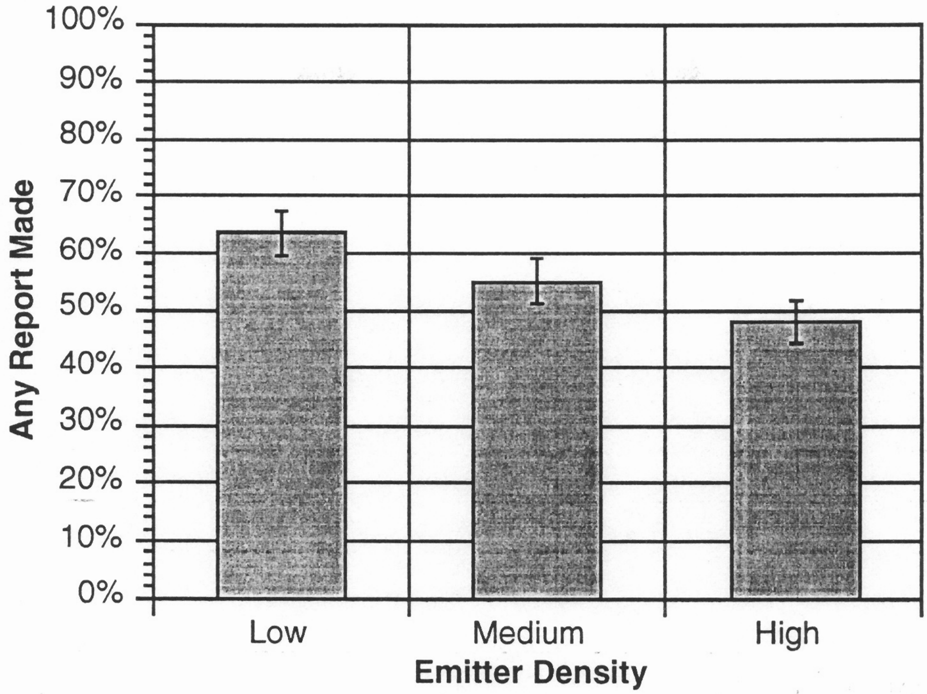


Figure 12. *Main effect of emitter density on percent of verbal reports made by EW operators.* (Error bars indicate +/- 1 standard error of the mean units)

Accuracy of emitter function reports. Table 10 shows the ANOVA summary table for the percent of correct emitter function reports. The main effects of Emitter Type and Time-on-Watch were significant ($\alpha = 0.10$). No other ANOVA effects were statistically significant.

TABLE 10

ANOVA Summary Table for Functional Recognition Accuracy of Emitter Function

Source	df	MS	F	G-G* epsilon	G-G* corrected p-values
Subjects	7				
Emitter Type	2	5.58	18.25	0.9243	**0.0002**
Emitter Type * Subject	14	0.31			
Emitter Density	2	0.05	0.65	0.8232	0.5114
Emitter Density * Subject	14	0.08			
Time Block	3	0.28	3.87	0.5856	**0.0539**
Time Block * Subject	21	0.07			
Type * Density	4	0.11	0.72	0.4676	0.4945
Type * Density * Subject	28	0.15			
Type * Time Block	6	0.22	2.31	0.5083	0.1049
Type * Time Block * Subject	42	0.09			
Density * Time Block	6	0.02	0.23	0.5964	0.9047
Density * Time Block * Subject	42	0.11			
Type * Density * Time Block	12	0.15	1.80	0.3261	0.1596
Type * Density * Time Block * Subject	84	0.08			
Total	287				

Figure 13 shows the main effect of Emitter Type on the percent of correct emitter function reports given by the EW operators. A *post hoc* Newman-Keuls test indicates the percent of verbal reports with a correct function component is greater for HAH emitters than that for FSG and NAS emitters ($p < 0.10$). Specifically, the percent of HAH emitter reports with correct function components was about 1.92 times higher than that for FSG and NAS emitter reports (i.e., 86 versus 44 percent).

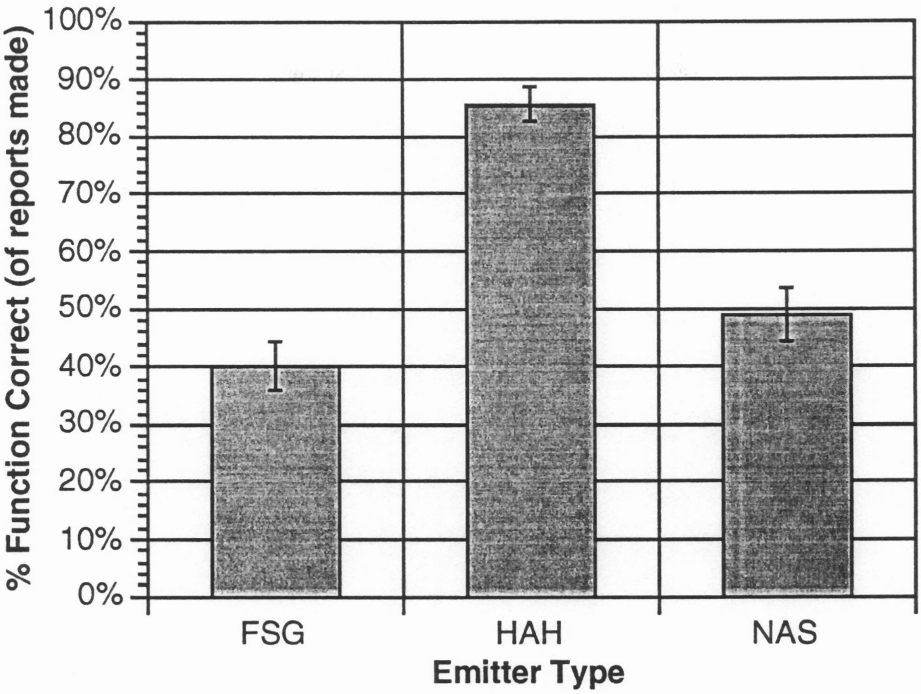


Figure 13. *Main effect of emitter type on percent of correct emitter function reports made by EW operators.* (Error bars indicate +/- 1 standard error of the mean units)

Figure 14 shows the main effect of Time-on-Watch on the percent of correct emitter function reports given by the EW operators. A *post hoc* Newman-Keuls test indicates the percent of verbal reports with a correct function component was greater in the first hour as compared to the third hour ($p < 0.10$). Specifically, the percent of emitter reports with a correct function component was about 1.29 times higher in the first hour than in the third hour (i.e., 67 versus 52 percent).

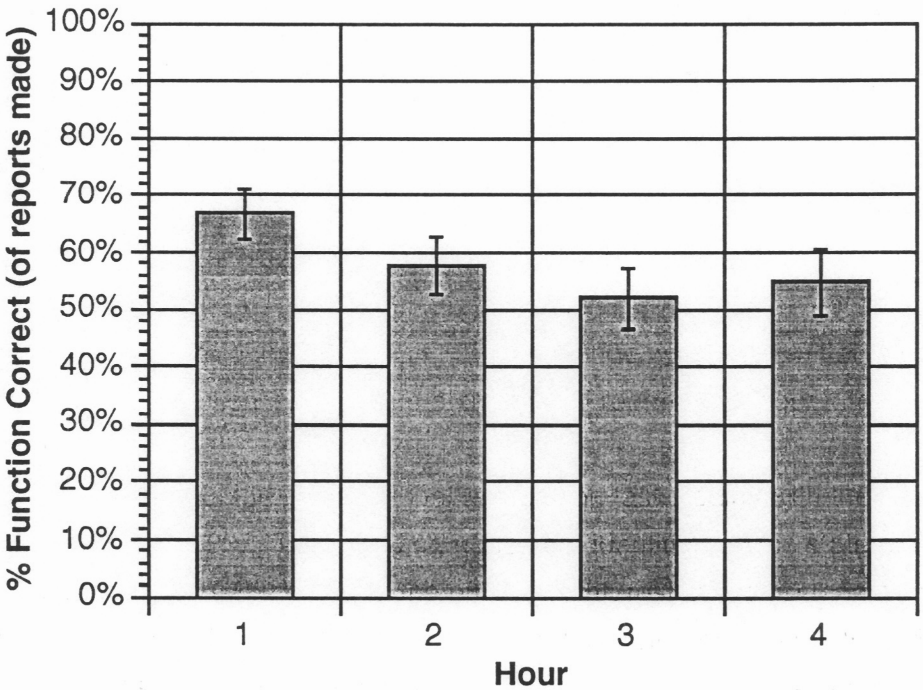


Figure 14. *Main effect of Hour on Watch on percent of correct emitter function reports made by EW operators.* (Error bars indicate +/- 1 standard error of the mean units)

Accuracy of emitter platform reports. Table 11 shows the ANOVA summary table for the percent of correct emitter platform reports. The main effect of Emitter Type was significant ($\alpha = 0.10$). The two-factor interaction effect of Emitter Type * Hour on Watch also was significant ($\alpha = 0.10$).

TABLE 11

ANOVA Summary Table for Functional Recognition Accuracy of Emitter Platform

Source	df	MS	F	G-G* epsilon	G-G* corrected p-values
Subjects	7				
Emitter Type	2	7.64	21.84	0.7240	**0.0004**
Emitter Type * Subject	14	0.35			
Emitter Density	2	0.34	2.55	0.9393	0.1180
Emitter Density * Subject	14	0.13			
Time Block	3	0.18	1.44	0.6952	0.2683
Time Block * Subject	21	0.12			
Type * Density	4	0.06	0.53	0.6666	0.6447
Type * Density * Subject	28	0.11			
Type * Time Block	6	0.47	6.12	0.3947	**0.0079**
Type * Time Block * Subject	42	0.08			
Density * Time Block	6	0.14	1.92	0.4825	0.1597
Density * Time Block * Subject	42	0.07			
Type * Density * Time Block	12	0.12	1.87	0.3815	0.1316
Type * Density * Time Block * Subject	84	0.06			
Total	287				

Figure 15 shows the main effect of Emitter Type on the percent of correct emitter platform reports given by the EW operators. A *post hoc* Newman-Keuls test indicates the percent of verbal reports with a correct platform component is larger for HAH emitters than that for NAS emitters, which in turn is larger than that for FSG emitters ($p < 0.10$). Specifically, the percent of HAH emitter reports with a correct platform component was about 1.91 times higher than that for NAS emitter reports (i.e., 87 versus 45 percent), and the percent of NAS emitter reports with a oorrect platform component was about 1.39 times higher than that for FSG emitter reports (i.e. 45 versus 33 percent).

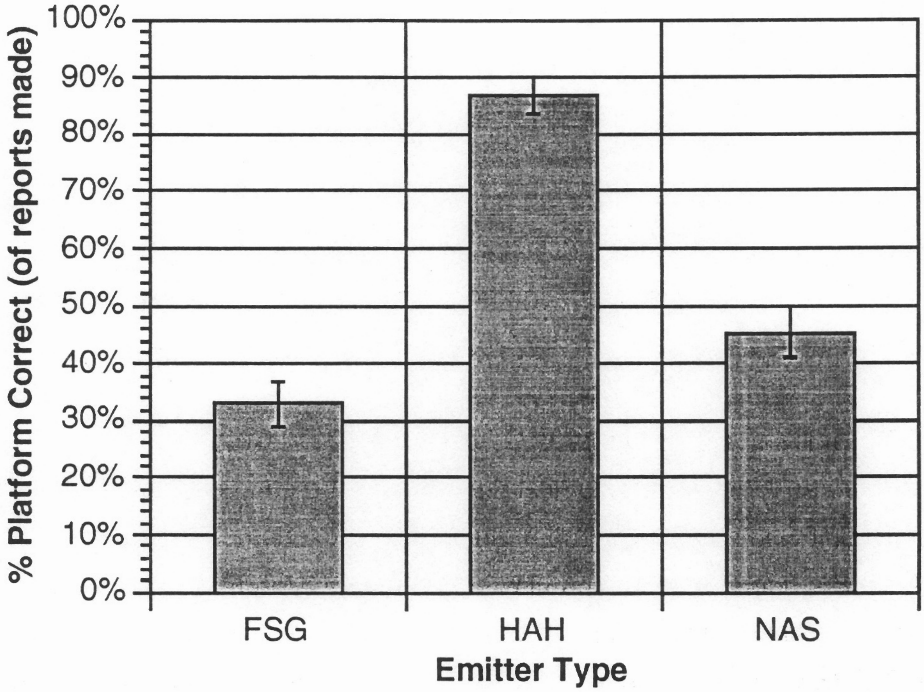


Figure 15. *Main effect of Emitter Type on percent of correct emitter platform reports made by EW operators.* (Error bars indicate +/- 1 standard error of the mean units)

Figure 16 shows the two-way interaction effect of Emitter Type * Hour-on-Watch on the percent of correct emitter platform reports given by the EW operators. A *post hoc* simple effects test, in conjunction with several Newman-Keuls tests on significant components of the interaction, indicate the percent of verbal reports with a correct platform component was greater for FSG emitters on the first hour of the watch, and also in the first hour FSG emitters were reported with correct platform components more than NAS emitters. The decline in the accuracy of FSG emitter platform reporting in the later hours of the watch may be attributed to the lack of criticality of these emitters (they are friendlies and not a threat). In the second and fourth hours, NAS emitters' platforms were reported correctly more often than FSG emitters'. NAS emitters' platforms were reported correctly more often in the fourth hour than the third. HAH emitters' platforms were reported correctly more often than NAS or FSG emitters in all four hours, and were reported correctly more often in the second hour than the third. All of these effects are statistically significant ($p < 0.10$), and the *post hoc* analyses are shown in Tables 12 and 13.

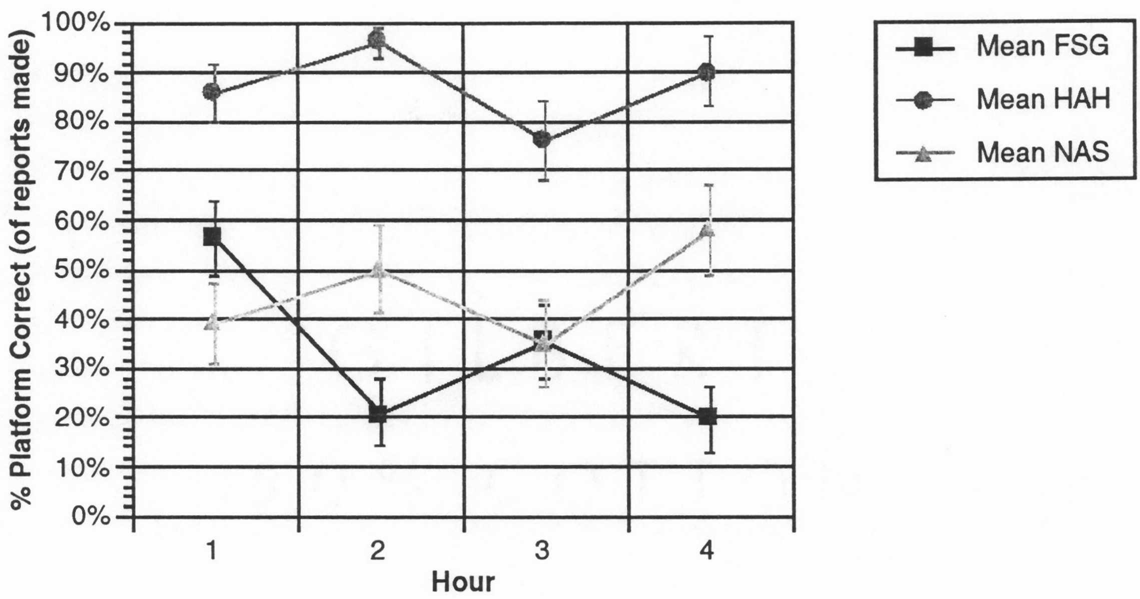


Figure 16. *Two-way interaction effect of Emitter Type * Hour on Watch on percent of correct emitter platform reports made by EW operators.*
(Error bars indicate +/- 1 standard error of the mean units)

TABLE 12

Simple Effects test for interaction of Emitter Type * Hour on Watch on Percent of Correct Emitter Platform Reports.

Main Effect	at Level of	MSeffect	MSerror	F	p
Type	1st Hour	1.321	0.077	17.221	**0.001**
Type	2nd Hour	3.449	0.077	44.962	**0.001**
Type	3rd Hour	1.366	0.077	17.807	**0.001**
Type	4th Hour	2.917	0.077	38.021	**0.001**
Hour	FSG	0.699	0.077	9.110	**0.001**
Hour	NAS	0.249	0.077	3.241	**0.031**
Hour	HAH	0.167	0.077	2.181	**0.105**

TABLE 13

Newman-Keuls tests on the Interaction of Emitter Type * Hour on Percent of Correct Emitter Platform Reports.

Main Effect	at Level of	Level of Effect	Means			
Type	1st Hour			0.563	0.856	
		NAS	0.392	0.171*	0.464*	
		FSG	0.563		0.293*	
		HAH	0.856			
	2nd Hour			0.497	0.960	
		FSG	0.208	0.289*	0.752*	
		NAS	0.497		0.463*	
		HAH	0.960			
	3rd Hour			0.351	0.759	
		FSG	0.341	0.010	0.418*	
		NAS	0.351		0.408*	
		HAH	0.759			
	4th Hour			0.576	0.892	
		FSG	0.195	0.381*	0.697*	
		NAS	0.576		0.316*	
		HAH	0.892			
TB	FSG			0.208	0.341	0.563
		4th Hour	0.195	0.013	0.146	0.368*
		2nd Hour	0.208		0.133	0.355*
		3rd Hour	0.341			0.222*
		1st Hour	0.563			
	NAS			0.392	0.497	0.576
		3rd Hour	0.351	0.041	0.146	0.225*
		1st Hour	0.392		0.105	0.184*
		2nd Hour	0.497			0.079
		4th Hour	0.576			

* indicates p<0.10

<u>Accuracy of emitter owner reports</u>. Table 14 shows the ANOVA summary table for the percent of correct emitter owner reports. The main effect of Emitter Type was significant ($\alpha = 0.10$). The two-factor interaction of Emitter Type * Hour on Watch was statistically significant ($\alpha = 0.10$).

TABLE 14

ANOVA Summary Table for Functional Recognition Accuracy of Emitter Owner

Source	df	MS	F	G-G* epsilon	G-G* corrected p-values
Subjects	7				
Emitter Type	2	14.10	49.58	0.9111	**0.0001**
Emitter Type * Subject	14	0.28			
Emitter Density	2	0.03	0.27	0.7543	0.7074
Emitter Density * Subject	14	0.11			
Time Block	3	0.05	0.76	0.6751	0.4853
Time Block * Subject	21	0.07			
Type * Density	4	0.08	1.10	0.7327	0.3721
Type * Density * Subject	28	0.07			
Type * Time Block	6	0.23	3.80	0.4844	**0.0269**
Type * Time Block * Subject	42	0.06			
Density * Time Block	6	0.09	1.82	0.4124	0.1875
Density * Time Block * Subject	42	0.05			
Type * Density * Time Block	12	0.06	1.07	0.3305	0.3894
Type * Density * Time Block * Subject	84	0.05			
Total	287				

Figure 17 shows the main effect of Emitter Type on the percent of correct emitter owner reports given by the EW operators. A *post hoc* Newman-Keuls test indicates the percent of correct owner components of the verbal reports for HAH emitters are larger than that for FSG and NAS emitters ($p < 0.10$). Specifically, the percent of correct HAH emitter owner components of the reports was about 4.16 times higher than for the FSG and NAS emitter reports (i.e., 87 versus 21 percent, respectively).

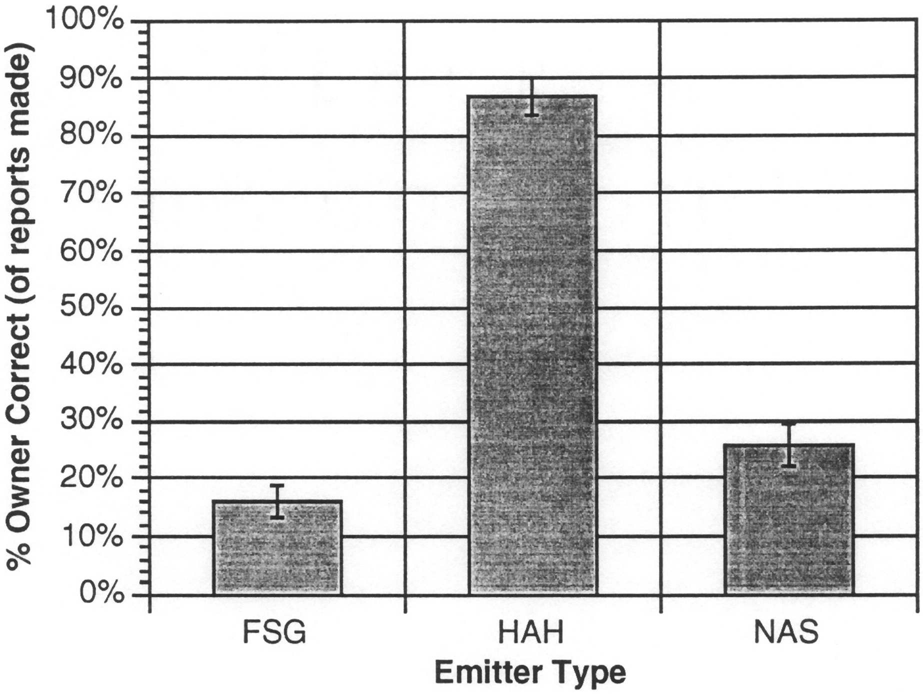


Figure 17. *Main effect of Emitter Type on percent of correct emitter owner reports made by EW operators.* (Error bars indicate +/- 1 standard error of the mean units)

Figure 18 shows the two-way interaction of Emitter Type * Hour on Watch on the percent of correct emitter owner reports given by the EW operators. A *post hoc* simple effects test followed by Newman-Keuls tests on significant components of the interaction indicates the percent of correct owner components of the verbal reports for HAH emitters was greater than that for other emitters, that NAS emitters owner components were correctly reported more often than FSG emitters in the fourth hour, and than NAS emitters in the first and third hours, and that HAH emitters' owner components were reported correctly more often in the second hour than the third ($p < 0.10$). The *post hoc* analyses are shown in Tables 15 and 16.

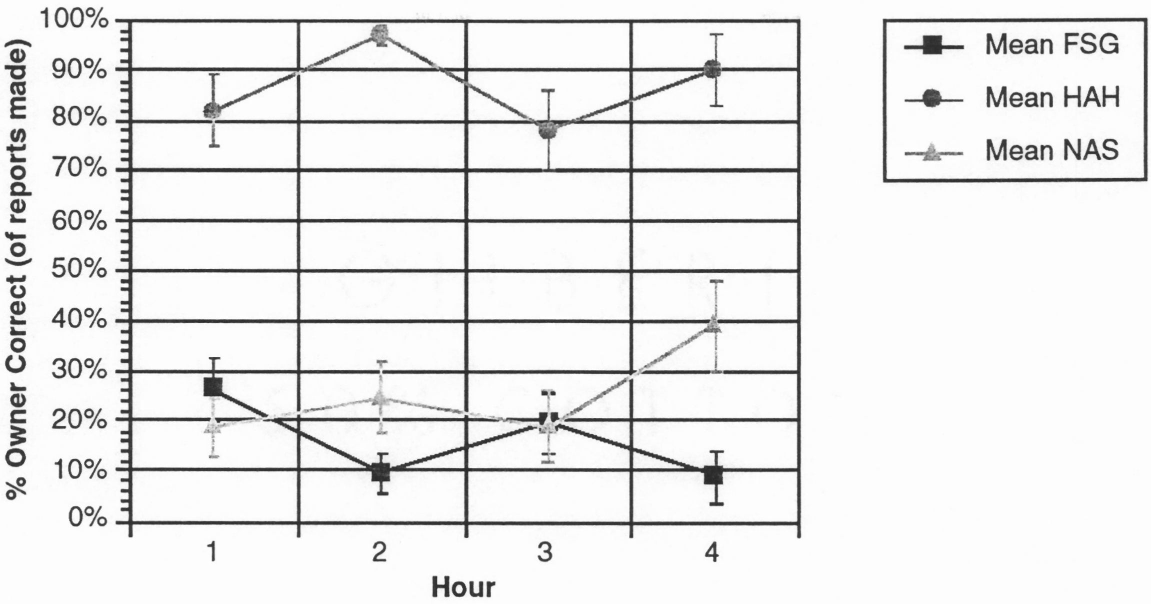


Figure 18. *Two-way interaction effect of Emitter Type * Hour on Watch on percent of correct emitter owner reports made by EW operators.*
(Error bars indicate +/- 1 standard error of the mean units)

TABLE 15

Simple Effects test on the interaction of Emitter Type * Hour on Watch on percent of correct emitter owner reports made by EW operators.

Main Effect	at Level of	MSeffect	MSerror	F	p
Type	1st Hour	2.853	0.062	46.247	**0.001**
Type	2nd Hour	5.228	0.062	84.763	**0.001**
Type	3rd Hour	2.776	0.062	45.012	**0.001**
Type	4th Hour	3.938	0.062	63.844	**0.001**
Hour	FSG	0.165	0.062	2.681	**0.059**
Hour	NAS	0.193	0.062	3.132	**0.036**
Hour	HAH	0.164	0.062	2.653	**0.061**

TABLE 16

Newman-Keuls tests on the Interaction of Emitter Type * Hour on percent of correct emitter owner reports made by EW operators.

Main Effect	at Level of	Level of Effect	Means			
Type	1st Hour			0.263	0.820	
		NAS	0.189	0.074	0.631*	
		FSG	0.263		0.557*	
		HAH	0.820			
	2nd Hour			0.253	0.971	
		FSG	0.095	0.158*	0.876*	
		NAS	0.253		0.718*	
		HAH	0.971			
	3rd Hour			0.196	0.784	
		FSG	0.194	0.002	0.590*	
		NAS	0.196		0.588*	
		HAH	0.784			
	4th Hour			0.383	0.892	
		FSG	0.091	0.292*	0.800*	
		NAS	0.383		0.509*	
		HAH	0.892			
TB	FSG			0.095	0.194	0.263
		4th Hour	0.091	0.004	0.103	0.172*
		2nd Hour	0.095		0.099	0.168*
		3rd Hour	0.194			0.069
		1st Hour	0.263			
	NAS			0.196	0.253	0.383
		1st Hour	0.189	0.007	0.064	0.194*
		3rd Hour	0.196		0.057	0.187*
		2nd Hour	0.253			0.130*
		4th Hour	0.383			
	HAH			0.820	0.892	0.971
		3rd Hour	0.784	0.035	0.107	0.187*
		1st Hour	0.820		0.072	0.151
		4th Hour	0.892			0.079
		2nd Hour	0.971			

* indicates p<0.10

EW Team Performance

This section expands upon the overall analyses of functional recognition time and accuracy scores. Specifically, the statistical analyses presented in this section examine the characteristics of operator performance in terms of individual team performance levels.

Figure 19 shows the average performance scores obtained for the eight teams participating in the laboratory study. The average functional recognition time across the eight teams was 40.82 seconds (S.E.M. = 6.77 seconds), while the average percent of verbal reports given was 54.11 percent (S.E.M. = 9.01 percent).

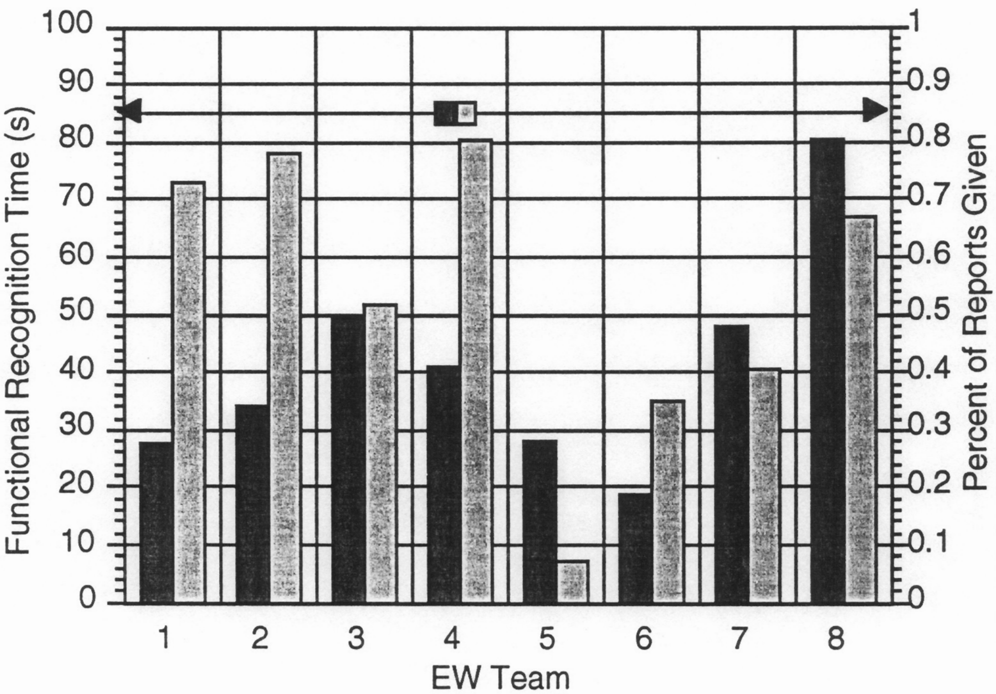


Figure 19. *Overall functional recognition time and percent of verbal reports given for the EW teams.*

Figure 20 shows the accuracy of the verbal report components given by the EW teams. The average accuracy of the emitter function component was 76.01 percent (S.E.M. =

4.71 percent), the emitter platform component was 72.63 percent (S.E.M. = 3.51 percent), and the emitter owner was 58.60 percent (S.E.M. = 6.11 percent).

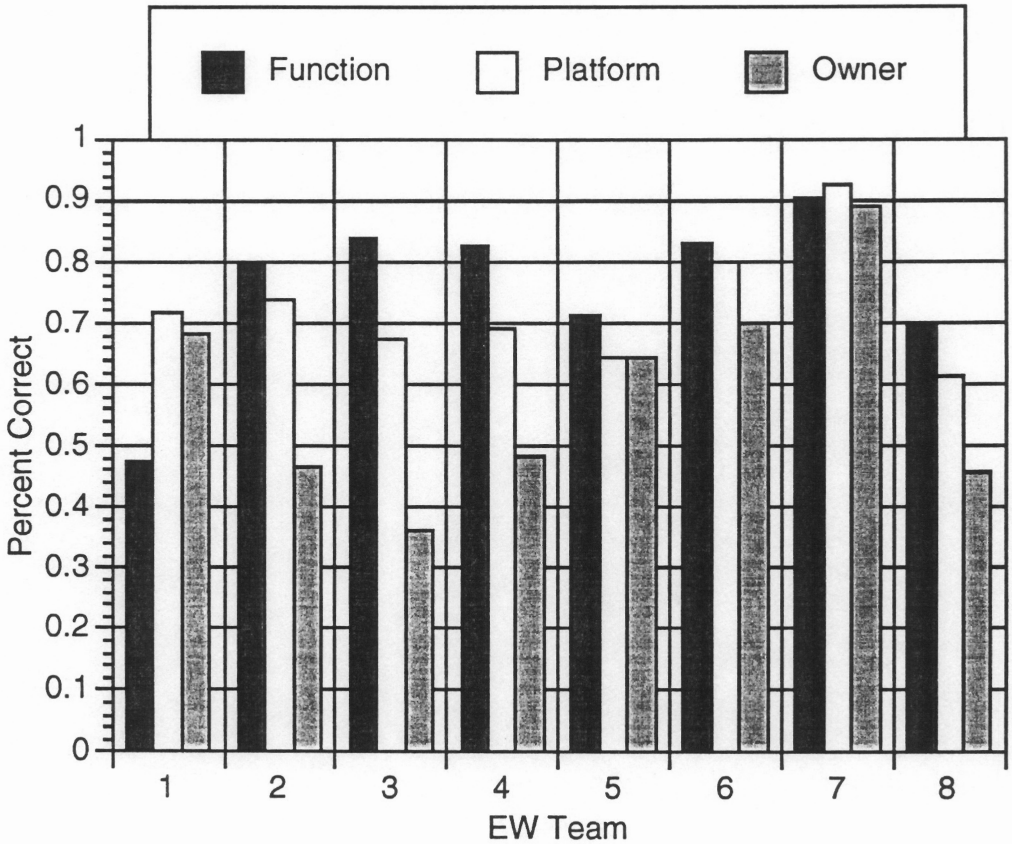


Figure 20. *Percent correct of verbal report components given by the EW teams.*

A histogram is used to create a new variable from the laboratory data, Proficiency Level. To detail the procedure proposed here, suppose it is desirable to establish three Proficiency Level rating categories: Low, Medium, and High. With the assumption that each Proficiency Level category is equally important, the Low, Medium, and High ratings can be defined as cumulative percentage points on a performance histogram. That is, two-thirds of all personnel will perform below the High Proficiency Level rating and one-third of personnel will perform below the Low Proficiency Level rating. In other words, the Proficiency Level categories can be computed as:

$$Y = \int_0^a x\, H(x)\, .dx \text{ where } \begin{Bmatrix} \text{Low} = a \text{ for } Y = \frac{1}{3} \\ \\ \text{High} = a \text{ for } Y = \frac{2}{3} \end{Bmatrix}, \qquad \text{(Eq. 1)}$$

in which H(x) denotes a normalized performance histogram having a unit area.

Figure 21 illustrates the results of calculating Eq. 1 for the functional recognition times obtained in the laboratory work. The performance histogram peaks near 6 seconds, and it trails off near 60 seconds. Using these data and Eq. 1, the High Proficiency Level cut-off point occurs at 9 seconds and the Low Proficiency Level cut-off occurs at 26 seconds.

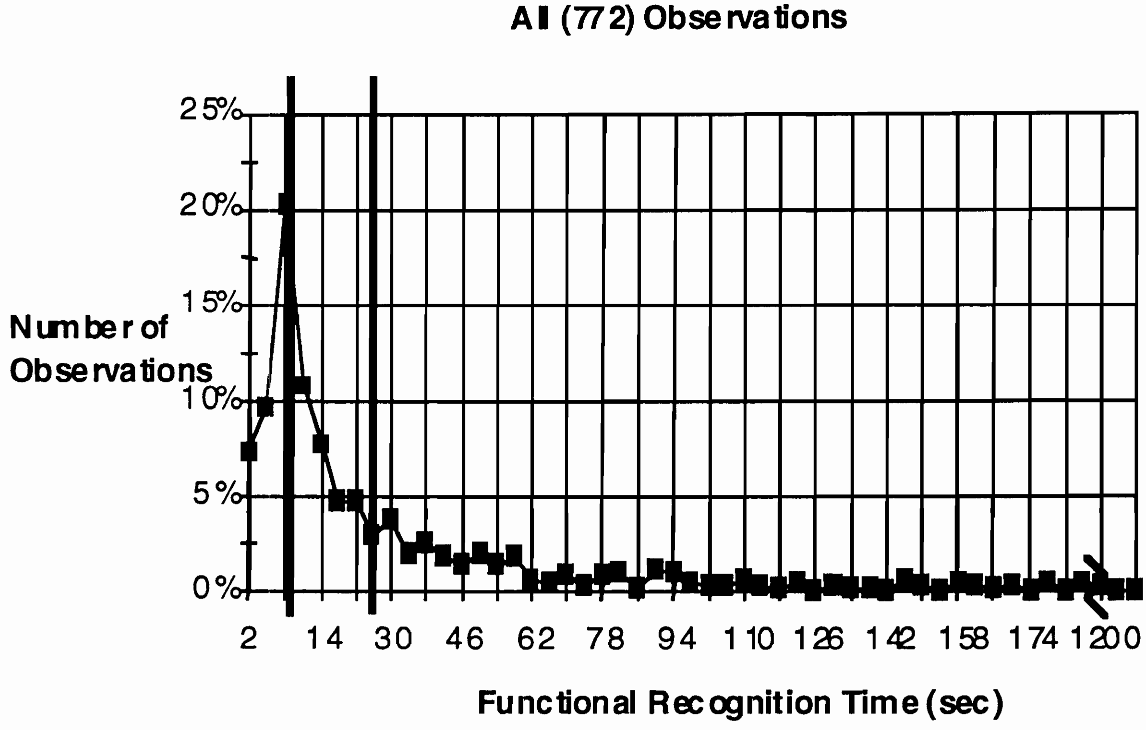


Figure 21. *Histogram of functional recognition time.*
(Shaded lines indicate 33% and 66% points.)

The two Proficiency Level cut-off points mentioned above can be used to rate the EW teams in terms of overall low, medium, and high Proficiency Level ratings. Table 17 lists the median functional recognition times for each EW team. Additionally, Table 17 lists the Proficiency Level category rating for each team, based on a straightforward comparison of the median times with the two Proficiency Level cut-off points (i.e., a team is rated in the highest Proficiency Level category that has an upper cut-off point greater than the team's median score).

TABLE 17

Performance Ratings for EW Teams

Team	Median Time	Category	Mean Time (s)	% Function Correct	% Platform Correct	% Owner Correct
1	11	Medium	36.22	72	71	52
2	14	Medium	36.22	72	71	52
3	15	Medium	36.22	72	71	52
4	12	Medium	36.22	72	71	52
5	14	Medium	36.22	72	71	52
6	9	High	26.18	86	84	78
7	9	High	26.18	86	84	78
8	44.5	Low	88.46	71	64	49

Pathway Analyses

A descriptive analysis of pathways used by the EW operators was performed on the data collected during the validation study. The pathway descriptions are listed in Table 4. Tables 18-20 present the percent usage values for each path under various combinations of Emitter Type, Emitter Density, and EW team Proficiency Level.

Table 18 shows differences in strategies used for different emitter types. FSG emitters were sequenced to after a parameter change more frequently than before a parameter change. This observation stems from the FSG emitter's increased saliency after it locks on to a target with its guidance function. NAS emitters, however, undergo parameter changes less often than FSG emitters and, therefore, were sequenced to initially rather than after a change. HAH emitters were brought into close control in fairly equal portions of before and after parameter changes. Of these emitters, some were easier to functionally recognize before they had parameter changes than others.

TABLE 18

Path percentages by Emitter Type

	Emitter Type			
Path	FSG	NAS	HAH	Totals/3
SEQ	16.9	59.8	38.3	38.3
HOOK	6.2	12.7	20.6	13.2
SEQ-SIG		1.0		0.3
HOOK-SIG			0.9	0.3
UPDT-SEQ	57.2	21.0	30.2	36.1
UPDT-HOOK	18.6	8.3	9.7	12.2
UPDT-SEQ-SIG	1.1			0.4
UPDT-HOOK-SIG	1.3	0.8	1.0	1.0

Table 19 shows the strategies used by operators across the Emitter Density conditions. In general, EW operators evaluated emitters most often by using the SEQUENCE FAB as opposed to the HOOK FAB. Also, the EW operators used the SIGNAL SELECT FAB infrequently. These observations hold across emitter evaluations before either before or after a parameter change event.

TABLE 19

Path percentages by Emitter Density

	Emitter Density			
Path	LOW	MED	HIGH	Totals/3
SEQ	36.1	35.4	43.5	38.3
HOOK	12.9	13.2	13.3	13.2
SEQ-SIG	1.3	0.7		0.3
HOOK-SIG		0.8	1.0	0.3
UPDT-SEQ	37.8	39.7	30.8	36.1
UPDT-HOOK	12.2	15.7	11.1	12.2
UPDT-SEQ-SIG		1.1		0.4
UPDT-HOOK-SIG	1.4	1.1	0.9	1.0

Table 20 shows the strategies used by EW operators of various Proficiency Level category ratings. Low Proficiency Level operators use the stiff stick and HOOK FAB frequently, whereas medium and high Proficiency Level operators use the SEQUENCE FAB more often. Medium Proficiency Level operators also used the SEQUENCE FAB often following an emitter parameter change, perhaps to take advantage of easier emitter identification after a parameter change.

TABLE 20

Path percentages by Operator Proficiency Level

		Level		
Path	**LOW**	**MED**	**HIGH**	**Totals/3**
SEQ	32.8	36	46.2	38.3
HOOK	34.0	12.7	11.7	13.2
SEQ-SIG			3.4	0.3
HOOK-SIG	7.7	1.6		0.3
UPDT-SEQ	28.2	40.0	33.4	36.1
UPDT-HOOK	19.9	12.2	13.6	12.2
UPDT-SEQ-SIG			4.2	0.4
UPDT-HOOK-SIG	7.7	1.0	3.5	1.0

A full table of all of the partial probabilities for each strategy given each combination of Emitter Type, Emitter Density, and operator Proficiency Level is given in Appendix C.

Comparison of Observed and Actual Data

For each scenario run in the Laboratory Validation Experiment, DX Data were collected and stored in a separate file. After the experiment was concluded, the SHARP PAD Software, using the DX files as input, was used to calculate the time spent and the standard deviation of that time for each node in the MicroSAINT model for each emitter of interest (e.g., missiles in the Hostile Air Homing scenario). Each node in the MicroSAINT model represents a step in the functional recognition task. Additionally, as detailed in the section on Model Population, probabilities for following each path from node to node in the model were calculated from the DX data (using SAS). Using these times and probabilities, the MicroSAINT model was populated, that is, the times were used to calculate a probability distribution for each node in the model, representing predicted time spent by the operator performing that step, for each density/emitter type combination, and the node-to-node probabilities were input.

To demonstrate the accuracy of the MicroSAINT model, the model was executed once for each emitter of interest that occurred in the laboratory validation study, then the resulting functional recognition times were sorted by ascending value and paired with the sorted actual times observed in the experiment. Figure 22 shows the plot of predicted versus observed functional recognition times. It is evident from Figure 22 that there was a high degree of correlation between the actual and predicted times to functionally recognize an emitter, especially for observed times up to 170 seconds. Although these initial results of the model showed high levels of overall correlation, they also highlighted areas of concern at extreme ranges of the model, both high and low.

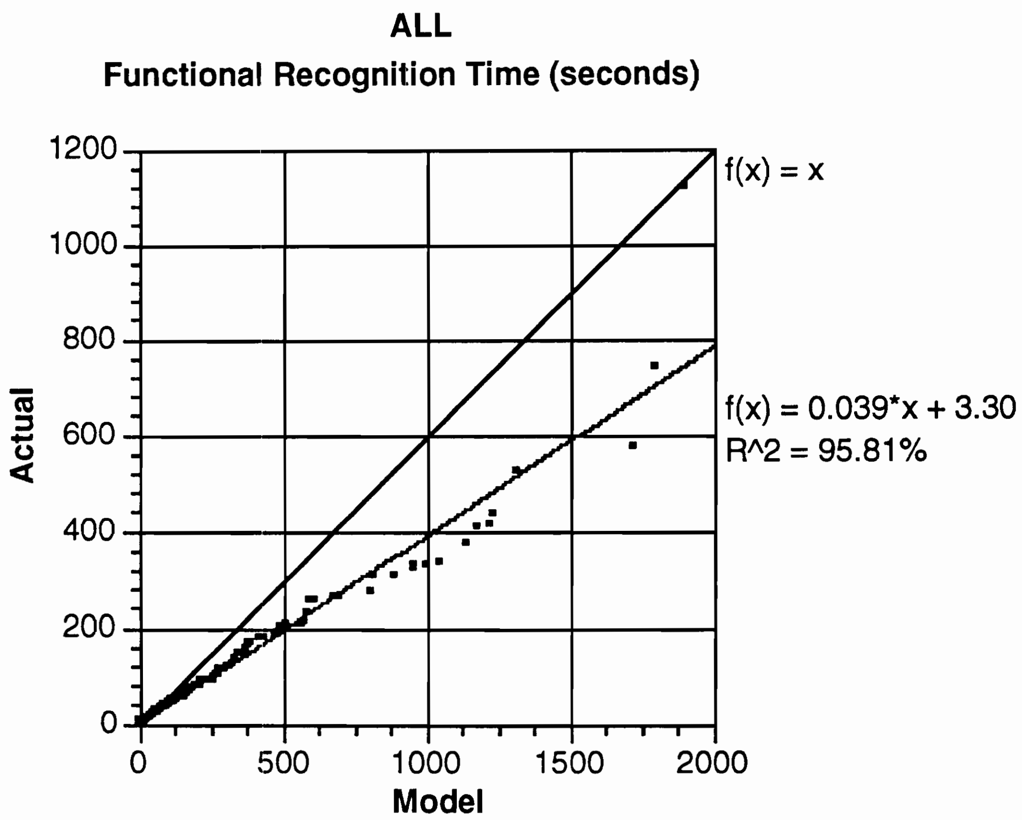


Figure 22. *Plot of actual versus originally predicted functional recognition times.*

At the extreme low end of the range, the model predicts performance times between zero and one second. From the task analysis and laboratory study, recognition times were not that quick. This result likely stemmed from the gamma distributions used to predict node times. The gamma distribution used (characteristics provided by the MicroSAINT software) begins at a large probability level while the time value is zero, and falls off gradually. This creates a large number of zero to very short task times, while the distribution of actual task times (see Figure 21) begins at zero on both axes (even as it ramps up quickly to a large probability density at low functional recognition time values). Because of this, a fixed minimum value of 0.75 seconds was added to the final node of the model to shift the distribution positively and prevent these spurious predictions.

At the extreme high end of the range (greater than two minutes), the revised model predictions become less linearly related to the actual values from the laboratory study. This is likely due to additions to the actual task network that were not considered in PAM (as directed by the task analysis guidelines developed). Specifically, the revised task network model does not handle task sequences that allow emitters of interest to be let out of close control. This occurs when the operator is attending to other emitters or other tasks (such as drinking coffee). Although the task network (and the revised model) does include these nodes, their population was entirely empirical; that is, the values used for populating the nodes in the revised model came from experimental data and therefore include any other activities that the operator performs. For example, if it actually takes an operator five seconds to notice a friendly guidance radar in moderately dense environments, and one time out of three he takes an extra second to glance at his watch, the aggregate value modeled will be five and one-third seconds. This additional third of a second is included even though the activity of glancing at the watch is not. Similar to this problem is looping back and forth through these nodes (e.g., taking the same emitter into and out of close control many times before reporting on it). Because the revised model assumes independent events, the probabilities for looping between such nodes are empirical and there is no "intelligence" in the revised model to endorse or limit such looping based on actual events or concerns of the EW operator. This problem also is a reason for proportional over-prediction by the revised model. These problems are all handled simply by acknowledging that there is an upper limit (on task completion time in this case) to the applicability of the simulation. A correlation plot of the revised model within its useful range is shown in Figure 23.

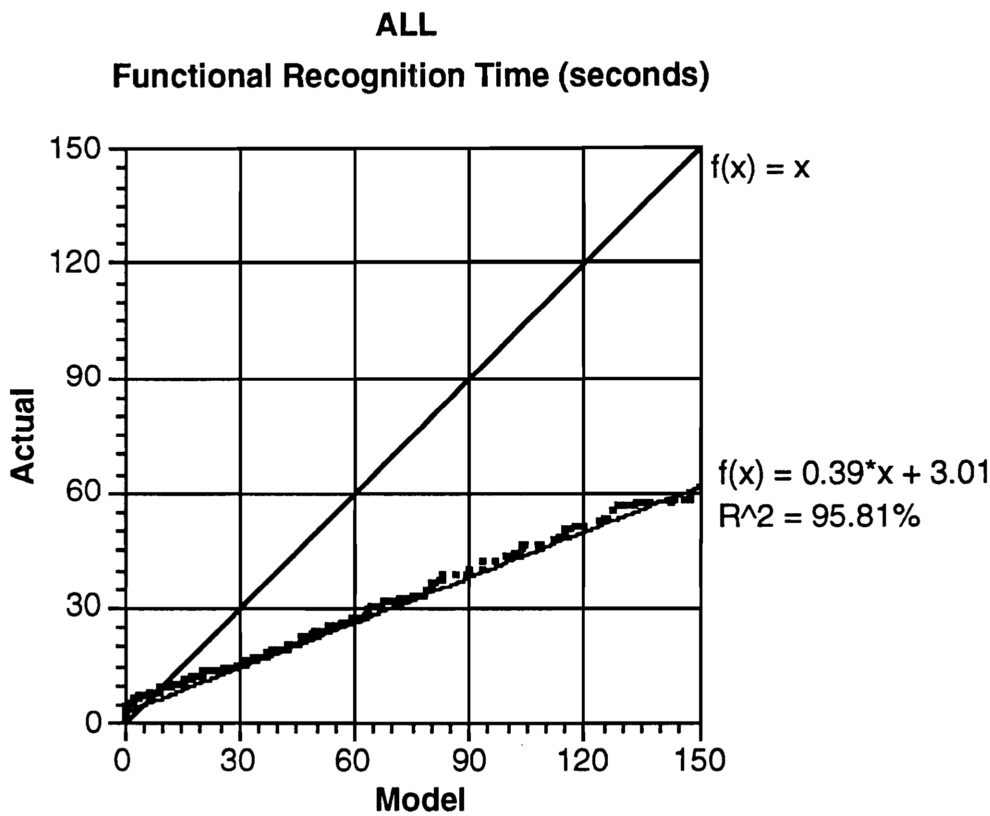


Figure 23. *Plot of actual versus revised predicted functional recognition times.*

Additional correlations were performed between the results of the revised model and the results from the laboratory study. These were calculated for each combination of Emitter Type and Emitter Density. A table of these correlations is shown as Table 21. Graphs of the correlations are shown in Appendix C.

TABLE 21

Correlation Parameters by Emitter Type and Emitter Density

Emitter Type	Emitter Density	r^2(%)	Slope	Intercept
HAH	HIGH	98.06	0.39	1.49
	MED	95.27	0.72	-5.08
	LOW	78.67	0.12	12.07
NAS	HIGH	94.07	0.51	1.87
	MED	96.35	0.56	-10.58
	LOW	93.88	0.08	6.57
FSG	HIGH	94.87	0.39	24.98
	MED	87.40	0.24	-1.55
	LOW	87.11	1.85	-31.55

The revised model was re-cast in terms of the strategies taken by EW operators. Each of the eight task completion strategy paths (i.e., the eight levels of the Path variable) were pulled ("unraveled") from the revised simulation model. The nodes involved in a strategy path were set end-to-end, with the probability of proceeding from one to the next set to unity. The strategy paths were placed in parallel. Mean times, standard deviations, and distributional information contained within nodes was kept.

The purpose of this manipulation was to show that the decomposition of the task and the empirical values of each node are robust. Even though not all task completion strategies are included in the revised model, and not all actions can be accounted for, pieces of the revised model can be mixed and matched according to the theory of the task - its goals. Good correlations between actual and predicted values for these revised model incarnations based on task completion strategy paths shows by inference the correctness of the task analysis breakdown. Further, as this process is iterated, revising and manipulating the simulation model and correlating predictions with corresponding portions of the data collected during experimentation, the task itself and the operator's performance of it is better understood.

For paths 5-8, those strategy paths occurring after a parameter change, additional nodes were added to the front of the path to reflect the parameter change. First, the operator was assumed to have sequenced to the emitter before the parameter change. This was necessary because an "Update Alert" does not occur unless the original alert has been cleared by use of the Sequence FAB. Second, the operator was assumed to have let the emitter of interest out of close control. This was assumed since typically there is a one minute delay between an emitter's initial onset and its parameter change, and the operator would likely be attending to other emitters. A node from the revised model "Out CC No Alert" represents this action, thus providing prediction values (this was a "populated" node) from the laboratory study data. Following the bringing of the emitter into close control and then going on to another emitter, there is a node from the model for an "Update Alert." These three nodes form the basis for all of the task completion strategy paths that include an emitter parameter change. Further nodes from the new task completion strategy path models for each of the four parameter change paths depend upon the strategy path taken, and are the same as the full paths for emitter functional recognitions that do not include parameter changes. As examples: for path 2 (HOOK) the nodes "New Emitter," "In CC Alert," and "Verbal Report" constitute the full path; whereas, for path 6 (HOOK after parameter change) the nodes "In CC No Alert," "Out CC No Alert," "Out CC Updt Alert," and "In CC Updt Alert," "Verbal Report" constitute the full path.

The task completion strategy path models were developed using the parameter of Proficiency Level, in addition to parameters of Emitter Type and Emitter Density. Proficiency Level was defined in the previous section which analyzed differences between operators. The mean times, standard deviations, and distributional information contained within nodes in the task completion strategy path models were calculated using Emitter Type and Emitter Density as parameters, and were taken from the corresponding revised full task simulation model data. The probabilities used for the likelihood of traveling each strategy path were taken from the laboratory study data. They were the probabilities observed that operators of each Proficiency Level chose a given path, within the Emitter Type and Density condition. These probabilities are shown in Appendix C. With these three variables as parameters, 27 possible correlations were enabled: one for each combination of the Emitter Type, Emitter Density, and Proficiency Level variables. The correlations were between the predicted values of that task completion strategy path model and the portion of actual laboratory results observed with those operators, for those emitters, under those conditions. A generalized task completion strategy path model diagram is shown in Figure 24. A table of correlation parameters, one for each combination of the three variables, is given in Table 22. Graphs of each correlation are given in Appendix C.

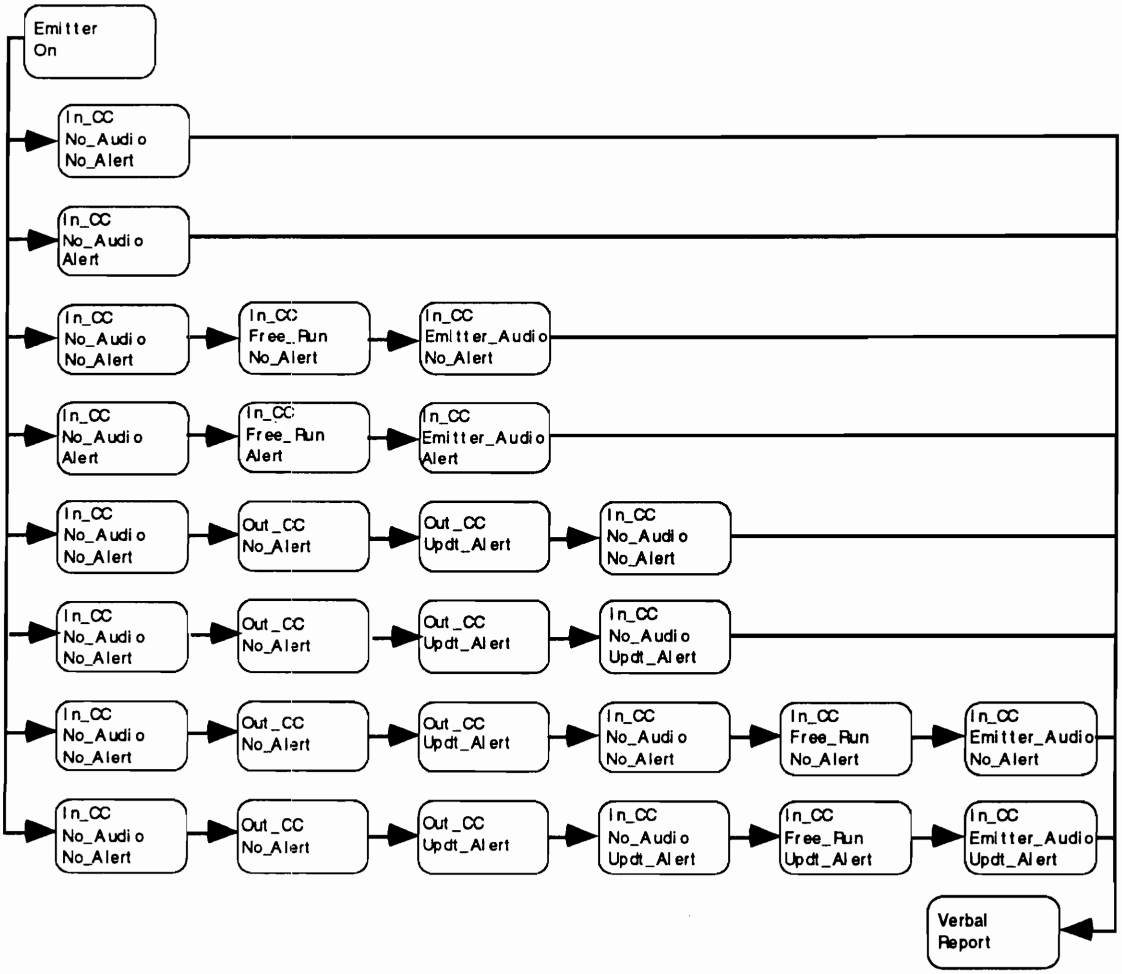


Figure 24. *Task completion strategy path model generalization.*

TABLE 22

Correlation parameters by Emitter Type, Emitter Density, and Proficiency Level

Emitter Type	Emitter Density	Proficiency Level	r^2(%)	Slope	Intercept
HAH	HIGH	HIGH	86.06	0.37	0.64
		MED	78.75	0.42	2.49
		LOW	76.74	0.65	28.14
	MED	HIGH	73.23	1.71	-10.43
		MED	74.74	0.71	-7.61
		LOW	92.26	1.75	-14.42
	LOW	HIGH	98.13	0.68	-1.59
		MED	73.17	0.86	-7.82
		LOW	81.97	0.46	11.10
NAS	HIGH	HIGH	94.82	1.90	-1.14
		MED	85.28	0.42	3.51
		LOW	97.00	0.98	111.54*
	MED	HIGH	55.30	9.00	-152.49*
		MED	85.39	0.86	-12.52
		LOW	95.71	2.26	27.51
	LOW	HIGH	98.28	0.74	3.89
		MED	89.79	0.70	-14.35
		LOW	82.66	1.09	1.59
FSG	HIGH	HIGH	65.59	0.08	-3.83*
		MED	91.02	0.27	3.92
		LOW	69.74	0.59	-9.10
	MED	HIGH	97.30	0.27	2.65
		MED	98.71	0.14	0.073
		LOW	87.68	1.45	-39.07
	LOW	HIGH	90.08	0.17	6.89
		MED	66.04	0.94	-34.73
		LOW	90.67	1.15	-6.04

* Few data points

DISCUSSION

This section of the dissertation provides a general discussion of the findings of this work. It addresses the functional recognition time and accuracy values observed in the validation study, the functional recognition strategies employed by EW operators, and the approaches available for employing the PAM for other task analysis environments.

Data Collection Paradigm

The PAM methodology developed in this work relies on the continuous monitoring of EW operator performance. During operator work periods, performance data are collected on the EW operators' handling of observable events. Specifically, AN/SLQ-32(V) DX data were collected through the EWOBT PC/DX capability. The EPNs were recorded from the onset of a new emitter event until the verbal report made by the EW operator concerning a functional recognition decision. Although the data collection paradigm provides on-line and objective data regarding operator performance, in this particular instance it relied substantially on the verbal reports produced by EW operators. The findings of this work indicate that EW operators verbally reported on approximately one-half of the emitters of interest despite their instructions to report on all emitters. Nevertheless, the data collected in this work provide clear and statistically reliable findings on EW operators' functional recognition performance.

The findings of this work show that functional recognition times vary across emitter types; HAH emitters were recognized faster than the non-threat (i.e., FSG and NAS) emitters. This finding is consistent with two observations of EW operator training. First, EW operators are trained to identify threatening emitters, such as missiles. Therefore, these emitters are considered as higher priority items than the non-threat emitters. Second, EW operators are trained to make verbal announcements regarding the detection of threatening emitters, whereas non-threatening emitters usually are not announced to the EW supervisor. These two observations underlie the functional recognition data trends observed in this work.

Given the caveats above, the findings of this work indicate that missile emitters are functionally recognized approximately three times quicker than non-threatening emitters. This observation is noteworthy since non-threatening emitters may require immediate processing by the EW operator under some operational conditions. Also, the average functional recognition times for HAH emitters were about 22 seconds (across all emitter density levels). Given the limitations of the laboratory simulation, this observation provides an objective insight to the minimum time requirements for functional recognition decisions to be expected aboard ships by EW operators.

The findings on functional recognition time also indicate that performance does not vary a great deal across time-on-watch, at least for the conditions examined in this work. Specifically, functional recognition times for HAH emitters remained relatively constant across the four-hour watchstand. For the two non-threat emitter classes examined, functional recognition times decreased slightly during the second half of the watch for FSG emitters and remained constant throughout the watch for NAS emitters. These data trends suggest that the effects of operator fatigue and boredom were not influencing operator performance during the data collection sessions. It is, however, acknowledged that the effects of operator fatigue during an actual watchstand, as well as over the course of a deployment, are significant. The lack of fatigue effects in the laboratory validation study may stem from the high motivation levels of the EW participants during the shore-based test sessions.

Accuracy

The accuracy of functional recognition decisions was defined in terms of three essential components of the EW operator's verbal report: Function, Platform, and Owner. Accuracy analyses were performed separately for each of these components. It is likely that the most important component may be the emitter Function, while the next most important component may by the emitter Platform. The remaining decision component may involve elements of an emitter identification response and, therefore, it is considered as a less critical component of the functional recognition decision. Additionally, the accuracy analyses made no attempt to integrate the component decisions scores into a single performance rating. It may be desirable to integrate these components according to a weighted summation scheme (i.e., 50% function decision plus 30% platform decision plus 20% owner decision equals 100% functional recognition accuracy).

The findings of this work indicate that EW operators functionally recognized HAH emitters about 86 percent of the time, whereas they recognized non-threat emitters about 44 percent of the time. Given that these percentage values were determined from the number of reports given, and that the operators reported about one half of the emitters of interest, these accuracy ratings are surprisingly low. Although EW operator performance may be improved through informational aids (e.g., naval and air orders of battle, emitter publications, familiarity with the engagement situation), the laboratory environment and the emitter scenarios probably underlie the low accuracy levels.

Regarding the accuracy of the emitter Function component, EW operators recognized HAH emitters more often than FSG and NAS emitters. The difference in Function accuracy is about 2:1. This observation is consistent with expectations based on EW training. That is, EW training emphasizes the recognition of hostile emitters. Moreover, the HAH emitter presents clearly identifiable signals on the ANSLQ-32(V) (i.e., constant alert tone, rapid bearing drift), whereas the non-threat emitters present more varied signal signatures.

The accuracy findings for the emitter Function component also suggest that performance decreases slightly with time-on-watch. The performance decrement was about 15-20% during the second half of the four-hour watchstand. While this decrement is statistically significant, its magnitude may have little practical effect (although, it is suspected that the performance decrement is greater in shipboard environments).

The findings for the emitter Platform and Owner components follow similar trends to those observed for the emitter Function component. That is, HAH emitter platforms were recognized more accurately than FSG and NAS emitter platforms. It is believed that this data trend stems from the fact that homing emitters can only exist on airborne platforms and, therefore, once the Function component is recognized for the HAH emitter, its Platform and perhaps its Owner components are known.

PAM Applications

The observations collected during the laboratory validation study were used to populate the PAM MicroSAINT model. These model values were extracted from video tape analyses as well as from the ANSLQ-32(V) DX data. The MicroSAINT model then was used to predict the overall functional recognition time values observed in the laboratory test. The correlation between the observed and predicted functional recognition values was quite high (i.e., $R^2 = 0.958$; see Figure 23). This statistical result indicates that the structure of the MicroSAINT model reliably and validly tracks EW operator performance during functional recognition tasks. This statement is limited by a few factors: (1) the actual data were obtained in a laboratory environment, (2) the actual data were obtained under stimulated low, medium, and high emitter density levels, and (3) the actual data do not reflect the influences of shipboard stress factors. Nevertheless, the results obtained thus far clearly support the continued development and application of the model and the methodology.

The lack of a one-to-one fit between the model results and the experimental data can be attributed to both the distributional characteristics of the model and the assumption of independent events by the model. The distributional choice was limited to one of four options, and even though the Gamma distribution chosen matched certain characteristics of performance, it may tail off too slowly. A lack of independence in events could enable excess looping between nodes in the model based on experimentally determined decision probabilities that were actually based on reasoned choices made by the operators. Even with these caveats, the use of a linear calibration technique enables the reliable prediction of the models to enable them to serve as a useful tool in task analysis.

Further correlations of the PAM model to the laboratory data using the Emitter Type and Emitter Density parameter variables show that the model is sensitive to the use of parametric variables built into the simulation. These correlations were also sufficiently high to warrant the generalization of the statement.

Lastly, the revised model was rebuilt into an alternate form highlighting the strategy choices of EW operators (the task completion strategy path models), and a derivative variable Proficiency Level was used to provide a third factor for use as a parameter. Good correlations with these analyses show that the simulation methodology is robust enough that, *post hoc*, new analyses can be performed on predicted data using re-structured models with validity. Further research in this direction could possibly put limits on this type of technique.

Conclusions

The PAM is intended to occupy a middle ground between impractically cumbersome task analysis techniques such as formal languages used in the field of computer science for interface and task description and the "softer" task analysis techniques used often in human factors engineering such as the operational sequence diagram. These latter techniques often fail to provide the extent of useful descriptive information that the PAM may be able to provide.

The development and validation of the simulation model shows that a complex task can be analyzed objectively to provide information for the description, assessment, and prediction of the task, if the proposed guidelines for task analysis and description are used. This methodology based on observable events and actions, an extension of traditional task analysis techniques, should provide human factors engineers with a new tool to improve performance assessment, training design, and to provide new information and analysis methods to aid in system design.

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APPENDIX A. AN/SLQ-32A(V) BACKGROUND

The AN/SLQ-32A(V) is an integral part of the CIC aboard ships. The AN/SLQ-32A(V) is a Antiship Missile Defense System (ASMD) System. The AN/SLQ-32A(V) detects emitters in the electromagnetic environment surrounding the installed platform. The AN/SLQ-32A(V) detects emitters depending on their distance from the ship, the power of their radar signal, and the environmental conditions.

Figure A-1 illustrates the AN/SLQ-32A(V) DCC. The AN/SLQ-32A(V) system can be used with other equipment, such as an oscilloscope, to classify emitters by their range from the ship (rather than threat level). Beaton (1991) provides a human factors review of the AN/SLQ-32A(V) DCC.

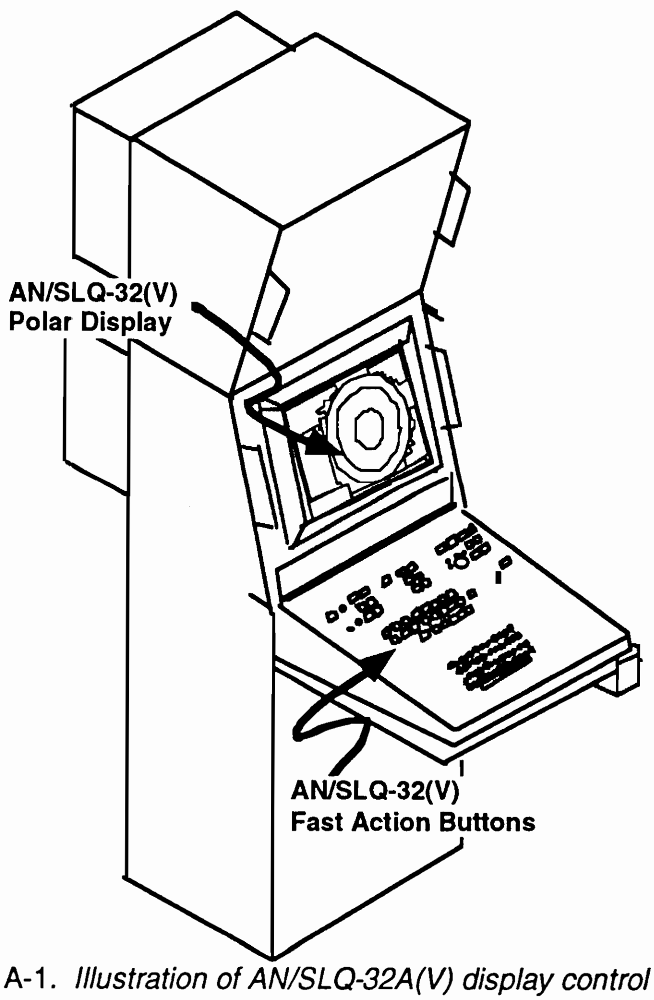
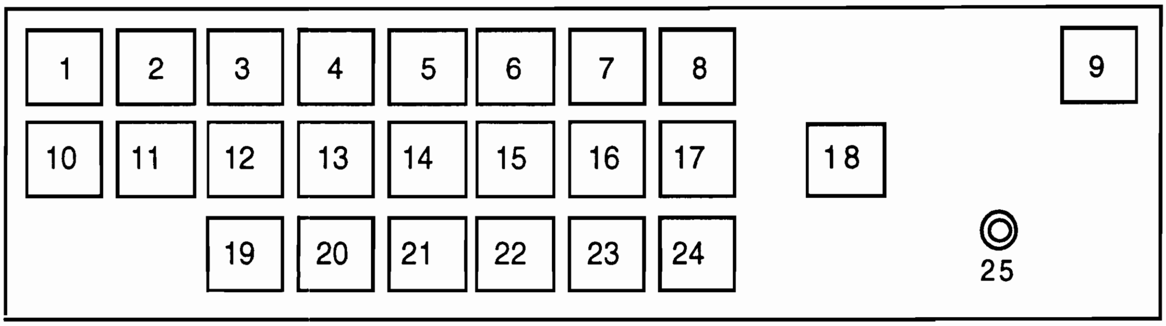


Figure A-1. *Illustration of AN/SLQ-32A(V) display control console.*

Two important areas on the AN/SLQ-32A(V) DCC are the FABs and the Polar Display screen. The FABs and the Polar Display represent the primary input and output components of the AN/SLQ-32A(V) operator. The FABs are pre-programming input buttons associated with the processing of emitters (the keyboard is the remaining input device). Figure A-2 shows the layout and function of FABs on the AN/SLQ-32A(V) DCC.



1 SOT
2 ANAL
3 ALERT INHIBIT
4 SLQ-32 POLAR
5 DISTR ENGAGED
6 PLTFRM CORREL
7 SIGNAL SELECT
8 ENTRY
9 HOOK
10 READ LIBRARY
11 ESM INHIBIT
12 ECM INHIBIT
13 TRU BRG / REL BRG
14 LAMPS POLAR
15 DESIG ID
16 LIBRARY ENTRY
17 ID RSRCH
18 SEQ
19 INHIBIT REVIEW
20 IR PORT
21 DECOY STATUS
22 IR STBD
23 COUNTER TARGET
24 CDS SEND
25 ISOMETRIC JOYSTICK

Figure A-2. *Fast action buttons on AN/SLQ-32A(V) DCC.*

The AN/SLQ-32A(V) Polar Display is the operator's main source of visual information about detected emitters. Figure A-3 illustrates the information areas on the AN/SLQ-32A(V) Polar Display. All emitters detected by the AN/SLQ-32A(V) are presented symbolically on this screen, along with a textual listing of emitter parameters. The Polar Display shows the bearing of the emitters but not their range, and it classifies the emitters based on their threat level to the ship (e.g., friendly emitters appear in the innermost ring, missiles appears in the middle ring, and unknown emitters appear in the outermost ring).

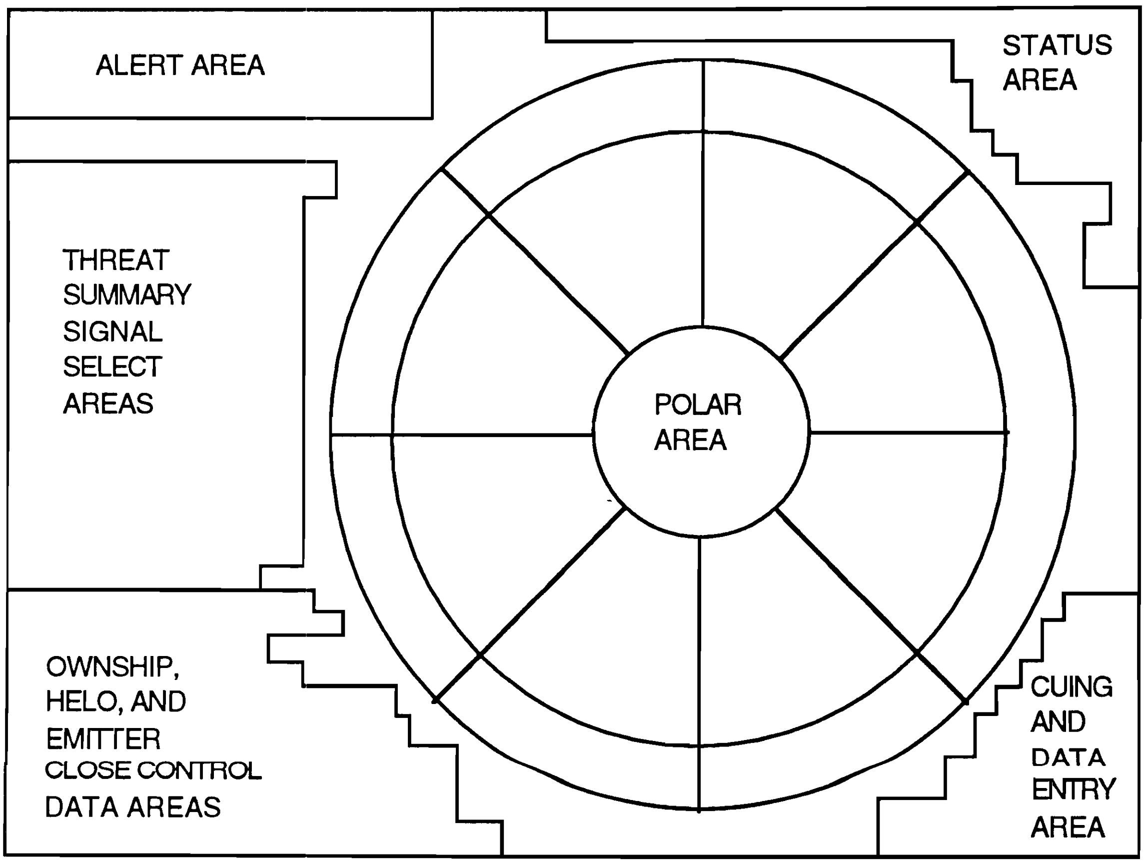


Figure A-3. *Information areas of AN/SLQ-32A(V) polar display screen.*

Another important feature of the AN/SLQ-32A(V) DCC is its audio output subsystem. Pressing the SIGNAL SELECT FAB (No. 7 in Figure A-2) enables the operator to listen to the emitter signal on a speaker or set of headphones. Listening to the signal allows the operator to determine the emitter's scan type (e.g., homing, search, guidance), scan frequency, and scan period (i.e., time period for radar to sweep a search area). Because emitter signals are unique, experienced EW operators often can functionally recognize them from the audio signal.

APPENDIX B. INSTRUCTIONS TO PARTICIPANTS

1. Conduct the watch as you would aboard ship, reporting as you normally would to each other and the TAO. Additionally, report particular emitters of interest as follows:

   If the experimenter asks for HAH emitters, report normally

   If the experimenter asks for NAS emitters, report your functional recognition of all of these emitters.

   If the experimenter asks for FSG emitters, report your functional recognition of all of these emitters.

2. Do not use any inhibits.
3. Band 1 is unavailable; do not open Band 1.
4. You are allowed no breaks once the scenario has begun unless absolutely necessary (e.g., to go to the restroom). Please go to the restroom, smoke cigarettes, etc. before entering the EWATC for the start of each scenario. If the operator must leave the EWATC for any reason, the AN/SLQ-32(V) is to go unmanned during that period -- the supervisor is not allowed to take over for the operator.
5. Do not press the Read Library FAB.
6. The experimenter will read simulated incoming messages throughout each scenario and acknowledge verbal reports. This is the extent of the experimenter's participation; the experimenter cannot answer questions once the scenario has begun.
7. You may construct an on-line library if you wish. Blank tapes are located on top of each AN/SLQ-32(V).
8. Do not write on the prepared SIGINT log provided by the experimenter. Start each scenario's SIGINT log on a separate sheet.
9. Please notify the experimenter as soon as you notice any of the following:
   a. Audio from most of the emitters in the scenario ceases.
   b. No alerts occur in a five-minute period.
   c. The AN/SLQ-32(V) clock halts.
   d. Any differences between the AN/SLQ-32(V) system response in the EWATC versus an AN/SLQ-32(V) aboard ship.
10. The following are known differences between the AN/SLQ-32(V) in the EWATC and an AN/SLQ-32(V) aboard ship:
    a. Audio is slow to respond to operator actions; you may hear an emitter that is not signal selected until the system catches up and realizes that you've gone to a new emitter.

b. If you have an emitter signal selected you will not hear an alert, but you will still see the box appear on the wagon wheel and see the alert notice appear at the upper left of the screen.

c. Audio sometimes gets stuck in Signal Select FREE RUN mode (you'll hear all emitters on the beam port no matter how many times you press the Signal Select FAB).

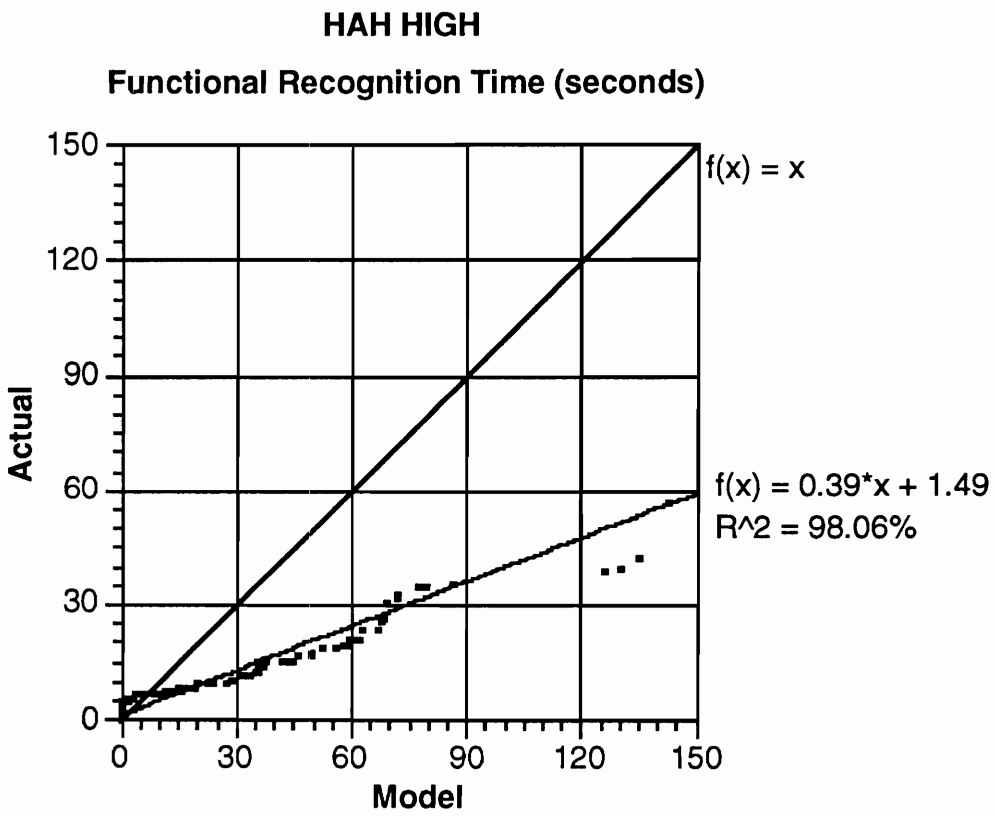
APPENDIX C. ANALYSIS DETAIL

Table C-1

Task Completion Strategy Path Probabilities (in %)

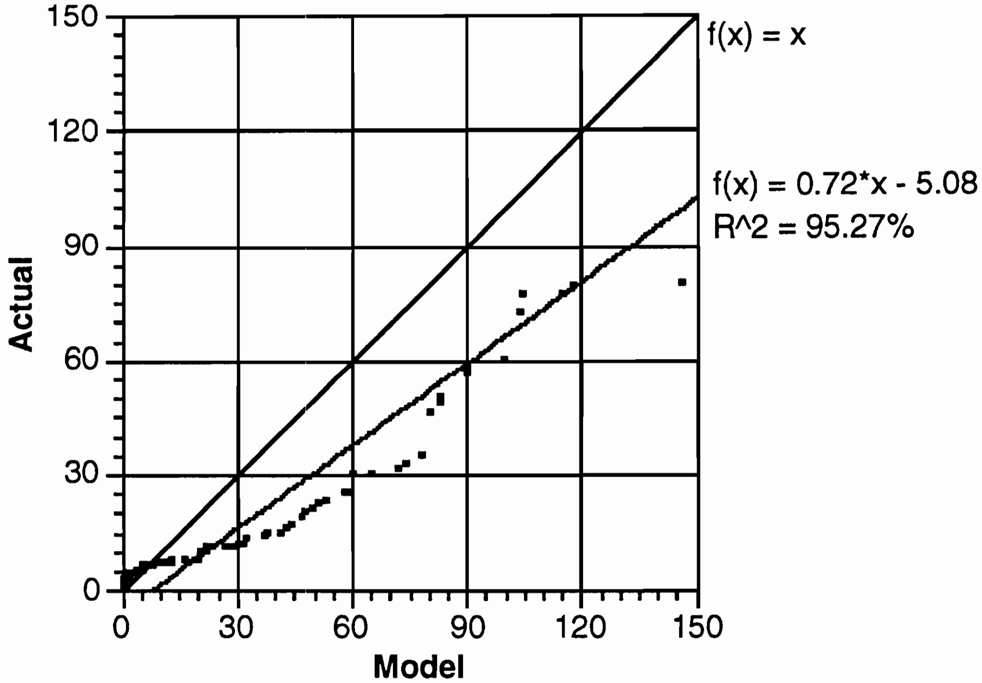
Emitter Type	Emitter Density / Proficiency Level / Path	LOW			MED			HIGH		
		LOW	MED	HIGH	LOW	MED	HIGH	LOW	MED	HIGH
FSG	1	33.3	21.9	30.8	16.7	5.6	4.2	15.8	15.9	25.0
	2	16.7	9.4		8.3	3.7		10.5	9.1	2.5
	3									
	4									
	5	33.3	62.5	53.8	58.3	64.8	70.8	31.6	53.4	47.5
	6	16.7	6.3	15.4	8.3	25.9	20.8	42.1	20.5	22.5
	7						4.2			
	8				8.3				1.1	2.5
NAS	1	66.7	48.8	54.2	47.4	58.0	89.5	28.6	66.1	66.1
	2	22.2	7.0	16.7	36.8	12.5		28.6	15.3	8.9
	3			4.2			2.6			
	4									
	5		34.9	8.3	15.8	29.5	7.9	7.1	16.9	23.2
	6	11.1	9.3	16.7				28.6	1.7	1.8
	7									
	8							7.1		
HAH	1		27.7	40.9	15.4	28.8	54.3	38.5	51.2	50.8
	2	75.0	19.1	9.1	46.2	26.0	11.4	61.5	12.6	21.5
	3									
	4				7.7				1.6	
	5		36.2	36.4	23.1	31.5	34.3		30.7	18.5
	6	25.0	17.0	9.1	7.7	13.7			3.1	9.2
	7									
	8			4.5					0.8	

Revised Simulation Model Correlation Graphs:

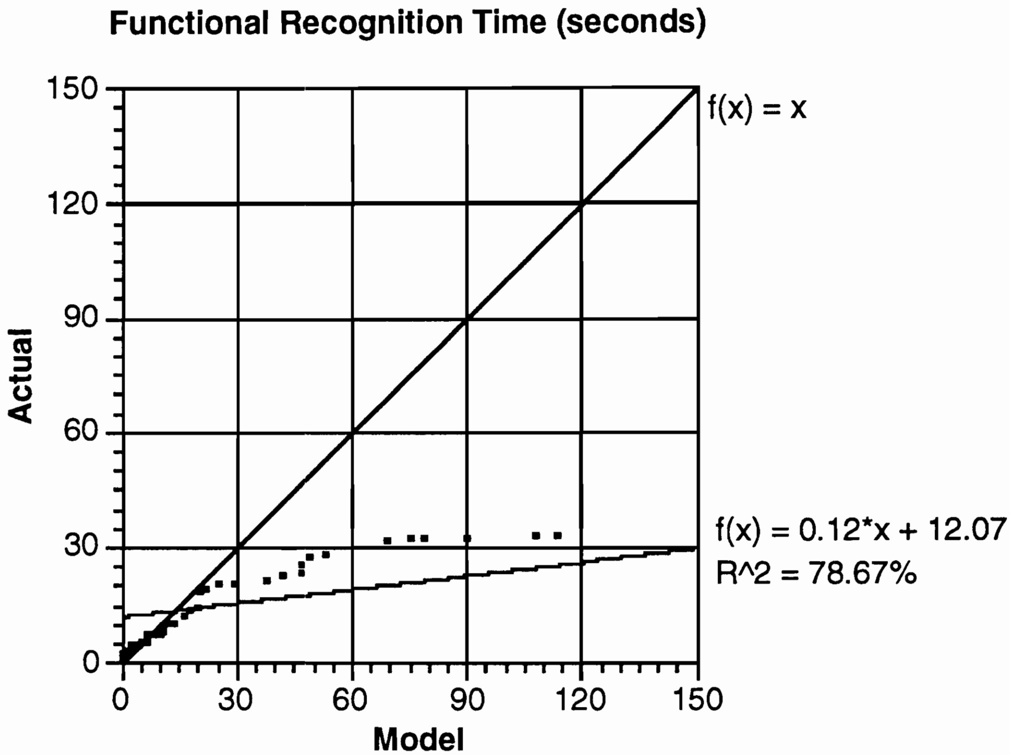


HAH MED

Functional Recognition Time (seconds)

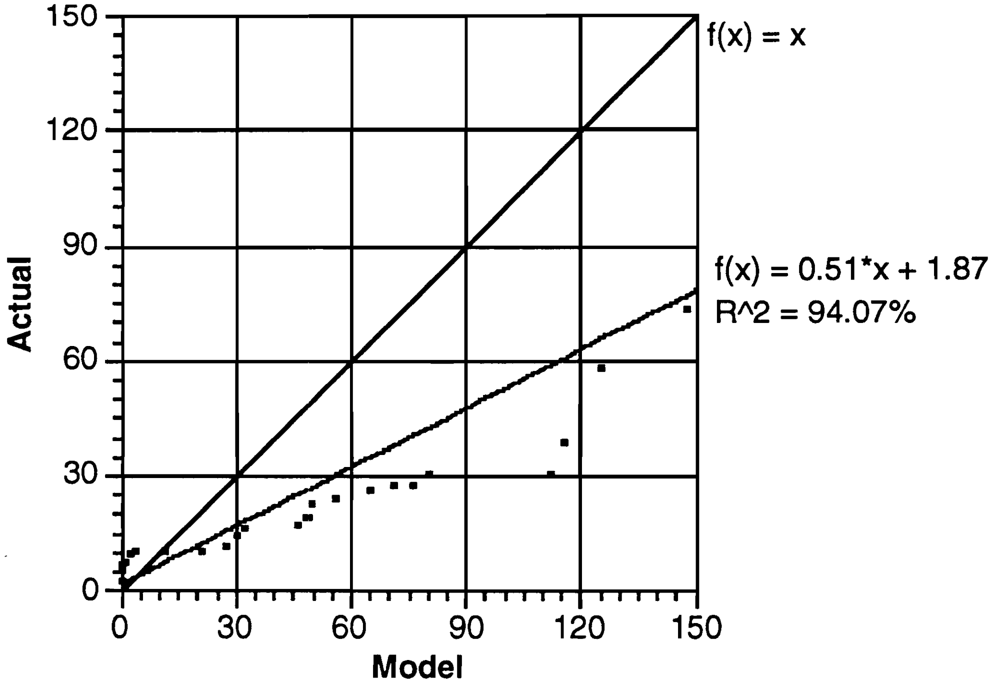


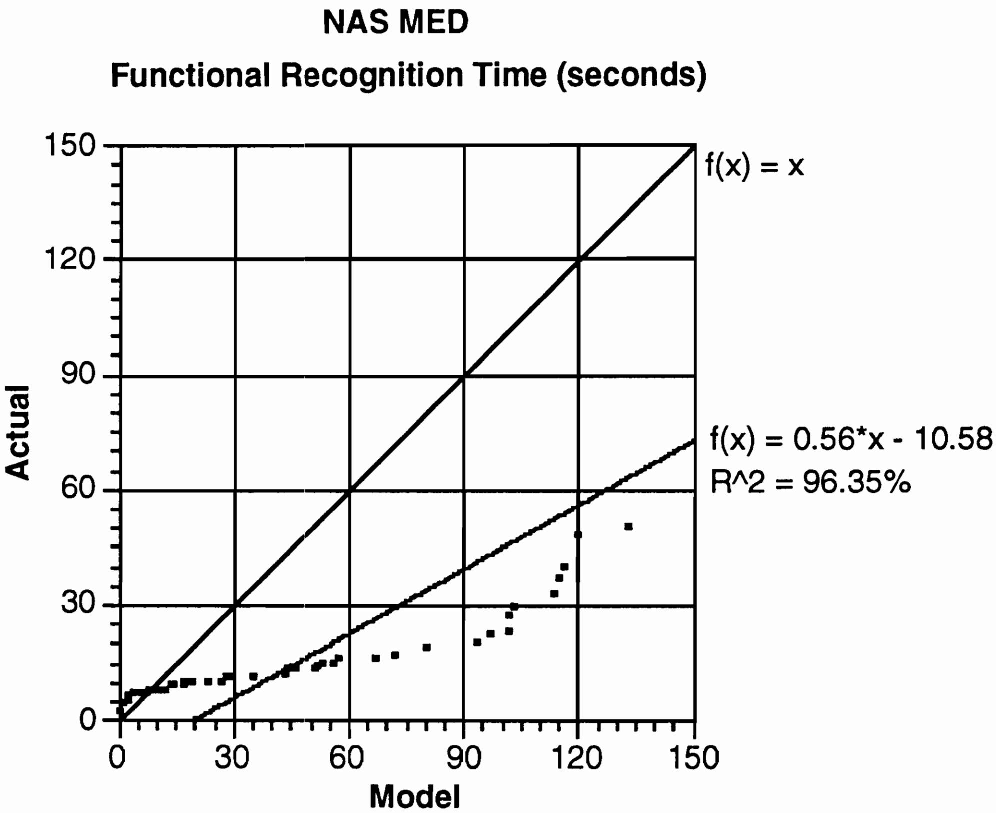
HAH LOW


Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 0.12*x + 12.07
R^2 = 78.67%

NAS HIGH

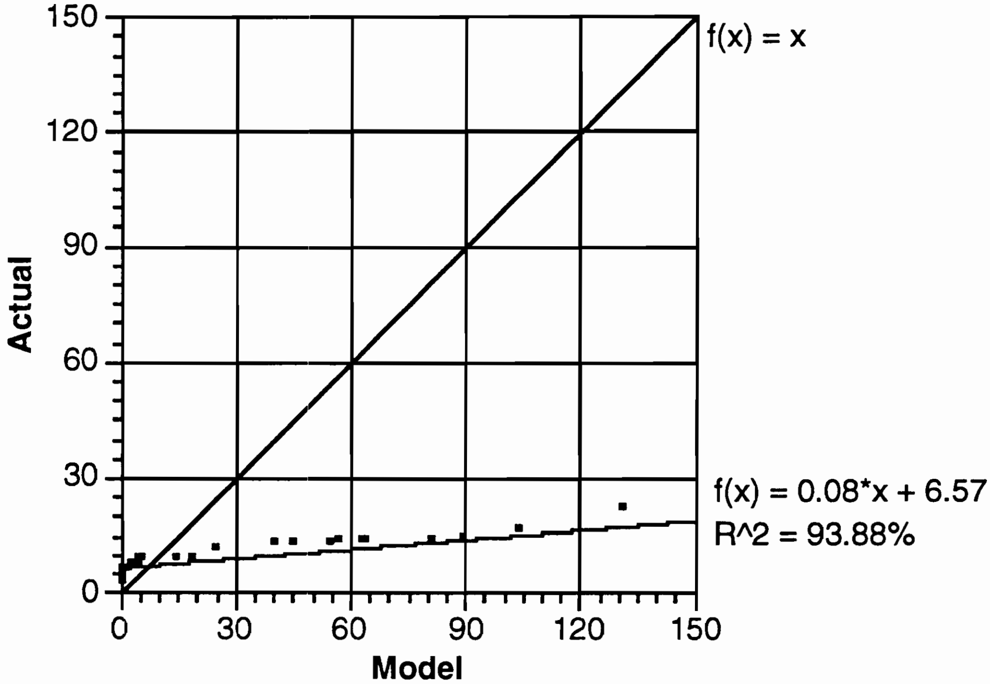
Functional Recognition Time (seconds)

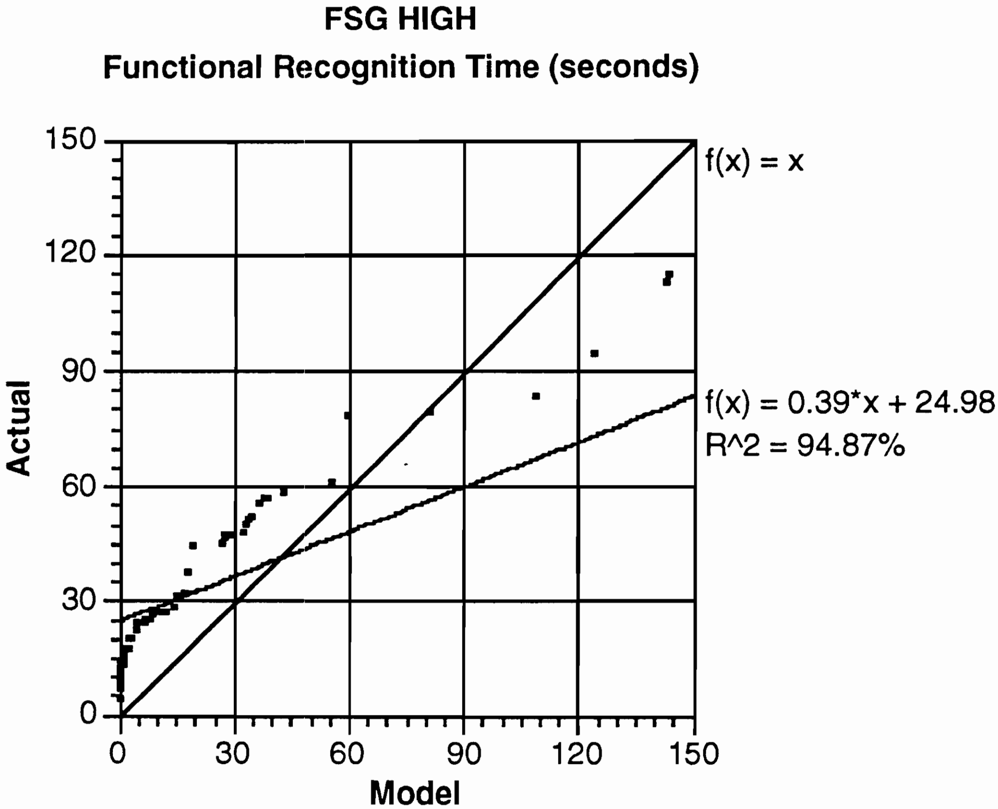


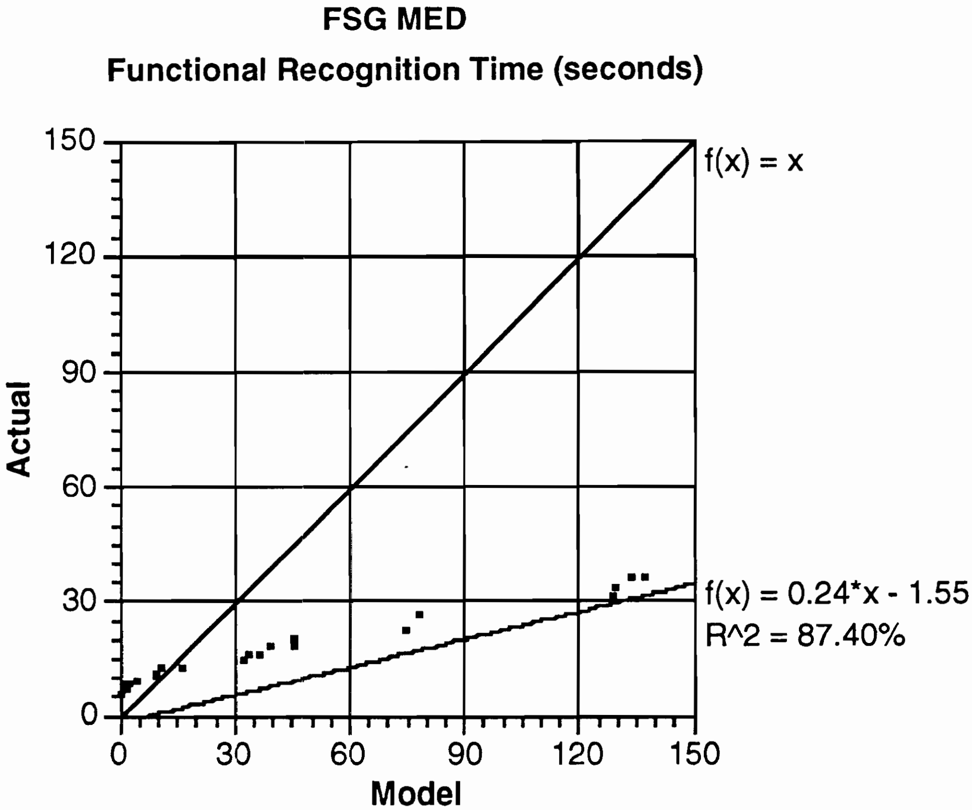

NAS MED
Functional Recognition Time (seconds)
f(x) = x
f(x) = 0.56*x - 10.58
R^2 = 96.35%
Actual
Model
0
30
60
90
120
150

NAS LOW

Functional Recognition Time (seconds)

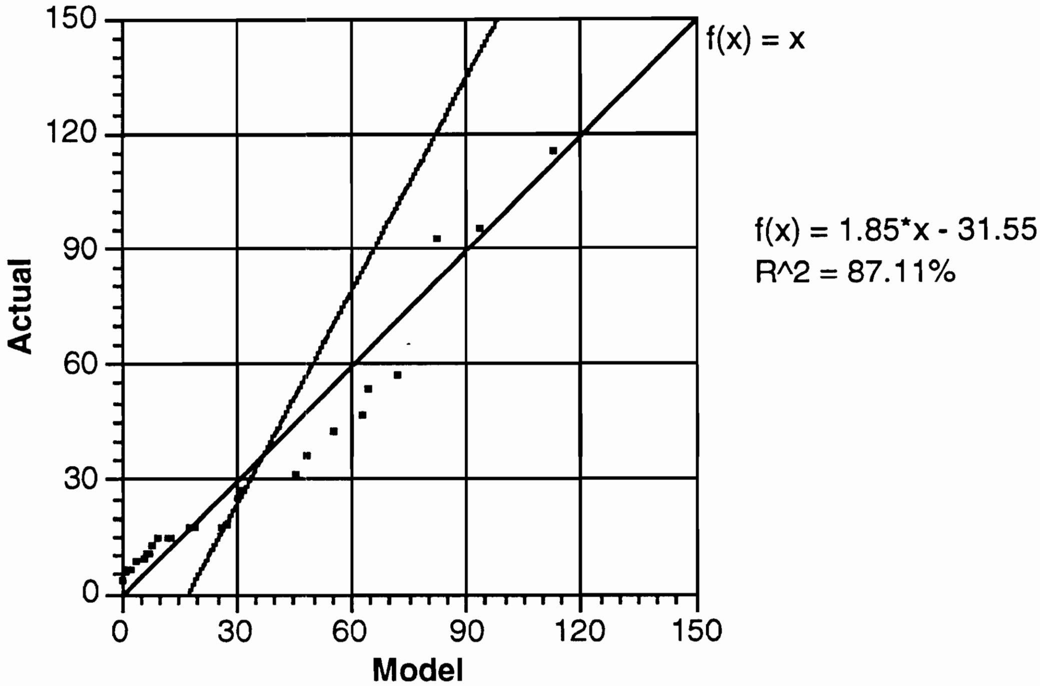



FSG HIGH
Functional Recognition Time (seconds)
150
120
90
60
30
0
0
30
60
90
120
150
Actual
Model
f(x) = x
f(x) = 0.39*x + 24.98
R^2 = 94.87%

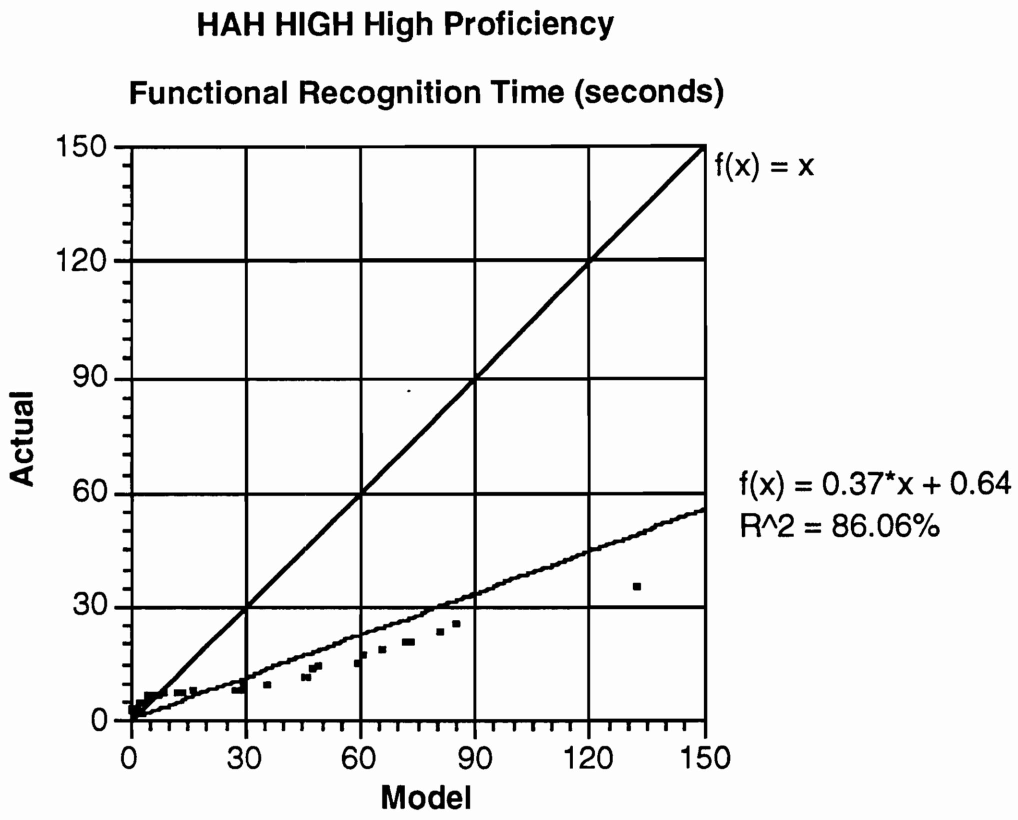

FSG MED
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 0.24*x - 1.55
R^2 = 87.40%

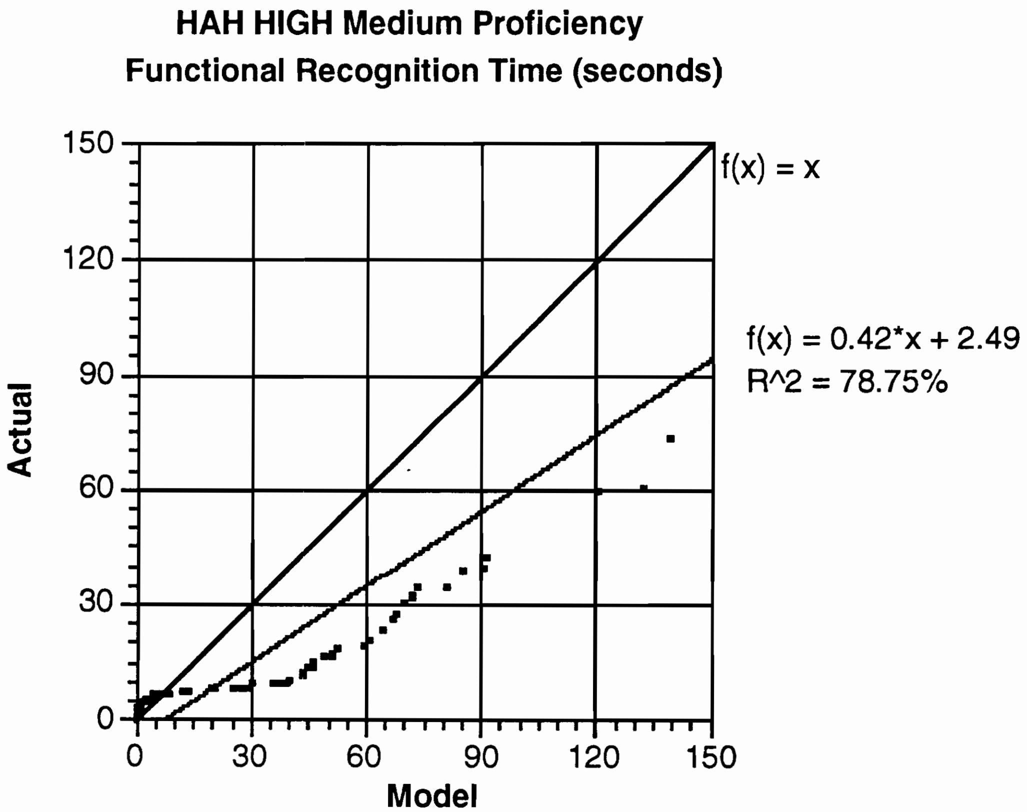
FSG LOW

Functional Recognition Time (seconds)

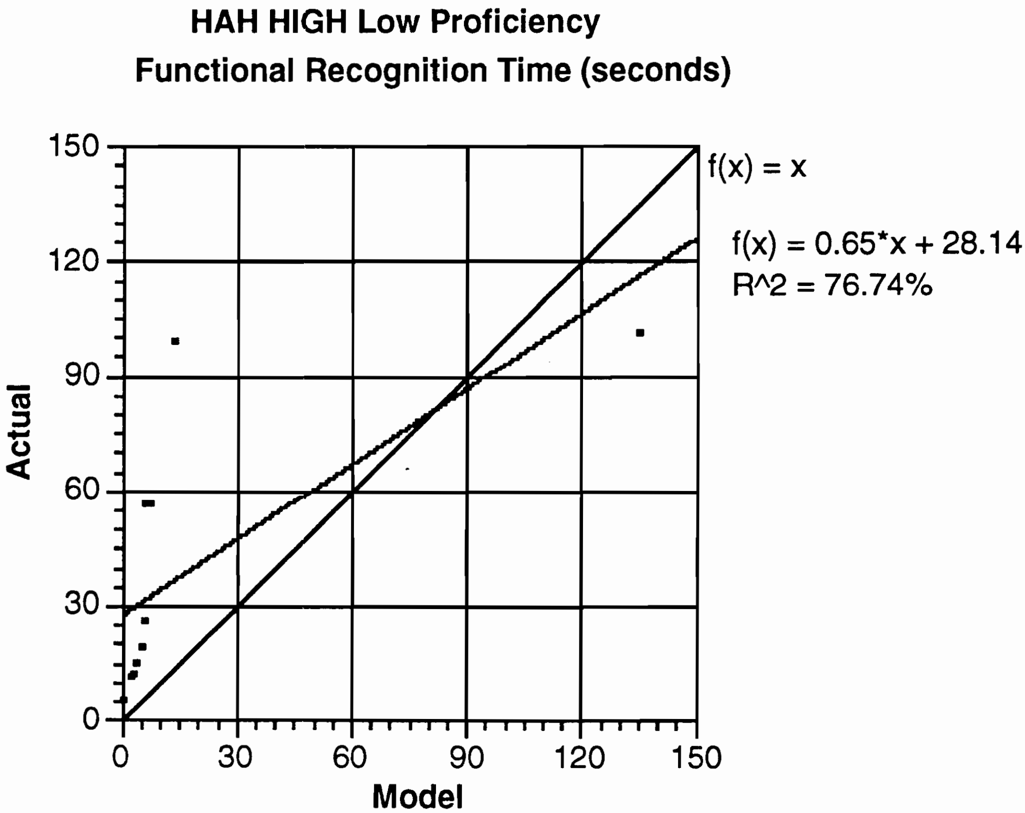


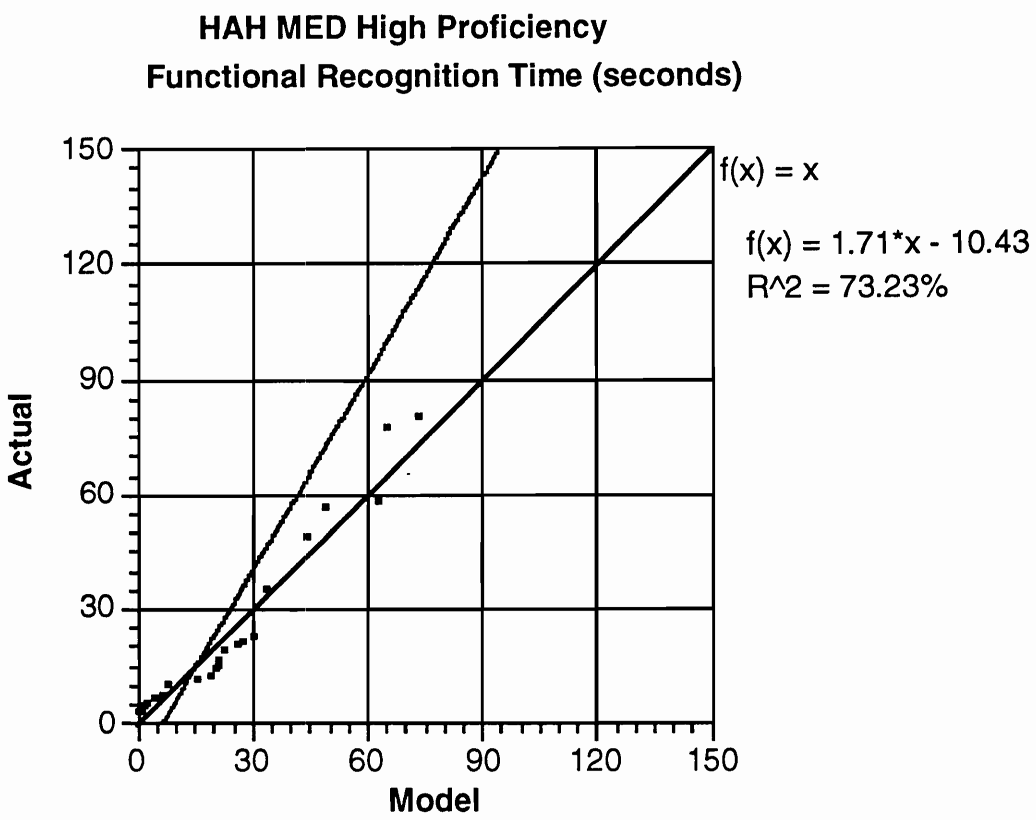
Task Completion Strategy Model Correlation Graphs:

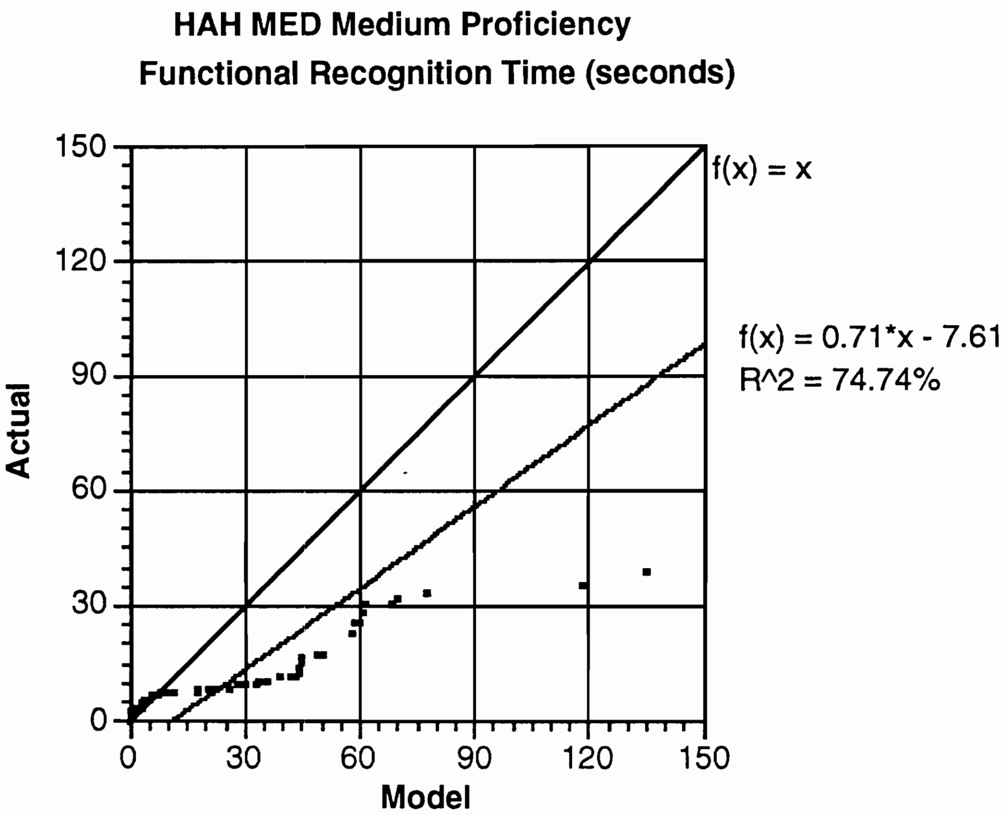




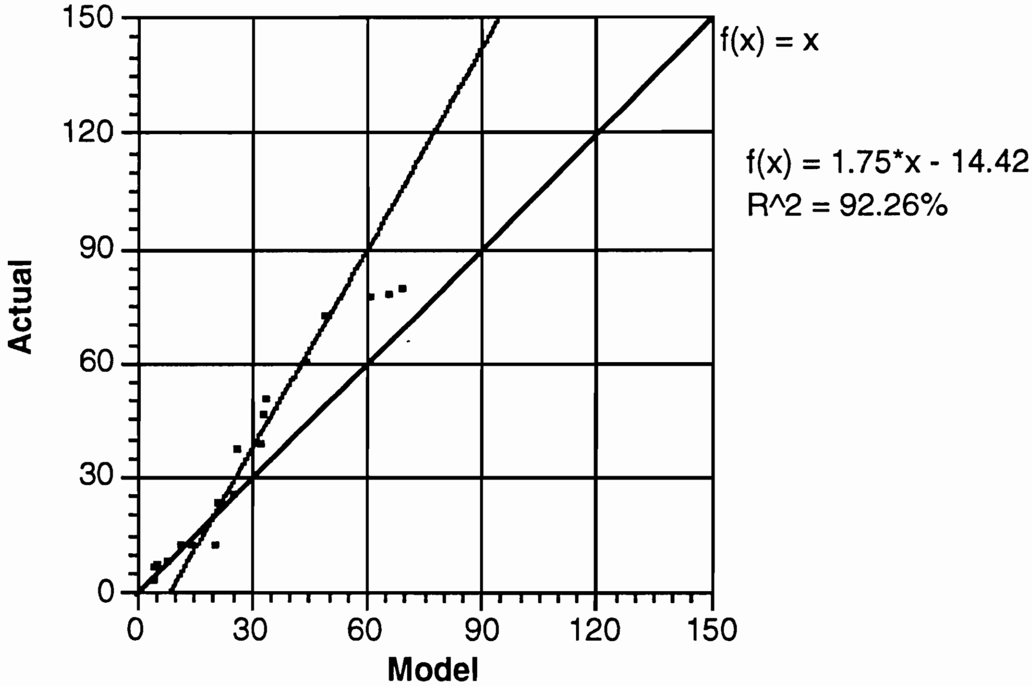
HAH HIGH Medium Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 0.42*x + 2.49
R^2 = 78.75%

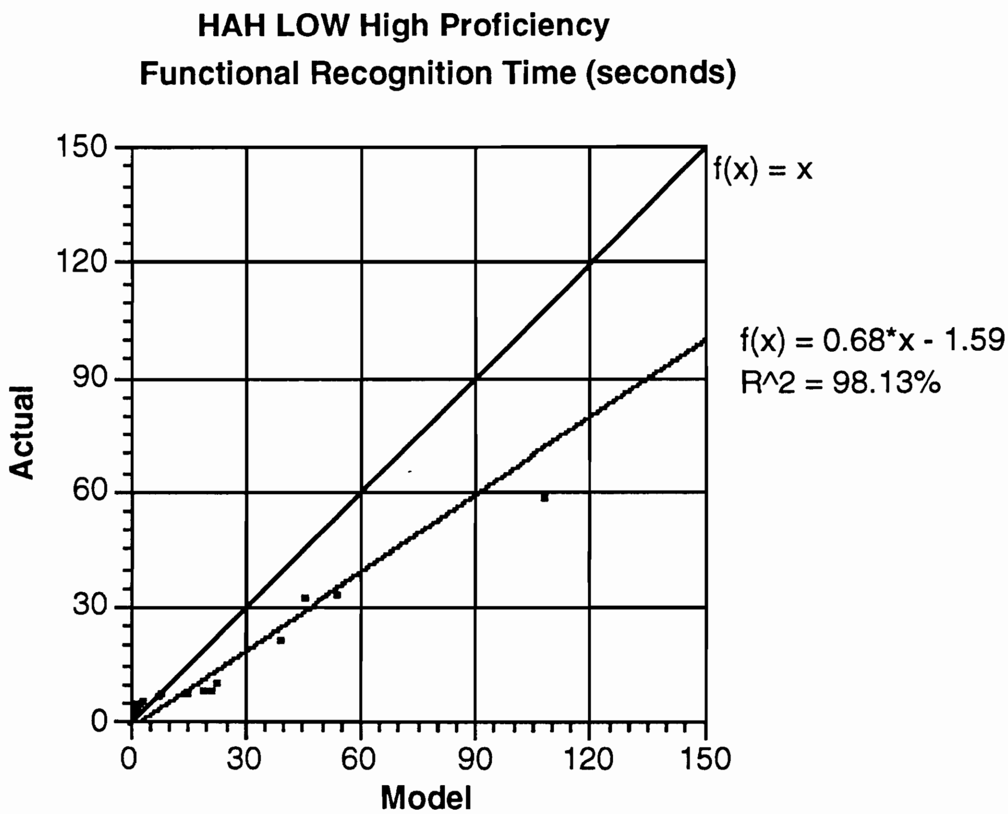

HAH HIGH Low Proficiency
Functional Recognition Time (seconds)
f(x) = x
f(x) = 0.65*x + 28.14
R^2 = 76.74%
Actual
Model
0
30
60
90
120
150

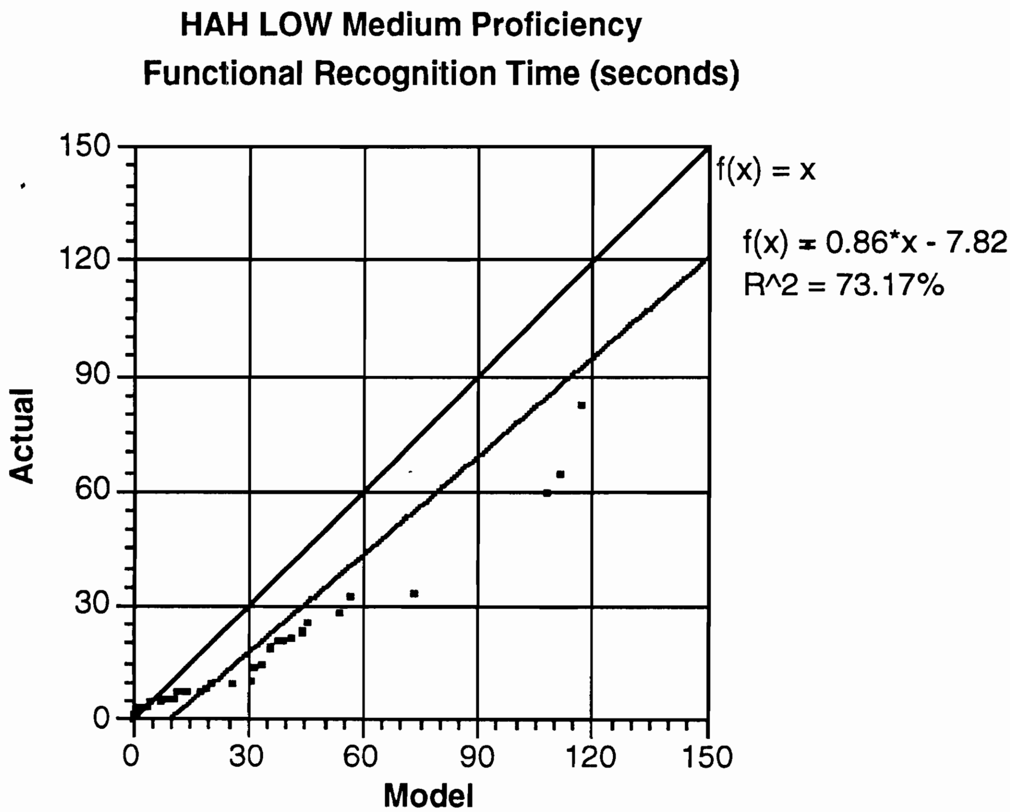

HAH MED High Proficiency
Functional Recognition Time (seconds)
f(x) = x
f(x) = 1.71*x - 10.43
R^2 = 73.23%
Actual
Model
0
30
60
90
120
150

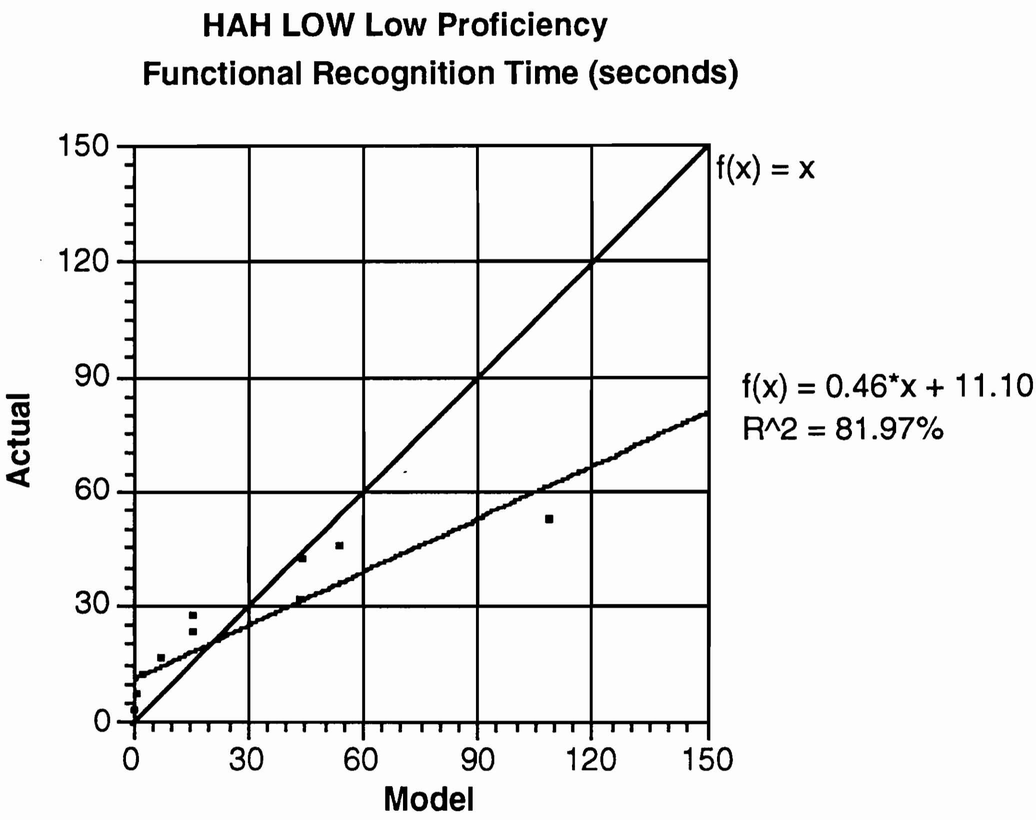

HAH MED Medium Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 0.71*x - 7.61
R^2 = 74.74%

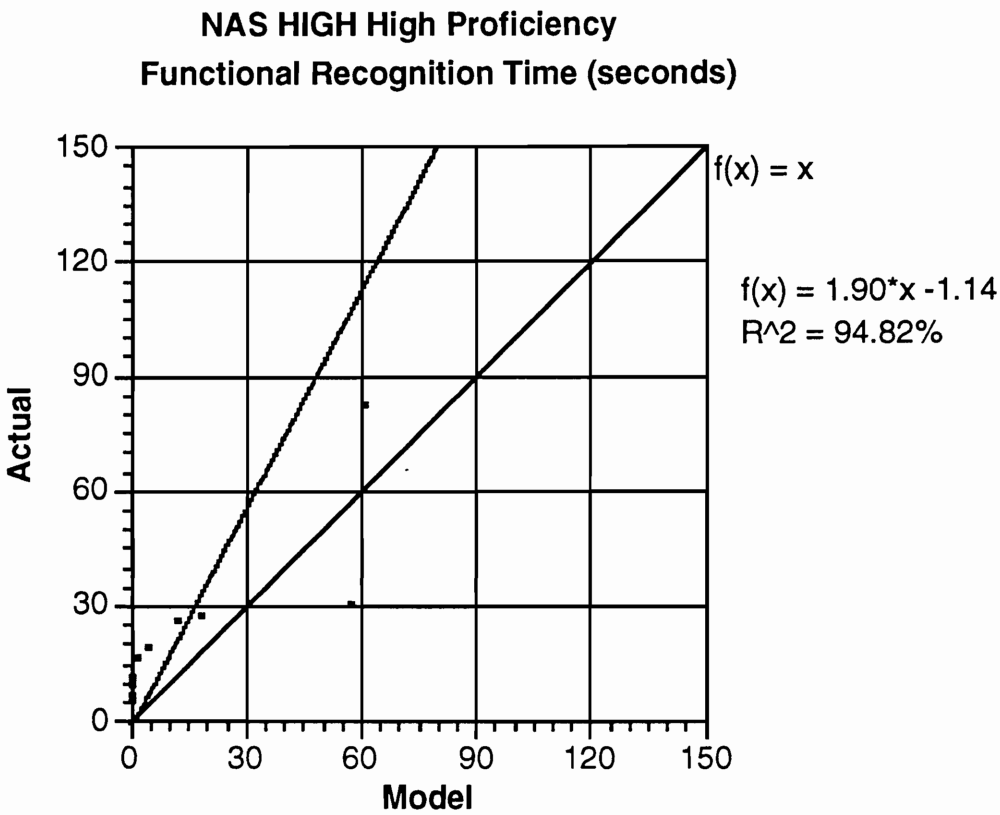
HAH MED Low Proficiency
Functional Recognition Time (seconds)

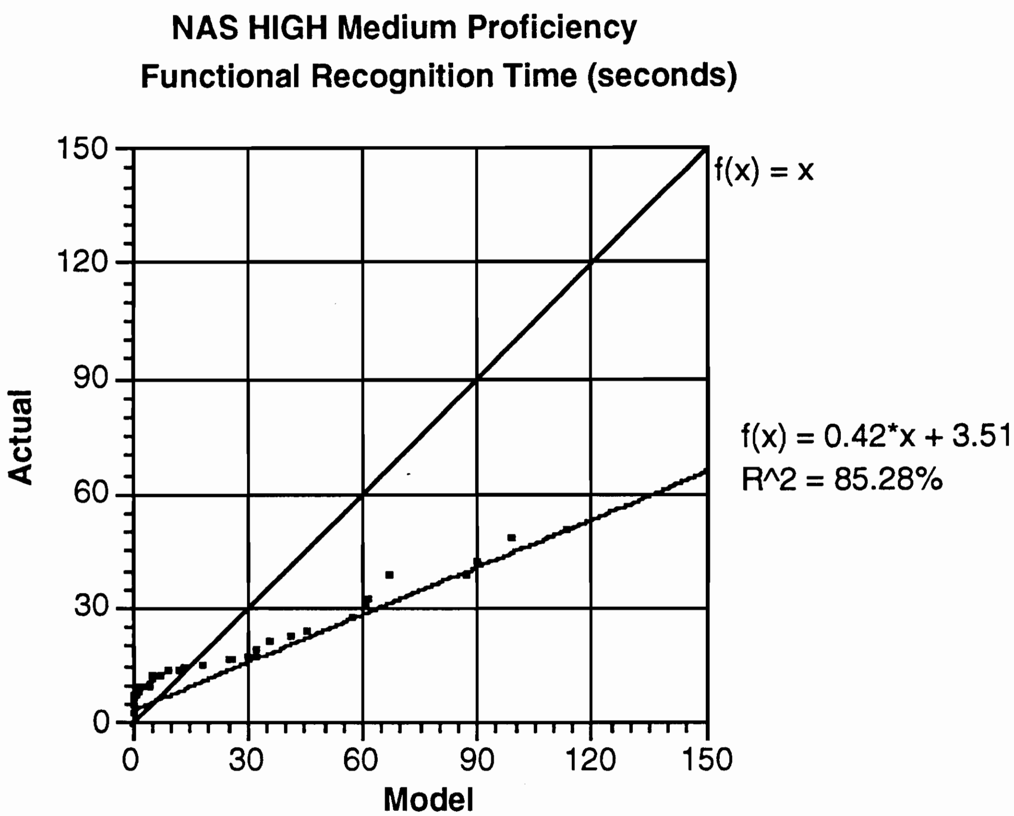



HAH LOW High Proficiency
Functional Recognition Time (seconds)
f(x) = x
f(x) = 0.68*x - 1.59
R^2 = 98.13%
Actual
Model
0
30
60
90
120
150

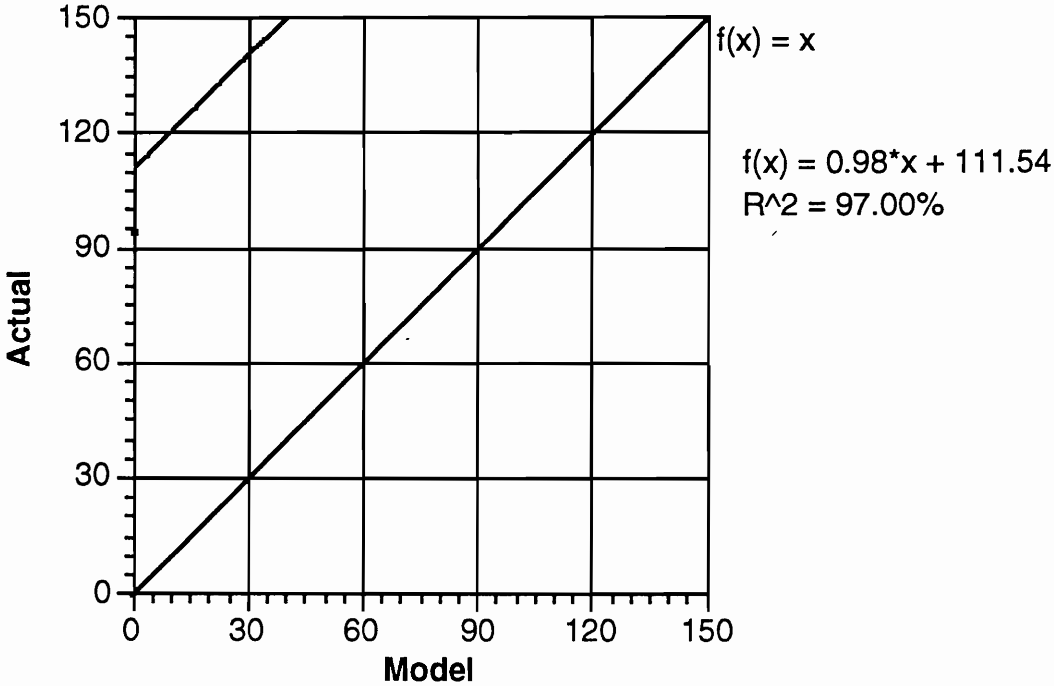

HAH LOW Medium Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 0.86*x - 7.82
R^2 = 73.17%

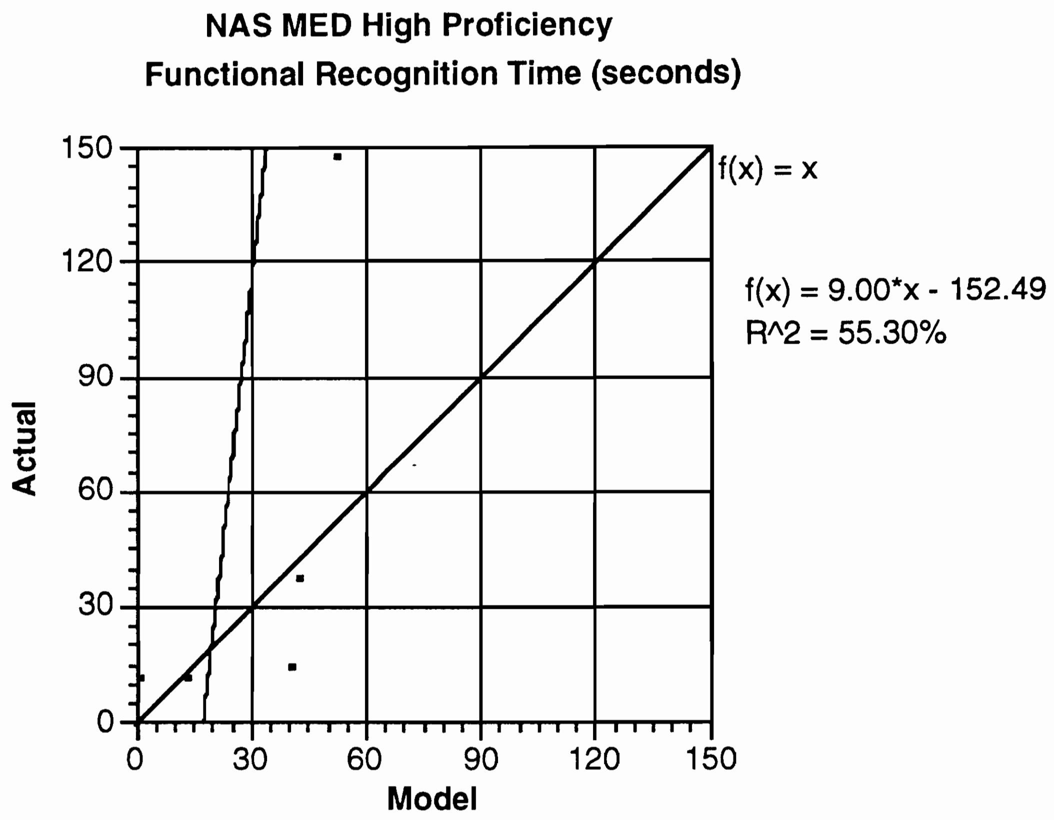

HAH LOW Low Proficiency
Functional Recognition Time (seconds)
f(x) = x
f(x) = 0.46*x + 11.10
R^2 = 81.97%
Actual
Model
0
30
60
90
120
150


NAS HIGH High Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 1.90*x -1.14
R^2 = 94.82%


NAS HIGH Medium Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
0
30
60
90
120
150
Actual
Model
f(x) = x
f(x) = 0.42*x + 3.51
R^2 = 85.28%

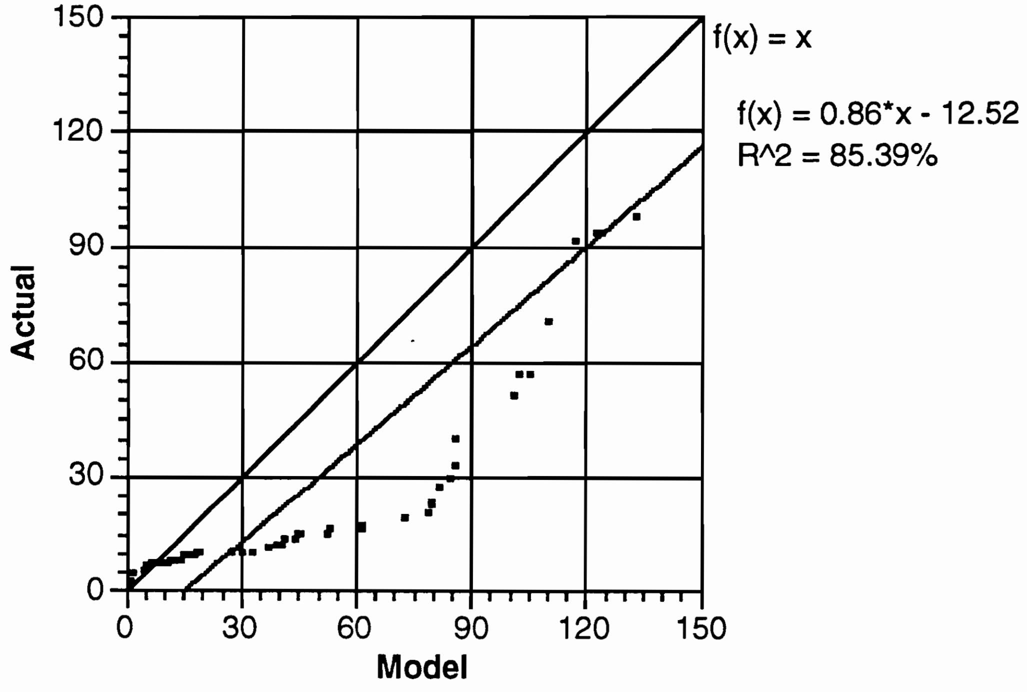
NAS HIGH Low Proficiency
Functional Recognition Time (seconds)



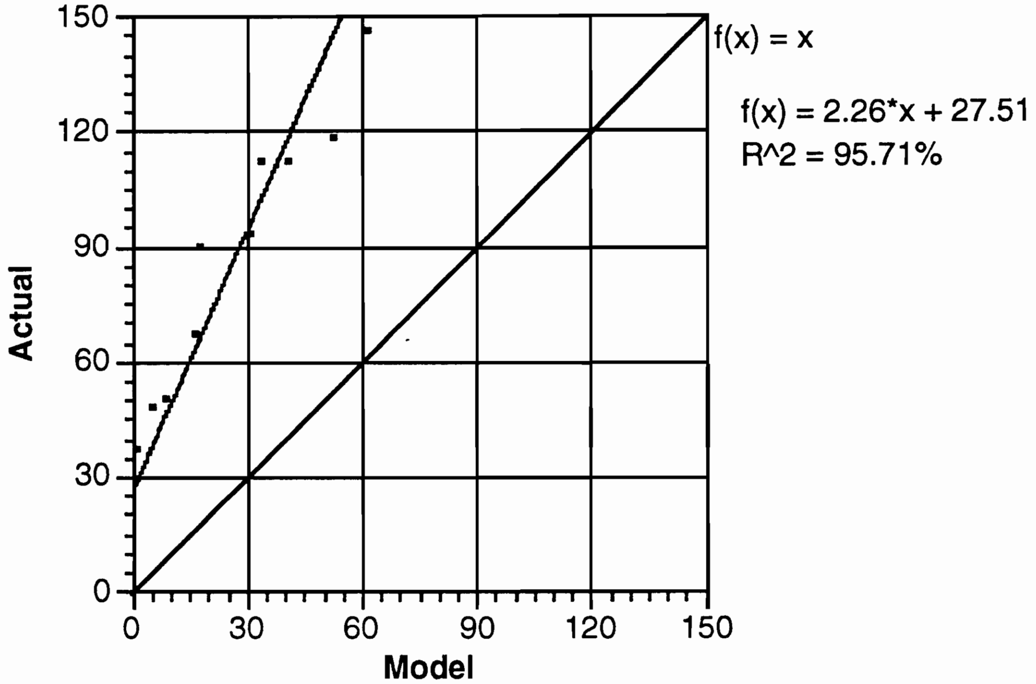


NAS MED High Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 9.00*x - 152.49
R^2 = 55.30%

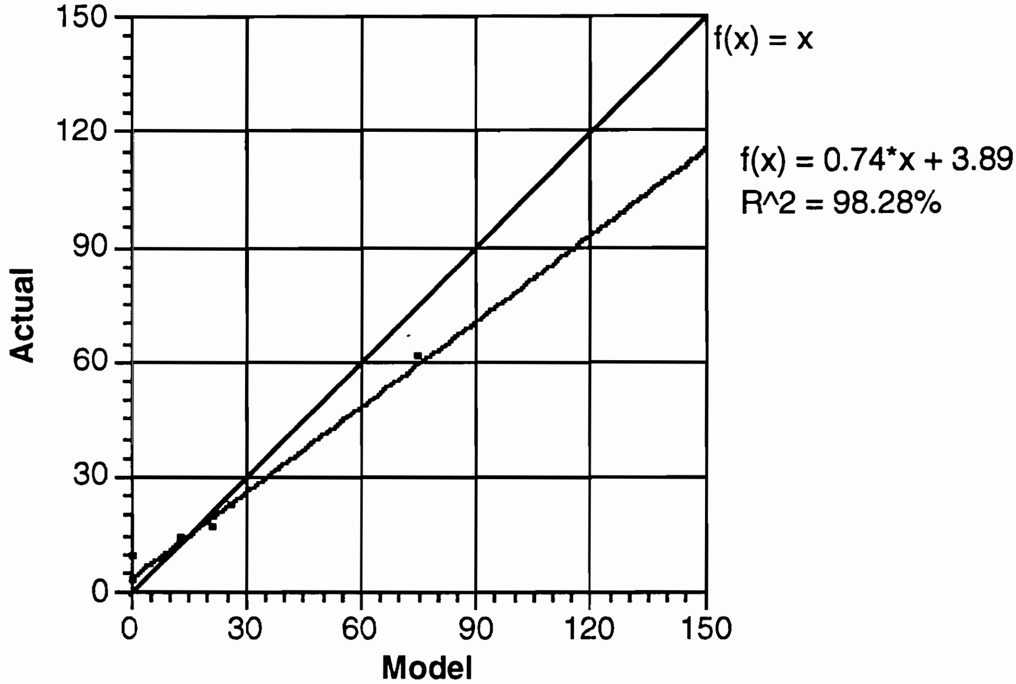
NAS MED Medium Proficiency
Functional Recognition Time (seconds)

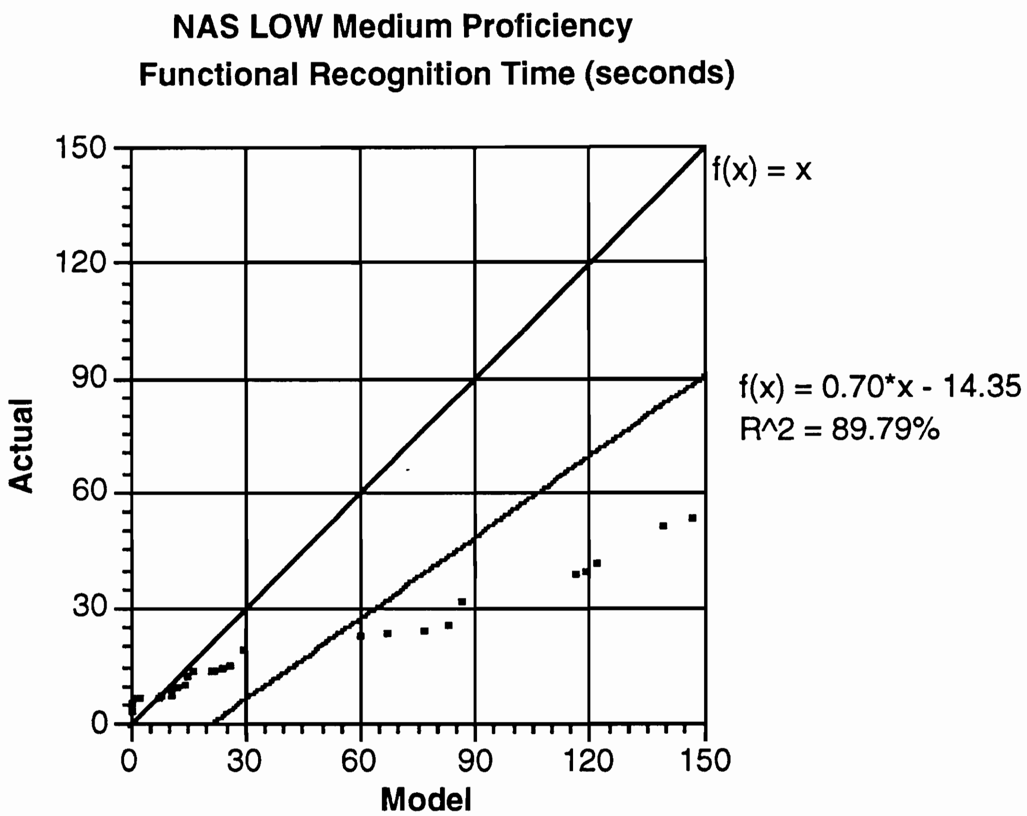


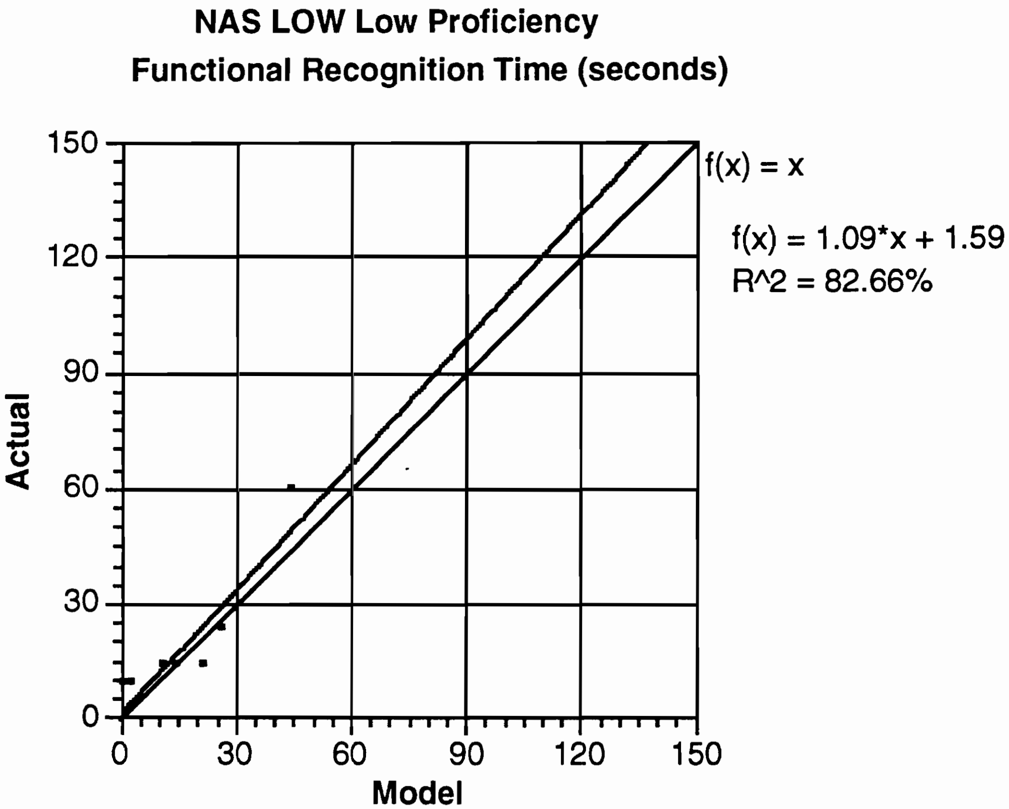
NAS MED Low Proficiency
Functional Recognition Time (seconds)

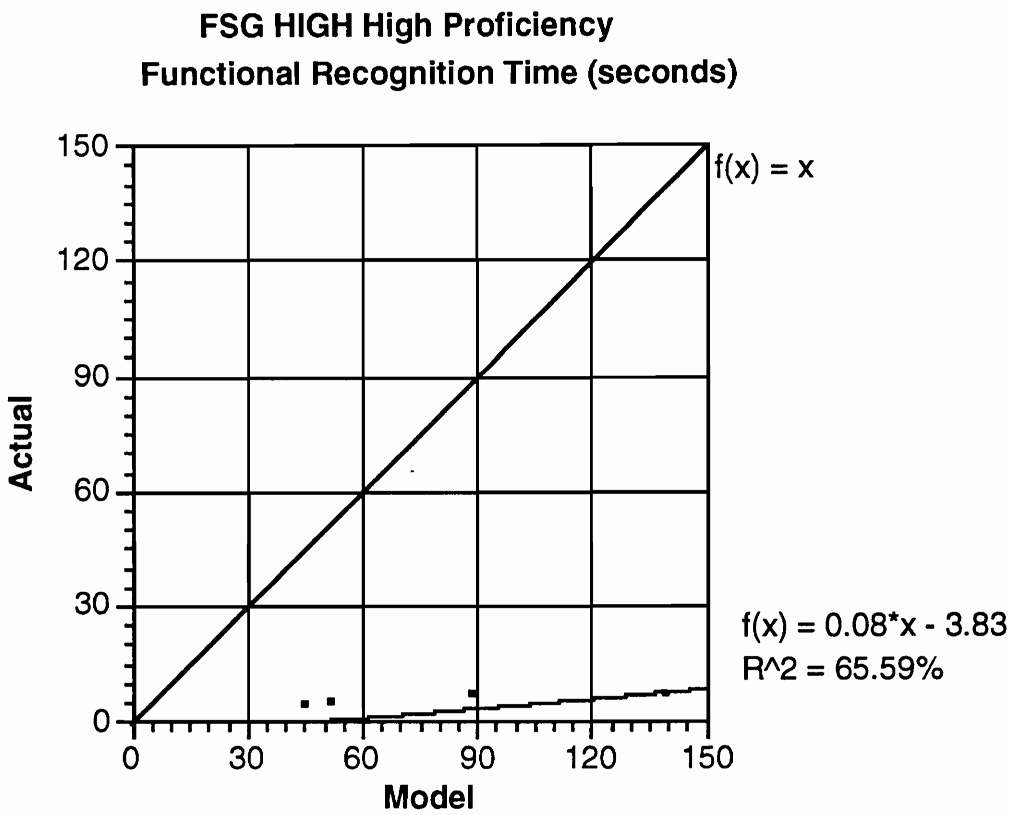


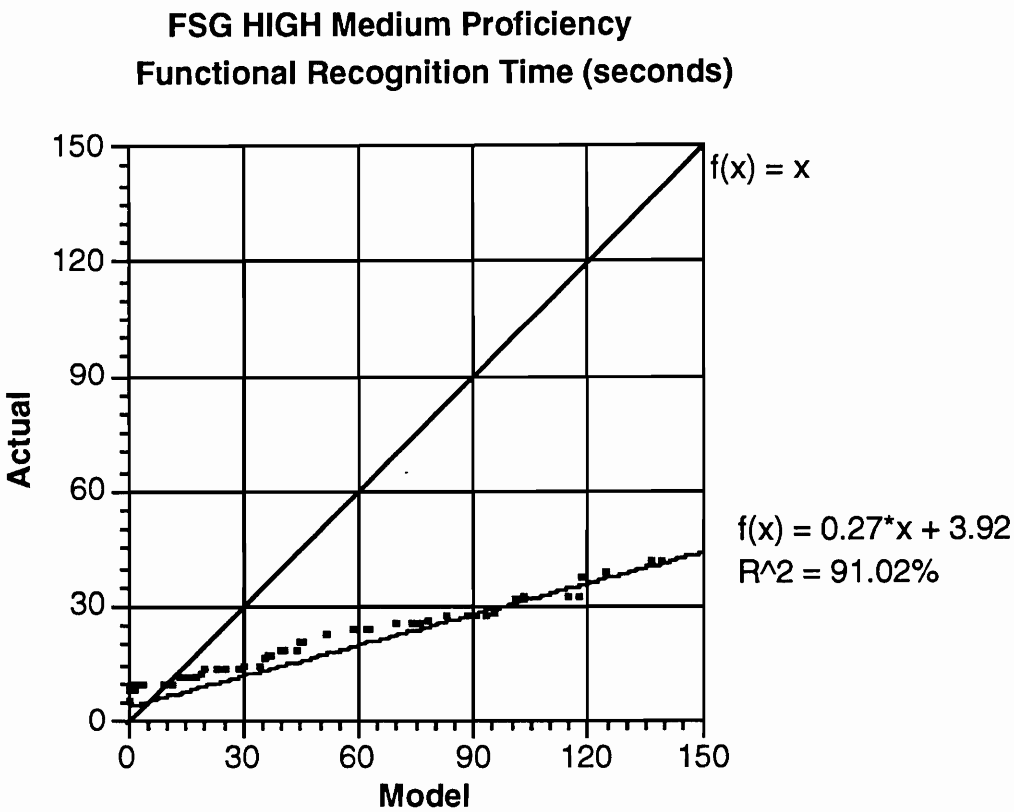
NAS LOW High Proficiency
Functional Recognition Time (seconds)

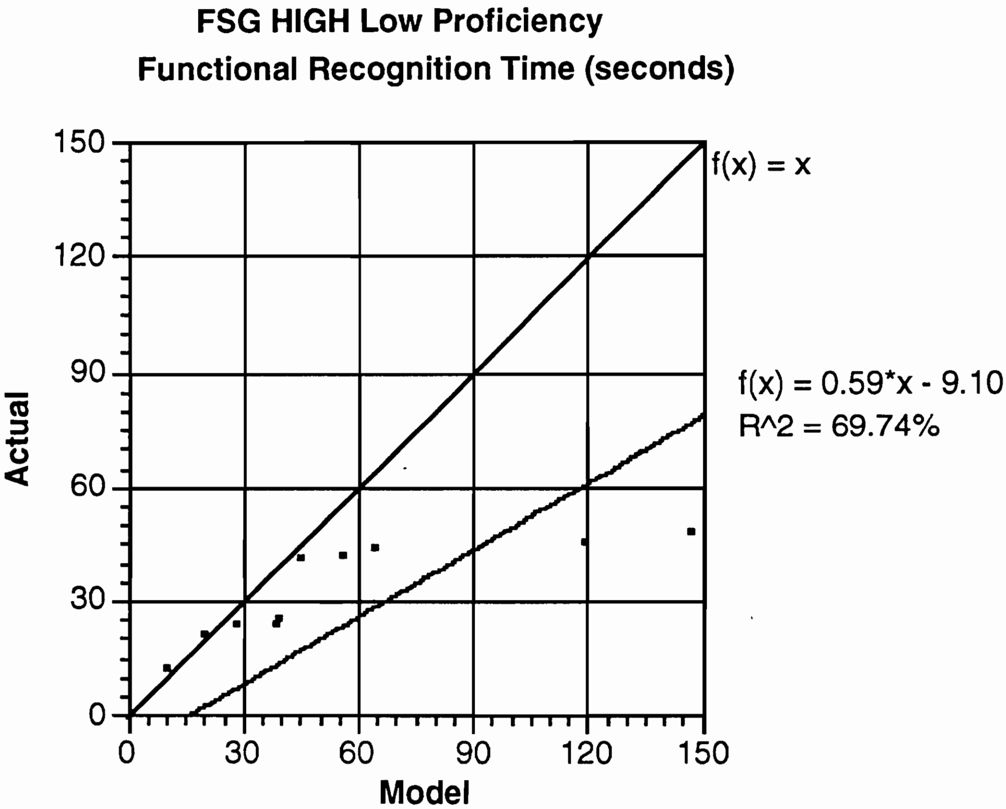


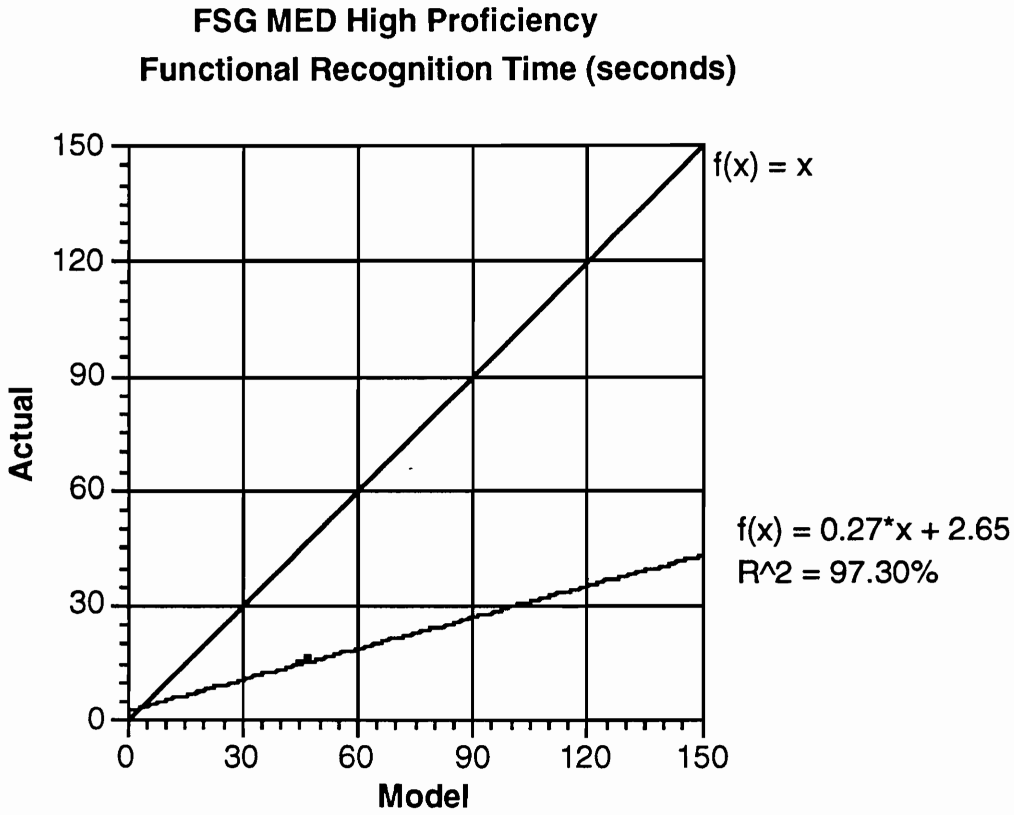

NAS LOW Medium Proficiency
Functional Recognition Time (seconds)
Actual
Model
f(x) = x
f(x) = 0.70*x - 14.35
R^2 = 89.79%
150
120
90
60
30
0

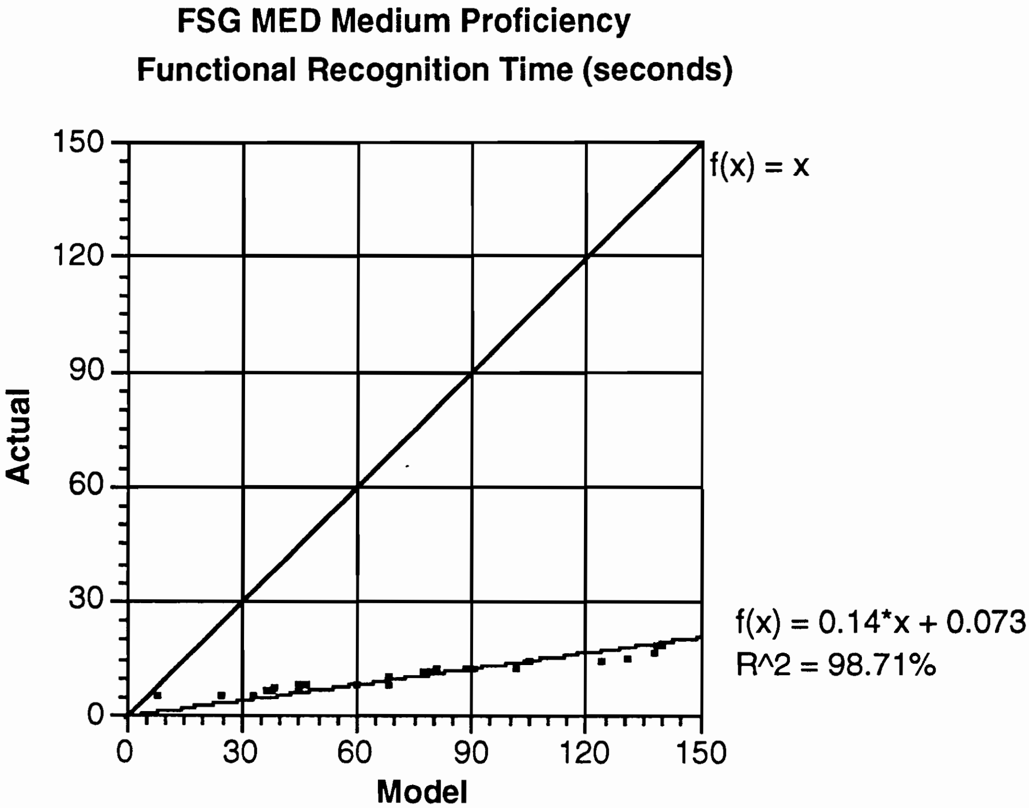

NAS LOW Low Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 1.09*x + 1.59
R^2 = 82.66%


FSG HIGH High Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 0.08*x - 3.83
R^2 = 65.59%

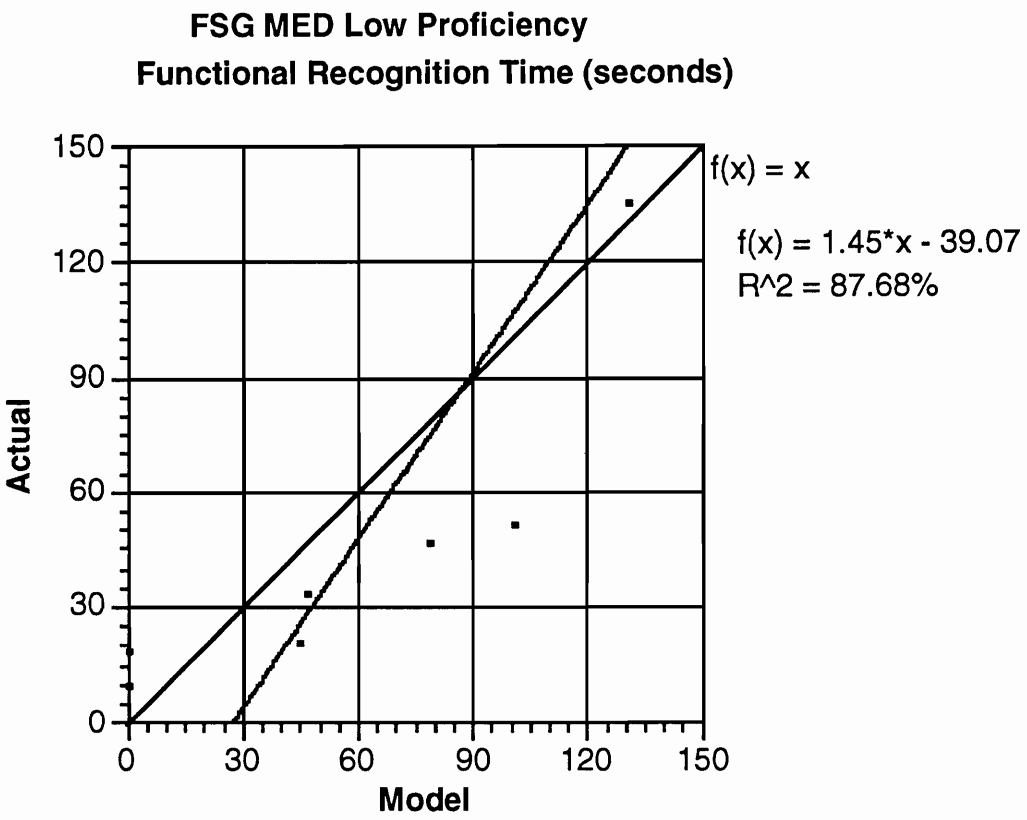

FSG HIGH Medium Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 0.27*x + 3.92
R^2 = 91.02%


FSG HIGH Low Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
0
30
60
90
120
150
Actual
Model
f(x) = x
f(x) = 0.59*x - 9.10
R^2 = 69.74%

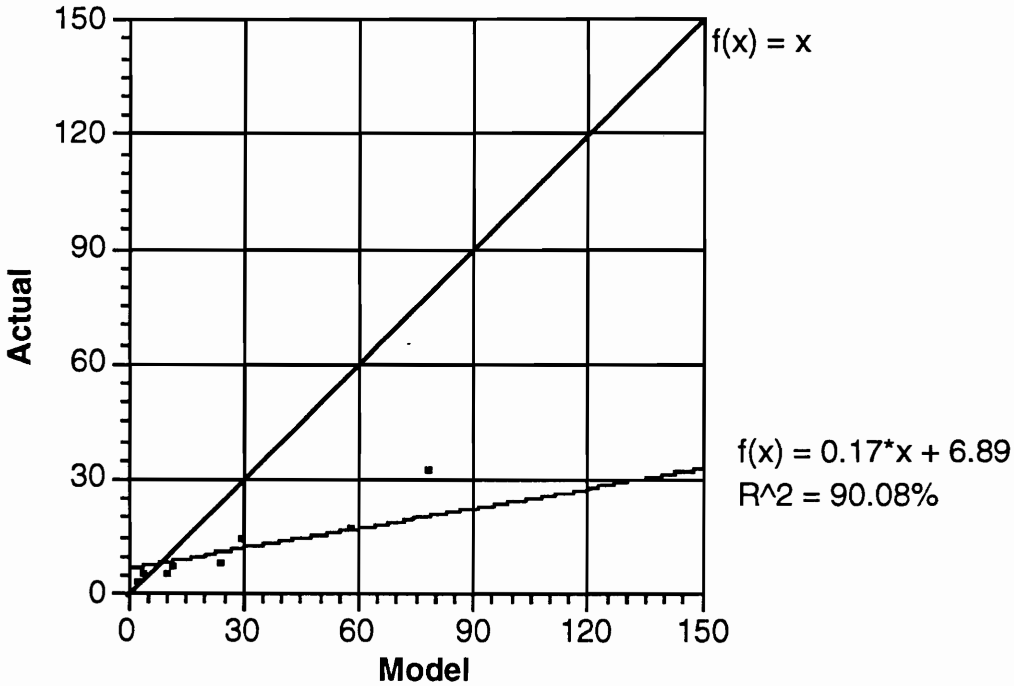

FSG MED High Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 0.27*x + 2.65
R^2 = 97.30%

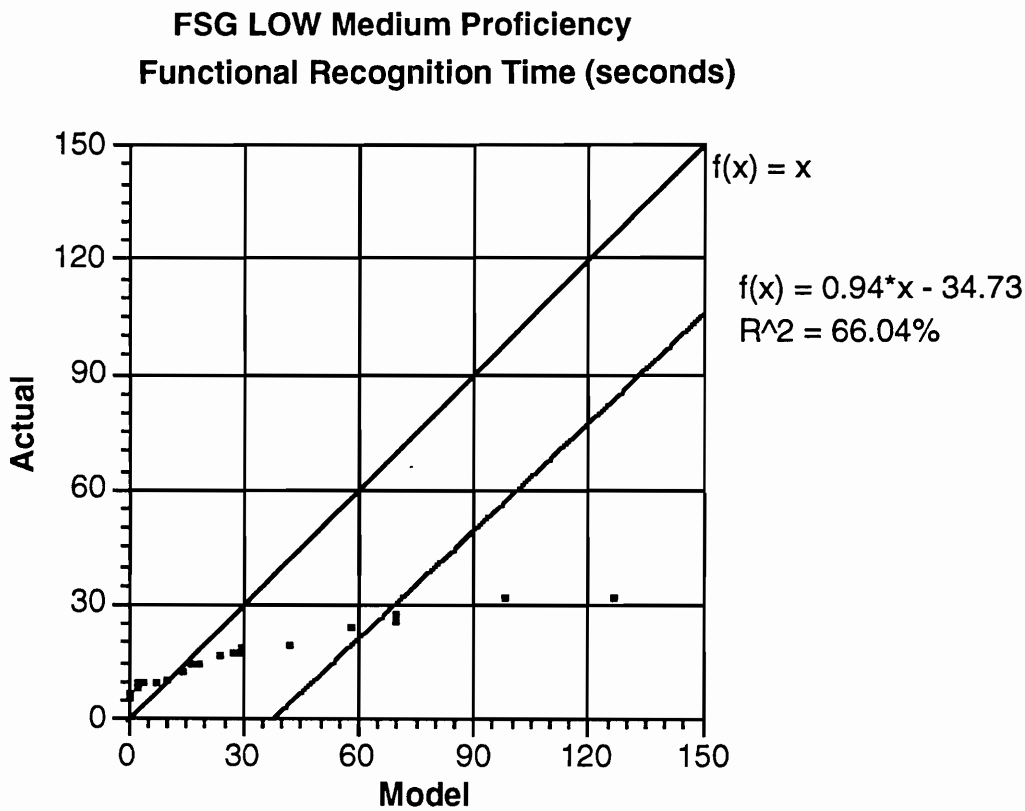


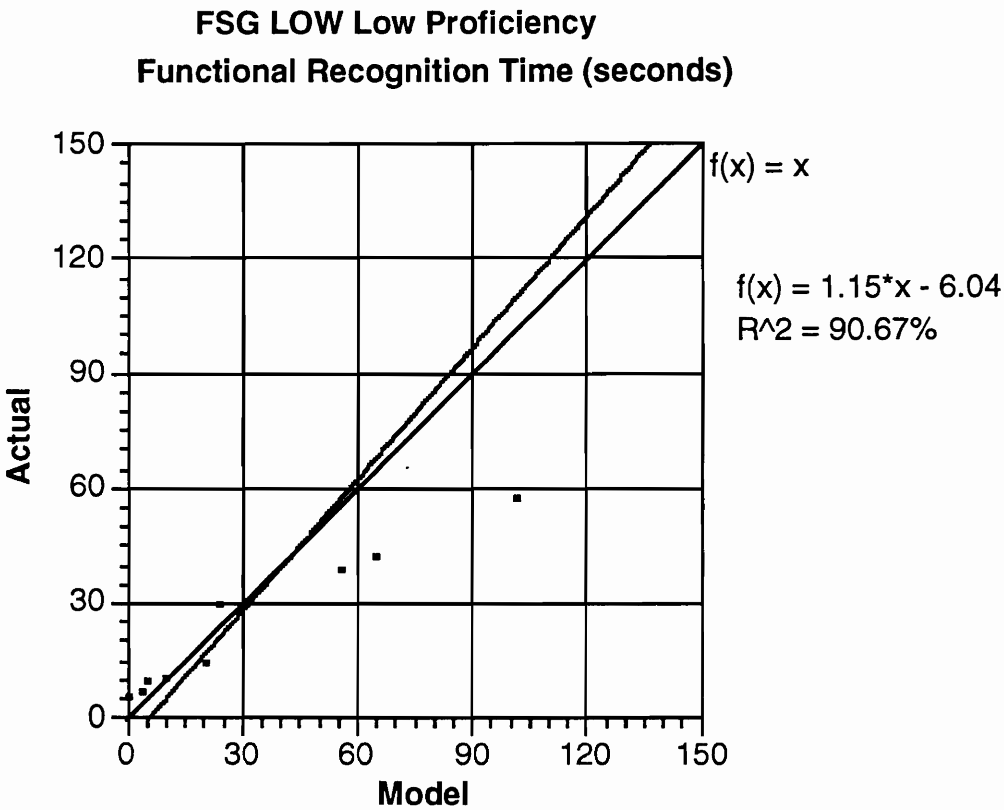
FSG MED Medium Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 0.14*x + 0.073
R^2 = 98.71%


FSG MED Low Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 1.45*x - 39.07
R^2 = 87.68%

FSG LOW High Proficiency
Functional Recognition Time (seconds)




FSG LOW Medium Proficiency
Functional Recognition Time (seconds)
150
120
90
60
30
0
Actual
0
30
60
90
120
150
Model
f(x) = x
f(x) = 0.94*x - 34.73
R^2 = 66.04%


FSG LOW Low Proficiency
Functional Recognition Time (seconds)
Actual
Model
0
30
60
90
120
150
f(x) = x
f(x) = 1.15*x - 6.04
R^2 = 90.67%

APPENDIX D. MODEL DATA

Node population data listing for the revised task network model, by condition:

TYPE	DENS	NODE	N Obs	Mean	Std Dev
FSG	HIGH	0	185	23.9564865	62.0748039
		1	2	169.1240000	239.1774545
		2	2	23.8660000	33.2156339
		5	244	151.4659474	191.4557333
		6	246	4.9145347	9.0994389
		7	55	7.3994545	15.4331392
		8	23	8.0390000	13.4225279
		9	92	20.4189348	60.0401216
		10	31	3.0331613	1.9199759
		11	13	5.8330769	10.3042576
		12	8	7.4035000	9.6840530
		13	347	52.6310649	99.8953892
		14	247	5.0129715	10.3511229
		15	41	8.5228537	10.7163394
		16	24	13.6435417	18.4948195
		17	69	8.4280580	15.2055499
		18	103	17.7166796	23.8732617
	LOW	0	55	16.8207273	55.8165524
		5	67	68.3208710	132.5359590
		6	75	12.7160133	26.3937821
		7	16	2.1780625	3.0524142
		8	8	24.2227500	40.4416116
		9	20	17.1096000	64.9263797
		10	16	4.7365625	2.6968353
		13	79	140.3493387	208.2704828
		14	59	14.8921017	32.7392261
		15	2	2.4975000	0.7686251
		16	2	31.7330000	.
		17	32	26.3302812	40.3770353
		18	23	17.8295217	21.2185800
	MED	0	101	25.6616931	66.5477828
		5	124	163.0866410	189.3391373
		6	133	11.0523910	36.6255824
		7	29	5.4166897	8.2370780
		8	15	9.8164000	16.0006147
		9	64	19.3898750	67.9154522
		10	22	3.0941818	1.9509880
		11	4	3.8145000	4.4034622
		12	2	1.4050000	1.0097485
		13	227	103.3872560	148.0548287
		14	184	7.3729728	16.3530378
		15	28	11.9871786	26.5124975
		16	16	13.4138125	19.3290613
		17	37	15.5033784	19.5878937
		18	47	18.3861489	24.7986809

HAH	HIGH	0	222	13.4254865	50.1609892
		1	12	1.1555000	2.5014775
		2	13	4.3774615	4.6858004
		3	4	0.7200000	0.6538512
		4	3	16.3550000	6.5366194
		5	174	26.4335887	37.8955192
		6	253	3.4160316	7.9281975
		7	40	5.5628750	9.8071896
		8	20	22.4831500	19.6304966
		9	29	2.8096897	7.3680713
		10	27	3.7767407	5.0988810
		11	6	4.8702000	3.6389438
		12	2	23.8165000	13.2236039
		13	68	22.7369362	28.2299300
		14	48	6.8906042	14.2826170
		15	9	11.3523333	27.6450819
		16	6	10.6563333	14.6760176
		17	42	8.2165952	9.8944889
		18	25	11.9807200	9.6596798
	LOW	0	78	4.9522821	7.4512008
		5	51	20.3788684	33.7839442
		6	87	5.8477586	12.6944701
		7	17	4.9684706	4.8756741
		8	7	7.3641429	8.7402324
		9	17	1.7432941	2.7009251
		10	11	3.5525455	1.8814436
		11	3	3.0626667	2.2269648
		12	2	19.6645000	12.8728790
		13	39	19.6372903	40.3481113
		14	32	11.5771250	24.5708336
		15	6	3.5375000	5.7398203
		16	3	4.8956667	5.4122181
		17	12	14.2300000	18.0256144
		18	14	20.0061429	23.8770168
	MED	0	142	11.5158803	25.0118034
		2	1	3.6960000	.
		5	123	22.1218182	39.7190758
		6	157	6.0464331	10.7716676
		7	36	7.9183056	11.4497000
		8	14	14.0595714	13.2499022
		9	35	11.3381714	36.7698654
		10	21	2.4136667	1.2165191
		11	4	3.1437500	4.0532797
		12	2	7.9750000	5.1463232
		13	61	15.3964737	26.8613005
		14	56	4.7597857	9.4020289
		15	7	5.1574286	10.7866718
		16	5	18.2002000	11.4715911
		17	36	9.3236389	10.2829533
		18	16	6.0700625	6.0535946

NAS	HIGH	0	186	37.7681667	95.4514252
		5	377	120.2809385	172.3657848
		6	328	5.8589421	17.7868153
		7	44	10.6021136	15.9102239
		8	26	20.1256154	23.2702807
		9	39	31.3319487	107.2638185
		10	22	4.3682727	4.3148200
		11	4	3.1077500	1.6839361
		12	3	2.8400000	1.3590158
		13	103	63.6707042	113.6873106
		14	76	6.9879079	17.0818446
		15	3	31.1950000	19.7627204
		16	1	18.4520000	.
		17	102	10.8167157	13.0234570
		18	31	9.5090000	10.4931762
	LOW	0	80	12.6429750	29.7637282
		1	1	0	.
		2	1	10.6500000	.
		5	150	101.9149256	115.2157752
		6	174	12.3530920	33.7019866
		7	15	20.7441333	24.9669720
		8	5	33.2768000	67.1240614
		9	13	0.2759231	0.9948548
		10	14	4.4070714	2.7221176
		11	1	5.3230000	.
		13	59	57.1150000	107.6227246
		14	44	7.8930909	14.4880136
		15	8	23.3598750	28.4504467
		16	3	35.5353333	26.8432588
		17	17	20.8016471	25.6727168
		18	17	29.0135882	33.5433729
	MED	0	148	31.0374054	49.9010672
		1	1	0	.
		2	1	4.3260000	.
		5	163	155.6510092	193.5722306
		6	194	11.1854227	29.3566828
		7	29	27.3046897	52.5257407
		8	12	7.0541667	8.8279342
		9	25	36.1494400	114.7883434
		10	14	2.9278571	0.9967665
		11	4	7.2505000	10.1725803
		12	2	18.1955000	0.9524728
		13	41	125.1571579	135.5971524
		14	40	11.6378750	22.2493107
		17	51	15.3246863	17.3469271
		18	4	24.2432500	12.7044091

Node link probabilities for the revised task network model, by condition:

---------------------- TYPE=FSG DENS=HIGH FROM=0 -----------------------

TO	Frequency	Percent
2	1	0.5
6	182	98.4
20	2	1.1

---------------------- TYPE=FSG DENS=HIGH FROM=1 -----------------------

TO	Frequency	Percent
2	1	50.0
6	1	50.0

---------------------- TYPE=FSG DENS=HIGH FROM=2 -----------------------

TO	Frequency	Percent
1	2	100.0

---------------------- TYPE=FSG DENS=HIGH FROM=5 -----------------------

TO	Frequency	Percent
6	63	25.8
9	62	25.4
17	69	28.3
20	15	6.1
21	35	14.3

---------------------- TYPE=FSG DENS=HIGH FROM=6 -----------------------

TO	Frequency	Percent
5	175	71.1
7	39	15.9
10	20	8.1
20	11	4.5
21	1	0.4

---------------------- TYPE=FSG DENS=HIGH FROM=7 -----------------------

TO	Frequency	Percent
5	16	29.1
8	23	41.8
11	3	5.5
20	13	23.6

---------------------- TYPE=FSG DENS=HIGH FROM=8 -----------------------

TO	Frequency	Percent
5	12	52.2
7	7	30.4
20	4	17.4

---------------------- TYPE=FSG DENS=HIGH FROM=9 ----------------------

TO	Frequency	Percent
10	4	4.3
14	88	95.7

---------------------- TYPE=FSG DENS=HIGH FROM=10 ----------------------

TO	Frequency	Percent
9	25	80.6
11	4	12.9
20	2	6.5

---------------------- TYPE=FSG DENS=HIGH FROM=11 ----------------------

TO	Frequency	Percent
9	5	38.5
12	8	61.5

---------------------- TYPE=FSG DENS=HIGH FROM=12 ----------------------

TO	Frequency	Percent
9	1	12.5
11	6	75.0
20	1	12.5

---------------------- TYPE=FSG DENS=HIGH FROM=13 ----------------------

TO	Frequency	Percent
14	159	45.8
18	103	29.7
21	85	24.5

---------------------- TYPE=FSG DENS=HIGH FROM=14 ----------------------

TO	Frequency	Percent
13	222	89.9
15	24	9.7
21	1	0.4

---------------------- TYPE=FSG DENS=HIGH FROM=15 ----------------------

TO	Frequency	Percent
13	17	41.5
16	24	58.5

---------------------- TYPE=FSG DENS=HIGH FROM=16 ----------------------

TO	Frequency	Percent
13	20	83.3
15	3	12.5
20	1	4.2

---------------------- TYPE=FSG DENS=HIGH FROM=17 ----------------------

TO	Frequency	Percent
5	42	60.9
7	9	13.0
10	7	10.1
20	11	15.9

---------------------- TYPE=FSG DENS=HIGH FROM=18 ----------------------

TO	Frequency	Percent
13	88	85.4
15	14	13.6
20	1	1.0

----------------------- TYPE=FSG DENS=LOW FROM=0 -----------------------

TO	Frequency	Percent
6	55	100.0

----------------------- TYPE=FSG DENS=LOW FROM=5 -----------------------

TO	Frequency	Percent
6	20	29.9
9	5	7.5
17	32	47.8
20	5	7.5
21	5	7.5

----------------------- TYPE=FSG DENS=LOW FROM=6 -----------------------

TO	Frequency	Percent
5	42	56.0
7	9	12.0
10	10	13.3
20	14	18.7

----------------------- TYPE=FSG DENS=LOW FROM=7 -----------------------

TO	Frequency	Percent
5	7	43.8
8	8	50.0
20	1	6.3

----------------------- TYPE=FSG DENS=LOW FROM=8 -----------------------

TO	Frequency	Percent
5	5	62.5
7	2	25.0
20	1	12.5

---------------------- TYPE=FSG DENS=LOW FROM=9 ----------------------

TO	Frequency	Percent
14	20	100.0

---------------------- TYPE=FSG DENS=LOW FROM=10 ----------------------

TO	Frequency	Percent
9	15	93.8
20	1	6.3

---------------------- TYPE=FSG DENS=LOW FROM=13 ----------------------

TO	Frequency	Percent
14	39	49.4
18	23	29.1
21	17	21.5

---------------------- TYPE=FSG DENS=LOW FROM=14 ----------------------

TO	Frequency	Percent
13	55	93.2
15	2	3.4
20	2	3.4

---------------------- TYPE=FSG DENS=LOW FROM=15 ----------------------

TO	Frequency	Percent
16	2	100.0

---------------------- TYPE=FSG DENS=LOW FROM=16 ----------------------

TO	Frequency	Percent
13	1	50.0
21	1	50.0

---------------------- TYPE=FSG DENS=LOW FROM=17 ----------------------

TO	Frequency	Percent
5	14	43.8
7	5	15.6
10	6	18.8
20	7	21.9

---------------------- TYPE=FSG DENS=LOW FROM=18 ----------------------

TO	Frequency	Percent
13	23	100.0

------------------------ TYPE=FSG DENS=MED FROM=. ------------------------

TO	Frequency	Percent

Frequency Missing = 2

------------------------ TYPE=FSG DENS=MED FROM=0 ------------------------

TO	Frequency	Percent
6	97	96.0
20	4	4.0

------------------------ TYPE=FSG DENS=MED FROM=5 ------------------------

TO	Frequency	Percent
6	36	29.0
9	39	31.5
17	37	29.8
20	5	4.0
21	7	5.6

------------------------ TYPE=FSG DENS=MED FROM=6 ------------------------

TO	Frequency	Percent
5	89	66.9
7	23	17.3
10	14	10.5
20	7	5.3

------------------------ TYPE=FSG DENS=MED FROM=7 ------------------------

TO	Frequency	Percent
5	7	24.1
8	15	51.7
11	2	6.9
20	5	17.2

------------------------ TYPE=FSG DENS=MED FROM=8 ------------------------

TO	Frequency	Percent
5	9	60.0
7	2	13.3
12	1	6.7
20	3	20.0

------------------------ TYPE=FSG DENS=MED FROM=9 ------------------------

TO	Frequency	Percent
10	1	1.6
14	63	98.4

---------------------- TYPE=FSG DENS=MED FROM=10 ----------------------

TO	Frequency	Percent
9	21	95.5
11	1	4.5

---------------------- TYPE=FSG DENS=MED FROM=11 ----------------------

TO	Frequency	Percent
9	3	75.0
12	1	25.0

---------------------- TYPE=FSG DENS=MED FROM=12 ----------------------

TO	Frequency	Percent
9	1	50.0
11	1	50.0

---------------------- TYPE=FSG DENS=MED FROM=13 ----------------------

TO	Frequency	Percent
14	121	53.3
18	47	20.7
21	59	26.0

---------------------- TYPE=FSG DENS=MED FROM=14 ----------------------

TO	Frequency	Percent
13	166	90.2
15	17	9.2
20	1	0.5

---------------------- TYPE=FSG DENS=MED FROM=15 ----------------------

TO	Frequency	Percent
13	11	39.3
16	16	57.1
20	1	3.6

---------------------- TYPE=FSG DENS=MED FROM=16 ----------------------

TO	Frequency	Percent
13	8	50.0
15	8	50.0

---------------------- TYPE=FSG DENS=MED FROM=17 ----------------------

TO	Frequency	Percent
5	19	51.4
7	4	10.8
10	7	18.9
20	7	18.9

TYPE=FSG DENS=MED FROM=18

TO	Frequency	Percent
13	43	91.5
15	3	6.4
20	1	2.1

TYPE=HAH DENS=HIGH FROM=.

TO	Frequency	Percent

Frequency Missing = 1

TYPE=HAH DENS=HIGH FROM=0

TO	Frequency	Percent
2	11	5.0
6	185	83.3
20	26	11.7

TYPE=HAH DENS=HIGH FROM=1

TO	Frequency	Percent
2	2	16.7
6	10	83.3

TYPE=HAH DENS=HIGH FROM=2

TO	Frequency	Percent
1	8	61.5
3	4	30.8
20	1	7.7

TYPE=HAH DENS=HIGH FROM=3

TO	Frequency	Percent
1	1	25.0
4	3	75.0

TYPE=HAH DENS=HIGH FROM=4

TO	Frequency	Percent
1	3	100.0

TYPE=HAH DENS=HIGH FROM=5

TO	Frequency	Percent
6	58	33.3
9	15	8.6
17	42	24.1
20	9	5.2
21	50	28.7

---------------------- TYPE=HAH DENS=HIGH FROM=6 ----------------------

TO	Frequency	Percent
5	140	55.3
7	30	11.9
10	22	8.7
20	61	24.1

---------------------- TYPE=HAH DENS=HIGH FROM=7 ----------------------

TO	Frequency	Percent
5	6	15.0
8	20	50.0
11	1	2.5
20	13	32.5

---------------------- TYPE=HAH DENS=HIGH FROM=8 ----------------------

TO	Frequency	Percent
5	10	50.0
7	2	10.0
20	8	40.0

---------------------- TYPE=HAH DENS=HIGH FROM=9 ----------------------

TO	Frequency	Percent
10	3	10.3
14	26	89.7

---------------------- TYPE=HAH DENS=HIGH FROM=10 ----------------------

TO	Frequency	Percent
9	13	48.1
11	5	18.5
20	9	33.3

---------------------- TYPE=HAH DENS=HIGH FROM=11 ----------------------

TO	Frequency	Percent
9	1	16.7
12	2	33.3
20	2	33.3
21	1	16.7

---------------------- TYPE=HAH DENS=HIGH FROM=12 ----------------------

TO	Frequency	Percent
20	2	100.0

---------------------- TYPE=HAH DENS=HIGH FROM=13 ----------------------

TO	Frequency	Percent
14	22	32.4
18	25	36.8
21	21	30.9

---------------------- TYPE=HAH DENS=HIGH FROM=14 ----------------------

TO	Frequency	Percent
13	38	79.2
15	7	14.6
20	3	6.3

---------------------- TYPE=HAH DENS=HIGH FROM=15 ----------------------

TO	Frequency	Percent
13	2	22.2
16	6	66.7
20	1	11.1

---------------------- TYPE=HAH DENS=HIGH FROM=16 ----------------------

TO	Frequency	Percent
13	5	83.3
15	1	16.7

---------------------- TYPE=HAH DENS=HIGH FROM=17 ----------------------

TO	Frequency	Percent
5	22	52.4
7	8	19.0
10	2	4.8
20	10	23.8

---------------------- TYPE=HAH DENS=HIGH FROM=18 ----------------------

TO	Frequency	Percent
13	24	96.0
15	1	4.0

----------------------- TYPE=HAH DENS=LOW FROM=0 -----------------------

TO	Frequency	Percent
6	68	87.2
20	10	12.8

----------------------- TYPE=HAH DENS=LOW FROM=5 -----------------------

TO	Frequency	Percent
6	19	37.3
9	6	11.8
17	12	23.5
20	1	2.0
21	13	25.5

----------------------- TYPE=HAH DENS=LOW FROM=6 -----------------------

TO	Frequency	Percent
5	43	49.4
7	14	16.1
10	9	10.3
20	21	24.1

----------------------- TYPE=HAH DENS=LOW FROM=7 -----------------------

TO	Frequency	Percent
5	4	23.5
8	7	41.2
11	1	5.9
20	5	29.4

----------------------- TYPE=HAH DENS=LOW FROM=8 -----------------------

TO	Frequency	Percent
5	1	14.3
12	1	14.3
20	5	71.4

----------------------- TYPE=HAH DENS=LOW FROM=9 -----------------------

TO	Frequency	Percent
14	16	94.1
20	1	5.9

---------------------- TYPE=HAH DENS=LOW FROM=10 -----------------------

TO	Frequency	Percent
9	8	72.7
11	2	18.2
20	1	9.1

---------------------- TYPE=HAH DENS=LOW FROM=11 -----------------------

TO	Frequency	Percent
9	1	33.3
12	1	33.3
20	1	33.3

---------------------- TYPE=HAH DENS=LOW FROM=12 ----------------------

TO	Frequency	Percent
9	2	100.0

---------------------- TYPE=HAH DENS=LOW FROM=13 ----------------------

TO	Frequency	Percent
14	16	41.0
18	14	35.9
20	1	2.6
21	8	20.5

---------------------- TYPE=HAH DENS=LOW FROM=14 ----------------------

TO	Frequency	Percent
13	27	84.4
15	4	12.5
20	1	3.1

---------------------- TYPE=HAH DENS=LOW FROM=15 ----------------------

TO	Frequency	Percent
13	2	33.3
16	3	50.0
20	1	16.7

---------------------- TYPE=HAH DENS=LOW FROM=16 ----------------------

TO	Frequency	Percent
13	1	33.3
15	1	33.3
20	1	33.3

---------------------- TYPE=HAH DENS=LOW FROM=17 ----------------------

TO	Frequency	Percent
5	3	25.0
7	3	25.0
10	2	16.7
20	4	33.3

---------------------- TYPE=HAH DENS=LOW FROM=18 ----------------------

TO	Frequency	Percent
13	9	64.3
15	1	7.1
20	4	28.6

---------------------- TYPE=HAH DENS=MED FROM=. ----------------------

TO	Frequency	Percent

Frequency Missing = 1

----------------------- TYPE=HAH DENS=MED FROM=0 -----------------------

TO	Frequency	Percent
2	1	0.7
6	131	92.3
20	10	7.0

----------------------- TYPE=HAH DENS=MED FROM=2 -----------------------

TO	Frequency	Percent
20	1	100.0

----------------------- TYPE=HAH DENS=MED FROM=5 -----------------------

TO	Frequency	Percent
6	26	21.1
9	20	16.3
17	36	29.3
20	6	4.9
21	35	28.5

----------------------- TYPE=HAH DENS=MED FROM=6 -----------------------

TO	Frequency	Percent
5	85	54.1
7	31	19.7
10	18	11.5
20	23	14.6

----------------------- TYPE=HAH DENS=MED FROM=7 -----------------------

TO	Frequency	Percent
5	10	27.8
8	14	38.9
11	2	5.6
20	10	27.8

----------------------- TYPE=HAH DENS=MED FROM=8 -----------------------

TO	Frequency	Percent
5	9	64.3
7	3	21.4
20	2	14.3

----------------------- TYPE=HAH DENS=MED FROM=9 -----------------------

TO	Frequency	Percent
14	34	97.1
20	1	2.9

---------------------- TYPE=HAH DENS=MED FROM=10 -----------------------

TO	Frequency	Percent
9	14	66.7
11	2	9.5
20	5	23.8

---------------------- TYPE=HAH DENS=MED FROM=11 -----------------------

TO	Frequency	Percent
12	2	50.0
20	2	50.0

---------------------- TYPE=HAH DENS=MED FROM=12 -----------------------

TO	Frequency	Percent
9	1	50.0
20	1	50.0

---------------------- TYPE=HAH DENS=MED FROM=13 -----------------------

TO	Frequency	Percent
14	22	36.1
18	16	26.2
21	23	37.7

---------------------- TYPE=HAH DENS=MED FROM=14 -----------------------

TO	Frequency	Percent
13	48	85.7
15	2	3.6
20	6	10.7

---------------------- TYPE=HAH DENS=MED FROM=15 -----------------------

TO	Frequency	Percent
13	2	28.6
16	5	71.4

---------------------- TYPE=HAH DENS=MED FROM=16 -----------------------

TO	Frequency	Percent
13	3	60.0
15	1	20.0
20	1	20.0

---------------------- TYPE=HAH DENS=MED FROM=17 -----------------------

TO	Frequency	Percent
5	20	55.6
7	2	5.6
10	3	8.3
20	11	30.6

---------------------- TYPE=HAH DENS=MED FROM=18 -----------------------

TO	Frequency	Percent
13	8	50.0
15	4	25.0
20	4	25.0

---------------------- TYPE=NAS DENS=HIGH FROM=. -----------------------

TO	Frequency	Percent
21	2	100.0

Frequency Missing = 3

---------------------- TYPE=NAS DENS=HIGH FROM=0 -----------------------

TO	Frequency	Percent
6	185	99.5
20	1	0.5

---------------------- TYPE=NAS DENS=HIGH FROM=5 -----------------------

TO	Frequency	Percent
6	143	37.9
9	13	3.4
17	102	27.1
20	2	0.5
21	117	31.0

---------------------- TYPE=NAS DENS=HIGH FROM=6 -----------------------

TO	Frequency	Percent
5	277	84.5
7	21	6.4
10	13	4.0
20	17	5.2

---------------------- TYPE=NAS DENS=HIGH FROM=7 -----------------------

TO	Frequency	Percent
5	12	27.3
8	26	59.1
11	3	6.8
20	3	6.8

---------------------- TYPE=NAS DENS=HIGH FROM=8 -----------------------

TO	Frequency	Percent
5	12	46.2
7	10	38.5
12	2	7.7
20	2	7.7

---------------------- TYPE=NAS DENS=HIGH FROM=9 ----------------------

TO	Frequency	Percent
10	2	5.1
14	36	92.3
20	1	2.6

---------------------- TYPE=NAS DENS=HIGH FROM=10 ----------------------

TO	Frequency	Percent
9	20	90.9
11	1	4.5
20	1	4.5

---------------------- TYPE=NAS DENS=HIGH FROM=11 ----------------------

TO	Frequency	Percent
9	3	75.0
12	1	25.0

---------------------- TYPE=NAS DENS=HIGH FROM=12 ----------------------

TO	Frequency	Percent
9	3	100.0

---------------------- TYPE=NAS DENS=HIGH FROM=13 ----------------------

TO	Frequency	Percent
14	40	38.8
18	31	30.1
21	32	31.1

---------------------- TYPE=NAS DENS=HIGH FROM=14 ----------------------

TO	Frequency	Percent
13	74	97.4
15	2	2.6

---------------------- TYPE=NAS DENS=HIGH FROM=15 ----------------------

TO	Frequency	Percent
13	2	66.7
16	1	33.3

---------------------- TYPE=NAS DENS=HIGH FROM=16 ----------------------

TO	Frequency	Percent
13	1	100.0

---------------------- TYPE=NAS DENS=HIGH FROM=17 ----------------------

TO	Frequency	Percent
5	78	76.5
7	13	12.7
10	7	6.9
20	4	3.9

---------------------- TYPE=NAS DENS=HIGH FROM=18 ----------------------

TO	Frequency	Percent
13	26	83.9
15	1	3.2
20	4	12.9

----------------------- TYPE=NAS DENS=LOW FROM=. -----------------------

TO	Frequency	Percent

Frequency Missing = 1

----------------------- TYPE=NAS DENS=LOW FROM=0 -----------------------

TO	Frequency	Percent
2	1	1.3
6	71	88.8
20	8	10.0

----------------------- TYPE=NAS DENS=LOW FROM=1 -----------------------

TO	Frequency	Percent
6	1	100.0

----------------------- TYPE=NAS DENS=LOW FROM=2 -----------------------

TO	Frequency	Percent
1	1	100.0

----------------------- TYPE=NAS DENS=LOW FROM=5 -----------------------

TO	Frequency	Percent
6	102	68.0
9	1	0.7
17	17	11.3
20	1	0.7
21	29	19.3

----------------------- TYPE=NAS DENS=LOW FROM=6 -----------------------

TO	Frequency	Percent
5	130	74.7
7	10	5.7
10	14	8.0
20	20	11.5

----------------------- TYPE=NAS DENS=LOW FROM=7 -----------------------

TO	Frequency	Percent
5	5	33.3
8	5	33.3
11	1	6.7
20	4	26.7

----------------------- TYPE=NAS DENS=LOW FROM=8 -----------------------

TO	Frequency	Percent
5	1	20.0
7	3	60.0
20	1	20.0

----------------------- TYPE=NAS DENS=LOW FROM=9 -----------------------

TO	Frequency	Percent
14	13	100.0

---------------------- TYPE=NAS DENS=LOW FROM=10 -----------------------

TO	Frequency	Percent
9	11	78.6
20	3	21.4

---------------------- TYPE=NAS DENS=LOW FROM=11 -----------------------

TO	Frequency	Percent
9	1	100.0

---------------------- TYPE=NAS DENS=LOW FROM=13 -----------------------

TO	Frequency	Percent
14	31	52.5
18	17	28.8
21	11	18.6

---------------------- TYPE=NAS DENS=LOW FROM=14 -----------------------

TO	Frequency	Percent
13	39	88.6
15	5	11.4

---------------------- TYPE=NAS DENS=LOW FROM=15 -----------------------

TO	Frequency	Percent
13	4	50.0
16	3	37.5
20	1	12.5

---------------------- TYPE=NAS DENS=LOW FROM=16 ----------------------

TO	Frequency	Percent
13	2	66.7
20	1	33.3

---------------------- TYPE=NAS DENS=LOW FROM=17 ----------------------

TO	Frequency	Percent
5	14	82.4
7	2	11.8
20	1	5.9

---------------------- TYPE=NAS DENS=LOW FROM=18 ----------------------

TO	Frequency	Percent
13	14	82.4
15	3	17.6

---------------------- TYPE=NAS DENS=MED FROM=. ----------------------

TO	Frequency	Percent
21	1	100.0

Frequency Missing = 1

---------------------- TYPE=NAS DENS=MED FROM=0 ----------------------

TO	Frequency	Percent
2	1	0.7
6	145	98.0
20	2	1.4

---------------------- TYPE=NAS DENS=MED FROM=1 ----------------------

TO	Frequency	Percent
6	1	100.0

---------------------- TYPE=NAS DENS=MED FROM=2 ----------------------

TO	Frequency	Percent
1	1	100.0

---------------------- TYPE=NAS DENS=MED FROM=5 ----------------------

TO	Frequency	Percent
6	48	29.4
9	7	4.3
17	51	31.3
20	3	1.8
21	54	33.1

----------------------- TYPE=NAS DENS=MED FROM=6 -----------------------

TO	Frequency	Percent
5	122	62.9
7	17	8.8
10	10	5.2
20	45	23.2

----------------------- TYPE=NAS DENS=MED FROM=7 -----------------------

TO	Frequency	Percent
5	7	24.1
8	12	41.4
11	4	13.8
20	6	20.7

----------------------- TYPE=NAS DENS=MED FROM=8 -----------------------

TO	Frequency	Percent
5	2	16.7
7	6	50.0
12	1	8.3
20	3	25.0

----------------------- TYPE=NAS DENS=MED FROM=9 -----------------------

TO	Frequency	Percent
14	25	100.0

---------------------- TYPE=NAS DENS=MED FROM=10 -----------------------

TO	Frequency	Percent
9	14	100.0

---------------------- TYPE=NAS DENS=MED FROM=11 -----------------------

TO	Frequency	Percent
9	3	75.0
12	1	25.0

---------------------- TYPE=NAS DENS=MED FROM=12 -----------------------

TO	Frequency	Percent
9	1	50.0
20	1	50.0

---------------------- TYPE=NAS DENS=MED FROM=13 -----------------------

TO	Frequency	Percent
14	15	36.6
18	4	9.8
21	22	53.7

---------------------- TYPE=NAS DENS=MED FROM=14 -----------------------

TO	Frequency	Percent
13	38	95.0
20	2	5.0

---------------------- TYPE=NAS DENS=MED FROM=17 -----------------------

TO	Frequency	Percent
5	34	66.7
7	6	11.8
10	4	7.8
20	7	13.7

---------------------- TYPE=NAS DENS=MED FROM=18 -----------------------

TO	Frequency	Percent
13	4	100.0

VITA

Charles A. Green was born October 24, 1968. He received his Bachelor's degree in Mechanical Engineering from the University of Illinois at Urbana in 1990, and his Master's degree in Industrial and Systems Engineering - Human Factors Engineering from Virginia Polytechnic Institute and State University in 1992. His interests include human-computer interaction, computer supported cooperative work, and global networking via the Internet.

Charles Green

Charles A. Green