Approaches at KAIST NICIE Lab to quantifying situation awareness in nuclear power plant MCRs

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Abstract: Situation awareness (SA) continues to receive a considerable amount of attention from the ergonomics community. But, techniques to measure SA have normally used expert judgment or a self-rating method so far. One of the problems of these techniques is inconsistency of results. So, empirical and analytical studies on an objective and quantitative SA measurement methods have been carried out at Nuclear I&C and Information Engineering Lab (NICIE Lab) in Korea Advanced Institute of Science and Technology (KAIST). Empirical studies are based on physical and cognitive human behaviors, whereas analytical studies are mainly based on Bayesian inference. Eye movement signals and verbal protocol analysis were used for empirical approaches to obtain objective measures. *FIR* and *SAE* measures showed feasibility of an eye-tracking method for robust application. TSA score based on a verbal protocol analysis also showed its possibility of team SA (TSA) quantification. Bayesian inference was used for analytical approaches of SA quantification. The analytical quantification method was further expanded to consider some of the important human properties, and a SA modelling tool called '*CoRSAGE, ver01*" was developed.

Keyword: situation awareness; quantification; empirical approach; analytical approach

1 Introduction

Systems become complex due to competitive business environment and safety issues, and thus more tasks are being assigned to nuclear power plant (NPP) operators to run plants safely and efficiently. Operators accomplish those given tasks by exerting series of cognitive activities, such as monitoring, detection of data or information, diagnosis, decision making, response planning, and implementation[1]. Thus the chief concern of the NPP management has been to enhance operators' performance of those activities and to improve human-machine interface (HMI) in recent decades. One of the most well-known ways of evaluating human cognitive activities and the performance of HMI is to measure operator's situation awareness (SA). This paper reviews studies on quantitative SA evaluation methods of NPPs operators for both human performance and HMI improvement at NICIE Lab in KAIST.

2 Situation Awareness (SA)

2.1 What is SA?

Although there are many perspectives on SA because its functional role and usage are dependent on industrial specific environments and tasks, the term 'SA' has been pervasively used to describe individual's dynamic understanding of 'what is going on' in the specified environment[2]. Most popularly cited one in a general term is Endsley's summarized definitions that SA is perception of elements of 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)[3].

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2.2 How has SA been measured?

Several SA measurement techniques have been developed for various purposes. SA measurement techniques are categorized according by applied methods; performance index methods, questionnaire/survey methods, subjective evaluation methods, and physiological methods[2,4]. Among them, Situation Awareness Global Assessment Technique (SAGAT) and Situation Awareness Rating Technique (SART) approaches are by far the most commonly applied during individual and team SA assessment. SA measurement techniques mainly rely on verbal examinations of critical incidents. According to SA measurement techniques' technical distinction, they are;

- Freeze probe techniques; SAGAT
- Real time probe techniques; Situation Present Assessment Method[5]
- Self-rating techniques; SART
- Observer rating techniques; Situation Awareness Behavioral Rating Scale[6]

Typical measurement techniques, other than those mentioned above, are as follows.

- Process indices; eye tracking, verbal protocol analysis, *etc*.

3 Empirical approaches

The purpose of empirical approaches is to investigate objective relationship between some distinct human behaviors (both in physical and cognitive) and SA. Experiments were conducted from the individual level to the team level.

3.1 An individual SA measure[7]

3.1.1 Biomedical signal analysis

Eye movement was chosen as a suitable biomedical signal for an objective SA measurement. The number or the duration of eye fixation is obtained from the eye-tracking system (ETS). The ETS (FaceLAB™ 3.0)[8] was utilized for the measurement of eye movement data for the study.

3.1.2 An Attention-resource Effectiveness Measure

In order for operators to effectively monitor and detect the state of a system, they should allocate their attentional resources to valuable information sources. We developed two measures of attentional-resources effectiveness in information searching at NPP's HMI. Three principles are applied from cost–benefit analysis for the development of attentional-resources effectiveness measures[9].

3.1.2.1 Fixation-to-Importance Ratio[10]

For most operators, the primary means of information input is through the visual channel. If attentional resource effectiveness for an individual information source is specified with the number and the duration of eye fixation of an operator, fixation-to-importance ratio (*FIR*) is given by the following Eqs. (1) – (3).

$$FIR^N(i) = \frac{N_i / \sum_{i=1}^{k} N_i}{\omega_i / \sum_{i=1}^{k} \omega_i} \tag{1}$$

$$FIR^D(i) = \frac{D_i / \sum_{i=1}^{k} D_i}{\omega_i / \sum_{i=1}^{k} \omega_i} \tag{2}$$

$$FIR(i) = \frac{FIR^N(i) + FIR^D(i)}{2} \tag{3}$$

where, $FIR^N(i)$ is the *FIR* with respect to number of fixations, $FIR^D(i)$ the *FIR* with respect to duration of fixations, N_i (or D_i) the number (or duration) of eye fixation on information source i, k the total number of information sources, and ω_i the importance of information source i.

3.1.2.2 Selective Attention Effectiveness

The second principle is that relative attentional resources spent on an information source should be equal to the relative importance of the information source in order to maximize attentional resource effectiveness. Consequently, all $FIR(i)$ should approach unity. The third principle is that an overall measure for attentional-resource effectiveness is the averaged absolute values of $[FIR(i)\text{-}1]$ for all information sources:

$$SAE = \frac{\sum_{i=1}^{k} |FIR(i) - 1|}{k} \tag{4}$$

where, *SAE* is the selective attention effectiveness. Hence, *SAE* should approach zero to maximize overall attentional-resource effectiveness.

3.1.3 Experiments and results

The objective of the experiments is to investigate the relationship between the *SAE* and SA. Endsley's SA model was used for comparison. The experiments were conducted on a FISA2/PC PWR type NPP real time micro-simulator, which was developed at KAIST with Chosun University. Figure 1 shows a view of eye fixation data on a nuclear steam supply system of the simulator.

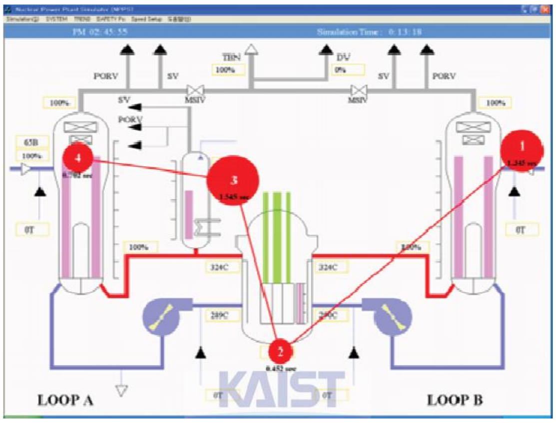

Fig. 1. GUI of FISA2/PC PWR type NPP simulator.

The subjects were 15 graduate students (14 males and 1 female) with nuclear engineering background for 5.2 years in average. 6 diagnosis tasks including steam generator tube rupture - loop A (SGTR (A)) and steam line break - loop B (SLB (B)) out of 14 diagnostic tasks were randomly given to the subjects. The *SAE* and SA measures were evaluated for the diagnosis tasks in four cases: (1) before training, (2) after training, (3) before training after 6 months of (1) and (2), (4) after training after 6 months of (1) and (2).

Perception failure rate (*PFR*), which is calculated from the subject's answers to the trends of selected process parameters, is used as a measure of detection (level-1 SA). Diagnosis score (*DS*) which is calculated from the subject's diagnosis results (correct=1 and false=0) multiplied by confidence level (*e.g.*, 100 % or 50 %) is used as a measure of understanding and projecting the near future (level-2 and 3 SA). Finally, the *PFR* and the *DS* are incorporated into a SA score as follows:

$$SA\ score = 50 \times (1 - PFR) + 0.5 \times DS \qquad (5)$$

Two levels of information sources such as component and indicator levels are considered for the evaluation of the informational importance. The component level is the higher level. The results of the experiments are summarized in Figures 2, 3, 4 and Table 1. The results show clear correlations between the *SAE* and the SA measures. All pearson-correlation coefficients are higher than 0.9 and all values of R^2 are also higher than 0.8. Hence, it is concluded that the *SAE* can be used as a SA measure.

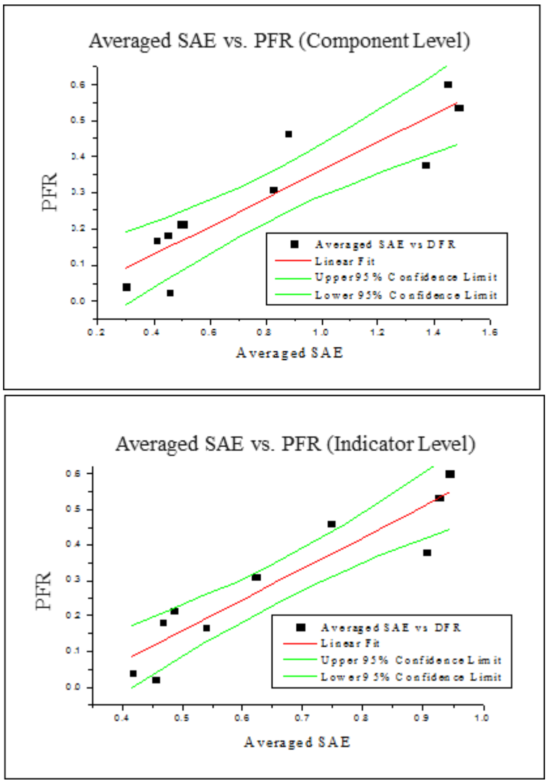

Fig. 2. Comparison between *SAE* and *PFR*.

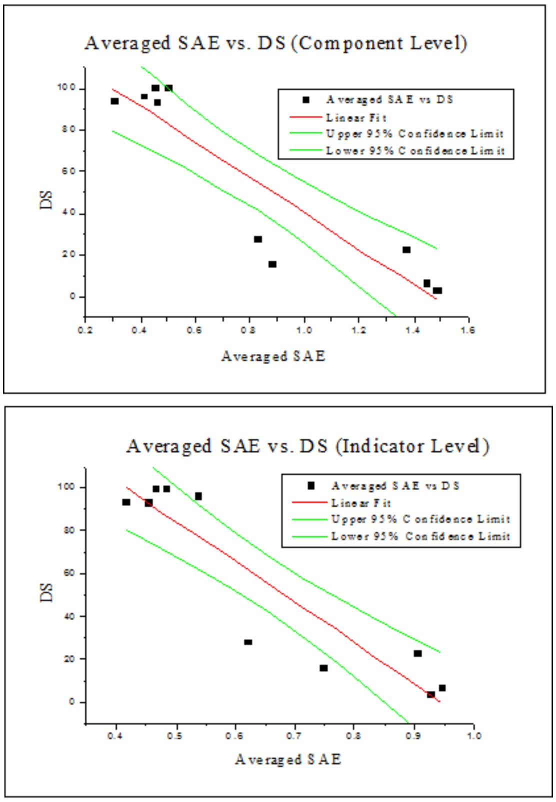

Fig. 3. Comparison between *SAE* and *DS*.

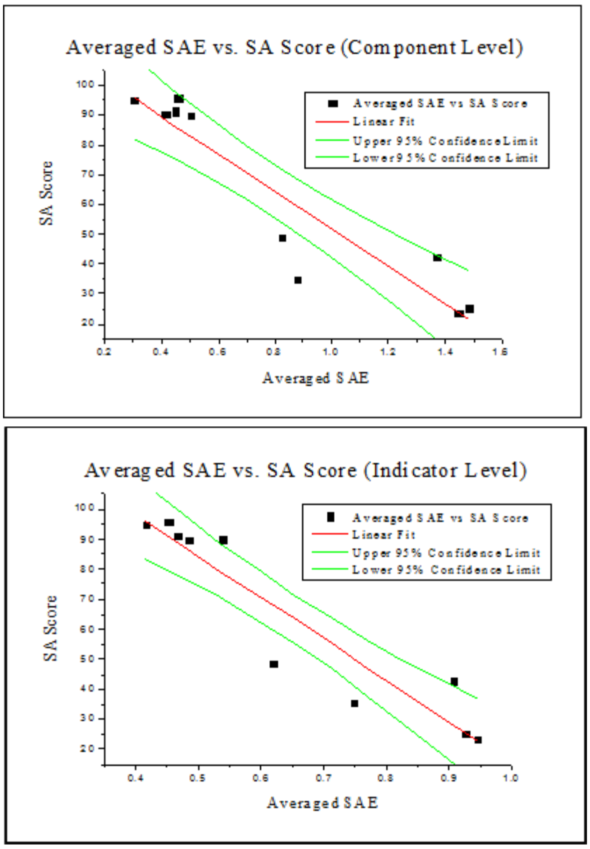

Fig. 4. Comparison between *SAE* and *SA Score.*

Table 1. Results of the Experiments.

Level	*SAE* vs. *PFR*	*SAE* vs. *DS*	*SAE* vs. *SA score*
Component	ρ=0.9047 R^2=0.8186	ρ=0.9149 R^2=0.8370	ρ=0.9304 R^2=0.8657
Indicator	ρ=0.9287 R^2=0.8625	ρ=0.9225 R^2=0.8510	ρ=0.9435 R^2=0.8901

Generally, a subject who has a good mental model or a high level of expertise is expected to more effectively monitor and detect the states of a system than a subject who has a poor mental model for a low level of expertise. The proposed measures of attentional resources effectiveness, *SAE* and *FIR*, are thought to be able to reflect this kind of characteristics, and thus to represent the effectiveness of selective attention in monitoring and detection of tasks. Also, information sources, which are important but infrequently fixated, can be found out by examining *FIR*. In addition, effective monitoring and detection are examined as a prerequisite for correct SA. Hence, the measures developed in this research can be used as a good indicator of NPP operators' SA.

3.2 A team SA measure[11,12]

Modern systems are complex and focused on not just physical tasks, but on elaborate perceptual and cognitive tasks as well. Complex and dynamic environments such as that of a main control room (MCR) in a NPP are operated by operation teams, so team situation awareness (TSA) is cited as an important factor. Understanding TSA can provide a window onto the characteristics of team acquisition as well as the performance of a complex skill.

3.2.1 Verbal protocol analysis[13]

Verbal protocol data are regarded as all types of information being verbalized in the course of mental processes. Development of a well-defined speech act coding scheme is vital to conduct a verbal protocol analysis[14]. Among various speech act coding schemes, the speech act coding scheme, developed by the Korea Atomic Energy Research Institute (KAERI)[15] to analyze NPP operators, is adopted and specific elements in the speech act coding scheme for the corresponding cognitive activities required for TSA were derived.

3.2.2 Development of TSA measurement method

3.2.2.1 Construction of logical connections between team communications and TSA

The information processing tasks were broken down into their constituent elemental information processing steps to understand the decision-making activity. A SA model was developed as a high level model of the tasks that the operator has to perform, and each of the individual tasks within the high level model was then described further in activity flow diagrams. Operators in a main control room (MCR) need to perform cognitive activities, such as 'identification' and 'recognition' to have Level 1 SA. They also require 'identification' and 'determination' for Level 2 SA, and 'prediction for Level 3 SA. An important finding was that certain cognitive activities were required before each level of SA is gained. As a result of the research, cognitive activities of 'observation' for level 1 TSA, 'identification' for Level 2 TSA, and 'prediction, evaluation, and definition' for Level 3 TSA were required to achieve each level of TSA. Overall processes for developing concrete connections between team communications and TSA is shown in Figure 5.

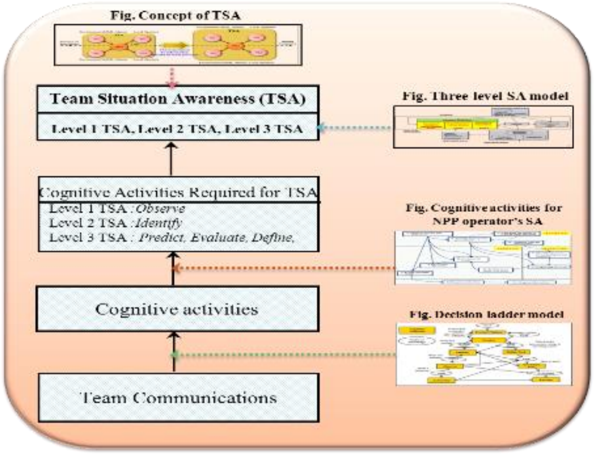

Fig. 5. Overall processes for making logical connections between team communications and TSA.

3.2.2.2 TSA measurement

A human has goal-oriented characteristics, therefore even though the task is proceduralized, operator first sets the goal of the task, and perceives the task by structuring the task steps as the means to achieve goal. To consider the quality of the TSA and importance of the higher level TSA, SA information requirements which can be derived using goal-means task analysis is used since there can be difference of the quality of TSA based on the amount of actual information used. Thus, equation for measuring TSA (see Eq. (6)) can be suggested as calculating the number of relevant communications used to construct each level of TSA with considering situation awareness information requirements as shown in the Figure 6.

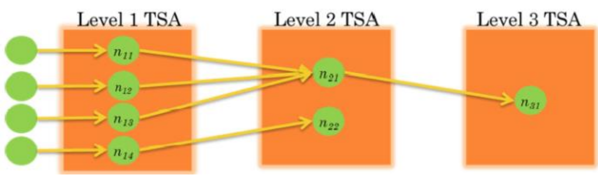

Fig. 6. An example for measuring TSA with modified TSA measurement method.

$$\text{TSA Scores} = \sum_i \sum_j C(n_{ij}) \begin{cases} i = 1, 2, 3 \ldots m \\ j = 1, 2, 3 \ldots m \end{cases} \quad (6)$$

where, $C(n_{ij})$ is the number of relevant communications used to construct node n_{ij} (jth node in level i TSA)

4 Analytical approaches

The present aim of analytical approaches is to find a possible way to express human cognitive processes through mathematical methods. So far, the most logical and suitable way is to apply Bayesian inference. The ultimate goal of the research is to connect human and the ideal mathematical theory to express the real situations as accurate as possible without any extra experiments for V/V.

4.1 An ideal operator's SA measure[16]

4.1.1 Computational SA update

Bayesian inference was chosen to best describe production rules in a quantitative manner because it is a kind of way to express a production rule (WHEN(IF)-THEN logic). We employed following two assumptions to define NPP operators' mental model.

(1) Different kinds of plant state can be modeled to be mutually exclusive.
(2) Operators have deterministic rules on plant dynamics.

Let X indicates the states of the NPP, a set of Y_i (i=1,2,…,m) indicates various information sources, such as indicators and annunciators. Then, X and Y_i are defined as follows:

$$X = \{x_1, x_2, \ldots, x_l\} \quad (9)$$
$$Y_i = \{y_{i1}, y_{i2}, \ldots, y_{in_i}\} \quad (10)$$

where, $i = 1, 2, \ldots, m$.

Deterministic rules of IF-THEN can be described mathematically by conditional probabilities as follows:

$$P(y_{ij}|x_k) = \begin{cases} 1, & \text{if } y_{ij} \text{ is expected on } x_k \\ 0, & \text{if } y_{ij} \text{ is not expected on } x_k \end{cases} \quad (11)$$

If the operator observes y_{ij} in a set of indicators Y_i, then the probability of a state of the NPP x_k is revised according to:

$$P(x_k|y_{ij}) = \frac{P(y_{ij}|x_k)P(x_k)}{\sum_{h=1}^{l} P(y_{ij}|x_h)P(x_h)} \quad (12)$$

Physical meaning of the result from Bayesian inference was used to represent operator's level of confidence in doing given tasks. Thus the level of confidence in operator's mind can be updated by repeating Eq. (12) with upcoming information.

4.1.2 Knowledge-driven Monitoring

We assumed that an ideal operator search information with knowledge-driven monitoring. Knowledge-driven monitoring is described based on the expected information from each indicator, which can be calculated based on the information theory. The detailed explanation is described in the reference by Kim and Seong[17]. The expected information T from an indicator Y_i is given as follows,

$$T(X;\ Yi) = H(X) + H(Yi) - H(X;\ Yi) \qquad (7)$$

$$H(A) = \sum_i p(a_i) log_2 \frac{1}{P(a_i)} \qquad (8)$$

a_i is an information source, where i = 1, 2, 3…m.

The manual control is assumed to be determined by the situation model of human operators. It is assumed that the relations between the situation model of human operators and the manual control are also deterministic.

4.2 Consideration of human properties[18,19]

Endsley pointed out that the human cognitive processes are important for the development of SA. She explains that the cognitive processes, such as perception, attention, pattern matching, and metacognitive processes, are affected by both task and system factors and individual factors. Thus we selected the following three factors to be implemented in the proposed model by considering their major impact on SA: Attention, working memory decay, and mental models.

4.2.1 Attentions

Since operators acquire necessary information by virtue of attention, attention provides the basis of situation awareness achievement. The proposed model assumes that both the salience level and the information value (*IV*) of information sources are the main factors for determining an attention allocation. We define the perception index (*PI*) of the information source as follows:

$$PI = \sqrt{SL \times IV} \qquad (14)$$

where, *SL* is the salience level and *IV* is the normalized information value of the information source.

4.2.2 Mental model

Learning, education, training, and other experiences enable operators to form appropriate mental models on plant dynamics in their long-term memories. Bayesian networks offer nodes, arcs, and conditional probability tables, and these can be used to encode an operator’s knowledge on plant dynamics, so-called a mental model. There are two methods for encoding operator’s knowledge in a Bayesian network. One is the deterministic rules that Kim and Seong[20] prefer, another is the probabilistic rules that Miao *et al.*[21] suggested. The proposed model uses the probabilistic rules to encode operators’ mental models

4.2.3 Working memory decay

In the proposed model, SA is retained in working memory because it would be updated whenever operators attend indicators (information sources) during situation assessment. Formulas to explain working memory decay can be suggested as two types: a power law and an exponential law. Elliott and Anderson[22] argues that memory decay in categorization work is closer to a power law than an exponential law. However, exponential decay formulas, which we employed, seems to be more popular[23].

4.3 Development of quantitative SA measurement tool

Training is also frequently listed in general applications of SA evaluation. Unfortunately, almost all methods are either subjective or qualitative, and often unpractical for a training purpose. Additionally, unlike practice of SA in HRA, the usage of SA in training needs real-time feedback to trainees to yield better results. Thus applicability of such methods to time restricted real training programs is supposed to be very low. Since the problems indicate, the core matter of using SA in training is the lack of well-developed or robust measurement tools. Therefore, an intuitive and easy-to-use program for a real time SA measurement called ***Co***mputational ***R***epresentation of ***S***ituation ***A***wareness with ***G***raphical ***E***xpression (*CoRSAGE*) was developed based on the PN and Bayesian inference.

4.3.1. Development of components and rules

A German mathematician Carl Adam Petri defined a general purpose tool for mathematically describing relationship between conditions and events which was called a PN. To achieve one of the main purposes of the tool – easy handling –PN was used for graphical manipulation of human information processing. The PN enables a discrete event system of any kind whatsoever to be modeled. To make graphical expression simpler, three components were newly proposed: a non-volatile memory token, a volatile memory token, and an inference transition.

Generally, the more pieces of information comes to the operator, the more expected events are created in operator’s mind. In reality, operators do not consider such many possible events. So, we assumed that operator could only handle the maximum of four events in dynamic situation based on several literatures about the limited capacity of human working memory. To implement this phenomenon to the tool, three rules below were set to determine some of undecided probabilities. Summarized descriptions of the rules are:

(1) *Threshold probability rule*: When an event has probability that is less than threshold, the event is considered to be negligible,
(2) *Initial probability of an expected event rule*: When a new event is generated by observing information, the initial probability of the event is taken from the least probable event, and
(3) *Event substitution rule*: When new events are generated by observing information, new events are given initial values according to 'the initial probability of an expected event rule' and substituted for the least probable event. Then, the value of the least probable event is divided by the number of the rest events and added to each event.

CoRSAGE is a Windows based program and the example result of produced by *CoRSAGE* is shown in Figure 7.

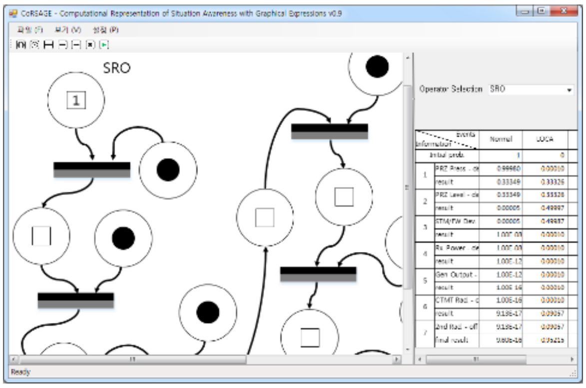

Fig 7. An example result by *CoRSAGE*.

5 Summary and conclusion

Evaluation of SA has been one of the important topics in the human factors engineering (HFE) society because SA evaluation results can be used for many purposes. But, many of the SA measurement techniques are based on either expert judgment or self-rating. Although, these techniques may produce profound insight of operator's SA in a descriptive manner, problem is that the results are not always consistent. Moreover, techniques developed so far do not consider much about SA of teams. To overcome these weaknesses of current SA measurement techniques, quantitative SA measurement methods have been studied with two main streams in NICIE Lab. One is the empirical approach, while the other is the analytic approach. The major results conducted by NICIE Lab. until now are summarized as follows:

(1)Eye movement signals and verbal protocol analysis were used to obtain objective measures.
(2)FIR and SAE measures showed feasibility of the eye-tracking method for robust application.
(3)TSA score based on verbal protocol analysis also showed its possibility of team SA quantification.
(4)Bayesian inference was used for analytic approach of SA quantification.

Measuring SA using Bayesian theory has been controversy, so tool was made and sets of simulation training conducted by real NPP operators were video recorded for V/V of the Bayesian inference based method. Lastly, some researchers view that measuring SA in a quantitative manner is not a proper way. But, we believe that the quantitative method we developed will show a new perspective of SA measurement and its applications.

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