Journal of the Korean Nuclear Society
Volume 25, Number 3, September 1993

Model Developments for Quantitative Estimates of the Benefits of the Signals on Nuclear Power Plant Availability and Economics

Poong Hyun Seong
Korea Advanced Institute of Science and Technology
(Received February 4, 1993)

원자력발전소의 가용도와 경제성에 신호가 주는 이득의 정량적 산출을 위한 모델개발

성풍현
한국과학기술원
(1993. 2. 4 접수)

Abstract

A novel framework for quantitative estimates of the benefits of signals on nuclear power plant availability and economics has been developed in this work. The models developed in this work quantify how the perfect signals affect the human operator's success in restoring the power plant to the desired state when it enters undesirable transients. Also, the models quantify the economic benefits of these perfect signals. The models have been applied to the condensate feedwater system of the nuclear power plant for demonstration.

요　　약

원자력 발전소 운전원에게 발전소 상태를 정확히 알려주는 완벽한 신호가 원자력 발전소 전체의 가용도와 경제성에 얼마만한 영향을 주는가에 대한 정량적인 분석이 이 논문에서 수행되어졌다. 이 분석을 위한 기본 모델들이 개발되어졌고 이 모델들은 발전소가 정상상태에서 비정상상태로 바뀌어갈때 운전원이 발전소가 완전히 비정상상태로 가기전에 발전소를 정상상태로 회복시키는 것에 완벽한 발전소 신호가 얼마만큼 영향을 주는가를 정량화 하였다. 또한 이러한 완벽한 신호가 경제적으로 얼마만큼의 이득을 주는가도 정량화 하였다. 이 모델 적용의 대상으로는 응축 및 주급수 시스템을 선정하였다.

1. Introduction

For the purpose of reducing human error probability in real time diagnosis when a nuclear condensate feedwater system enters transients, three implementations can be made. The first is to simplify the hardware design of the system: Costs and benefits of this approach have been researched [1, 2]. The second is to use many dependable component signals which can indicate the current component configurations reliably. The last implementation is the combination of the above two methods simplifying the hardware system design and using many reliable component signals at the same time.

In this work, a novel framework for a quantitative estimate of the benefits of using reliable component signals in plant availability and plant economics is developed and demonstrated. In order to quantify the benefits of using component signals, we need to develop some models for availability calculation and for replacement electricity cost calculation. Also a proper database must be provided. In the following section these models are discussed. After the discussion, some results using these models and a database is presented. In order to avoid calculational complexity at this preliminary stage of analysis of the reliability and economic impact of the signals, some assumptions are necessary: One important assumption made in this analysis is that the component signals are perfect. A perfect component signal is defined to be the signal which always indicates the current component configuration correctly.

2. Model Development

In order to estimate the availability of a system, one needs to know how often the system fails and how long it takes for the system to be restored for operation. In this section, models for system failure rates and availability are developed.

2.1. Initial System Failure Rate

The evaluation of average condensate feedwater system failure rate per year according to its number of components is not straightforward. It is seen that the average system failure rate is not only dependent on the number of components and their reliabilities in a system but also on the configuration of the system.

In this work, the fault tree method is used for the quantification of average system failure rate per year. Since the components in a condensate feedwater system are monitored components which are repaired whenever they fail, the unavailability of the minimal cut sets must be used in order to calculate the system failure rate per year. A cut set of a system is defined as a set of system events which, if they all occur, will cause system failure. A minimal cut set of a system is a cut set that has no other cut set as a subset[3]. These unavailabilities are summed up to get the total system unavailability using rare event approximation as follows:

$$Q_s \approx \sum_{i=1}^{v} Q(i) \tag{1}$$

Eq.1 is valid since the failure rate is much smaller than the repair rate, i.e. $\mu \gg \lambda$ due to the rare event approximation.

The minimal cut sets for the condensate feedwater system are usually the first or second order minimal cut sets. To quantify the unavailabilities of the minimal cut sets, Markovian models [3] have been used. The steady–state unavailability of minimal cut sets have been used in this work. For the first order minimal cut sets, the steady–state unavailability of minimal cut set is as follows:

$$Q(i) = \frac{\lambda_i}{\lambda_i + \mu_i} \tag{2}$$

For the second order minimal cut sets in which one component is in standby and the other is operating, and failure rates of the two components are different, unavailability of the minimal cut set is follows:

$$Q(i) = \frac{\lambda_o \lambda_s}{2\mu(\lambda_o + \mu) + \lambda_o \lambda_s} \tag{3}$$

For the second order minimal cut sets in which two components are active–parallel, and the failure rates are different, the following result can be obtained:

$$Q(i) = \frac{2\lambda_1 \lambda_2 \mu + \lambda_1 \lambda_2 (\lambda_1 + \lambda_2)}{2\mu^3 + 3(\lambda_1 + \lambda_2)\mu^2 + (4\lambda_1 \lambda_2 + \lambda_1^2 + \lambda_2^2)\mu + \lambda_1 \lambda_2 (\lambda_1 + \lambda_2)}$$

$$\approx \frac{\lambda_1 \lambda_2}{(\lambda_1 + \mu)(\lambda_2 + \mu)}$$

For all the unavailabilities which are discussed above, it is assumed that there are enough repairmen, repair rates of the components are the same for all the components, and the standby component does not fail when in standby mode.

Once the unavailability of the condensate feedwater system, Q_s, has been calculated using equations 1–4, the following equation is used to estimate initial system failure rate :

$$Q_s=\frac{\lambda_I}{\lambda_I+\mu} \tag{5}$$

Therefore, λ_I is obtained as

$$\lambda_I=\frac{\mu Q_s}{1-Q_s} \tag{6}$$

In the above discussion, only the machine–related system failures have been considered to estimate the initial system failure rate. However, it is important to note that the system can enter transients initially by human errors. These human errors are so random that it is difficult to set up a proper database of the probabilities of these human errors. In this work, human contributions of initial system failures are not considered due to the lack of data.

It is important to note that the initial system failure rate does not change according to the number of component signals when we only consider the system failures caused by machine–related failures.

2.2. Mitigated Final System Failure Rate

Whenever a system enters a transient, the operator is expected to mitigate the transient. A procedure of mitigation can be described in an event tree and shown in Fig.1. Whether or not the system fails initially is shown in stage 1 in Fig.1. Whether or not the operator succeeds in diagnoses is shown in stage 2. Stage 3 shows whether the situation is corrected successfully when the operator diagnoses the system successfully or when he fails to diagnose. In most situations the probability that the system will be corrected successfully when the operator does not diagnose the system correctly is very low. However, this case is also counted in the event tree. Stage 4 shows whether the system finally fails or not. "F" indicates the failure cases in Fig.1. Therefore, the mitigated system failure rate can be expressed as follows :

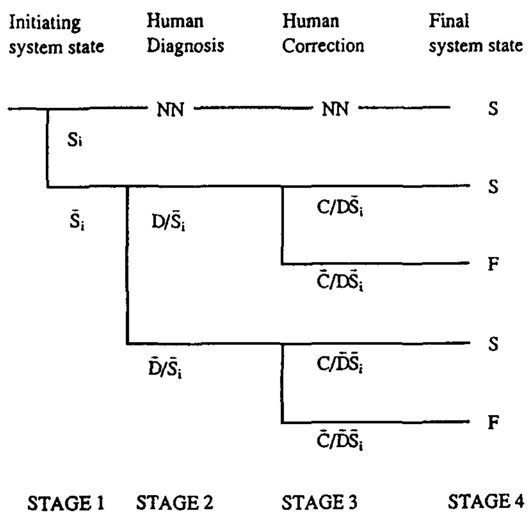


Fig. 1. Event Tree of a Transient Mitigation

$$\lambda_F=\lambda_I[P(\bar{D}/\bar{S}_I)\,P(\bar{C}/\bar{D}\bar{S}_I)+P(D/\bar{S}_I)\,P(\bar{C}/D\bar{S}_I)] \tag{7}$$

We already have noted that the initial system failure rate caused by hardwares does not change according to the number of component signals. The most important impact of the component signals on the system availability is due to the dependence of human error probability in real time diagnosis, $P(D/\bar{S}_I)$, on the number of component signals. The models describing the human error probability in real time diagnosis given the limit of m tries (HEP(m)) and the average number of tries that an operator has to make to diagnose the system (ANTTD) when we assume that the operator always searches the failed component following the descending order of the component unreliabilities can be set up. If an operator is assumed to check the system components in a descending order of their unreliabilities whenever a system enters transient, the HEP in real time diagnosis and the ANTTD of the system can be calculated using the following two simple formulas:

$$HEP = 1 - \frac{1}{\lambda_T} \sum_{i=1}^{m} \lambda\,(PR(i)), \quad (8)$$

$$ANTTD = \frac{1}{\lambda_T} \sum_{i=1}^{n} i\,\lambda\,(PR(i)), \quad (9)$$

$$\text{where, } \lambda_T = \sum_{j=1}^{n} \lambda\,(j),$$

Using the models shown in Eqs. 8 and 9 to quantify the difficulty in diagnosing a system when a system enters transients, we can estimate the $P(D/\bar{S}_i)$ and $P(\bar{D}/\bar{S}_i)$ in Eq.7. Since we assume that the component signals are perfect, it is important to note that the diagnostic difficulty with a perfect component signal will be the same as the diagnostic difficulty without the corresponding component.

2.3. Availability Analysis

Availability of a system is a measure of how much of the time that a system is available for use when necessary. In this work, the steady-state availability is used for availability analysis,

$$A(\infty) = \lim_{t \to \infty} A(t) \quad (10)$$

The availability of a system is dependent both on the failure rates of the system and on the durations of down states (i.e., unavailable states) of the system. The duration of this down state is the mean time to repair (MTTR). The mean time to repair can be broken down further: it is composed of diagnosis time, actual repair and testing time, and the time for administrative work. MTTR varies according to the nature of system failure. Therefore, we need to consider the MTTR for each of the failures separately for an exact calculation. The MTTR's for active components such as pumps and motor operated valves, however, do not vary greatly (Table 1). Therefore, in order to construct a simple availability model, an average value of MTTR for the active components has been used in this work.

A condensate feedwater system can also change states due to the failure of passive components such as pipes and heat exchangers. Usually, large scale failures of the passive components do not occur so often as the failures of active components. Once the passive components fail, however, their repair times are usually very long. This is the reason why the failures of the passive components are important in availability calculation even though their failures have not been considered in system uncertainty calculation in this work.

A condensate feedwater system can also be in failed state for two other reasons. One is the failure of interfacing non-condensate feedwater systems such as the turbine system. The other is refueling.

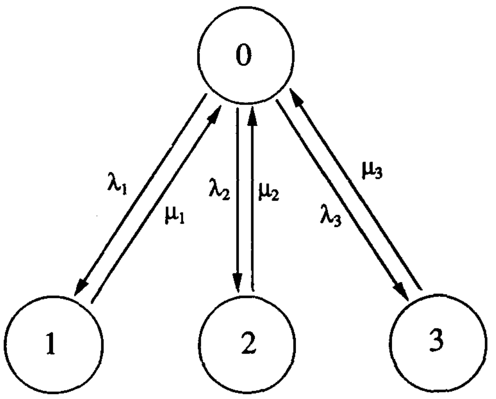
The failed states of condensate feedwater system due to the failures of non-condensate feedwater systems are not considered separately in this work because the target system is fixed on a condensate feedwater system. Condensate feedwater system failures due to refueling have been considered in this work to accommodate the variation in refueling downtime.

Table 1. Mean Time to Repair of the Components

hours

	Generic	Sequoyah
feedwater pump	29.0	56
booster pump	–	56
condensate pump	15.0	–
drain pump	19.7	–
all MOV's	58.8	32
feedwater heater	720	1140

* These values are 20 times of the original data for minor failure



STATE 0: NORMAL OPERATING STATE
STATE 1: SHORT-TERM PLANT SHUTDOWN STATE DUE TO ACTIVE COMPONENT FAILURES
STATE 2: LONG-TERM PLANT SHUTDOWN STATE DUE TO MAJOR PASSIVE COMPONENT FAILURES
STATE 3: REFUELING PLANT SHUTDOWN STATE

Fig. 2. State Transition Diagram for Availability Analysis of a Condensate Feedwater System

Therefore, in the availability model developed in this work, three failure modes of the condensate feedwater system are considered. A Markovian model is used for the availability quantification. Fig.2 shows the state transition diagram of the condensate feedwater system. Then the steady-state availability of the condensate feedwater system can be quantified by the following equation :

$$A=\frac{\tau_{F_1}\tau_{F_2}\tau_{F_3}}{\tau_{F_1}\tau_{F_2}\tau_{F_3}+\tau_{R_1}\tau_{F_2}\tau_{F_3}+\tau_{F_1}\tau_{R_2}\tau_{F_3}+\tau_{F_1}\tau_{F_2}\tau_{R_3}} \quad (11)$$

2.4. Economic Benefit of Component Signals

For the condensate feedwater system the availability of the system is not the sole factor in design decision making. The other important factors for the condensate feedwater system are the thermal efficiency and the capital cost. These three factors comprise a utility function for final decision making. However, for analyzing the economic impact of the component signals, and the system availability is the most relevant design decision factor and only this availability is considered in this work. The availability of a system can be translated into electricity cost through the replacement electricity cost. If a power plant is unavailable, the utility company must buy the replacement electricity from the local electricity pool. The electricity bought from the local electricity pool is called replacement electricity. The cost of the replacement electricity is the major economic penalty of system unavailability.

If the unavailability of a system is Q, the replacement electricity cost per year is

$$RC=8760\ e_r\ QR \quad (12)$$

The present worth of lifetime replacement electricity cost due to the condensate feedwater system unavailability, RCL, is obtained as follows : [4]

$$RC=8760\ \frac{e_r\ RQ}{x-y_{e_r}}(1-\exp((y_{e_r}-x)T) \quad (13)$$

Maintenance and the repair costs for failed components should also be included as another penalty for the less unavailable system. It is assumed that this repair cost is much less important in comparison with the replacement electricity cost and has not been considered in this work in order to keep the model simple.

3. Results

The models developed in section 2 are applied to a condensate feedwater system of different number of component signals. System configuration of this condensate feedwater system has 40 active components and is shown in Fig.3. In order to apply the models, a database in table 3 and 4 is used. The data in Table 3 follows the generic data in Table 2. The component signal has been installed to the most unreliable component first and then to the next unreliable component and so on as the number of signals increases.

The cost evaluation calculation has been automated by two steps of calculations using two com-

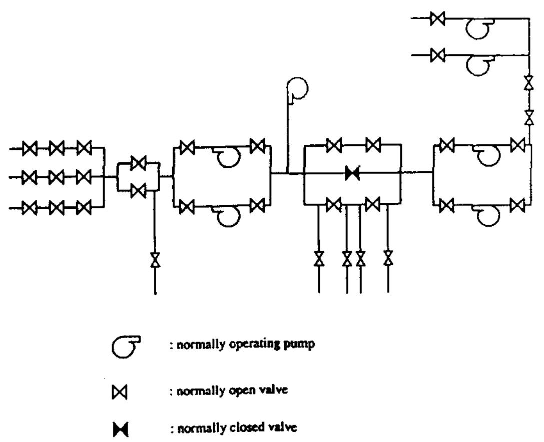


Fig. 3. Active Components Configuration of Complex Condensate Feedwater System

Table 2. Failure Rates of the Components

10^{-5}/hr

	Generic data	Seabrook	Sequoyah
feedwater pump	11.9	103*	41
booster pump	2.99	3.36	2.62
condensate pump	2.99	3.36	2.62
drain pump	14.5	103*	41.0
stand-by pump	–	3.42	2.62
feedwater control valve	2.00	–	1.32E-2
other MOV's	1.66	9.27E-3	1.32E-2
feedwater heater major fail	9.17E-2**	–	6.69E-3**

* originally for turbine driven pumps

** these values are the one tenth of the original data for minor failure

Table 3. Reliability data used in sample evaluations

	Item	Data
failure rate	feedwater pump	11.9E-5/hr
	stand-by feedpump	2.99E-5/hr
	booster pump	2.99E-5/hr
	condensate pump	2.99E-5/hr
	drain pump	14.5E-5/hr
	feedwater cont. valve	2.00E-5/hr
	other MOV's	1.66E-5/hr
	feedwater heater	9.17E-7/hr
mean time to repair (MTTR)	active component	30 hours
	feedwater heater	720 hours
	refueling	25 days

Table 4. Other Data Used in Sample Evalutions

Item	Data
power rating	1000 MWe
replace. elec. cost	40 mills/kwhre
fuel cost	$ 1.8E6/MTHM
burnup rate	33000 MWD/MTHM
price escal. rate	0.9
discount rate	0.6
plant lifetime	35 years
pump cost	$ 5.0E5
valve cost	$ 1.0E5
feedheater cost	$ 1.5E6
commission success probability	0.01
commission error probability	0.01
number of tries allowed	3

puter programs. Results of the quantification are given in Fig.4 to Fig.9. Fig.4~8 show the results of applying the models given in Equations 9, 8, 7, 11, and 13, respectively. Fig. 9 simply shows the value of Fig.8 divided by the number of component signals. The ANTTD reaches its maximum when there are three component signals, which is shown in Fig.4. When there is no component signal, an operator can begin diagnosing the system by checking the most unreliable 3 components such as a drain pump and two feedwater pumps first and he will find out the failed component in a relatively few tries. If there are three component signals for the three most unreliable components and if the system failure is not due to these three components, the operator will have some difficulty in beginning to diagnose the failed system because the failure rates of the components are almost equal and the average number of tries to diagnose the system is high when the system fails due to the components which do not have their corresponding signals. However, the operator can diagnose the system perfectly when the system failures are due to the components which have signals and this makes the overall diagnosability of the system increase as the number of component signal increases. With the similar reason, the HEP(3) shown in Fig.5 begins to show the high values at the point with the 3 component signals. However, HEP(3) is mostly dependent on the reliabilities of the 3 most unreliable components which do not have the component signals (Eq. 8) whereas the ANTTD depends on those of all the components (Eq. 9). It is the

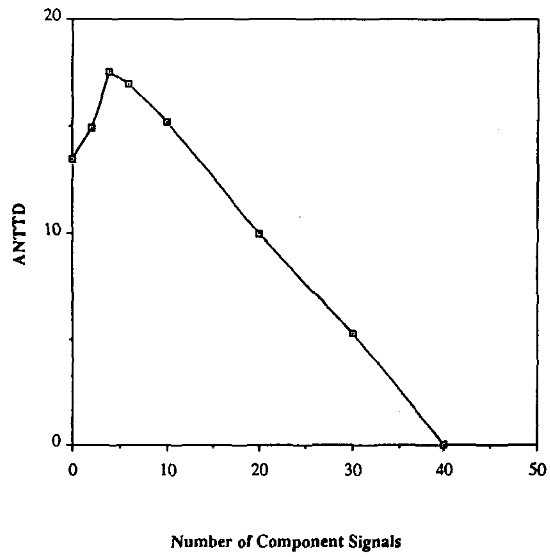


Fig. 4. Average Number of Tries To Diagnoses the System

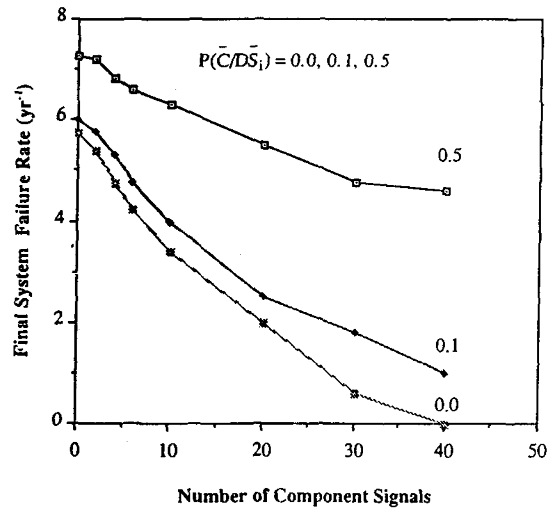


Fig. 6. Final System Failure Rate

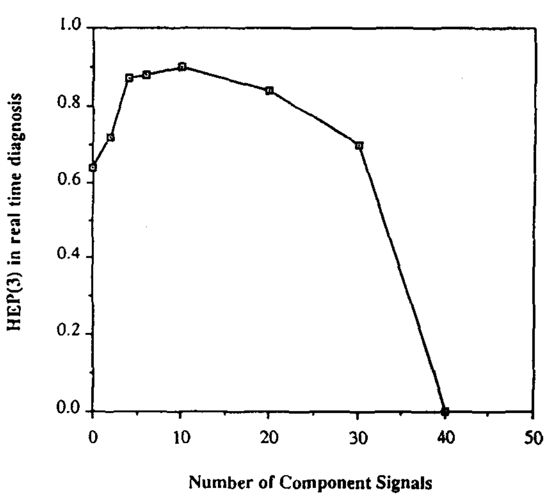


Fig. 5. HEP (3) in Real Time Diagnosis

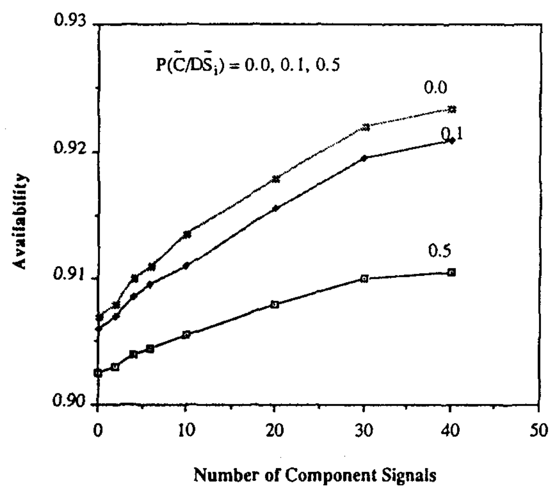


Fig. 7. Availability

reason why the Fig. 4 and 5 do not show the exactly the same shape. In Fig.6, we can see the final system failure rate is monotonically decreasing. The differences in final system failure rates among three cases in Fig.6 are due to the differences in the commission error probabilities, $P(\bar{C}/D\bar{S}_i)$. It is clear that final system failure rate is larger when the commission error probability is larger. Fig.7 shows the availability of the system. The system with 40 component signals has better availability of about 1.5% than the system without any signal when we assume the commission error probability is zero. We can see that the benefit of availability by having many perfect component signals decreases as the commission error increases. Fig.8 shows the economic benefit of the signals by saving the replacement electricity due to higher availability. For the typical nuclear power plant of 1000MWe, the lifetime cost saving by using 40 perfect component signals will be about 120 million dollars. This result indicates that the power plant can have the economic benefit due to the reduced difficulty in real-time diagnosis by having many good component signals instead of simplifying the system design. The benefits of simplified design in other areas, however, must be

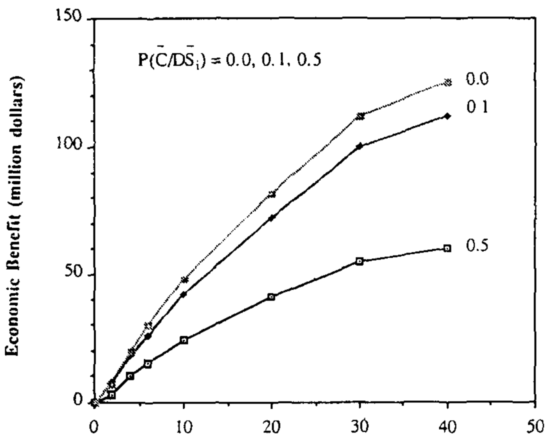


Fig. 8. Economic Benefit

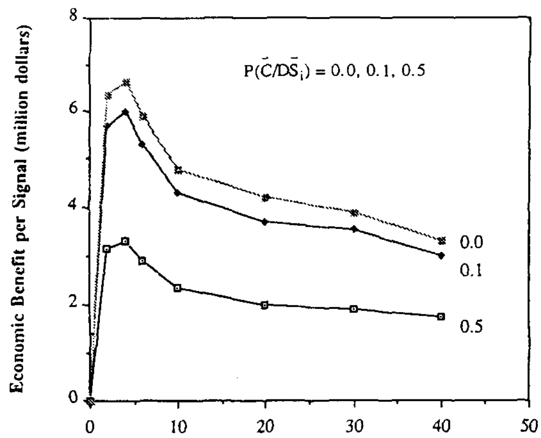


Fig. 9. Economic Benefit Per Signal

considered for a fair comparison. Fig.9 shows the average economic benefit per one perfect component signal. Accepting all the assumptions that have been made, this economic benefit of having one component signal can be interpreted as the amount of money that may be spent for the very high quality component signal.

4. Conclusions

In this work, a novel framework for quantitative estimate of the impact of perfect signals on the nuclear power plant availability and economics is developed. Using this framework, despite some critical assumptions, we could roughly estimate how much economic benefit we can achieve by using good signals in nuclear power plants. This work is believed to be more beneficial when we could extend the work for imperfect signals in the future work.

Nomenclature

Q_s	system unavailability
Q(i)	unavailbility of minimal cut set i

N	number of minimal cut sets
μ	repair rate
μ_i	repair rate of component i
λ_i	failure rate of component i
λ_o	failure rate of the operating component
λ_s	failure rate of the standby component while it is operating
λ_I	initial system failure rate
λ_F	(mitigated) final system failure rate
λ_T	sum of failure rates of all the components
$P(\bar{D}/\bar{S})$	probability that the operator fails to diagnose the system when the system is in transient
$P(D/\bar{S})$	probability that the operator succeeds diagnosing the system when the system is in transient
$P(\bar{C}/\bar{D}\bar{S})$	probability that the operator fails in correcting the system when he fails in diagnosing the system
$P(\bar{C}/D\bar{S})$	probability that the operator fails in correcting the system when he succeeds in diagnosing the system
m	number of tries allowed for a real time diagnosis
n	total number of compoments
PR(i)	i^{th} highest unreliable component
$\tau_{F_i}=1/\lambda_i$	mean time to failure of the system into failure state i
$\tau_{R_i}=1/\mu_i$	mean time to repair of the system from failure state i
RC	replacement electricity cost
RCL	present worth lifetime replacement electricity cost
e_r	unit replacement electricity cost (mills/kwhre)
R	power rating(MWe)
Y_{e_r}	escalation rate of replacement electricity cost (yr^{-1})
x	discount rate (yr^{-1})
T	plant lifetime (yr)

References

1. Poong H. Seong, "A Methodology for Simplification of Light Water Reactor System Design", Ph.D. Thesis, M.I.T., (June 1987).
2. Poong H. Seong, Vincent P. Manno and Michael W. Golay, "Application of a Power Plant Simplification Methodology : The Example of The Condensate Feedwater System", Nuclear Engineering and Design 110, p 33~46, 1988.
3. N. J. McCormick, "Reliability and Risk Analysis", Academic Press Inc., (1981).
4. M. J. Driscoll, "Nuclear Energy Economics and Policy Analysis", Class Notes, M.I.T. Subject No. 22.341, (September 1985).