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A Method of Signal Transmission Path Analysis for Multivariate Random Processes

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A method for noise analysis called "**STP (signal transmission path) analysis**" is presentd as a tool to identify noise sources and their propagation paths in multivariate random proceses.

Basic idea of the analysis is to identify, via time series analysis, effective network for the signal power transmission among variables in the system and to make use of its information to the noise analysis. In the present paper, we accomplish this through two steps of signal processings; first, we estimate, using noise power contribution analysis, variables which have large contribution to the power spectrum of interest, and then evaluate the STPs for each pair of variables to identify STPs which play significant role for the generated noise to transmit to the variable under evaluation. The latter part of the analysis is executed through comparison of partial coherence function and newly introduced partial noise power contribution function.

This paper presents the procedure of the STP analysis and demonstrates, using simulation data as well as Borssele PWR noise data, its effectiveness for investigation of noise generation and propagation mechanisms.

Key Words; Signal Transmission Path Analysis, Noise Analysis, Noise Power Contribution Ratio, Partial Coherence, Partial Noise Power Contribution Ratio, Noise Source Investigation, Cause-Consequence Analysis, Detection, Feedback, Borssele Reactor Noise.

多変数不規則過程に対する信号伝達経路解析手法

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（1984年4月13日受理）

多変数不規則過程の雑音源及びその伝播機構を明らかにするための一手法として，「信号伝達経路解析」という雑音解析手法を提案した。

本手法の基本的な考え方は，時系列解析を通じて評価しているシステムの各変数間での信号パワー伝達ネットワークを同定し，そこで得られた情報をもとに雑音解析を行おうとするものである。本論文では，この解析を二つの信号処理手続きにより達成する；即ち，まずノイズ寄与率解析を用いて着目している変数のパワースペクトルに対し，どの変数の雑音源の寄与が大きいかを明らかにし，次に各変数間の信号伝達経路を評価して発生した雑音がどのような伝播経路を経て着目している変数に伝達されているかを明らかにする。後者の解析はパーシャルコヒーレンスと本論文で新たに導入されたパーシャルノイズ寄与率の相互比較を通じて行われる。

本論文では，信号伝達経路解析の手順を示すとともに，シミュレーションデータ及びBorssele炉（PWR）の炉雑音データの解析を通じて，本手法が雑音発生と伝播のメカニズムを解明する上で有効であることを明らかにした。

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I. Introduction

Process signals from a nuclear reactor plant fluctuate randomely around their mean values due to various disturbances occurring in the system. Usually, these fluctuations contain rich information on the status of the plant operational condition. Therefore, if we can identify their noise sources and quantify their contributions by a suitable noise analysis method, it will be quite useful for surveillance and diagnosis of the reactor plant. With a view toward this, extensive work has been devoted to noise analysis for power reactors/1/-/3/. A recent survey, however, indicates that clarifying noise sources and their propagation mechanisms is still one major area in which certain significant problems remain unsolved/4/. One of the primary reason for this difficulty is due to complicated processes intrinsic in the power reactor noise, i.e., processes accompanied by complicated nuclear- and thermohydraulic-couplings as well as various feedback effects.

Another reason for this difficulty lies in the fact that there have been very few noise analysis methods which can be of direct use to investigate noise generation mechanisms. In this area of investigation, there have been considerable number of noise analysis works conducted in the past. The analysis tools used are diverse from auto-/cross-power spectral density, ordinary coherence, and partial and multiple coherence to noise power contribution functions. Although they may have been effective for individual studies, however, neither of these functions has a potential of providing complete information on the noise sources and their propagation mechanisms especially when dealing with a multivariate system with closed-loops amongst the variables concerned.

Earlier, spectral analysis in terms of auto-/cross-power spectral density(APSD, CPSD) and ordinary coherence(OCH) functions via methods such as fast Fourier transform(FFT) or Blackman-Tukey(B-T) has been a popular tool for experimental studies in investigating noise sources. Typically, Sides and co-workers examined noise signatures in terms of OCH function for various combination of in-core neutron detector signals to discuss neutron noise sources in BWR/5/. However, this method often provides not more than phenominological information, since all the stochastic processes involved are represented in an integrated form in those functions and thus it is not possible to isolate therefrom one particular process from others. Therefore, it is rather common that the analysis is performed in conjunction with considerations using a physical model or with confirmatory experiments/6/-/8/.

Partial coherence(PCH) in multivariate noise analysis is another method which has been used in the reactor noise field. The method has been applied to a BWR noise by Fukunishi/9/ and to a PWR noise by Dragt/10/ in order to investigate neutron noise sources as well as to separate the neutron noise into local and global effects. Oguma/11/ and Kleiss/12/ also performed the partial coherence analysis for BWR noise but with different algorithms from the conventional one, in which a particular emphasis was placed upon correctly dealing with feedback effect acting in the system. The PCH analysis itself intends to evaluate direct correlation between a selected pair of variables when eliminating effects of other variables. Hence, for example, through comparison with OCH representing the net correlation between the two variables, one may separate variables with common noise source from others. In this way, the PCH is expected to be a useful tool for the present noise analysis purpose.

On the other hand, multivariate noise analysis based upon time series modeling in terms of autoregressive(AR) or autoregressive-moving average(AR-MA) representation has come into use recently in the reactor noise field with succssful applications/13/-/22/ and is steadily gaining acceptance. The main advantage of this approach is that if the noise sources are mutually uncorrelated, one can identify dynamic characteristics of feedback loops as well as separate the noise source characteristics. Of various techniques on the basis of the time series modeling, the most commonly utilized for reactor noise analysis is the noise power contribution(NPC) analysis proposed by Akaike/23/. This method allows the APSD of a measured variable to be decomposed into contributions of noise sources driving the corresponding variables, whereby one may identify the principal noise source or causal relationship of signal transmission. The method has been first applied by Fukunishi/13,14/ to estimate neutron noise sources in a BWR, which was then followed by Kitamura and co-workers/15/ to study PWR noise and by Oguma/16/, Matsubara/17/, Bergdahl and Espefält/18/, Kitamura and Upadhyaya/19/, and Kanemoto and co-workers/20,21/ to study BWR noise.

However, in some cases both the PCH and NPC functions are not necessarily sufficient tools for such a problem as clarifying the noise generation and propagation mechanisms in multivariate stochastic systems. That is, as will be examined in Sec. **II**, the PCH function in principle does not provide information on the causal relationship between the two variables. The NPC function as well is not suited to examine whether or not there exists a direct path which transmits signal power from one variable to the other in the multivariate system. Rather it evaluates from the global point of view the noise source power which is transmitted through all possible paths to the variable of interest. No unified method is known so far which has general applicability to various problems using terminologies such as noise source estimation, causality analysis, identification of noise propagation paths and so forth.

In view of developing an effective method for the present noise analysis purpose, this paper presents a method called "**STP (signal transmission path) analysis**". It intends to identify, through the time series analysis, effective network for the signal power transmission among variables employed in the noise analysis and to utilise the information obtained therefrom to the nois source investigation. The present author claimes that important in getting insight into the noise generation mechanism is to identify both variables and STPs which have significant contribution to the power spectrum under evaluation. The basic idea of the STP analysis has already been proposed by the present author/24,25/ and also independently by Upadhyaya et. al./26/ for bivariate system. In this paper, we extend it to multivariate system and present the analysis procedure.

In Sec.II, theory of the STP analysis will be developed, where we mathematically derive three functions, i.e., NPC, PCh and PNPC functions, and show that their mutual comparison allows to determine effective STPs as well as to estimate principal noise source in the system. The procedure of the STP analysis based on a multivariate autoregressive modeling will be given in Sec. III, which will be demonstrated, in Sec. IV, to work correctly through noise analysis of simulation data. As a practical application, the STP analysis was performed for Borssele PWR noise data measured during its steady power operation.

Through the application to simulation data as well as to Borssele noise data, it will be demonstrated that the STP analysis presented here is capable of dealing with various problems associated with noise source investigation in more unified and comprehensive manner, with the results providing less ambiguity in the interpretation than conventional methods.

II. Theoretical Basis of The STP Analysis

II.A Statement of The Problem

Consider a multivariate linear, discrete time, stochastic system with r-dimensional measurement variables $\{x_1(s),\ x_2(s),\ \ldots,\ x_r(s)\}$ given by the following equation;

$$x_i(s) = \sum_{\substack{j=1 \\ (i \neq j)}}^{r} G_{ij}(z^{-1})x_j(s) + n_i(s), \qquad (i=1,\ 2,\ \ldots,\ r) \tag{1}$$

where $G_{ij}(z^{-1})$ is the open-loop transfer function of x_i to x_j and z^{-1} a backward shift operator. The variable n_i indicates the noise term inducing random variation in the system via x_i, and hence is called the noise source of x_i. It is assumed that n_i is subject to independent stationary random process with zero mean value and the APSD of $Q_{ii}(f)$. Here it should be noted that Eq.(1) allows a case in which there exists a closed-loop between a pair of variables, e.g., between x_i and x_j via transfer functions $G_{ij}(z^{-1})$ and $G_{ji}(z^{-1})$. Therefore, the feedback effect is taken into account automatically in this system representation. Using a vector form, the system equation is written by

$$\mathbf{X}(s) = \mathbf{G}(z^{-1})\mathbf{X}(s) + \mathbf{N}(s) \tag{2}$$

where $\mathbf{X}$ is the r-dimensional measurement vector with x_i in the i-th element, $\mathbf{N}$ the r-dimensional noise source vector with n_i in the i-th element, and $\mathbf{G}(z^{-1})$ the (rxr)-dimensional transfer function matrix with $G_{ij}(z^{-1})$ in the (i,j)-element and zeros in all the diagonal elements. Defining the closed-loop transfer function of $\mathbf{X}$ to the noise source $\mathbf{N}$ as $\mathbf{H}(z^{-1})$, the system equation can also be written as

$$\mathbf{X}(s) = \mathbf{H}(z^{-1})\mathbf{N}(s), \tag{3}$$

where $\mathbf{H}(z^{-1})$ is related to the transfer function $\mathbf{G}(z^{-1})$ by

$$\mathbf{H}(z^{-1}) = \{\mathbf{I} - \mathbf{G}(z^{-1})\}^{-1}. \tag{4}$$

It is seen from Eq.(1) that the observed signal x_i consists of the sum of the signals transmitted from other variables via the corresponding transfer functions, and the noise source n_i. Dynamic relationship among these variables are illustrated in Fig. 1, where between x_i and other input variables are connected by the respective STPs with the corresponding path transfer function. The present STP analysis aims at obtaining, through multivariate time series analysis, both qualitative and quantitative information on the effective network of the signal power transmission in the system. It should be noted here that the present STP analysis cannot be replaced by evaluating individual transfer functions G_{ij}'s, because the transfer function itself is merely concerned with the potential of the STP to transmit the signal but not with actual signal power transmitted through the associated STP. In order for the method to be effective for the present noise analysis purpose, it must be capable of evaluating the following items;

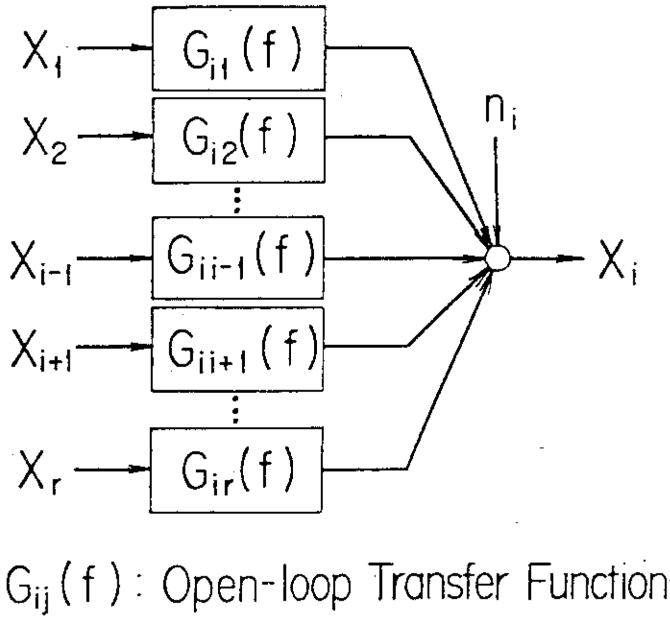


Fig. 1 Block diagram showing the input-output relationship for a multi-variate dynamic system.

(a) Which variable gives the most significant influence on the APSD of interest (estimation of the source variable).

(b) Whether or not there exits direct correlation between each pair of variables (evaluation of direct correlation).

(c) Whether or not there exitsts feedback effect between the two variables (detection of feedback).

(d) With the direct correlation but no feedback, to which direction the signal is propagated, or in other words, which variable is the cause and which one is the effect (determination of causal relationship).

As an effective way to accomplish this, we carry out the present STP analysis in two steps; first we estimate the variable, among those employed in the analysis, which contributes the most to the APSD under evaluation (evaluation for the item (a)), and then evaluate item (b) through (d) in terms of partial spectral decomposition. For the first step, we perform this using the NPC analysis. For the second step, we introduce a new function called **"partial noise power contribution(PNPC) function"** and will show that comparison of the PCH and PNPC functions between a selected pair of variables enables evaluation for items (b) through (d). Combination of the information thus derived from the two steps of the noise analysis will be shown to allow identification of the noise sources and their propagation paths in multivariate random processes.

In what follows, we will develop mathematical derivation of functions used in the present STP analysis together with consideration of their mutual relationship.

II.B Derivation of Noise Power Contribution Function

With a minor calculation using Eqs.(2) to (4), we can derive APSD and CPSD functions for the measurement variables as

$$P_{ii}(f) = \sum_{k=1}^{r} |h_{ik}(f)|^2 Q_{kk}(f),$$
$$P_{ij}(f) = \sum_{k=1}^{r} h_{ik}(f) h_{jk}^{*}(f) Q_{kk}(f), \tag{5}$$

where $h_{ij}(f)$ represents the (i,j)-element of H(f). The superscript * denotes the complex conjugate and frequency f is related to the shift operator by

$z^{-1} = \exp(-j2\pi f)$.

In Eq.(5) the portion in the APSD of x_i which is contributed by the noise source n_j is given by

$$q_{ij}(f) = |h_{ij}(f)|^2 Q_{jj}(f). \tag{6}$$

Hence, designating the NPC ratio from n_j to x_i as $\Gamma_{ij}(f)$, it is defined by

$$\Gamma_{ij}(f) = \frac{q_{ij}(f)}{P_{ii}(f)} = \frac{|h_{ij}(f)|^2 Q_{jj}(f)}{\sum_{k=1}^{r} |h_{ik}(f)|^2 Q_{kk}(f)} . \quad (i,j = 1,\ 2,\ \ldots,\ r) \tag{7}$$

Obviously, $\Gamma_{ij}(f)$ satisfies

$$\sum_{j=1}^{r} \Gamma_{ij}(f) = 1 . \tag{8}$$

We can use Eq.(7) in identifying the variable x_j of which noise source

$Q_{jj}(f)$ contributes the most to the APSD $P_{ii}(f)$. Namely, x_j is regarded as the the source variable to $P_{ii}(f)$, if the magnitude of $\Gamma_{ij}(f)$ is larger than any other Γ_{ik}'s (k=1, 2, ..., r, k≠j) around the frequency of interest. This analysis is used to be called **"noise power contribution analysis"**. We can use this analysis to estimate the source variable mentioned in item (a). Generally speaking, however, this analysis does not yield information about through which STPs the fluctuation is transmitted from x_j to x_i, what role the STPs play in determining the measured APSD pattern and so forth. This is because, as seen from Eq.(3), the transfer function h_{ij} used to evaluate the NPC ratio is a function of all the STP transfer functions and therefore the portion of the power which is transmitted via a particular STP does not appear in an explicit manner in the NPC function.

II.C Derivation of Partial Coherence and Partial Noise Power Contribution Functions

Consider a direct dynamic relationship between a pair of variables among those in Eq.(1), after removing all the linear effects of other variables. For simplicity, we take here the variable pair $(x_1\ x_2)$ Let $x_{1|3...r}$ and $x_{2|3...r}$ denote conditioned variables for x_1 and x_2, respectively, with the linear effects of $\{x_3, x_4, ..., x_r\}$ on x_1 and x_2 removed. Then they satisfy

$$\begin{pmatrix} x_{1|3...r}(s) \\ x_{2|3...r}(s) \end{pmatrix} = \begin{pmatrix} 0 & G_{12}(z^{-1}) \\ G_{21}(z^{-1}) & 0 \end{pmatrix} \begin{pmatrix} x_{1|3...r} \\ x_{2|3...r} \end{pmatrix} + \begin{pmatrix} n_1(s) \\ n_2(s) \end{pmatrix}, \tag{9}$$

which represents a subsystem made up of dynamic interrelation between x_1 and x_2, and of the noise sources n_1 and n_2 alone. Following the same procedure as obtaining Eq.(5), spectral density functions of $X_{1|3...r}$ and $x_{2|3...r}$ can be calculated to give

$$\begin{aligned} P_{11|3...r}(f) &= \{|G_{12}(f)|^2 Q_{22}(f) + Q_{11}(f)\}/D, \\ P_{22|3...r}(f) &= \{|G_{21}(f)|^2 Q_{11}(f) + Q_{22}(f)\}/D, \\ P_{12|3...r}(f) &= \{G_{12}(f)Q_{22}(f) + G^*_{21}(f)Q_{11}(f)\}/D = P^*_{21|3...r}(f), \end{aligned} \tag{10}$$

where $D = |1 - G_{12}(f)G^*_{21}(f)|$ and $|.|$ denotes the absolute value; $P_{11|3...r}(f)$ and $P_{22|3...r}(f)$ are the APSDs of $x_{1|3...r}$ and $x_{2|3...r}$, respectively, and

$P_{12|3...r}(f)$ is the CPSD between them. Hence they are often called conditioned power spectral density functions with respect to x_1 and x_2, when eliminating the effects of $\{x_3, x_4, ..., x_r\}$ on these variables. This manipulation to derive the conditioned spectra can also be interpreted that they represent the spectra obtained when cutting-off all the possible STPs transmitting the signals to x_1 and x_2 from the remaining variables.

The coherence function between $x_{1|3...r}$ and $x_{2|3...r}$ is then give by

$$\gamma^2_{12|3...r}(f) = \frac{|P_{12|3...r}(f)|^2}{P_{11|3...r}(f)P_{22|3...r}(f)}$$

$$= \frac{|G_{12}(f)Q_{22}(f) + G^*_{21}(f)Q_{11}(f)|^2}{\{|G_{12}(f)|^2Q_{22}(f) + Q_{11}(f)\}\{|G_{21}(f)|^2Q_{11}(f) + Q_{22}(f)\}} , \qquad (11)$$

which represents the partial coherence function between x_1 and x_2 when conditioned by $\{x_3, x_4, ..., x_r\}$. The partial coherence analysis in terms of Eq.(11) was first introduced by the present author/11/ to investigate a BWR noise. The main advantage of the present PCH analysis as compared with the conventional one/27/ is that it can be applied even to systems with feedback constituting closed-loops among variables employed in the analysis. More detailed discussion of the PCH function and its relation to the conventional one is given in Ref.(28).

The concept of the NPC analysis can be applied without any modification to the conditioned variables. Namely, in Eq.(10), denoting the ratio of the portion in the APSD of $x_{1|3...r}$ which is contributed by n_2, to the net APSD as $\Gamma_{12|3...r}(f)$, and that of $x_{2|3...r}$ which is contributed by n_1, to the net APSD as $\Gamma_{21|3...r}(f)$, then they are given by

$$\Gamma_{12|3...r}(f) = \frac{|G_{12}(f)|^2Q_{22}(f)}{|G_{12}(f)|^2Q_{22}(f) + Q_{11}(f)} ,$$

$$\Gamma_{21|3...r}(f) = \frac{|G_{21}(f)|^2Q_{11}(f)}{|G_{21}(f)|^2Q_{11}(f) + Q_{22}(f)} , \qquad (12)$$

Therefore, $\Gamma_{12|3...r}(f)$ represents the NPC ratio of n_2 to x_1 when all the STPs from $\{x_3, x_4, ..., x_r\}$ have been eliminated. Since this conditioning procedure is the same as that when deriving the PCH function, the present NPC ratio is termed **"partial noise power contribution(PNPC) function"**.

In summary, the PNPC function is the NPC function defined for conditioned spectra.

II.D STP Analysis Using NPC, PCH and PNPC Functions

Contrary to the NPC analysis, the PCH and PNPC functions yield explicit information on the STP acting between a pair of variables under evaluation. That is, the PCH function represents the direct correlation taking place via the STPs between the two variables, and the PNPC function the direct power contribution of one variable's noise source to another variable via the corresponding STP. By comparing Eqs.(11) and (12), we can deduce important relations between the PCH and PNPC functions which lend themselves to evaluate effective STPs between the two variables;

i) If there is no direct STP between x_1 and x_2, i. e., $G_{12}(f) = G_{21}(f) = 0$, then both the PCH and PNPC functions become zero for frequencies of interest.

ii) If there is one direct STP with causal direction from x_1 to x_2, i. e., $G_{12}(f) = 0$ and $G_{21}(f) \neq 0$, then $\Gamma_{12|3...r}(f)$ becomes zero and $\Gamma_{21|3...r}(f)$ takes a value between zero and unity. Moreover it is also noted in this case that the nonzero PNPC function should agree with the PCH function in the frequencies under evaluation. Similar argument holds also for the case $G_{21}(f) = 0$ and $G_{12}(f) \neq 0$.

iii) If there are bilateral STPs between x_1 and x_2, i. e., $G_{12}(f) \neq 0$ and $G_{21}(f) \neq 0$ and hence a feedback effect exists between them, then both PNPC functions take values between zero and unity. In addition to that they differ from the PCH in that frequency region.

Therefore, comparison of the PCH and PNPC functions enables to evaluate direct correlation, to determine causal relationship as well as to detect feedback effect between the two variables. We call the comparison of the two functions as **"PCH-PNPC comparison"** or **"PCH-PNPC analysis"**.

Taking into account the results obtained in this section through mathematical consideration of the NPC, PCH and PNPC functions, the STP analysis is carried out in two steps; fist we evaluate each NPC function for all the variables employed in the analysis, and then perform PCH-PNPC comparison for each pair of variables.

III. Procedure of The STP Analysis Based on MAR Modeling

The STP analysis presented in the previous section can be performed using an MAR modeling technique. A multivariate stationary random process can be represented by the following MAR model;

$$x_i(s) = \sum_{j=1}^{r} a_{ij}(z^{-1})x_j(s) + e_i(s), \qquad (i=1,\ 2,\ \ldots,\ r) \tag{13}$$

where

$$a_{ij}(z^{-1}) = \sum_{m=1}^{M} A_{ij}(m)z^{-m}, \tag{14}$$

and $A_{ij}(m)$ denotes the AR coefficient and M the model order. The additive term $e_i(s)$ expresses the noise source of the system which is subject to a white Gaussian random process with zero mean and the variance σ_{ii}. If all the noise sources e_i's (i=1, 2, ..., r) are mutually uncorrelated, the covariance between any pair of noise sources becomes zero.

Since Eqs.(1) and (13) should represent the same time series, the following relations hold between these two equations;

$$n_i(s) = \frac{1}{1 - a_{ii}(z^{-1})} e_i(s), \tag{15}$$

$$G_{ij}(z^{-1}) = \frac{a_{ij}(z^{-1})}{1 - a_{ii}(z^{-1})}. \tag{16}$$

Using Eq.(15), the APSD of the noise source n_i can be expressed as

$$Q_{ii}(f) = \frac{dt\ \sigma_{ii}}{|1 - a_{ii}(f)|^2}, \tag{17}$$

where dt denotes the data sampling interval.

Therefore, once the MAR modeling is accomplished the present STP analysis can be performed by substituting the MAR coefficients and the variances of the noise sources into Eqs.(16) and (17) and thereby calculating the NPC, PCH and PNPC functions described in the previous section.

Only a remaining problem in executing the present analysis based on the MAR modeling is that the identified STP transfer functions and the noise source spectra must uniquely correspond to those of the underlying physical system. This condition, which is generally called the identifiability of feedback system, is known to be satisfied if the white noise sources of the identified MAR model are mutually uncorrelated./29/ In the present study the assumption of the noise source independency is validated if $\sigma_{ij}/\sqrt{\sigma_{ii}\sigma_{jj}}$

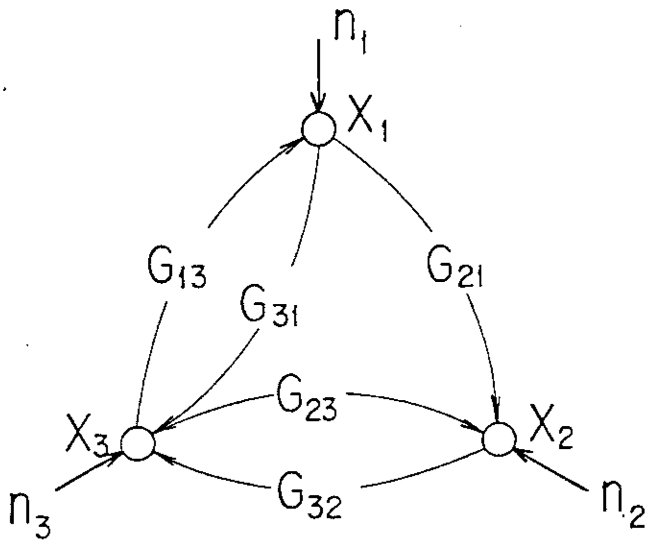
is sufficiently small, where σ_{ij} denotes the estimate of the covariance between e_i and e_j, and σ_{ii} and σ_{jj} are the estimate of their variances, obtained in the MAR modeling. In some cases in the practical application of the STP analysis, existence of the correlation among some noise sources may severely affect the result and could mislead the interpretation. Useful checking methods for the noise source independency and for the identifiability of the transfer function in a feedback loop have been proposed by different authors/30/-/33/. It is recommended here to validate, as strictly as possible, the present STP analysis from various points of view using those different methods.

Summarizing the procedure of the STP analysis based on the MAR modeling, we can perform it in the following steps;

1) identify the MAR model for a given set of multivariate time series data,
2) check the noise source independency,
3) perform the NPC analysis to identify a variable of which noise source contributes the most to the variable concerned,
4) perform the PCH-PNPC comparison for each pair of variables to evaluate the STPs, and
5) evaluate noise propagation paths based on the results from 3) and 4).

IV. Simulation Study

In order to demonstrate the effectiveness of the STP analysis, a simulation study was carried out for a set of time series data generated by a three variable stochastic model set on the analog part of a hybrid computer. As illustrated in Fig. 3, the system between x_1 and x_2 is composed of an open-loop structure with signal flow direction from x_1 to x_2, between x_1 and x_3 of a closed-loop structure with negative feedback, and between x_2 and x_3 of a closed-loop structure with positive feedback. Transfer functions in the respective STPs consist of low-pass filters with different dynamic characteristics from each other. Random noise signals used to drive the system are those recorded on an analog data recorder. They are mutually independent and bandwidth limited white Gaussian noise with a cut-off frequency at 10 Hz. In carrying out the simulation study, the recorded noise signals were regenerated to apply to the model set on the analog computer and then to measure the simulation data. The resultant output signals were fed into the digital part of the computer through A/D converter to perform the analysis. For a set of time series data thus derived, a three variable AR model was identified and then checked



$$G_{21}(s) = \frac{100}{S^2 + 14S + 100}$$

$$G_{13}(s) = \frac{1.2}{0.4S + 1}$$

$$G_{31}(s) = \frac{-1}{(0.4S+1)(0.5S+1)}$$

$$G_{23}(s) = \frac{0.5}{0.1S + 1}$$

$$G_{32}(s) = \frac{1.2S+2}{(S+1)(0.2S+1)}$$

Fig. 2 Graphical representation of the three variable system used for the simulation study.

with the independence assumption for its three noise sources. The data set used for the model identification was composed of time series data with a sampling interval of 0.02 sec. and the sample size of 4000.

The purpose of the present STP analysis is to demonstrate its potential for identifying the STP network of the system under evaluation. According to the analysis procedure as described in the previous section, first, the NPC analysis is performed. The results obtained are shown in Fig. 3 in the cumulative form. From these figures it is seen that all the noise sources in the low frequency region contribute considerably to each variable. However, the NPC analysis cannot give further insight into the noise propagation mechanism, unless having recourse to PCH-PNPC analysis.

Second, PCH-PNPC comparison is made for each pair of variables with the results shown in Fig.4. Between x_1 and x_2, the PCH and PNPC functions from x_1 to x_2 agree relatively well in the frequency range of interest, and another PNPC functions takes a value close to zero for all frequencies(Fig.4-i). Accordingly, it is judged that

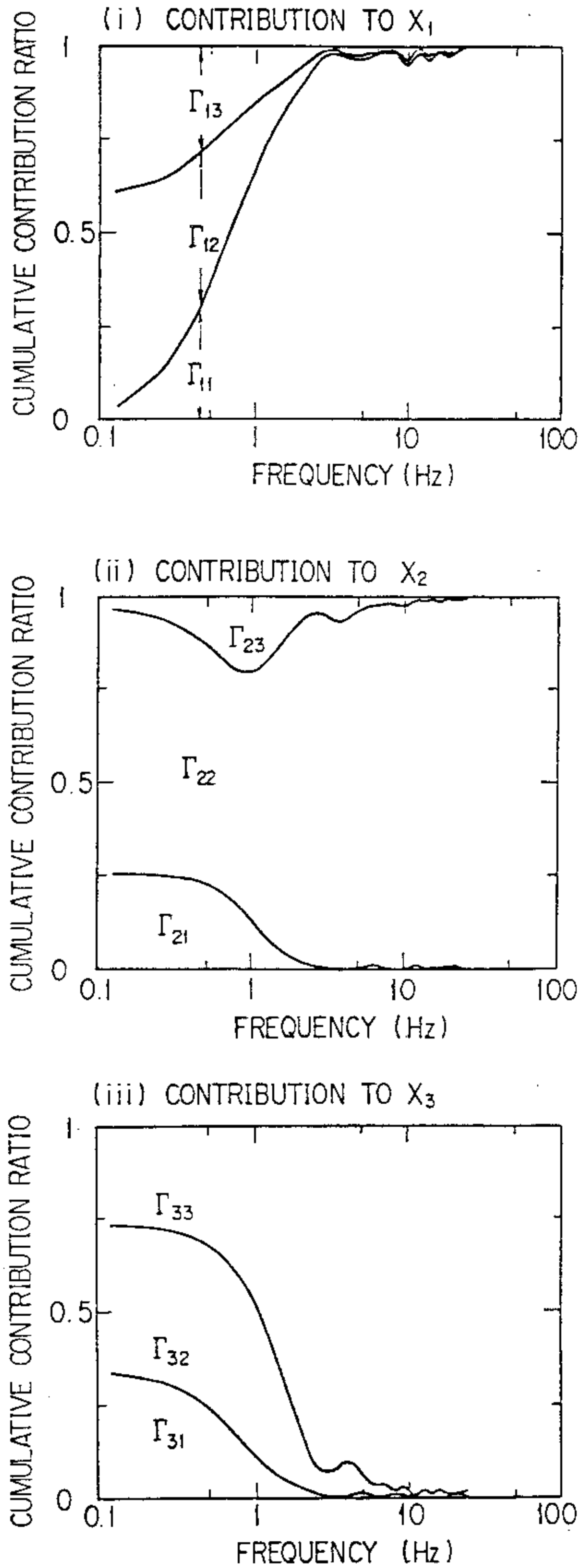


Fig. 3 Noise power contribution functions calculated for the simulation data.

between these two variables is of an open-loop structure with the STP from x_1 to x_2. The PNPC ratios are appreciably high between x_1 and x_3 (Fig.4-ii). In addition, both PNPC functions differ from the PCH function, indicating a feedback effect acting between them. For the variable's pair x_2 and x_3, similar consideration results in feedback effect acting between them (Fig.4-iii). The high coherence in low frequencies in this case is due to the positive feedback effect.

Evaluating the STPs based on the results of the NPC analysis and PCH-PNPC comparison, we can easily identify the STP network as illustrated in Fig. 2. Moreover, for example, we can interpret based on this information that the large noise power contribution of x_2 to x_1 in the low frequency region (Fig.3-i) is brought about through the medium variable x_3 but not via direct influence from x_2 to x_1. Generally, this kind of interpretation for the noise propagation mechanism cannot be available without the aid of the PCH-PNPC analysis. The present STP analysis indicates its potential of evaluating the direct correlation, detecting feedback as well as determining causal relationship among variables employed in the analysis.

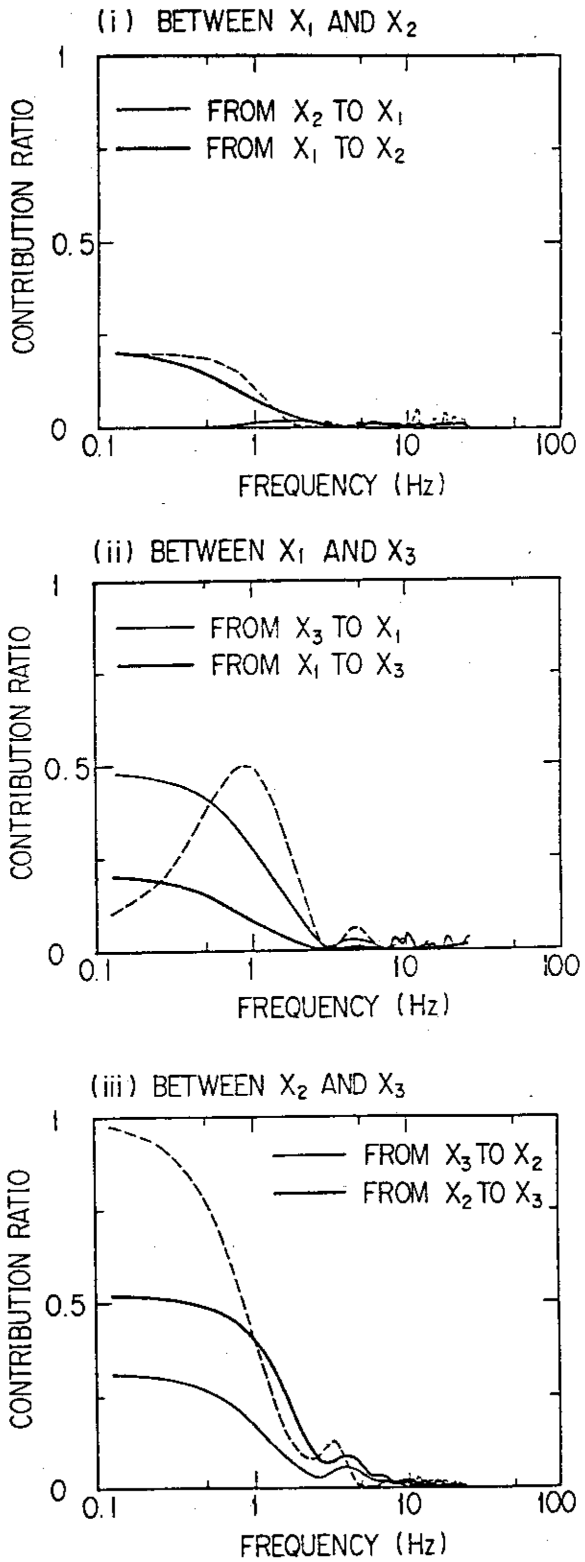


Fig. 4 Comparison of partial coherence and partial noise power contribution functions (PCH-PNPC comparison) for the simulation data, where dashed line expresses the partial coherence and the rela line the partial noise power contribution ratio.

V. STP Analysis for Borssele Reactor Noise

As an application of the present method to a practical problem, the STP analysis is carried out for noise data from the Borssele reactor. The Borssele reactor is a PWR with two coolant loops which is operated at the rated power of 450 MWe. Of various process signals, we consider here results from the analysis for four combination of signals; two ex-core neutron signals, logarithmic(LOG) and linear(LIN) channels 180 degree apart from each other against the reactor core, and two pressure signals, YA01 and YA02 in the coolant loop No.1 and No.2, respectively. The neutron detector LIN channel is located in the side of the loop No.1 and the LOG channel in the side of the loop No.2. Figure 5 shows the cross section of the Borssele reactor plant indicating positions of ex-core neutron detectors and pressure sensors in the primary loop system.

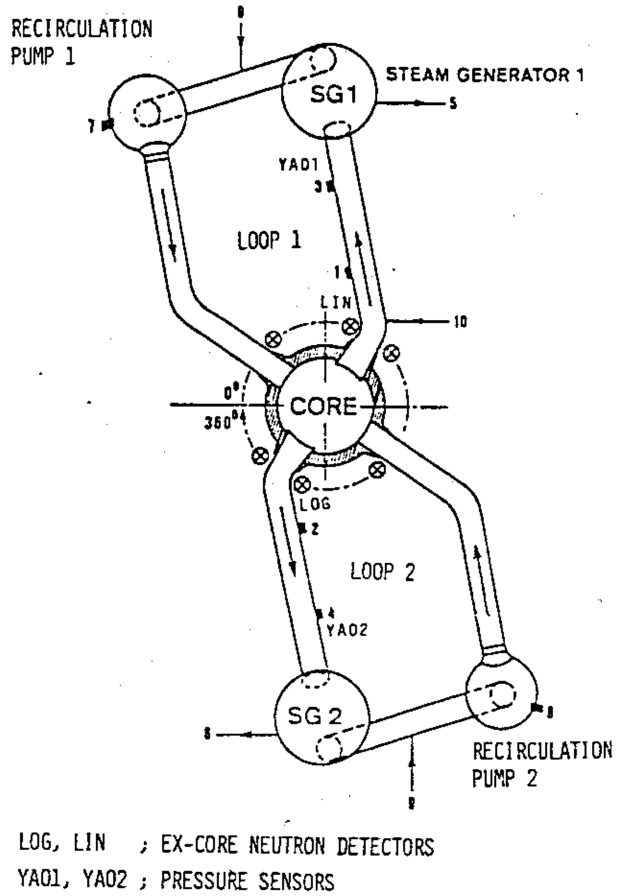


Fig. 5 Cross section of the Borssele reactor plant showing the positions of ex-core neutron detectors and pressure sensors used for the noise analysis.

The aim of the analysis is to estimate noise sources and their propagation paths among the four variables. Time series data used in the present analysis consist of sample size of 4000 with a sampling interval of 0.01 sec.

The STP analysis is carried out according to the procedure described in Sec. III. Shown in Fig.6 are APSDs of the four variables derived from the identified MAR model. The APSD of the LOG channel has remarked peaks at

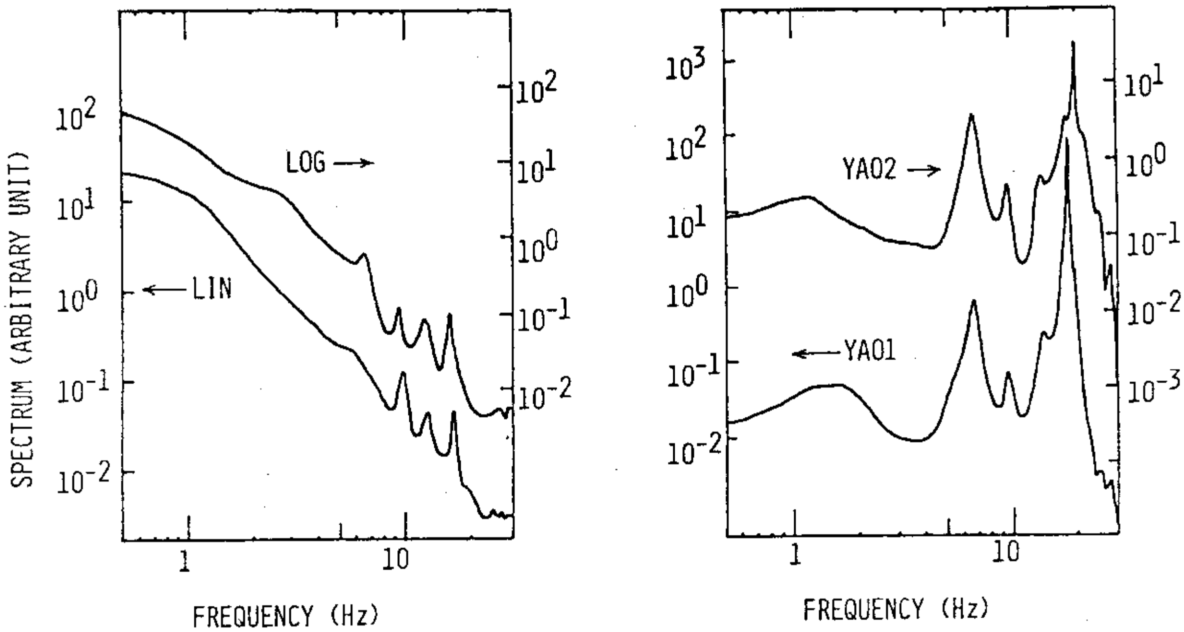


Fig. 6 Auto-power spectral densities of neutron (LOG, LIN) and pressure (YA01, YA02) signals measured during the steady power operation in the Borssele reactor.

about 6.5, 9.2, and 15 Hz, and that of the LIN channel at about 9.2, 12 and 15 Hz. The pressure YA01 has clear spectral peaks at about 6.5, 9.2, 14 and 18 Hz, and YA02 has those at about 6.5, 9.2, 14 and 20 Hz, respectively.

In order to estimate source variables leading to those spectral peaks, first we perform the NPC analysis. The result is shown in Fig.7, from which the followings can be seen;

- o LOG channel neutron signal is considerably influenced by the pressure noise sources at frequencies about 6.5 and 9.2 Hz, indicating that the corresponding spectral peaks are due to the pressure fluctuations in the two loops. The similar feature is seen for the 9.2 Hz peak of LIN channel APSD (Fig. 7-i).
- o Each pressure signal is strongly influenced by the noise source of another pressure in frequencies 3 to 10 Hz, suggesting mutual interraction, or feedback effect, acting between the two pressures (Figs. 7-iii, -iv).
- o In the frequency region from 10 to 20 Hz, each neutron signal is influenced by the noise source of another neutron especially at about 12 and 15 Hz, indicating the mutual interference between the two neutron

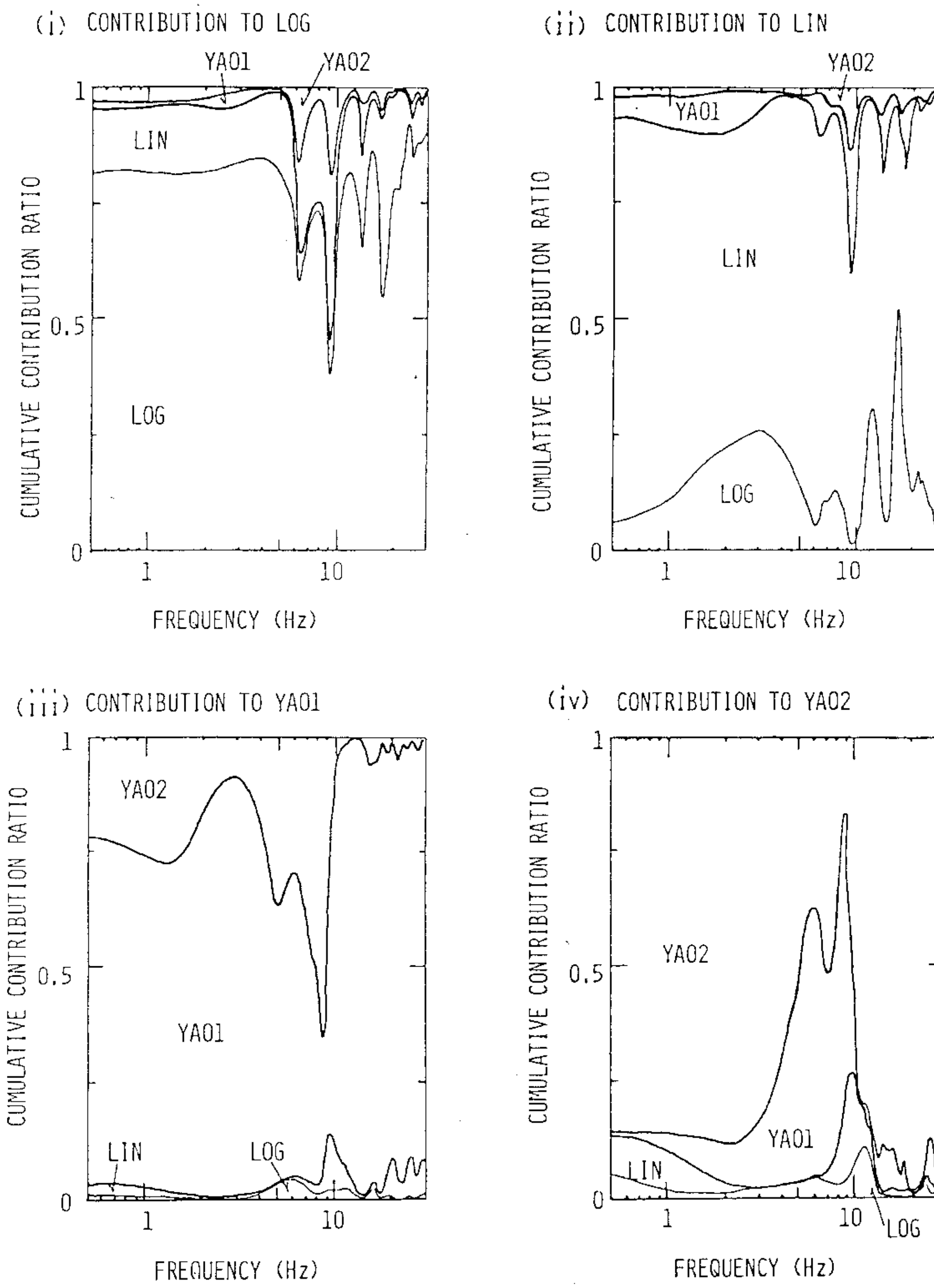


Fig. 7 Noise power contribution functions calculated for the respective neutron and pressure signals.

signals (Figs. 7-i, -ii). On the other hand, the NPC functions of the individual pressure signals in this frequency range is predominated by the contribution of their own noise sources (Figs. 7-iii, -iv), indicating that the APSD peak at 18 Hz in YA01 and that at 20 Hz in YA02 are not, at least, due to variations of other three variables.

Next, the PCH-PNPC comparison is made between the respective pair of variables, of which results are shown in Fig. 8.

Between the two neutron signals, both functions take relatively large value around 12 and 15 Hz (Fig. 8-i). The two neutron detectors, LOG and LIN channels, are located in the opposite side against the reactor core. The spectral peaks at 12 and 15 Hz of the ex-core neutron detector signals are known to be due to the core barrel motion(CBM)/34/. Therefore, the above mentiond peaks of the PCH and PNPC functions can be regarded as another indication of the CBM. The similar phenomenon is suggested in frequencies 3 to 5 Hz, too. On the other hand, both the PCH and PNPC ratios become small in frequencies 7 to 10 Hz, indicating that the spectral peak in this frequency region must be accounted for by the effects of other variabes, i. e., the effect of pressures.

In Figs. 8-ii and 8-iii, the PCH-PNPC comparison is made between LOG and YA01 and between LIN and YA01, respectively, from where around 9 Hz the signal is propagated from the pressure to neutron. This implies that the 9.2 Hz spectral peak in the neutron signals is due to pressure fluctuations.

Between the two pressure signals, both the PCH and PNPC ratios are very high in frequencies 3 to 10 Hz (Fig.8-iv), indicating the strong direct interaction between them.

Comparison of the NPC and PNPC functions also yields useful information. Of particular interest here is that 6.5 Hz peak seen in the NPC function from the pressure to the LOG channel (Fig.7-i) disappears in the corresponding PNPC function (Fig.8-ii). As developed in Sec.II, the present PNPC function is obtained after cutting off the STPs between the two pressures with strong dynamic interaction. Accordingly, it is inferred that the 6.5 Hz peak in the LOG channel APSD stems not from the individual pressure fluctuations but from mutual dynamic interaction between the two pressures. Contrary to this, noise power contribution from the pressure to neutron is considerably high in both the PCH and PNPC functions (Figs. 7-i, 7-ii and Figs. 8-ii, 8-iii), which indicates the neutron spectral peak at 9.2 Hz to be induced by the inheent fluctuations of the primary loop pressres an thus suggests a differnt nise generation mechanism from the case of 6.5 Hz APSD peak.

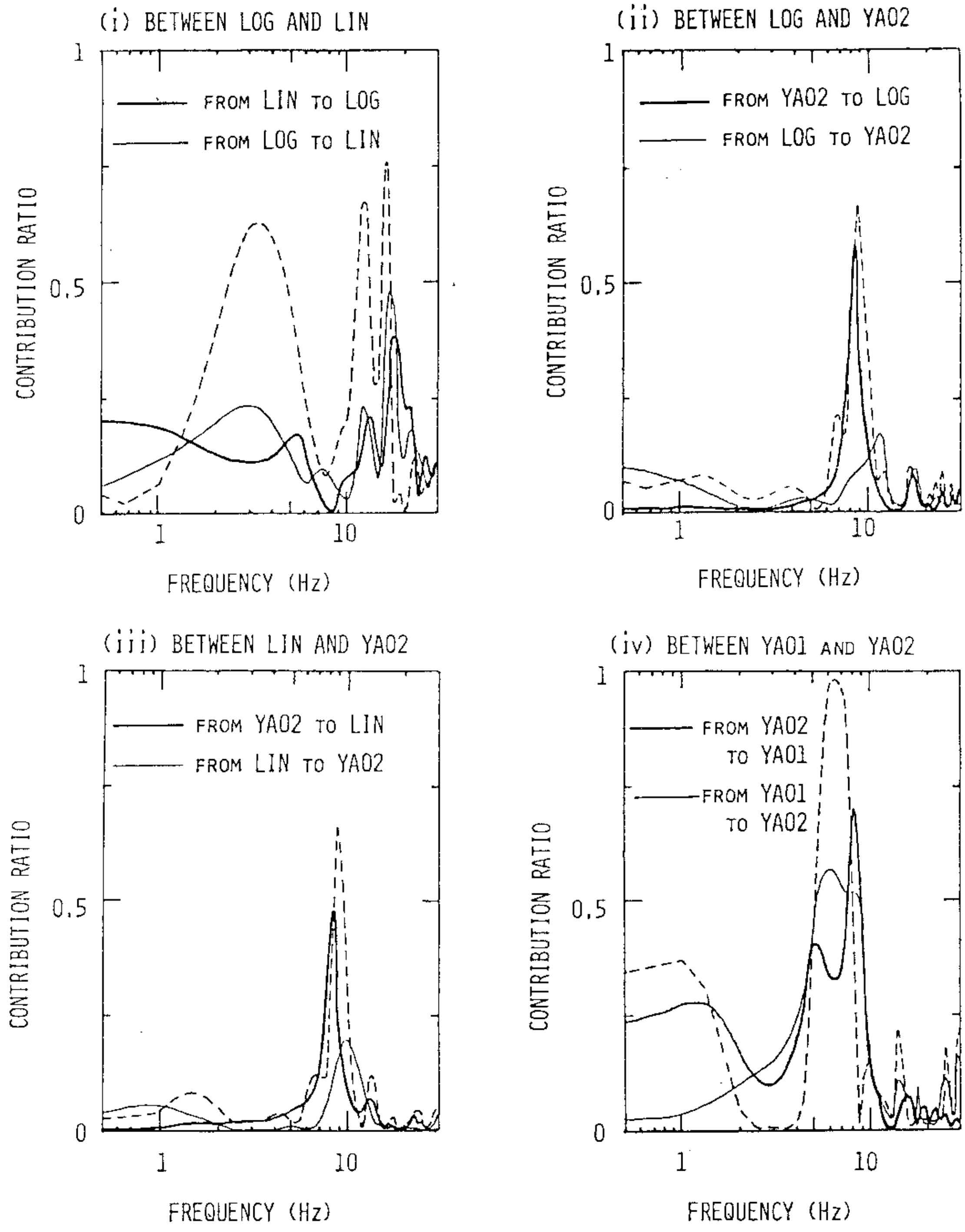


Fig. 8 Comparison of partial coherence and partial noise power contribution functions (PCH-PNPC comparison) for each pair of signals used for the Borssele reactor noise analysis, where the dashed line represents the partial coherence and the real line the partial noise power contribution ratio.

The Borssele reactor noise has been extensively studied by Dragt and Türkcan/6/,/34/ for several years, through which some of the noise generation mechanisms have already been made clear. According to their results, 12 and 15 Hz peaks in the ex-core neutron spectra are, as mentioned previously, due to the CBM, and the spectral peaks above 10 Hz in the pressures to local pressure fluctuations in each coolant loop. The 9.2 Hz peak called a reactivity effect stems from pressure fluctuations. The 6.5 Hz peak is attributed to a standing wave in the primary coolant loop system. The results from the present STP analysis clearly supports these earlier findings.

VI. Conclusion

The STP analysis was proposed as a method for noise analysis for investigation of noise generation and propagation mechanisms in multivariate random processes and its analysis procedure on the basis of the MAR modeling was presented.

Through noise analysis for the simulation data as well as for the Borssele reactor noise data, it was demonstrated that the method is effective for identifying the STP network in the system, detecting feedback, determining causal relationship, identifying the noise sources and so forth.

Generally speaking, problems of noise source identification, cause-and-effect analysis and detection of feedback in the multivariate noise analysis are in most cases intimately related to each other and must be treated in a unified manner. The STP analysis presented in this paper is one method enabling this and thus allows execution of the noise analysis in more systematic and comprehensive manner than conventional methods so far available.

Acknowledgment

The author is deeply indepted to Drs. J. E. Dragt and E. Turkcan for permision to present the result of the STP analysis for the Borssele reactor noise.

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