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Development of an Integrated Decision Support System to Aid the Cognitive Activities of Operators in Main Control Rooms of Nuclear Power Plants

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***Abstract*—In safety critical systems, especially in nuclear power plants (NPPs), human error has been introduced as one of the serious causes of accidents. In order to prevent human errors, many efforts have been made to improve main control room (MCR) interface designs and to develop decision support systems that allow convenient MCR operation and maintenance. In this paper, an integrated decision support system to aid the cognitive process of operators is proposed for advanced MCRs in future NPPs. This work suggests support system design considered an operator's cognitive process. Various kinds of support systems for advanced MCRs have been developed or are in development. Therefore, a design basis regarding what kinds of support systems are appropriate for MCR operators is necessary. The proposed system supports not merely a particular task, but also the entire operation process based on a human cognitive process model. It supports the operator's entire cognitive process by integrating support systems that support each cognitive activity. Furthermore, two decision support systems are developed. The fault diagnosis advisory system is to make the task of fault diagnosis easier and to reduce errors by quickly suggesting likely faults based on the highest probability of their occurrence. The operation validation system is to provide an advisory function to supervise and validate the operator's actions during abnormal environments.**

I. Introduction

A. Background

In safety critical systems, especially in nuclear power plants (NPPs), human error has been introduced as one of the serious causes of accidents. From 80s, the importance of human error in NPPs has been considerably concerned. In an analysis of abstracts of 180 significant events reported to have occurred in the United States, it was found that 48% of the incidents were attributed to human factor failures [1]. In order to prevent human errors, many efforts have been made to improve main control room (MCR) interface designs and to develop decision support systems that allow convenient MCR operation and maintenance. The decision support of operational performance is needed to assist the operator, particularly in coping with plant anomalies, so that the failures of complex dynamic processes can be managed as quickly as possible with minimum adverse consequences.

B. Objectives

In order to design useful decision support systems, a design basis and a systematic frame are needed. Various decision support systems have been developed, and others are in development. As MCRs evolve, more decision support systems will be adapted to them. However, according to the evaluation results for decision support systems in several papers, a decision support system does not guarantee an increase in an operator's performance [2,3]. Some support systems could degrade an operator's situational awareness capability and could increase an operator's mental workload. When several kinds of decision support systems are used, a design basis is necessary to solve problems regarding what kinds of decision support systems are most efficient, what kinds are most appropriate.

This paper proposes an integrated decision support system to aid the cognitive activities of operators (INDESCO). The objective of the INDESCO is to design an integrated decision support system for advanced MCRs by suggesting decision support systems to aid operators' cognitive processes and by integrating these support systems into one system based on the human cognitive process. In this paper, an operator's operation processes were analyzed with respect to the human cognitive process, and systems that support each activity of the human cognitive process were suggested. Furthermore, two kinds of decision support systems were developed as components of the INDESCO.

II. Cognitive Process Model for Operators in NPPs

In this paper, major cognitive activities for NPP operations underlying A Technique for Human Error Analysis (ATHEANA) [4],[5] are used. The major cognitive activities for NPP operations underlying ATHEANA are: (1) monitoring and detection, (2) situation assessment, (3) response planning, and (4) response implementation.

Decision support systems to improve operators' performance can be categorized into two approaches [6]. One approach is the improvement of the displays of MCRs, which can be called "indirect support." Improved display systems using integrated graphic displays, configurable displays, and ecological interface designs and information systems, such as an alarm system, are some of the indirect support systems. They improve the operators' perceptions and awareness abilities. If indirect support systems are added, operators can perceive the plant status more easily and quickly using the information provided by the improved display system and obtain the digested data from the information system. Therefore, indirect support systems can improve the performance of the monitoring and detection activity in the operators' cognitive process. The other approach is the development of decision support systems, which can be called "direct support." These include intelligent advisors, alarm systems, computer-based procedures, fault diagnostic systems, and computerized operator support systems, which are based on expert systems or knowledge-based systems. These direct support systems support other three cognitive activities. For example, as shown in Fig. 1, several indirect and direct support systems can be added as part of the advanced HMI.

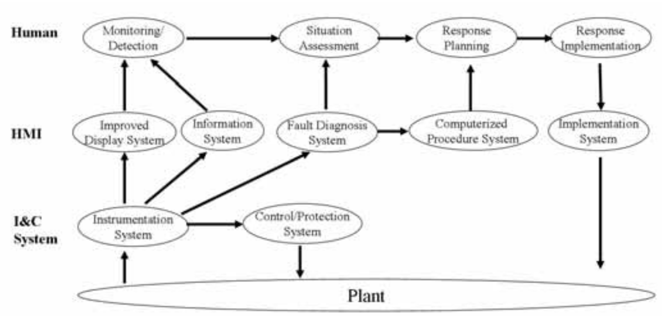

Fig. 1. NPP operation process with the indirect and the direct support systems

III. Integrated Decision Support System to Aid Operator's Cognitive Activities

The main idea of the INDESCO is to suggest decision support systems to aid operators' cognitive activities and to integrate these support systems into one system. The INDESCO is not a system which helps a task or supports one or two cognitive activities. It supports every major cognitive activity by integrating support systems that support each cognitive activity. Since the INDESCO can perform the same operation process as operators' in order to support the cognitive process of the operators, it is possible to detect human errors in operation processes. The system is a kind of advisory system for preventing human errors.

Various indirect or direct support systems can be added to human machine interfaces (HMIs) to support the activities of cognitive processes. There are various indirect and direct support systems, and all of them support activities of the operator's cognitive process. Among these many systems, appropriate support systems could be selected based on the cognitive process, thus enhancing operational efficiency. For example, several kinds of support systems are selected, and their related cognitive activities are shown in Fig. 2. A display system, which is one of the indirect systems, is to support the monitoring and detection activity. A fault diagnosis system, a computerized procedure system, and an operation validation system are kinds of direct systems supporting three other cognitive activities. In addition, there are an alarm prioritization system, an alarm analysis system, a corresponding procedure suggestion system, and an adequate operation suggestion system. Since the latter four systems can be implemented as sub-systems of the former four systems, the former four systems could be classified into main support systems.

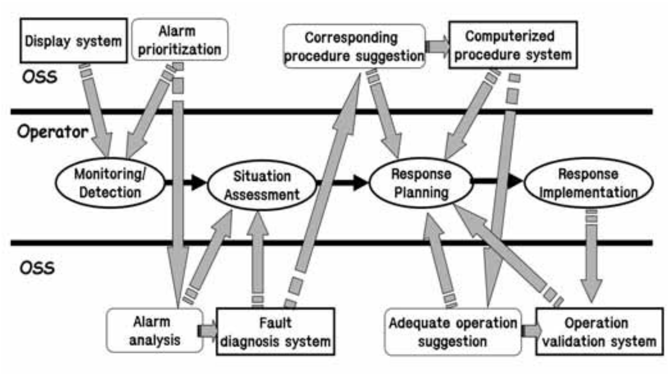

Fig. 2. Operator support systems based on human cognitive process model

Firstly, a display system supports the monitoring and detection activity. The display system is for an efficient display and interface design, and it involves the improvement of the integrated graphic displays, configurable displays, and an ecological interface design. The display systems also improve the operators' perception and awareness abilities: operators can perceive the plant status more easily and quickly using the information from the improved display system and can obtain the digested data from the information system. Additionally, an alarm system supports the monitoring and detection activity.

Secondly, a fault diagnosis system is suggested to support the situation assessment activity. The fault diagnosis system detects faults and informs the operators of the results; therefore, it makes the situation assessment easier by quickly supplying the diagnosis results. Fault diagnosis systems have been developed using knowledge bases [7], neural networks [8],[9], genetic algorithms [10], and other means.

Thirdly, a computerized procedure system supports the response planning activity. Operators in NPPs generate plans to operate and maintain NPPs according to written operating procedures. Thus, a computerized procedure system can be helpful for response planning activity. Since the content of the paper based operating procedure is written in fixed format in natural language, sometimes the information would be overwhelming and become difficult to continuously manage the steps. Because of the deficiencies of the paper based operating procedure, the developments and implementations of computerized procedure system have been begun since 80s. In a computerized procedure system, information about procedures and steps, relations between the procedures and steps, and the parameters needed to operate the plant are displayed [11],[12].

Lastly, for response implementation activity, the operation validation system validates the actions performed by the operators. If the actions that are taken by the operators are in the operation candidate list, and are reasonable, then the actions will be performed without interruption. However, if the actions are obviously inadequate for the current situation, the operation validation system interrupts the actions and warns the operators. This system gives operators a chance to check and to confirm their actions. Several research papers have addressed operation validation systems [13].

Based on the aforementioned main support systems, several sub-systems are suggested. The alarm prioritization system allows operators to focus on the most important alarms. It supports the monitoring and detection activity. The alarm analysis system could be one kind of fault diagnosis system or a sub-function of a fault diagnosis system. It identifies or diagnoses the current situation by analyzing alarms. It supports the situation assessment activity. The corresponding procedure suggestion system and the adequate operation suggestion system may be advanced functions of the computerized procedure system. In abnormal situations, the fault diagnosis system identifies faults. After identifying the faults, an appropriate operating procedure necessary to manage the current situation is selected by the corresponding procedure search system based on the diagnosis results. Operators can recognize which operating procedure should be performed by the system, and errors of incorrect procedure selection can be reduced. Adequate actions for the following operations are listed on an operation candidate list by the adequate operations suggestion system. Operators can decide which operations are needed from the list.

Several support systems are suggested as appropriate to support the cognitive process efficiently. They facilitate the operator's whole operation process: monitoring plant parameters, diagnosing the current situation, selecting corresponding actions for the identified situation, and performing the actions. As main support systems for cognitive activities, four support systems are selected: the display system, the fault diagnosis system, the computerized procedure system, and the operation validation system.

IV. Fault Diagnosis System

A fault diagnosis system is a kind of decision support system. The objective of a fault diagnosis system is to make the task of fault diagnosis easier, to reduce errors, and to ease the workload of operators by quickly suggesting likely faults based on the highest probability of their occurrence. During the first few minutes after a fault occurrence, operators in an MCR must perform highly mentally workloaded activities. The operators may be overworked and disorder may result. Information overload and stress may severely affect the operators' decision-making ability just when it is required most [14]. In such situations, using a fault diagnosis system will be very helpful in that it will enhance operators' decision-making ability and reduce their workload.

In this paper, the fault diagnosis advisory system (FDAS) is developed [8]. In order to perform better than other fault diagnosis systems, the FDAS proposed here has three main objectives. The first objective is to analyze the plant status and show a fault list in real time. Reasonable results should be generated using information up to the current time through analysis of dynamic trends. The second objective is to perform fault diagnosis in more detail. Most existing fault diagnosis systems are able to tell operators what the fault is but cannot provide details on fault size or location. The third objective is to consider and handle both analogue and digital inputs. To satisfy these three objectives, two kinds of neural networks that consider time factors are used in this work.

For a more accurate and detailed diagnosis, both digital and analogue inputs are considered in the FDAS using two kinds of neural networks. Digital inputs such as alarms, trip parameters, statuses of valves, and statuses of devices are handled by the modified dynamic neural network (MDNN), while analogue inputs such as values of instruments are handled by the dynamic neuro-fuzzy network (DNFN). First, inputs are clustered according to their types. Next, the two neural networks generate each output using clustered inputs. Finally, results and their reliabilities are generated by combining the results of these two neural networks. The process is a duplicated calculation in which quite a few variables of analogue and digital inputs represent the same things. Alarms are turned on and off according to their related instruments. When systems like the safety injection or valves like the steam generator isolation valves are operated, the values of related instruments will change and we can perform fault diagnoses using just one type of input. However, we may be able to get more certain results using both neural networks as the two can complement each other.

One of the critical issues for fault diagnosis systems is their level of reliability because, without a high level of reliability, operators will not trust their fault diagnosis system. When a fault diagnosis system gets the wrong inputs because of failed instruments or devices, undesirable outputs could be generated. Also, an unexpected situation could lead to the misdiagnosis of a fault. If operators must always consider such misdiagnoses, the fault diagnosis system is meaningless. The FDAS proposed here increases the reliability of the diagnosis result by using two independent neural networks. As mentioned above, the MDNN and the DNFN in the FDAS perform independent fault diagnoses using different inputs, thereby complementing each other and generating a more reliable result. When the results of the MDNN and the DNFN differ, operators can see the discrepancy and can double-check the results. On the other hand, if the results of both neural networks are very close, then operators can be confident that the results are accurate and reliable. After each neural network generates results, final results are calculated based on the results of the two neural networks, and their reliabilities are also calculated according to the similarity between the results of the MDNN and the DNFN.

A. Modified Dynamic Neural Network

The MDNN handles digital inputs and identifies faults by analyzing the occurrence sequences of alarms and their patterns. The faults have quite different alarm patterns according to their positions or sizes. In order to diagnose faults using alarm patterns, three things should be considered. The first is noisy inputs. Because lots of inputs are used for fault diagnosis, noisy inputs caused by certain plant conditions or failed instruments are likely. Because such noisy inputs can adversely affect results, efforts must be made to prevent noisy inputs from influencing the output. An ability to handle noisy inputs or informal inputs is necessary. Secondly, fault analyses are not performed in a fixed time because there is no time limit. An ability to generate reasonable results with only information up to the current time step is also necessary. The last is the time deviation problem. For a fault diagnosis system using alarm patterns, the time deviations of alarm patterns are quite important. An input of training scenarios will not be the same as that of real faults at exactly the same time step. Time deviations in alarm occurrences will probably exist. If inputs delayed a few time steps affect the output, the output will be quite different from the desired result. In a fault diagnosis system, even a small input deviation may propagate and eventually cause incorrect results because many faults have very similar input patterns. Therefore, the fault diagnosis system should be able to handle this kind of time deviation problem.

Neural networks can handle the first problem because they are able to deal with noisy inputs and informal inputs. The second problem can be solved by using dynamic neural networks because these networks consider time factors and can perform real-time analysis. However, the third problem cannot be solved by conventional neural networks or by existing dynamic neural networks because neither has the necessary functions to solve the time deviation problem. Therefore, in this work, a MDNN is proposed to solve that problem.

Basically, the MDNN suggested in this work is based on the multi-layer Perceptron but the MDNN has three distinct features: time-varying weight factors and offsets, a final output layer, and a calculation method to obtain outputs. The structure of the MDNN is shown in Fig. 3.

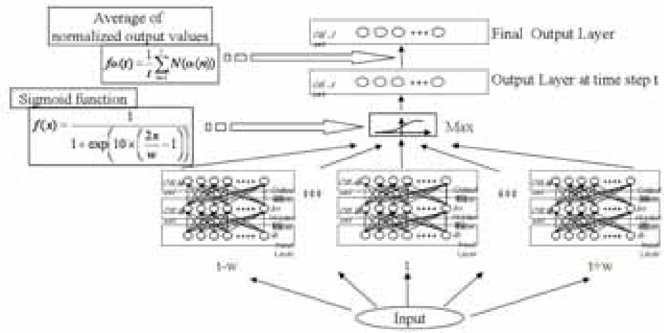

Fig. 3. Output calculation process at time step ‘t’

Firstly, in the MDNN, all weight factors and offsets are the functions of time that have different values at each time step. That is, the MDNN can be regarded as an assembly of many static neural networks for each time step. The values of weight factors and offsets are independent of the values at other time steps. Secondly, the multi-layer Perceptron does not have the final output layer that is a function of the MDNN. The units in hidden layer and output layer have the time functions for offsets and the units in final output layer have offset values. While the analysis for each time step is performed in the former two layers, the final decision is made regardless of the time step in the latter layer. If one or more alarm signals are incorrectly generated at some time steps, the output values will probably be incorrect as well. These undesirable values can propagate through the iterative process, and can cause an inaccurate final result; moreover, if these incorrect values affect the final output values, an incorrect decision will be made. To prevent this, the consistency of values of the output layer should be considered in the final output. Lastly, in the MDNN, the output of the current time step is obtained considering networks of not only the current time step but also of the previous and the next time step. An input of training scenarios will not be the same as that of real faults at exactly the same time step. Time deviations for alarm occurrences will probably exist, so the MDNN should consider the deviations. Therefore, to obtain an output in the MDNN, networks of previous and next time steps are also used. The calculation process is shown in Figure 11. Outputs of these networks are calculated by a sigmoid function that gives relative importance to the outputs, and finally the maximum value is selected. Equation (1) represents the sigmoid function used in this system.

$$f(x) = \frac{1}{1+\exp\left(10\times\left(\frac{2x}{w}-1\right)\right)} \tag{1}$$

where
x: difference between a current time step and a target time step
w: considering range

B. Dynamic Neuro-Fuzzy Network

Another neural network used in the FDAS is the DNFN. In the previous section, we said the time deviation problem is one of the most serious problems. However, the time deviation problem is not important for the analogue input analysis. For digital inputs, delayed inputs can seriously influence outputs because they have discrete values: all or nothing. Since analogue input is continuous, delayed inputs are not as important as digital inputs. Therefore, we just used feedbacks of outputs to analyze dynamic processes. In order to consider the values of instruments, the DNFN is used to an advantage. For a relatively small fault, it can take several minutes for the first alarm to be triggered. However, we can detect the fault before the first alarm is triggered by performing trend analyses of instruments.

The DNFN analyzes dynamic processes. Feedbacks at the previous step are used for part of the inputs at the current step. The DNFN contains four layers as shown in Fig 4: an input layer, a fuzzification layer, a fuzzy function layer, and a defuzzification layer.

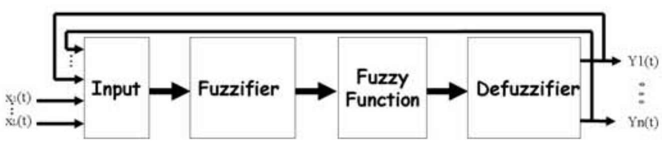

Fig. 4. Structure of the DNFN

Basically, the DNFN is based on the neuro-fuzzy network shown in Fig. 5, so the equations used in the DNFN are same and calculation processes are also same as those of the neuro-fuzzy network. In the DNFN, variables used in the neuro-fuzzy network are converted into time functions, and equations for the feedbacks are added.

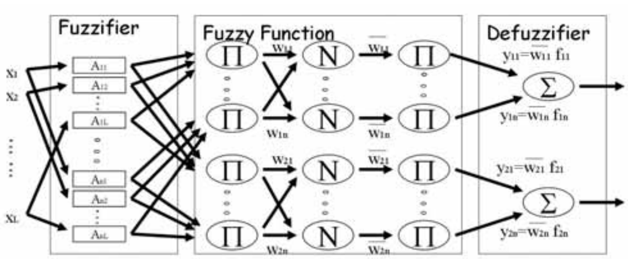

Fig. 5. Structure of the neuro-fuzzy network

If x1(t) isAi1(t) AND…AND xL(t) is AiL(t) AND u1(t) is Bi1(t) AND…AND uM(t) is BiM(t),
then yi(t) is fi (t,x1,….,xL,u1,….,uM)

where

$x_j(t)$: jth input at time step t

$u_k(t)$: kth feedback at time step t

$A_{ij}(t, x_j(t))$: antecedent membership functions of each input for the ith rule at time step t

$B_{ik}(t, u_k(t))$: antecedent membership functions of each feedback for the kth rule at time step t

$y_i(t)$: output of the ith rule at time step t

$$f_i(t, x_1(t),..x_L(t), u_1(t),..u_M(t)) = \sum_{j=1}^{L} q_{ij}(t)x_j(t) + \sum_{j=1}^{M} q'_{ik}(t)u_k(t) + r_i(t) \quad (2)$$

$q_{ij}(t)$: weighting value of the jth input onto the ith rule at time step t

$q'_{ik}(t)$: weighting value of the kth feedback onto the ith rule at time step t

$r_i(t)$: bias of the ith rule output at time step t

M: number of feedbacks

The output at time step t is obtained as follows:

$$y(t) = \sum_{i=1}^{n} \overline{w}_i(t) f_i(t) \quad (3)$$

where,

$$\overline{w}_i(t) = \frac{w_i(t)}{\sum_{i=1}^{n} w_i(t)} \quad (4)$$

$$w_i(t) = \prod A_{ij}(t, x_j(t)) \quad (5)$$

$$A_{ij}(t, x_j) = e^{-((x_j(t) - c_{ij}(t))^2 / 2\sigma_{ij}(t)^2)}$$

$$B_{ij}(t, x_j) = e^{-((x_j(t) - c'_{ij}(t))^2 / 2\sigma'_{ij}(t)^2)} \quad (6)$$

where

$c_{ij}(t)$: peak position of the membership function for the ith rule and jth input at time step t

$\sigma_{ij}(t)$: sharpness of the membership function for the ith rule and jth input at time step t

$c'_{ik}(t)$: peak position of the membership function for the ith rule and kth feedback at time step t

$\sigma'_{ik}(t)$: sharpness of the membership function for the ith rule and kth feedback at time step t.

V. OPERATION VALIDATION SYSTEM

The objective of developing the operation validation system (OVS) is to provide an advisory system to supervise and validate the operator's actions during abnormal environments (i.e., to reduce operators' commission errors). The system imbedded in a virtual simulated operational environment provides for operational validation and quantitative evaluations.

The function of operational validation provides a checking mechanism for operators, when they want to do some operations which are not included in operating procedures. All operators' actions in simulated environment are classified into three levels according to their different potential threat as shown Fig. 6:

Level 1. The operations not permitted by plant's safety system: the operations are considered to be with strong potential threats to the safety of NPPs that must be directly denied.

Level 2. The operations not included in operating procedure: the operations are considered to be inappropriate for current situations so that corresponding confirmations from operators are needed. Operators can choose to confirm or cancel their operations according to the possible results of the operation simulated by the OVS.

Level 3. The necessary operations included in operating procedure: the operations are considered to be currently needed and directly permitted. Nevertheless, operators can still choose to validate the operation to check the possible influence of the operation.

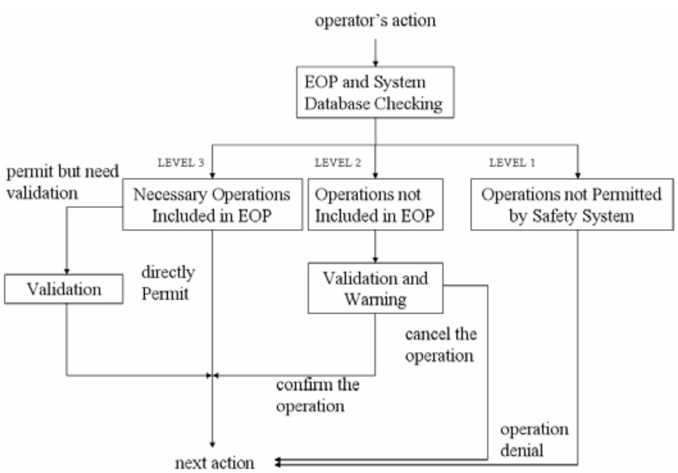

Fig. 6. Algorithm of operation validation

The OVS provides both qualitative and quantitative effects analysis of operators' action. They are used for different purposes: quantitative evaluation would be shown simultaneously with the confirmation inquiry to operators. Therefore, operators can examine the possible results of their expected operations and accordingly perform confirmation or cancellation. On the other hand, the quantitative evaluation provides more detailed information to operators. The trend of some key plant parameters under operators' action is generated. The quantitative evaluation is an optional function because the operator may not need to know the long time trend of specified plant parameter in order to make decisions.

In the prototype development, only four kinds of transients were generated and used for training: LOCA, FLB, SGTR, and SLB. After training, the neural networks were stored by types in the database and only will be selected to use when it obtained the information from the FDAS. The FDAS provides comparatively accurate information about transients' type, severity and location to operators. This information is used as a reference for choosing trained neural networks from the database. After the specified neural networks were selected, the initialization for running the OVS was finished.

The main algorithm for system operation is shown in Figure 7. After system initialization is finished, the current plant status parameters are imported to the system. Parameters are first normalized and inputted to the input layer of the trained neural network. The operational results are calculated according to the operator's action. The time for generating qualitative report and quantitative evaluation is different. For the qualitative report, only one neural network (T = 200 sec) is used, thus the time for calculation is nearly negligible. For the quantitative evaluation, much more neural networks (T=current time+1 sec to T=current time+200 sec) are used and the results are incorporated from all the outputs. Therefore the time for calculation is much more than the one for generating qualitative report. Hence the quantitative evaluation is developed as an optional function for operator's reference.

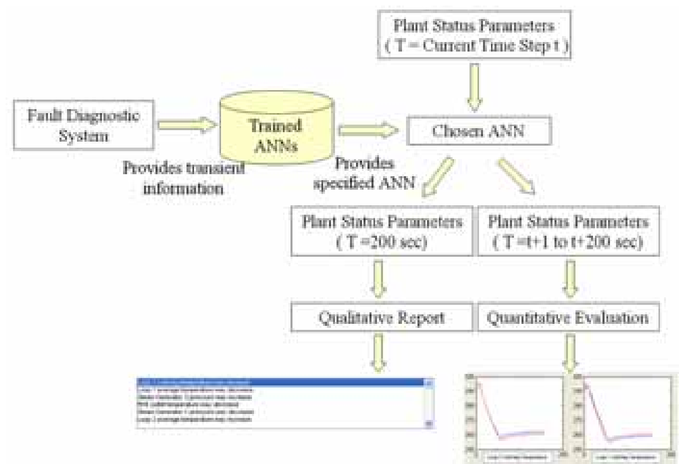

Fig. 7. Operation of analysis function

VI. SUMMARY AND CONCLUSION

Operational tasks in MCRs are mentally taxing activities, and human error has been identified as the most serious cause of accidents in NPPs. For advanced MCRs, which are fully digitalized and computerized systems, improving HMIs and developing an operator support system can help prevent human errors. In this paper, an integrated decision support system to aid operator's cognitive activities has been suggested as a design basis of support systems for advanced MCRs. The main idea of our research is to suggest appropriate support systems to aid every activity of the human cognitive process and to integrate the support systems into one system to obtain better performance. The INDESCO supports not merely a particular task, but also the entire operation process based on a human cognitive process model. The operators' operation processes are analyzed based on the human cognitive process model and the optimum support systems that support each activity of the human cognitive process are suggested. In terms of the human cognitive process, the major cognitive activities for NPP operations derived from ATHEANA are used. Based on this analysis, several systems supporting the major cognitive activities are suggested. All of the suggested systems are integrated into one system and work together. They facilitate the operator's whole operation process: monitoring plant parameters, diagnosing the current situation, selecting corresponding actions for the identified situation, and performing the actions.

Furthermore, two decision support systems were developed in this paper. The FDAS is a fault diagnosis system based on two kinds of dynamic neural networks. The FDAS can analyze the plant status and show an fault list in real time. The results of these two neural networks can complement each other and generate a more reliable result. When the results of the MDNN and the DNFN differ, operators will doubt the results and will double-check them. On the other hand, if the results of the two neural networks are very similar, then operators can be quite confident of the results. The prototype of the FDAS showed good performance for all four kinds of test cases: a trained case, an untrained case, a trained case with a failed instrument, and an untrained case with a failed instrument. In order to make a more reliable and efficient fault diagnosis system, many more situations, variables, and unexpected situations should be considered. When the FDAS is extended to more diverse situations and to more various inputs, it is expected to be able to obtain more reliable results. Another system is the OVS for operation validation. The OVS provides two important functions for operators: validated check of operations, and qualitative and quantitative effects analysis of operations. Human errors, including omission errors and commission errors, significantly threaten the safety of NPPs, especially in abnormal environments that suitable actions to assess and relieve the situation must be performed by operators. The computerized procedure system provides a checking scheme so that operators' omission errors can be considerably reduced. The OVS provides an additional function for the control panel to supervise and validate operator's actions. Thus the operators' commission errors can be expected to be effectively reduced. Since the FDAS is the prior system of the OVS, The accuracy of the OVS is strongly related to the FDAS (i.e., if FDAS could not provide correct type of the transient, then the OVS's results would be incorrect). The analysis of the reliability of the developed systems should be further studied.

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