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Evaluation of User Interfaces in Plant Operations by Using Human Information Processing Models

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Evaluation of User Interfaces in Plant Operations by Using Human Information Processing Models *

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Abstract

The development of user interfaces involves three iterative steps: design, prototyping and evaluation. In this research, we propose two methodologies to support user interface evaluation. Static evaluation is performed to assess the visual effect of graphic panels, while dynamic evaluation is done to evaluate alarm systems in an emergency.

In static evaluation, a visual performance model is presented to evaluate graphic panels from the viewpoint of human perception. Based on Weber-Fechner's law, we calculate the visual strength of each graphic item to evaluate its visual performance, i.e. its capability to communicate a distinct message to human operators. Visually weak items on a panel and the possible causes of such weakness are found by comparing their visual strength with a threshold. According to these findings and some guidelines for improvement, the panel is modified.

Based on the model human processor proposed by Card et al., we represent an operator model, which substitutes for a human operator as a virtual subject to evaluate the plant alarm systems. The operator model includes a perceptual processor, short-term (STM) and long-term memories (LTM), a cognitive processor, and a motor processor. Knowledge bases for variable information, failure-symptom relations, and alarm management, as well as an abnormal-state-supervising procedure, are constructed in the long-term memory. The operator model automatically generates a fault detection and identification (FDI) track in an emergency, which consists of perception, cognition,

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STM, and LTM subtasks. By analyzing the FDI track, we evaluate the usability of alarm systems.

Both static and dynamic evaluation approaches are applied to a boiler plant simulator for training. We modify the overview, engineering and operational panels based on the results of the static evaluation. Evaluation results of the modified panels show the visual performance is improved. Based on the dynamic evaluation, alarm settings of the boiler plant are adjusted, and FDI performance is improved. These achievements show that the proposed quantitative evaluation methodology can be used as a support tool for the design of graphic panels and alarm systems.

Keywords:
operator model, plant operation, graphic panel, visual performance, alarm system, model-based evaluation, fault detection and identification

List of Publications

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2. **Liu, X.**, Kosaka, H., Noda, M., and Nishitani, H.: Model-based dynamic evaluation to support the design of alarm systems—Part 1: Development of virtual subject, *Journal of the Society for Industrial Plant Human Factors of Japan* (accepted).

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3. **Liu, X.**, Kosaka, H., Noda, M., and Nishitani, H.: Model-based approach to graphic panel evaluation for plant operations, Proceedings of PSE Asia 2005 (The 3rd International Symposium on Design, Operation and Control of Chemical Processes) pp. 615-620, Seoul, Korea, August 18–19, 2005.
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2. **Liu, X.**, Kosaka, H., Noda, M., and Nishitani, H.: Support tool for design of graphic panels in plant operations, Proceedings of the Human Interface Symposium 2005, pp. 173–178, Fujisawa, Sep. 15–17, 2005.
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1 INTRODUCTION

1.1 Background

In recent years, industrial processes are becoming increasingly complex while being manipulated by fewer operators. At the same time, companies are demanding high standards of safety, reliability, quality, and efficiency. Many aspects such as instrumentation, control strategy, user interface, alarm management, and operation support system are involved in meeting these demands. As shown in Fig. 1.1, a human supervisory control system is generally composed of three parts: operator, machine, and user interface. User interfaces of supervisory control and data acquisition software supply information about plant situation, and receive commands from a human operator. Simultaneously, user interface software needs to access real-time data to display. All of these functions are implemented through one or several visual display terminals (VDT) such as cathode-ray tube (CRT) or liquid crystal display (LCD) monitors in a distributed control system (DCS). User interfaces are critical for the overall performance of the human supervisory control system. Especially, the hardware technology has been highly advanced for high resolution, high reliability, and high sampling rate control instruments with network communication functions. The problem of user interfaces can be viewed as two powerful information processors (human and computer) attempting to communicate with each other via a highly constrained interface [1]. A user interface in plant operations may bottleneck human performance of plant operations.

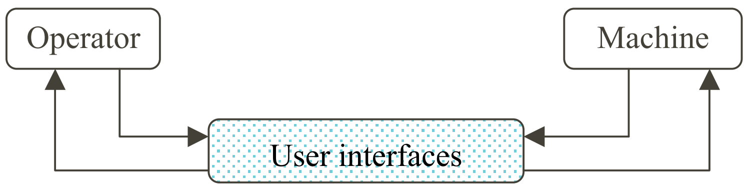


Figure 1.1 Architecture of human-machine interaction

User interfaces are the aggregate of means by which users interact with a particular machine, device, computer program or other complex systems [2]. They provide input to allow users to control a system and output to allow the system to inform/feedback the users. Comparing with user interface systems of everyday things, user interfaces in plant operations are used by skillful human operators and these are safety critical. Intuitive and friendly user interfaces are desired in daily life, but correct, consistent and quick responses are emphasized for the user interfaces in plant operations. For effective operations, colors and shapes are coded as defined meanings. The type of colors with coding of process information is restricted owing to human memory's limitation. Symbols and icons must be drawn following an established standard. Alarm management system defines how to present an alarm and requires corresponding acknowledgement operations. As an important goal, the user interfaces in plant operations are required to minimize workload of the operators, especially in an emergency.

The development of user interface systems involves three iterative steps: design, prototyping, and evaluation [3]. Usability evaluation is an important means to improve user interfaces. Usability is a term used to denote the ease with which people can employ a particular tool or other human-made object in order to achieve a particular goal. As the ISO ergonomics definition [4][5], usability is a measure of "the effectiveness, efficiency and satisfaction with which specified users can achieve specified goals in a particular environment". The effectiveness is measured as the accuracy with which the users are able to achieve specified goals. Efficiency on the other hand means the resources with which the goals were achieved. Satisfaction refers to freedom from discomfort and the positive attitudes to the use of the product [6]. A user interface system may have very different levels of usability when used in different application context. The context includes the users, their tasks, their goals, and equipment as well as the physical and social environment in which the system is being used. As for effectiveness of user panels for plant monitoring, it is a problem about if these panels correctly illustrate the actual plant system, efficiency is a problem about whether these panels supply enough information of the plant system, and satisfaction is decided by an operator's frustration level when performing a monitoring task.

To evaluate the usability of a user interface system, we need solve the problem of "gulf of evaluation" [7]. The so-called gulf is the degree to which the system or artifact provide representations that can be directly perceived and interpreted in terms of the expectations and intentions of the user. In other words, the gulf of evaluation is the difficulty of assessing the state of the system and how well the artifact supports the discovery and interpretation of that state [8]. “The gulf is small when the system provides information about its state in a form that is easy to get, is easy to interpret, and matches the way the person thinks of the system”. A number of user panels are used in a monitoring and supervising system and several panels may be involved in a simple task. It is difficult to evaluate these panels as a whole. Many malfunctions may probably occur, and it is insufficient to evaluate the user interfaces by intentionally causing one malfunction. Complex situation in process control is also unpredictable. Obviously, there is a gulf to evaluate user interfaces in plant operations

In addition, human operators should be involved into the usability evaluation, because they are on the front line of real-time operations making decisions that directly impact plant safety and reliability [9]. To decrease the influences of individual differences on experimental results, also, it is necessary to investigate various situations and many human subjects for an evaluation, which is a time-consuming and costly process. A promising solution to compensate the human subject-based evaluation is the human model-based evaluation approach, which is widely used in the domains of piloting [10], car driving [11], and plant operation [12].

1.2 Related Researches

Under a certain hardware environment, human performance is decided by two aspects: human and user interface. Correspondingly, studies on human errors and usability evaluation are involved. Various human models are built for these two domains. Several of these models were investigated in this research.

1.2.1 Model Human Processor

As shown in Fig. 1.2, model human processor (MHP) proposed by Card et al. [13], is used to explain and predict how a human responds to stimulus. The model human processor is composed of memories and processors. The memories are characterized by

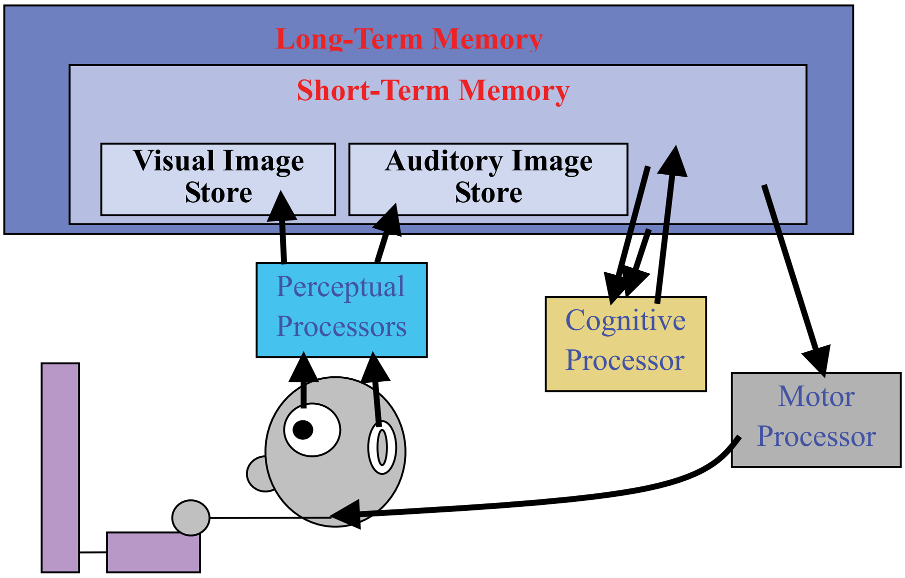


Figure 1.2 Model human processor

storage capacity, decay time and type of coding, and the processors by cycle time. The values of these attributes were determined by empirical studies.

Three subsystems are included in the model human processor: perceptual, cognitive, and cognitive subsystems. The perceptual subsystem consists of sensors and associated buffer memories. A visual image store and an auditory image store hold the output of the sensory system after the output is symbolically coded. The cognitive subsystem receives symbolically coded information from the sensory image stores in the short-term memory and uses previously stored information in long-term memory to make decisions about responses. The motor subsystem carries out the responses.

The model human processor is a conceptual model, which only supplies a research framework. It can be employed to various applications after embedding information processing procedures and related data.

1.2.2 Operator model for nuclear power plant

Takano et al. at the Central Research Institute of the Electric Power Industry (CRIEPI) proposed a simulation system for the behavior of an operating group (SYBORG) to simulate and analyze the cognitive process of operators and the behavior of operation teams [14][15]. SYBORG simulates behavior of three operators - one is the leader of the team and the others are followers with different roles. It is assumed that the leader does not observe or touch the control panel. The leader model collects information of the plant via communication.

The operator model consists of the attention, thinking, action and utterance micro models. The thinking micro models introduces the "mental model mechanism", that describes and illustrates how operators predict plant behavior and make decisions to prevent the deterioration of its conditions. It was developed based on cognitive science, group dynamics and also on interviews with nuclear power plant operators. Each operator model has some knowledge bases (KBs). They store knowledge pertaining to the relations between (1) events and parameters, (2) events and causes, (3) change of parameters and interlock, (4) change of parameter and carrying out countermeasures, etc.

The above operator model is not enough for simulating the complete behavior of the operator. So, some other characteristics related to the team behavior have been incorporated. Thus, authors introduced the HHI (Human-Human Interface) model that has the task assignment, disagreement and utterance management micro models, which considers personality, credibility, position, etc.

The SYBORG considers a large scale of knowledge bases and is applied to simulate some particular situations. However, its application is restricted for several cases. Complex structure is helpful to simulate details of human behavior, but it introduces many uncertain factors as well. In this research, its mental model mechanism is referred and built into a knowledge base.

1.2.3 Simple Model of Cognition

Hollnagel proposed a simplified model of cognition (SmoC) [16] as shown in Fig. 1.3. SmoC illustrates four types of human behaviors. According to this model, a person observes and identifies a visual or auditory signal, interprets the signal, plans and decides what operator has to do and finally initiates and executes an action.

In the case of plant operation, the first step of the SMoC information-processing model addresses the observation and identification of graphic items on user panels. The second step describes how an operator interprets and organizes the information into a

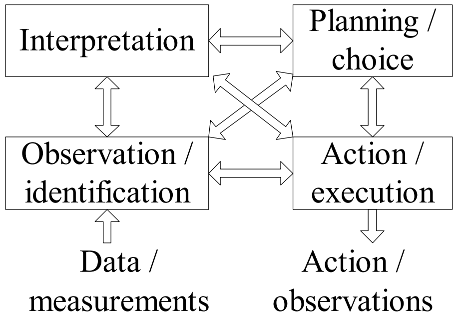


Figure 1.3 Simple model of cognition

memory unit. The third step addresses the planning and decision-making processes involved. The fourth step refers to execution of the planned actions.

Corresponding to model human processor, these four types of human behaviors are executed by three processors. Cognitive processor performs interpretation, plan and choice. Perceptual processor concerns observation and identification. Motor processor involves action and execution. SmoC provides a sequence of these human behaviors, and some middle steps may be bypassed during the information processing.

1.2.4 Operator model incorporating mental and physical states

As a previous study, Jin et al. proposed a cognitive information-processing model incorporating mental and physical states to simulate a plant operator's behavior under abnormal situations and analyze human error mechanism [17].

Based on this operator model, perceptual errors in the monitoring mode and cognitive errors in fault diagnosis are examined. Some parameters in the human model can be tuned for quantitative analysis of the various types of human errors. It can also be used to study ways of coping with these human errors.

The previous operator model is constructed by an operator in a heuristic way and its results depend on the model builder. In this study, we need an effective simulation method with reasonable knowledge bases that can be built as a set of rules.

1.3 Research Objectives

As is mentioned in the previous sections, usability evaluation for user interfaces in plant operations is the topical problem of this research. By investigated some conceptual and practical human models, the first objective of this study is to build an operator model for usability evaluation.

The usability evaluation is performed in two stages: static evaluation and dynamic evaluation. Static evaluation only considers the image properties of user panels, such as color and size of graphic items. Dynamic evaluation is used to evaluate alarm system definitions in emergencies. Accordingly, a visual performance model should be constructed based on the psychophysical characters of human beings, and then a cognitive information-processing model with knowledge bases of plant operations is required.

For the dynamic evaluation, human behavior of fault detection and identification (FDI) is the focus of this research. In an emergency, it is important to timely detect abnormalities and identify failure causes. From the viewpoint of FDI performance, user interfaces in plant operations are evaluated and improved. The second research objective is to create rules for knowledge bases construction. Human model based method is flexible to investigate various situations, but it is necessary to define rules for knowledge bases construction. Even if it is impossible to precisely mimic the behavior of a time-variant human operator with learning and adaptation abilities, simulation with rational rules may approximates the actual cases to a certain extent.

The third objective is to find an effective evaluation and improvement procedure for user interfaces. Some scenarios should be defined to meet this requirement.

1.4 Outline of the Thesis

The thesis is composed of five chapters. Chapter 1 briefly introduces research background and related studies, and then clarifies the objectives of this study. Chapter 2 describes the experimental environment. All case studies are based on this environment. The plant model is a boiler plant simulator used for training, but the evaluation method can be extended for all kinds of chemical plant system. Static evaluation method is described in the chapter 3 and case studies show its effectiveness. Chapter 4 depicts the dynamic evaluation approach. Construction of knowledge base and procedure are demonstrated. The proposed operator model based on these knowledge bases and procedure is used to evaluate the alarm systems. Evaluation results prove the usefulness of this approach. The entire study is concluded in chapter 5 and future work is also listed there.

2 EXPERIMENTAL ENVIORNMENT

2.1 Overview of Boiler Plant Simulator

A boiler plant simulator for training is installed in a distributed control system (DCS), which includes a field control station (FCS) and several PC-based information command stations (PICSes). The DCS is made by Yokogawa Electric Corporation and can be equipped as an actual control system in a chemical plant. All real-time data in the plant simulator are accessed by using the object linking and embedding for process control (OPC) technology.

Figure 2.1 shows a sketch of the system's data communication. The boiler plant simulator is used as a plant model. Through the special field device network, FCS is connected with PC1 on which an OPC DA (data access) sever is installed. Another computer PC2 is connected to PC1 via the local area network. According to the OPC DA standard, the user interface model in PC2 can access the plant model in real time.

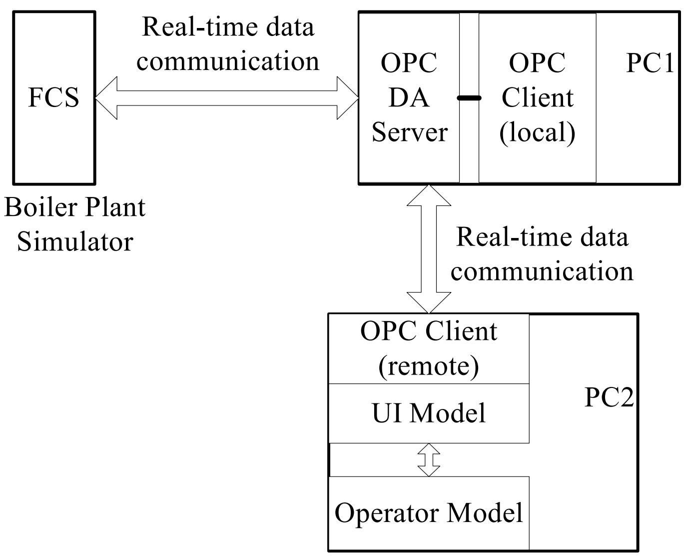


Figure 2.1 Sketch of data communication

A process flow diagram of the boiler plant simulator is shown in Fig. 2.2. Tags of continuous process variables in the simulator are listed in Table 2.1. As a target state, the simulated boiler plant produces 80 ton per hour of superheated steam at 485ºC. The whole plant control system includes four subsystems of control: feeding water, steam temperature, combustion, and furnace pressure. In normal situations, the demand load of the simulated boiler plant randomly changes from 77.9 to 82.4 t/h, which determines the normal ranges of all variables in the plant. Table 2.2 shows the normal fluctuation of process variable (PV) and manipulated variable (MV) values. The user interface system of the boiler plant includes the following panels: overview, operational, engineering, trend, and alarm summary, etc. Figure 2.3 shows the overview panel as an example.

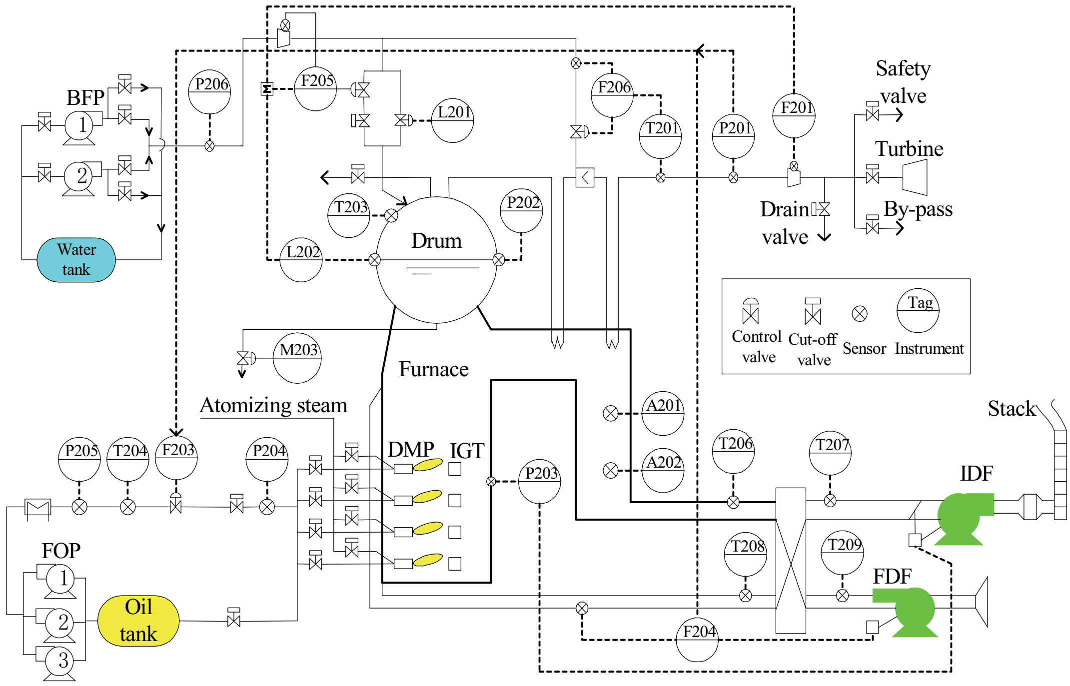


Figure 2.2 Process flow diagram of a boiler plant simulator

Table 2.1 Tags in boiler plant simulator

Tag	Description
A201	Oxygen concentration
A202	CO concentration
C208	O_2 and CO analyzer selector
F201	Main steam flow rate
F202	Fuel flow rate
F203	Fuel auto selector
F204	Air flow rate
F205	Drum feedwater flow rate
F206	Desuperheater spray flow rate
L201	Drum water level control (for a small valve)
L202	Drum water level control (for a large valve)
M203	Drum blow valve control
P201	Main steam pressure
P202	Drum pressure indicator
P203	Furnace pressure
P204	Burner-head pressure
P205	Fuel pump outlet pressure
P206	BFP outlet pressure
R080*	Wind speed
R034*	Fuel oil viscosity
T201	Main steam temperature (for control)
T202	Main steam temperature (for measurement)
T203	Drum water temperature indicator
T204	Fuel temperature

*R080 and R034 are not measurement points

Table 2.2 Normal fluctuation of PV and MV values

Tag	Low PV value	High PV value	Low MV value	High MV value
A201	2.61%	2.78%	49.1%	49.9%
A202	23.5 ppm	25.7 ppm	0%	0%
C208	-	-	49.1%	49.9%
F201	77.9 t/h	82.4 t/h	-	-
F202	6.78 t/h	7.23 t/h	51.1%	53.7%
F203	51.1%	53.7%	51.1%	53.7%
F204	67.9%	71.9%	47.7%	55.5%
F205	75.59 t/h	81.11 t/h	42.9%	44.7%
F206	1.68 t/h	1.88 t/h	40.61%	43.49%
L201	-1.63 mm	1.12 mm	0%	0%
L202	-1.63 mm	1.12 mm	75.9 t/h	81.4 t/h
P201	79.3 Kg/cm^2	80.6 Kg/cm^2	67.9%	72.3%
P202	83.3 Kg/cm^2	84.6 Kg/cm^2	-	-
P203	-14.9 mmH_2O	-5.8 mmH_2O	66.1%	72.9%
P204	3.75 Kg/cm^2	4.1 Kg/cm^2	0%	0%
P205	12.6 Kg/cm^2	12.9 Kg/cm^2	-	-
P206	96.7 Kg/cm^2	97.2 Kg/cm^2	-	-
T201	480.4ºC	489.8ºC	1.67 t/h	1.88 t/h
T202	480.4ºC	489.8ºC	-	-
T203	297.9ºC	298.8ºC	-	-
T204	89.1ºC	90.0ºC	-	-

-: unavailable item.

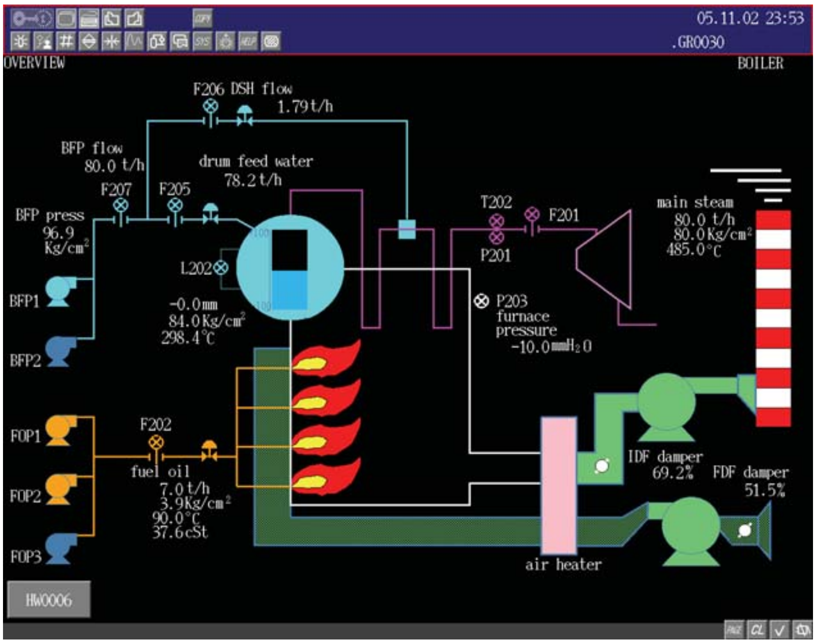


Figure 2.3 Overview panel

2.2 Assumed Malfunctions

We assume the following eleven malfunctions in the boiler plant:

Mal-1: Indicated by FOP1 failure. A fuel pump (FOP1) failure decreases fuel oil flow rate (F202) and burner-head pressure (P204). The FOP1 icon flashes in red, so this malfunction is easy to identify.

Mal-2: Indicated by burner extinction. Extinction of all burners decreases the pressure (P201) and flow rate (F201) of the main steam. After this malfunction, the icons of the burner's fire disappear.

Mal-3: Indicated by FDF degradation. A forced draft fan (FDF) degrades, which reduces air intake (F204) and pressure in the furnace. Air/fuel ratio control correspondingly decreases the fuel oil flow rate. The FDF icon flashes after this malfunction.

Mal-4: Indicated by IDF trip. An induced draft fan (IDF) trip reduces air exhaust and increases furnace pressure. The IDF icon flashes in this case.

Mal-5: Indicated by oil heater failure. It causes a drop of oil temperature (T204), and then the oil flow rate decreases due to viscosity (R034) increase.

Mal-6: Indicated by P204 sensor failure. Burner-head pressure sensor (P204.PV) failure forces the measured variable to remain at a low value. This fully opens a control valve of the fuel flow rate. Then the fuel oil flow rate increases out of control.

Mal-7: Indicated by a fuel leak. It actually decreases the oil flow rate to burners and causes a state where the heat is insufficient to produce the desired steam flow rate.

Mal-8: Indicated by BFP1 trip. A water-feeding pump (BFP1) trip interrupts the water supply to the drum and the desuperheater, which may explode the water tube. This malfunction can be detected by BFP1's flashing icon.

Mal-9: Indicated by a water leak. Water tube leak increases furnace pressure (P203). Water flow rate (F205) slightly decreases.

Mal-10: Indicated by O_2 sensor failure. Oxygen sensor (A201.PV) clings to a small value that causes an increase of the air/fuel ratio.

Mal-11: Indicated by turbine trip. This drastic malfunction causes sharp changes of many variables.

2.3 Alarm System

In the monitoring and supervising software of the DCS, function blocks are defined as the basic unit for performing control and calculations. Continuous control, sequence control (sequence tables and logic charts) and calculations are performed by function blocks. These blocks are interconnected in a manner similar to the conventional instrument flow diagrams and combined to design the control function. Each function block, denoted by a tag name, represents the smallest unit of control, for example, a tag name F201 is used to indicate a PID function block for a flow rate controller. A tag in plant control system has several items that are defined for various alarm limits. Table 2.3 shows an example for a PID function block.

In this research, two upper, two lower and a rate-of-change limits of a PV value are considered for alarm settings. These limits are denoted by the symbols HH, PH, PL, LL, and VL, respectively. Fault detection and identification also concerns two alarm limits of an MV value, which is denoted as MH for MV upper limit and ML for MV lower limit. When a variables value exceeds one of its upper limit or becomes less than its lower limit, an alarm will appear with sound and flashing marks.

Table 2.3 Data items of a PID function block related to alarm management

Symbol (data item)	Description	Modifiable	Range
ALRM	Alarm status	NO	-
AFLS	Alarm flashing	NO	-
AF	Alarm check	NO	-
AOFS	Alarm suppression	OK	-
SH	Process variable (PV) scale high limit	NO	-
SL	Process variable (PV) scale low limit	NO	-
HH	High-high alarm (limit)	OK	SL~SH
LL	Low-low alarm (limit)	OK	SL~SH
PH	High alarm	OK	SL~SH
PL	Low alarm	OK	SL~SH
VL	Velocity (rate-of-change) alarm	OK	±(SL~SH)
DL	Deviation alarm	OK	±(SL~SH)
MSH	Manipulated Variable (MV) scale high limit	NO	-
MSL	MV scale low limit	NO	-
MH	MV ouput high alarm	OK	MSL~MSH
ML	MV ouput low alarm	OK	MSL~MSH
SVH	Setpoint high limit	OK	SL~SH
SVL	Setpoint low limit	OK	SL~SH

Alarm status shows the status information of a function block or tag. Table 2.4 lists all of the alarm statuses in the DCS.

Table 2.4 Alarm statuses

Symbol	Description	Symbol	Description
NR	Normal	VEL+	Velocity alarm +
HH	High-high alarm (status)	VEL-	Velocity alarm -
HI	High alarm	MHI	Output high alarm
LO	Low alarm	MLO	Output low alarm
LL	Low-low alarm (status)		

If a tag's PV value is in its normal range, its alarm status is NR, and if its PV value exceeds its high alarm limit PH, its alarm status is HI. Here, PH is a symbol used to define a tag's high alarm limit, such as F201.PH=85.0 t/h, and HI is used to show the alarm status of a tag, which means its PH alarm limit is violated.

Process alarms indicate the abnormity of process system, while system alarms reflect the hardware malfunctions of ICS and FCS. In this study, we only consider process alarms.

Sound and flashing marks with an alarm require the operator to acknowledge the alarm information. After acknowledgement, the alarm sound will be eliminated and flashing will be paused. Figure 2.4 shows the sequences of alarm acknowledgement.

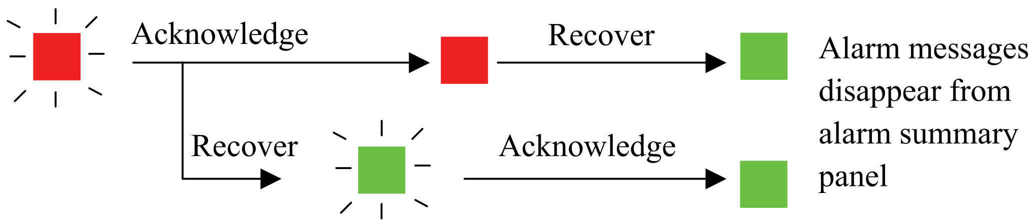


Figure 2.4 Alarm acknowledgment

Alarm messages can be displayed on several user interfaces, as shown in Fig. 2.5. A message window, which is always on top of the monitoring screen, can show the latest alarm. The five latest alarms are listed in the process alarm window, which can be summoned from the message window. On the alarm summary panel, we can check the 200 latest alarms. Figure 2.6 shows the tuning panel through which alarm limits can be directly modified.

2.4 Summary

This chapter describes the experimental environment of this study, based on which all case studies are shown. The hardware structure of data communication in this research is firstly introduced. Then, the objective plant system with its alarm user interfaces is briefly described.

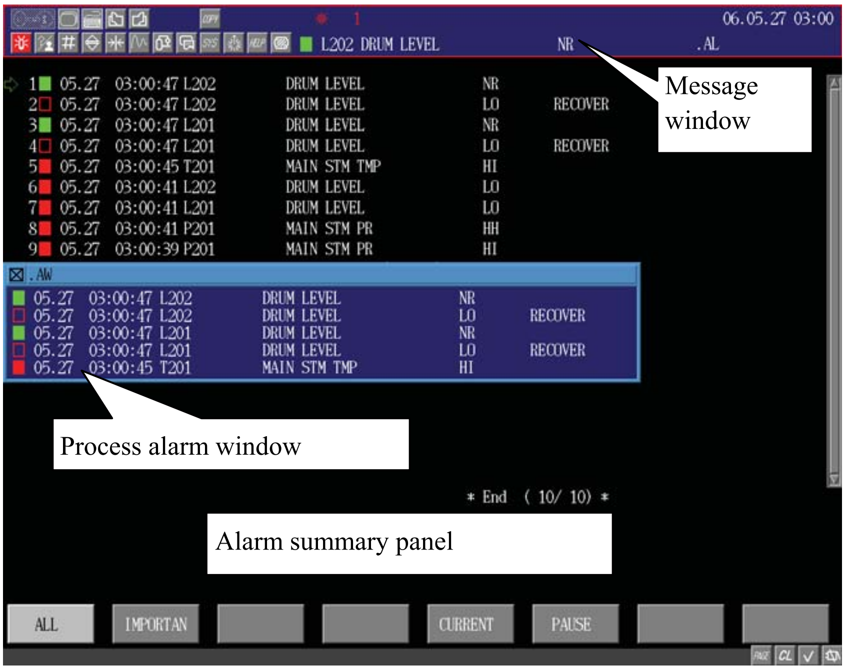


Figure 2.5 User interfaces for alarm message

Figure 2.6 Tuning panel to modify alarm limits

3 STATIC EVALUATION OF GRAPHIC PANELS

In this chapter, a visual performance model was proposed to evaluate graphic panels from the viewpoint of human perception. Based on this model, the visual performance of graphic panels is automatically evaluated without using human subjects.

3.1 Visual Performance Model of Operator

3.1.1 Weber-Fechner's Law

In the 19th century, E. H. Weber and G. Fechner originated psychophysics, a subdiscipline of psychology, to investigate the relationship between physical stimulus and psychological sensation. Classical psychophysics encompasses four general perceptual problems: detection, discrimination, recognition, and scaling [18]. Detection is the problem of determining whether a signal or stimulus is present, and it relates to the absolute sensitivity of sensory systems. Discrimination is the problem of deciding whether two stimuli are identical. For simplification, we assume that two stimuli differ by a small amount along a single dimension; a typical case might be, for example, two valve icons whose shape and background and foreground colors are the same but whose sizes are different. The smallest size difference to be distinguished between two icons is called a just-noticed-difference, or the difference threshold. Recognition is the problem of matching a detected object to human mental imagery, or judging what the object is. Scaling is the problem of applying scales to intensities of sensations.

Weber-Fechner's law quantifies the sensation of weight as shown in Equation (3.1).

$$\Psi = k \log(I), \tag{3.1}$$

where the strength of psychological sensation Ψ can be calculated by the logarithm of stimulus intensity I, multiplied by a constant parameter k. Only when Ψ is large enough for human perception can the stimulus be detected. We focus on the detection problem of human perception in the light of Weber-Fechner's law.

3.1.2 Visual Strength Model

When we view a graphic panel, the icons of various shapes and many characters on the panel are detected. The color, size, and shape of each graphic item determine its stimulus intensity and then cause human visual sensation. In this research, we investigate the visual performance of graphic panels and quantify such sensation according to the strength of visual sensation, called visual strength.

Based on common sense, the relations between visual strength and an item's color, size, and shape are observed as follows:

(1) An item's visual strength is in logarithmic proportion to the color difference between the item and its background. An item with vivid color is more easily detected than an item with dull color.

(2) An item's visual strength is in logarithmic proportion to the size of the item. We can capture large icons quickly.

(3) Even if two items have the same color and size, the visual strength of a blinking icon is larger than that of a static icon, and an alphanumeric character item has smaller visual strength than a static icon.

(4) If the color difference or size of an item is changed to zero, the visual strength is zero.

(5) Color difference and size of an item have cross influences. If the size of two items that are identical except for their color is adjusted within the same range, the visual strength of the vivid one increases more obviously.

(6) Human attention level influences the detection performance of items.

According to Weber-Fechner's law and the above observations, we define an item's visual strength V:

$$V = A_p \prod_{i=1}^{2} \log_2 \left(1 + \frac{b_i x_i}{a_i}\right) \quad , \tag{3.2}$$

where A_p indicates perceptual attention level, x_1 is the color difference between the item and its background, x_2 is the item's size measured by the minimum rectangular region containing it, a_1 and a_2 are the standard values of x_1 and x_2, respectively, and b_1 and b_2 are coefficients by other factors. If $b_i x_i$ is larger than a_i, the corresponding logarithmic part is larger than 1, which means the item has higher perceptibility.

The International Commission on Illumination (CIE) recommended an approximately uniform color space named CIELAB, which has three dimensions L^*, a^*, and b^*. In the CIELAB color space, an equal Euclidian distance within this color space nearly corresponds to an equal perceived color difference. The L^* axis is known as the lightness and extends from 0 (black) to 100 (white). The other two coordinates a^* and b^* represent redness-greenness and yellowness- blueness, respectively. Samples for which a* = b* = 0 are achromatic, and thus the L* axis represents the achromatic scale of grey from black to white. In this research, the color difference x_1 of two colors given by these L* a* b* values can be calculated by:

$$x_1 = \sqrt{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2}\ . \tag{3.3}$$

3.1.3 Model Parameter Tuning

Attention resource is a human factor that affects visual performance. In the following case study, we assume the perceptual attention level A_p is good (0.8) for the evaluation of graphic panels [19]. a_1 is set as the color difference between black and white in the CIELAB color space (100). b_1 is set to 2.5 for blinking icons.

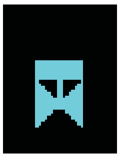
In the study of anatomy, the fovea region in a human visual field has acuter visibility than its peripheral region. a_2 is defined as the area of the fovea region, i.e. 4267 pixel^2, when the viewing distance is 600 mm according to JIS Z8513 [20]. b_2 is defined according to the shape of an item. Symbols of instruments are regarded as static icons. The parameter values are summarized in Table 3.1.

As an illustrative example, the visual strengths of some items are shown. The size of the static valve icon shown in Fig. 3.1 is 879 pixel^2. According to Equation (3.2), the visual strengths of the valve icon for 15 different colors are listed in Table 3.2. Figure 3.2 shows six character items of different sizes, whose visual strengths are listed in Table 3.3.

Table 3.1 Default values of all parameters in human perception model

Parameter	A_p	a_1	a_2	b_1		b_2			
				Shape1	Others	Shape1	Shape2	Shape3	Shape4
Default	0.8	100	4267pixel^2	2.5	1	1	2	2	1

shape1: blinking icon; shape2: static icon; shape3: instrument; shape4: character.



(Size: 879 pixel^2)

Figure 3.1 Valve icon

Table 3.2 Visual strength of the valve in 15 colors

Color	VS [-]	Color	VS [-]
Steel Blue	0.287	Orange	0.448
Gray	0.341	Red	0.464
Deep Sky	0.371	Spring	0.488
Pink	0.374	Magenta	0.499
Violet	0.405	Yellow	0.516
White	0.414	Blue	0.517
Cyan	0.426	Lime	0.544
Yellow Green	0.439	-	-

VS: visual strength.

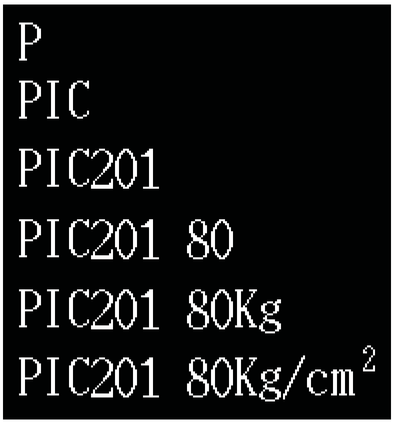


Figure 3.2 Six character items of different sizes

Table 3.3 Visual strength of six character items

Item	Size [pixel^2]	Visual strength [-]
P	252	0.069
PIC	672	0.176
PIC201	1586	0.380
PIC201 80	2047	0.470
PIC201 80Kg	2709	0.589
PIC201 80Kg/cm^2	4016	0.792

3.2 Evaluation and Improvement Procedures

Figure 3.3 shows the procedure used to evaluate and improve graphic panels, which consists of the following steps:

(1) Set A_p, a_1, a_2, b_1, and b_2 for the visual performance model.
(2) Extract all iconic and character items on a target graphic panel and record the information.
(3) Scan throughout the panel and record the visual strength of all graphic items.
(4) According to the scanning results and experience, define visual strength thresholds.
(5) Judge whether every item is sufficiently perceptible.
(6) Some additional checks for visual strength distribution are carried out. These are explained in 3.2.2.
(7) Analyze the weak points of the panel.
(8) Modify the graphic panel based on findings for weak items.
(9) Steps (1) ~(8) are repeated until an acceptable graphic panel is achieved.

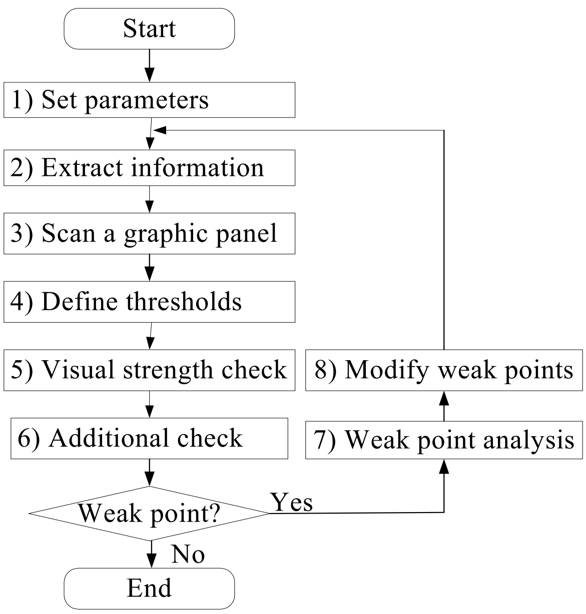


Figure 3.3 Flow chart of evaluation and modification

The first criterion to identify a weak point on a graphic panel is the visual strength of each graphic item. If an item's visual strength is less than a specified threshold, that item is a weak item for human perception and needs to be revised. In addition to the visual strength check for every item, four other checks are made to ensure effective improvement: average visual strength, visual strength standard deviation of all items, effective area ratio of the total area of all items in a graphic panel to that of the entire panel, and average area for one item.

After making these checks, the sizes or/and colors of weak items are adjusted to obtain a higher visual performance. The improvement guidelines include:

1) Add enough information for weak items such as tag name or other descriptive words.
2) Adjust the character's font size.
3) Combine redundant items.
4) Introduce an icon for a character item.
5) Adjust color definition.

Guidelines 1)-3) modify the size of an item; guideline 4) changes the shape of an item; with 5) color is adjusted. However, we must comply with the specifications or general standards of graphic panel design and maintain the consistency of all items when we adjust these factors.

The improvement principles depend on the types of panels. Generally, the overview and engineering panels should be clear and concise. Therefore, adjusting these layouts is the main work of revision. In addition, items on the overview panel should be grouped by equipment configuration in the plant site. On the other hand, items on the engineering panel must be placed according to their roles in the control systems. Operational panels should have a good consistency and be designed based on a general rule for graphic panels.

3.3 Case Study

3.3.1 Objective User Panels

We evaluated the graphic panels of the boiler plant simulator. In order to effectively improve a graphic panel, all graphic items on the panel are divided into two groups by their importance levels. Important-level items include: 1) icons of principal equipment, for example, pumps, fans, drum, and heater; 2) key process variables such as flow rate, temperature, and pressure of main steam and status of burners; 3) important valves, for example safety valve SV19, bypass valve SV21, main steam drain valve SV22, and turbine valve SV20. The remaining items are categorized as common-level items.

A simulator manufacturer provided six graphic panels for DCS training with the boiler plant simulator, and these are shown in Figures 3.4-3.9. An overview panel (a) is used for general monitoring, three operational panels (b), (c), and (d) are used for manipulation of subsystems, and two engineering panels (e) and (f) are employed by engineers to configure control schemes. We show the evaluation and improvement of the overview panel, shown in Figures 3.10 in detail. We also briefly introduce the evaluation and improvement results of other panels.

3.3.2 Evaluation Results

Two visual strength thresholds, for important and common items, are determined according to the evaluation results by an expert in panel design. The visual strength thresholds of important and common items on the original overview panel were determined as 0.65 and 0.6, respectively. In total, there are 21 important items and 12 common items on this overview panel. After the overview panel was scanned throughout, we checked every item's visual strength and found six weak items, which are marked by rectangles in Fig. 3.10. The weak items and their possible causes are listed in Table 3.4.

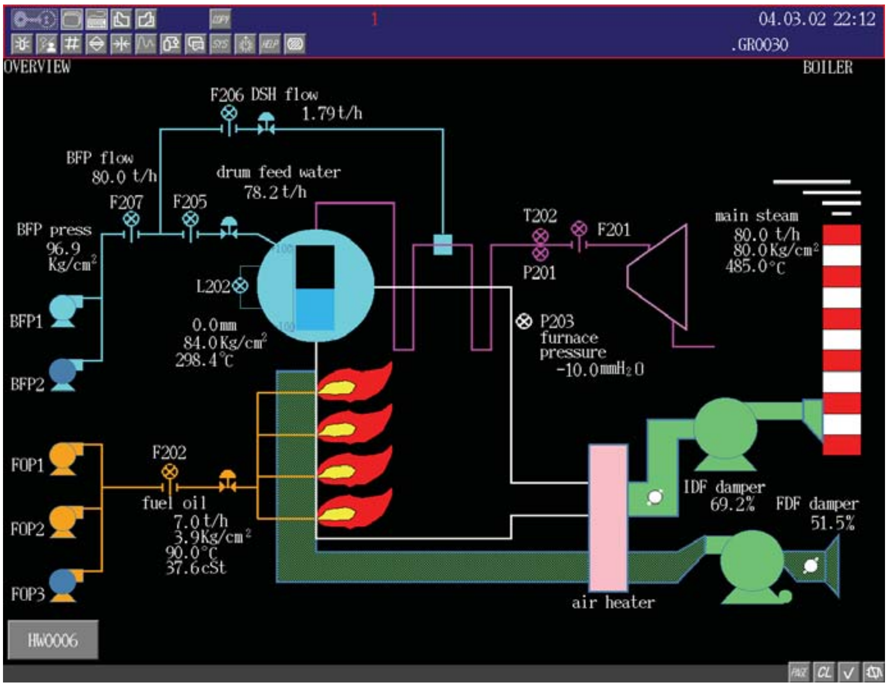


Figure 3.4 Overview panel

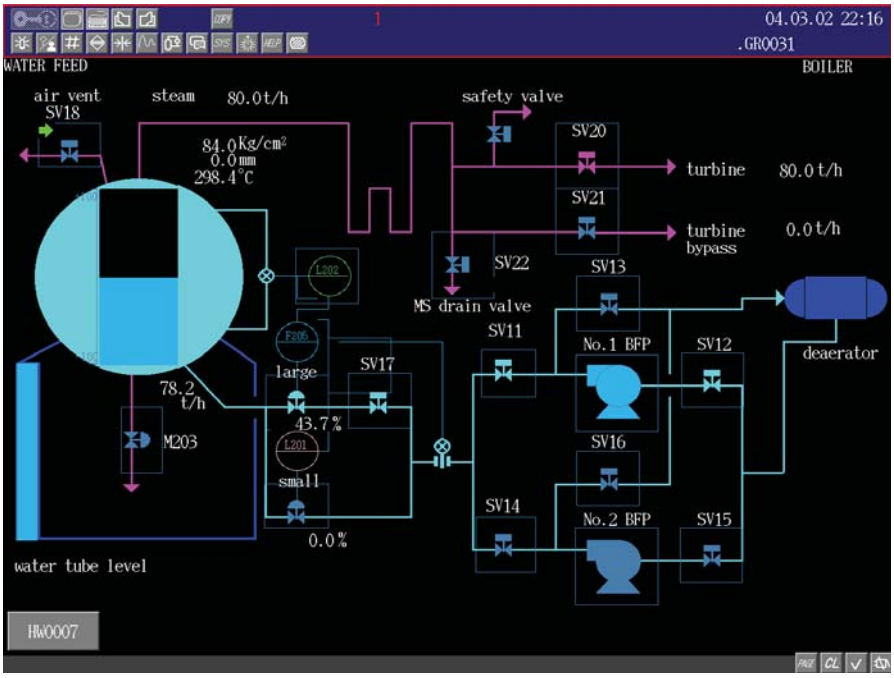


Figure 3.5 Operational panel for water supply

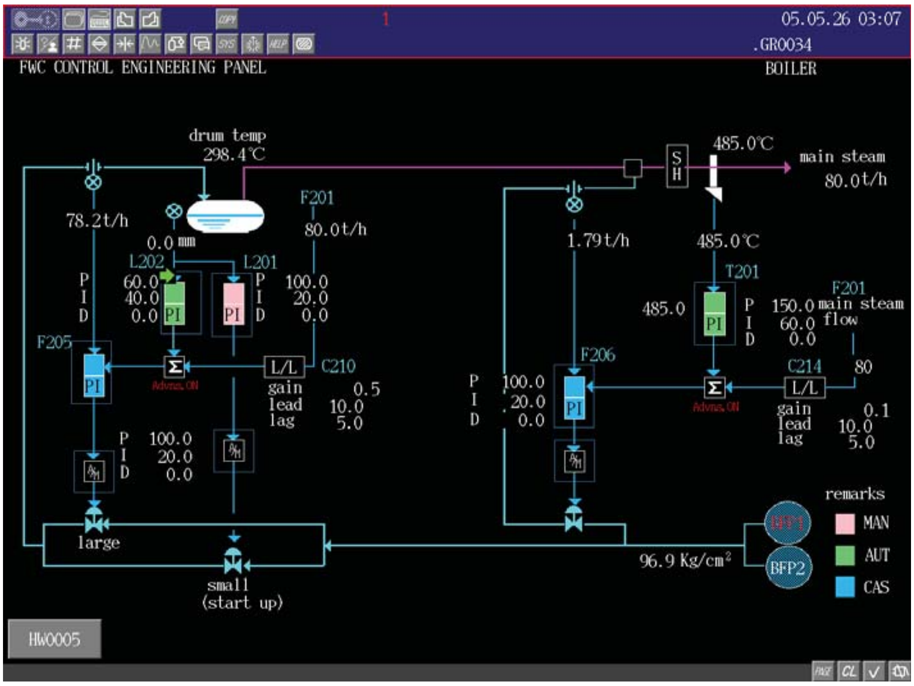


Figure 3.6 Operational panel for fuel supply

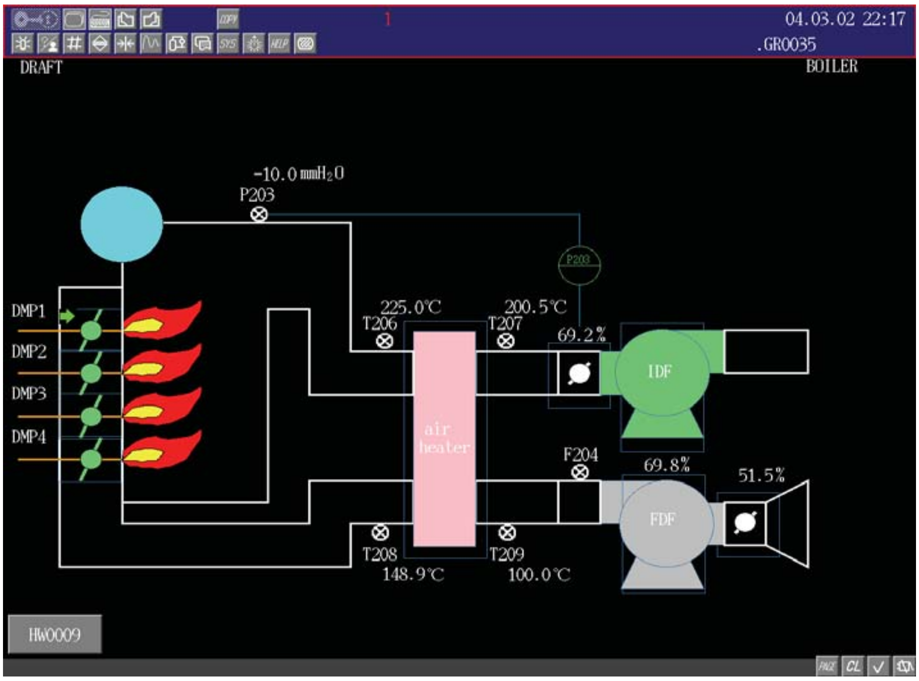


Figure 3.7 Operational panel for ventilation

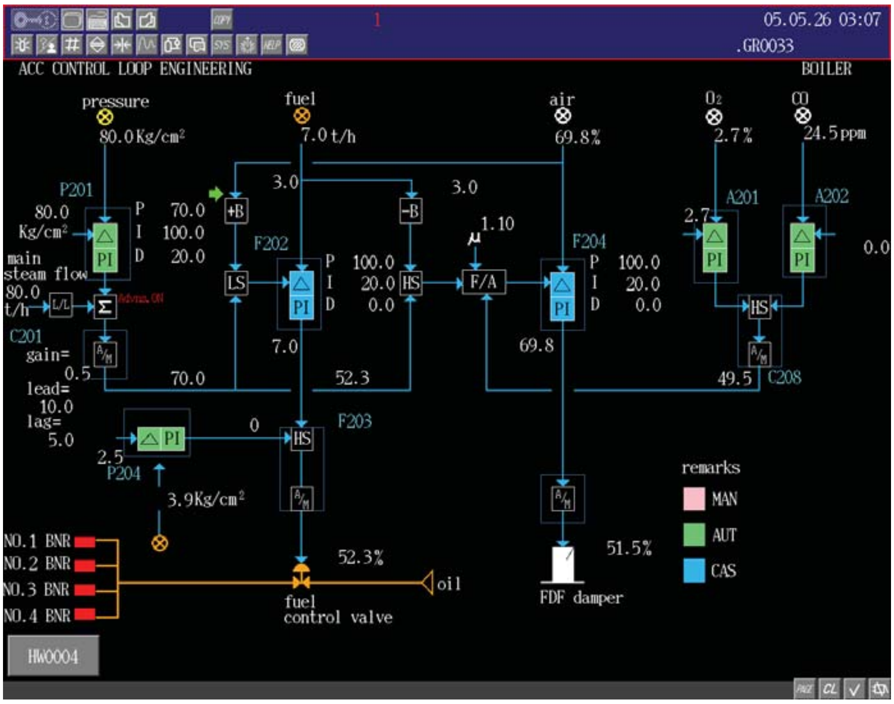


Figure 3.8 Engineering panel for combustion control

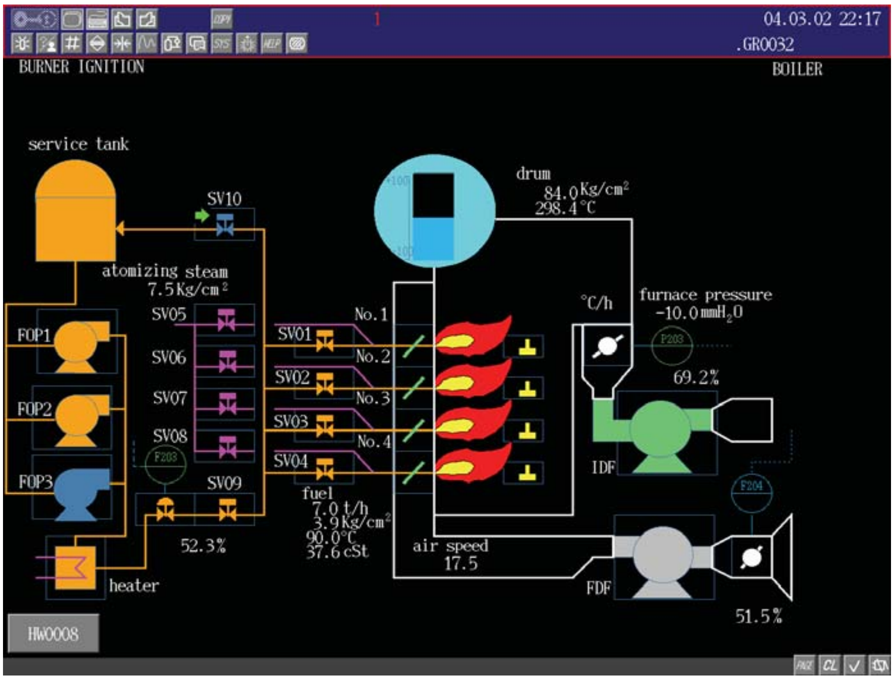


Figure 3.9 Engineering panel for water feeding control

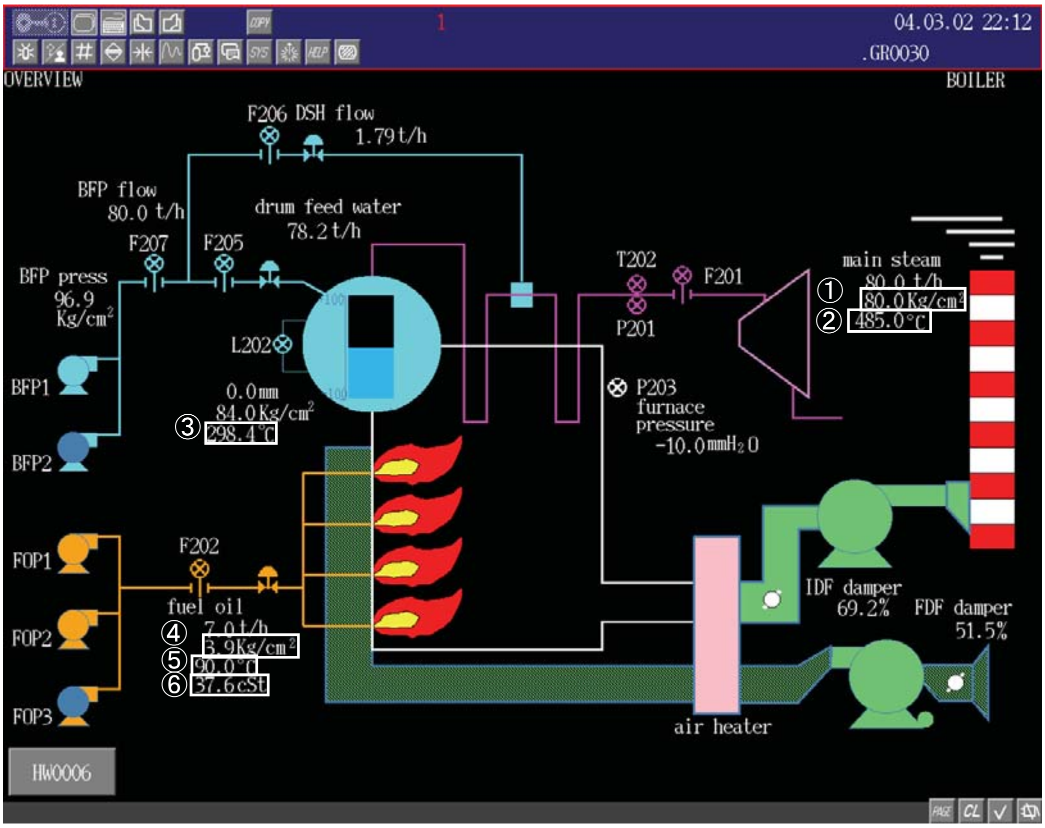


Figure 3.10 Original overview panel

Table 3.4 Weak items on original overview panel

Index No.	Importance level	Name	Shape	Size [pixel²]	Color	Value	Visual strength	Cause
①	Important	P201.PV	Character	2952	White	80Kg/cm²	0.629	a
②	Important	T202.PV	Character	1923	White	485°C	0.446	a
③	Common	T203.PV	Character	1890	White	298.4°C	0.440	a
④	Common	P204.PV	Character	2664	White	3.9Kg/cm²	0.581	a
⑤	Common	T204.PV	Character	1721	White	90°C	0.407	a
⑥	Common	R034.CPV	Character	1957	White	37.6cSt	0.453	a

Causes: a: size; b: color difference. Index Numbers are indicated in Fig. 6.

By following improvement guidelines 1) and 3), the original panel was modified as shown in Fig. 3.11. The modified parts are marked by rectangles. In addition to the weak items listed in Table 3.4, several other items are adjusted to maintain consistency in the panel. After modification, we again evaluated the new panel, and the histograms of visual strength for both the original and modified overview panels are shown in Fig. 3.12. Obviously, the original overview panel is improved and there is no weak item on the modified panel. Through the modification, the average visual strength of all items on the overview panel is increased from 1.46 to 1.64. The average area for one item is increased from 7620 to 8154 pixel^2.

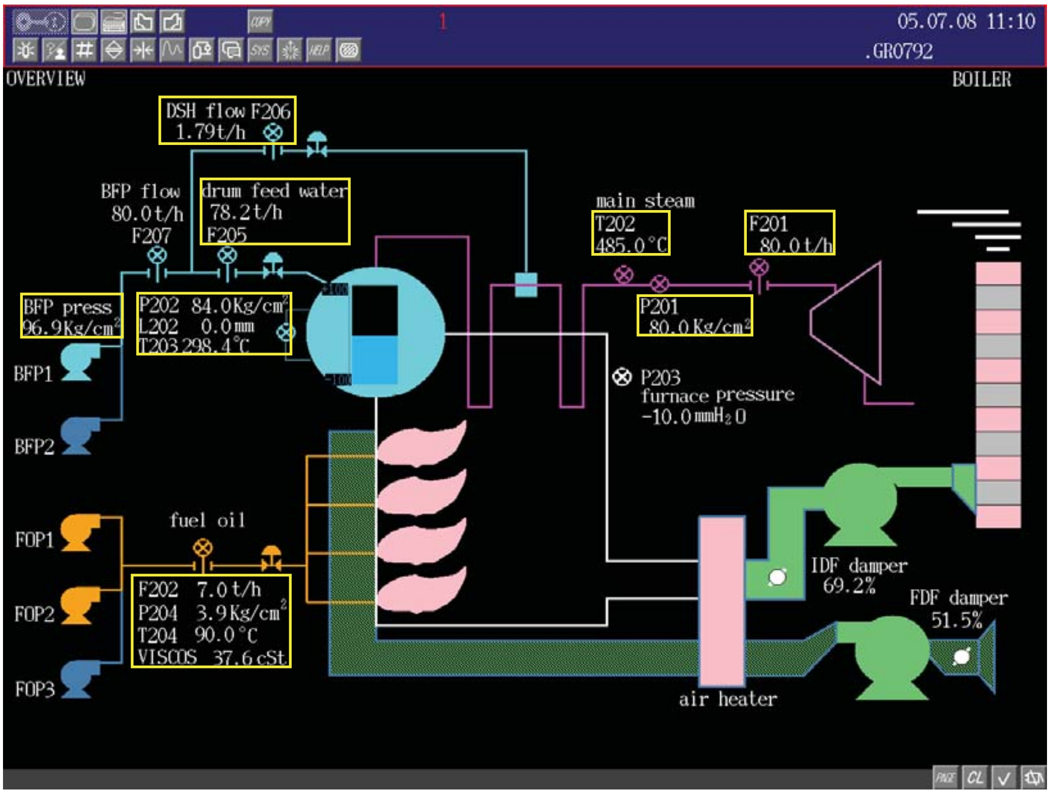


Figure 3.11 Modified overview panel

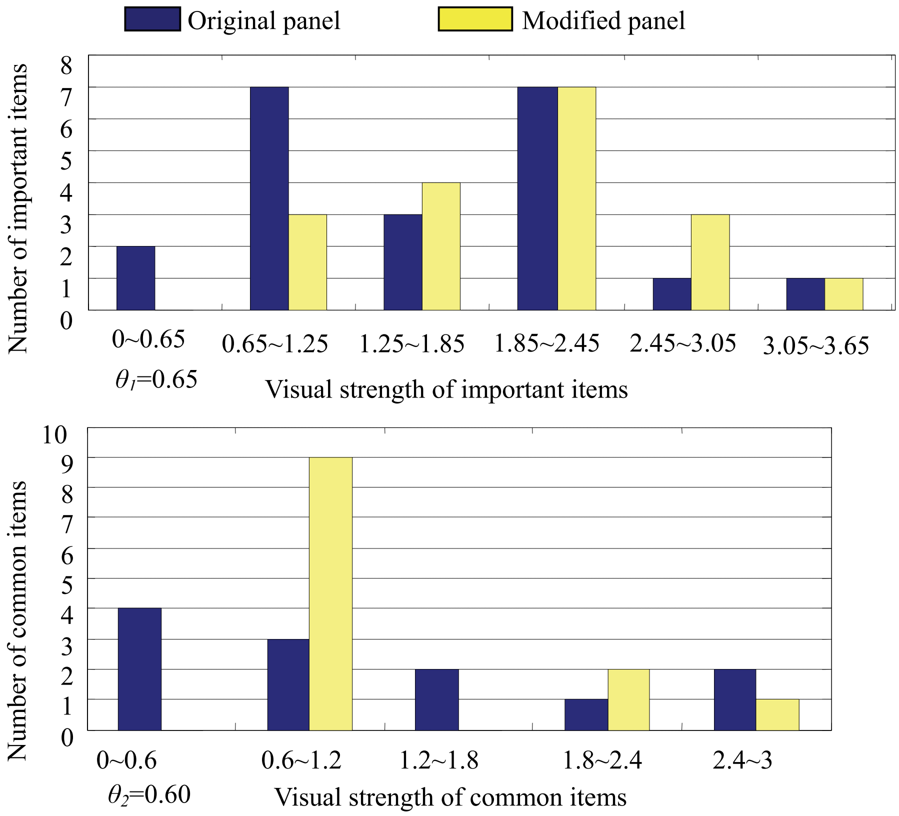


Figure 3.12 Histograms of visual strength for original and modified panels

3.3.3 Improvement of User Panels

Figures 3.13-3.18 shows six improved panels through model-based evaluation. All of the evaluation and improvement results for the six panels are listed in Table 3.5 and Table 3.6, respectively. The average visual strength of the six panels increased, especially that of the overview panel. The visual strength standard deviation of the five panels became smaller, which means the visual strength difference among items of the same importance level decreased. Even though the effective area ratios of the two engineering panels decreased, their average visual strengths increased. This is the effect of the layout and size adjustments made for engineering panels, by which extremely large items are compressed and small items are expanded. Because some redundant items are combined in pairs, the overview panel's average area per item increased but its effective area ratio decreased.

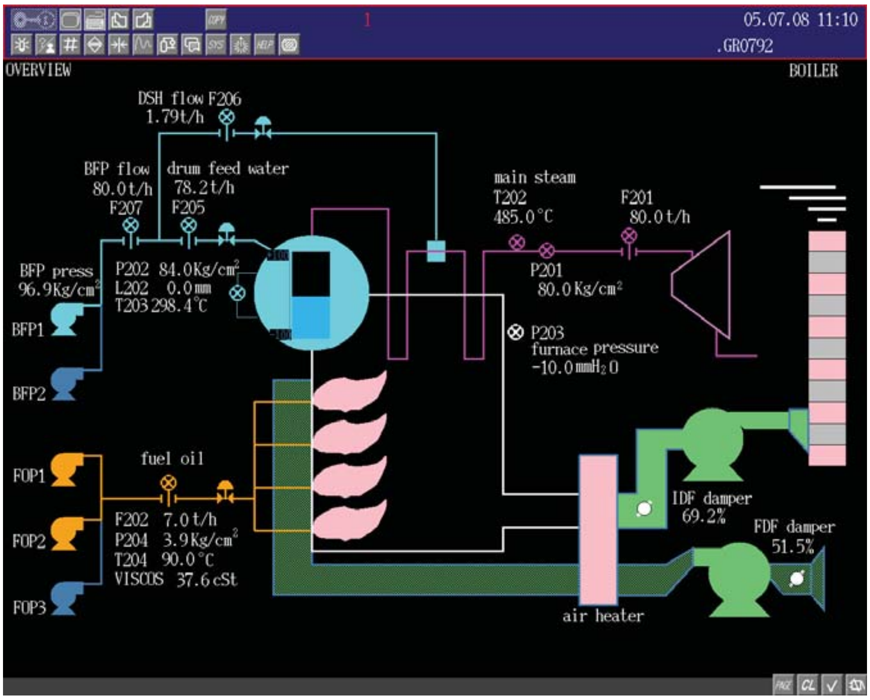


Figure 3.13 Modified overview panel

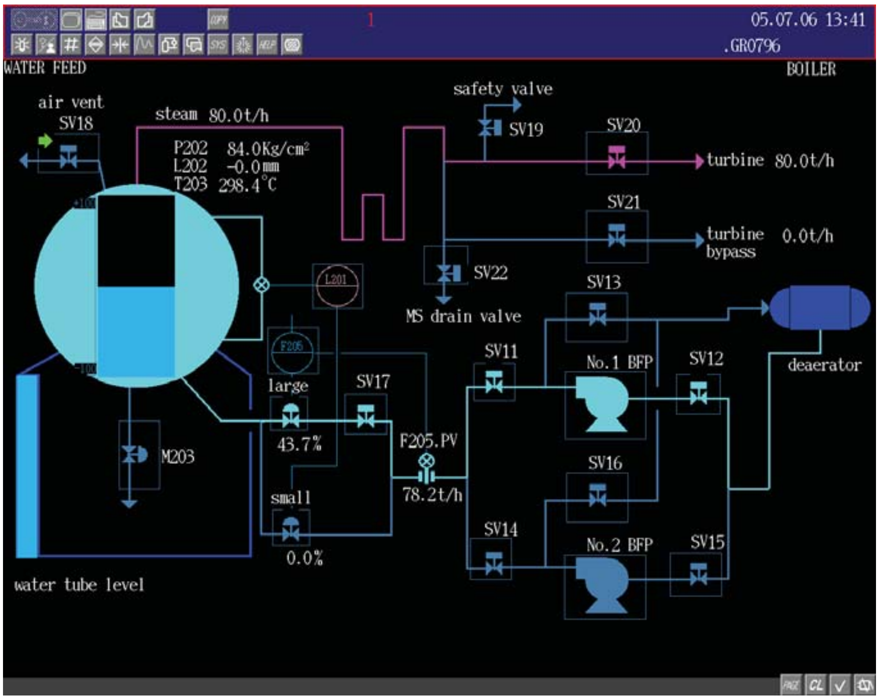


Figure 3.14 Modified operational panel for water supply

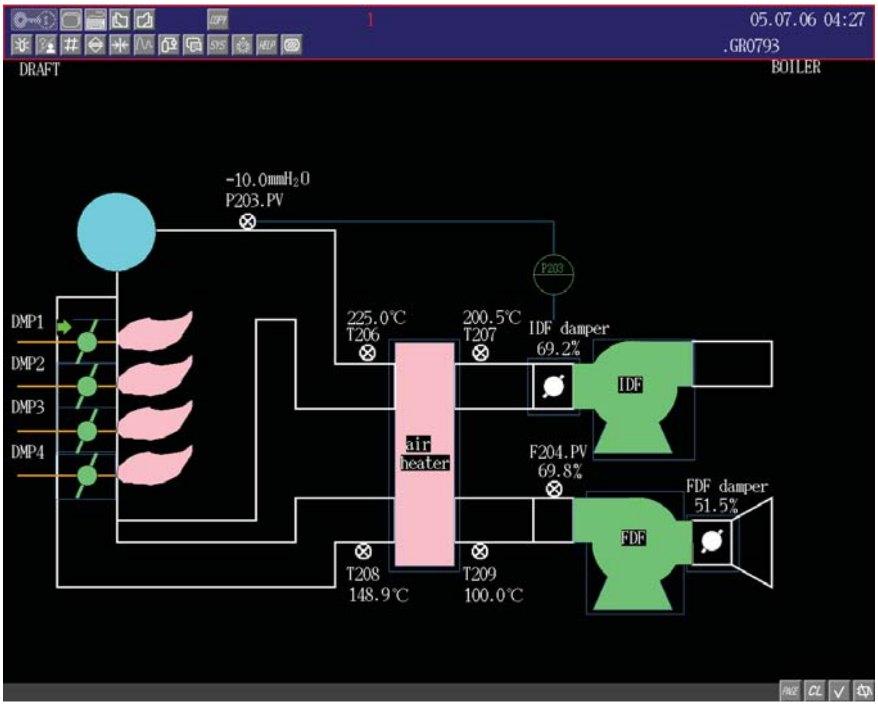


Figure 3.15 Modified operational panel for fuel supply

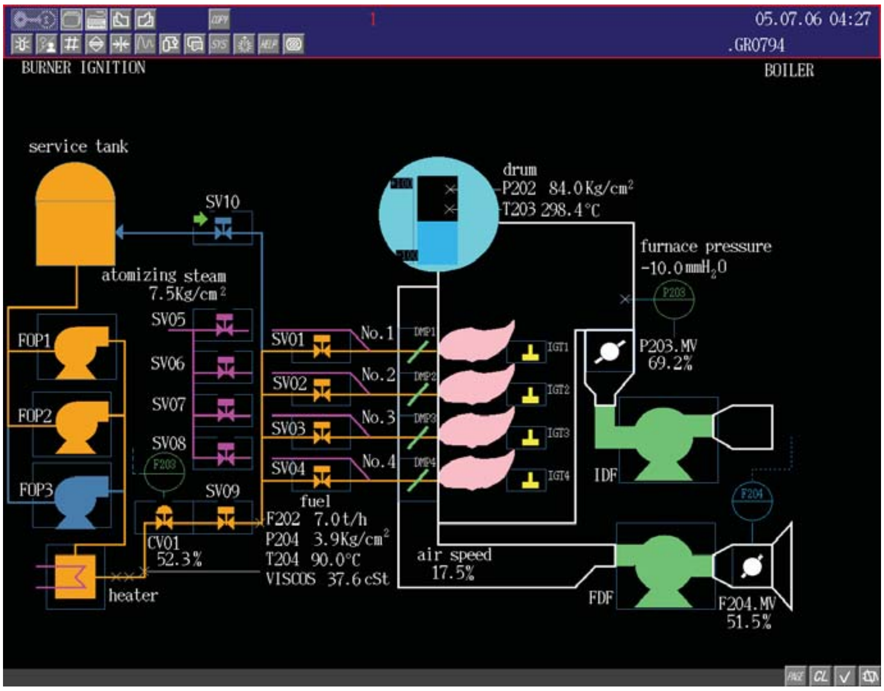


Figure 3.16 Modified operational for ventilation

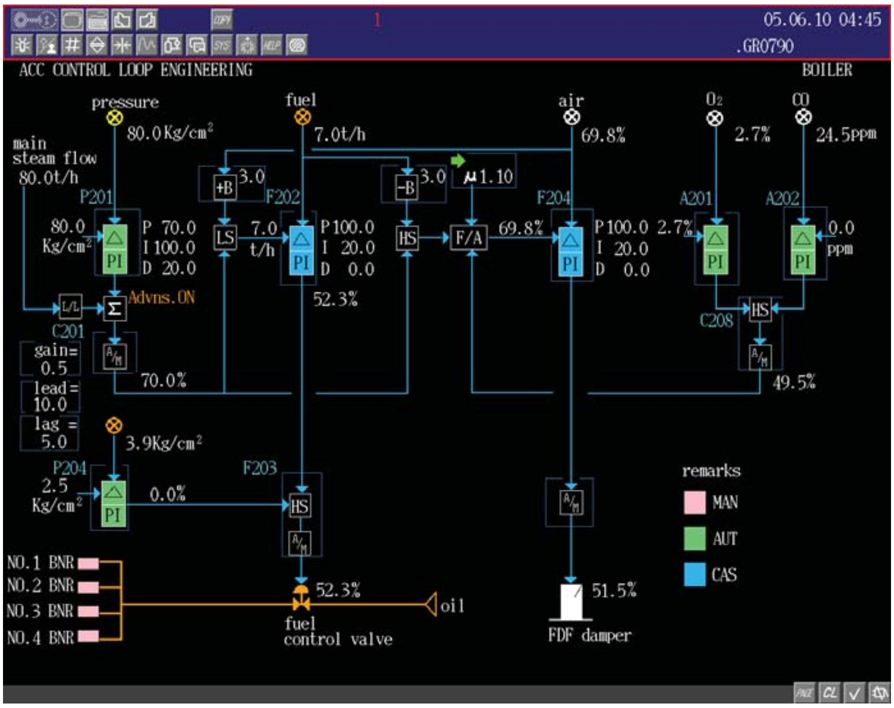


Figure 3.17 Modified engineering panel for combustion control

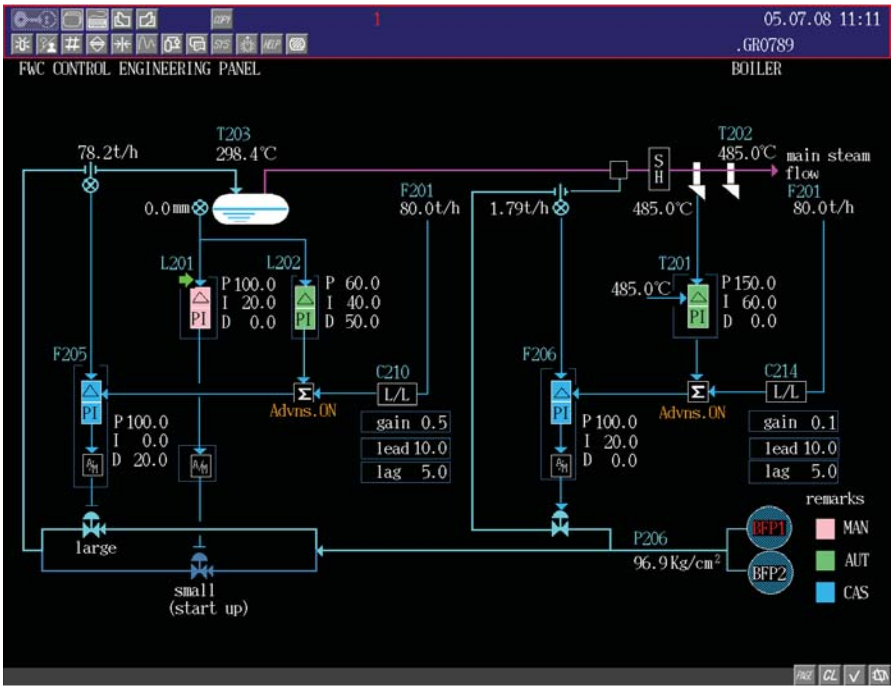


Figure 3.18 Modified engineering panel for water feeding control

Table 3.5 Summary of the evaluation results for original graphic panels

Panel types	Graphic panel	Number of Important items (weak items)	Number of common items (weak items)	Total (weak items)
Overview panel	(a)	21 (2)	12 (4)	33 (6)
Operational panels	(b)	11 (1)	15 (1)	26 (2)
	(c)	25 (0)	27 (10)	52 (10)
	(d)	9 (0)	11 (0)	20 (0)
Engineering panels	(e)	13 (1)	32 (7)	45 (8)
	(f)	20 (2)	20 (0)	40 (2)

Table 3.6 Improvement by modification

(Result of original panel→result of modified panel)

Graphic panel	Average visual strength	Standard deviation of visual strength	Effective area ratio [%]	Average area per item [$pixel^2$]
(a)	1.46→1.64	0.77→0.74	19.2→18.7	7620→8154
(b)	1.33→1.41	0.80→0.77	18.8→19.8	9501→10000
(c)	1.21→1.38	0.76→0.66	17.3→20.0	5276→6106
(d)	1.59→1.75	0.72→0.86	14.9→16.0	9733→10485
(e)	1.13→1.17	0.68→0.59	19.0→18.3	5535→5331
(f)	1.21→1.22	0.56→0.42	17.8→16.9	5836→5554

3.4 Summary

After scanning a graphic panel, a designer can see a list of two groups of items with the same importance level in ascending order of visual strength. Then, based on this information and the designer's experience, he/she judges whether the items with lower visual strength need to be improved. As a result of this judgment, two thresholds are provisionally determined. Through the automatic evaluation using the visual strength check and additional checks, weak items are identified with their causes.

Based on these findings, the designer can modify the graphic panel. The modified panel is also evaluated. The thresholds can be adjusted again according to the new evaluation results, since these might have been overestimated or underestimated in the first trial. The final values of thresholds for three types of graphic panels are summarized in Table 3.7. The character items with four threshold values are shown in Fig. 3.19. The overview panel is monitored to detect an emergency, so its threshold values are the highest among all panels. Because a human operator does not often manipulate controllers through engineering panels, the threshold values for important and common items on engineering panels are identical and small.

Table 3.7 Thresholds of three types of graphic panels

Thresholds	Overview panels	Operational panels	Engineering panels
θ_1	0.65	0.60	0.35
θ_2	0.60	0.55	0.35

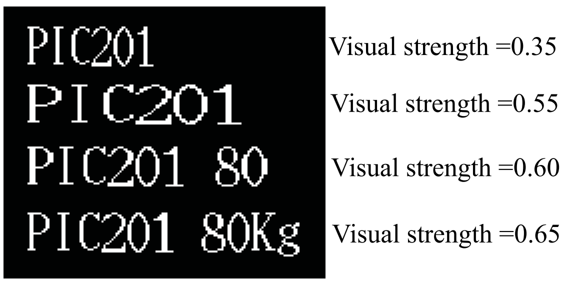


Figure 3.19 Visual strength values of four character items

The parameters in visual performance model a_i and b_i can also be tuned by using the paired comparison method. Expert operators or graphic panel designers can evaluate a few of the graphic items by comparing their intensities of sensation in a pair. These items are ranked according to the evaluation results by humans and applied scales of their visual strength. In Equation (3.2), x_1 and x_2 of each item can be measured. A_p is assumed as a constant. Therefore, all of the a_i and b_i can be determined based on the scaled visual strength values and nonlinear curve fitting.

Based on the visual performance model for static evaluation of graphic panels, six graphic panels of a boiler plant simulator were evaluated from the viewpoint of human perception. Through this model-based approach, weak items were found with their reasons and then modified. The evaluation results showed that the visual performance of these modified panels improved. The presented model-based approach can be used as a support tool in the early stages of graphic panel design.

4 DYNAMIC EVALUATION OF ALARM SYSTEM

4.1 Introduction

A user interface in plant operations may bottleneck human performance of plant operations, especially in an emergency. An alarm system is an essential part of a user interface system because it provides vital support to plant operations by warning operators of situations that need their attention. Statistics [21] shows that in Japan's chemical plants there were typically 200 alarms per day per operator in 2005, which indicates that alarms are very common in plant operations. Therefore, the design of an effective alarm system is a key issue in meeting expected demands.

A poorly designed alarm system causes nuisance alarms, standing alarms, and alarm flooding, and it can even result in incidents or accidents. For example, the explosion and fires at the Texaco Refinery in Milford Haven, the UK, in 1994 resulted in plant damage costing nearly US $72 million and significant production losses. The operators failed to prevent this accident partly because of a bad alarm system, which forced the operators to respond to one alarm every 2-3 seconds (20-30 alarms/min) in 5 hours and finally led up to the accident [22][23].

The Engineering Equipment and Materials Users Association (EEMUA) issued a comprehensive guideline for designing, implementing, evaluating, improving, and buying alarm systems. It lists four key design principles of alarm systems:

(1) Each alarm should alert, inform, and guide.
(2) Every alarm should have a defined response.
(3) Adequate time should be allowed for the operator to carry out his defined response.
(4) Alarm system should be explicitly designed to take account of human limitations.

These principles mean that it is impossible to design an effective alarm system without direct or indirect participation of operators. To investigate various situations, however, a great number of subjects are required in the human subject-based experiments, which is a time-consuming and costly process. A model-based evaluation approach is a promising solution to this problem. In this chapter, we focus on the evaluation of alarm settings by analyzing the fault detection and identification (FDI) behaviors based on an operator model. The evaluation approach involves cognitive modeling [24] and task analysis techniques [25] for CRT-based plant operations.

As an objective plant system of this study, a boiler plant simulator for training is introduced that focuses on the process, the alarm system, and malfunctions. We select a fuel leak malfunction as an illustrative example, describe its cause-effect analysis and FDI track generation under the actual alarm system, and finally show the modification effects. Evaluation and modification results of the three alarm systems are shown based on the evaluation procedure.

4.2 Operator Model

4.2.1 Model Structure

As a model human processor on the PC [13], we built the operator model shown in Fig. 4.1. It is a metaphor of a human operator as an information processing system, which typically consists of a perceptual processor, short-term and long-term memories, a cognitive processor, and a motor processor.

In every scenario under abnormal situations, the operator models' main tasks are monitoring graphic panels with alarm messages and identifying causes of failure. In other word, the operator model is used as a virtual subject. The perceptual processor focuses on a certain few items or areas that are determined by the operator models' knowledge bases. After capturing a target item, the perceptual processor directly stores it into the short-term memory (STM).

A set of three knowledge bases (KBs) for variable information (VI), alarm management (AM), and failure-symptom relation (FS) is built in the long-term memory (LTM). VI-KB is a mapping of all related user panels in an operator's brain when a process is normal and stable. AM-KB is applied to convert an alarm status to a symptom. FS-KB contains all of the known failures with these symptoms as a bipartite graph.

As well as three knowledge bases in the operator model, an abnormal state supervising procedure (ASSP) is implemented. Through the STM, the cognitive processor sends commands to the motor processor to move a gaze point or to push a button to confirm the status of the associated variables. The motor processor executes commands from the cognitive processor.

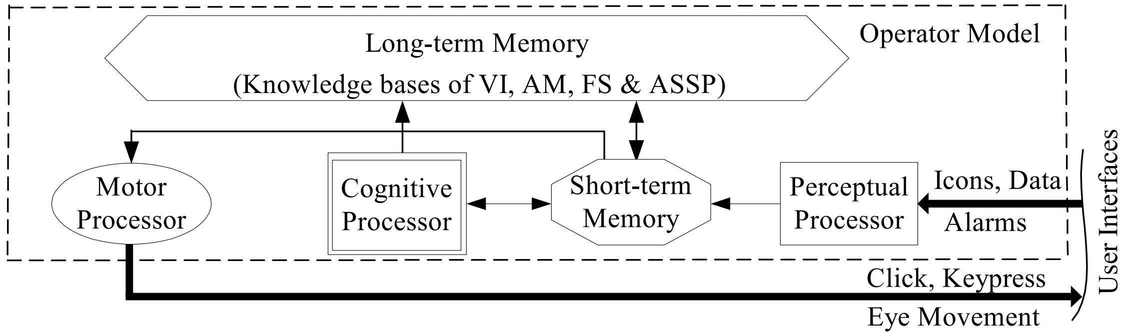


Figure 4.1 Structure of operator model

4.2.2 Knowledge Bases

Variable Information Knowledge Base (VI-KB)

VI-KB includes color, position, and normal range of each process or control variable on the user panels. It is stored as a table; for example, Table 4.1 shows a part of VI-KB for a user panel of a boiler plant. In simulation, the virtual subject consults the table to find the position of a relevant graphic item.

Table 4.1 Example of VI-KB for a user panel

Process variable	Color	Shape	Coordinates [pixel]		Normal operating condition	
			X	Y	Low value	High value
F201.PV	White	data	1107	346	76.9 t/h	83.4 t/h
F202.PV	White	data	202	666	6.7 t/h	7.3 t/h
F204.MV	White	data	1182	768	46.7%	56.5%
F205.PV	Cyan	icon	307	300	74.6 t/h	82.1 t/h
F206.PV	Cyan	icon	349	162	1.58 t/h	1.98 t/h
P201.PV	White	data	1120	369	78.3 Kg/cm^2	81.6 Kg/cm^2
P201.PV	Magenta	icon	777	390	78.3 Kg/cm^2	81.6 Kg/cm^2
P202.PV	White	data	322	507	82.3 Kg/cm^2	85.6 Kg/cm^2
P203.PV	White	data	837	513	-16.9 mmH_2O	-3.8 mmH_2O
P203.MV	White	data	1045	741	65.1%	73.9%
P204.PV	White	data	304	804	3.6 Kg/cm^2	4.25 Kg/cm^2
P206.PV	White	data	79	366	95.7 Kg/cm^2	98.2 Kg/cm^2
T201.PV	White	data	1090	396	477.4 ºC	492.8 ºC
T202.PV	Magenta	icon	778	331	477.4 ºC	492.8 ºC
T203.PV	White	data	291	535	293.9 ºC	302.8 ºC
T204.PV	White	data	274	828	88.1 ºC	91 ºC

Alarm Management Knowledge Base (AM-KB)

Once a malfunction occurs, some process variables change outside of their normal ranges. These changes are used as symptoms of malfunctions and denoted as "***.High" or "***.Low" according to the tendency of the change. AM-KB in the operator model has rules, each of which converts an alarm status to a symptom; an example is shown in Table 4.2.

In the plant monitoring system, the following alarm limits are used: high (PH), low (PL), high-high, low-low, and rate-of-change (VL) alarms for process variables (PV), and high (MH) and low (ML) alarms for manipulated variables (MV). If these alarm limits are exceeded, their corresponding alarm statuses become HI, LO, HH, LL, VEL+ or VEL-, MHI, and MLO, respectively.

Table 4.2 Example of conversion rule from alarm status to symptom in AM-KB

Alarm status	HI, VEL+, MHI, HH	LO, VEL-, MLO, LL
Symptom	.High	.Low

Failure-symptom Relation Knowledge Base (FS-KB)

FS-KB is built based on a cause-effect analysis as follows:

(1) Supposing a malfunction occurs, analyze the stationary effects of failure propagation based on the physical or logical relations between process variables, which are usually obtained in the process flow sheets and control loop diagrams.

(1') If a plant simulator is available, cause a malfunction and record the response data for all process and manipulated variables. The response data are helpful for revising the results obtained in the first step.

(2) Draw failure propagation chains from cause to effect.

(3) Except for a root failure cause, all of the nodes in the obtained chains are classified into symptoms.

(4) Repeat steps (1)-(3) for other assumed malfunctions as failure causes.

The relations between failure causes and symptoms after enough time for propagation can be represented as a matrix form according to the results of cause-effect analysis for all assumed malfunctions. For instance, Table 4.3 shows the matrix, where F_m is mth failure cause and S_n is nth symptom; FL_m is the number of all symptoms for the mth failure cause, and SL_n is the number of all causes related to the nth symptom. FL and SL values reflect the complexity of cause and effect, respectively. In the matrix, a row corresponds to a symptom and a column corresponds to a failure cause. If a failure cause F_m can cause a symptom S_n, the element in the nth row and mth column is set to 1. Obviously, the total value in the nth row is SL_n, and the total value in the mth column is FL_m.

Table 4.3 Matrix of cause-effect relation

	F_1	F_2	....	F_m	....	F_M	SL value
S_1	0	1	....	1	....	0	SL_1
S_2	1	1	....	0	....	0	SL_2
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
S_n	1	0	....	1	....	1	SL_n
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
S_N	0	1	....	1	....	1	SL_N
FL value	FL_1	FL_2	....	FL_m	....	FL_M	

The FS-KB is illustrated by a bipartite graph shown in Fig. 4.2. The graph has two layers. The upper layer shows all failure causes and the lower one shows all symptoms. FL_m is the number of links connected with F_m and SL_n is the number of links connected with S_n. The association strength $AS_{m,n}$ of an FS link between F_m and S_n is defined as follows: for any (m, n)

$$AS_{m,n} = \frac{\dfrac{w_{m,n}}{SL_n}}{\displaystyle\sum_{k \in A_m} \frac{w_{m,k}}{SL_k}}, \tag{4.1}$$

where $w_{m,n}$ indicates a weight of the F_m-S_n link, and A_m is a set of indices of all symptoms connected with F_m. In other words, $AS_{m,n}$ is a contribution ratio of S_n to failure cause F_m. For any failure cause, the total AS of all links in set A_m is normalized to 1.0, but the value becomes 1.0 after complete propagation.

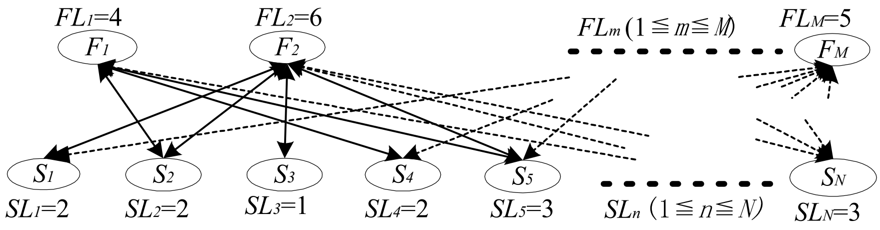


Figure 4.2 Failure-symptom links

4.2.3 Abnormal State Supervising Procedure (ASSP)

A human operator has various tactics to identify a failure cause in an emergency, for instance, excluding possible failure causes until the true cause, confirming all related symptoms for each failure cause, or a combination of these. We assume the following procedure is activated after detecting an alarm. The outline of the procedure is shown in Fig. 4.3.

(1) Detect an alarm.
(2) Based on AM-KB, interpret the detected alarm as the *n*th symptom S_n.
(3) Based on FS-KB, assume that the failure causes that connect to all alarmed symptoms are a set of possible failure causes, and reject other failure causes without a connection to S_n.
(4) Select one failure cause F_m whose AS value $AS_{m,n}$ is the largest among those of the possible failure causes.
(5) If all possible failure causes are rejected, return to step (3) to start a new round of confirmation.
(6) Select the next symptom $S_{n'}$ that connects to F_m in descending order of AS values.
(7) Confirm $S_{n'}$ by checking the trend data of its corresponding process variable $Tag_{n'}$ on a user panel.
(8) If a new alarm is detected, restart the procedure.
(9) If the trend data of $Tag_{n'}$ accords with $S_{n'}$, add the $AS_{m,n'}$ of the link between $S_{n'}$ with F_m to the total AS value.
(10) If the trend data of $Tag_{n'}$ does not accord with $S_{n'}$ and F_m has been rejected, return to step (6), otherwise reject F_m from the set of possible failure causes.
(11) Consider the identification to be successfully accomplished when the total AS becomes larger than the specified threshold.

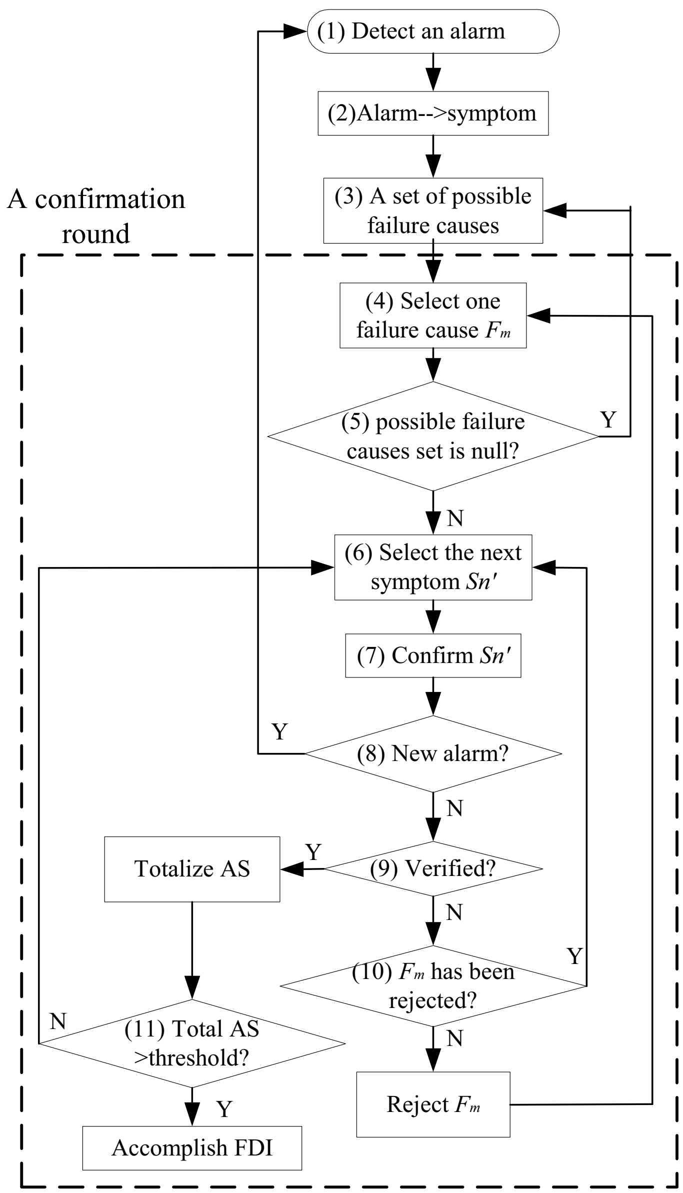


Figure 4.3 ASSP

The ASSP can cope with multiple alarms. When a new alarm comes, the set of possible failure causes will be modified by considering corresponding symptom of the new alarm, and then a new round of confirmation starts. Symptoms converted from alarms can remove a failure cause from the set of possible failure cause, but the other symptoms detected from operational panels only temporarily reject a possible failure cause. If a possible failure cause is temporarily rejected, in the next round of confirmation, it will be confirmed again. If a failure cause has ever been rejected because a symptom is not verified, in the following rounds of confirmation, even if the symptom is not yet verified, it will not reject the failure cause again. The dash-lined area in Fig. 4.3 shows a confirmation round.

4.3 FDI Track Generation

Human behaviors in the FDI process are classified into physical and mental subtasks. The latter includes perception, cognition, STM, and LTM activities; for example, reading an alarm message, remembering a previous alarm, searching for a symptom in the KB, and rejecting a failure cause are perception, STM, LTM, and cognition subtasks, respectively. An FDI track is an information flow diagram composed of these subtasks. In this study, the FDI track from detecting an alarm to achieving failure cause identification is generated automatically based on the proposed ASSP of the operator model.

Even a simple operation may include a lot of subtasks. This makes the human behavior analysis very troublesome. However, according to the structure of the operator model shown in Fig. 4.1, we can define a part of the subtask sequence as an operational stage. Every operational stage has at least one STM subtask, which may follow after a perception, cognition, or LTM subtask. Therefore, an operational stage is processed in the order of perception, cognition, LTM, and physical subtask, but it may not include all types of subtasks.

Figure 4.4 shows an example of the generation of an FDI track after an alarm of T201.LO. The first subtask is a perception subtask, through which the virtual subject captures the alarm message. Then, the STM subtask is performed to store the alarm information. Through AM-KB, the alarm information is converted to a symptom T201.PV.Low and stored into the STM. The following physical subtasks are performed to acknowledge the alarm, and the first operational stage ends here. Sequentially, the cognitive processor searches possible failure causes and the next symptom to confirm. From LTM, the failure cause with the maximum *AS* value, i.e. fuel leak, and its corresponding symptom, P203.PV.High, are recognized and stored into the STM, as the second stage. The cognitive processor searches the information of P203.PV and then obtains the related information of P203.PV from the LTM. According to the position information of P203.PV stored in the STM, the virtual subject switches to the overview panel from the alarm summary panel. The third operational stage is accomplished here. From the overview panel, P203.PV is captured by the perceptual processor and then stored into the STM. The cognitive processor rejects the failure cause, fuel leak, because P203.PV.High is not verified. After the fourth operational stage, the FDI process continues until the total *AS* value is larger than the specified threshold.

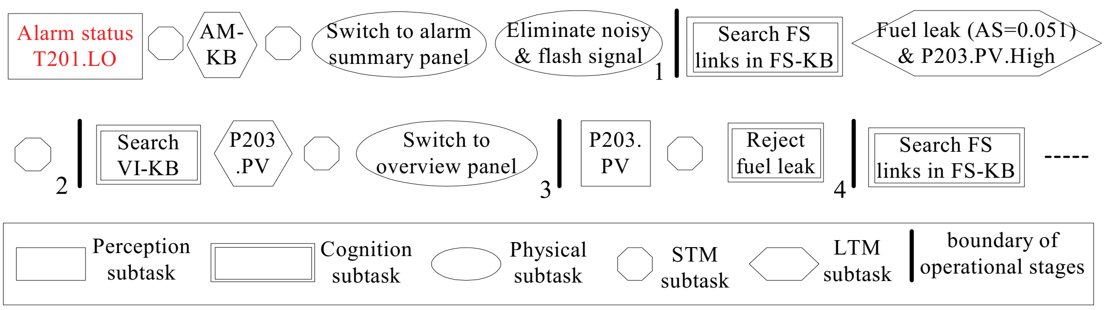


Figure 4.4 FDI track generation after an alarm

4.4 Evaluation Procedure

EEMUA guidance [23] stipulates the number of alarms displayed in 10 minutes following a major plant upset as a criterion of the acceptability of an alarm system. If the number of alarms in 10 minutes is under 10, the alarm system may be manageable for an operator. If it is 20~100, the operator may feel difficulty in handling these alarms. The worse condition is when it exceeds 100, which leads to the operators abandoning use of the alarm system. Here, we count the number of alarms during FDI. Because the FDI process is commonly accomplished in a minute, the average rate of alarm appearance should be less than 10 per minute. The number of operational stages indicates the difficulty of an FDI. This is not a criterion for evaluating an alarm system but it can be used to compare two systems. We also focus on the total length of eye movement. This indicates the effort of a physical subtask, which can be decreased by an efficient alarm system. The elapsed time of the FDI process is also an important criterion. It is estimated in every operational stage and affected by the number of operational stages. The elapsed time for a scenario is a sum of the earliest alarm appearance time and the elapsed time for the FDI, which reflects the general performance of the alarm system. In this study, we consider all of these criteria for various situations to evaluate an alarm system.

By analyzing the FDI track, we can evaluate alarm systems with the following criteria:

(1) Tag and status of the earliest alarm.
(2) Time from the beginning of malfunction to the earliest alarm.
(3) Number of alarms during the FDI process.
(4) Number of operational stages.
(5) Total length of eye movements.
(6) Elapsed time of the FDI process.
(7) Elapsed time for a scenario.

Earliest alarm is an important clue guiding the FDI process. If the first symptom converted from the earliest alarm has a close relation to the failure cause, it can shorten the time of the FDI process. To detect abnormality earlier, the earliest alarm should appear in a timely manner without introducing a nuisance alarm.

This research mainly concerns the evaluation of alarm settings, which has been introduced with AM-KB. Figure 4.5 shows an example of how to configure effective alarm limits [23]. Four zones in the figure indicate four types of plant states: target, normal, upset, and shutdown states. A control system commonly works to restrict all variables within the target operating condition under the normal state. When the plant becomes the upset state from the normal state, HI or LO alarms let the operator know of abnormal situations under the normal state. High-high (HH) or low-low (LL) alarms are provided to inform the operator of critical situations. If the operator fails to recover the plant to the normal state, an emergency shut down (ESD) system will be activated.

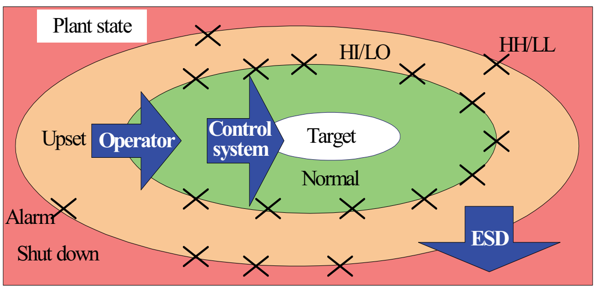


Figure 4.5 Effective alarm settings

In practice, the three boundaries in Fig. 4.5 may be vague, and the choice of alarm settings is complicated. Inadequate alarm settings can cause standing, fleeting, nuisance, and repeating alarms, and these may result in alarm flooding. To avoid these problems, the amplitude and duration of acceptable fluctuations should be determined based on the analysis of a certain number of malfunctions. In order to ensure that an alarm system is usable and effective under all operation conditions, its performance should be assessed during design and commissioning. Regular auditing should be continued throughout a plant life to confirm that good performance is maintained.

By using the operator model as a virtual subject, we can evaluate an alarm system through the following procedure.

(1) List up all available malfunctions in an objective plant.
(2) Build VI-KB, FS-KB, and AM-KB based on process and control system design information, cause-effect analyses, operational experience, and expert reviews of the objective plant.
(3) Through FDI simulations by using the operator model, obtain the resulting FDI track and evaluation criterion for each malfunction.
(4) Evaluate the alarm system and modify alarm settings if necessary.
(5) Repeat steps (1)-(4) until an acceptable result is obtained.

In evaluation, an alarm system is evaluated based on the integral FDI performance after causing the assumed malfunctions. The user interface model supplies real-time process data or off-line data of a plant system or a plant model, including the response of manual operation such as calling a graphic panel.

To construct a sufficient FS-KB is an important work for the dynamic evaluation. Here, an illustrate example shows the cause-effect analysis in case of fuel leak malfunction. Before evaluation, the cause-effect analysis for eleven malfunctions should be done for FS-KB construction.

Based on the procedure mentioned in section 4.2.2, we drew failure propagation chains after a fuel leak, as shown in Fig. 4.6. Lines with double arrows mean the relation of material and energy balances, and lines with an arrow indicate the function of control loops. A thick-lined rectangle means a symptom whose corresponding variable has alarm limits, and a thin-lined rectangle means a symptom whose corresponding variable does not have an alarm limit. A rectangle with a dot line means a symptom whose corresponding variable is unavailable on existing user panels. Fuel leaks affect the air component (A201.PV and A202.PV) in the furnace and the drum's condition (P202.PV and T203.PV). Steam condition (P201.PV and T201.PV) varies, and this changes the air draft state (P203.PV) and fuel oil supply (F202.MV). Table 4.4 shows part of FS-KB for the FDI process. In the fuel leak column (Mal-7) in Table 4.4, elements corresponding to the 15 available symptoms are set to 1.

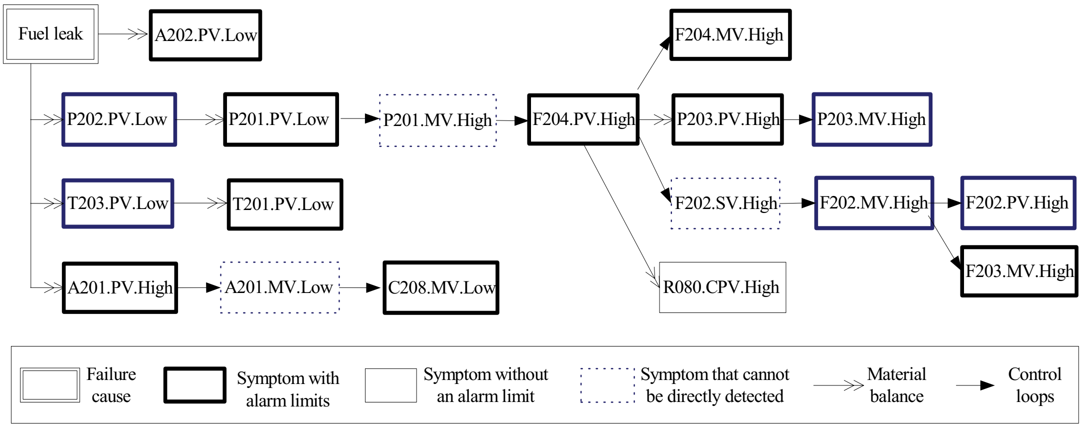


Fig. 4.6 Cause-effect analysis for fuel leak

Table 4.4 Part of failure-symptom knowledge base

Failure cause / Symptom	Mal-1	Mal-2	Mal-3	Mal-4	Mal-5	Mal-6	Mal-7	Mal-8	Mal-9	Mal-10	Mal-11	*SL*
FOP1.Icon.Flash	1	0	0	0	0	0	0	0	0	0	0	1
Burner1.Fire.No	0	1	0	0	0	0	0	0	0	0	0	1
FDF.Icon.Flash	0	0	1	0	0	0	0	0	0	0	0	1
F202.PV.HIGH	0	1	0	0	0	1	1	0	0	0	0	3
A201.PV.HIGH	1	1	0	0	1	0	1	0	0	0	0	4
R080.CPV.HIGH	0	1	0	0	0	1	1	0	0	1	0	4
F202.MV.HIGH	1	1	0	0	1	0	1	0	0	0	0	4
F204.PV.HIGH	0	1	0	0	0	1	1	0	0	1	0	4
C208.MV.LOW	1	1	0	0	1	0	1	0	0	0	0	4
P203.PV.HIGH	0	0	0	1	0	1	1	0	1	1	0	5
P203.MV.HIGH	0	0	0	1	0	1	1	0	1	1	0	5
F203.MV.HIGH	1	1	0	0	1	1	1	0	0	0	0	5
T201.PV.LOW	1	1	1	0	1	0	1	0	0	0	0	5
T203.PV.LOW	1	1	1	0	1	0	1	0	0	0	0	5
A202.PV.LOW	1	1	0	0	1	0	1	0	0	1	0	5
P201.PV.LOW	1	1	1	0	1	0	1	1	0	0	0	6
P202.PV.LOW	1	1	1	0	1	0	1	1	0	0	0	6
F204.MV.HIGH	0	1	1	1	0	1	1	0	0	1	0	6
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
FL	18	18	18	9	19	16	15	10	5	8	6	

4.5 Case Study

Four malfunctions were abandoned in the evaluation scenarios even though operator model can identify all eleven malfunctions based on corresponding symptoms. Mal-8, which presents a direct alarm of a BFP1 trip, is unsuitable for this study because fault identification is not needed in this case. Since Mals-9 and -10 can only cause such slight fluctuation that an abnormality cannot appear for a long time, they should be identified with some monitoring tactics other than an alarm system. If we do not filter repeating alarms, Mal-11 always causes alarm flooding which is not the focus of our current interest.

4.5.1 Evaluation and Improvement of Alarm System A

In the existing alarm system of the simulator denoted as alarm system A, 21 continuous process variables with 123 alarm limits are shown in Table 4.5. The settings of alarm system A were designed by the boiler plant simulator's manufacturer. Most alarm limits in Table 4.5 cannot be violated because they are set at their extreme values. Tags with possibly violated alarm limits in the simulation are indicated in bold. There are only 12 process variables with 28 possibly violated alarm limits in alarm system A.

Table 4.5 Settings of alarm limits in alarm system A

Tag \ Limit	HH	PH	PL	LL	VL	Unit 1	MH	ML	Unit 2
A201	10	10	**1.5**	**0.5**	10	%	100	0	%
A202	**275**	**150**	0	0	500	ppm	100	0	%
C208	-	-	-	-	-	-	**60**	**40**	%
F201	100	100	0	0	100	t/h	-	-	-
F202	10	10	0	0	10	t/h	100	0	%
F203	-	-	-	-	-		100	**40**	%
F204	100	100	**25**	**20**	100	t/h	100	0	%
F205	100	**90**	0	0	100	t/h	100	0	%
F206	10	10	0	0	10	t/h	100	0	%
L201	100	**50**	**-50**	-100	200	mm	100	0	%
L202	**95**	**50**	**-50**	**-95**	200	mm	100	0	t/h
P201	**90**	**85**	**75**	**70**	100	Kg/cm^2	100	0	%
P202	100	100	0	0	100	Kg/cm^2	-	-	-
P203	100	**50**	**-50**	-100	200	mmH_2O	100	0	%
P204	15	15	**2.2**	**2**	15	Kg/cm^2	100	0	%
P205	15	15	0	0	15	Kg/cm^2	-	-	-
P206	100	100	0	0	100	Kg/cm^2	-	-	-
T201	**520**	**500**	**480**	**470**	300	ºC	10	0	t/h
T202	600	600	0	0	600	ºC	-	-	-
T203	400	400	0	0	400	ºC	-	-	-
T204	100	100	0	0	100	ºC	-	-	-

Unit 1: unit of HH, PH, PL, and LL; Unit 2: unit of MH and ML;
Bold: tags with alarm limits that may be violated.

A failure cause is identified when its total *AS* value exceeds a threshold, defined as 0.6. After a fuel leak is caused in alarm system A, the alarm statuses that appeared during the FDI process are listed in Table 4.6. Figure 4.7 is the resulting FDI track, and the thick vertical bars indicate operational stages with their sequence numbers. The track was generated based on the proposed ASSP in the operator model. Figure 4.8 shows a screenshot of the evaluation process. An eye movement trajectory is displayed on the graphic panel. In this research, the trajectory of gate points is drawn by line segments.

Table 4.6 Alarms after fuel leak in alarm system A

No.	Time after fuel leak [s]	Alarm status
1	15	T201.LO
2	20	C208.MLO
3	45	P201.LO

Figure 4.7 FDI track of fuel leak under alarm system A

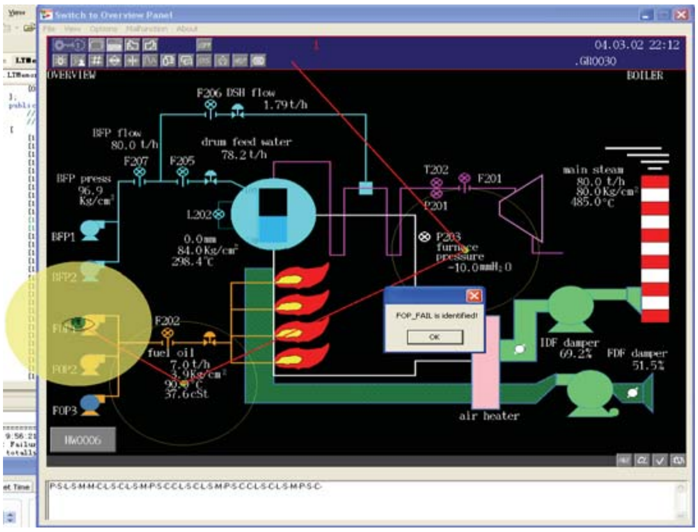


Fig. 4.8 Screenshot of evaluation program

Through AM-KB, an alarm message for T201.LO was interpreted as symptom T201.PV.Low, which is connected with the following failure causes: FOP1 failure (Mal-1), burner extinction (Mal-2), FDF degradation (Mal-3), oil heater failure (Mal-5), and fuel leak (Mal-7). The corresponding *AS* values of the links between symptom T201.PV.Low and the above five failure causes were 0.010, 0.010, 0.010, 0.015, and 0.051, respectively. Based on the ASSP, the operator model started to identify the failure cause from the fuel leak. Comparing the Mal-2 column with Mal-7 in Table 4.4, it found that most Mal-7 symptoms are also Mal-2 symptoms and that P203.PV.High is an important symptom to distinguish Mal-7 from Mal-2. The operator model gave high weight to symptom P203.PV.High, so it began symptom confirmation from P203.PV.High. Most weights for symptoms are set as 1, except some symptoms have definite relation with a failure cause. Failure cause can be quickly identified if these symptoms are early verified. Soon after the malfunction, only a few variables became out of normal ranges. At the 13th operational stage, a new alarm was issued, and ASSP was restarted. This is called an FDI round.

In the second round, P203.PV.High was not verified again, but a second alarm, C208.MLO appeared. After totaling the *AS* values for each failure cause, the operator model continued to confirm P203.PV.High for Mal-7. Based on ASSP, even if P203.PV.High was not verified, the next symptom for Mal-7, F202.PV.High was sequentially confirmed and verified. Symptoms FOP1.Icon.Flash, Burner1.Fire.No, and FDF.Icon.Flash have the highest weight to calculate the total *AS* values for Mals-1, -2, and -3, respectively; so these malfunctions can be easily rejected in the FDI process. In the Mal-7 column of Table 4.4, except symptoms T201.PV.Low, C208.MV.Low, and P201.PV.Low that were shown by alarms, symptoms F202.PV.High, F202.MV.High, A201.PV.High, F204.PV.High, T203.PV.Low, and F203.MV.High were sequentially verified for Mal-7. Since several variables were not abnormal before FDI was accomplished, some corresponding Mal-7 symptoms were not successfully verified. Finally, 48.7 seconds after the earliest alarm, the true failure cause was identified when the total *AS* value of the fuel leak became larger than 0.6.

Table 4.7 shows the evaluation results of alarm system A. Alarm T201.LO appears four times as the earliest alarm, which gives the complexity of FDI. Figure 4.9 shows the changes in the total *AS* value after Mal-7. On the other hand, the earliest alarms of Mals-4, and -6 appear 60 seconds later after the malfunctions occurred, which makes it difficult to cope with these failures. Generally, the evaluation mainly shows the two weaknesses of alarm system A: the earliest alarms appear too late for some malfunctions and the Mal-7 FDI costs too many operational stages and has a long distance of eye movement.

Table 4.7 Evaluation results of alarm system A

Criterion \ Malfunction	Mal-1	Mal-2	Mal-3	Mal-4	Mal-5	Mal-6	Mal-7	Total
Earliest alarm	T201.LO	T201.LO	F203.MLO	P203.HI	T201.LO	A201.LO	T201.LO	
Earliest alarm appearance [s]	26.3	13.7	5.4	65.7	50.2	96.2	17.8	275.3
Number of alarms during FDI	1	1	1	1	1	1	3	9
Number of operational stages	13	10	4	16	7	16	162	228
Eye movement distance [cm]	61.6	47.6	30	120.9	37.1	76.3	848.2	1221.7
Elapsed time for FDI [s]	4.3	3.6	2.4	6.3	3.2	6.8	48.7	75.3
Elapsed time for scenario [s]	30.6	17.3	7.8	72	53.4	103	66.5	350.6

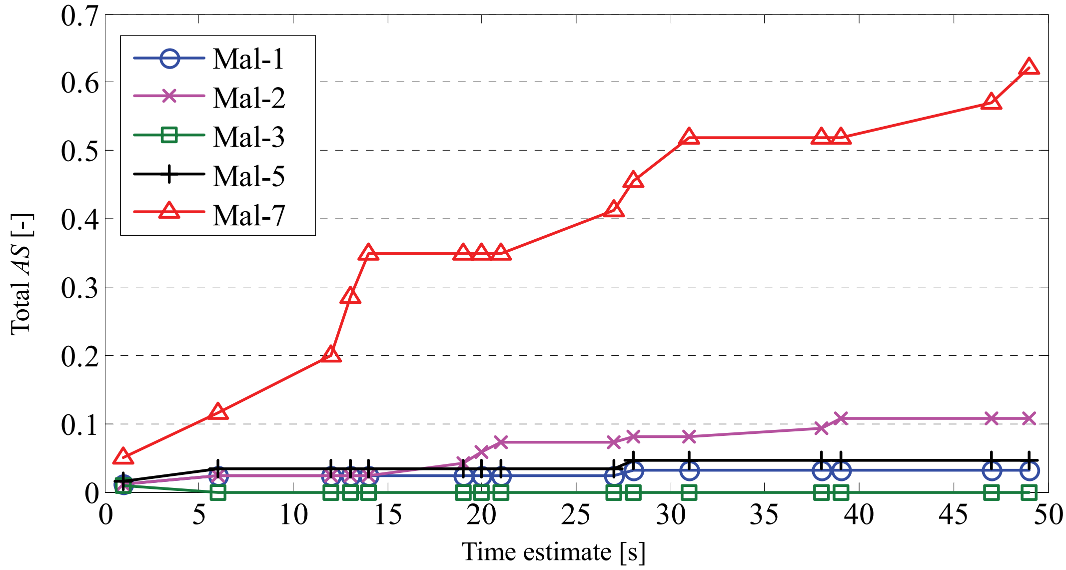


Figure 4.9 Changes in total AS values for alarm system A

We collected the measured data of the 29 variables that have alarm limits and obtained their normal ranges. Accordingly, we tightly redefined the PH, PL, and VL values. A margin was defined as 2% of a variable's measurement range. As shown in Fig. 4.10, PH value is defined as the maximum value of a variable in normal fluctuation plus the margin; PL value is set to the minimum value of the variable in normal fluctuation minus the margin; VL is set to the value of the maximum rate of change plus a small value. The alarm system B is build according to these setting instructions.

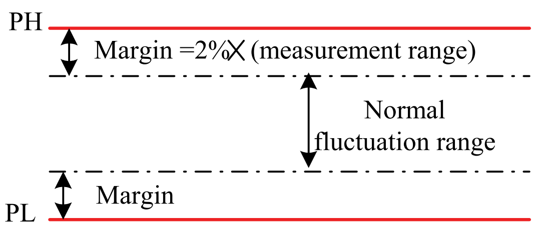


Figure 4.10 Setting of PH and PL

4.5.2 Evaluation and Improvement of Alarm System B

Table 4.8 shows the new settings of alarm limits, Figure 4.11 illustrates the changes in total *AS* values after a fuel leak for alarm system B. and Table 4.9 lists the evaluation results of alarm system B. The earliest alarms are presented very early but more alarms appear in the case of fuel leak (Mal-7), which disturb the FDI process. In addition, burner-head pressure sensor failure (Mal-6) causes a P201.VEL- alarm very quickly, but it might be too early to detect other abnormalities. Worst of all, improper VL settings incurred repeating alarms. The evaluation results show that strict alarm settings near corresponding normal fluctuation ranges may be ineffective. Useless alarms misguided the FDI process, increased the number of operational stages and the distance of eye movement, and complicated the FDIs of Mals-3, -6, and -7.

According to the evaluation results of alarm system B, we retained the limits such as F202.PL, P203.PL, P203.PH, T204.PL, and F202.PH at strict levels, loosened the limits of F204.PL, P201.PL, and T201.PL, and reset A201.PH, F204.PH, F205.PL, F206.PL, P202.PL, P204.PH, P205.PL, and T203.PL to their extreme values. These alarm settings have been adjusted several times to obtain better FDI performance, and the final solution is called alarm system C.

Table 4.8 Settings of alarm system B

Tag \ Limit	HH	PH	PL	LL	VL	Unit1	MH	ML	Unit2
A201	10	**2.98**	**2.41**	**0.5**	**0.21**	%	100	0	%
A202	**275**	**35.7**	0	0	**10**	ppm	100	0	%
C208	-	-	-	-	-	-	**60**	**40**	%
F201	100	**84.4**	**75.9**	0	**2.19**	t/h	-	-	-
F202	10	**7.43**	**6.58**	0	**0.22**	t/h	100	0	%
F203	-	-	-	-	-		100	**40**	%
F204	100	**73.9**	**66**	**20**	**2.06**	t/h	100	0	%
F205	100	**83.1**	**74**	0	**2.66**	t/h	100	0	%
F206	10	**2.08**	**1.5**	0	**0.22**	t/h	100	0	%
L201	100	**50**	**-50**	-100	**4.15**	mm	100	0	%
L202	**95**	**5.01**	**-5.33**	**-95**	**4.15**	mm	100	0	t/h
P201	**90**	**82.6**	**77**	**70**	**2.02**	Kg/cm^2	100	0	%
P202	100	**86.6**	**81**	0	**2.02**	Kg/cm^2	-	-	-
P203	100	**9.76**	**-18.9**	-100	**4.09**	Kg/cm^2	100	0	%
P204	15	**4.41**	**2.2**	**2**	**0.32**	Kg/cm^2	100	0	%
P205	15	**13.3**	**12**	0	**0.31**	Kg/cm^2	-	-	-
P206	100	**99.2**	**94.7**	0	**2.02**	Kg/cm^2	-	-	-
T201	**520**	**496**	**474**	**470**	**6.11**	ºC	10	0	t/h
T202	600	600	0	0	**12.1**	ºC	-	-	-
T203	400	**307**	**290**	0	**8.01**	ºC	-	-	-
T204	100	**92**	**87.1**	0	**2.01**	ºC	-	-	-

Characters in shading: modified items from alarm system A

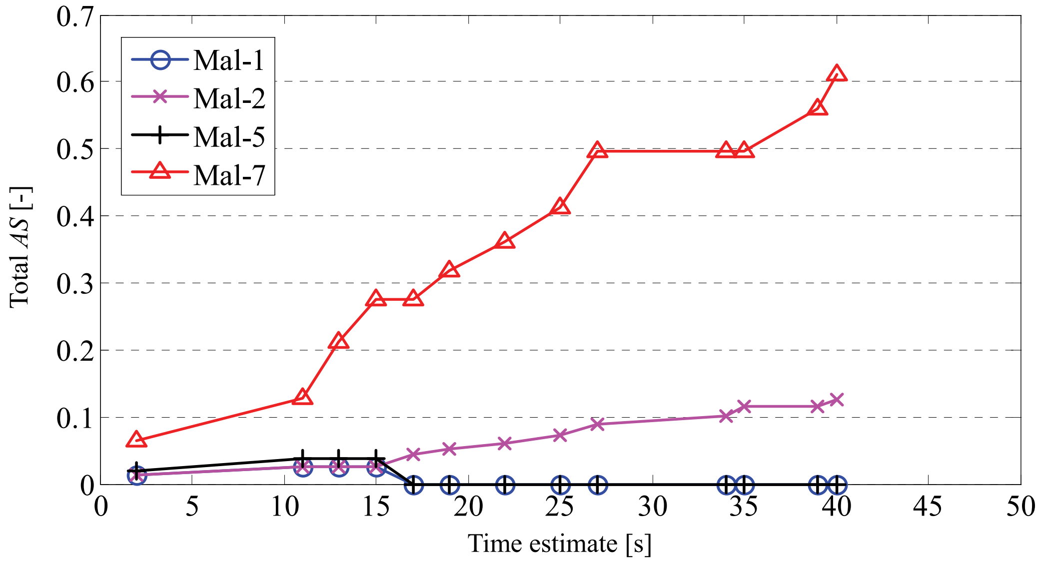


Figure 4.11 Changes in total *AS* values for alarm system B

Table 4.9 Evaluation results of alarm system B

Criterion \ Malfunction	Mal-1	Mal-2	Mal-3	Mal-4	Mal-5	Mal-6	Mal-7	Total
Earliest alarm	P204.VEL-	P203.LO	F204.LO	P203.HI	T204.LO	P204.VEL-	A201.HI	
Earliest alarm appearance [s]	8.8	2.8	3.9	12.2	12.7	1.4	14.6	56.4
Number of alarms during FDI	2	1	2	1	2	3	8	19
Number of operational stages	8	7	8	16	8	190	110	347
Eye movement distance [cm]	44.5	34.8	54.2	120.9	42.3	1028.8	512.2	1837.7
Elapsed time for FDI [s]	5.1	3.1	5.2	6.2	5.0	65.6	41.3	131.5
Elapsed time for scenario [s]	13.9	5.9	9.1	18.4	17.7	67	55.9	187.9

4.5.3 Evaluation and Improvement of Alarm System C

Table 4.10 shows the new alarm settings. Figure 4.12 illustrates the changes in total *AS* values after a fuel leak for alarm system C. Comparing with Fig. 4.9 and Fig. 4.11, we see that alarm system C effectively helps distinguish failure causes and shortens the time to accomplish the FDI process. Table 4.11 lists the three alarms after a fuel leak by using alarm system C. These alarm messages supplied useful information to identify the failure cause.

The fuel leak FDI is just an illustrative example. We evaluated alarm systems for seven malfunctions (Mal-1 ~ Mal-7) and repeated the evaluations for a better solution.

Table 4.12 shows evaluation results of alarm system C. Most of earliest alarms are presented faster than system A. Even early alarms are helpful to detect abnormalities. Since FDI needs to confirm a certain number of symptoms, it may cost an operator model more time to verify additional symptoms after these alarms, for example, the cases of Mals-5 and -6. The corresponding earliest alarms for the seven malfunctions are F202.LO, P203.LO, F203.MLO, P203.HI, T204.LO, F202.HI, and C208.MLO, respectively, which effectively warn of the typical abnormalities of the corresponding malfunctions. Generally, alarm system C decreases the number of operational stages, the total length of eye movement, and the elapsed time for FDI of seven malfunctions. The number of alarms during FDI is basically acceptable. Alarm system C is not an optimum solution for some malfunctions, but it is important to evaluate the alarm system as a whole.

Table 4.10 Settings of alarm system C

Tag \ Limit	HH	PH	PL	LL	VL	Unit1	MH	ML	Unit2
A201	10	10	**2.41**	**0.5**	10	%	100	0	%
A202	**275**	**35.7**	0	0	500	ppm	100	0	%
C208	-	-	-	-	-	-	**60**	**40**	%
F201	100	**84.4**	**75.9**	0	100	t/h	-	-	-
F202	10	**7.43**	**6.58**	0	10	t/h	100	0	%
F203	-	-	-	-	-		100	**40**	%
F204	100	100	**25**	**20**	100	t/h	100	0	%
F205	100	**83.1**	0	0	100	t/h	100	0	%
F206	10	**2.08**	0	0	10	t/h	100	0	%
L201	100	**50**	**-50**	-100	200	mm	100	0	%
L202	**95**	**5.01**	**-5.33**	**-95**	200	mm	100	0	t/h
P201	**90**	**82.6**	**75**	**70**	100	Kg/cm^2	100	0	%
P202	100	**86.6**	0	0	100	Kg/cm^2	-	-	-
P203	100	**9.76**	**-18.9**	-100	200	Kg/cm^2	100	0	%
P204	15	15	**2.2**	**2**	15	Kg/cm^2	100	0	%
P205	15	**13.3**	0	0	15	Kg/cm^2	-	-	-
P206	100	**99.2**	**94.7**	0	100	Kg/cm^2	-	-	-
T201	**520**	**496**	**470**	**465**	300	ºC	10	0	t/h
T202	600	600	0	0	600	ºC	-	-	-
T203	400	**307**	0	0	400	ºC	-	-	-
T204	100	**92**	**87.1**	0	100	ºC	-	-	-

Characters in shading: modified items from alarm system B

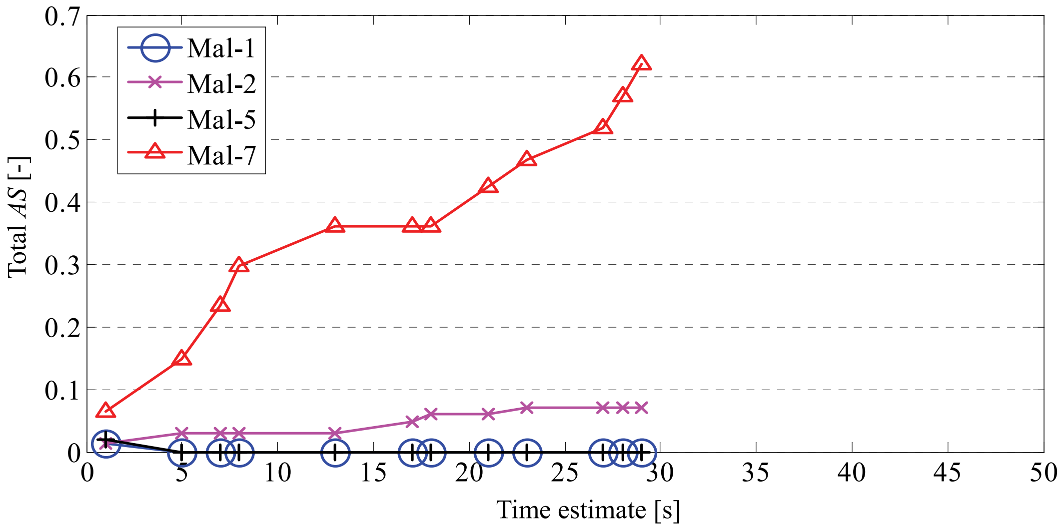


Figure 4.12 Changes in total *AS* values for alarm system C

Table 4.11 Alarms after fuel leak for alarm system C

No.	Time after fuel leak [s]	Alarm
1	23	C208.MLO
2	29	F202.HI
3	45	P201.LO

Table 4.12 Evaluation results of alarm system C

Criterion \ Malfunction	Mal-1	Mal-2	Mal-3	Mal-4	Mal-5	Mal-6	Mal-7	Total
Earliest alarm	F202.LO	P203.LO	F203.MLO	P203.HI	T204.LO	F202.HI	C208.MLO	
Earliest alarm appearance [s]	9.4	2.9	5.1	12.1	13.3	53.8	24	120.6
Number of alarms during FDI	1	1	1	1	1	2	3	10
Number of operational stages	7	7	4	16	4	36	83	157
Eye movement distance [cm]	32.0	34.8	30.0	120.9	24.9	144.2	383.3	770.1
Elapsed time for FDI [s]	3.1	3.1	2.6	6.0	2.5	13.0	28.8	59.1
Elapsed time for scenario [s]	12.5	6	7.7	18.1	15.8	66.8	52.8	179.7

4.6 Summary

A quantitative evaluation approach based on an operator model was proposed for evaluating alarm systems during emergencies. Three alarm systems were involved in the evaluation. Alarm system A was designed by the manufacturer, so its design principles are not clear. To investigate the influence of alarm limits on FDI performance, alarm limits in alarm system B are defined near to their normal fluctuation range. Based on the evaluation results, alarm system C is defined by trial and error method. Through this model-based method, we located the weaknesses in alarm systems A and B. Evaluation results shows that alarm system C is the best solution. The presented method can be used to support alarm system design and evaluation.

5 CONCLUSION AND FUTURE WORK

5.1 Conclusion

In this study, a visual performance model and a comprehensive cognitive information-processing model were proposed for static evaluation of graphic panels and dynamic evaluation of alarm systems, respectively.

For static evaluation, the color, size, and shape of each graphic item are viewed as stimulus intensity and can cause human visual sensation. The visual performance model is used to quantify such sensation according to visual strength. Evaluation results showed that the visual performance model could be used as a support tool in the early stages of graphic panel design.

Dynamic evaluation is used to rationalize the alarm system from the viewpoint of improving plant operator's fault detection and identification (FDI) performance under emergency situations. Based on Card's model human processor, a cognitive information-processing model workable on the PC is developed as a virtual subject to detect and identify failure causes. Seven assumed malfunctions were caused in evaluation scenarios. The virtual subject detected the first symptom while the earliest alarm appeared and then identify the failure cause by checking several related process variables and monitoring alarm information. The virtual subject automatically generated the FDI track. Evaluation criteria were quantified according to the FDI track. Weaknesses of alarm settings were located. After adjusted the related alarm limits, the FDI performance was improved as a whole. The presented method can be used to support alarm rationalization. The knowledge bases are built based on general knowledge, and these knowledge bases are easily modified for additional malfunctions. These features are useful for practical applications.

Both evaluation methods supply quantitative results. Construction of operator model for dynamic evaluation is simple and can be easily extended to various abnormal situations and plant systems. Knowledge bases are built in predefined rules, which means the evaluation results are independent of model designer. By following the predefined rules, almost all kinds of failure causes in a plant system can be considered in evaluation scenarios. A few of evaluation criteria are helpful to find weaknesses in an alarm system.

5.2 Future work

It is assumed that fault detection and identification begins from the earliest alarm in the dynamic evaluation, which makes the evaluation unavailable for some malfunctions. A normal state monitoring procedure should be defined to early detect abnormalities before an alarm appears. Abnormal state supervising procedure only involves one supervising tactic. Different rejection and confirmation tactics and their mixtures for fault identification should be investigated. Attention allocation, limitations of short-term memory capability, and mental state and workload estimation may be introduced to the operator model in the future.

Even though the operator model based methods are flexible and stable, fidelity of the simulation is a key issue when we compare the model-based evaluation with a human operator's evaluation. Each human operator may have special characters and different thinking methods with others. In this thesis, the proposed approaches are just utilized for finding fundamental latent weaknesses. However, because the models can be extended easily, we are going to customize the operator models for diverse human operators and various situations in the future.

A combination of operator models, experimental methods, and other usability testing techniques provide a practical approach to usability evaluation and prediction of task performance time and accuracy. The relationship between experiments with human subjects and experiments with an operator model is illustrated in Fig. 5.1 [26]. Experimental studies provide the calibration data to validate the structural and parametric components of the operator model and increase their predictive power. Once validated, operator models can be used to help focus the usability testing on those areas where model predictions are not consistent with expectations or observations.

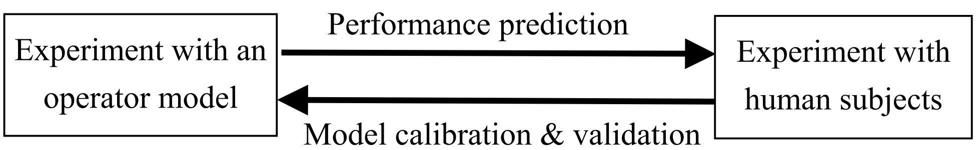


Figure 5.1 Synergy of modeling and experimental approaches

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