HMM-Based Transient Identification in Dynamic Process

Kee-Choon Kwon

Abstract : In this paper, a transient identification based on a Hidden Markov Model (HMM) has been suggested and evaluated experimentally for the classification of transients in the dynamic process. The transient can be identified by its unique time dependent patterns related to the principal variables. The HMM, a double stochastic process, can be applied to transient identification which is a spatial and temporal classification problem under a statistical pattern recognition framework. The HMM is created for each transient from a set of training data by the maximum-likelihood estimation method. The transient identification is determined by calculating which model has the highest probability for the given test data. Several experimental tests have been performed with normalization methods, clustering algorithms, and a number of states in HMM. Several experimental tests have been performed including superimposing random noise, adding systematic error, and untrained transients. The proposed real-time transient identification system has many advantages, however, there are still a lot of problems that should be solved to apply to a real dynamic process. Further efforts are being made to improve the system performance and robustness to demonstrate reliability and accuracy to the required level.

Keywords : transient identification, hidden Markov model, statistical pattern recognition.

I. Introduction

Transient identification in the dynamic process means classifying the type of transients by interpreting the major plant variables and operating status of the equipment. The transient is defined as when a process proceeds to an abnormal state from a normal state. The term identification, as applied to an engineering system or process, means the classification of the cause which brought an undesirable state or failure of the system. The identification can be done at several different levels, e.g. *component, subsystem, function or event* [1]. For the proposed transient identification system, identification is made at the event level to determine which transient has occurred in the dynamic process. It is necessary to identify the type of transient through continuous monitoring of the dynamic process such as the Nuclear Power Plants (NPPs) during its early stage to provide sufficient information to the human operators in order to assist for proper operator action selection to prevent a more severe situation or to mitigate the accident consequence [2].

Typical transients in NPPs are associated with unique, time-dependent patterns of major variables and equipment status. This time dependent pattern may be used to identify the transient; hence, identification can be treated as a pattern classification problem [3]. It is difficult to identify the transient by a human operator when the preceding patterns of some transients are very similar and the patterns change further with time. Recently, attempts have been made to solve transient identification problems using a computer-based system

In this transient identification problem, the classification may involve spatial and temporal patterns. Temporal patterns usually involve ordered sequences of data appearing with time. Spatial patterns mean the unique pattern of each transient, variations of the same transient which may occur under different operating modes or at different break sizes.

The transient identification systems for NPPs have been developed using techniques such as an Artificial Neural Network (ANN) [4, 5], fuzzy logic [6], nearest neighbors modeling optimized by using a genetic algorithm [7], adaptive template matching [8], and observer-based residual generation [9]. All of these systems are still considered as a prototype or are under evaluation and have not yet been applied to real operating NPPs.

The ANN and fuzzy logic approach can absorb spatial variations, but can not provide proper solutions for temporal variations. So it is reasonable to adopt a double stochastic approach for the classification of the patterns. The Hidden Markov Model (HMM), a double stochastic process, enables modeling of not only spatial phenomena but also time scale distances. The HMM can be used to solve classification problems associated with time series input data such as speech signals or plant process signals, and can provide appropriate solutions by its modeling and learning capabilities, even though it does not have the exact knowledge to solve the problems. Most of the HMM applications for pattern classification in dynamic processes have a typical architecture to solve a spatial-temporal problems, but the target systems are different as in dynamic obstacle avoidance of mobile robot navigation, radar target, human action, American sign language, heart signals, sonar signals, two-handed actions, conditions of an electrical machine, deep space network antenna, moving light displays, environmental noise, and human genes in DNA. But the HMM has never been applied for transient identifications in NPPs.

The goal of this paper is to provide a real-time transient identification system for use in NPPs which demonstrate the spatial and temporal modeling and learning capabilities with hidden Markov models. To demonstrate these capabilities, simulated NPP parameters are collected and clustered to build hidden Markov models for transient identification purposes.

II. Hidden Markov model for transient Identification

The problem of transient identification is defined as the recognition of transient types, ω_i given the sequential input patterns X_t at time t. The input pattern X_t is mathematically defined as an object described by a sequence of features at time t [10].

Manuscript received : July. 16, 1999 , Accepted : March. 22, 2000
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※ This work has been carried out under the nuclear research and development program by Ministry of Science and Technology.

$$X_t = (x_1, x_2, \cdots, x_i, \cdots, x_d) \quad (1)$$

The space of input pattern X_t consists of the set of all possible patterns:

$X_t \subset \Re^d$; $\Re^d$ is a d-dimensional real vector space.

The k observed input data up to time t is defined as Φ_{t-k} :

$$\Phi_{t-k} = \{X_{t-k-1}, \cdots, X_{t-1}, X_t\}. \quad (2)$$

The set of possible transient classes ω_j at time t forms the space of classes Ω :

$$\Omega = \{\omega_1, \omega_2, \cdots, \omega_c\}, \text{ } c \text{ is the number of classes.} \quad (3)$$

The classes Ω are assumed to be mutually exclusive and exhaustive. The recognition task can be considered to be the finding of function f , which maps the space of input patterns Φ_{t-k} to the space of classes Ω :

$$f : \Phi_{t-k} \rightarrow \Omega \quad (4)$$

A dynamic process often exhibits sequentially changing behavior. If the one short-time period is defined as *frame*, the probability of the *frame* transition is different from each transient in NPPs. Therefore, the probability of *frame* existence and the transition between *frames* can be statistically modeled. The probability of a transient occurring in an NPP is already given and is called the *a priori* probability. When a transient has occurred in NPPs, the type of transient can be determined only by selecting the type of transient ω_j with the highest *a priori* probability $P(\omega_j)$ This decision is obviously unreasonable. It is more reasonable to determine the type of transient after observing the trend of time-series major variables, namely, to get the conditional probability $P(\omega_j \mid \Phi_{t-k})$. This conditional probability is called the *a posteriori* probability. Decision-making based on the *a posteriori* probability is more reliable, because it employs both *a priori* knowledge together with observed time-series data [11].

Classification of the unknown pattern X_t corresponds to finding the optimal model $\hat{\omega}$ that maximizes the conditional probability, $P(\omega_j \mid \Phi_{t-k})$, the probability that the system is in class ω_j at time t given that Φ_{t-k} was observed at time t, $P(\omega_j \mid \Phi_{t-k})$ over the type of transient ω_j . We can apply Bayes rule to calculate *a posteriori* probability,

$$P(\hat{\omega} \mid \Phi_{t-k}) = \max_{\omega} \frac{P(\Phi_{t-k} \mid \omega_i)P(\omega_i)}{P(\Phi_{t-k})}, \quad (5)$$

where

$$P(\Phi_{t-k}) = \sum_{i=1}^{c} P(\Phi_{t-k} \mid \omega_i)P(\omega_i). \quad (6)$$

The conditional probability, observing Φ_{t-k} given that the system is in class ω_j at time t, $P(\Phi_{t-k} \mid \omega_j)$ comes from comparing the shapes of the transient models with input observations, while the *a priori* probability $P(\omega_j)$ comes from the transient probability which represents how often the transient appears in the NPP. Since $P(\Phi_{t-k})$ is independent of $\hat{\omega}$, we get

$$P(\hat{\omega}|\Phi_{t-k}) \propto P(\Phi_{t-k}|\hat{\omega})P(\hat{\omega})$$
$$= \max_{\omega}[P(\Phi_{t-k} \mid \omega_i)P(\omega_i)]. \quad (7)$$

In fact, *a priori* probability $P(\omega_j)$ can be calculated in NPPs, and should satisfy the following equation,

$$\sum_{i=1}^{c} P(\omega_i) = 1. \quad (8)$$

But the transient identification system does not cover all of the transients occurring in NPPs, and consequently can not satisfy eq. (8). Therefore, the present observed data controls the decision. $P(\Phi_{t-k} \mid \omega_j)$ is called the likelihood of $\hat{\omega}$ with respect to the set of samples. In real implementation, *a priori* probability $P(\omega_j)$ can be assumed that the occurring probabilities of all transients are equal [12]. The maximum likelihood estimate of $\hat{\omega}$ is, by definition, that value of $\hat{\omega}$ that maximizes $P(\Phi_{t-k} \mid \omega_j)$. In this identification problem, HMM is used to estimate the conditional probability $P(\Phi_{t-k} \mid \omega_i)$. By using HMM, the pattern variability in parameter space and time can be modeled effectively [11, 13].

Using HMMs in a classification problem with the Bayes rule and maximum likelihood training requires two things: the evaluation of $P(\Phi_{t-k} \mid \omega_i)$ for the implementation of the Bayes rule and the maximization of the likelihood for the training of the classifiers. Fortunately, there exist computationally efficient procedures for these two tasks. HMM parameters are estimated from the Baum-Welch algorithm and guarantee a finite improvement on each iteration in the sense of maximization of likelihood. An HMM is trained for each transient from a set of training data, and an iterative maximum likelihood estimation of model parameters from observed time-series data. Incoming observations are classified by calculating which model has the highest probability for producing that observation. The detailed definition of HMM is described in reference [14].

III. Transient identification system

1. Preprocessing

Training and test data from the test simulator should be converted to a proper codebook which is input data for HMM identifier. Preprocessing means to make a codebook, and this method is divided into two techniques, normalization and vector quantization.

The input symptom vector to be used for vector quantization have same value as displayed in a real plant instrument because it is directly received from the test simulator or the plant computer in NPPs. The range of input data values are significantly different. Therefore, it should be normalized before using the input data of the clustering algorithms. Normalization is one of several transformation techniques. It has the effect of reducing the parameters to a common range. This provides a measure that allows the relative importance of any factor or interaction to be identified more clearly. It improves the numerical accuracy of the regression and the computation of significance.

If the distribution of the variable's values are of normal distribution, it is reasonable to be normalized by maximum value. But, most of the values of the specified variable are distributed in upper region in case of normalized by maximum value. It is undesirable to use the input data of the clustering algorithms. It is more reasonable to normalize between its minimum and maximum values. In similar way, it can be also considered that mean centered normalization. In the mean centered normalization method, data between mean and minimum or maximum range is linearly distributed. In other way, we can consider non-linear data distribution of between mean and minimum or maximum range considering the standard deviation.

Features may be represented by continuous, discrete, or discrete-binary variables. It is expected that the feature vector contains most of the classification information available from the object. Feature extraction is an important task for classification or recognition. In feature extraction, data can be transformed from high-dimensional pattern space to low-dimensional feature space. Vector quantization (VQ), the process of approximating a block of continuous amplitude signals by a discrete signal is one method of feature extraction. The idea is to quantize each continuous vector to one of a relatively small number of template vectors, which together comprise what is called a codebook. The sequence of codebook indices obtained in this way forms the desired sequence of discrete symbols. In this paper, two VQ methods, k-means algorithm and Self-Organizing Map (SOM) [15] are introduced to compare the identification capability.

2. Real-time test environment

It is more realistic to receive training and test data directly from the operating NPPs. But severe transient or accident seldom occur in real NPPs and it is almost impossible to make transient conditions only for experimental purpose. Therefore it is necessary to use the simulator for operator training or simulation code ready for safety analysis to implement and test the transient identification system. In this implementation, the test simulator was modified from the compact nuclear simulator which is installed at the Korea Atomic Energy Research Institute Nuclear Training Center for training non-operator personnel to fit testing the transient identification system. The test simulator is divided into two major parts: a mathematical modeling program, which executes the plant dynamic modeling program in real-time; and a supervisory program that manages user instructions.

The mathematical modeling programs consist of static and dynamic parts. The initial state, a 100% full power condition is set up in the static calculation, which is performed once before the start of the dynamic calculation. The dynamic calculation is performed every 0.2 second to represent a real-time mathematical modeling simulation. The test simulator provides the function to activate 79 predefined malfunctions This function realizes the transient or accident condition to get training data and to test the transient identification system [16].

3. Data collection

The nine typical transients are selected among different postulated transients that may occur in NPPs in consideration of the simulation capability of the test simulator because the purpose of this paper is to demonstrate the capability of hidden Markov models that apply to the transient identification problem. The description of the target transients are as follows:

1) ATWS (Anticipated Transient Without Scram)
2) FWLB (FeedWater Line Break inside containment)
3) LOCA (small Loss Of Coolant Accident)
4) LSLC (Loss of Steam generator Level Controller signal)
5) MSIV (Main Steam Isolation Valve closure)
6) MSLI (Main Steam Line break Inside containment)
7) MSLO (Main Steam Line break Outside containment)
8) PORV (Power Operated Relief Valve stuck open)
9) SGTR (Steam Generator Tube Rupture)

The input symptom vector is a collection of the principal variables and the status of major equipment from the transient simulation in the test simulator. The major variables and equipment status used to identify the nine different types of transients and one normal state are summarized in Table 1.

There are two types of data, i.e., training data and test data The training data are needed to train the clustering algorithm and HMM identifier. To test the classification capability of the HMM identifier, test data are also needed. The training and test data are collected from the test simulator. It is needed to get more widely spread training data per transient to design a reasonable classifier. In this experiment, we considered different operating modes and different break sizes in each transient. The HMM may absorb the variations from the different operating modes and different break sizes in a transient.

The training data are provided off-line from the test simulator. Major variables and the equipment status are combined for the input symptom vector in each transient when the test simulator emulates a transient situation. The transients are simulated in the test simulator by activating the malfunctions during normal operation, then get major variables, such as temperature, pressure, flow, pump on/off status, or valve open/close status. The training data are collected from different operating modes, such as 50%, 55%, 60%, 65%, 70%, 75%, 80%, 85%, 90%, 95% of reactor power and full power and different break size in each transient and normal state. Each training data consist of around 60 time interval input vectors. Each time interval is 1 seconds, and this means around 1 minute of data are collected.

Table 1. List of input vector variables.

No	Variable description	Unit
1	Pressurizer pressure	kg/cm^2
2	Pressurizer level	Normalized
3	Reactor coolant average temperature	Deg C
4	Steam generator pressure	kg/cm^2
5	Steam generator level	Normalized
6	Reactor power	%
7	Reactivity	%dk/k
8	Average fuel temperature	Deg C
9	Feedwater line flow	m^3/hr
10	Main steam line flow	m^3/hr
11	Steam flow from steam generator	m^3/hr
12	Steam pressure from steam generator	kg/cm^2
13	Secondary radiation monitoring	MicroC/cc
14	Containment pressure	kg/cm^2
15	Containment temperature	Deg C
16	Containment humidity	%
17	Pressurizer relief tank pressure	kg/cm^2
18	Pressurizer relief tank temperature	Deg C
19	Net electrical power	MWe
20	Position of main steam isolation valve	Normalized
21	Reactor trip signal	Digital

The test data are collected off-line and on-line. The off-line test data are collected by the same method as training data. But they are collected by different operating modes and different break sizes to generate diverse test cases such as trained operating modes and non-trained break sizes, non-trained operating modes and trained break sizes, non-trained operating modes and non-trained break sizes, and trained operating modes and trained break sizes. The on-line test data for any operating modes or any break sizes are gathered directly from the real-time test simulator through data communication between test simulator and the transient identification process. The test simulator is executed every 0.2 second and the calculated simulation variables are stored in the shared memory The transient identification process receives on-line test data from the shared memory every one second.

4. Real-time transient identification system

The major component of transient identification system are vector quantizer and HMM identifier. Fig. 1 shows the block diagram of the implemented transient identification system. First, the collected training data are normalized, then the training data are used to train the vector quantizer with off-line. The trained vector quantizer will be used to vector quantize the test data. A vector quantized codebook of training data are the training input set of the HMM identifier.

The test symptoms are vector quantized to give input codebook of the HMM identifier. In this implementation, the *k-means* algorithm or SOM are used to cluster the input vector into L disjoint sets. In this implementation, the 300 were chosen for an optimal solution after several attempts, meaning that every input vector is assigned to one of 300 clusters. The codebook size is 60, which means the system receives 60 time interval input vectors every one minute to classify the types of transients. In the initial one minute, the test results are incorrect because the codebook size is less than 60. The system should wait until it receives one minute amount of input vectors. This initial stage is called the "Ready mode." During the next time step, the system receives another 60 time interval input vectors as sliding window method. To get input symptom vector every second, the system should be implemented with a real-time.

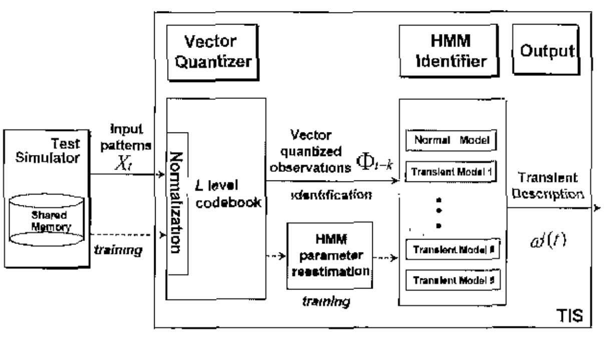

Fig. 1. A block diagram of transient identification system.

A left-to-right HMM has been considered appropriate for processing those signals whose properties change over time. The underlying state sequence associated with the model has the property that as time increases, the state index increases or stays in the same state. That is, the state always proceeds from left to right. The basic model consists of six states which have less than two direct transitions to the right state. Few initial conditions are given to this model, and these initial conditions are equivalent to all transient models The re-estimation algorithm of the HMM may give a local minimum of the likelihood function. It is important to choose initial estimates of the HMM parameters so that the local minimum is the global minimum. Experience has shown that the uniform initial estimates work well. We also choose uniform initial estimates in this implementation by assuming that the observation symbol probability is equivalent to each state.

The training is performed by a forward algorithm and a backward algorithm, and making a re-estimate from the Baum-Welch algorithm in each model, given the multiple input observations [11]. The re-estimation is done until the convergence condition, $P(O|\overline{\lambda}) \geq P(O|\lambda)$, i.e., the new model estimates are more likely to produce the given observation sequence O, is satisfied in each model. The probability, $P(O|\lambda)$, is calculated by the optimal path which is obtained by the Viterbi algorithm for the given input observations in each model. The transients are classified by examining which model has the highest probability for the given input observations. The prototype of transient identification system was implemented in an HP747*i* industrial workstation and the programming was done using "C" language.

IV. Experimental results

In this section, experimental test results for a base model are described. Then, the selected model is suggested and the improved model is proposed to improve identification accuracy. The base model consists of Max-min normalization method, SOM clustered by training and test data. and 6 states HMM identifier. The experimental tests have been carried out after training of the vector quantizer and HMM identifier. Table 2 shows the results of the base model off-line test. In this experiment, there are the following four test cases to compare the trained or non-trained data for operating modes and break sizes.

- Case I : Trained operating mode, Non-trained break size.
- Case II : Non-trained operating mode, Trained break size.
- Case III : Non-trained operating mode, Non-trained break size.
- Case IV : Trained operating mode, Trained break size.

Table 2. Off-line test results for base model.

Case / Transient	Case I	Case II	Case III	Case IV	Average Except Case IV
ATWS	-	100	-	100	100
FWLB	100	100	100	100	100
LOCA	27.3	100	30.0	100	51.6
LSLC	45.5	100	50.0	100	64.5
MSIV	-	100	-	100	100
MSLI	0.0	100	0.0	100	32.3
MSLO	72.7	80.0	70.0	100	74.2
PORV	100	100	100	100	100
SGTR	100	100	100	100	100
Average	63.6	97.8	64.3	100	76.8

As presented in this table, most of transients are correctly identified when given trained break size and non-trained operating mode. But in the case of non-trained break size, the recognition rate is remarkably lower than the trained break size. There is almost no difference when comparing the case of the trained and the non-trained operating mode. But the identification rate for the non-trained break size is lower than the non-trained operating mode. We estimated that the HMM can absorb these break size differences. But in real implementation, the HMM can not completely absorb the break size differences. In the case of IV, with both trained operating mode and trained break size, the identification rate is 100%. This means the trained data can be completely identified.

The on-line test for base model was performed using on-line test data which covers various operating modes and break sizes for each transient. The on-line test results are depicted in Fig. 2. The total identification rate of the on-line test reaches 95.8% within 79 seconds, but the immediate detecting rate is only 44.3%. In the case of LOCA, MSLI, or PORV, the transients are correctly identified from incorrect transients. In the initial stage of these transients, there are no distinctive features between preceding patterns of identified and misidentified transients. The distinctive features appeared after a few seconds, then, the HMM identifier was able to identify the correct transient types. It takes several tens of seconds to detect a SGTR transient because its distinctive features appear after several tens of seconds in a real situation.

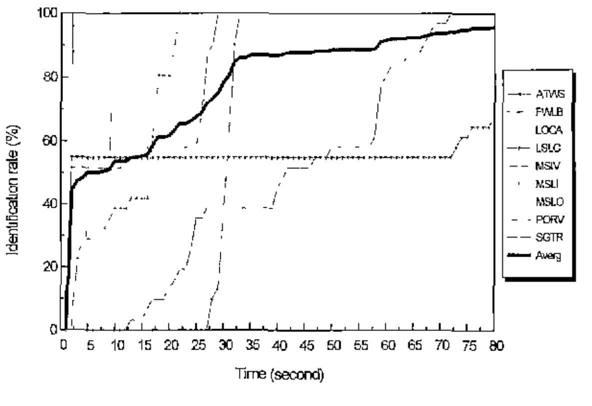

Fig. 2. On-line identification rate for base model.

The selected model will be suggested according to the results of the previous experimental tests. The selected model means adopting a proper normalization method, clustering algorithm, and the number of HMM states. According to the results of previous experimental tests, the selected model has Max-min normalization method, k-means clustering algorithm, and six states of left-to-right HMM. The normalization methods are compared based on the assumption that the input normalization might influence the result of classification. The Max-min method has advantages in the present case. Consequently, the Max-min method is chosen for the selected model. To choose the proper clustering algorithm, two types of clustering methods are compared. Considering the results, the k-means algorithm has better performance than SOM. Finally, the k-means algorithm method with training data is chosen to implement the selected model. There are no effect on the identification rate based on the number of states in the HMM. The selected model adopts 6 states as the number of state in the HMM.

The total identification rate of the selected model is 100% within 17 seconds, and its immediate detecting rate is 54.0%. The total identification and immediate detecting rate of the selected model is higher than the base model. In the selected model, the detecting rate of correct transients from incorrect transients is significantly reduced from the base model. According to the results of the above experimental tests, it can be concluded that the selected model has good performance. But it can not be said that the selected model is robust. Therefore, three more experimental tests such as superimposing random noise, adding systematic error, and testing by untrained transients were performed to verify a robustness of the selected model.

The random noise is superimposed on to the original test data except two variables such as position of the main steam isolation valve and reactor trip signal. The terminology "2% of random noise" means maximum ±2% of random noise is superimposed on to test data in the normalizing progress. The test results of superimposing random noise are depicted in Fig. 3. In the case of 2% to 8% of random noise, the identification rates are same as no random noise case. The identification rate decreases slightly at 10% of random noise. But, the identification rate is abruptly decreased more than 12% of random noise. It can be said that the proposed transient identification system is robust within 10% of random noise. In neural network applications, the recognition rate is linearly decreased by increasing the noise level [2], or the recognition rate is maintained to 16% of noise level, then the rate abruptly decreases [17].

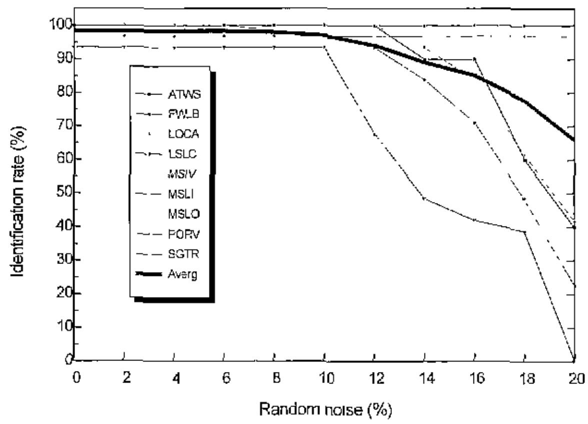

Fig. 3. Test results of superimposing random noise.

Additional tests are performed where the systematic error signal is added differently from the random noise. The first error signal is a "loss of pressurizer level signal" which has large variations when the transients occur. In this case, the identification rate is significantly lower than with no error signal. From this test result, to ensure the performance of the transient identification system, valid signals through a signal validation process should be provided. In the application of a neural network case, the system can identify the transient properly even though some sensor signals are missed [5]. But the second error signal is a "loss of main steam flow signal" that has small variations when the transients occur. In this case, the identification rate is the same as if there was no error signal. This means the error signal which has small variations have almost no effect in identification rate.

It is desirable that the never-trained transient should be classified as an unknown transient. In particular, a severe accident can happen because of an inadequate operation due to incorrect identification. The implemented system can classify the unknown transient like the other neural network applications [3, 9, 12]. It is classified as unknown transient that the output path probability of the HMM identifier is less than the threshold which is the least output path probability from all test data. In the test results, three untrained transients are classified as unknown transients. But four untrained transients are identified as normal states. In the case of the incorrect classification, the HMM identifier may not be exactly identified because the clustering results are very similar to the misclassified transient.

In the selected model, there still exist temporary misclassified transients. Finally, two heuristic training approaches are attempted to improve the classification accuracy. One of these approaches is corrective training [18]. The heuristic corrective training method re-estimate model parameters using validation data set which are not included in training or test data set. After re-estimation of HMM parameters using training data set, perform transient identification on the validation data. If any transient is misclassified, adjust the estimated model parameters to reduce the probability of misclassified transients.

The other heuristic approach is principal component method. The principal component is applied to increase discriminating power between two transients which are expressed by similar patterns. This method add weighting factor to important variables that have large impact on identification results when vector quantization is progressed. Consequently, the classification rate is slightly increased when principal component method is applied. In conclusion, Fig. 4 shows the classification rate of three on-line tests depend on time. The classification rate of selected model is much better than base model, and the classification rate of improved model is a little better than selected model.

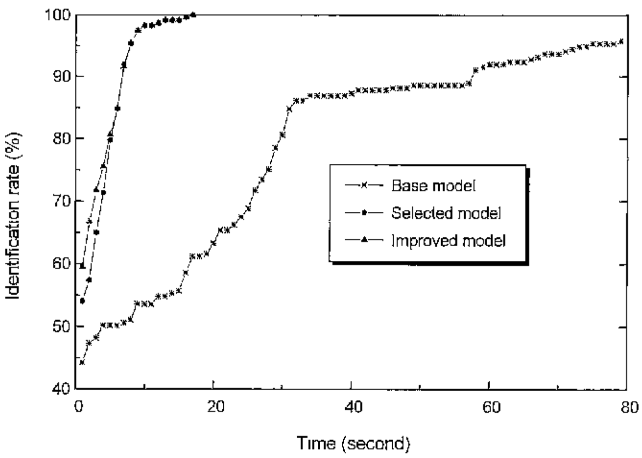

Fig. 4. On-line identification rate for three models.

V. Conclusions

The proposed transient identification system has lots of advantages as described above. However, there are still a lot of problems that should be solved before it can be actually applied to an operating NPPs. Further efforts are being made to improve the system performance and robustness to demonstrate reliability and accuracy to the required level. It is a severe drawback that the training data are extremely rare compared with other applications. The HMM-based identifier is more difficult to train properly since they tend to require more training data. It is more desirable to get additional training data, however. it is a difficult job in this area. Therefore, research for the modified HMM structure or new algorithm for the estimation of HMM parameters is suggested. As shown in experimental tests, the identification performance heavily depends on clustering methods. It is important to find more efficient clustering method which is suitable for the proposed system. The HMM-based identifier can not completely resolve the "don't know" issue which is the hot topic in this research field. It should be considered the "don't know" issue in the future. It also needs to seek a fitness measure to confirm the degree of belief. Besides improvements described in the improved model, it needs to be integrated with other features such as knowledge processing [19] or neural network [20] to improve its accuracy.

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