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Application of Dynamic Reliability Analysis Method to the CANDU Pressurizer System

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Abstract

DYLAM (DYnamic Logical Analytical Methodology) and its related methodologies are reviewed and found to have many favorable characteristics. Previous studies have shown that the DYLAM methodology represents an appropriate tool to study dynamic analysis. A hybrid model which is a synthesis of the DYLAM model, a system thermodynamic simulation model and a neural network predicative model, is implemented and used to analyze dynamically the CANDU pressurizer system. This study demonstrates that the hybrid model for system reliability analyses is effective.

1. Introduction

In recent years the growing sentiment that system dynamic and their interaction with the random evolution of component or operator states was inadequately treated by classical methodology resulted in the development of new models[1]. These new models are reviewed in this paper.

The usual approaches for probabilistic accident evaluation do not satisfactorily take into account the dynamic aspects of the random interaction between the "physics" of the transients and the "logic" of the system. The presence of control loop, the human interventions, protection system and failure delay system which the occurrence of cut set causes a top event condition only after a significant condition and a significant time delay are difficult to treat[2],[3]. In order to remove these limitations and to fill the gap between the need of more realistic analysis and available tools, dynamic methods have been developed. Among these dynamic methods, Discrete Event Trees (DYLAM) is particularly suitable for treating complex dynamic systems comparing other dynamic methods.

2. DYLAM(Dynamic Logical Analytical Methodology)

2.1. Basic Features of the DYLAM Approach

The DYLAM method can be seen as a systematic attempt to combine the stochastic and physical behavior. It is different from other traditional techniques such as Event/Fault tree analysis because the impacts of hardware system failures on the progress of physical parameters are immediately evaluated by solving the governing equations for new system conditions. Since the DYLAM consider the process simulation and changes of the system structure due to control and due to random events in a combined way, it can be seen that the DYLAM has the capability to perform a systematic and dynamic analysis.

The way in which a fault tree model is constructed and then analyzed is as follow. At first, the undesired condition for the system is identified and then the fault tree is constructed by top-down deductive reasoning by linking the TOP event to its more proximate causative sub events and these down to the primary events. On the other hand, DYLAM is based on bottom up procedures for identifying the sequences of events that can lead to undesired conditions. Component modeling consists of identification of the different failure or degradation states in which a component may be. Once the components have been modeled, implicitly, the system has been described for all its possible states[4], [5].

On the other hands, there are concerns that DYLAM cannot handle a complex system due to the combinatorial explosion of the generated sequences. Thus, in real application, it should deploy cut-off approach by which may decrease the accuracy of the result.

2.2. The Basic Steps of DYLAM

The basic steps to implement DYLAM can be summarized as follows[1], [3].

2.2.1. Component Modeling

DYLAM analysis proceeds bottom-up. No explicit model needs to be established for the system. However, the different failure or degradation models for the components constituting the system should be constructed, and then the component models have to be associated with the probability parameters which characterised the system states, and then the state transitions with a mathematical equation need to be calculated to describe the physics of the component those conditions.

Following component' s transition probabilities can be modelled;

(i) Constant probabilities;
(ii) Stochastic transition;
(iii) Functional dependent transition;
(iv) Stochastic and functional dependent transitions;
(v) Conditional probability;
(vi) Stochastic transition with variable transition rates;

2.2.2. System Equation Modeling

To implement the system, non-linear algebraic equations have been solved. Considering large computational times, the physical models to be adopted should be as simple as possible compatible with the requirements of the analysis.

2.2.3. Top Event Definition

The next step is to define undesired system states. These are defined in physical quantitative terms rather than hardware states and Top event analysis determines when a particular accident sequence simulation should be terminated.

2.2.4. Event Sequence Generation Rules

To exploit all possible accident sequences, following procedure is applied; Firstly starting at t=0 and some user-defined initial state, secondly the system physical model is used to determine the system variable value change in the next step Δt; thirdly at the end of the first time interval $(0, \Delta t)$, all possible system state transitions are identified and transition likelihoods are calculated.

When the probability of the initial sequence becomes less than or equal to a fraction of the initial probability,

$$P(A_0, t) \leq P(A_0,t_0) * Wlim$$

where Wlim : the fractional probabilistic threshold,

$P(A_0,t_0)$: the initial probability,

$P(A_0,t)$: the probability of the initial sequence at t

branch point is triggered. Here P(A,t) consists of the probability of remaining in the initial state and birth probability for the descendent sequence. If the probability satisfies the upper condition, branch point is generated. These new states are then used to provide boundary conditions for the physical variable updating. Until an absorbing state is reached, all possible event sequences continuously are generated in the same manner.

3. Simulation

In order to better understand the features of DYLAM code when applied to the reliability analysis of a dynamic system, dynamic behavior of a CANDU type pressurizer has been chosen as a case study. The preparation works are required to implement CANDU pressurizer model using DYLAM and also to describe DYLAM results obtained.

A hybrid model has been developed for assessing pressurizer transient. The hybrid model is composed of 3 parts :

i) DYLAM code;

ii) System thermodynamic simulation code;

iii) Neural network code.

Since DYLAM is a simulation-based dynamic approach, to analyze system reliability, system thermodynamic simulation code is needed. However, to reduce calculation time and to enhance the efficiency, data required for the transient behavior of the system other than pressurizer were generated using neural technique model developed.

3.1. Neural Network Back-propagation Fitting

Neural network methodology is an emerging technology which gained considerable momentum in the early 90' s. Wide spread applications have been made in e.g. medicine, finance, sensor, forecasting, industrial measurement, plant simulation[6], [7].

Generally, the power plant physics simulation codes involves of a large number of variables. That means for implementing DYLAM, it should involve considerable physical data as required restart values. When considering the computing effort, this is not an efficient way to simulate whole system on every component states in order to obtain the behavior of a subsystem[8], [9]. In other word, a drawback of DYLAM is that it is a total system technique and can be relatively inefficient because of very many variables involved to get a restart values and considerable computational time required if one is wishing to focus on a particular subsystem such as the pressurizer.

Here, the neural network was used for estimating physical variables to implement DYLAM such as SAMSON(Sever Accident Management System On-line Network) uses expert systems as well as neural networks trained with the backpropagation learning algorithm to make prediction[10].

In developing a model which represents system

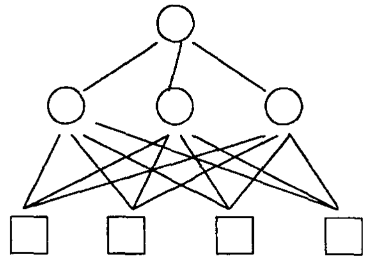


Fig. 1. A Tow-layer Feed Forward Network.

behavior, it is the topology of the network, together with the neuron, or node, processing function, which determines the accuracy and degree of the representation.

The most popular method for learning in multilayer is called back-propagation. Example inputs are presented to the network, and if the network computes an output vector that matches the target, nothing is done. If there is an error (a difference between the output and target), then the weights are adjusts to reduce this error. Using the back-propagation algorithm, the weight update rule is

$$W_{j,i} \leftarrow W_{j,i} + \alpha \times a_j \times Err_i \times g'(in_i)$$

where Err i is the error (Ti - Oi), g' is the derivative of the activation function g that transforms the weighted sum into the final value as the unit's activation value aj, α is the learning rate and Wj,i is the weight on the link from unit j to unit i[11], [12].

When figure predictions rely on previous network outputs which are fed back to network inputs, the usefulness of the neural network model has been frequently noted. Since this application describes system dynamics, the integration of dynamics into the network should be required. The most concise network representation of a dynamic system is obtained by using network inputs comprised of past input and output data. In this application (Fig. 2), the following configurations for process modeling, so called predictor structure, has been adopted.

In this application 45 event sequences are trained and applied to above network configuration, and it generates nonlinear equation to represent system behavior. The reason why 45 sequences are chosen is that using 10 time steps and 2 components generates ${}_{10}C_2 \times 2$ possible failure sequences. It is reasonable to say that these sequences explain the system behavior generally. The applying activation rule for this study is Sigmoid function $(1/(1+e^{-x}))$.

In neural network model, for input data, outlet header pressure at previous time (P_{t-1}), outlet header temperature at previous time (T_{t-1}), surge flow rate at pervious time (F_{t-1}), power fraction, pressure in pressurizer (P), pressurizer level (L), and heat generated in pressurizer (Q) are needed. And outlet header pressure (P_t), outlet header temperature (T_t) and surge flow rate (F_t) are updated.

These trained data generate a non linear equation. The computer code used to generate training data was the CANDU simulation code which is under development in IAE.(Institute for Advanced Engineering)

The following figure (Fig 3) shows the back-propagation neural network used to model the performance of a pressurizer during the power transition.

3.2. DYLAM Modeling

The stepback power transient procedure was chosen to simulate the behavior of the pressurizer. Pressurizer is composed of heaters and bleed valve. In step power transient procedure, the steam bleed valve does not act. So, in this application, only heaters need to be considered. Furthermore to reduce calculation time component grouping rule was adopted.

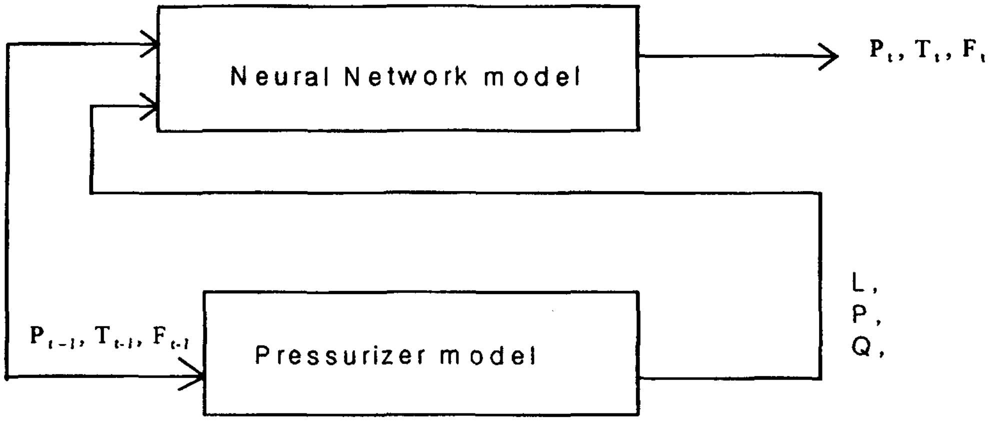
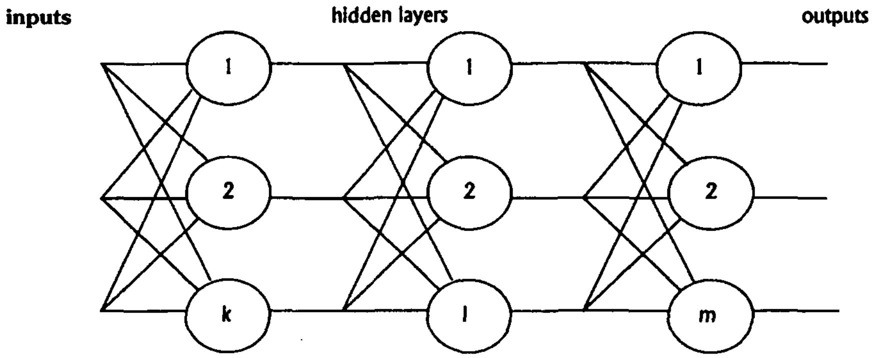


Fig. 2. Dynamic System Predictor Structure.



Here k=8 (including one bias neuron)
1=8 (including one bias neuron)
m=3

Fig. 3. Typical Feedforward Neural Architecture.

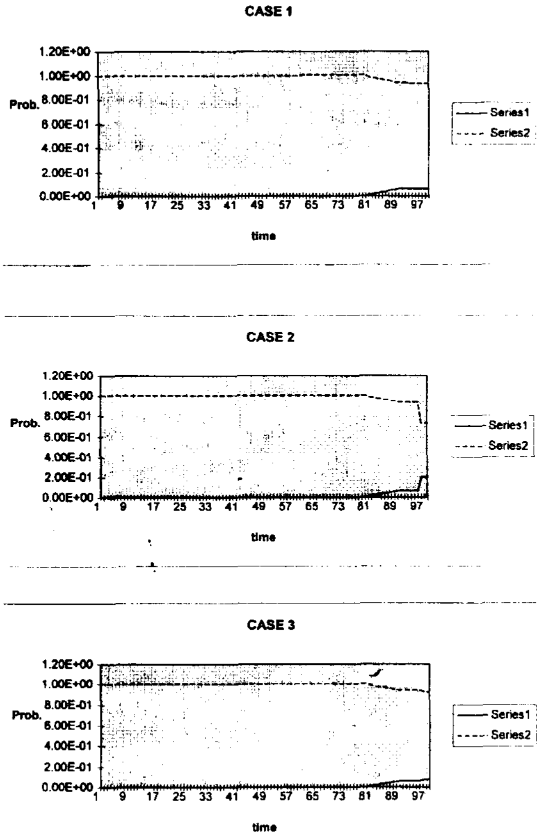
Component 1 represents a variable heater and component 2 represents four on-off heaters.

Two different top conditions depending on outlet header pressure were chosen. When the outlet header pressure is below a prescribed value, the fail Top condition is triggered. The mission time is 100 seconds and during the mission time, reactor power is reduced from full power by 60 %.

The following assumptions were made to use DYLAM :

- The components failure behavior are statistically independent of each other
- All the components have the same nominal conditions at time zero.
- A failed component can not be repaired during the mission time.

As mentioned in the previous section, data required for the transient behavior of the system other than pressurizer were generated using the neural technique model developed for the present neural network.



Here, Series 1 : Probability of Fail TOP Event
Series 2 : Probability of Success TOP Event

Fig. 4. TOP Event Probability of Each Case Study.

3.3. Numerical Results

To demonstrate the thermal hydraulic model of pressurizer combined with neural network modeling, stepback power transient event was simulated as a case study. The probabilities of TOP event (see 3.2) are calculated with two different top conditions depending on outlet header pressure.

CASE 1

When the components have a probabilistic behavior that depends on time according to constant transition rates between states, the following assumptions are made :

- All the components behave stochastically
- The failure rates of the components are $\lambda_1=3.0 \times 10^{-5}$, $\lambda_2=7.0 \times 10^{-4}$ respectively for component 1, component 2.

CASE 2

When the components have a probabilistic behavior that depends on the time and is also functionally dependent on a physical variable of the system, the following assumptions are made :

All the components states are subject both to stochastic transitions and to transitions due to the effects of process physical variables (pressurizer water temperature : TZ1)

- All the components are normal at initial pressurizer water temperature
- Functional dependent transition probabilities are :

$P_{00}(TZ\uparrow 305℃) = 0.8$, $P_{01}(TZ\uparrow 305℃) = 0.2$,
$P_{10}(TZ\uparrow 305℃) = 0.0$, $P_{11}(TZ\uparrow 305℃) = 1.0$,
$P_{00}(TZ\downarrow 305℃) = 0.8$, $P_{01}(TZ\downarrow 305℃) = 0.2$,
$P_{10}(TZ\downarrow 305℃) = 0.0$, $P_{11}(TZ\downarrow 305℃) = 1.0$

Here, $P_{ij}(TZ\uparrow 305℃)$: Probability that the components change state from i to j when TZ1 approaches 305℃ from below that temperature

$P_{ij}(TZ\downarrow 305℃)$: Probability that the components change state from i to j when TZ1 approaches 305℃ from above that temperature

CASE 3

When the components have a probabilistic behavior that depends on time according to variable transition rates between states which are function of a process variable, the following assumptions are made :

- All the components have the transition rates which are function of TZ1(including time).
- All the components are in normal condition at the initial pressurizer water temperature.
- Variable transition rates of between the states (i) TZ1 < 305℃, ii) TZ1 ≥ 305℃) are :

When TZ1 < 305℃, $\lambda_1 = 3.0 \times 10^{-4}$

$\lambda_2 = 7.0 \times 10^{-3}$

When TZ1 < 305℃, $\lambda_1 = 3.0 \times 10^{-5}$

$\lambda_2 = 7.0 \times 10^{-4}$

Here, it should be mentioned that λ_1 and λ_2 are not the values of actual plant database instead arbitrarily chosen.

4. Discussion and Conclusions

The pressurizer dynamic behaviour during the stepback plant operation was analysed using DYLAM. The simulation results are shown in Fig.5. Comparing with CASE1, CASE3 generates higher TOP event probability while CASE2 can generate higher TOP event probability than CASE3. The reason is that CASE2 has high functional dependent transition probabilities at TZ1=350℃ also CASE3 has higher transition rates when TZ1<350℃ than CASE1.

Using the dynamic analysis required the use of time-consuming implicit algorithms and other sophisticated solution methods to solve systems of differential equations. In order to overcome these difficulties, a hybrid model which is a synthesis of the DYLAM model, a system thermodynamic simulation model and a neural network predicative model, has been used and shows the computational efficiency. This study has values in which this is the first attempt to combine DYLAM and neural network model. By this study, we considered particular features of dynamic reliability analysis of DYLAM. This study offers further development of the present hybrid model using a more realistic neural network predicative model with real failure data of the component.

In summary, from the present study, the following conclusions can be drawn

1) The major advantage of DYLAM related approach is that it can realistically model physical behavior, since it includes the physical equations governing system behavior. But, it should be noticed that major advantage of DYLAM is limited due to the simplified T/H model.
2) DYLAM has its particular value in that it can provide a comprehensive and structured approach for studying dynamic problems.
3) Use of DYLAM is unrealistic when used to analyze complex system without introducing truncation rules that can effect accuracy of representation.
4) It is demonstrated that an effective methodology for system reliability analysis is a hybrid model which is a synthesis of the following three models : i) DYLAM model; ii) system thermodynamic simulation model; iii) neural network predicative model.

References

1. G.Cojazzi, P.C. Cacciabue, "The DYLAM Approach for the Reliability Analysis of Systems with Dynamic Interactions", EUR 15266EN
2. Cacciabue & G. Cojazzi, "A Human Factor Methodology for Safety Assessment based on the DYLAM Approach", ISEI/IE 2502/93
3. N.Siu, "Risk Assessment for Dynamic System : An Overview", Reliability Engineering and System Safety, Vo1.43, pp43 (1994).
4. Amendola & G. Reina, "Event Sequences and Consequence Spectrum : A Methodology for Probabilistic Transient Analysis" , Nuc. Sci. and Eng. Vo1.77, pp297 (1981).
5. A.Amendola, "Accident Sequence Dynamic

Simulation versus Event Trees", Reliability Engineering and System Safety, Vol. 22, pp3-25 (1988).

6. Timothy Masters, "Practical Neural Network Recipe in C++", Academic Press. Inc. (1992).
7. Malcom Taylor and Paulo Lisboa, "Techniques and Application of Neural Network", Ellis Horwood Workshops (1993).
8. Cacciabue, A.Carpinano and C.Vivalda, " Expanding the Scope of DYLAM Methodology to Study the Dynamic Reliability of Complex Systems : the case of chemical and volume control in nuclear power plants", Reliability Engineering and system safety, Vol. 36, pp 127-136 (1992).
9. Cojazzi. G., Cacciabue,P.C. & Parisi, P., "DYLAM-3, A Dynamic methodology for Reliability Analysis and Consequences Evaluation Industrial Plant. Theory and How to use", IEI/SET 2/92/92 (1993).
10. Risk & Safety Management Consortium, "Integrated Plant Management System", ASCA Technical Paper (1994)
11. G.F.Page, Gomm and D. Williams, "Application of neural networks to modeling and control", Chapman & Hall (1992)
12. Stuart Russel, Peter Norvig, "Artificial Intelligence, A Modern Approach", Prentice Hall (1994)