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A Quantitative Vigilance Measuring Model by Fuzzy Sets Theory in Unlimited Monitoring Task

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Abstract. The theory of signal detection has been applied to a wide range of practical situation for a long time, including sonar detection, air traffic control and so on. In general, in this theory, sensitivity parametric index d' and bias parametric index β are used to evaluated the performance of vigilance. These indices use observer's response "hit" and "false alarm" to explain and evaluate vigilance, but not considering reaction time. However, the reaction time of detecting should be considered in measuring vigilance in some supervisory tasks such as unlimited monitoring tasks (e.g., supervisors in nuclear plant). There are some researchers have used the segments of reaction time to generate a pair of probabilities of hit and false alarm probabilities and plot the receiver operating characteristic curve. The purpose of this study was to develop a quantitative vigilance-measuring model by fuzzy sets, which combined the concepts of hit, false alarm and reaction time. The model extends two-values logic to multi-values logic by membership functions of fuzzy sets. A simulated experiment of monitoring task in nuclear plant was carried out. Results indicated that the new vigilance-measuring model is more efficient than traditional indices; the characteristics of vigilance would be realized more clearly in unlimited monitoring task.

Keywords: Vigilance, Sustained Attention, Fuzzy Sets, Signal Detection, Unlimited Task

1. INTRODUCTION

After system automation, the role of the human operator has changed from that of an active controller to a decision maker and manager, a shift from active to supervisory control (Proctor and Zandt, 1994). The monitoring responsibility includes monitoring automation operating system, starting or shutting off the system and restoring the order, its duty emphasizes question judgment and solution. Therefore, the efficiency of carrying out mostly not directly comes from automatic devices, but panels. As a result of the automated system monitoring task is mostly more boring work, such as: the radar- monitoring, supervisor in a nuclear power plant. Under such an irrevocable work environment, loss of vigilance leads to accidents. When the activity is to be performed for a continuous period of time, the ability to maintain attention or vigilance may be severely impaired. The task is much more difficult if attention must be maintained on some sources of information for the occurrence of infrequent, unpredictable events over long periods of time (Warm and Jeruson, 1984). Smit *et al.* (2004) found that vigilance decreases due to hard mental work, this result may present by the performance of misses, false alarms and reaction times. The ability to maintain vigilance for such events typically declines

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over times, a phenomenon known as the vigilance decrement. Therefore, the vigilance performance measuring value is an important index to improve supervisory environment. A good measurement of vigilance performance can help to understand observers' alert maintenance ability for prolonged periods, further, to approve monitoring environment, to combat the vigilance decrement. The theory of signal detection is a model of perceptual processing that is often used to characterize performance effectiveness in signal detection situations because it permits the derivation of independent measures of perceptual sensitivity and response bias (Kenneth *et al.* 1986; Wickens, 1992). There are two most common sensitivity measuring indices : parametric index d' and its nonparametric analog A'. The most common bias measures are the parametric index β and the nonparametric indices B'_H and B'' (Hodos, 1970; Grier, 1971). Although, in previous researches, these indices were also used to measure vigilance performance, however, there are some restricts on these indices. The main reason is that the reaction time is free response in some supervisory environment. For example, the supervisory monitor in nuclear power plant, he or she must monitor the cooling water level to keep in safety for a long time. This task can be defined as unlimited monitoring task. Therefore, the vigilance performance-measuring index should not only emphasize "Yes" or "No" in decision activity but include reaction time. A reliable detection measure of response bias is particularly critical in this study field, because alterations in response bias are a predominant feature of vigilance performance (Parauraman and Davies, 1977; Parasuraman, 1979).

According to the characteristics of unlimited monitoring task, the stimuli and responses will be of the continuous type and time-series. So some researchers studied the measures of sensitivity and bias obtained from reaction time. Reaction time provides the principal measure in tasks with supra-threshold signals. Silverstein *et al.* (1998) used sensitivity (d') and reaction time to assess the ability of individuals with schizophrenia to sustained attention to visual stimuli. Szalma *et al.* (2004) discussed the effects of sensory modality and task duration on performance by percentages of correct detections and reaction time in sustained attention. Egan *et al.* (1961) used a task without discrete events and without specified observation intervals. Signals were presented at times unknown to the observer, who was free to respond at any time, (i.e., free response). Because stimuli and response form a continuous, mixed time series, classifying the observer's response into hits and false alarms is difficult. Egan *et al.* (1961) developed a technique to cope with the problem. They plotted the observer's response rate as a function of time following a signal. Response rate rose sharply immediately following a signal and then fell to a constant, low level a few seconds later. The probabilities of hits and false alarms were equated with the areas under the two segments of the distribution. By inducing observers to adopt different criteria for reporting targets they were able to generate pairs of hit and false alarm probabilities and plot the receiver operating characteristic curve. However, if we can integrate the concept of hit, false alarm and response time, the measurement of vigilance should be more efficient in unlimited hold tasks. Using membership function of the fuzzy theory is an extremely good method. In view of the domain of decision response, the different weighting value can be assigned, then use fuzzy logic to evaluate the vigilance performance. So, the purpose of this study was to propose a quantitative vigilance-measuring model by fuzzy sets, and verified with other indices by a simulation experiment.

2. MODEL DEVELOPMENT

In unlimited monitoring task, if system appears exceptionally, some unusual signals will appear and must be detected by operator. These external stimuli will generate human neural activity in the brain. Therefore, on the average there will be more sensory or neural evidence in the brain when a signal is present than when it is absent. We refer to the quantity X as the evidence variable. Therefore, if there is enough neural activity, X exceeds a critical threshold X_C, and the operator decides "yes." If there is too little, the operator decides "no." Notice that in the unlimited monitoring task, the abnormal signal will continue and also be more and more intense. Because the amount of energy in the signal is typically low in the early stages, the average amount of X generated by signals is not much greater and less than the criterion, therefore the subject will not say "yes." After period of time, the signal gradually strengthens to let X exceed the criterion X_C, the operator will say "yes." However, it may not be the best time of detecting. This variation is shown in Figure 1. Sometimes, the average amount of X generated by signals in the environment is not much greater than the average generated when no signals are present (noise). Furthermore, the quantity of X varies continuously even in the absence of a signal because of random variations in the environment and in the operator's own "baseline" level of neural firing (Wickens, 1992). This variation is shown in Figure 2. Therefore, even when no signal is present but false alarm, X will sometimes exceed the criterion X_C, and the operator will say "yes." It is apparent that perfect performance is that in which no misses or false alarms occur.

However, no mater what condition, when the detection time approaches the best reaction time, the performance of monitoring task should be the best. If the detection is too early or too late, the performance should be poor. Therefore optimal detection time is the same important as decision activity (yes or no). Using fuzzy logic to evaluate the domain of detection and decision will be a new approach. It could expand the traditional two values logic evaluation to multiple-valued logic and continuous type. Therefore the difference of vigilance in the monitoring "also this also other" task would be described more clearly.

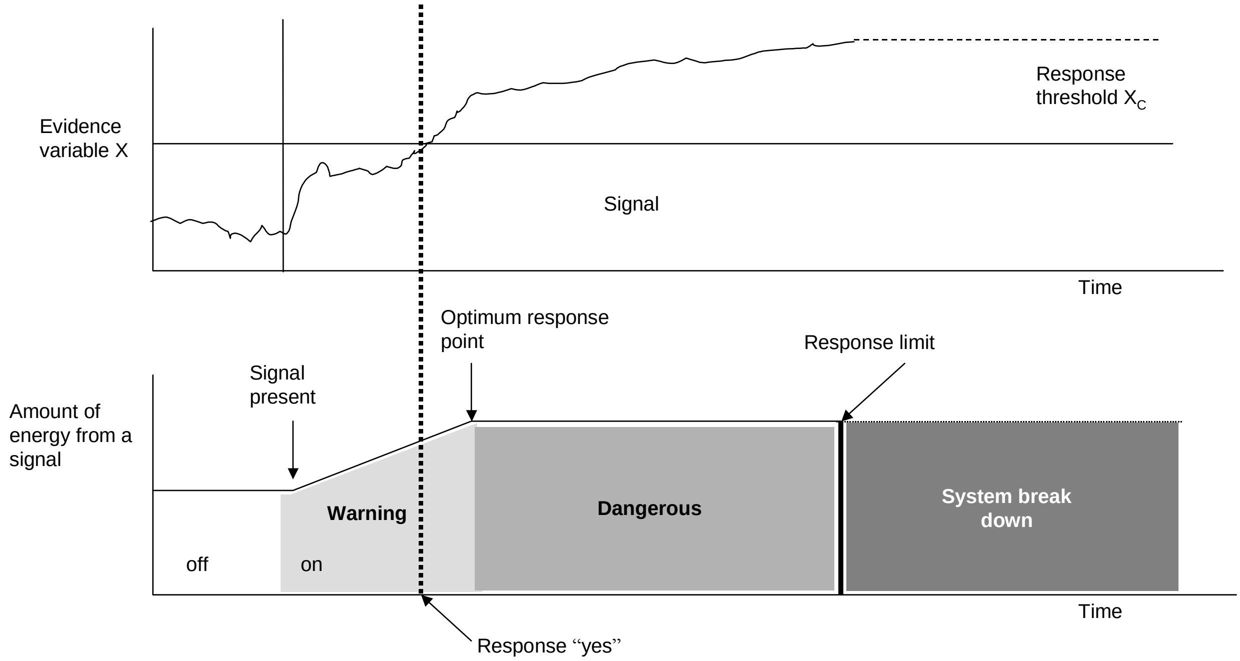

Figure 1. The change in the evidence variable x caused by signal in the unlimited monitoring task

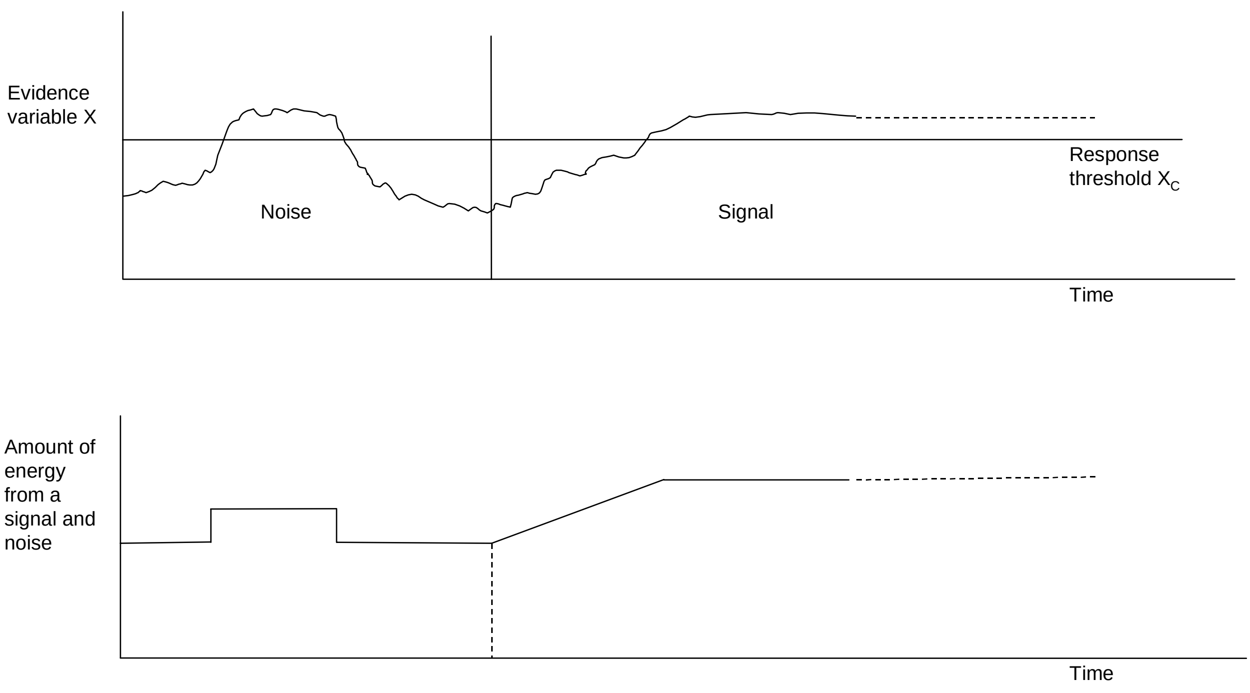

Figure 2. The change in the evidence variable x caused by signal and noise

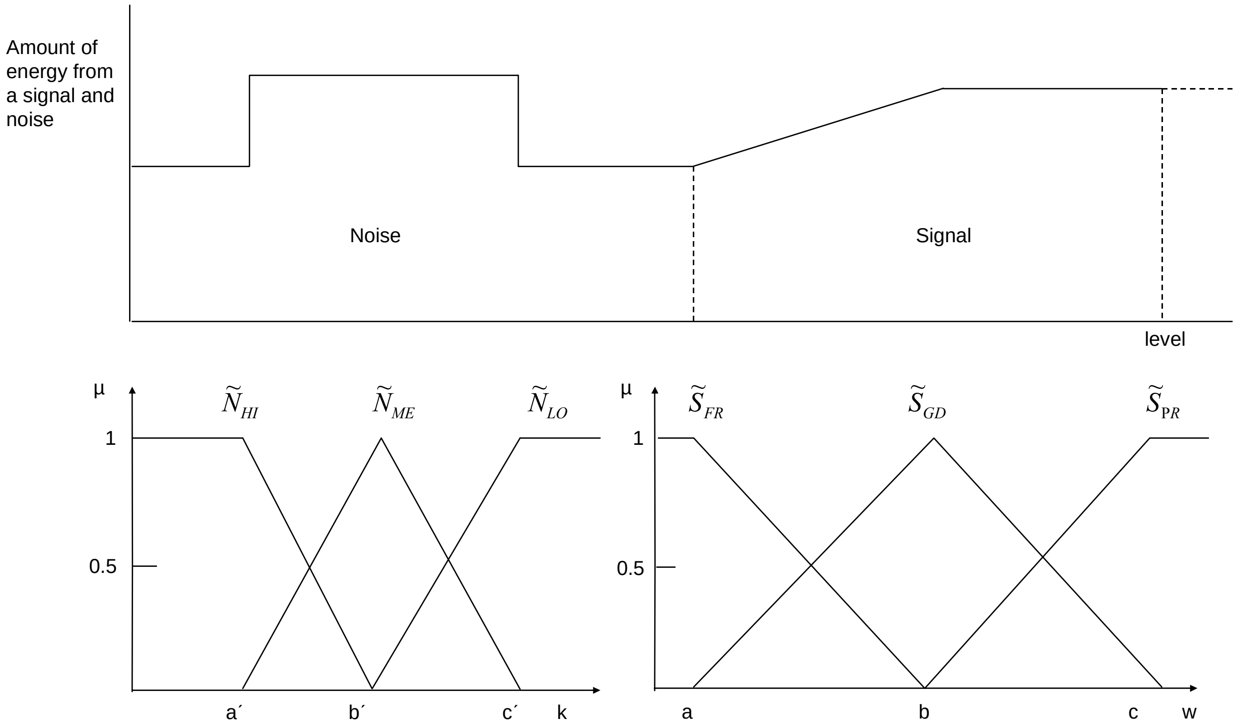

Figure 3. The membership functions of "*ability of signal detecting*" and "*ability of false alarm*"

A fuzzy logic is a set of IF-THEN rules. The linguistic statements of the IF-part are obtained by fuzzyfication of numerical input values, the statements of the THEN-part are defuzzyficated to numerical output values (Zadeh, 1973; Driankov, 1996) Assume the fuzzy rule consists of N rules as follows:

R_j(jth rule):

IF x_1 is A_{j1} and x_2 is A_{j2} and … and x_n is A_{jn}

THEN y_1 is O_{j1} and y_1 is O_{j2} … and y_m is O_{jm}

Where j = 1, 2, …, N, x_i (i = 1, 2, …, n) are the input variables to the fuzzy system, y_k (k = 1, 2, …, m) are the output variables of the fuzzy system, and A_{ji} and O_{jk} are linguistic terms characterized by their corresponding fuzzy membership function $\mu_{A_{ji}}(x_i)$ and $\mu_{O_{jk}}(y_k)$.

Reminding the behavior of human decision-making, we use two factors to construct vigilance performance measuring model: one is the "ability of signal detecting"(Hit), another is the "ability of false alarm" (False alarm). Let us consider the fuzzy set $\tilde{S}$, which represents the linguistic notion "*Ability of signal detecting.*" The fuzzy set is described by the attributes "Good on signal detecting ability" (GD), "Fair on signal detecting ability" (FR) and "Poor on signal detecting ability" (PR). The membership function of $\mu_{S_{GD}}(w)$ is denoted as triangular function: Γ(w; a, b, c). The membership function of $\mu_{S_{FR}}(w)$ is denoted as trapezoid function: Λ(w; a, b). The membership function of $\mu_{S_{PR}}(w)$ is denoted as trapezoid function: L(w; b, c). The $\tilde{N}$ is defined as fuzzy set which represents the linguistic notions "A*bility of false alarm*" including three elements of the domain: "*High false-alarm*" (HI), "*Medium false-alarm*" (ME) and "Low false-alarm" (LO). The membership function of $\mu_{N_{HI}}(k)$ is denoted as trapezoid function: Γ(k; a´, b´). The membership function of $\mu_{N_{ME}}(k)$ is denoted as triangular function: Λ(k; a´, b´, c´). The membership function of $\mu_{N_{LO}}(k)$ is denoted as trapezoid function: L(k; b´, c´). These membership functions are shown in Figure 3.

The output fuzzy set $\tilde{V}$ can be described as the linguistic notion "*Performance of vigilance*" is described by five attributes: "Excellent", "Fine", "Good", "Fair" and "Poor". Let y represents the degree of vigilance performance. If the value of y is high means that the performance of vigilance is high. According to the fuzzy control theory, the concept of "quantization" and "uniform" was used to discretize the continuous domain [-25,125] into six segments by five judgment criterion: 0, 25, 50, 75 and 100. Therefore, we can define the membership function of $\mu_{V_{PR}}, \mu_{V_{FR}}, \mu_{V_{GD}}, \mu_{V_{FN}}, \mu_{V_{EX}}$ as triangular function. Figure 4 shows these membership functions in the domain [-25,125].

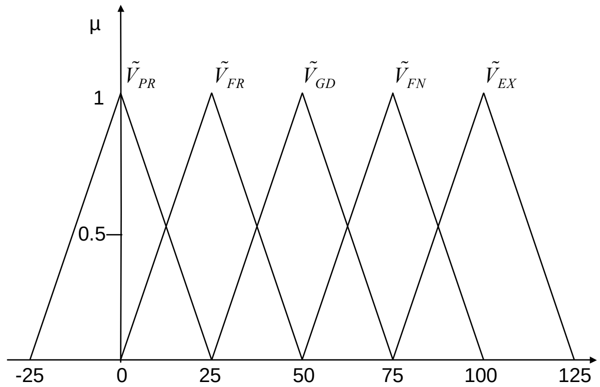

Figure 4. The membership function of "*Performance of vigilance*"

Table 1. Rule base for vigilance performance

Vigilance Performance		*Ability of signal detecting*		
		Poor	Fair	Good
Ability of false alarm	High	Poor	Fair	Good
	Median	Fair	Good	Fine
	Low	Good	Fine	Excel

Rule base is an important part in fuzzy inference. There are nine rules designed in the rule base: multiplying three attributes of the linguistic variable "A*bility of false alarm*" by three attributes of the linguistic variable "*Ability of signal detecting*". Let us consider the i-th rule of the form:

$$\text{Ri : IF w } \textit{is } S^{(i)} \text{ AND k } \textit{is } N^{(i)} \text{ THEN y } \textit{is } V^{(i)}, \quad (1)$$

where $S^{(i)}$, $N^{(i)}$ and $V^{(i)}$ are the linguistic values taken by w, k and y in the i-th rule. These relations can be defined in matrix notion as shown in Table 1.

The degree of fulfillment of the premise of each rule is calculated by combining the membership functions $\mu_S(w)$ and $\mu_N(k)$ into one membership function $\mu_V(y)$.

$$\forall \text{ w, k}: \ \mu_V(y) = \min(\mu_S(w), \mu_N(k)) \quad (2)$$

The final output vigilance alarm value y* is computed by the Center-of-Area method (in the literature also referred to as Center-of-Gravity method), which is well-known defuzzification method (Driankov, 1996).

$$y^* = \frac{\sum_{i=0}^{100} y_i \cdot \mu_{\tilde{V}}(y_i)}{\sum_{i=0}^{100} \mu_{\tilde{V}}(y_i)}. \quad (3)$$

3. EXPERIMENT

An experiment is conducted to verify the effect of the vigilance-measuring model. The experiment is done on the simulated Auxiliary Feed-Water Monitoring System and Heat Sink and Demineralized Water System, which are shown in Figure 5 and Figure 6 (Roth-Seefrid, and Fischer, 1988). There are four steam generators (SG1, SG2, SG3 and SG4), if any SG is under low water level, the subject must detect and inject water. These SGs are fed by the startup and shutdown system (SSS). If the SSS is failure or water level is lower, this experimental design is 5.2 m, the emergency feed-water system (EFS) should be start.

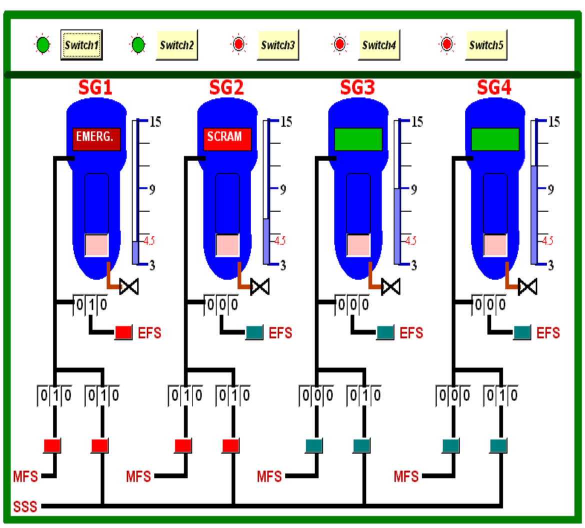

Figure 5. An simulated Auxiliary Feed-Water Monitoring System

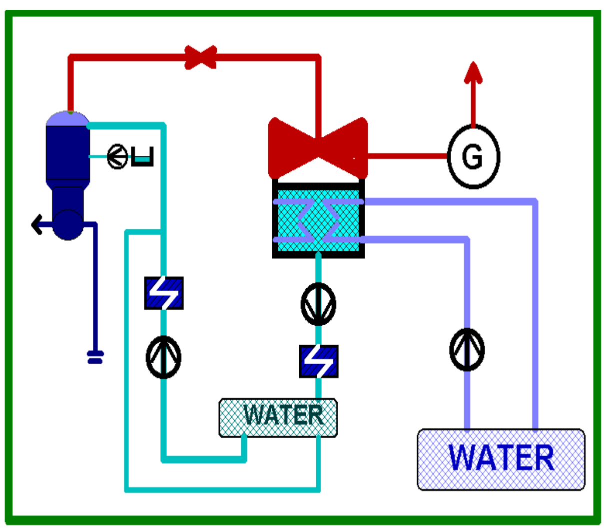

Figure 6. Heat Sink & Demineralized Water Store System

However, sometimes the EFS will fail, when the SGs level is below 5 m the manual feed-water system (MFS) should be start by operator. There are alarm signals designed above the SG, when water level is below 5 m, these signals will flash. However, sometimes, the warning signals will appear exceptionally, for example, the alarm signals flash at water level 6m or not work at water 5 m. The operator must detect and make a correct decision: starting MFS (Hit) or not (Correct rejection).

3.1 Tasks

There are 16 Subjects requested to monitor the cool water feeding situations of SGs and guarantee the system security. If he/she detects the feed water level appears unexceptionally, the manual feed-water system (MFS) should be start immediately. Each subject must accept the training (at least 3 times) to learn how to control the simulated system.

3.2 Experimental design

Onsidering the experiment where we are interested in determining the effect of four parameters, which influenced the performance on decision-making. These four control factors in the study were A – *Alarm status (including None signal, Alarm)*, B – *Emergency complexity (including SG1, SG1 +SG2, SG1+SG2+SG3, SG1+SG2+SG3+SG4)*, C – *Vigilance situation (including urgent condition occurring one time per five minutes and ten minutes)*, D –*Alarm Timing* (*including Alarm at critical level, Alarm beforehand 0.5 m of critical level).* There are two dependent variables designed including: (1) Subject's response water level value: Recording the water level value of subject starts MFS; (2) "Hit" rate: if the operator detect the SG is emergency and start the MFS between 4.95m and 5.05m, defined as "Hit." (3) "False Alarm" rate: if the SG is safety but disturbed by warning signal and not turn off the signal before 5.95 m, defined as "false alarm".

4. RESULTS AND DISCUSSION

In an automation environment, "miss" is type I error; it may cause system shutdown and more serious consequences in automation. "False alarm" is type II error; the result will lose benefits of automation and increase operator's workload and errors. Therefore, in general type I error (miss) is serious than Type Ⅱ error (false alarm). It means that this characteristic should be considered in the vigilance performance-measuring model. The results of experiments were shown in Table 2 and Figure 7. We can find that the rate of false alarm is equal in trial 1 and 3, but the rate of hit is not; therefore the vigilance performance should be different and trial 1 should be better than trial 3. The fuzzy logical value and *d'* have the same result. However, the β violates the principle, therefore, the fuzzy logical model and *d'* are more efficient than β in this study.

Table 2. L_{16} orthogonal array and data summary by experiment of Feed-Water Simulation System

Trials	A 2 3	B 7 8 15	C 1	D 10	A × C 3	B × C 6	B × C 9	B × C 14	C × D 11	Fuzzy Logical Value: Signals detection level	Fuzzy Logical Value: Noise rejection level	Fuzzy Logical Value: Performance	Two-value Logical Value: Rate of Hit	Two-value Logical Value: Rate of False Alarm	β	d'
1	1	1	1	1	1	1	1	1	1	4.97	5.96	88.5	0.8	0.3	0.81	1.37
2	1	4	1	2	1	1	2	2	2	4.85	5.85	67.1	0.3	0.7	0.81	1.37
3	1	2	1	1	1	2	1	2	1	4.94	5.95	82.6	0.6	0.3	1.11	0.78
4	1	3	1	2	1	2	2	1	2	4.90	5.89	73.8	0.4	0.6	1.00	0.51
5	2	2	1	2	2	2	1	2	2	5.03	5.91	88.0	0.8	0.5	0.70	0.84
6	2	3	1	1	2	2	2	1	1	4.99	5.94	90.9	0.9	0.4	0.31	1.81
7	2	1	1	2	2	1	1	1	2	5.03	5.96	92.3	0.8	0.3	0.81	1.37
8	2	4	1	1	2	1	2	2	1	4.93	5.90	78.1	0.6	0.6	1.00	0.00
9	1	4	2	1	2	1	2	1	2	4.89	5.89	72.8	0.4	0.6	1.00	0.51
10	1	2	2	2	2	1	1	2	1	4.96	5.89	81.7	0.7	0.6	0.90	0.27
11	1	3	2	1	2	2	2	2	2	4.92	5.91	77.3	0.5	0.5	1.00	0.00
12	1	1	2	2	2	2	1	1	1	4.96	5.94	85.2	0.7	0.4	0.90	0.78
13	2	4	2	2	1	2	2	2	1	5.07	5.84	80.1	0.6	0.7	1.11	0.27
14	2	1	2	1	1	2	1	1	2	4.99	5.98	94.8	0.9	0.2	0.43	2.40
15	2	2	2	2	1	1	2	1	1	5.02	5.92	89.6	0.8	0.5	0.70	0.84
16	2	3	2	1	1	1	1	2	2	4.98	5.94	88.9	0.8	0.4	0.73	1.10

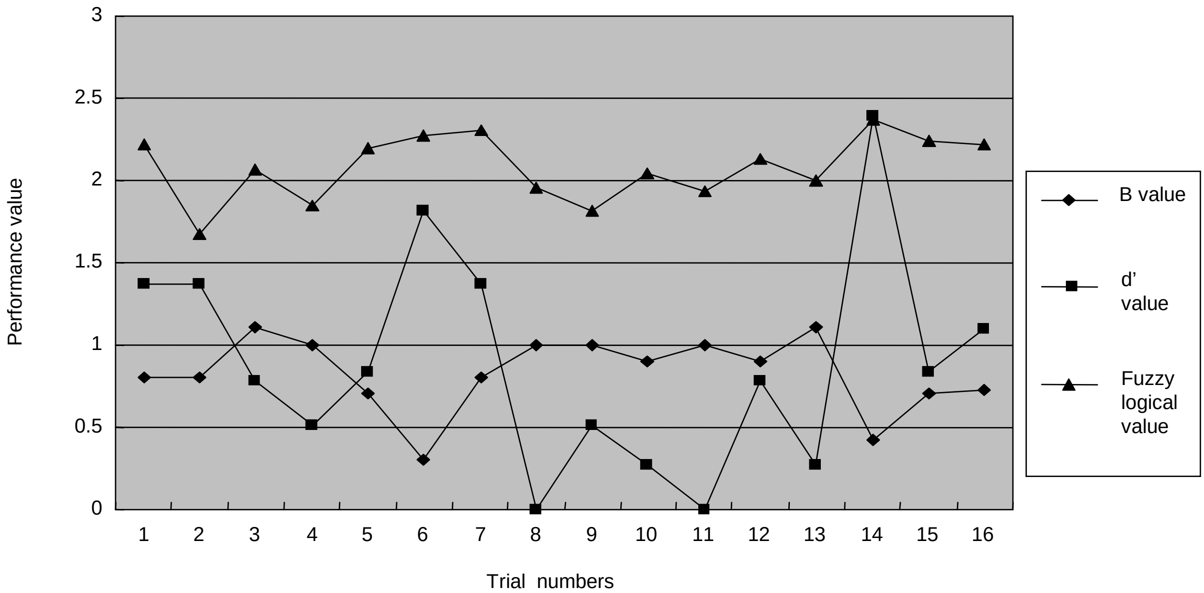

Figure 7. Plots of value of Fuzzy logical value and other indices in sixteen trial

The correlation coefficient between index *d'* and fuzzy logical model was 0.569. What is the difference? We can find that in trial 4 and 9 subjects detected the noise signal at the same water level 5.89 m, but the time to start MFS (manual feed-water system) was different. In trial 4, the time was closer the critical water level 5 m. Therefore the vigilance performance in trial 4 is better than trial 9. And in trial 8 and 11 the rate of hit is equal to false alarm, the *d'* value is zero. It means that the index will be low sensitivity when the rate of hit is equal to false alarm. However, the fuzzy logical model could clearly present this characteristic than *d'*. On the other hand, in trial 2 and 7 the rates of hit and false alarm are extreme difference, however, the value of *d'* is equal to β. It means that these indices appear scotoma. The fuzzy logical model could demonstrate this obvious difference (67.1: 92.3).

In this study, we can find that the fuzzy logical model and index *d'* used to evaluate vigilance performance are more efficient than β. However, if the operator response is low rate in "Hit", the *d'* value will be non-efficient.

5. CONCLUSIONS

In this study, a quantitative fuzzy logical vigilance-measuring model with relation to human decision-making in unlimited monitoring task was proposed and verified by the simulation experiment. The main findings of this study are as follows:

a) In general, sensitivity parametric index *d'* and bias parametric index β are used to evaluated the performance of vigilance. These indices only used observer's response "yes" or "no" to explain and evaluate vigilance. However, some supervisory tasks such as unlimited monitoring tasks (e.g., supervisors in nuclear plant), the reaction time is longer. These indices are unable to present this characteristic, but the fuzzy logical model could.
b) A good vigilance performance-measuring model should consider the difference among Type I error (miss), Type Ⅱ error (false alarm) and reaction time in unlimited monitoring tasks. Using fuzzy sets to evaluate the domain of decision response could conform to this condition. It could expand the traditional two values logic evaluation to multiple-valued logic and continuous type. Therefore the difference of vigilance in the monitoring "also this also other" task would be described more clearly.
c) The fuzzy logical model and *d'* are more efficient in response sensitivity than β in this study. The correlation coefficient between index *d'* and the fuzzy model is 0.569. However, if the operator response is low rate of "Hit", the *d'* value will be non-efficient. The fuzzy logical model could avoid this result.
d) By using fuzzy sets and fuzzy rule base, the fuzzy logical model combined the "*Ability of signal detecting*" and "A*bility of false alarm*" to evaluate vigilance.

According to the result of fuzzy inference, therefore we can take one step ahead to analyze and design when and how to call operator's attention at the right time by setting an adapted vigilance performance alarm to reduce the probability of human decision-making error.

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