A REVIEW OF STUDIES ON OPERATOR'S INFORMATION SEARCHING BEHAVIOR FOR HUMAN FACTORS STUDIES IN NPP MCRS

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This paper reviews studies on information searching behavior in process control systems and discusses some implications learned from previous studies for use in human factors studies on nuclear power plants (NPPs) main control rooms (MCRs).

Information searching behavior in NPPs depends on expectancy, value, salience, and effort. The first quantitative scanning model developed by Senders for instrument panel monitoring considered bandwidth (change rate) of instruments as a determining factor in scanning behavior. Senders' model was subsequently elaborated by other researchers to account for value in addition to bandwidth.

There is also another type of model based on the operator's situation awareness (SA) which has been developed for NPP application. In these SA-based models, situation–event relations or rules on system dynamics are considered the most significant factor forming expectancy.

From the review of previous studies it is recommended that, for NPP application, (1) a set of symptomatic information sources including both changed and unchanged symptoms should be considered along with bandwidth as determining factors governing information searching (or visual sampling) behavior; (2) both data-driven monitoring and knowledge-driven monitoring should be considered and balanced in a systematic way; (3) sound models describing mechanisms of cognitive activities during information searching tasks should be developed so as to bridge studies on information searching behavior and design improvement in HMI; (4) the attention–situation awareness (A–SA) modeling approach should be recognized as a promising approach to be examined further; and (5) information displays should be expected to have totally different characteristics in advanced control rooms. Hence much attention should be devoted to information searching behavior including human-machine interface (HMI) design and human cognitive processes.

KEYWORDS : Monitoring, Information Searching, Visual Sampling (Scanning), Attention, Situation Awareness (SA), Nuclear Power Plant (NPP)

1. INTRODUCTION

The primary role of operators in main control rooms (MCRs) of nuclear power plants (NPPs) is to supervise and operate an NPP. As the design of instrumentation and control (I&C) systems for various plant systems including NPPs is rapidly moving toward fully digitalized I&C [1,2], the role of the operator in advanced NPPs is shifting from that of a manual controller to supervisor or decision-maker [3]. Accordingly, the operator's tasks involve an increasing amount of cognitive work. Operator tasks in NPPs are performed through a series of cognitive activities such as monitoring the environment, detecting data or information, understanding and assessing situations, diagnosing symptoms, decision-making, planning responses, and implementing those responses [4]. The diagnostic task has been considered one of the most complex and mental resource-demanding tasks in NPPs, and it is crucial to NPP safety because decision-making and relevant responses are affected directly by diagnosis results. Monitoring and detection should be accomplished effectively for accurate and timely diagnosis. In other words, effective information searching (monitoring and detection) plays a crucial part in enhancing NPP safety.

Research on modeling of visual information acquisition can be generally categorized into two types. Psychologists have extensively modeled visual search processes [5-8]. These models have been useful in both basic laboratory studies as well as more applied domains such as those involved in searching graphs [9], maps [10], menus [11], or roadway environments [12]. Attention has been paid to locating a single target and search time in such models.

In contrast to search models, another sort of model has focused on supervisory control/sampling. Four key features distinguish these models on supervisory control/ sampling from the psychologists' models above [13].

1. The operator supervises a series of dynamic processes such as temperature gauges and aircraft movements.
2. The primary focus is on noticing critical events at relatively consistent spatial locations rather than finding critical targets at uncertain locations.
3. The key dependent variable is not target detection reaction time (RT), but is instead the proportion of visual attention distributed to various areas of interest (AOIs) as a function of the quantitative properties of those AOIs.
4. The process of defining specified AOIs means that the challenge in visual attention is not so much knowing where to look (e.g., to find a target), but in knowing when to look and where to assure that the dynamic processes are under control, and that the necessary information to understand those processes is retrieved in a timely manner.

One characteristic of many of the information searching models is the use of optimal strategies of attention allocation, designed to maximize or minimize some benefit or cost function, given the scarcity of visual attention resources.

An important area of interest in human factors studies has been the design and evaluation of human-machine interfaces (HMI). A prerequisite for orderly progress in this important area is the development of systematic quantitative models for HMI design and evaluation.

In this paper, existing models of information searching behavior are reviewed and some implications learned from previous studies on such behavior will be addressed for use in human factors studies in NPPs.

In Chapter 2, attention, situation awareness (SA) and the relationship between the two will be addressed to understand the process of information acquisition. Studies on information searching behavior are reviewed in Chapter 3, along with various prescriptive and descriptive models. The implications learned from the review will be presented in Chapter 4. Finally, we summarize and conclude the paper in Chapter 5.

Several terms such as monitoring behavior, visual sampling (or scanning) behavior, and data acquisition behavior are used synonymously with information searching behavior in this study, even though subtle differences in meaning may exist between these terms.

2. ATTENTION AND SITUATION AWARENESS

Stages of information processing depend on mental or cognitive resources, a sort of pool of attention or mental effort that is of limited availability and can be allocated to processes as required [14]. With regard to attentional resources, there are two aspects of attention: selecting information sources for further information processing and dividing attention between tasks.

Selection of information sources to attend to is typically driven by four factors: salience, expectancy, value, and effort [14]. Salience refers to stimuli in the environment such as alarms, alerts, or some remarkable indication representing deviation from a normal situation. With expectancy our attention is shifted to specific sources which are most likely to provide information. The frequency of looking at or attending to information sources is modified by how valuable it is to look at. Finally, selective attention may be inhibited if it is effortful compared to its value.

A strategy must be selected for dividing attention or allocating resources between tasks when there are many tasks to perform [15,16]. Perception or understanding is accomplished by 3 simultaneous processes: a bottom-up process, a top-down process, and the unitization (or matching) of the two processes. The bottom-up process is derived by stimuli or salient information sources through a sensing mechanism. After detecting the stimulus, the information is matched to a mental model which is established based on knowledge and experience. Expectancy derived from the mental model leads to effective selection of information sources, which is the top-down process. A series of the bottom-up process, the top-down process, and unitization is a process of perception or understanding.

How people direct their attention has a fundamental impact on their situation awareness (SA). Endsley [17] reviewed the definitions of SA and provided a general one: "situation awareness is the perception of the elements in the environment within a volume of time and space (Level 1 SA), the comprehension of their meaning (Level 2 SA), and the projection of their status in the near future (Level 3 SA)". SA is frequently considered a crucial key to improving performance and reducing error [18]. As shown in the TMI accident, correct SA is one of the most critical contributions to safe operation in NPPs [19]. Jones and Endsley [20] found that the single most frequent causal factor associated with SA errors involved situations where all the needed information was present, but was not attended to by the operator (35% of total SA errors).

Operators in NPPs selectively attend to important information sources to effectively develop SA when an abnormal or accidental situation occurs. Selective attention to important information sources is continued while maintaining SA as well. Hence, effective information searching should correlate with correct SA.

There are a lot of information sources that should be monitored in NPPs but operators have only limited capacity for attention and memory. Operators must continuously decide where to allocate their attentional resources because it is impossible to monitor all information sources simultaneously. This kind of cognitive skill is called selective attention. Selective attention is the ability to shift attention to what is important and ignore what is irrelevant.

Operators use this cognitive skill to overcome the limitations of human attention, making use of both top-down and bottom-up processes [14].

Monitoring that is driven by a bottom-up process is referred to as data-driven monitoring, while monitoring that is driven by a top-down process is referred to as knowledge-driven monitoring (also known as model-driven monitoring). Data-driven monitoring is highly affected by the salience of the information sources, while knowledge-driven monitoring is highly affected by the situation model of the operator (operator understanding of the current situation).

Operators try to understand what is going on when an abnormal situation occurs in an NPP. They receive information from indicators or other operators and process the information to establish a situation model based on their mental model. As O'Hara et al. [21] have summarized, a situation model is an operator understanding of a specific situation, and the model is constantly updated as new information is received.

The term mental model refers to general knowledge governing the performance of highly experienced operators. This includes expectancies on how the NPPs will behave in various abnormal situations. For example, when a LOCA (loss of coolant accident) occurs, the pressurizer pressure, temperature, and level will decrease, and the containment radiation will increase. These expectancies form rules on NPP dynamics and operators' mental models are established based on these rules. There are representative dynamics in NPPs which should be established in the operator's mental model through training and experience. When an abnormal situation or accident occurs, operators usually first recognize it by the onset of salience such as an alarm or deviation in process parameters from normal conditions. They then develop their SA or establish their situation model by selectively attending to important information sources. The maintenance of their SA or confirmation of their situation model is accomplished by iterating the selective attention.

3. STUDIES ON OPERATOR'S INFORMATION SEARCHING BEHAVIOR

3.1 Classical Studies on Pilot Eye Movements

The first studies on human visual sampling (or information searching) behavior were done for flight maneuver tasks by Jones, Milton, and Fitts in the late 1940s and early 1950s [22-24]. In all, they analyzed over 500,000 frames of movie film taken during flights under various conditions by more than 40 pilots.

Fitts' group found that the mean duration of fixation on instruments in cockpits was 0.6 sec (0.4 to 1.4 sec), with a standard deviation of 0.12 during flight under various conditions. Similar values for dwell times have been found in a laboratory monitoring task [25] and for radar operators [26]. Moray [27] remarked that a figure of about 0.5 sec can be used as a lower bound on dwell times in real-life tasks, even though shorter times may be observed in laboratory experiments when static rather than dynamic patterns are used as displays. Fitts' group suggested that dwell time was a function of the difficulty of reading the instrument and of interpreting the data from it. The transition probabilities of fixations from one instrument to the next (link value) seemed to be a function of the arrangement of instruments on the panel, and the fixation duration varied by a factor of two between instruments, suggesting considerable differences in the ease with which information could be extracted. The difference in the relative fixation frequencies was more than ten to one, and it was concluded that this was due to their relative importance [24]. While there was a slight tendency for the more experienced pilots to move their eyes more quickly, and for their fixation durations to be slightly shorter, the effects were small. Also, they found that there was only a very small proportion of time during which the pilots were not looking at any instrument, perhaps less than 5%, which was thought to be related to the question of "cognitive lock-up" or "cognitive tunnel vision".

The results of Fitts' group studies were used to develop a more optimized layout of the instrument panel at that time.

3.2 Senders' Model

The first quantitative analytic model of visual sampling was made by Senders et al. [25,28,29]. Senders has since reexamined their initial work and provided new and simpler mathematical derivations [30]. Senders' models assume that the power spectrum of the displayed signal is the only determinant of the operator's monitoring behavior. These models were developed in light of the work of Fitts' group on the eye movements of pilots in cockpits and Shannon's mathematical theory of communication [31]. Although Shannon's theory mainly concerned discrete information, Senders et al. used the theory of continuous information to model monitoring behavior, assuming that the observer was a classical Shannon communication channel and that the task of the operator (observer) was to reconstruct the signal. That is, the operator is assumed to be trying to extract all the information from the observed signal, such that the observations would be necessary and sufficient to make a copy of the displayed function on the basis of the sampled values [27].

Let the observer monitor a random signal with limited bandwidth, W Hz. It can be shown that if the bandwidth is W Hz it is necessary and sufficient that it be sampled at $2W$ Hz, and that an ideal channel can reconstruct the signal from observations taken at intervals spaced $1/2W$ sec apart. This is the sampling theorem or Nyquist theorem; the corresponding sampling interval is often referred to as the Nyquist interval. A human observer who behaved like such a channel would sample a signal $2W$ times per sec, and if the display were, for example, an instrument in an aircraft cockpit, one would expect the instrument to be examined $2W$ time per sec.

Single Instrument: An instrument i will generate a sequence of pointer positions in time, $f_i(t)$. A power density spectrum $\Phi_i(\omega)$ can be computed from $f_i(t)$. Assume that $\Phi_i(\omega)$ has a maximum frequency (cutoff frequency) of W_i. The maximum sampling rate for periodically taken samples of the function $f_i(t)$ will be $2W_i$, if $f_i(t)$ is to be specifiable from the samples. The information generation rate from the instrument can also be calculated, if a permissible RMS error of readout by the observer and root mean square (RMS) amplitude of the signal [31]. Shannon showed that the information generation rate for a continuous, band-limited Gaussian function of time $f_i(t)$ of RMS amplitude A is given by

$$\overline{H}_i = W_i \log_2 \frac{A_i^2}{E_i^2} \text{ [bits/sec]} \qquad (1)$$

where E_i is the RMS error that is permissible in the observation (i.e., the required precision).

Our ideal observer samples at a rate which permits the reconstruction of the signal from the samples. Therefore, he or she must sample with a fixation frequency FF_i, which is at least equal to $2W_i$. If FF_i is exactly equal to $2W_i$, the average amount of information which he or she must assimilate at each sampling is

$$\overline{H}_i = \log_2 \frac{A_i}{E_i} \text{ [bits]}. \qquad (2)$$

Hick [32] and Hyman [33] showed a linear relation between average response time (RT) and the average information transmitted (I_T) as:

$$RT = a + bI_T \qquad (3)$$

where a and b are constants.

If the ideal observer is assumed to have a fixed input channel capacity, the duration of each fixation, D_i, should also be linearly related to the amount of information to be taken at each observation. Therefore, D_i can be calculated as:

$$\overline{D_i} = K \log_2 \frac{A_i}{E_i} + C \text{ [sec]} \qquad (4)$$

where K has the dimensions of time per bit, and C (with dimensions: time per fixation) is a constant to account for movement time and minimum fixation time. A_i is related to the possible range of values which the instrument could present and E_i is a measure of the accuracy to which the instrument must be read. For the conditions specified, the attentional demand or workload placed on our observer by instrument i is clearly the product T_i of the fixation frequency FF_i and fixation duration D_i as:

$$T_i = \overline{FF_i} \times \overline{D_i} = 2KW_i \log_2 \frac{A_i}{E_i} + 2W_iC \text{ [sec]}. \qquad (5)$$

Multiple Instrument Displays: For a complex of m instruments, the total workload placed on the ideal observer can be calculated by summing the individual workloads of m instruments.

$$\text{Min } T_m = 2\sum_{i=1}^{m} W_i \left[K \log_2 \frac{A_i}{E_i} + C \right] \text{ [sec]}. \qquad (6)$$

This result can be used in the design of instrument panels. For example, let T be the unit time; then $T >$ Min T_m, one can try to add instrument j to the set of instruments. W_i and A_i can be determined or estimated from known parameters of the system to be monitored or controlled; E_i can be determined or estimated from the system requirements. Therefore, the decision to add or not to add can be made rationally: if $T_j +$ Min $T_m \le T$, add.

As a consequence of the sampling performed by the observer on the various instruments of a set, transitions will be made from one instrument to another and frequency distributions of such transitions will be generated. It is assumed that a transition starting from instrument i may end on any instrument, including instrument i, in accordance with the probabilities of fixation on each instrument. Over a sufficiently long time interval, the relative number of fixations on each instrument will be an estimate of the probability of fixation on that instrument.

$$P_i = \frac{T \times FF_i}{T\sum_{i=1}^{N} FF_i} = \frac{FF_i}{\sum_{i=1}^{N} FF_i} \qquad (7)$$

The probability of a transition between instrument a and instrument b is P_aP_b; the probability of transitions in both directions, $P_{\overline{ab}}$, is

$$P_{\overline{ab}} = 2P_aP_b. \qquad (8)$$

Since some transitions will be made to the instrument that is already being fixated on, and hence will not be visible, a correction is needed, and the final equation becomes

$$P_{o\overline{ab}} = \frac{2P_aP_b}{1-\sum_{i=1}^{N} P_i^2} \tag{9}$$

where $P_{o\overline{ab}}$ is the probability of an observable transition between instruments a and b.

The following experiment was used to test the model. Four ammeters were mounted on a board at the four corners of a square, and a movie camera was mounted in the middle of the array so that the eye movements of an operator could be filmed. The meters were separated by a visual angle of about 60°. The observer was told to monitor the array and to press a button whenever a pointer exceeded a specified limit. The meters were driven by quasi-random forcing functions made of sums of sinusoids, since it is known that such displays when properly chosen are for most purposes indistinguishable from truly random signals by human observers. Each meter had a different bandwidth, from less than 0.05 Hz to about 0.6 Hz. Thus each instrument was characterized by its bandwidth W_i Hz for the ith instrument, and each should have been sampled at a rate of $2W_i$ fixations per sec. Pressing the button had no effect on the display. Five highly practiced observers participated in the experiment as subjects. The results are shown in Fig. 1 and Fig. 2.

Senders' model predicts that the data points should lie on the solid diagonal line shown in Fig. 1. The obtained data points are linear and monotonic, increasing in bandwidth, as predicted, and they depart only slightly from the predicted line. High-bandwidth sources are undersampled and low-bandwidth sources oversampled by the standard of the sampling theorem.

The assumption that the observer was behaving according to the sampling theorem can account for a large proportion of the experimental variance. Moreover, Fogel [34] showed that if an observer could detect both instantaneous position and velocity when making an observation, then the appropriate sampling rate would be W Hz, not $2W$ Hz. This could account for the apparent "undersampling" of high bandwidths, and the data have been reanalyzed by Senders [30] in the light of Fogel's theorem. It appears to account for much of the undersampling in a systematic way.

The measured fixation durations or dwell times were also in agreement with the predictions of the model. Since the ratio A/E was identical for all instruments, Equation (2) predicts that the fixation durations should also be identical and independent of the signal bandwidth. The results are shown in Fig. 2.

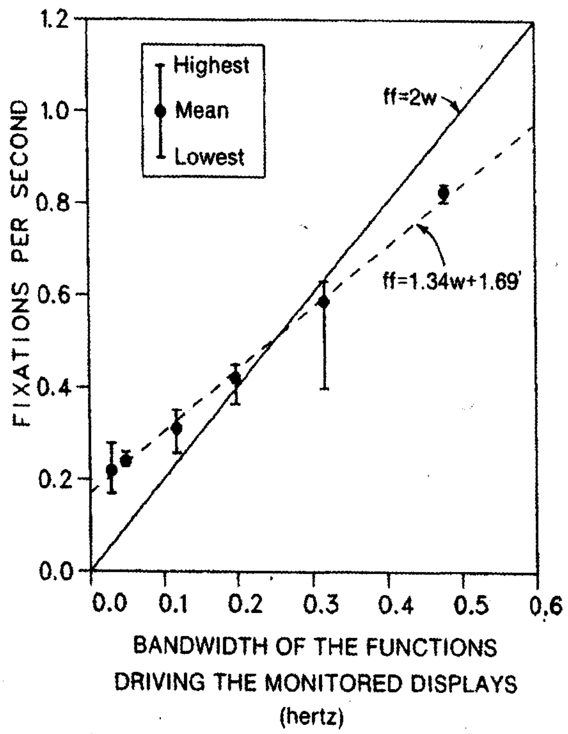

Fig. 1. Relation between Fixation Frequency and Bandwidth of the Observed Signal [25]

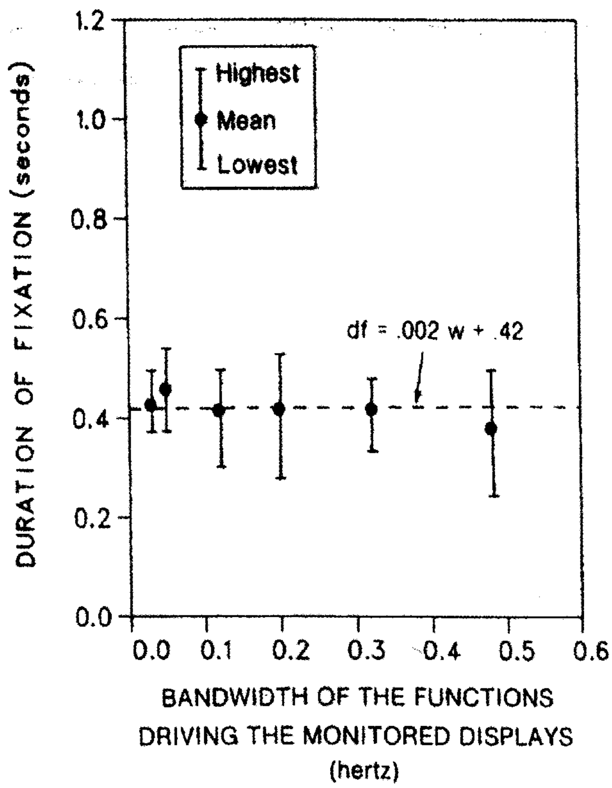

Fig. 2. Relation between Fixation Duration and Bandwidth of the Observed Signal [25]

Table 1. Obtained and Calculated Transition Probabilities [29]

Transition	Calculated Transition Probabilities	Obtained Transition Probabilities
$P_{4\text{-}3}$	0.364	0.324
$P_{4\text{-}2}$	0.293	0.297
$P_{4\text{-}1}$	0.131	0.133
$P_{3\text{-}2}$	0.117	0.112
$P_{3\text{-}1}$	0.052	0.051
$P_{2\text{-}1}$	0.042	0.040
	0.999	0.957

Senders obtained the transition probabilities calculated on the basis of Equation (9) and the observed transition probabilities, as shown in Table 1.

This correspondence suggests that the observers were, on average, distributing their samples in accord with the base probabilities that each instrument would be sampled.

The work of Senders et al. [29] is impressive and is rightly regarded as a classic in the field of monitoring. However, the studies of Senders et al. [29,30] are unsatisfactory as analogs of "real-life" tasks. In particular, it is unusual to find conditions where all the displays are of equal importance. It also seems intuitively compelling that a pilot would fixate on a low-bandwidth display that conveyed information vital to safe flight more than a higher-bandwidth display that provided trivial information. Summarizing the settings for his models, Senders [30] stated:

Although in the real world of monitoring there are alarm lights and sounds which make imperative demands for attention, the models do not consider these. Instead all the models deal only with the steady state, no emergency condition. It is assumed that when an emergency arises and an alarm operates, the behavioral rules change. Some quite different model is needed for that state of affairs... Neither theory nor model attempts to take into account fatigue, motivation or anything else of purely psychological nature.

A strict interpretation of the implications of the sampling theorem would lead to the conclusion that sampling must be periodic and determined by the bandwidth of the displayed process if all other factors are excluded. This seems inherently unlikely for real tasks and Senders at al. [29] pointed out that a number of factors might be expected to modify the basic sampling demands and produce aperiodicity. Senders et al. proposed several models for such aperiodic processes [30]. Each of these models predicts a sampling interval that is shorter than that predicted on the basis of the pure sampling theorem. The main limitation of these models is that they are not likely to apply to low-bandwidth functions such as are found in process control [27].

3.3 Carbonell's Model

Carbonell [35,36] introduced the concepts of queuing theory and payoffs and emphasized the importance of the operator's actions. Carbonell defined the cost of an observation in terms of the probability of missing a significant event in a process that was not being observed. The postulated sampling strategy was to select an instrument that made the cost of the observation on the instrument a minimum.

The model is based on the following assumptions:

1) Each time the observer looks at one instrument, he is postponing the observation of others.
2) The observer makes an intelligent decision before looking at an instrument each time, i.e., he tries to minimize the risk involved in not observing the other instruments.
3) This risk is represented by the probability that the readings may, while not being observed, exceed a certain threshold leading to some catastrophic result (such as negative altitude or lack of fuel).
4) The time involved in reading each instrument will be supposed to be a constant (on the order of 1/3 of a second) for all instruments. If the observer looks at one instrument for a longer time, it is considered as a second (third, etc.) consecutive reading of the same instrument. In other words, the observer chooses this instrument again to minimize his total cost.
5) The observer's task in visually sampling his instruments is part of a feedback loop closed through his control actions. (It must be said that all previous models considered visual sampling as an open loop task).

Let M be the number of instruments to be monitored and t the moment at which an observation is made. Let $C(t)$ be the total cost of not looking at any instrument at all at time t and C_i the cost associated with instrument i exceeding its established threshold. It is supposed to be independent of time for a given mode of operation (normal horizontal flight, takeoff, landing, etc.) but the observer changes it when he switches from one mode of operation to another. Let $P_i(t)$ be the probability that an instrument i will exceed its threshold L_i at instant t.

Probabilities and costs will be related by

$$C(t)=\sum_{i=1}^{M}\frac{C_iP_i(t)}{1-P_i(t)}. \tag{10}$$

The total cost C above is really the cost of not looking at any instrument. The total cost of looking at a particular instrument j at instant t will be:

$$C_j'(t) = C(t) - C_j P_j(t) \cdot \quad (11)$$

The postulated strategy is to select the instrument j that makes $C_j'(t)$ a minimum, i.e., $C_jP_j(t)$ a maximum. Equation (11) is justified on the basis that by looking at instrument j, one removes the uncertainty with respect to it; but because of the finite time taken by each observation the uncertainty with respect to the other instruments may increase.

While the costs remain fixed throughout the experiment, the probabilities of exceeding L do not, but are conditional as:

$$P_i(t) = P[y_i(t) \geq L_i | y_i(t - \Delta_i(t)) = YO_i(t)] \quad (12)$$

where

t = Observation time.
$y_i(t)$ = Value indicated by instrument i.
$\Delta_i(t)$ = Length of time units since last sampling of instrument i before time t.
$YO_i(t)$ = Last reading of instrument i before time t.
L_i = Threshold value.

Carbonell rejected the assumption that the process being monitored is a zero-mean Gaussian process. That assumption is usually justified on the grounds that most real processes vary in a random fashion around their set points. Carbonell instead noted that in any marginally stable or unstable system divergence is likely to be progressive unless corrected. For instance, a manually controlled aircraft if rolled by a wind gust will not return to straight and level flight without action by the pilot. The sequence of events can be modeled as a type of random walk that only control actions can return to the equilibrium, set point condition.

The overall probability of the value of the ith instrument at time t, given its value as observed at t_0, is

$$P_i(y_i(t) = Y_i | y_i(t_0) = YO_i) = \frac{1}{\sqrt{(2\pi[\sigma_i(t-t_0)]^2)}} \exp\left[-\frac{(y_i - YO_i \exp[-(t-t_0)K_i])^2}{2[\sigma_i(t-t_0)]^2}\right] \cdot \quad (13)$$

If the process being monitored were a zero-mean Gaussian process, $\rho_i(t-t_0)$ would have been used instead of $exp[-(t-t_0)K_i]$, ρ_i being the autocorrelation function of the random process. The probability of exceeding the limit L never decreases with the passage of time unless a new observation is made.

In Carbonell's model, the decision to make an observation was placed in a queuing theory context. Each instrument queues for service with a priority to preempt the queue that depends on the estimated probability of the value displayed on that instrument now being above L, given the value at the last time it was observed. Carbonell was not able to solve the queuing problem analytically, and he resorted to numerical simulation to show the properties of the model. Later Carbonell, Ward, and Senders [36] obtained empirical data to test the model using a flight simulation with experienced pilots and the model performed well. Table 2 shows the correlation between observed data and the predicted data from Senders' original fixed Nyquist interval model and Carbonell's model. Three pilots (D.M., P.M., and J.F.) were flying a simulated approach to Logan Airport. The entries are correlation coefficients. In every case, Carbonell's model gives a better fit to the data.

3.4 Crossman, Cooke, and Beishon's Model

Crossman, Cooke, and Beishon [37] describe experiments on process control and the relation between process control monitoring and the classical "vigilance" experiment where observers detect rare signals in a context of characteristically impoverished sensory input. They did not develop a quantitative model but noted that the entropy associated with a source will grow as time passes following an observation that has reduced the entropy of the observer's estimate to zero. Entropy is the measure of uncertainty in Shannon's information theory as:

$$H(X) = \sum_{i=1}^{n} P(x_i) \log_2 \frac{1}{P(x_i)} \quad (14)$$

where $\sum_{i=1}^{n} P(x_i) = 1 \cdot$

Table 2. A comparison of the Predictions of Carbonell's and Senders' [27]

Pilot	Phase of Mission: Descent		Turn		Approach	
	Nyquist	Queuing	Nyquist	Queuing	Nyquist	Queuing
D.M.	0.905	0.966	0.730	0.874	-	-
P.M.	0.190	0.994	0.940	0.983	0.653	0.917
J.F.	-	-	0.903	0.984	0.263	0.837

They suggested a model that is similar to the variable Nyquist interval model of Senders et al. [29,30] and also made some interesting suggestions for aiding monitoring in monotonous situations such as allowing the operator to set an alarm that will ring at the interval deemed most appropriate to ensure an adequate observation of the process.

Crossman et al. [37] provided valuable discussions on the relation between monitoring and action in process control and it is worth quoting their conclusions at length:

The operator's basic minimum rate of sampling in the two process control tasks studied was determined by system bandwidth as predicted by Senders's application of the Shannon-Wiener sampling theorem, provided that account is taken of the allowed error tolerance by calculating an "effective bandwidth".

However, a much more detailed analysis of factors contributing to the operator's uncertainty, its rate of growth over time, and the cost attached to sampling is needed to give even moderately accurate estimates of sampling rate in the various circumstances encountered when they rose above minimum.

The problem of sampling could not be divorced from the more general problem of control, which in turn raised questions of required accuracy, cost of error, operator's knowledge of system structure, degree, type and predictability of disturbance, and effects of response lag.

While forgetting was not positively identified as a cause of increased sampling rates, the data were consistent with this possibility.

Crossman et al. also suggested the following empirical generalizations about sampling behavior on the basis of their analyses.

1. *When a variable is at its desired value and the system is correctly adjusted so that there is no residual drift due to small errors of control setting, the "background" sampling rate is determined by the highest frequency component of random disturbance that has an amplitude great enough to cause excursions exceeding the allowed tolerance. This is the "effective bandwidth" which the system presents to input noise.*
2. *When a variable is within the specified range but the system is not quite correctly adjusted so that it tends to drift off, sampling rate is determined by rate of drift, and rises when the variable is near either of the limits of its tolerance range.*
3. *When a variable is outside its tolerance band and the operator is making large stepwise control changes in an attempt to correct it, a sample is taken after each control change at a time when response is expected to have reached some 80% of its final value: if this sample is not followed by a further control change, one or two further samples are taken at similar intervals. Control changes whose effect is expected to be less than enough to exceed the tolerance range are not subject to this rule, which only applies when the operator is uncertain of the precise effect of control changes.*
4. *Sampling rate rises whenever general observation of the system or its surroundings shows that anything unusual may be happening, even though it is not known to be relevant to the particular variable sampled.*
5. *Operators may estimate the change rate of a variable either by prolonged observation during one sample, or by remembering its value at one sample and comparing it with the next. In general they do not attempt to estimate higher derivatives.*

The Crossman et al. study is an excellent example of the importance of field studies as a complement to analytic models of the kind proposed by Senders, even though it did not yield sufficient data for statistical analysis.

3.5 Smallwood's Internal Sampling Model

In another analysis of the data of Senders et al. [25], Smallwood [38] proposed an "internal sampling model" that viewed the sampling process as one whereby the human operator tried to maintain and update some internal image or model of the system being controlled and its environment.

The operator's "internal model of his environment" is termed as a mechanism by which the most recent perceptions are used to update the state of information. The model is based on the following assumptions: (1) the human operator

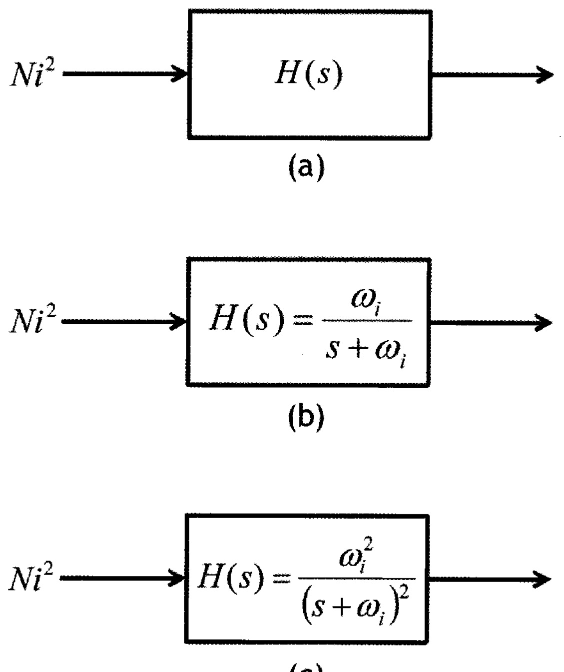

Fig. 3. Some Possible Internal Models: (a) Linear Time- invariant, (b) First-order, (c) Second-order [38]

bases his state of information about his environment upon an internal model of the environment formed as a result of past perceptions of that environment; and (2) the human operator behaves optimally with respect to his task and his current state of information within his physical limitations.

The first step in the formulation is to consider the form of the internal model that describes the operator's view of the instruments he is monitoring. The operator's model is assumed to be of the form in Fig. 3 (a): i.e., that the instrument readings are the result of passing white Gaussian noise through a linear time-invariant filter. Figs. 3 (b) and (c) show the two forms of this filter that will be considered. The first-order filter in Fig. 3 (b) has a transfer function,

$$H_1(s) = \frac{\omega_i}{s+\omega_i} \tag{14}$$

while the second-order filter in Fig. 3 (c) has a transfer function,

$$H_2(s) = \frac{\omega_i^2}{(s+\omega_i)^2} \tag{15}$$

where index i indicates the instrument.

Suppose that some t seconds ago, the operator observed the amplitude and all derivatives $[x_o, \dot{x}_o, \ddot{x}_o, \cdots]$ of the ith instrument and suppose further that he has had no additional information since that time. It is useful now to encode the operator's current state of information about the ith instrument in terms of a probability density function (PDF) over the current amplitude of the instrument. We shall label this PDF $f_i(x|D)$, where x is the current amplitude of the ith instrument and can be considered a random variable. The symbol D represents the data available to the operator (e.g., the amplitude and derivatives $[x_o, \dot{x}_o, \ddot{x}_o, \cdots]$ of the instrument t seconds ago). A basic result from the theory of stochastic processes [39] states that this distribution is Gaussian,

$$f_i(x|D) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left[-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right] \tag{16}$$

where, μ_i and σ^2_i are the mean and variance of the distribution, respectively.

A moderate amount of mathematics produces expressions for μ_i and σ^2_i for each of the two internal models under consideration. For the first-order internal model they are

$$\mu_i = x_0 e^{-\omega_i t} \tag{17}$$

$$\sigma_i^2 = \frac{\omega_i N_i^2 1}{4}\left[1 - e^{-2\omega_i t}\right]. \tag{18}$$

For the second-order model they are

$$\mu_i = x_0(1+\omega_i t)e^{-\omega_i t} + \dot{x}_0 e^{-\omega_i t} \tag{19}$$

$$\sigma_i^2 = \frac{\omega_i N_i^2 1}{8}\left[1 - (1 + 2\omega_i t + 2\omega_i^2 t^2)e^{-2\omega_i t}\right]. \tag{20}$$

Since the task of the operator is to detect those occasions when the magnitude of any of the instrument readings is greater than a given threshold, a particularly important parameter of the operator's state of information will be the probability for each of the instruments that it has exceeded the threshold. If the threshold magnitude is L, then the probability for the ith instrument is defined as:

$$P_i(D) = \int_{-\infty}^{-L} f_i(x|D)dx + \int_{L}^{\infty} f_i(x|D)dx. \tag{21}$$

The data set D will contain the time since the ith instrument was last observed, the amplitude observed at that time and the rate observed at that time (cf., depending on whether the first- or second-order internal model is used).

The second major assumption stated that the human operator behaves optimally with respect to his internal model. Switches in attention to the instrument occur for which $P_i(D)$ is maximum. That is, the operator redirects his attention to the instrument whose current probability of exceeding the threshold is maximum.

Senders' data were used to compare the predicted data calculated with Smallwood's internal sampling model. The second-order internal model yielded a sampling behavior that lies well within the individual variations of the five subjects, while the first-order model does not. This result suggests that the observation and use of rate information may be an important component of the operator's internal model.

3.6 Models Based on Optimal Estimation Theory (OET)

Optimal control theory (OCT) has been applied to studies on human control, estimation, and decision [40-44]. Especially, Wewerinke and Stein have done useful studies related to monitoring behavior based on OCT [45,46]. Wewerinke assumes that the task of the observer is to detect the occurrence of failure in the system being observed, that is, a change in the statistical properties of one or more of the observed processes. To do this the observer keeps a running estimate of the mean and variance of each variable, updating it at each observation by means of a Kalman filter, which provides the best estimate of the true value of the function given observation noise in the observer's nervous system.

Optimal estimation theory (OET) provides a general method for obtaining a best estimate of the state of a system when the displayed variables are corrupted by either exogenous noise due to poor instrument design or endogenous "observation" noise in the nervous system. The noises make it impossible to make an exact measurement of the true value of the displayed variable. Moray's excellent review on this method is referenced in this section [27].

The observer wishes to make the best estimate of the value of the variable x_i. The observations are corrupted by noise, v_i, and delayed between observation and estimation by a delay τ. Let $\hat{x}_i$ be the estimate of the true x_i and the measurement that is obtained by the observer

$$y_i = x_i + v_i. \tag{22}$$

Since the observed process is dynamic, a new estimate of x must be obtained at each instant k, $k=1,2,\ldots,n$. The best way to do this is to form a running mean and a running variance, and to update them after each observation. The resulting statistic is then based on the whole past history of observations. For convenience consider the noise to be zero- mean Gaussian. Then the required equations are

$$\hat{x}_k = \frac{1}{k}\sum_{j=1}^{k} y_j \tag{23}$$

at time k, and this estimate can be updated at time $(k+1)$ by forming

$$\hat{x}_{k+1} = \hat{x}_k + \frac{1}{k+1}\left(y_{k+1} - \hat{x}_k\right). \tag{24}$$

The error of the estimate is

$$\tilde{x}_k = x_k - \hat{x}_k \tag{25}$$

at time k, and the variance of the estimate is $\tilde{x}_k^2$. If we could find an operation to minimize this error of the estimate we would have the desired best estimate, and for the single variable the answer is to minimize in an RMS error.

Note that at each instant we would have two sources of information, the running best estimate left from our previous measurements and our new current measurement, which is noisy. This suggests a choice of strategy. If the measurements are known to be noisy, it would be best to rely on the estimate, since it has averaged out the noise over the sequence of observations. However, if the measurements are relatively noise-free, the new measurements should be used. To decide which strategy is best requires an operation to allocate weights to old and new elements of the estimation procedure.

Next consider the observer to be confronted by a state vector of the system variables (available as displayed variables) and necessary and sufficient to define the system state. In general there will be no unique set and if all the variables in the system were displayed, different operators might choose different sets for their state vector.

As an example, suppose the operator to be controlling or monitoring a two-axis compensatory tracking task. The state vector might be $<x,\dot{x},y,\dot{y}>$, where x is the position of the target on the x axis, $\dot{x}$ its velocity, y is the position on the $\dot{y}$ axis, and y its velocity on that axis. If the bandwidth of the forcing function were very low, or if the duration of observations were artificially curtailed, then the observer might be unable to see the velocity components and the vector would collapse to $<x,y>$. Suppose further that each variable in the state vector is, prior to the observer's operating on it, corrupted by its own independent zero-mean Gaussian white noise.

Equations (22) to (25) can be rewritten as vectors of variables. Bold letters, **X**, **Y**, **V**, and so on, will be used to represent vectors and matrices.

$$\mathbf{Y} = \mathbf{H}_k\mathbf{X}_k + \mathbf{V}_k \tag{26}$$

where $\mathbf{H}_k$ is a transition matrix that defines the system dynamics.

Let the symbols (–) and (+) stand for values of the various variables just before and just after the update has been made in the calculation of running means and variances. Then,

$$\hat{\mathbf{X}}_k(+) = \mathbf{K}'_k\hat{\mathbf{X}}_k(-) + \mathbf{K}_k\mathbf{Y}_k \tag{27}$$

and the problem is to find values for $\mathbf{K}$, $\mathbf{K}'$ that will optimize the estimation in the face of the noise.

The estimation errors are $\tilde{\mathbf{x}}_k(+)$ and $\tilde{\mathbf{x}}_k(-)$ and are defined by

$$\tilde{\mathbf{X}}_k(+) = \mathbf{X}_k - \hat{\mathbf{X}}_k(+) \tag{28}$$

and

$$\tilde{\mathbf{X}}_k(-) = \mathbf{X}_k - \hat{\mathbf{X}}_k(-). \tag{29}$$

It can be shown that the best estimate is given by

$$\hat{\mathbf{X}}_k(+) = \tilde{\mathbf{X}}_k(-) + \mathbf{K}_k\left[\mathbf{Y}_k - \mathbf{H}_k\hat{\mathbf{X}}_k(-)\right], \tag{30}$$

where $\mathbf{K}_k$ is called the Kalman gain matrix and is the heart of the Kalman filter. To estimate $\mathbf{K}_k$, the error covariance matrix is defined as

$$\mathbf{P}_k(+) = \mathbf{E}\left[\tilde{\mathbf{X}}_k(+)^T\right] \tag{31}$$

where $\mathbf{E}$ is the expectation operator and $\tilde{\mathbf{x}}_k(+)^T$ is the transpose of $\tilde{\mathbf{x}}_k(+)$. The diagonal elements of this matrix are the variances of its elements, and the other elements are the cross-covariance between the errors of the estimates of the several variables.

The noise covariance matrix may be defined as

$$\mathbf{R}_k = \mathbf{E}\left[\mathbf{V}_k\mathbf{V}_k^T\right]. \tag{32}$$

It can be shown that the solution is to set

$$\mathbf{K}_k = \mathbf{P}_k(+)\mathbf{H}_k^T\mathbf{R}_k^{-1}. \tag{33}$$

This minimizes the scalar cost function

$$\mathbf{J}_k = \mathrm{trace}\left[\mathbf{P}_k(+)\right], \tag{34}$$

which can be shown to be the optimal solution.

Note that the diagonal elements of $\mathbf{P}_k$ are variances and the "trace" operator is the sum of those diagonal elements. Hence the minimization of the trace operator is analogous to minimizing the RMS value of the error of the scalar variable in the original example.

The Kalman gain matrix behaves as if it were proportional to the uncertainty in the estimate and inversely proportional to the uncertainty in the noise. So the filter will weight more heavily that element in the calculation that is better for producing an estimate of the real value of the state variable. If there is a delay τ (e.g., neural processing time between the receptors and the decision-making components in the brain), the prediction from the (–) and the (+) state can be used to compensate for the delay. If the operator is acting as a controller rather than an estimator, then the output of the predictor can be used to force a control action gain matrix that embodies equalization for the controlled element transfer functions and that can be tuned to minimize costs on the control actions. It is usually assumed in the latter case that operators will minimize RMS movement, both because it is a theoretically good goal and because work on human workload estimation empirically suggests that humans actually do so.

3.7 Sheridan's Model

Sheridan [47] modeled the process of choosing an optimal sampling interval through cost. Sheridan has defined the "supervisor" as a "person" or "function" which adjusts a control variable y in an effort to maximize a given value function V of the system's independent input x, control input y, and output z. A typical diagram is given in Fig. 4. Often this is called a learning or optimizing control system. It is easiest to think of V as a continuous earning rate (equivalent to money per unit time) and of x, y, and z as continuous in time.

Sheridan considered two extreme strategies in a process control system: (1) continuously observing each new value of x and adjusting y to maximize value (earning rate) $V(x, y)$ when x is known; (2) never observing x and adjusting y to maximize V on the basis of a prior probability distribution of x.

An optimal interval was assumed to be made between the two strategies. The theory used to analyze these two extreme strategies is derived from "information value theory" as presented by Howard [48].

First, the following assumptions and notation should be mentioned:

x = A random event with known probability density function (PDF) $\{x\}$

$V(x, y)$ = The value, gained per unit time, has known expected value $\langle V \mid xy \rangle$ when x and y are specified.

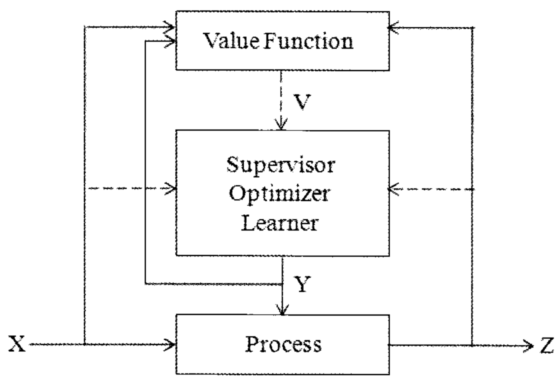

Fig. 4. Sheridan's Value-oriented Control System [47]

Then the expected value of $V(y)$ is

$$\langle V|y\rangle = \int_x \langle V|xy\rangle\{x\} \tag{35}$$

where $\int_x$ is a generalized summation over all x.

If the supervisor knows only the a priori distribution $\{x\}$ then his best strategy is to determine $<V \mid y>$ and adjust y to maximize this function, yielding the overall expected value of V in this case,

$$\langle V_1\rangle = \max_y \langle V|y\rangle = \max_y \int_x \langle V|xy\rangle\{x\} \tag{36}$$

that is, maximize the value of all joint occurrences of x, y over all occurrences of x given the $\{x\}$.

If the supervisor continuously observes the process and has perfect knowledge of x all the time, then his best strategy is to adjust y to maximize $<V \mid xy>$ for each successive x:

$$\langle V_2|x\rangle = \max_y \langle V|xy\rangle, \tag{37}$$

which leads to

$$\langle V_2\rangle = \int_x \langle V_2|x\rangle\{x\} = \int_x \left[\max_y \langle V|xy\rangle\right]\{x\}\cdot \tag{38}$$

In all cases, $\langle V_2\rangle>\langle V_1\rangle$.

The supervisor need not operate at either of the extremes, continuous observation of x and adjustment of y or a once-and-for-all setting of y. It is more often the case that knowledge of x can be updated periodically or whenever some threshold of uncertainty is reached. This

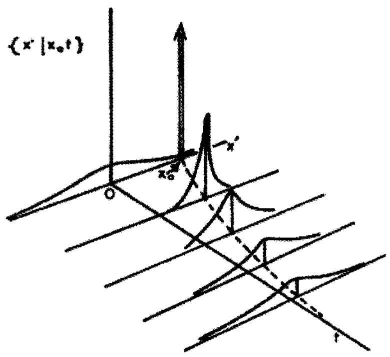

Fig. 5. Variation of State of Knowledge x' with Time t after Sample x_0 [47]

assumes x at time t after sampling correlates with x sampled.

Consider x' representing the supervisor's state of knowledge about x at some intermediate time between the two extremes csited above, at the one extreme knowing x exactly and at the other extreme knowing x only as a stationary random variable with PDF $\{x'|x_0t\}$, a function of time after a sampled and measured value $x'=x_0$ at $t=0$:

$$\{x'|x_0t\}_{t=0} = \text{an impulse at } x_0, \tag{39}$$

$$\{x'|x_0t\}_{t=\infty} = \{x\}. \tag{40}$$

$\{x'|x_0t\}$ can be assumed to have monotonically increasing variance and, assuming $\{x\}$ has a mean of zero, $\{x'|x_0t\}$ has a mean which systematically moves from x_0 to 0 as t goes from 0 to ∞, as illustrated in Fig. 5.

Now assume that the supervisor, through practice, has acquired a model of this conditional PDF. The supervisor's best strategy at each t is to optimize y based upon $\{x'|x_0t\}$, analogous to what he would do in Eq. (36) where he knows only $\{x\}$; but $\{x'|x_0t\}$ gives him better information about x.

His best estimate of value V_3 at this intermediate t, for the given x_0 and for alternative values of y he might choose to apply, is obtained by averaging over the known $\{x'|x_0t\}$ as in Eq. (35):

$$\langle V_3|x_0yt\rangle = \int_{x'} \langle V|x'y\rangle\{x'|x_0t\} \tag{41}$$

where $\langle V \mid x'y\rangle=\langle V \mid xy\rangle$. After selecting y to maximize $<V_3>$ for the given x_0 and t the supervisor has

$$\langle V_3|x_0t\rangle = \max_y \langle V_3|x_0yt\rangle = \max_y \int_{x'} \langle V|x'y\rangle\{x'|x_0t\}\cdot \tag{42}$$

In a manner analogous to Eq. (38), the supervisor knows that if he knew x_0 and t and were to select y optimally at each t based on an assumed model for $\{x'\}$, he can specify his expected return before the fact on the basis of the distribution of x_0,

$$\langle V3|t\rangle = \int_{x_0} \langle V3|x_0t\rangle\{x_0\}\cdot \tag{43}$$

But x_0 has the same prior distribution x,

$$\{x_0\} = \{x\} \tag{44}$$

which is known. Therefore, the supervisor can determine before the fact of knowing any particular x_0 that his expected earn rate at time t after a sample is

$$\langle V3|t\rangle = \int_x \langle V3|xt\rangle\{x\} = \int_{x_0}\left[\max_y \int_{x'} \langle V|x'y\rangle\{x'|x_0 t\}\right]\{x_0\} \cdot \quad (45)$$

This is the expected instantaneous rate of return to be obtained from continuous control t seconds after the sample. The average return over a period T is

$$\langle V3\rangle_T = \frac{1}{T}\int_{t=0}^{T}\langle V3|t\rangle \cdot \quad (46)$$

In order to decide how often to sample, the inherent cost of sampling must be considered. Now suppose that it costs C to take a sample. Then over a sampling interval T the cost of that sample per unit time would be C/T. The expected net value per unit time of sampling after each interval T would then be

$$\langle V_{net}\rangle_T = \langle V3\rangle_T - \frac{C}{T} \cdot \quad (47)$$

The optimum strategy is to pick up the sampling interval T which maximizes $<V_{net}>_T$.

The longer the supervisor waits to take the next sample, the cheaper the cost averaged over the waiting period. In addition the longer the delay the less valuable the last observation and the last control action. For a number of reasonable functions relating costs and autocorrelation functions, the difference between value and cost will be non-monotonic and the sample should then be taken at the point where the difference between the value and cost is a maximum (see Fig. 6).

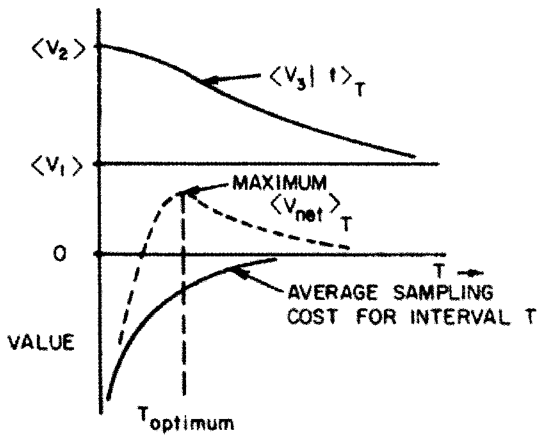

Fig. 6. Determination of Optimum T [47]

3.8 Kvalseth's Model based on Information Theory

Kvalseth's model [49,50] is based on information theory. He used information gain, entropy, and redundancy measures to analyze human monitoring of a Gaussian autoregressive process. He notes that for a Gauss-Markov process the entropy of an observation is given by

$$H(X) = \frac{1}{2}\log_2 2\pi\exp(\sigma^2) \cdot \quad (48)$$

The entropy of an observation made k intervals after an initial observation is

$$H(X_{n+k}|X_n) = \frac{1}{2}\log_2 2\pi\exp(\sigma^2)(k) \quad (49)$$

and the redundancy at the kth interval is

$$R(k) = -\left[\frac{1}{\log_2 2\pi\exp(\sigma^2)}\right]\log_2(1-\rho^2(k)) \quad (50)$$

where $\rho(k)$ is the value of the autocorrelation function at k intervals after the observations.

Kvalseth's experiment to investigate the effects of entropy and redundancy on sampling was unusual in that he did not use continuous signals. Instead, a series of numbers were printed on a teleprinter at equal intervals of time but were not displayed unless the operator asked to see a number. The aim was to detect moments when the number series had a value that exceeded a specified limit. In addition, costs were associated with making an observation.

The results were that after an observation subjects tended to wait until entropy had risen to 80-100% of its maximum value before taking their next sample, where the asymptotic value was about 3 bits per observation.

There are increasing numbers of digital displays in use in control rooms. Studies employing methods like Kvalseth's have an important role in understanding the monitoring behavior of operators using such displays.

3.9 Kvalseth's Cost Model

The effect of sampling and error cost on sampling frequency was analyzed in another experimental study by Kvalseth [51]. The importance of payoff structure has been explored in considerable detail by Kvalseth [49-51]. His data suggest that observers are usually suboptimal, although their behavior shows a significant positive correlation with the prediction of optimal models. Hence he considered another factor, cost. He allotted sampling cost and error cost to displays and then instructed the subjects to do the teleprinter monitoring task at minimum cost.

The major conclusion derived from this study was that both the sampling cost and the error cost had significant effects on the subjects' sampling behavior. An increase in the error cost with the sampling cost kept constant tended to cause an increase in the sampling rate. Similarly, the sampling rate tended to increase for a constant error rate when the sampling cost decreased.

3.10 Moray's Model

The work of Moray, Neil, and Brophy [52] and Moray, Richards, and Low [53] on the visual sampling behavior of radar operators was close in spirit to the modified models of Senders et al. [30]. They studied the eye movements of fighter aircraft controllers both in a simulator and while they were controlling real aircraft in practice interceptions.

There were marked changes in monitoring patterns at different phases of an interception. Markov analysis allows the estimation of the proportion of time devoted to the various features of the display and also an estimate of the mean first passage time (MFPT). MFPT is a particularly interesting statistic for describing the behavior of a dynamic multivariate system. Suppose the observer is currently looking at the echo of a fighter aircraft on the radar. The MFPT for the fighter estimates how long, on the average, will pass before the same echo is fixated on again. The MFPT for the tote board will estimate how long on the average will pass before the tote board is examined, given that the observer is currently looking at the fighter aircraft. Similarly MFPT can be estimated from any other starting point with respect to any other subsequent observation. The MFPT takes into account the fact that, between fixating on the fighter aircraft echo and, say, the echo of the enemy aircraft, there may be many different patterns of intervening fixations. It thus provides a powerful tool for estimating when the observer's monitoring behavior will be overloaded due to time pressure, given a knowledge of the fixation duration and the limits on the number of eye movements that can be made per second.

Moray et al. modeled the monitoring behavior by assuming that the main source of uncertainty was due to endogenous forgetting, that is, uncertainty caused by loss of information from memory rather than by the dynamics of the displays. They measured the rate at which controllers forgot the position of "radarlike" displays, using marks on a circular diagram on paper, and asking for estimates of the position of the marks at various intervals after the original was presented. They found that the standard deviation of the estimate of the position of the remembered mark was given by

$$\sigma = K + 0.02t^{\frac{3}{2}} \tag{51}$$

where t is the time since the "radar" had been seen, and K is a constant that depended on the difficulty of the display (e.g., how many echoes had to be remembered).

Eq. (51) means that uncertainty begins to become severe at around 15 sec. This is of the same order of magnitude as the time constant for forgetting, which one might infer from the observer's oversampling in Senders' experiment.

Moray et al. assumed that the observers had two uncertainty thresholds, and that if either one was exceeded the observer's attention was called to the appropriate feature of the display [53]. As uncertainty grew according to Equation (51) it would eventually exceed a threshold set in the light of the importance that the observer placed on that source of information. At that moment the eye would again fixate on that source. The second was a threshold related to the probability that two aircraft were unacceptably close to one another given their known courses and speeds and the time since the last observation. If the probability that the two aircraft were in the same airspace exceeded this threshold each was fixated in turn. If aircraft were then found to be in close proximity to one another, the first, forgetting, threshold was reset at each look, exponentially decreasing as the proximity increased. The result was that the observer became more sensitive to uncertainty as the aircraft approached one another.

3.11 Wickens et al.'s Model

Wickens et al. developed two models of information acquisition in visual scanning during aviation: a descriptive and a prescriptive model [13]. The descriptive model combined the four influencing factors on information searching behavior in dynamic environments: event salience, effort, expectancy, and value. This model is referred to as the SEEV (Salience, Effort, Expectancy, and Value) model.

In this model, the probability characterizing the distribution of visual attention across areas of interest (AOIs) is formulated as

$$P(A) = sS - efEF + (exEX) \times (vV). \tag{52}$$

Each term in capital letters is a characteristic of a particular environment that is determined by (1) the physical properties of events (Salience=S); (2) the physical distance between a previously fixated and a current AOI, or the demands of concurrent tasks (Effort=EF); (3) an information-related measure of event expectancy (e.g., bandwidth or event rate: Expectancy=EX); and (4) an objective measure of the value (=V) of processing information at the AOI in question (or the cost of failing to attend there). The coefficients, s, ef, ex, and v, represent the relative influence of these four factors on human scanning.

Salience and effort may exert a greater or lesser influence on scanning to the extent that designers have adhered to good human factors practice in designing display layouts by correlating effort with expectancy and salience with value. In particular, to the extent that high-expectancy, high- bandwidth sources of information are close together, this will attenuate the inhibitory role of effort in seeking information. Such a correlation represents the "frequency of use" principle of display layout design [54]. To the extent that valuable information is made salient when it occurs, this will assure the capture of attention when important events occur; for example, the role of alarms in good human factors practices [55]. Correspondingly, making less valuable events less salient will inhibit undesirable failures to focus attention appropriately.

While some previous models have defined the properties of each display purely in terms of bandwidth and value of events along that channel, Wickens et al.'s prescriptive model considers the many-to-one mappings of tasks to displays and displays to tasks in complex environments that requires the integration of models of information seeking with those of task management. This integration is shown schematically in Fig. 7.

At the top, the simpler models such as those of Senders [29] and Carbonell [35] assign tasks, values and bandwidths in a one–to–one mapping to AOIs. At the bottom, the structure of Wickens et al.'s model describes the framework of a pilot scanning three AOIs such as the instrument panel (IP), the outside world (OW), and a cockpit display of traffic information (CDTI) to support two different tasks.

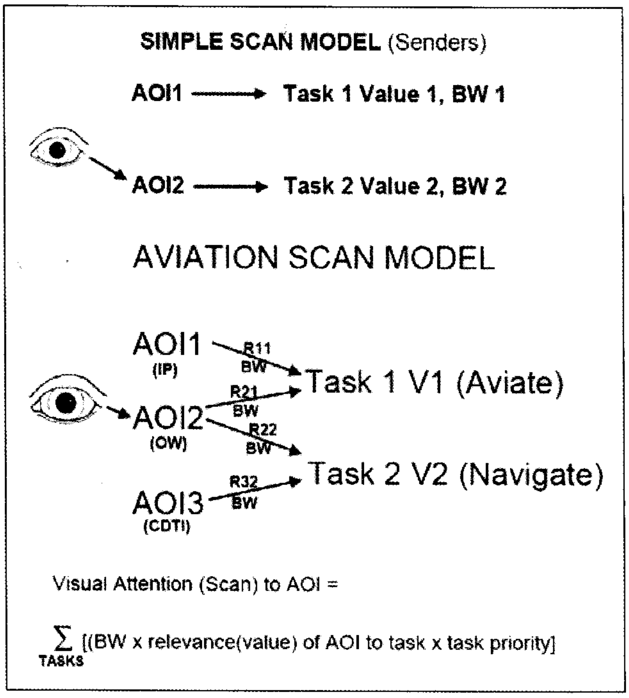

Fig. 7. Representation of Different Scanning Models [13]

Within aviation, there is a clearly established task priority hierarchy which sets aviating to be a more important task than navigating (although both are more important than communicating [56]). After all, a plane cannot navigate if its lift is not sufficient to keep it in the sky (a failure to aviate), whereas a plane can aviate (fly) even if its heading and altitude are unknown (failure to navigate). As shown in Fig. 7, this task hierarchy defines the importance or value (V) of AOIs.

As shown at the bottom of Fig. 7, an expected value model would predict that the probability of attending to a particular AOI is related to the sum, across all tasks supported by that AOI, of the value of those tasks, multiplied by the degree of relevance (importance) of the AOI for the task in question, and by the bandwidth of their informational "events" as:

$$P(AOI_i) = \sum_{t=1}^{n} (bB_t)(rR_t)(V_t) \tag{53}$$

where, t=tasks, numbering 1 to n.

Notice that expectancy is incorporated by bandwidth, while value is incorporated by the product of relevance and the value (rank) of the task in the priority hierarchy. Eq. (53) is obviously different from the original SEEV descriptive model, Eq. (52), in that the former does not contain the salience and effort factors. The prescriptive model was developed to assess the performance of well-trained pilots. Salience and effort are essentially matters of HMI design, not human performance.

In providing numerical predictions for the model, two general steps are required. First, bandwidth, relevance and value should be estimated. Second, the coefficients to the different parameters should be assigned across the varying conditions.

A "lowest ordinal algorithm" was adopted rather than trying to estimate absolute values for the parameters and coefficients. The values from highest to lowest were simply ordered (e.g., aviating priority is higher than navigating priority). Then the lowest values were assigned and, finally, the ordered values were rearranged according to the lowest assignment. This lowest ordinal algorithm has the advantage that coefficients can be set based on simple relationships that multiple model users should agree upon.

The prescriptive model was validated against the data from four experiments in which skilled pilots flew a high-fidelity visual flight simulator while engaged in traffic detection, with (Experiments 1, 3, and 4) and without (Experiment 2) a cockpit traffic display, and with different forms of data link displays (Experiment 4). All four experiments provided a good fit between model predictions and the percentage of time that pilots spent viewing different areas of interest in the airplane environment.

3.12 Miao et al.'s Situation Assessment Model

Miao et al. [57] viewed the process of situation assessment (SA*) as a diagnostic process from effects to possible reasons, instead of a deductive reasoning process in which a situation is assessed using production rules (i.e., events–situation rules) [58,59]. After events are detected, their likelihood (belief) impacts on the situations are evaluated by backward tracing of the situation–event relation (diagnostic reasoning) using Bayesian logic. The updated situation likelihood assessments then drive the projection of future event occurrences by forward inferencing along the situation–event relation (inferential reasoning) to guide the next step of event detection.

Miao et al. used a Bayesian inference process to describe the monitoring behavior of operators in NPPs (see Fig. 8), which was a remarkably noble approach. Its development consists of two steps: 1) developing a specially structured Bayesian belief network (BBN) to represent the SA mental model; and 2) developing a belief update (propagation and projection) algorithm to reflect SA* event propagation and projection.

The situation–event links illustrated in Fig. 8 define a situation S via a specification of the causal relationship between the situation S and its related events $E_1, E_2, \ldots, E_M$. The belief is updated according to

$$P(S|E_M) = \frac{P(E_M|S)\times P(S)}{P(E_M|S)\times P(S) + P(E_M \neg S)\times P(\neg S)}. \qquad (54)$$

The model assumes that operators maintain the situation–event relation in a probabilistic form. For example, if a LOCA occurs, the chances of a rapid pressurizer pressure level decrease, a slow level decrease, or no change are 85%, 10%, and 5%, respectively.

Miao et al.'s SA* model essentially describes the process of development of SA. Maintenance of SA was not considered in this SA* model. A valuable contribution of this study is that the important attributes such as diagnostic reasoning or Bayesian inference provided a valuable foundation for studies on information searching behavior in NPP operation, even though it is apparently not a model of monitoring behavior.

3.13 Wickens et al.'s A–SA Model

The A–SA model was developed to predict pilot errors (wrong turns) during taxiway operations (from runway to terminal) on airport surfaces [60,61]. It is composed of two modules, an attention module and a belief module, as shown in Fig. 9. A sequence of events (upper left) is attended (center) to a degree that is degraded by workload. Attended events provide evidence for the belief module (box at lower right), a belief that decays over time. The SA belief then contributes to a choice, at the bottom. In addition, the SA modulates the amount of attention. The attention module can be considered as a tool for lower-level SA (i.e., Level 1 SA in Endsley's model) and the belief module (cognitive SA-updating module) as that for higher- level SA (i.e., Level 2 & 3 SA in the Endsley model), respectively.

The output of the A–SA model is a value representing the operator's momentary state of SA, ranging from zero to unity (correct SA). The attention module was modeled based on Bundesen's theory of visual attention [62]. The attention to a given AOI is determined by the AOI's conspicuity (C), information value (V), and SA. The conspicuity describes the AOI's physical perceptibility, ranging from 0 (imperceptible) to 1 (easily noticed). Information value describes the effect of the AOI on SA, ranging from -1 to 1. A low value of -1 describes an item that is highly misleading of SA (e.g., a mislabeled taxiway). A neutral value of 0 describes an item that is irrelevant to maintaining SA (e.g., a discussion on an unrelated topic, a truck on an adjacent taxiway). A high value of 1 describes

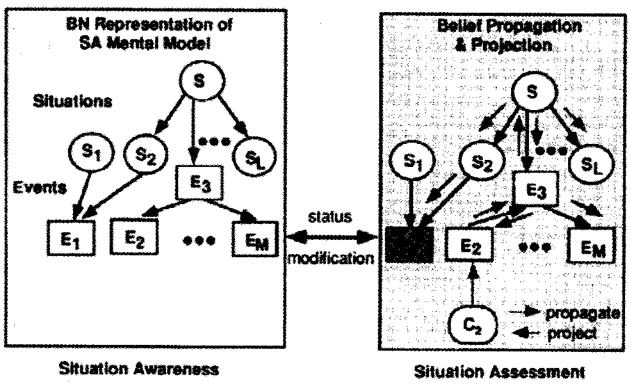

Fig. 8. Situation Assessment Model Using BBN [57]

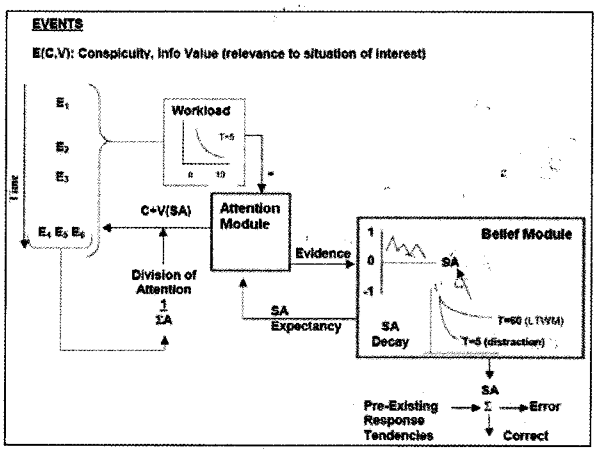

Fig. 9. Attention/Situation Awareness Model [61]

an item that is highly facilitative of SA (e.g., a sign which correctly labels the taxiway on which the pilot is supposed to turn).

As each stimulus (event or AOI) is encountered, it is assigned an attentional weight W according to the formula

$$W = C + SA \times V \,. \tag{55}$$

High SA guides attention toward objects and events further conducive to SA. As the value of SA approaches 1, AOIs with positive V are assigned greater attentional weight and AOIs with negative V are assigned less attentional weight. As SA decreases, conversely, the contribution of V to attentional weight is diminished, such that when SA reaches 0, attentional weight is determined exclusively by salience. This tendency captures the influence of top-down factors such as expectancy and the confirmation bias on evidence seeking. An AOI with V of 0 can still be assigned a relatively large attentional weight based on its salience, and thus can still influence SA. An AOI with a conspicuity of 0 may have a positive attentional weight as a result of its information value. The result of this is that an AOI which is imperceptible or even absent from the scene but which is anticipated and sought by the pilot can consume attentional resources.

In the time after an AOI has been first noticed, its attentional weight declines according to an exponential decay function. A result of this gradual decay is that processing of an AOI may add to cognitive load even for some time after the AOI has been passed. The residual attentional weight of an AOI which was attended prior to the current one-second interval is determined by an exponential decay function

$$W_{t+n} = W_t e^{-\left(\frac{\ln 2}{H_w}\right)n} \tag{56}$$

where, W_{t+n} is the AOI's attentional weight n seconds after the time t at which the AOI was initially encountered, W_t is the initial attentional weight (i.e., its attentional weight at the time it was first encountered), and H_w is the half-life for attentional weight as specified by the analyst.

The amount of attention allotted to a given AOI is determined by the ratio of that AOI's attentional weight to the summed attentional weights of all the AOIs within the current interval, and of all previously encountered AOIs as

$$A_i = C_i \times \left(\frac{W_i}{\sum W}\right) \tag{57}$$

where A_i is the amount of attention allotted AOI i, C_i is the conspicuity of the AOI, W_i is the attentional weight of the AOI, and $\sum W$ is the sum of the attentional weights of all the AOIs within the current temporal interval and of the residual attentional weights of all AOIs which were attended to earlier.

Conspicuity modulates the amount of attention allotted to an AOI, independently of its effect on attentional weight. Because the term $\sum W$ includes the residual weights of AOIs which were attended to earlier, the workload from previously attended stimuli is allowed to modulate attentional control. The model thus captures the degrading influence of cognitive load on SA.

The change in SA affected by the AOIs in a given interval is determined by a weighted mean of their information values, with V for each AOI being weighted by the AOI's attentional allotment A. This value will be referred to as the AOIs' net evidentiary value (NV). These weighted values are employed to update SA via an anchoring and adjustment process, described by Hogarth and Einhorn [63], capturing the effects of various cognitive biases (e.g., primacy and recency effects) on belief updating.

If NV is negative, then SA is updated according to the formula

$$SA_t = SA_{t-1} + SA_{t-1} \times NV \,. \tag{58}$$

If NV is positive, the SA is updated according to the formula

$$SA_t = SA_{t-1} + \left(1 - SA_{t-1}\right) \times NV \,. \tag{59}$$

If no new evidence is encountered, SA is assumed to decline according to an exponential decay function. This decay in the absence of new evidence reflects the fact that SA maintenance is resource limited.

$$SA_{t+n} = SA_t e^{-\left(\frac{\ln 2}{H}\right)n} \tag{60}$$

The model assumes a faster decay rate for SA during attentional processing of irrelevant stimuli (which provide no information to build SA) than during the absence of attention-demanding stimuli.

The attention module in the A–SA model incorporates the descriptive SEEV model using elements such as conspicuity (salience), workload (effort), SA in the calculation of attentional weight (expectancy), and information value (value).

3.14 Kim & Seong's Knowledge-driven Monitoring Model

Kim and Seong [64] argued that deterministic rules are more reasonable and realistic than the probabilistic

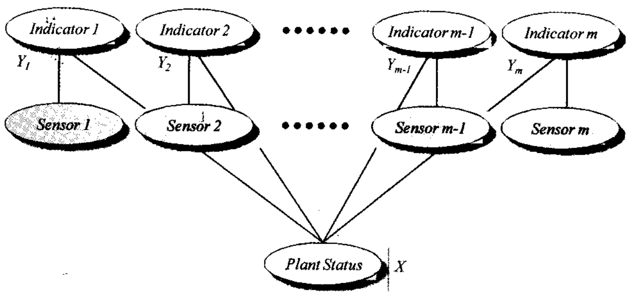

Fig. 10. Model of Operator's Rule Using BBN [64]

form used in the situation– event relation suggested by Miao et al. [57]. Kim and Seong developed another analytic model for situation assessment of NPPs based on Bayesian inference, adopting deterministic rules as a basis of the model [64]. Kim and Seong's SA* model is thought to be even more mature than Miao's.

In Kim and Seong's SA* model, it was assumed that the situation model of an NPP operator can be modeled using the representative states of the plant, and also that the mental model of an NPP operator can be modeled using the rules on the dynamics of the plant for the plant's representative states. A model for the mental model of an NPP operator is developed as shown in Fig. 10. X indicates the representative states of the plant, Y_i's (i=1,2,...,m) indicate various indicators, and Z_i's indicate various sensors. An example of operators' rules on the dynamics of the plant is, 'if the state of the plant is x_k then the value or the trend of the indicator Y_i is expected to be Y_{ij}'. The deterministic rules can be described mathematically using conditional probabilities as

$$P(y_{ij}|x_k)=\begin{cases}1, & \text{if } y_{ij} \text{ is expected upon } x_k \\ 0, & \text{if } y_{ij} \text{ is not expected upon } x_k\end{cases}. \tag{61}$$

If the operators observe Y_{ij} on the indicator Y_i, the probability of a state of the plant x_k can be revised as

$$P(x_k|y_{ij})=\frac{P(y_{ij}|x_k)P(x_k)}{\sum_{h=1}^{l} P(y_{ij}|x_h)P(x_h)}. \tag{62}$$

In addition, Kim and Seong [65] proposed a noble computational model for the knowledge-driven monitoring behavior of operators in NPPs. This model was based on the Bayesian SA* model and information theory. They assume that the probability that an operator shifts his or her attention to an information source after having a situation model is proportional to the information expected from the information source as

$$\begin{aligned} T(X;Y_i) &= \sum_{k=1}^{l}\sum_{j=1}^{n_i} p(x_k,y_{ij}) I(x_k;y_{ij}) \\ &= \sum_{k=1}^{l}\sum_{j=1}^{n_i} p(x_k,y_{ij}) \log_2 \frac{p(x_k|y_{ij})}{p(x_k)} \\ &\quad \vdots \\ &\quad \vdots \\ &= H(X)+H(Y_i)-H(X,Y_i) \end{aligned} \tag{63}$$

where $H(X)$ can be calculated using Eq. (14).

Kim and Seong's knowledge-driven monitoring model provides a sound mathematical basis describing knowledge-driven monitoring. Hence this model is thought to be helpful in developing a prescriptive model of information searching behavior. However, limitations and assumptions used in the Bayesian SA* model on which the knowledge-driven monitoring model is constructed should be treated carefully.

3.15 Ha & Seong's ARE Model

Ha and Seong have developed an attentional resource effectiveness (ARE) model for human factors studies on NPP operators [66]. This model is also based on the theory that selection of information sources to attend to is typically driven by four factors: salience, expectancy, value, and effort [14]. Similar to Wickens et al.'s prescriptive model [13], the ARE model was developed to evaluate human performance. Hence effort and salience were considered matters to be dealt with during HMI design.

The underlying principle of this model is that information sources should be selectively attended to according to their informational importance. To balance attentional resources with valuable information sources, what is needed is to apply cost-benefit principles, which are then translated to resource effectiveness principles. Two measures of attentional resource effectiveness have been developed such as FIR (fixation-to-importance ratio) and SAE (selective attention effectiveness). They are

$$FIR(i)=\frac{0.5\times\left(\dfrac{N_i}{\sum_{i=1}^{k} N_i}\right)+0.5\times\left(\dfrac{D_i}{\sum_{i=1}^{k} D_i}\right)}{\dfrac{\omega_i}{\sum_{i=1}^{k}\omega_i}} \tag{64}$$

where,

$FIR\,(i)$ = FIR of information source-i

N_i = the number of eye fixation on information source-i

D_i = the duration of eye fixation on information source-i

k = total number of information sources

ω_i = importance of information source-i

and

$$SAE=\frac{\sum_{i=1}^{k}|FIR(i)-1|}{k}. \tag{65}$$

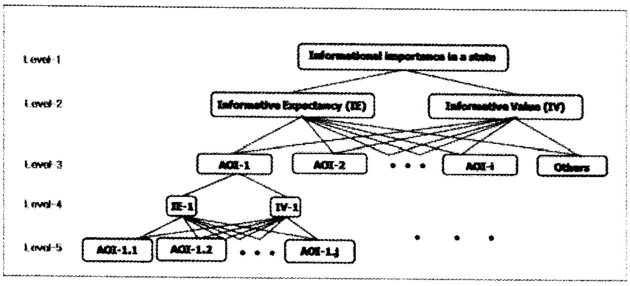

Fig. 11. Setting up the AHP Hierarchy [66]

Hence, FIR and SAE should approach unity and zero, respectively, to maximize overall attentional resource effectiveness.

The number or the duration of eye fixations is obtained using eye-tracking equipment. The importance of information sources is quantified using the analytic hierarchy process (AHP) [67].

The informational importance of a process variable was considered as a function of its ability to discriminate among competing hypotheses (abnormal states) of the cause of a plant symptom. Hence, a set of the informational importance for an abnormal state is evaluated by considering a symptom set which has the ability to be diagnostic across a set ofcompeting hypotheses. Considering existing studies on monitoring behavior, the attribute representing "the frequent change of the source (bandwidth)" is referred to as "informative value (IV)" and the attribute representing "the likelihood of the change (a set of symptoms)" as "informative expectancy (IE)" in this ARE model. Finally, the AHP hierarchy structure was established with IE, IV, and AOIs, as shown in Fig. 11.

Generally, a subject who has a good mental model is expected to more effectively monitor and detect the state of a system than a subject who has a poor mental model, which was demonstrated with the SAE and the FIR in an experimental study [66]. Deficiency in HMI design could be identified by analyzing the FIR: information sources important but not frequently fixated on were screened out by examining the FIR values of the information sources. Hence, the FIR and the SAE are thought to be promising measures of effectiveness in monitoring and detection during complex diagnostic tasks in NPPs. Especially, the SAE was correlated very well with several measures of SA and then proposed as an indicator of SA [68].

4. IMPLICATIONS FOR HUMAN FACTORS STUDIES IN NPPS

4.1 Major Determining Factors of Information Searching Behavior for NPP Operators

Generally, there is no dramatic change in the dynamics of NPPs during normal operating conditions. Attention has been paid to the visual sampling behavior of operators during abnormal states such as accident, incident, or transient conditions in NPPs [57,64,65]. Informational importance of a process variable should be a function of its ability to discriminate among competing hypotheses (abnormal states) of the cause of a plant symptom.

Visual sampling in NPPs is also dependent on expectancy, value, salience, and effort. Senders' original scanning model was subsequently elaborated by others (Carbonell [35,36], Smallwood [38], Kvalseth [49,50], Wickens [13], Moray [52,53], Ha and Seong [66]) to account for value in addition to bandwidth (event rate).

Bandwidth obviously plays an important role in monitoring behavior in NPPs. It permits operators not only to expect the location of valuable information sources (expectancy) but also to diagnose the state of the NPP in more detail if an abnormal situation occurs. In the example of the LOCA shown in Chapter 2, if an operator detects a set of symptoms such as decreases in pressurizer pressure, temperature, and level and an increase in containment radiation, the operator is supposed to assess the abnormal situation as a LOCA. The operator may want to seek further information about the LOCA such as the location of the leakage, the leakage amount (or diameter of the leakage breach), and so on, which can be assessed with a set of change rates of the process variables.

In the SA* models [57,64], a set of symptoms (i.e., rules in system dynamics or the situation–event relation) was considered an important feature directing the operator's attention. Symptoms generally have diagnostic attributes. It should be noted that there can be two kinds of symptom: a symptom representing a changed part (e.g., onset of an alarm or deviation in a process variable) and a symptom of a stationary part (e.g., a process variable in normal state). In the LOCA example, if the pressurizer pressure, temperature, and level decrease, then a LOCA and a steam generator tube rupture (SGTR) can be competing hypotheses. If there is no change in containment radiation, it will be an SGTR not a LOCA. In this case, containment radiation is a stationary symptom which has the ability to be diagnostic between a LOCA and an SGTR. Selective attention should be paid to stationary symptoms in order for operators to understand the situation correctly, even though those symptoms are not changed.

Hence, a set of symptomatic information sources including both changed and unchanged symptoms and bandwidth should be considered as determining factors governing information searching (or visual sampling) behavior in NPPs.

4.2 Data-driven vs. Knowledge-driven Monitoring

As Moray has pointed out [14], if the operator's memory for an observation becomes seriously deficient in about 15 sec, which was suggested by Senders and Moray [30,52], then it follows that not more than 30-40 displays can be efficiently monitored by a single observer (assuming that the displays are statistically independent). This follows from the 0.5 sec as a lower bound on dwell times in real-life tasks. On such an analysis it would seem that many control rooms must be seriously undermanned. However, there are usually considerable correlations between process variables in real systems. Such correlations could permit an observer to monitor a subset of the displays and to provide estimates of other variables. Such correlations exist in various plant systems, especially in NPPs and form obvious rules of the behavior of a plant system. The knowledge of such correlations is established as a form of the mental model. Hence knowledge-driven monitoring plays an important role in information searching behavior in NPPs. The following excerpts from the literature provide a meaningful basis for the development of models for the knowledge-driven monitoring of NPP operators.

- *"An operator is faced with an information environment containing more variables than can be realistically monitored. The real challenge comes from the fact that there are many potentially relevant things to attend to at any time, and the operator must determine what information is worth pursuing within a constantly changing environment. Then the operator must decide what to monitor and when to shift attention elsewhere. These decisions are strongly influenced by an operator's current situation model, which guides the allocation of attentional resources to sampling data from the environment based on its statistical properties, i.e. expected probability and correlation. The operator's ability to develop and effectively use knowledge to guide monitoring relies on the ability to understand the current state of the process." [21].*
- *"Performers (NPP operators) learn through experience where and when to look in their work environment to gain the greatest information, and selectively focus attention on these sources. In dynamic environments, such as NPPs, there is a tendency for operators to attend to those sources that change most frequently (i.e. contain the most information in terms of bits per unit of time), or are likely to change given the current situation. These are examples of top-down processing (e.g. based on their understanding of the current situation, operators develop expectations of information sources that will provide the most useful information). Monitoring based on top-down processing is referred to as model-driven or knowledge-driven monitoring. Proficient NPP operators rely on this capability to allow them to shift their attention between the many sources of information in the control room, especially when situations change; they learn which stimuli represent things that are likely to require their attention." [69].*

In summary, the knowledge-driven monitoring of NPP operators is highly affected by the operator's SA (operator understanding of the current situation) which forms the expectancy of information sources that will provide the most useful information. A set of the symptomatic information sources mentioned as one of the determining factors governing the information searching behavior in NPPs can be considered as a set (or subset) of information sources required for accurate SA.

Many of the studies on monitoring behavior in aviation have paid more attention to data-driven monitoring, which is affected by display attributes of the information sources (i.e., salience or bandwidth (change rate)). Bandwidth has been treated as a property representing expectancy (cf., the SEEV model [13]), because changing AOIs guide operators (or pilots) to important information sources in aviation (cf., some researchers considered bandwidth as an attribute of value). Bandwidth is also a determining factor in the monitoring behavior of operators in NPPs. For human factors studies including the development of a sound model of information searching behavior in NPPs, both data-driven monitoring and knowledge-driven monitoring should be considered and balanced in a systematic way. If there is no correlation between instruments only data-driven monitoring can be considered. However, as correlation between instruments grows closer, knowledge-driven monitoring should be considered according to the extent of the correlation.

Most of the models for aviation reviewed in this paper can describe only data-driven monitoring, whereas Miao et al.'s SA* model and Kim and Seong's knowledge-driven monitoring model can describe only knowledge-driven monitoring. Wickens et al.'s A-SA model and Ha & Seong's ARE model can describe both kinds of monitoring, even though limitations in their modeling exist.

4.3 Bridging Studies on Information Searching Behavior and the Improvement of HMI Design

The problems of a designer of HMI systems will be to decide which of the models best fits the context of the particular task for which a system is being designed and how to improve an existing HMI design or a prototype design through evaluation of human factors. Ha and Seong [70] have developed a computerized system for human performance evaluation in NPPs called the 'HUman Performance Evaluation Support System (HUPESS)'. HUPESS evaluates various objective and subjective performance measures regarding plant performance, personnel task performance, SA, workload, teamwork, and anthropometric/ physiological factors so that it can provide evidence of the safe operation of an NPP for integrated system validation [71]. Human performance measures for various aspects of human cognitive factors such as attention, SA, cognitive workload, communication, and so on generally give us performance results which reveal challenging attributes of HMI design. However, how to improve HMI design is left to the discretion of the designer, even though the evaluation results of human performance provide some implications for design modification. Hence systematic methods are needed to identify design deficiencies leading to poor performance and provide solutions for design improvement.

A human performance model in information searching tasks has been proposed in order to provide a framework that can be used effectively in evaluating HMI designs, providing implications for design modification and/or developing a training program [72]. Similar to the SEEV model [13], this human performance model includes the four determining factors of attention: salience, effort, expectancy, and value as shown in Fig.12. In this model, poor performance in information searching tasks was assumed to be coupled with difficulties (i.e., poor SA, frustration, excessive physical or/and mental load, etc.) caused by the operators' poor mental models or/and poor HMI design.

NPP operators may expect and value various information sources more clearly as their mental models are well-developed through experience and training. This is the reason why experts show better performance than novices in information search tasks [14,74]. On the other hand, salience and effort are matters to be considered during the design of an HMI. Information important to the situation of interest should be designed with an appropriate level of salience and ease of access. If an information source cannot be distinguished clearly from adjacent information sources, sometimes it may be missed by operators. In addition, if it is too difficult to find an information source important to understand a situation, an operator will eventually give up trying to find that information source. For example, the most important information may be presented in a well-designed display that requires only a moment to look at and process.

Ha and Seong [73] have developed an HMI evaluation method named DEMIS (difficulty evaluation method in information searching) for human factors studies in NPPs which is based on the human performance model in information searching tasks and Ha & Seong's ARE model.

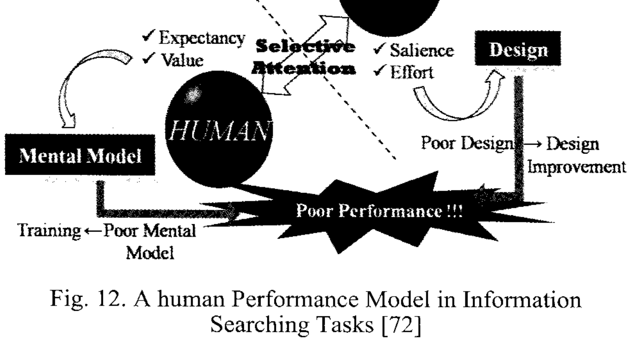

Fig. 12. A human Performance Model in Information Searching Tasks [72]

Human performance in information searching tasks is evaluated by analyzing the attentional resource effectiveness measures FIR and SAE. Operator mental models are evaluated by a questionnaire-based method. Then difficulties caused by poor HMI design (i.e., poor salience and/or heavy effort design) are evaluated by a focused interview (an effort and salience evaluation process) on AOIs which show poor performance (i.e., AOIs having poor FIR values far from unity). Then the root causes leading to poor performance can be identified in a systematic way.

Similar to the DEMIS approach, evaluation results of human performance should be translated into design improvements on the basis of not only the designer's or the evaluator's expertise or preference but also logical mechanisms. To accomplish this, sound models describing mechanisms of cognitive activities during information searching tasks should be developed so as to bridge studies on information searching behavior to design improvements in HMIs.

4.4 A-SA Modeling as a Promising Approach in NPPs

Attention and SA cannot be treated separately in NPP operation. Indeed, attention provides the foundation of correct SA. Especially in NPPs, the operator's information searching behavior is largely governed by not only data-driven monitoring but also knowledge-driven monitoring, which is highly affected by the operator's SA. Hence, in addition to attention, SA should be considered in modeling information searching behavior in NPPs.

Even though Wickens et al. have already formulated their A–SA model, it is not readily adaptable for NPP operation because it was developed for taxiway studies in aviation. Hence, an A–SA model tailored for NPP operation needs to be developed for human factors studies in NPPs.

4.5 Considerations for Studies in Advanced Control Rooms

The adoption of new technologies in the advanced control room (ACR) presents many new challenges. As the processing and information presentation capabilities of modern computers have increased, modern computer techniques have been gradually introduced into the design of ACRs of NPPs [1]. For example, CRT (or LCD)-based displays, large display panels, soft controls, a computerized procedure system, and an advanced alarm system were applied to the ACR of APR-1400 (Advanced Power Reactor-1400) [75].

As O'Hara and Robert [76] have pointed out, there are three important trends in the evolution of ACRs: increased automation, the development of compact and computer-based workstations, and the development of intelligent operator aids. Increases in automation have led to a shift of the operator's role from that of manual controller to supervisor or decision-maker. The role change is typically viewed as positive from a reliability standpoint since unpredictable human actions can be removed or reduced. Thus the operator can better concentrate on supervising overall system performance and safety by automating routine, tedious, physically demanding, or difficult tasks. However, inappropriate allocation of functions between automated systems and the operator may result in adverse consequences such as poor task performance, out-of-loop control coupled with poor SA, and so on [77]. In addition, the shift in the operator's role may lead to a shift from a highly physical to a highly cognitive workload, even though the overall workload can be reduced. Computer–based ACR workstations, which offer much flexibility with their software–driven interfaces such as various display formats (e.g., lists, tables, flow charts, graphs, etc.) and diverse range of soft controls (e.g., touch screens, mice, joysticks, etc.), are thought to affect operator performance as well. Information is typically presented in pre-processed or integrated forms rather than raw data of parameters and much information is condensed on a small screen. In addition, the operator is required to manage the display in order to obtain data and information that he or she wants to check. Hence, poorly designed displays may mislead and/or confuse the operator and thus excessively increase cognitive workloads, which can lead to human error.

Also, challenging issues related to information searching behavior coupled with the introduction of advanced technologies have been raised, such as the following [76]:

- Shift from physical to highly cognitive workload impairing the operator's ability to monitor and process all relevant data.
- Increase in the operator's cognitive workload associated with managing the interface, which is not the primary task.
- Difficulty in navigating through and finding important information which had been in a fixed, dedicated area in conventional control rooms.
- Loss of the ability to utilize well-learned rapid eye scanning patterns and pattern recognition from spatially fixed parameter displays.
- Loss of the operator's SA, making it difficult to assume direct control, which can result from increased automation and the use of operator aids.

Hence much attention should be paid to information searching behavior when advanced technologies are considered for adoption in the control room.

5. SUMMARY AND CONCLUSION

Previously developed models of information searching behavior were reviewed and implications learned from previous studies were addressed for use in human factors studies in NPPs. From this review, it is recommended that

1. A set of symptomatic information sources including both changed and unchanged symptoms and bandwidth should be considered as determining factors governing information searching (or visual sampling) behavior in NPPs,
2. Both data-driven monitoring and knowledge-driven monitoring should be considered and balanced in a systematic way,
3. Sound models describing mechanisms of cognitive activities during information searching tasks should be developed so as to bridge studies on information searching behavior and design improvement in HMI,
4. The attention–situation awareness (A–SA) modeling approach is thought to be promising,
5. As new technologies see wider application in the ACRs of advanced NPPs, information displays are expected to have totally different characteristics. Hence much attention should be paid to information searching behavior including HMI design and human cognitive processes.

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