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ON SYSTEM IDENTIFICATION USING PULSE-FREQUENCY MODULATED SIGNALS

ABSTRACT

Nonperiodic time quantization has proved very useful for the improvement of measurement and control systems. Very often nonperiodic time quantization is connected with pulse frequency modulation (PFM). In the present report some aspects of continuous system identification using PFM signals have been studied.

Two possibilities for application of PFM signals in system identification are considered. In accordance with these possibilities either the system is excited by PFM signals or the system output is observed with the help of a pulse-frequency converter. For both these cases effective computational schemes for estimation of the transfer function and the weighting function have been obtained. For the case of the weighting function estimate, the relationship with previously obtained estimates has been established.

The utility of the suggested estimates is illustrated by computer simulation.
For this purpose, several programs are given in the appendix.

PREFACE

This report is an attempt to apply pulse-frequency modulated signals when solving a system identification problem.
The motivation for the study was the very wide use of pulse-frequency signals in the practice of measurement and control systems. These signals are also used when modelling the transmission information nervous system.

Among the other reasons for this study was the fact that most of the work in the field of system identification is related to regular sampling from continuous signals. It leads to restrictions due to aliasing noise. To avoid this the aperiodic sampling can be implemented. There is no need to perform preliminary processing of a continuous signal before the aperiodic sampling, so this is more suitable in the case of "black-box" system identification.

This study was done while I was a guest in the Measurement and Control Group of the Eindhoven University of Technology. I would like to thank all the members of the group ER for their hospitality and for the continuous support. I would especially like to thank prof. P. Eykhoff for making it possible to finish this report and for the suggestions he made for improving it. Furthermore I am very grateful to Dr. A. van den Boom and Dr. A. Damen for their attention to this problem and for their suggestions in preparing this report.
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CONTENTS

1. INTRODUCTION

The problem of system identification has played an important role in designing simulation and testing of various technical and biological systems (Eykhoff, P. (1974), Eykhoff, P. (ed) (1981)).

The large number of existing works on this topic have paid great attention to the designing of identification methods using general purpose or specialized computers. In the case of identification of continuous systems these require the implementation of analog-to-digital (A/D) converters to introduce the measurement signals into the computer. As a rule in most studies only methods of system identification oriented on A/D converters with regular time quantization have been considered.

Apart from the A/D converters with regular time quantization converters with non-regular time quantization are also often used in modern control and measurements systems.
In some cases these are caused by peculiarities of control units and sensors, in other cases the non-regular time quantization is introduced in order to increase the efficiency of systems (Artemiev M.V. and A.V. Ivanovsky (1986))

The wide distribution of information converters with non-regular time quantization requires the designing of special methods of dynamic system identification which are aimed at the processing of the output signals of these converters.

One of the widely used types of systems with non-regular time quantization are systems with pulse-frequency modulated (PFM) signals. The time quantization of analog signals in these systems is performed with the help of a pulse frequency converter (PFC). The PFC transforms a continuous input signal into a series of identical pulses with variable frequency. It is well-known that PFM signals offer the advantage of converting them into digital form with high accuracy, noise protection, simplicity of integral transformations, convenience for the transmission over cable communication lines etc. (Novitsky, P.V. (1970), Bombi F. and D. Ciscato (1968)). All of these have led to the extensive use of PFM signals in technical systems (Pavlidis, T. and I.E. Jury (1965), Kuntsevich V.M. and Yu. M. Chekhovoi (1970), Broughton, M.B. (1973), Eidens, R.S. (1978), Tzafestas, S. and G. Frangatis (1979)) and also under modelling of biological systems (Bayly, E.J. (1968), Koenderink, J.J. and A. van Doorn (1913), Lange, D.G. and P.M. Hartline, (1979), Zeevi, Y.Y. and A.M. Bruchstein (1977)).

However, the non-linearity of PFC in conjunction with non-regular time quantization creates quite serious difficulties when solving problems of system identification using PFM signals.
Obviously this is the reason for the comparatively small number of papers published on this subject (Broughton, M.B. (1973), Knorring, V.G. and Ja. R. Jasick (1981)).

The purpose of the present report is to describe some methods of continuous open-loop system identification using PFM signals. The basis for this is the properties of PFM-signals and the theory of generalized functions.

Several possibilities of using of PFM signals on system identification are considered. In accordance with these possibilities either the output signal of PFC excites the system or the system output is observed with the help of PFC. For both of these cases the effective computational schemes for estimation of transfer and weighting functions were obtained.

In the report, the most attention is given only to the designing of the computational schemes suitable for system identification with PFM signal.

The properties of the obtained estimates are discussed very briefly and the discussion carries only an illustrative character. A deeper investigation of the obtained estimation properties can be the subject of further studies.

2. SOME EXAMPLES OF SYSTEMS WITH PFM-SIGNALS

Before we start the discussion of main problem it is useful to give some examples of the implementing of PFM signals in different systems.
It will permit us to formulate the problem more clearly.

Some of the vast fields of implementing of PFM signals are the automatic control systems. Fig. 1 shows a very simple example of a PFM control system.

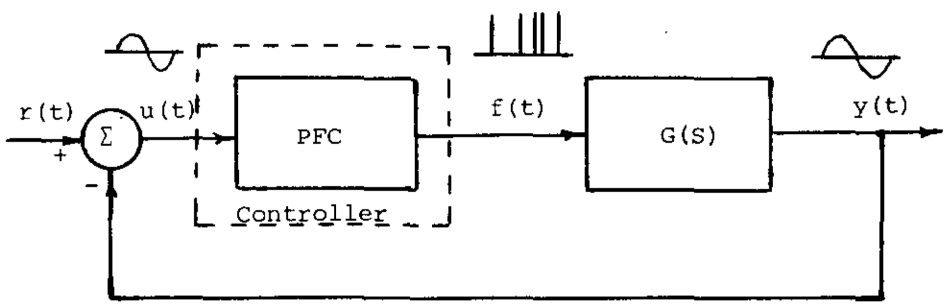

fig. 1 PFM feedback control system.

In this system the pulse output signal of PFC, f(t), is used to excite the linear plant with transfer function G(s). The error signal u(t) is the difference between requested plant output signal r(t) and the actual plant output signal y(t). Generally these signals are continuous. The PFC transforms the error signal u(t) into a pulse train f(t) with varying frequency. This pulse train directly drives the plant.
Often the plant is a stepper motor (robot control systems, attitude control systems of spacecrafts). Then the stepper motor has an output shaft velocity that is directly proportional to the input pulse train frequency f(t).

One can see from fig. 1 that the plant is directly excited by the output signal of the PFC and the continuous plant output is used as feedback.
It is also possible that the states of plant are used as feedback.

Fig. 2 shows a multivariable state feedback PFM control system.

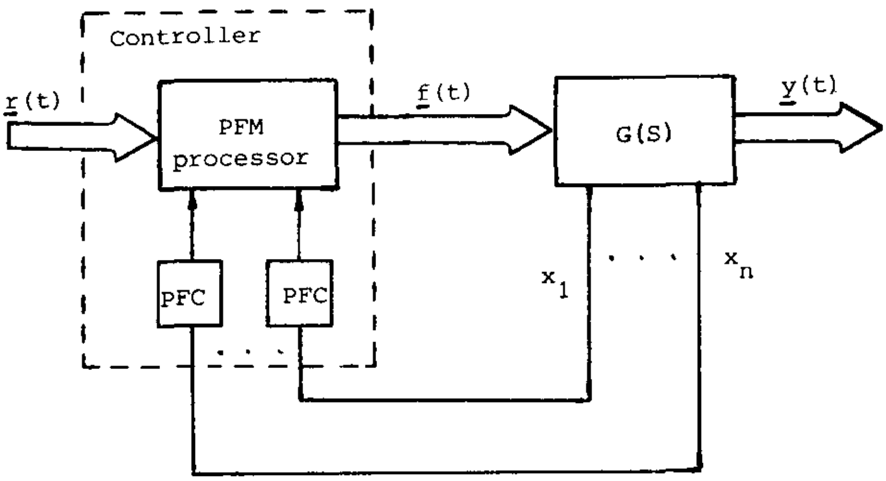

fig. 2 Multivariable state feedback PFM control system

In this case the controller consists of PFC's (to convert the analog signal to a PFM pulse train) and a PFM processor (to perform computations on PFM pulse trains (Tzafestas, S. (1979)).

Another example of the implementation of PFM signals is given by modern measurement systems working on line with a computer (fig. 3).

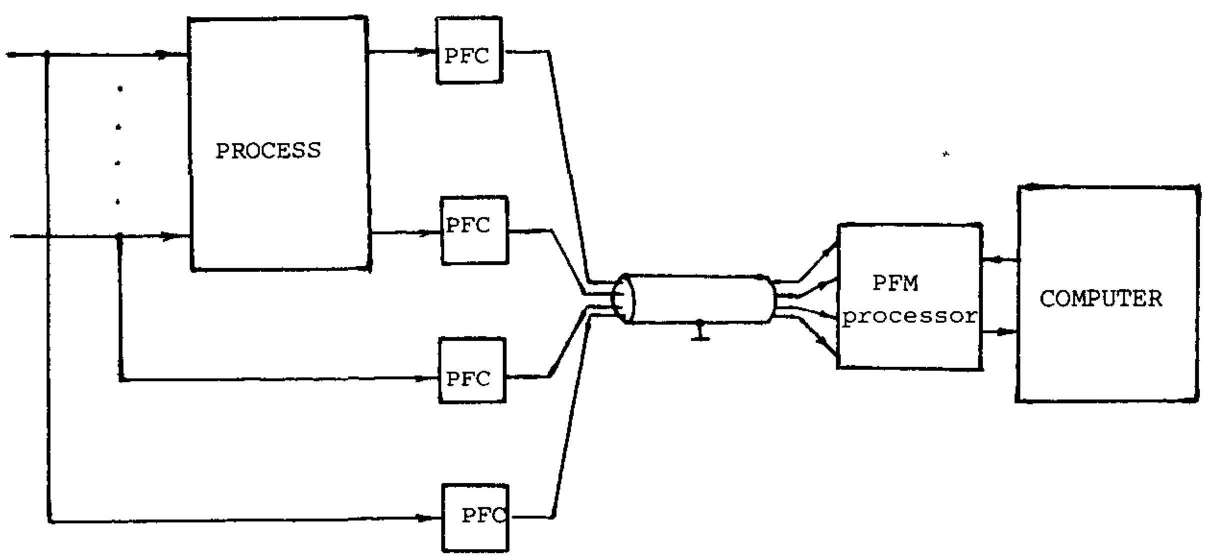

fig. 3 PFM measurement system

Here the PFM sensors convert the plant input and output signals into pulse trains, which are transmitted over cable communication lines to PFM processors. Then the PFM processor performs first stage processing and provides the input of digital signals into computers. The concrete examples of this type of systems are numerous measurement systems with pulse frequency sensors (Novitsky, P.V. (1970)).

Very close to PFM measurement systems are also the multichannel measurement systems of nuclear physics (Artemiev V.M. and A.V. Ivanovsky (1986)).

As it follows from fig. 3, in PFM measurement systems the inputs and outputs of process are observed with the help of PFM sensors.

PFM signals have been used to build various models of neurail nets (Bayly, E.S. (1968), Koenderink, J.J. and Doorn, A. (1973)). One of the possible models for transmission of information in nervous systems is shown on fig. 4.

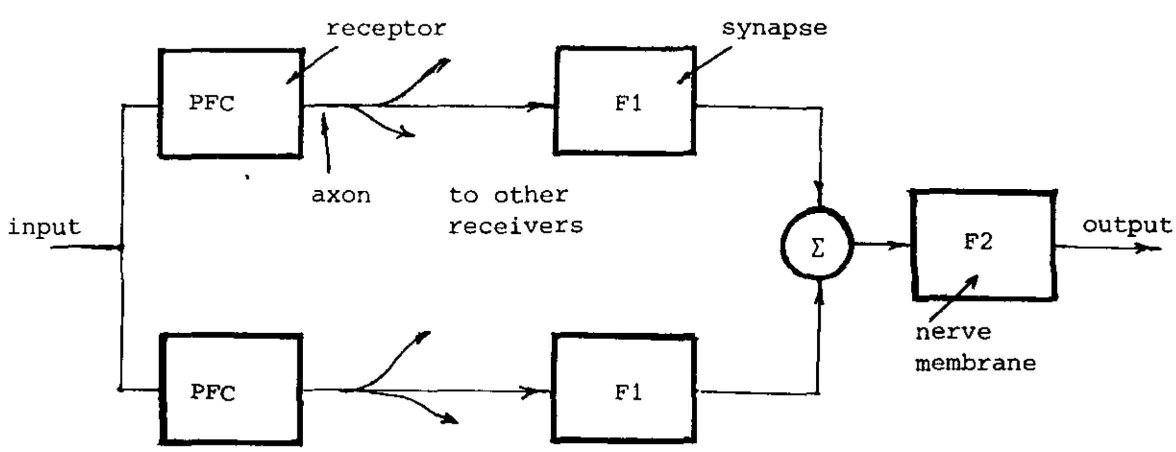

fig. 4 Model of transmission of information in nervous systems

This model consists of PFC's (receptors), communication channels (axons) and receivers (synapses and nerve membranes) which are represented as low-pass filters F1-F2.

In all the above-mentioned systems the implementation of PFM signals is caused either by special features of the process, by requirements of small noise influence or by necessity of transmission signals over communication lines etc.

From the given examples it is easy to see that there are three possibilities. First when the process is observed with the help of PFC (fig. 5a), second when the process is excited by output signals of PFC (fig. 5b) and thirdly when the process is excited by PFM-signals and the output of the process is observed with the help of PFC (fig. 5c).

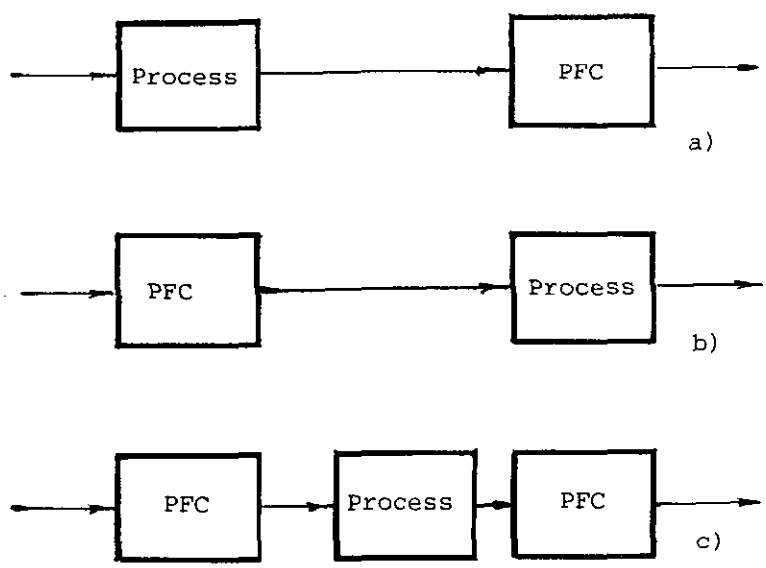

fig. 5 Positions of PF converters in the system

Let us consider the problem formulation in detail.

3. PROBLEM FORMULATION

Fig. 6 shows the general set-up of process, model, and PF converters and will be referred to when discussing the various methods.

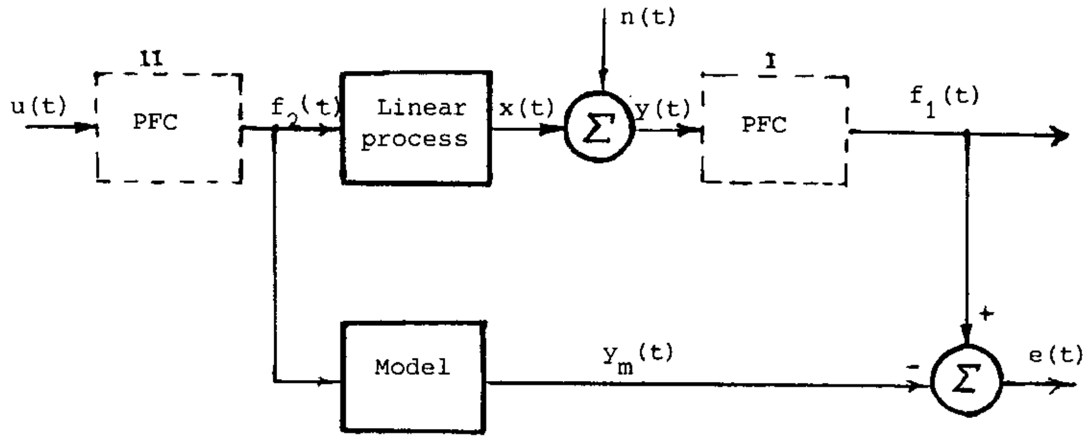

fig. 6 General set-up of process, model and PF converters

In accordance with above mentioned examples of PFM systems the PFC may be placed either at the output of the process (fig. 6, I) or at the input of the process (fig. 6, II) or simultaneously at both these places. As it follows from fig. 6 the discussion will be restricted further to SISO time invariant open loop system. We shall also assume that disturbance u(t) can be described as a realization of a stationary stochastic process with spectral density $\Phi_n(\omega)$.

Now the identification problems are formulated in the following way:

a. Generate the signal u(t), which directly excites a linear process and observe the output signal of PFC, $f_1(t)$.
Based on these two signals form the estimate of the transfer function $\hat{G}_T(j\omega)$

$$\hat{G}_T(j\omega) = \hat{G}(i\omega\ ;\ T,\ u(t),\ f_1\ (t)), \qquad (3.1)$$

where T is the time of observation of the signals u(t) and $f_1(t)$

b. Generate or observe the signal $f_2(t)$ exciting the linear process and observe the output signal y(t).
Based on these observations for the estimate of the weighting function $\hat{g}_T(t,A)$

$$\hat{g}_T(t,A) = \hat{g}(t,A;\ T,\ f_2(t),\ y(t)), \tag{3.2}$$

where A is a set of constant coefficients.

c) Generate or observe the signal $f_2(t)$ and observe the output signal of PF converter $f_1(t)$. Based on these observations form the estimate of the weighting function $\hat{g}_T(t,A)$

$$\hat{g}_T(t,A) = \hat{g}(t,A;\ T,\ f_2(t),\ f_1(t)) \tag{3.3}$$

It is obvious that the properties of the output signal of the PFC will play an important role in this discussion. Therefore we shall first consider the models of pulse-frequency (PF) converters and give descriptions of PFM signals, suitable for the solving of system identification and simulation problems.

4. MODELS OF PF-CONVERTERS AND DESCRIPTION OF PFM-SIGNALS

There are several models of PF converters (Kuntsevich, V.M. (1970), Pavlidis, T. (1965), Tzafestas, S. (1979)). Among them the models of integral PFC (IPFC), Sigma PFC (Σ PFC) and complete reset PFC (CR PFC) are more often used.

Here we shall consider in detail only the model of IPFC with single sign output pulses (SS IPFC). This type of PFC is very often used in measurement (Novitsky, P.V. (1970)) and control systems (Kuntsevich, V.M. (1970)) and for the modelling of nervous systems (Rosen, M. (1972), Zeevi, J.J. (1977)). Other types of PF converters will be examined very briefly.
The block-diagram of SS IPFC is shown in fig. 7.

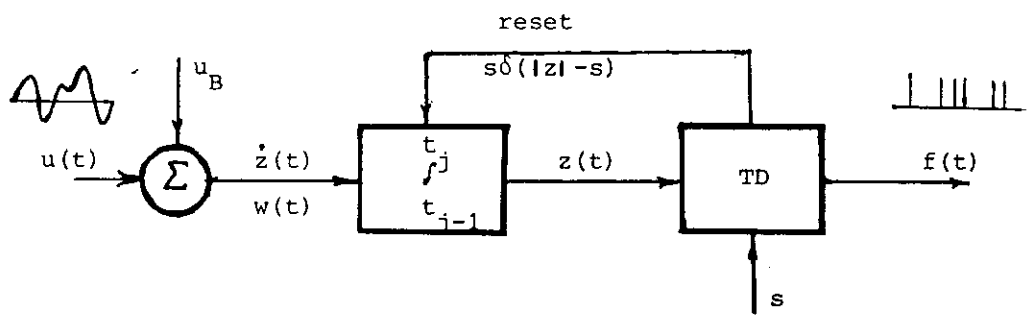

fig. 7 The Model of SS IPFC

The model consists of an adder, an integrator and threshold devices (TD). To the input signal u(t) of the PFC is added a bias u_B. This bias has been chosen in such way that $u_B > |u(t)|$ for any time moment t. Therefore the signal w(t) is always positive.

The integrator is integrating signal w(t) while z(t) is smaller than the value of threshold s. At time moment t_j

$$z(t_j) = \int_{t_{j-1}}^{t_j} w(t)dt = s, \quad j\text{-integer} \tag{4.1}$$

and the threshold device emits a delta pulse s $\delta(|z|-s)$. This pulse resets the integrator to zero and then all processes are repeated.

Because the signal z(t) has a discontinuity at time t_j we shall assume further that $z(t_j-0) = s$, and $z(t_j+0) = 0$.
The output of TD can be described as a sequence of delta pulses which are emitted at time moments t_j

$$f(t) = \sum_j \delta(t-t_j), \tag{4.2}$$

where $\delta(t)$ - is a Dirac delta function.

In case of need a special form of output pulses the model in fig. 7 is completed by an output-forming element with weighting function p(t). Then the output signal of PFC is equal to

$$f_p(t) = p(t)*f(t) = \sum_j p(t-t_j) \ . \tag{4.3}$$

The generalization of the IPFC model to the model of sigma PFC was introduced by Pavlidis T. and Jury E.I. (1965) (fig. 8).

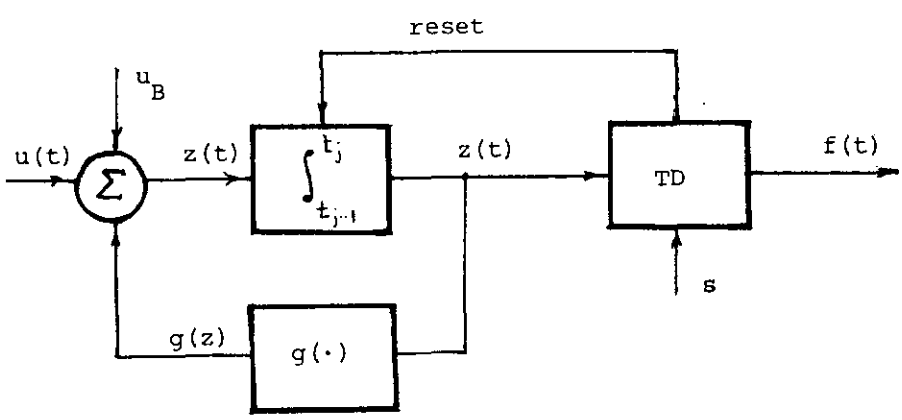

fig. 8 The model of sigma PFC (Σ PFC)

In this model the integrator has a feedback with operator g(.) If $g(z) = \alpha z$, where α is a constant coefficient, then the model in fig. 8 corresponds to neural PFC (NPFC), which is used to build models of neural systems.

For NPFC it is true that

$$\dot{z}(t) = u(t) - \alpha z(t) + u_B - s \delta(|z(t)|-s), \tag{4.4}$$

and

$$f(t) = \delta(|z(t)|-s). \tag{4.5}$$

On using (4.4) let us obtain the equations suitable for simulation of PFC's.

We shall first determine the time t_j when pulses are emitted.

Rewrite equation (4.4).

$$(e^{\alpha t} z(t))^1 = [u(t) + u_B - s \delta(|z(t) -s)]e^{\alpha t} \tag{4.6}$$

After integrating the expression (4.6) over the interval $[t_{j-1}, t_j]$ between two output pulses of PFC and consider that $z(t_{j-1}) = 0$ we obtain

$$t_j = \frac{1}{\alpha} \ln \frac{1}{s} \int_{t_{j-1}}^{t_j} [u(t) + u_B] e^{\alpha t} dt. \tag{4.7}$$

Let the input signal u(t) be constant over interval $[t_{j-1}, t_j)$

$$u(t) = u_{j-1}, \quad t \in [t_{j-1}, t_j). \tag{4.8}$$

Then the time interval $\theta_j = t_j - t_{j-1}$ between pulses is equal to

$$\theta_j = \frac{1}{\alpha} [\ln (u_{j-1}+u_B) - \ln (u_{j-1}+u_B-\alpha s)]. \tag{4.9}$$

From (4.9) it follows that for IPFC ($\alpha \to 0$) the interval θ_j can be determined by expression

$$\theta_j = s / (u_{j-1} + u_B) \tag{4.10}$$

The results (4.9) and (4.10) allow us to simulate the PFC in an iterative way if we know the input signal u(t) and the value of threshold s. Further we shall use these expressions for calculation of the intervals θ_j between pulses. Apart from these we have to also use the fact that

$$t_j = t_{j-1} + \theta_j. \qquad (4.11)$$

All examined models above of the PFC give clear ideas about the structure of PFC and can be implemented when simulating the PFC. But they are not convenient for the analysis of PFM systems, because they are not giving us non-iterative solutions.

Several approaches to design analytic models of PFM signals have been proposed. We shall take in account the model which was first obtained by Lee H.C. (1965) and then by Zeevi, J.J. (1977). In accordance with this model the output pulse train (4.2) of an IPFC can be described in the following form

$$f(t) = w(t)\left[\frac{1}{s} + \frac{2}{s}\sum_{n=1}^{\infty}\cos\left\{\frac{2\pi n}{s}\int_0^t w(\xi)\,d\xi\right\}\right]. \qquad (4.12)$$

Zeevi, J.J. had derived this equation on the basis of the theory of generalised functions and Lee, H.C. had modified the model of an IFPC in accordance with the fig. 9.

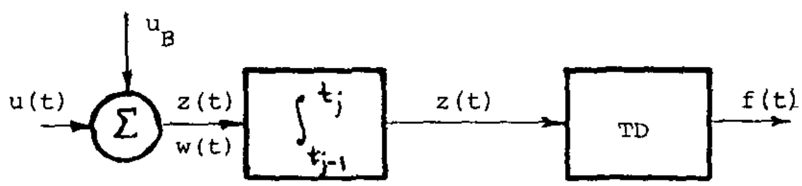

fig. 9 Model of an IPFC with multi threshold device

In this model the integrator has an unbounded output signal and the threshold device emits the new output pulse every time when the value of integral z(t) is increased above threshold s. (fig. 10).

Model (4.12) connects the output sequence of pulses f(t) with the input signal u(t) and considers this signal as a continuous time function. It permits us to analyse the PFM-signals and to show the important property of PFM-signals (see below). But this model is very complex for the design of identification algorithms.

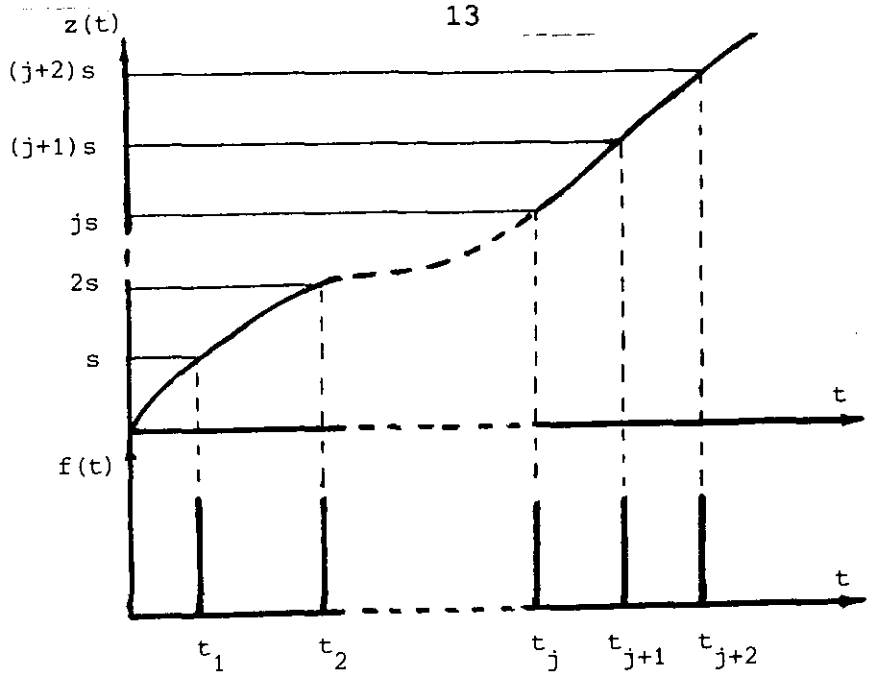

fig. 10 The time diagram of IPFC.

In order to obtain a suitable model of PFM-signals it is useful to remember that first of all a PFC converts information. This type of converter we call an analog-to-frequency converter, because the PFC-output signal frequency F(t) is proportional to the input signal u(t) (here and further we shall consider that u(t) includes u_B, u(t) > 0)

$$F(t) = k\, u(t)\ , \tag{4.13}$$

where k is a constant. Eq. (4.13) is true if we neglect the proper dynamic of the PFC.

There are several definitions of frequency: statistical definition, chronometric definition, phase and spectral definition (Knorring (1978)). In agreement with statistical definition the frequency is the ratio of the number of pulses $N(t,\tau)$ which occurs at interval $[t, t+\tau]$ to the length of this interval τ (fig. 11)

$$F(t) = \frac{N(t,\tau)}{\tau}\ . \tag{4.14}$$

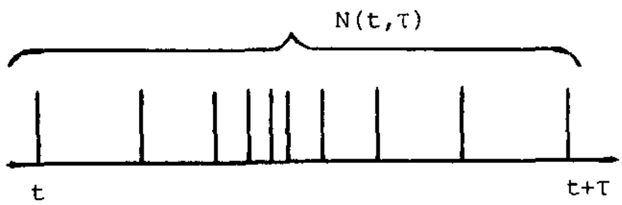

fig. 11 Statistic definition of frequency

We formally find the limit of this ratio when τ tends to zero; we obtain

$$F_M(t) = \lim_{\tau \to 0} \frac{N(t,\tau)}{\tau} = \sum_j \delta(t-t_j) \qquad (4.15)$$

Here index M means model. We shall further use this process, based on expression (4.15), to avoid confusion between true processes and models.

The same expression for $F_M(t)$ we can obtain starting from the phase definition of frequency

$$F(t) = \frac{1}{2\pi} \cdot \frac{d\,\varphi(t)}{dt} \quad . \qquad (4.16)$$

If we have a pulse train, then it is obvious that the phase $\varphi(t)$ increases with $2.\pi$ every time a pulse occurs. So we can write

$$\varphi_M(t) = \sum_j 2\pi\ 1(t-t_j) \qquad (4.17)$$

Substitute (4.17) into (4.16) we again obtain the model (4.15). It is easy to see that (4.17) corresponds to a piecewise step approximation of a continuous phase process $\varphi(t)$ (fig. 12).

If we use linear piecewise approximation of phase process
$\varphi(t)$ at $t_{j-1} \le t \le t_j$

$$\varphi_M(t) = (j-1)\ 2\pi + \frac{2\pi}{\theta_j} \cdot (t-t_{j-1}) \qquad (4.18)$$

then the frequency $F_M(t)$ is equal to

$$F_M(t) = \frac{1}{\theta_j}, \quad t \in [t_{j-1}, t_j] \tag{4.19}$$

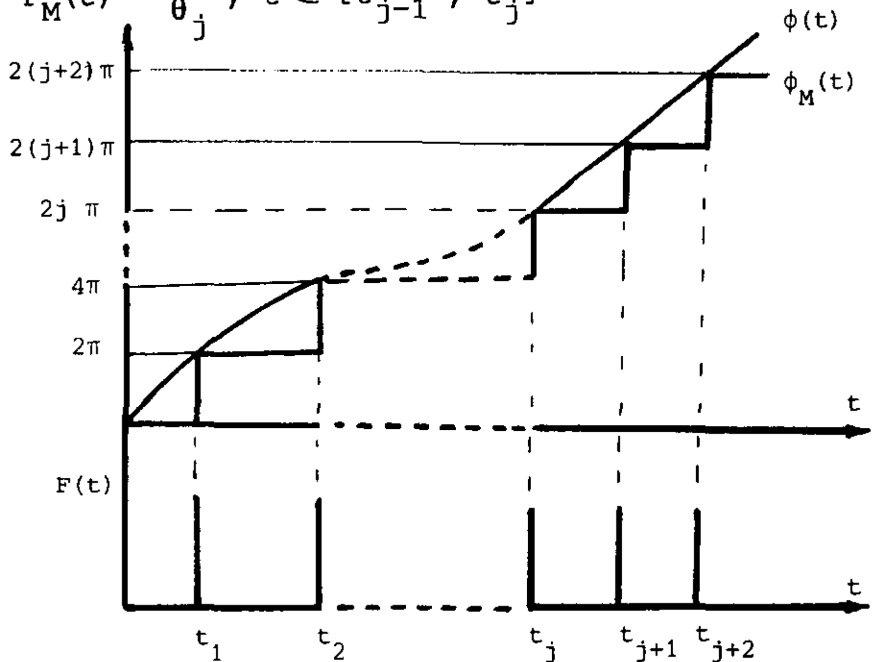

fig. 12. Phase definition of frequency

This gives us the chronometric definition of frequency.
Thus we may say that expression (4.15) is in agreement with the piecewise step approximation of the integral of input signal because from (4.13) and (4.16) it follows that

$$\varphi(t) = k \int_0^t u(\xi)\, d\xi \tag{4.20}$$

Eq. (4.19) corresponds to a linear piecewise approximation of integral in (4.20).
So, using the piecewise approximation in the above-mentioned sense and taking in account (4.13), we can write the model of signal u(t) when this signal is presented with the help of a pulse train frequency

$$u_M(t) = \frac{1}{k} \sum_j \delta(t - t_j) \ . \tag{4.21}$$

The last equation allows us to design models of output signals of continuous systems in the time domain, when these systems are excited by output signal of a PFC. We shall further use it when solving system identification problems.

However, we need to remember that (4.21) is a mathematical idealization and we can use it only in integral operators because we never talk about the "values" of a δ-function. We talk only about the values of integrals involving a δ-function.

As an example of the implemention of model (4.21) consider the Fourier transformation of signal u(t) over interval $[0,T]$

$$U(\omega) = \frac{1}{T} \int_0^T u(t)\ e^{-i\omega\tau}\, dt \quad . \tag{4.22}$$

After substituting u(t) by its model $u_M(t)$ (4.21) we obtain

$$U_M(\omega) = \frac{1}{kT} \sum_j {}^{-i\omega t_j} , \quad t_j \in [0,T] \ . \tag{4.23}$$

Let us define the conditions under which we can use formula (4.23), which allows us to compute the Fourier transformation of signal u(t).

From (4.12) it follows that

$$u(t) = s \sum_j \delta(t-t_j) - u_\Delta(t) \ , \tag{4.24}$$

where

$$u_\Delta(t) = 2\ u(t) \sum_{n=1}^{\infty} \cos \frac{2\pi n}{s} \int_0^t u(\xi)\,d\xi) \tag{4.25}$$

and $u(t) > 0$.

Because $s = 1/k$ (see 4.10) we rewrite (4.24) in this way

$$u(t) = u_M(t) - u_\Delta(t) \ . \tag{4.26}$$

Substitute (4.26) into (4.22), then

$$U(\omega) = U_M(\omega) - U_\Delta(\omega) \ . \tag{4.27}$$

Thus we can use model (4.21) and formula (4.23) for computation of the Fourier transformation of signal u(t) if

$$u_\Delta(\omega) = \frac{1}{T}\int_0^T 2\,u(t)\sum_{n=1}^{\infty}\cos\left(\frac{2\pi n}{s}\int_0^t u(\xi)\,d\xi\right)e^{-i\omega t}dt \approx 0 \tag{4.28}$$

Rewrite (4.28) in the following form

$$u_\Delta(\omega) = \frac{1}{T}\sum_{n=1}^{\infty}\frac{1}{\pi n}\int_0^T \cos p(t)\; e^{-i\omega\tau}dp(t) \tag{4.29}$$

where

$$p(t) = \frac{2\pi n}{s}\int_0^t u(\xi)\,d\xi\;. \tag{4.30}$$

Consider the integral

$$\int_0^T \cos p(t).e^{-i\omega t}dp(t) = \sum_j \int_{t_{j-1}}^{t_j} \cos p(t)\; e^{-i\omega t}dp(t) \tag{4.31}$$

Here we assumed that

$$T = \sum_j \theta_j\;. \tag{4.32}$$

For small $\omega(t_j - t_{j-1}) = \omega\,\theta_j$

$$\int_0^T \cos p(t).e^{-i\omega t}dp(t) \approx \sum_j e^{-i\omega t_{j-1}}\int_{tj-1}^{t_j} \cos p(t)dp(t) =$$

$$= \sum_j e^{-i\omega t_{j-1}} \sin\frac{2\pi n}{s}\int_{t_{j-1}}^{t_j} u(\xi)d\xi = 0 \tag{4.33}$$

Because

$$\int_{t_{j-1}}^{t_j} u(\xi)\,d\xi = s \tag{4.34}$$

Consequently the transition from (4.23) to (4.22) is possible only for small $\omega\theta_j$ and when $T = \Sigma_j\theta_j$. For these conditions

$$U(\omega) \approx U_M(\omega) \tag{4.35}$$

From this example one can see that in spite of the idealization the model (4.21) gives a suitable result in integral transformation.

Sometimes, when one needs an instant value of signal model $u_M(t_j)$, expression (4.19) can be useful. It occurs when one has to deal with a system which has a transfer function with equal orders of numerator and denominator.

5. THE ESTIMATION OF THE TRANSFER FUNCTION

Let us consider the problems of estimation of a transfer function (3.1), when the process is excited by a sinusoidal test signal from the generator (fig. 13), and the output y(t) is observed with the help of a PF converter

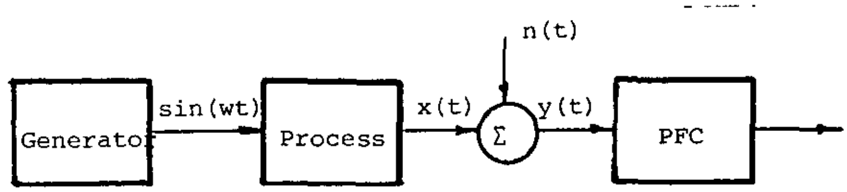

Fig. 13 Estimation of the transfer function

A commonly applied method is then to correlate the output y(t) with sin ωt and cos ωt respectively (Ljung, L. (1985 and 1987); Rake, H. (1980)).

So, if we would generate the input signal u(t) and observe only the output signal y(t) we would use the block-diagram of fig. 14 and could write

$$|\hat{G}_T(i\omega)| = \frac{2}{u^2} \sqrt{R^2{}_{yu}(0) + R^2{}_{yu}(\pi/2\omega)} , \qquad (5.1)$$

$$\arg \hat{G}_T(i\omega) = \arctan [R_{yu}(\tfrac{\pi}{2\omega})/R_{yu}(0)] , \qquad (5.2)$$

where

$$R_{yu}(0) = \frac{1}{T} \int_0^T y(t) \sin \omega t \, dt , \qquad (5.3)$$

$$R_{yu}(\tfrac{\pi}{2\omega}) = \frac{1}{T} \int_0^T y(t) \cos \omega t \, dt . \qquad (5.4)$$

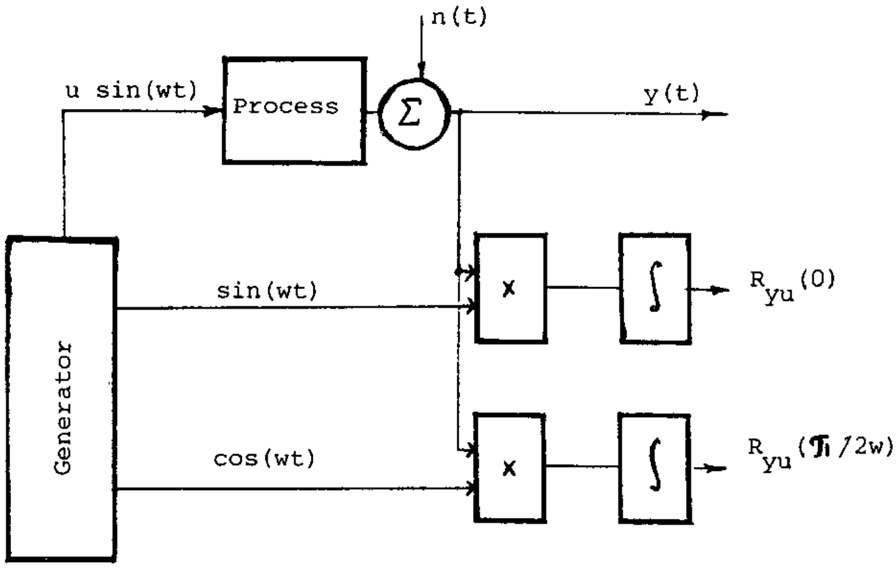

Fig. 14 Determination of the transfer function by correlation method

In our case the output process y(t) is represented by means of pulse-frequency train

$$y_M(t) = \frac{1}{k} \sum_j \delta(t-t_j) \ . \tag{5.5}$$

Substitute (5.5) in (5.3) and (5.4), then

$$R^M_{yu}(0) = \frac{1}{T} \int_0^T \frac{1}{k} \sum_j \delta(t-t_j) \sin(\omega t)\,dt = \frac{1}{kT} \sum_j \sin \omega t_j \ , \tag{5.6}$$

$$R^M_{yu}(\frac{\pi}{2\omega}) = \frac{1}{T} \int_0^T \frac{1}{k} \sum_j \delta(t-t_j) \cos(\omega t)\,dt = \frac{1}{kT} \sum_j \cos \omega t_j \tag{5.7}$$

$$|\hat{G}^M_T(i\omega)| = \frac{2}{kT} \sqrt{(\sum_j \sin \omega t_j)^2 + (\sum_j \cos \omega t_j)^2} \tag{5.8}$$

The block diagram which is in accordance with the equations (5.6–5.7) is shown on fig. 15.

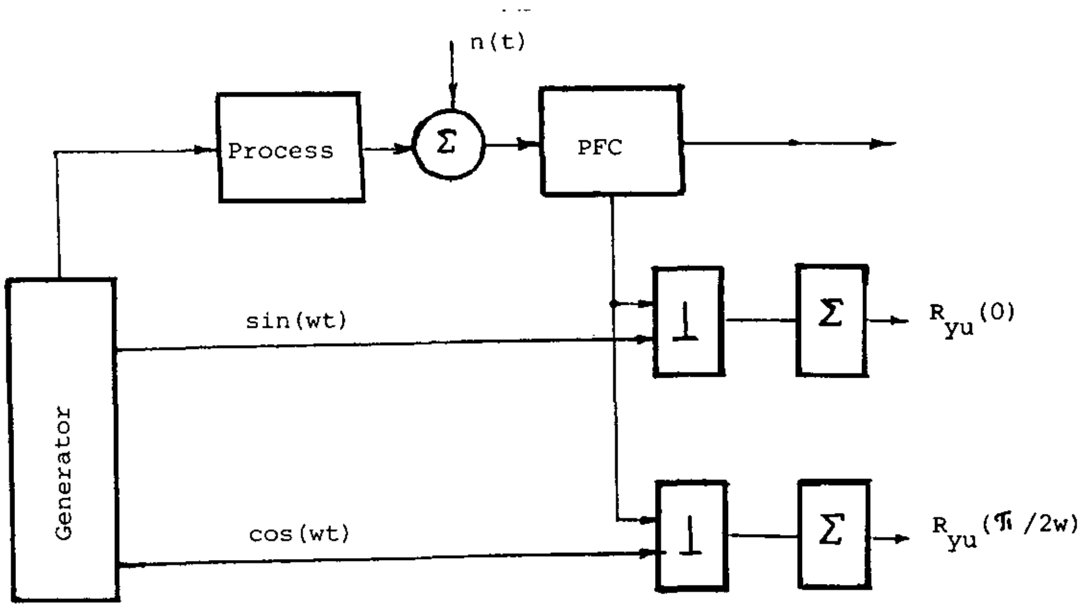

fig. 15 Block-diagram for PFM estimation of the transfer function

This block diagram for the estimation of a transfer function can be used when solving the testing problem.

Fig. 16 shows the simulation results of equations (5.6–5.8) in the case when there is no noise disturbance and process is described as a first order low pass filter with the transfer function $G(i\omega) = 1/(i\omega+1)$. These results were obtained with the help of program IND 1 (Appendix I).

The simulation was implemented for 10 periods of the input signal and for different values of average frequency F_a of the PFC. The maximum deviation ΔF of the frequency of the PFC output signal corresponded to 60% from average frequency F_a, so the maximum depth of the modulation $\Delta F/F_a$ was 0.6.

There are three lines in fig. 16. Line number 1 is the frequency response of the true process, line 2 corresponds to F_a = 50 Hz and line 3 corresponds F_a = 5 Hz. The difference between these lines

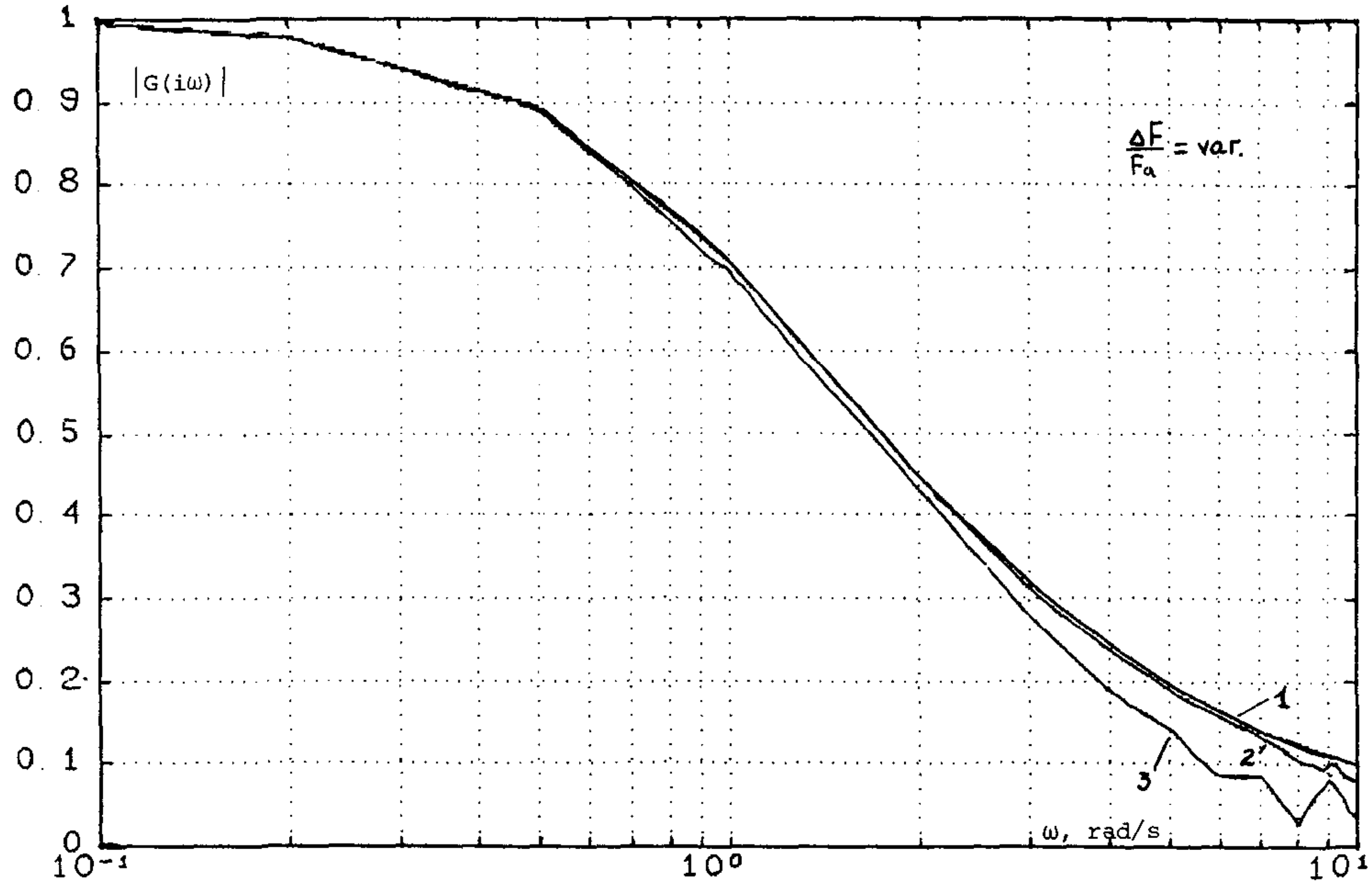

Fig.16. PFM estimation of the transfer function (program IND1)

is explained by the approximation property of model (4.21). Below we shall consider the approximation error. Apart from this the errors of calculation have played a certain role in the high frequencies of the input harmonic signal. At high frequencies the output signal of process becomes small and, consequently the input signal of the PFC is also small (fig. 15).
It leads to a decrease of the ratio $\Delta F/F_a$ and to an increase of the calculation error at high frequencies. In order to reduce this negative effect the program IND1 has been transformed into program IND4. In the last program the amplitude of input signal u(t) is increased at high frequencies in order to keep the ratio $\Delta F/F_a$ at the same level.

The results which were obtained in this way are shown in fig. 17. To show the difference between the true frequency response (line 1) and the PFN of the frequency response (lines 1 and 2) fig. 18 was obtained with logarithm scales in both axes. It is easy to see that the more F_a the better the estimate of the frequency and the phase response (see fig. 16, 17, 18 and 19). This is in agreement with (4.33).

As it is clear from (5.3) and (5.4)

$$R_{yu}(0) + i\, R_{yu}\left(\frac{\pi}{2\omega}\right) = Y_T(i\omega) \tag{5.9}$$

and

$$R_{yu}^{M}(0) + i\, R_{yu}^{M}\left(\frac{\pi}{2\omega}\right) = Y_T^{M}(i\omega) \tag{5.10}$$

The closer $Y_T^M(i\omega)$ to $Y_T(i\omega)$ the closer the estimate $\hat{G}_T^M(j\omega)$ to $G_T(j\omega)$.
That is the problem of estimation of transfer function can be transformed into the problem of estimation of $y_T(i\omega)$ with the help of formula (4.23).
General conditions of equality $Y_T(i\omega) = Y_T^M(i\omega)$ are determined if expression (4.29) is equal to zero.

Because there is no analytical solution for expression (4.29) we shall give here only the results of computer simulation (program

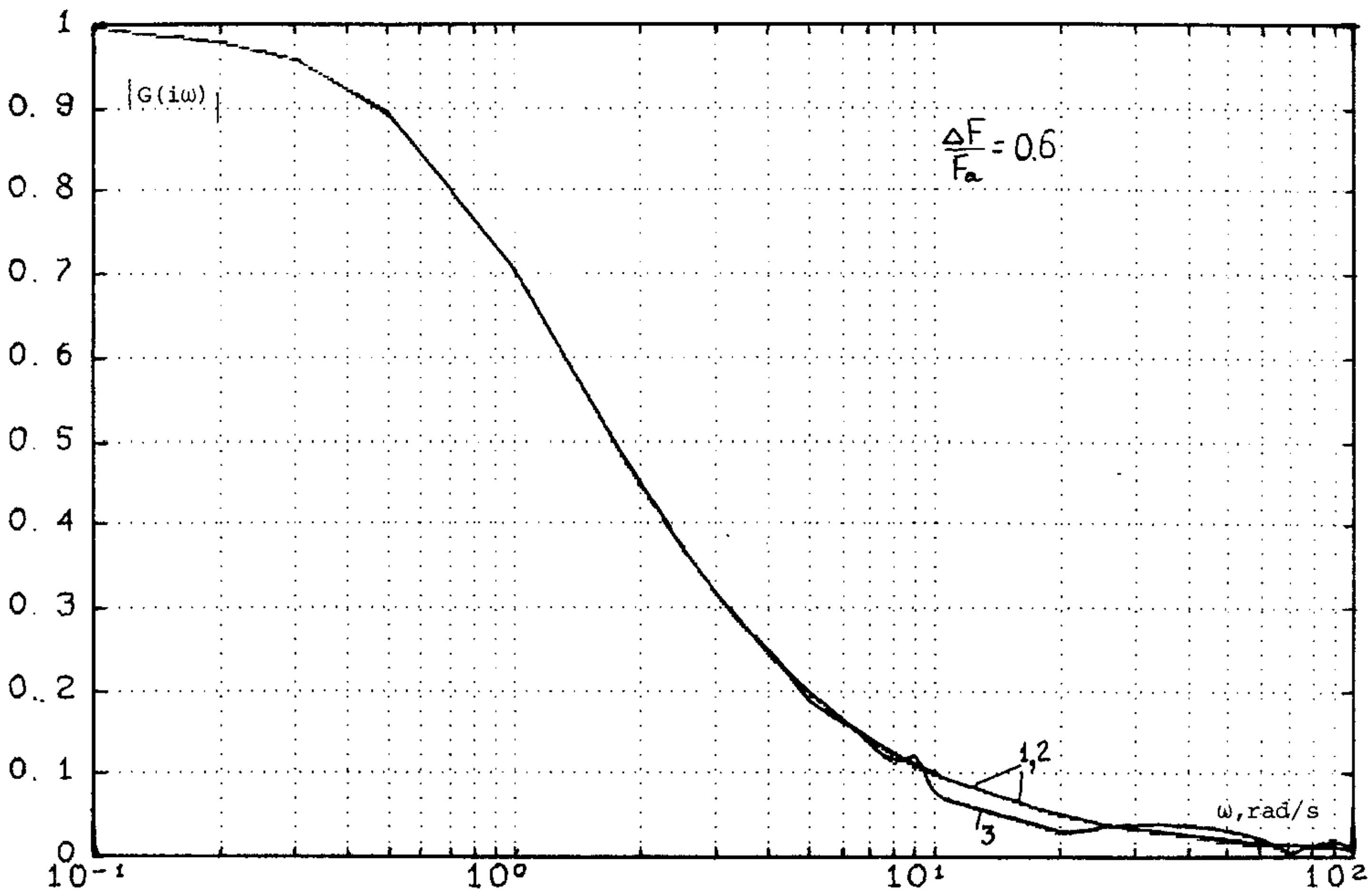

Fig.17. PFM estimation of the tranfer function (program IND4)

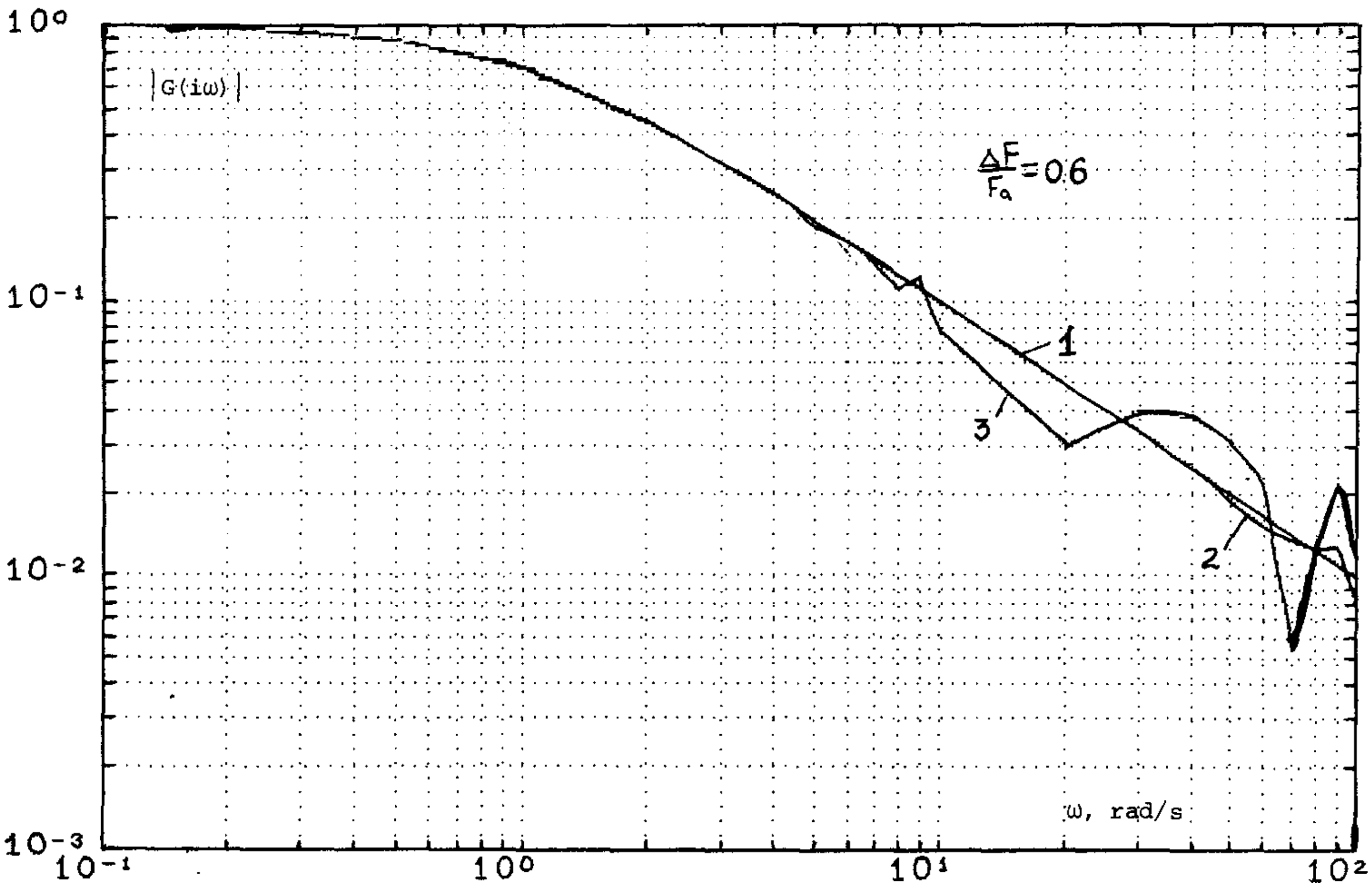

Fig.18. PFM estimation of the transfer function (program IND4)

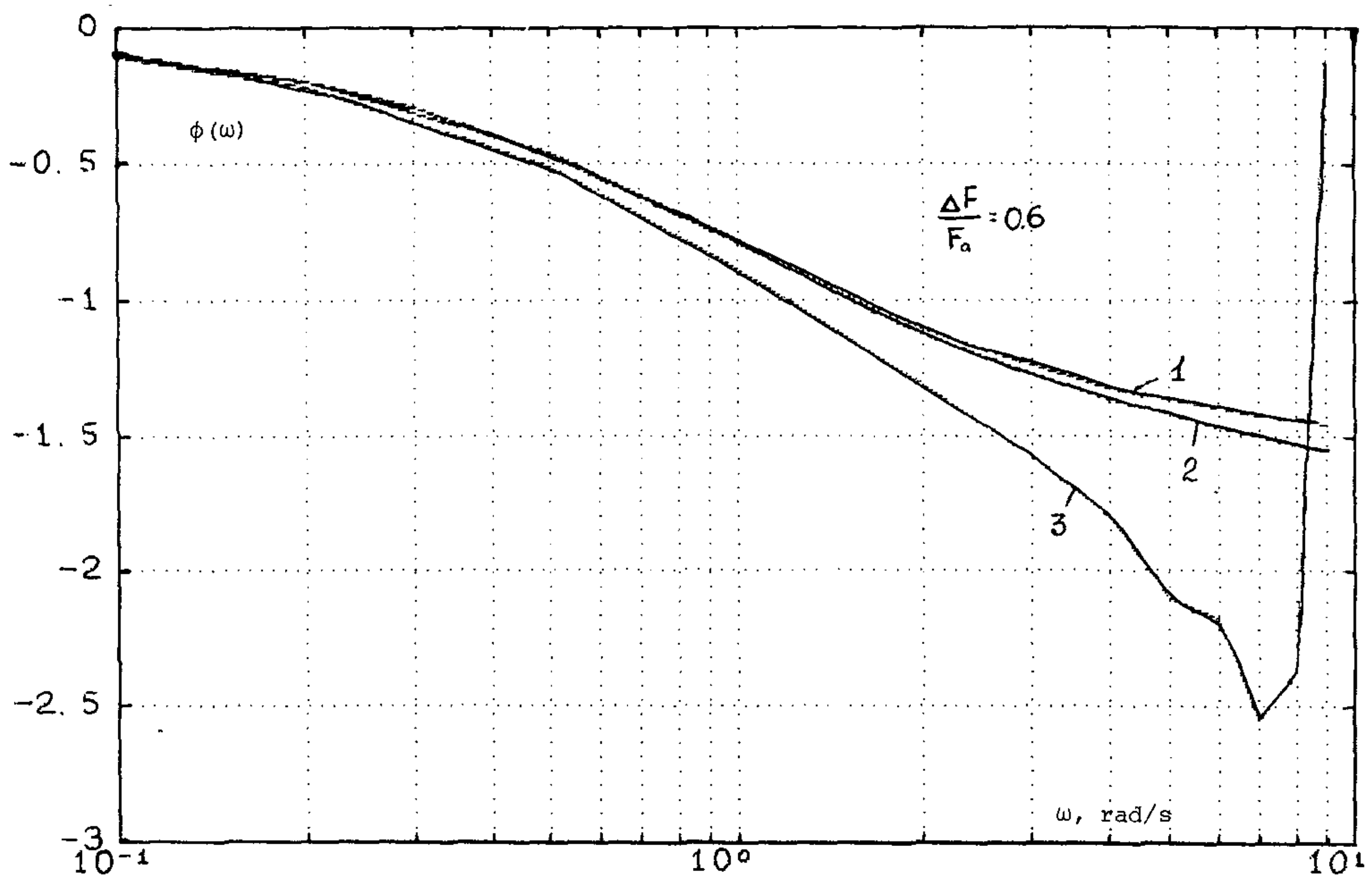

Fig.19. PFM estimation of the transfer function (program IND4)

IND2). Fig. 20 shows the relative approximation error

$$\gamma = \frac{|Y_T^M(i\omega)| - |Y_T(i\omega)|}{|Y_T(i\omega)|} \cdot 100\% \qquad (5.11)$$

as the function of the PFC average frequency when the input signal of PFC is $y(t) = \sin \omega t$, $\omega = 1$. The relative error γ is smaller than 0.1% if the average frequency F_a is more than 10 Hz or consequently the multiplication $\omega \theta_a = \omega/F_a$ is smaller than 0.1. There exist optimal values of the depth of modulation $\Delta F/F_a$ (fig. 21). They range from 0.2 to 0.4.

Fig. 22 shows the results of computer simulation when the depth of the modulation $\Delta F/F_a$ is equal to 0.3. In this case the signal y(t) included a noise disturbance u(t) (fig. 23). The signal to noise ratio was equal to 13.86 dB (program IND3).

Concluding, we notice that among the advantages of PFM estimation of the transfer function is the absence of multiplication operations in (5.6) and (5.7).
This permits us to realize it on digital devices in a very easy way.
It is also possible to see (fig. 17, line 3, point ω=10) that the estimate (5.8) gives suitable results when only about 3 samples occur on period of the harmonic signal. For the purpose of comparison fig. 24 shows the frequency response of the first order system when using PFM estimation (line 1) and the estimation with regular time quantization (line 2). The sampling frequency and the average frequency of PFC output signal were equal to 50 Hz. To draw fig. 24 the program IND4 and RTC were used. Line 3 on fig. 24 corresponds to the true process.

For the same conditions the PFM estimate has an error which is smaller than ordinary estimate based on regular time quantization. Thus in practice we can use PFM estimation of the transfer function in all cases when estimation with regular time quantization is used.
Apart from this, when testing the dynamic behaviour of PF-converters only the PFM estimation is possible.

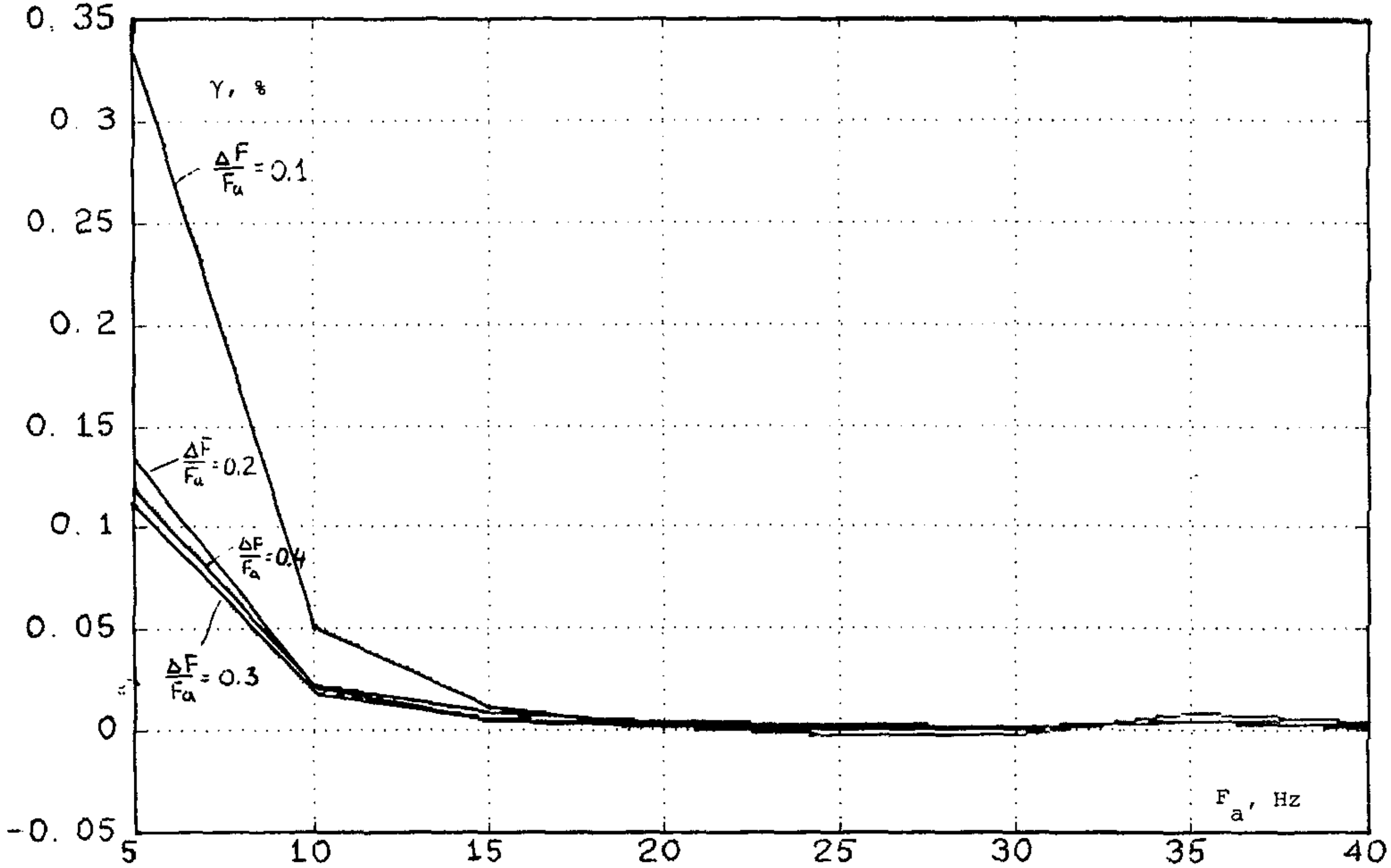

Fig.20. Relative approximation error (program IND2)

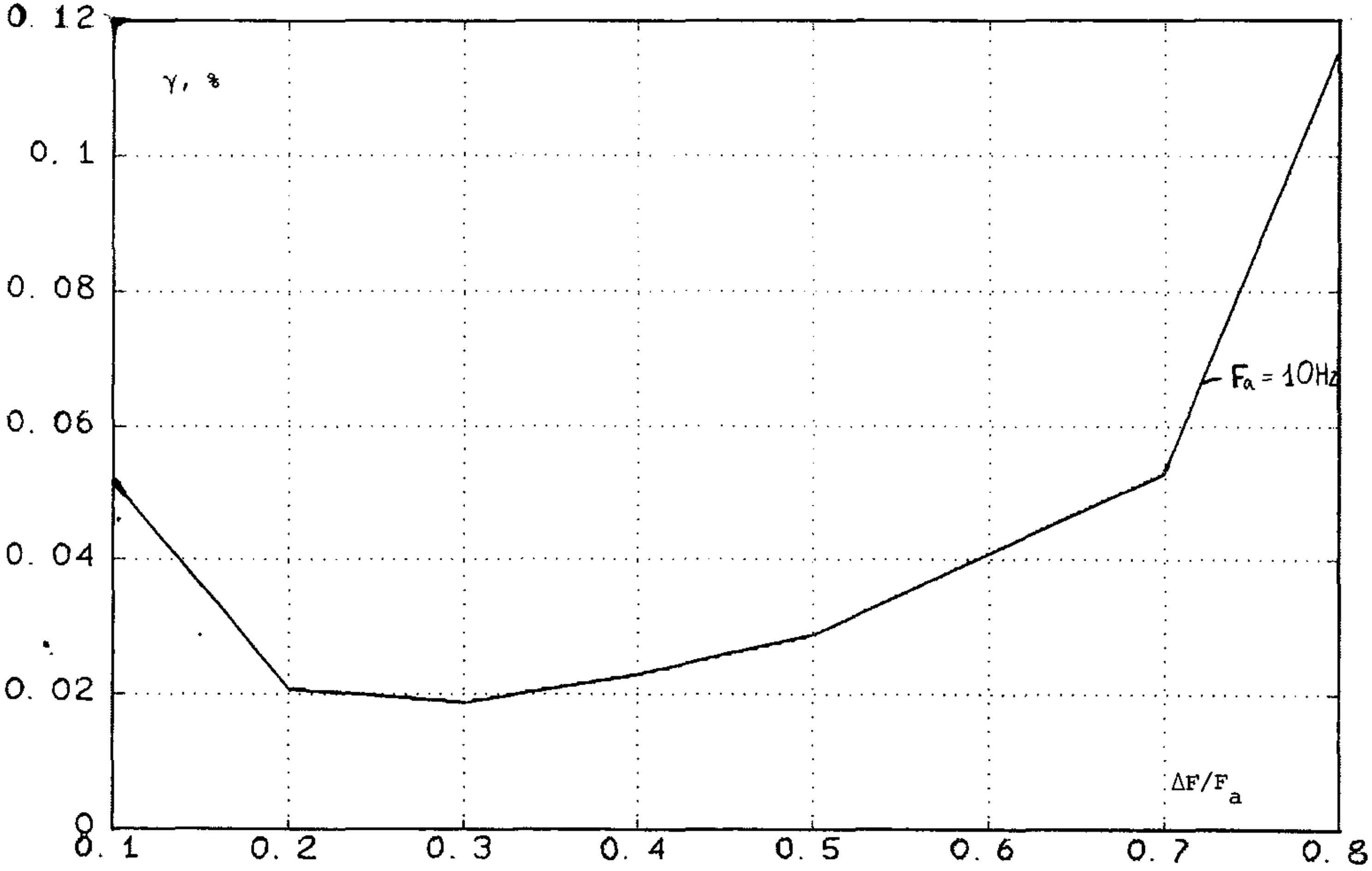

Fig.21. Relative approximation error (program IND2)

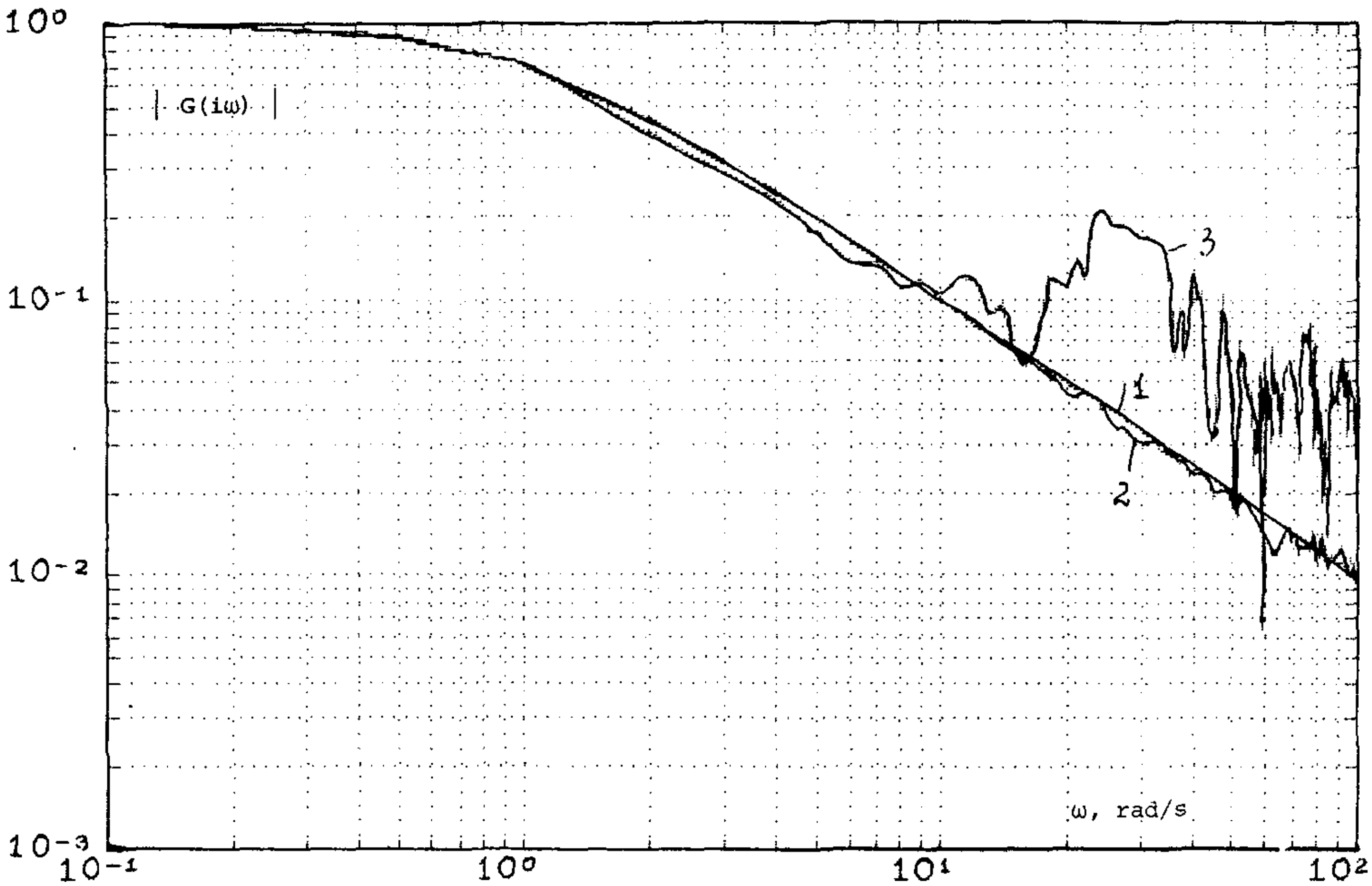

Fig.22. PFM estimation of the transfer function (program IND3)

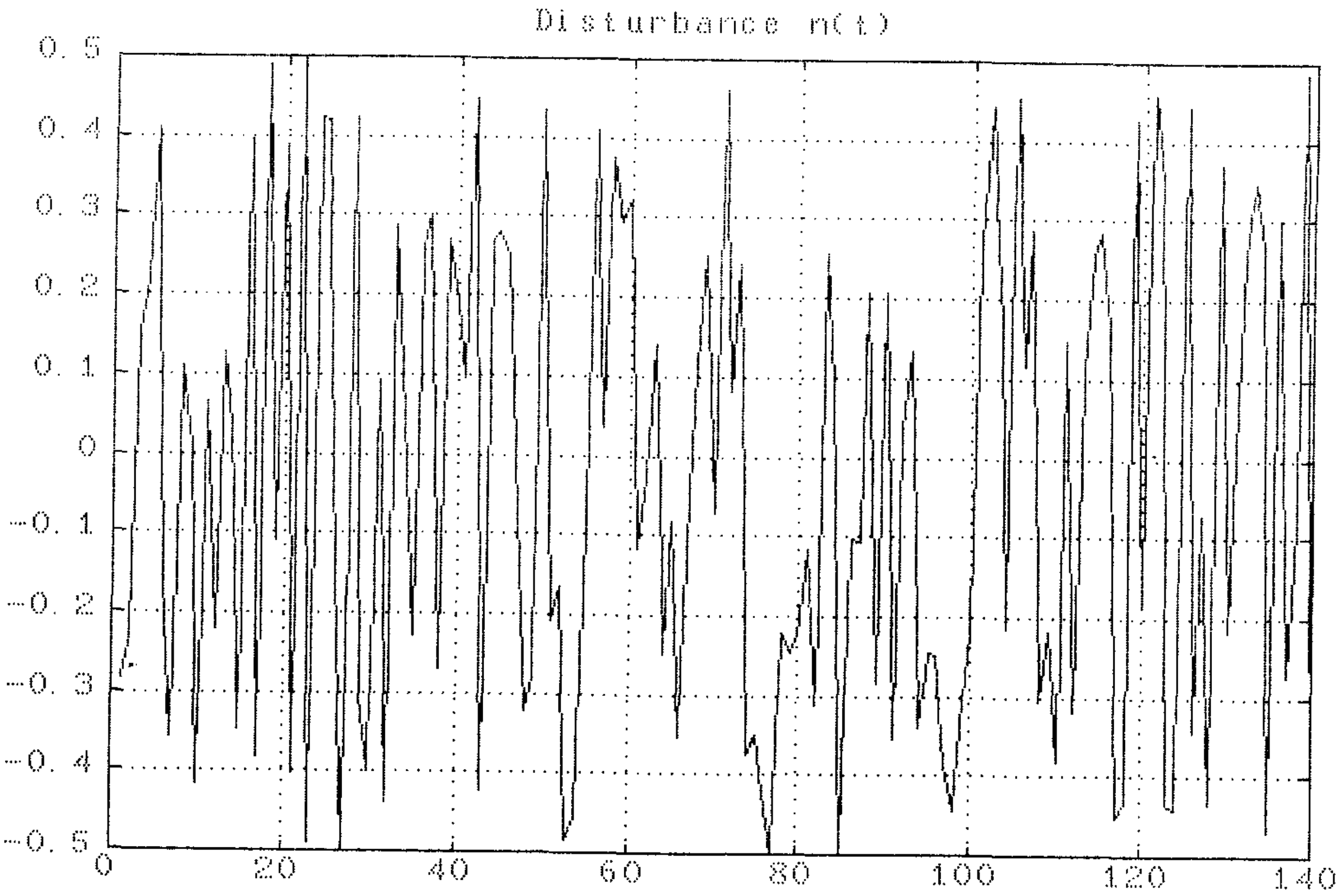

Fig.23. Noise disturbance n(t)

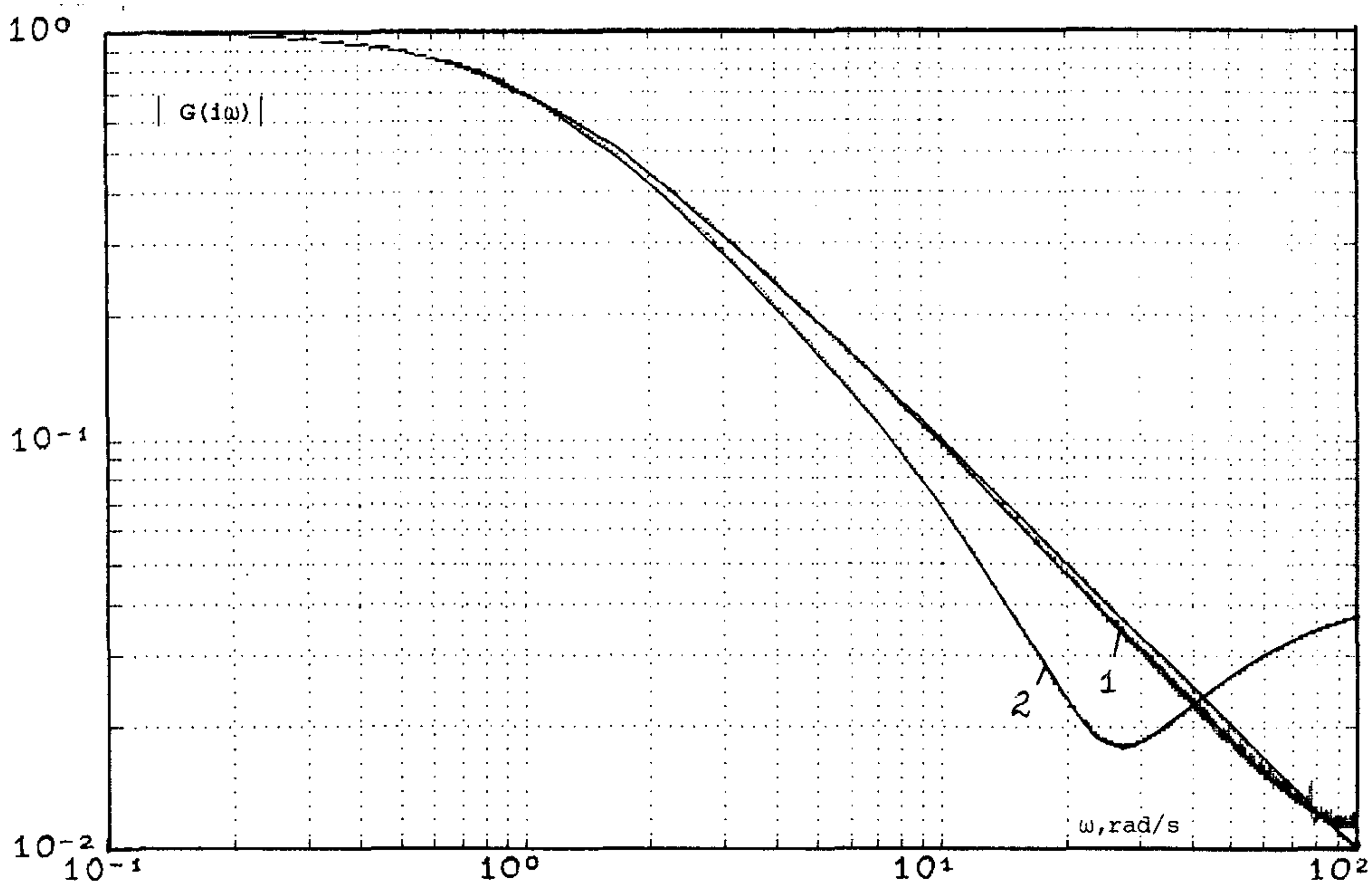

Fig.24 Comparison of the PFM estimate with regular time quantization estimate

6. ESTIMATION OF THE WEIGHTING FUNCTION

According to chapter 3 we have two problems (3.2) and (3.3). Firstly, consider the problem (3.2) when the linear process is excited by a pulse frequency signal (fig. 24).

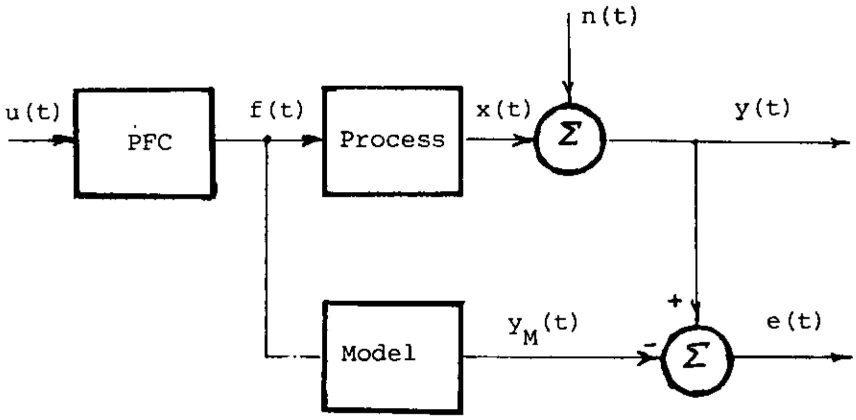

fig. 24 Estimation of the weighting function

The additive noise is assumed to be a stationary zero mean stochastic process with a spectral density $\Phi_{n(t)}(\omega)$.

The aim here is to estimate the weighting function of the linear process observing signals f(t) and y(t).
Let the model of the linear process have the weighting function g(t), which is represented over the interval [0,T] by equation

$$g(t) = \sum_{n=-\infty}^{\infty} A_n \varphi_n(t) \tag{6.1}$$

where $\varphi_n(t)$ are orthogonal functions.
Usually, orthogonal functions are determined by equations

$$\int_0^T \varphi_n(t) . \varphi_m(t) dt = \begin{cases} c_n , & m = -n \\ 0 , & m \neq -n \end{cases} \tag{6.2}$$

and

$$A_n = \frac{1}{c_n} \int_0^T g(t) . \varphi_n(t) dt \tag{6.3}$$

Now the problem of the weighting function estimation can be transformed into the problem of the estimation of coefficients A_n.

Theorem 6.1: Let the model of a linear process have the weighting function (6.1) and excited by signal

$$u_M(t) = \frac{1}{k} \sum_j \delta(t-t_j) , \tag{6.4}$$

then the estimate of coefficients A_n satisfy the criterion

$$J = \int_0^T [y(t) - y_M(t)]^2 dt \rightarrow \min, L = 1,2 \ldots \tag{6.5}$$

is equal to

$$\hat{A}_n = \frac{\int_0^T y(t) \sum_j \varphi_{-n}(t-t_j) dt}{\frac{1}{k} \int_0^T \sum_j \varphi_n(t-t_j) . \sum \varphi_{-n}(t-t_j) dt}, \tag{6.6}$$

where $t_j \in [0,T]$, if

$$\int_0^T \varphi_n(t-t_l) . \varphi_m(t-t_p) dt = 0 \quad , \quad m \neq -n \tag{6.7}$$

for any time moments t_ℓ and t_p .

Proof

For a linear process with weighting function (6.1) we have

$$y(t) = \int_0^T g(\tau) u(t-\tau) d\tau \tag{6.8}$$

Substituting (6.4) in the convolution integral (6.8) we obtain the output signal of the model

$$y_M(t) = \frac{1}{k} \sum_j g(t-t_j) = \frac{1}{k} \sum_j \sum_{n=-\infty}^{\infty} A_n \varphi_n(t-t_j) , \tag{6.9}$$

where $t_j \in [0,T]$.

Now,

$$J = \int_0^T [y(t) - \frac{1}{k} \sum_j \sum_{n=-\infty}^{\infty} A_n \varphi_n(t-t_j))]^2 dt \qquad (6.10)$$

To estimate the coefficients A_n in such way that criterion (6.10) will have a minimum, let us find the derivative $\partial J/\partial A_{-d}$

$$\frac{\partial J}{\partial A_{-d}} = -\frac{2}{k} \int_0^T \left[y(t) - \frac{1}{k} \sum_j \sum_{n=-\infty}^{\infty} A_n \varphi_n(t-t_j) \right] \left[\sum_j \varphi_{-d}(t-t_j) \right] dt \qquad (6.11)$$

and equate it to zero. Then

$$\int_0^T y(t) \sum_j \varphi_{-d}(t-t_j) dt =$$

$$\frac{1}{k} \int_0^T \left\{ \sum_{n=-\infty}^{\infty} A_n \sum_j \varphi_n(t-t_j) \right\} \left\{ \sum_j \varphi_{-d}(t-t_j) \right\} dt \qquad (6.12)$$

Rewrite the right part of equation (6.12)

$$\frac{1}{k} \sum_{n=-\infty} A_n \sum_{\ell} \sum_{p} \int_0^T \varphi_n(t-t_\ell) \cdot \varphi_{-d}(t-t_p) dt$$

In accordance with (6.7) the internal integral is equal to zero for any n, apart from n=d.
Then

$$\int_0^T y(t) \sum_j \varphi_{-d}(t-t_j) dt = A_d \frac{1}{k} \int_0^T \sum_j \varphi_{\ d}(t-t_j) \sum_j \varphi_{-d}(t-y_j) dt \qquad (6.13)$$

and hence (6.6) has been proved. □

In expression (6.6) the sum of the orthogonal function $\sum_j \varphi_n(t-t_j)$ can be treated as the output $y_n(t)$ of the very narrow band-pass filter which is excited by output signal of the PFC, i.e.

$$y_n(t) = \sum_j \varphi_n(t-t_j) \quad , \qquad t_j \in [0,T] \tag{6.14}$$

In this way the estimate (6.6) is in agreement with the block-diagram on fig. 25.

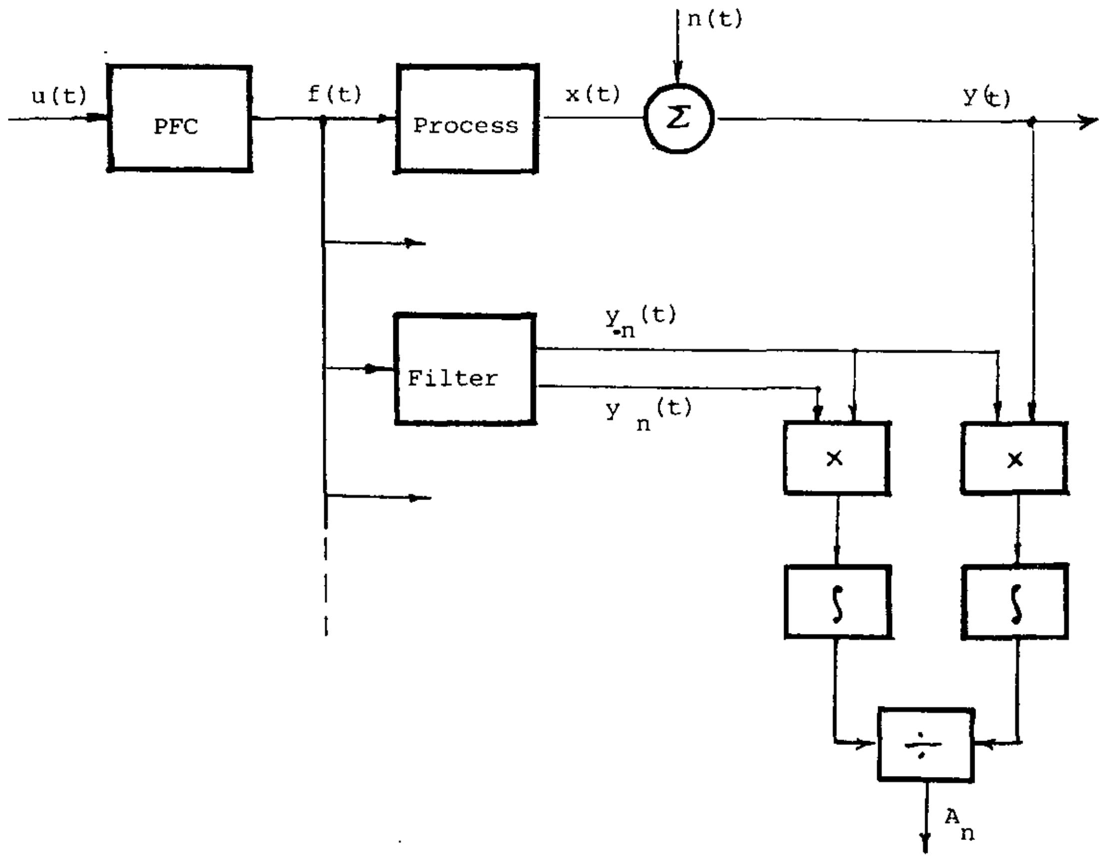

fig. 25 Estimation of the coefficients A_n

Fig. 25 reminds us of the estimating of the weighting function with the help of orthogonal filters, when the process is excited directly by signal u(t) (without using the PFC) (see Eykhoff, P. (1974) and Deich, A.M.(1979)).

The approach based on the use of orthogonal filters requires double orthogonality. It means that it is not enough only the orthogonality of functions $\{\varphi_n(t)\}$, these functions should be orthogonal with the weight of $\Phi_u(\omega)$, which is the spectral density of input signal. Because often the spectral density $\Phi_u(\omega)$ is unknown it leads to difficulties when implementing this approach.

In our case we used only one special condition, (6.7). This condition holds true for the trigonometrical and Radermacher functions and does not require the apriori knowledge of the $\Phi_u(\omega)$. This is one of the advantages of the proposed estimate (6.6). To find other orthogonal functions which are in line with (6.7) the auxiliary investigations should be performed.

We can obtain a simpler procedure for the estimation of the A_n if we lay further restriction on functions $\{\varphi_n(t)\}$.

Lemma 6.1: If the orthogonal functions satisfy the condition

$$\varphi_n(t-t_j) = \varphi_n(t).\varphi_n(-t_j) \tag{6.15}$$

for any time moment t_j and assumptions (6.1), (6.4 - 6.5) hold true, then the estimate of coefficient A_n is equal to

$$\hat{A}_n = \frac{\frac{1}{c_n}\int_0^T y(t).\varphi_{-n}(t)\,dt}{\frac{1}{k}\sum_j \varphi_{-n}(t_j)}, \qquad t_j \in [0,T] \tag{6.16}$$

Proof

From (6.15) and (6.2) it follows that

$$\int_0^T \varphi_n(t-t_\ell).\varphi_m(t-t_p)\,dt = \begin{cases} 0, & m \neq -n \\ c_n.\varphi_n(-t_\ell).\varphi_{-n}(-t_p), & m = -n. \end{cases} \tag{6.17}$$

Hence the condition (6.15) gives a stronger restriction than (6.7) and includes the latter.

The estimate (6.6) had been obtained by using the upper part of the condition (6.17). Let us take into account the second part of the condition (6.17), when m = -n.

Then the denominator of the estimate (6.6) is equal to

$$\frac{1}{k}\int_0^T \sum_j \varphi_n(t-t_j) \sum_j \varphi_n(t-t_j)\,dt =$$

$$= \frac{1}{k}\sum_j \varphi_n(-t_j).\sum_j \varphi_{-n}(-t_j) \int_0^T \varphi_n(t).\varphi_{-n}(t)\,dt$$

$$= \frac{c_n}{k} \sum_j \varphi_n(-t_j) \sum_j \varphi_{-n}(-t_j) \qquad (6.18)$$

Rewrite (6.6) using (6.18) and(6.15)

$$\hat{A}_n = \frac{\frac{1}{c_n} \sum_j \varphi_{-n}(t_j) \int_0^T y(t).\varphi_{-n}(t)\,dt}{\frac{1}{k} \sum_j \varphi_n(-t_j) . \sum_j \varphi_{-n}(-t_j)} \qquad (6.19)$$

As $\varphi_n(-t_j) = \varphi_{-n}(t_j)$ we obtain (6.16).□

Corrollary 6.1: In a particular case when

$$\{\varphi_n(t)\} = \{e^{i\omega_o nt}\} \;,\; \omega_o = 2\pi/T$$

the estimate (6.16) can be written in the form

$$\hat{A}_n = \frac{\frac{1}{T} \int_0^T y(t).e^{-i\omega_o nt}\,dt}{\frac{1}{k} \sum_j e^{-i\omega_o nt_j}} \qquad (6.20)$$

The next lemma shows the conditions under which the estimates (6.6) and (6.16) are unbiased.

Lemma 6.2: If the additive noise $n(t)$ is a stochastic stationary process with zero mean value $E[n(t)] = 0$ and the linear process excited by the signal (6.4) is in the model set (6.1), then the estimates (6.6) and (6.16) are unbiased.

Proof

Describe $y(t)$ as the sum

$$y(t) = x(t) + n(t) \qquad (6.21)$$

Then (6.6) is equal to

$$\hat{A}_d = \frac{\int_0^T x(t) \sum_j \varphi_{-d}(t-t_j)\,dt}{\frac{1}{k} \int_0^T \sum_j \varphi_{-d}(t-t_j) \sum_j \varphi_d(t-t_j)\,dt} + \qquad (6.22)$$

$$+ \frac{\int_0^T n(t) \sum_j \varphi_{-n}(t-t_j)\,dt}{\frac{1}{k}\int_0^T \sum_j \varphi_{-d}(t-t_j) \sum_j \varphi_n(t-t_j)\,dt} .$$

Due to the linear process is in the model set we can write

$$x(t) = y_M(t) = \frac{1}{k} \sum_j \sum_{n=-\infty}^{\infty} A_n \varphi_n(t-t_j) . \tag{6.23}$$

After substituting (6.23) in (6.22) and using (6.7) we obtain

$$\hat{A}_d = A_d + \frac{\int_0^T n(t) \sum_j \varphi_{-d}(t-t_j)\,dt}{\frac{1}{k}\int_0^T \sum_j \varphi_{-d}(t-t_j) \sum_j \varphi_d(t-t_j)\,dt} . \tag{6.24}$$

From this it immediately follows that $E[\hat{A}_d] = A_d$, if $E[n(t)] = 0$.
Therefore the estimate (6.6) is unbiased.
Using (6.23), (6.15) and (6.2) to prove this for the estimate (6.16) we obtain in the same way

$$\hat{A}_n = A_n + \frac{\frac{1}{c_d}\int_0^T n(t)\ \varphi_{-d}(t_j)\,dt}{\frac{1}{k}\sum_j \varphi_{-n}(t_j)} . \tag{6.25}$$

<u>Corrollary 6.2</u>: Consider the estimate (6.20).
The numerator of this estimate is the Fourier transformation $y_T(i\omega_n)$ of signal $y(t)$ over the interval $[0,T]$. The denominator is also the Fourier transformation $U_T^M(i\omega_n)$, of the model of input signal $u_M(t)$.
In agreement with L. Ljung (1985) let us determine the Fourier transformation as

$$y_T(i\omega_n) = \frac{1}{\sqrt{T}} \int_0^T y(t).e^{-i\omega_0 nt}\,dt. \tag{6.26}$$

Then (6.20) is equal to

$$\hat{A}_n = \frac{y_T(i\omega_n)}{T.\ U_T^M\ (i\omega_n)}\ . \tag{6.27}$$

Using these designations we can rewrite equation (6.25)

$$\hat{A}_n = A_n + \frac{N_T(i\omega_n)}{T.\ U_T^M(i\omega_n)} \tag{6.28}$$

From (6.28) it follows that the variance of the estimate (6.20) is equal to

$$E[(\hat{A}_n - A_n)^2] = E\left[\left(\frac{N_T(i\omega_n)}{T\ U_T^M(i\omega_n)}\right)^2\right] \approx$$

$$\approx \frac{\Phi_{n(t)}(\omega_n)}{T^2 |U_T^M(i\omega_n)|^2}\ , \tag{6.29}$$

where $\Phi_{n(t)}(\omega_n)$ is the spectral density of the noise disturbance n(t). Thus the higher the signal-to-noise ratio the less the variance of the estimate (6.20). So the estimates obtained above are not in contradiction with common knowledge.

In practice the output signal of a PFC cannot have the shape of delta-pulses. The real output pulses have certain amplitude and time length. It means that, in practice, estimates (6.6), (6.16) and (6.20) will give the values of coefficients A_n of the linear process which includes the pulse forming element. These coefficients can be recalculated if one knows the shape of pulses.
For the estimates obtained above we had not adopted any assumption about signal y(t), apart from that it is the output of a linear process with additive noise. Therefore, to obtain estimates (6.6), (6.16) and (6.20) there is no need to excite the process with the PFC output signal. It is enough to excite only the model (fig. 25).

In this case we deal with pulse-frequency modelling. It is interesting to establish the properties of the above obtained estimates for this case.

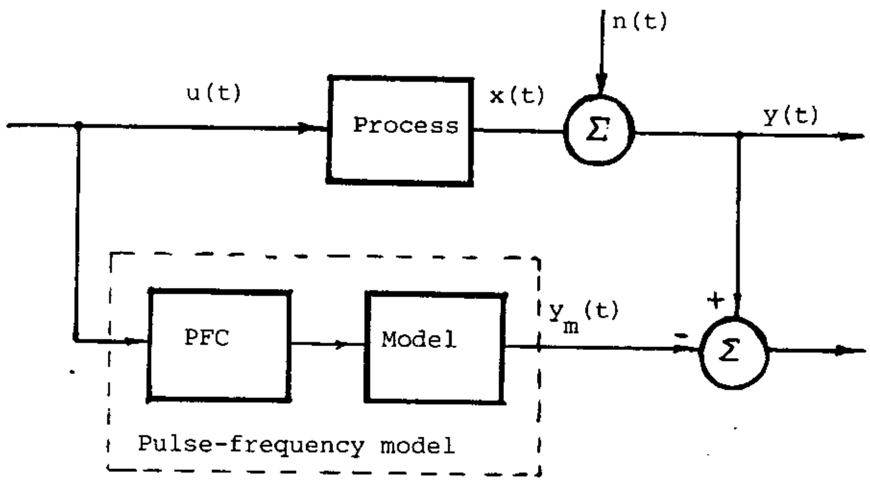

fig. 26 Pulse-frequency modelling

For the sake of simplicity and in order to find the relationships between pulse-frequency modelling and previous approaches consider only estimates (6.16) and (6.20).

Lemma 6.3: If the linear process is in the model set (6.1), and n(t) is a stochastic stationary process with zero mean value $E[n(t)]=0$, then for the case of pulse frequency modelling the mathematical expectation of the estimate (6.16) is equal to

$$E[\hat{A}_n] = A_n \cdot \frac{\int_0^T u(t)\ \varphi_{-n}(t)\,dt}{\frac{1}{k}\sum_j \varphi_{-n}(t_j)} \qquad (6.30)$$

Proof

The output of the linear process with weighting function (6.1)

$$x(t) = \int_0^T \sum_{n=-\infty}^{\infty} A_n\ \varphi_n(t-\tau)\ u(\tau)\,d\tau \qquad (6.31)$$

Then the estimate (6.16) can be rewritten

$$A_n = \frac{\frac{1}{c_n}\int_0^T \sum_{d=-\infty}^{\infty} A_d\{\int_0^T \varphi_d(t-\tau).\varphi_{-n}(t)dt\}\ u(\tau)d\tau}{\frac{1}{k}\sum_j \varphi_{-n}(t_j)} +$$

$$+ \frac{\int_0^T n(t)\ .\ \varphi_{-n}(t)dt}{\frac{1}{k}\sum_j \varphi_{-n}(t_j)} \qquad (6.32)$$

Because (6.15) gives

$$\int_0^T \varphi_d(t-\tau).\varphi_{-n}(t)dt = \begin{cases} 0 & , d \neq n \\ c_n.\varphi_n(-\tau) & , d = n \end{cases} \qquad (6.33)$$

and $E[n(t)] = 0$ then from (6.32) it follows (6.30).

<u>Corrollary 6.3</u>: For the estimate (6.20) under above mentioned conditions

$$E[A] = A_n\ .\ \frac{\int_0^T u(t).e^{-i\omega_0 nt}dt}{\frac{1}{k}\sum_j e^{-i\omega_0 nt_j}} \qquad (6.34)$$

As it had been shown in chapter 4 for sufficiently small values of the multiplication $\omega\ \theta_j$ and for $T = \sum_j \theta_j$ we can write

$$\int_0^T u(t)\ e^{-j\omega_0 nt}\ dt \approx \frac{1}{k}\sum_j e^{-i\omega_0 nt_j} \qquad (6.35)$$

or $\qquad U_T(i\omega_n) \approx U_T^M\ (i\omega_n)$.

Consequently, as it appears from (6.27), estimate (6.20) is approximately equal to

$$\hat{A}_n \approx \frac{Y_T(i\omega_n)}{T.\ U_T(i\omega_n)} \qquad (6.36)$$

and if $\theta_j \to 0$, then (6.34) tends to A_n.

If we rewrite (6.36) in the next form

$$\hat{A}_n \; T \approx \frac{Y_T(i\omega_n)}{U_T(i\omega_n)} = \hat{G}_T(i\omega_n) \qquad (6.37)$$

we obtain the estimate of the transfer function at frequency ω_n, because when no noise disturbance n(t) and $T \to \infty$, then

$$\frac{Y_T(i\omega_n)}{U_T(i\omega_n)} = A_n.T \quad \to \quad G(i\omega_n) \qquad (6.38)$$

According to L. Ljung (1985 and 1987) we shall call (6.37) as the empirical transfer function estimate (ETFE). So under certain conditions the estimate (6.20) leads to ETFE. It gives us an easier way to verify our conclusions and permits us to spread some properties of ETFE on the estimate (6.20).

In particular if $U_T(\omega_n) = 0$, then we simply consider that estimate (6.20) is undefined at the frequency ω_n. When input signal u(t) is periodic with period LT, then the variance of the estimate

$$\hat{A}_n.T = \frac{\int_0^{LT} y(t) \; . \; e^{-i\omega_0 nt} \, dt}{\sum_j e^{-i\omega_0 nt_j}} \quad , \qquad t_j \in [0,LT] \qquad (6.39)$$

decay as 1/L. When the input is a stochastic stationary process then the variance of the estimate (6.39) does not decrease as interval T increases. It remains equal to the noise-to-signal ratio at corresponding frequency. To improve the estimate (6.20) when noise occurs the smoothing ETFE spectral analysis can be implemented (L. Ljung (1985)).

In order to illustrate the PFM estimation of the ETFE the simulation of eq. (6.37) has been performed.

Fig. 27 shows how the PFM estimate of the ETFE depends on PFC average frequency. The line 1 corresponds to the true frequency response of the linear process, the lines 2 and 3 correspond to the

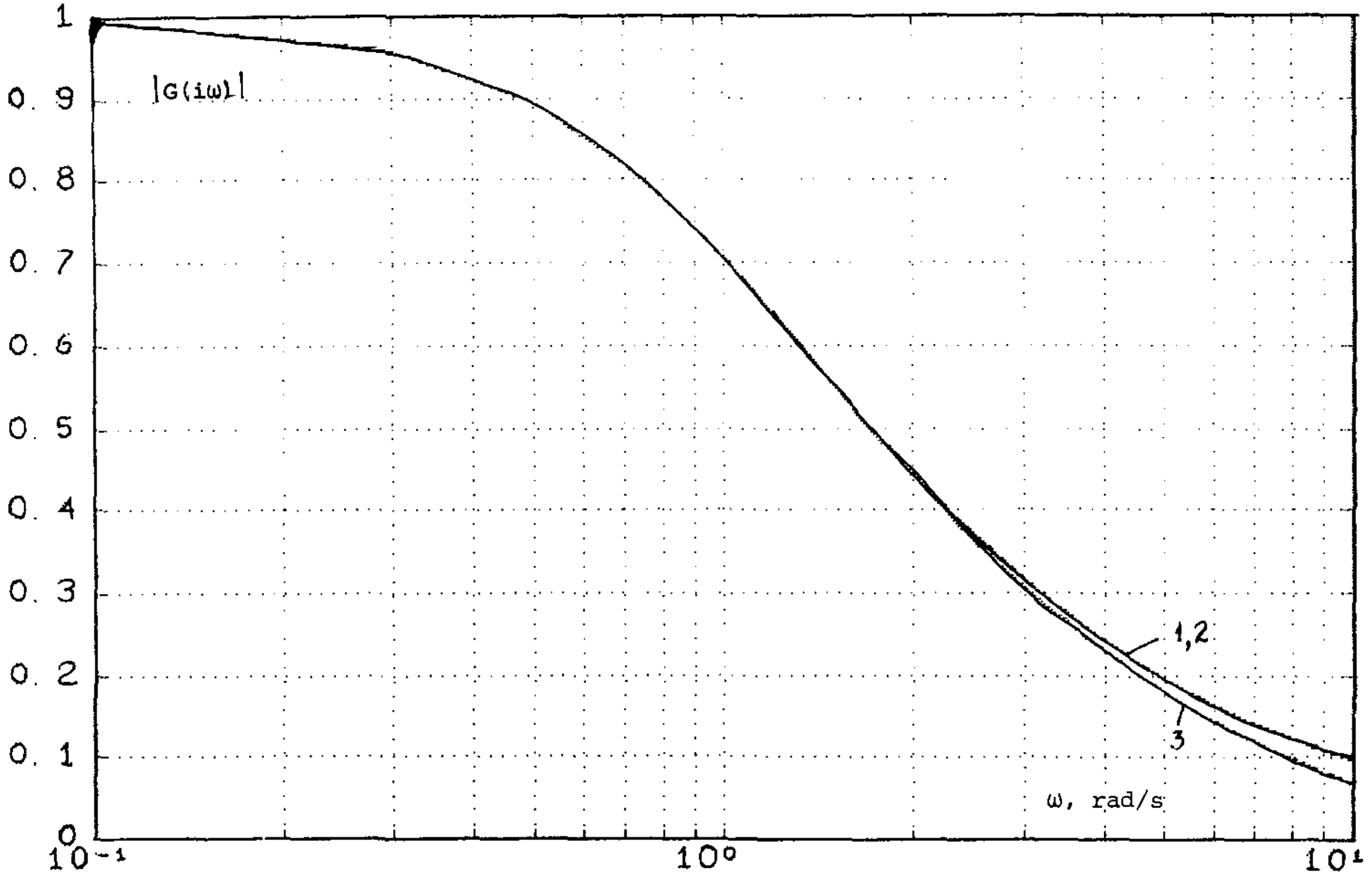

Fig.27. PFM estimate of the ETFE (program IDNWF1)

estimate of frequency response at average frequencies 20 Hz and 5 Hz. The higher the PFC average frequency, the closer the estimate to the true frequency response. This is in agreement with (6.35). Fig. 27 was obtained when there was no noise disturbance and the input signal u(t) had the rectangular shape (program IDNWF1). The integral in the formula (6.30) has been calculated in an analytical way.

In practice, one has to calculate this integral using numerical methods. For the digital hardware realization case we should consider that signal y(t) is constant during the time between two pulses of PFC. Then the integral in (6.20) is approximately equal to

$$\int_0^T y(t)\, e^{-i\omega_n t} dt \approx \sum_j y(t_j) \cdot \frac{i}{\omega_n} \cdot e^{-i\omega_n t_j} (1 - e^{-i\omega_n \theta_j}) \quad (6.40)$$

Fig. 28 shows the simulation results (program WF1N) for this. Here line 1 corresponds to the true frequency response of the linear process, line 2 corresponds to the PFM estimation of the frequency response (F_a = 20 Hz). The signal-to-noise ratio was 20 dB, 10 periods of the rectangular input signal were used to obtain this estimate. For the aim of comparison fig. 29 shows the estimate of the ETFE under regular time quantization (program RC1N). As is clear from fig. 28 and fig. 29 the PFM estimate at the same conditions has the smaller variance.

This fact also takes place for arbitrary input signal u(t). Figs. 30 and 31 show the simulation results when the input was represented by noise signal (program WFN1 and RC2N).

The result was due to aliasing noise under regular time quantization. To avoid this effect one should perform a preliminary analog processing of the input signals before regular time quantization. This is the main disadvantage of regular time quantization.

Now let us consider the problem (3.3) when the model of the process is excited by output signal of the PFC and the output signal of the process is also observed with the help of PFC (fig. 6). Then we can

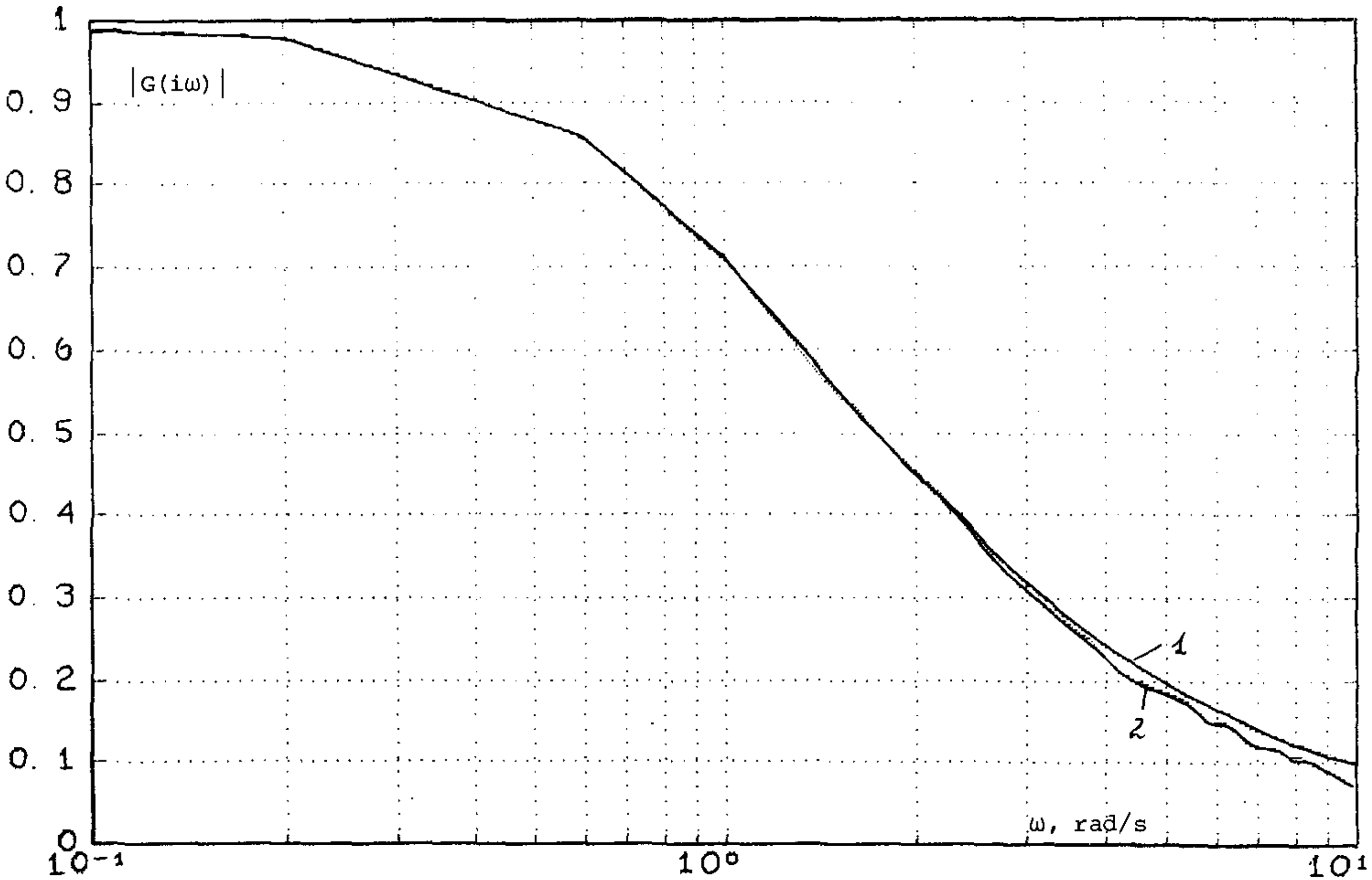

Fig.28. PFM estimate of the ETF (program WF1)

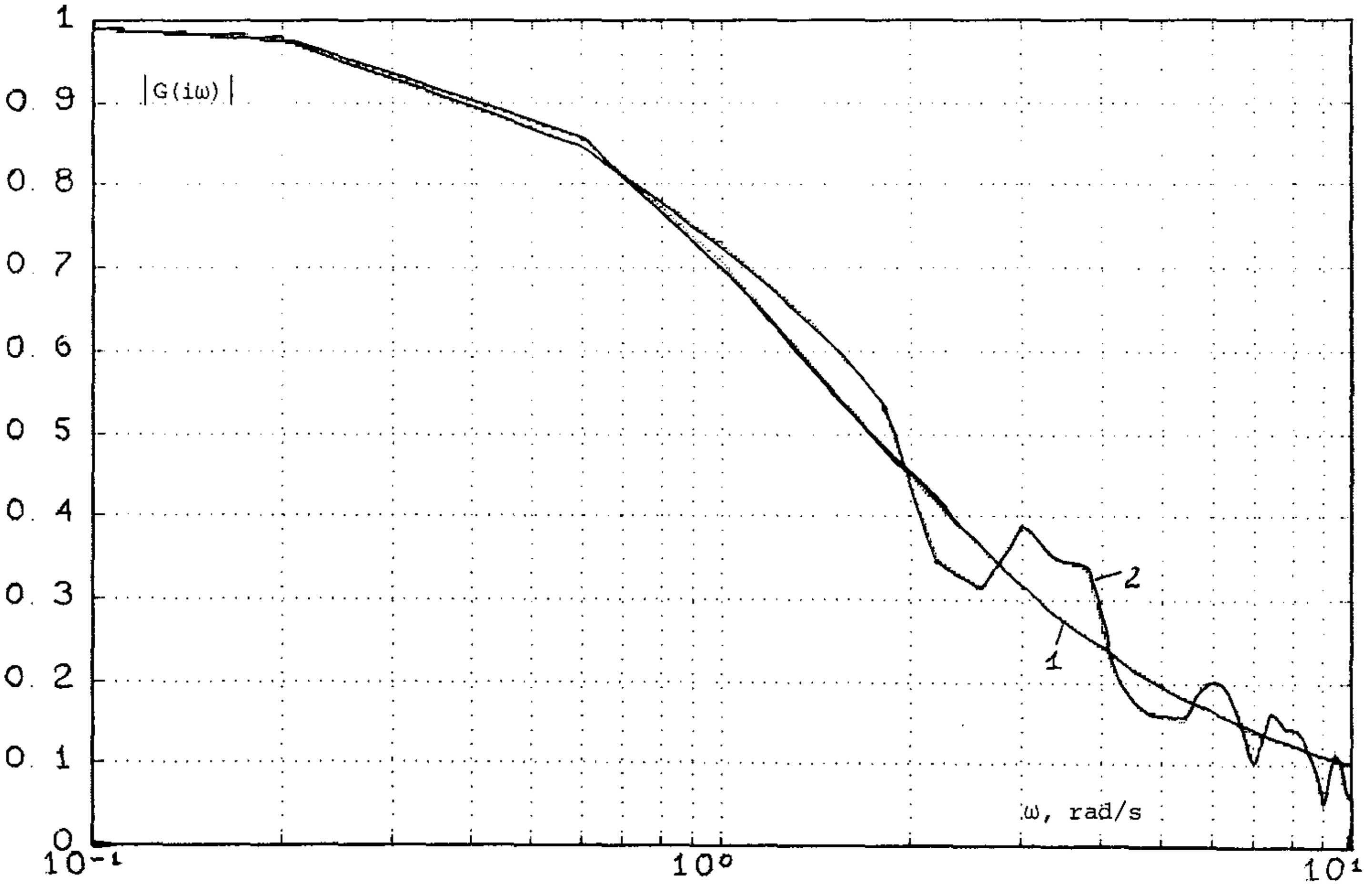

Fig.29. Regular time quantization estimate of the ETF (program RC1N)

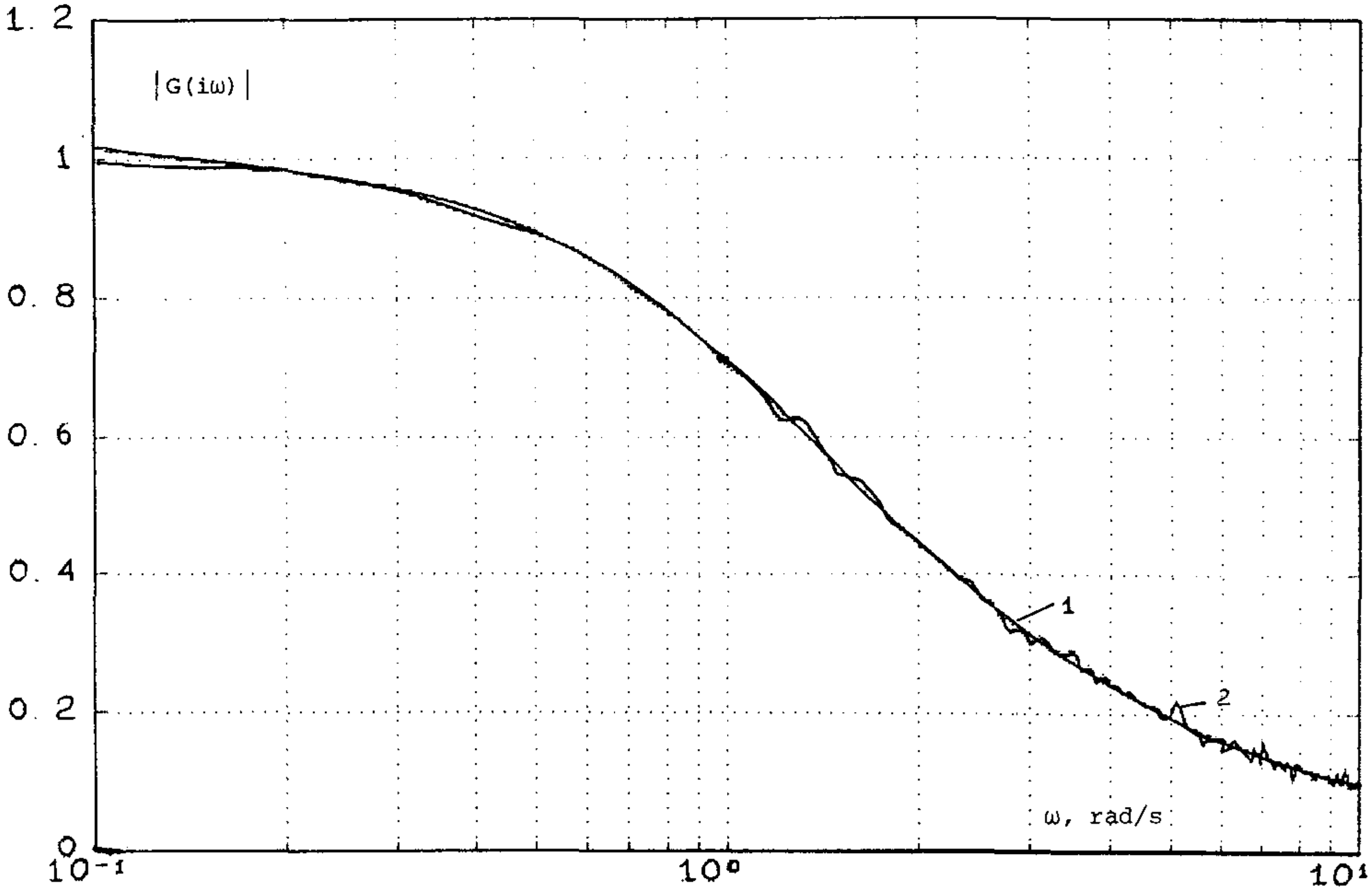

Fig.30. PFM estimate of the ETF (program WFN1)

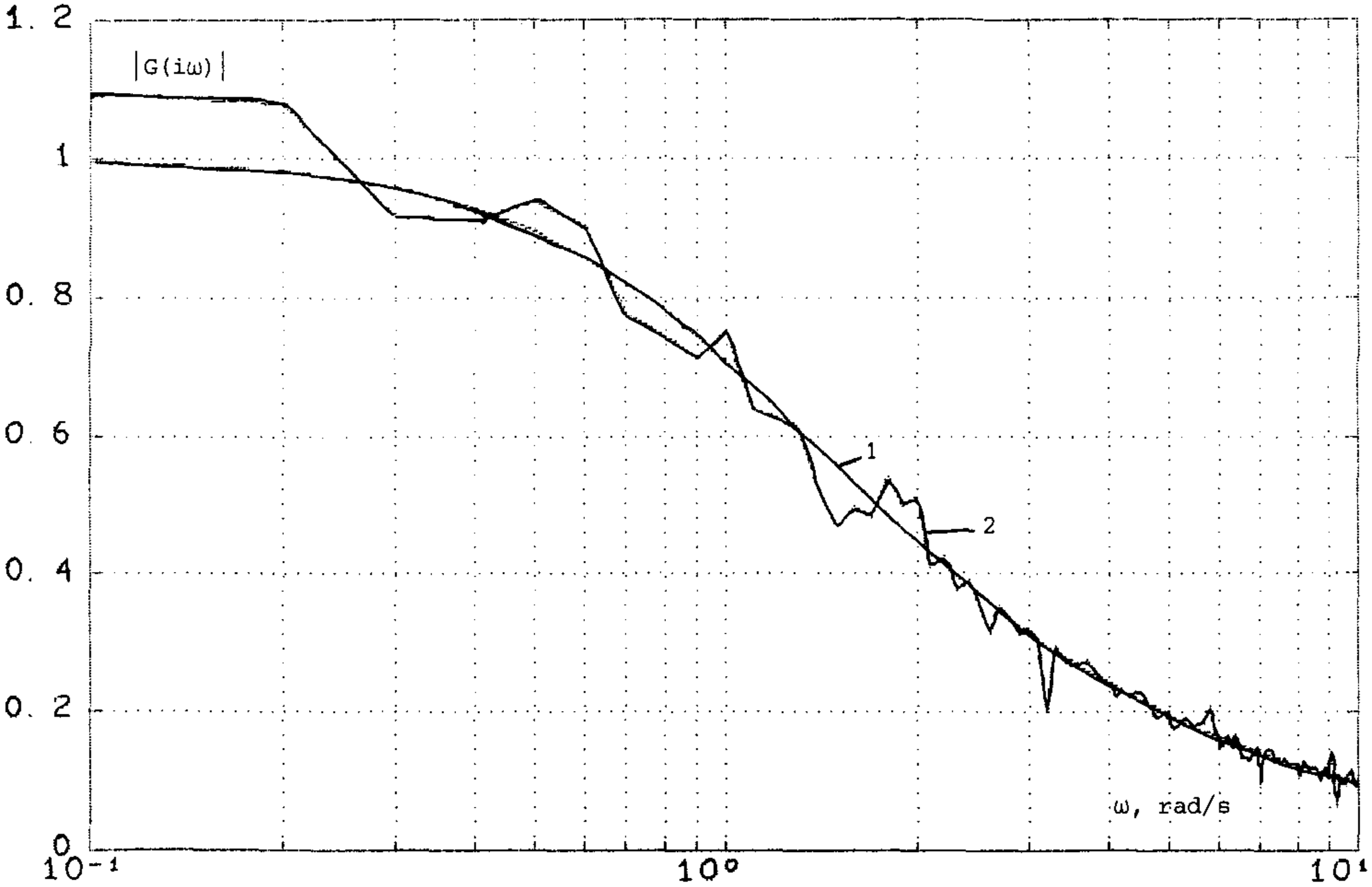

Fig.31. Regular time quantization estimate of the ETF (program RC2N)

formulate the next two lemmas.

Lemma 6.4: Let assumptions (6.1), (6.4), (6.5), (6.7) hold true and the output signal of process, observed with the help of the PFC, be described as

$$y_M(t) = \frac{1}{k} \sum_{\ell} \delta(t-t_{\ell}) \tag{6.41}$$

then the estimate of coefficients A_n is equal to

$$\hat{A}_n = \frac{\sum_j \sum_{\ell} \varphi_{-n}(t_{\ell}-t_j)}{\int_0^T \sum_j \varphi_n(t-t_j) \cdot \sum_j \varphi_{-n}(t-t_j)\, dt}, \tag{6.42}$$

where $t_j \in [0,T]$, $t_{\ell} \in [0,T]$

Proof

There are two ways to prove this lemma.

1) Consider criterion (6.5). Then

$$J = \int_0^T \left\{ \sum_{n=-\infty}^{\infty} \sum_j \frac{1}{k} A_n \varphi_n(t-t_j) - \frac{1}{k} \sum_{\ell} \delta(t-t_{\ell}) \right\}^2 dt \tag{6.43}$$

After equating the derivative

$$\frac{\partial J}{\partial A_{-d}} = \frac{2}{k} \int_0^T \left[\sum_n \sum_j \frac{1}{k} A_n \varphi_n(t-t_j) - \frac{1}{k} \sum_{\ell} \delta(t-t_{\ell}) \right] \tag{6.44}$$

$$\sum_j \varphi_{-d}(t-t_j)\, dt$$

to zero we obtain (6.42).

2) The proof of this lemma can be obtained immediately from theorem 6.1 if one substitutes in (6.6), instead of signal y(t), the expression (6.41). This is possible because when proving theorem 6.1 no assumption about signal y(t) has been made.

Lemma 6.5: If the orthogonal functions satisfy condition (6.15) and if assumptions (6.1), (6.4), (6.5), (6.41) hold true then

$$\hat{A}_n = \frac{\sum_{\ell} \varphi_{-n}(t_\ell)}{c_n \sum_j \varphi_{-n}(t_j)} \quad , \quad t_j \in [0,T],\ t_\ell \in [0,T] \quad . \qquad (6.45)$$

Proof

Consider the estimate (6.41). Using (6.15) we can write

$$\hat{A}_n = \frac{\sum_j \varphi_{-n}(-t_j) \sum_\ell \varphi_{-n}(t_\ell)}{\sum_j \varphi_n(-t_j) \cdot \sum_j \varphi_{-n}(-t_j) \int_0^T \varphi_n(t) \cdot \varphi_{-n}(t)\,dt} \qquad (6.46)$$

Taking into account that $\varphi_n(-t_j) = \varphi_{-n}(t_j)$ we obtain (6.45).

Corrolary 6.5: In a particular case when $\varphi_n(t) = e^{i\omega_o nt}$, $\omega_o = 2\pi/T$ the estimate (6.46) can be written in the form

$$\hat{A}_n = \frac{\sum_\ell e^{-i\omega_o nt_\ell}}{T \sum_j e^{-i\omega_o nt_j}} \quad . \quad \square \qquad (6.47)$$

Thus we have

$$\hat{A}_n = \frac{Y_T^M(i\omega_n)}{T\ U_T^M(i\omega_n)} \quad . \qquad (6.48)$$

The distinction of the estimate (6.48) from (6.27) is only in the fact that in expression (6.48) the nominator is the PFM Fourier transformation of the output signal model $y_M(t)$.

For sufficiently small $\omega\ \theta_j$ and $\omega\ \theta_\ell$ the estimate

$$\hat{A}_n T = \frac{Y_T^M(i\omega_n)}{U_T^M(i\omega_n)} \qquad (6.49)$$

gives us the estimate of the transfer function at the frequency ω_n.

Fig. 32 shows the simulation results of the estimate (6.49). As was expected, the higher the average frequency of the PFC, the closer the estimate to the true frequency response (Program IDNWF3).

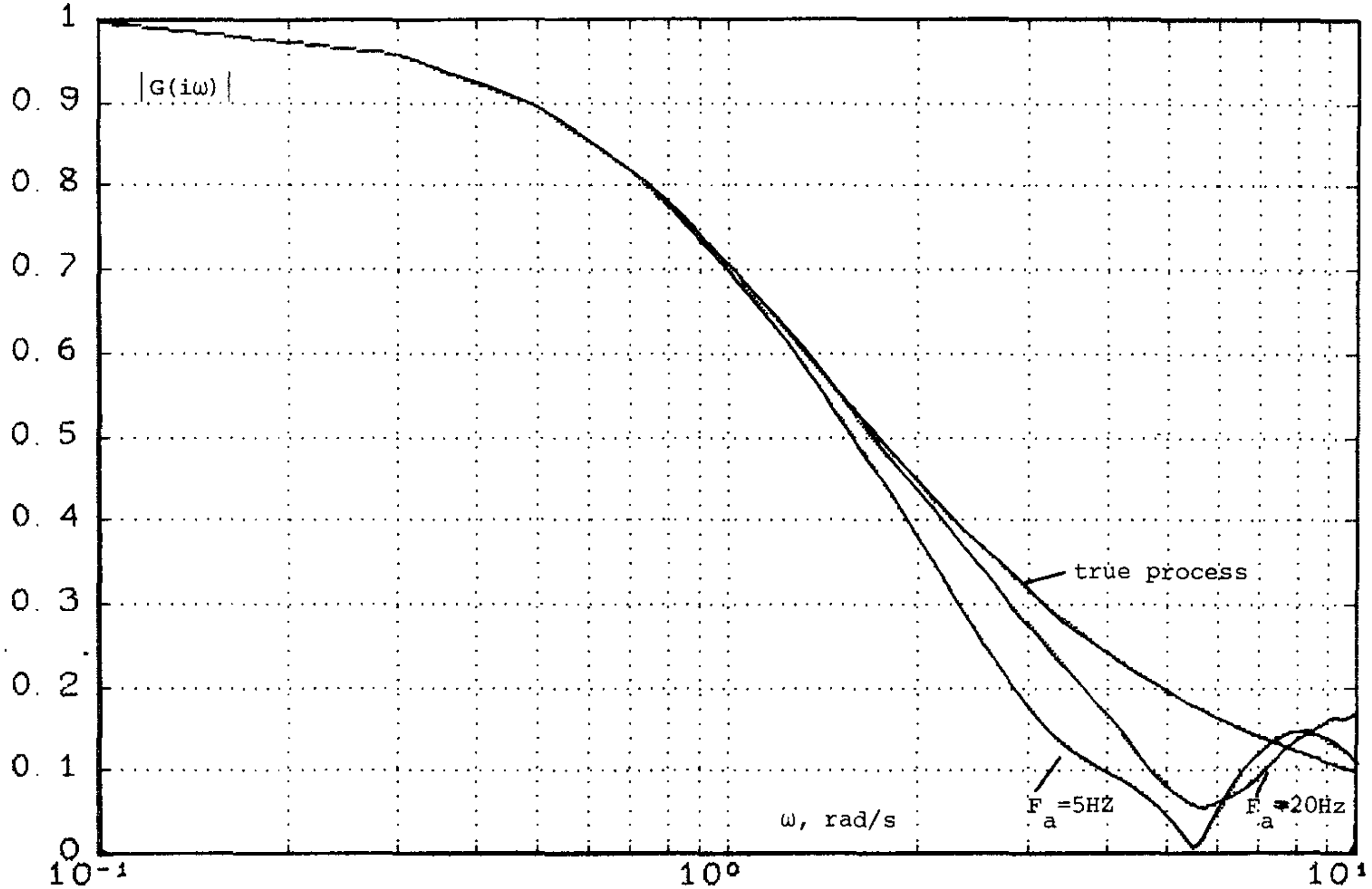

Fig.32. PFM estimate of the ETM (program IDNWFE)

7. CONCLUSIONS

Non-periodic time quantization has proved very useful for the improvement of measurement and control systems.
Very often non-periodic time quantization is connected with pulse-frequency modulation. In the present report some aspects of continuous system identification using PFM signals have been studied.

To design the transfer function and weighting function estimates based on the use of PFM signals several models of these signals were briefly reviewed. It has been shown that the continuous measurement signals can be represented by the sum of shifted Dirac delta functions.
This presentation follows from certain definitions of frequency and this is related to the piecewise step approximation of the integral of continuous measurement signals.

The PFM estimate of the transfer function has been obtained on the basis of the suggested presentation of continuous measurement signals and frequency analysis by the correlation method. The more attractive feature of this estimate is the simplicity of hardware digital realization. The simulation has shown that under equal conditions the PFM estimation of the transfer function gives a better result than the estimate based on periodic sampling data from continuous measurement signals.

A more interesting case of the implementation of PFM signals was connected with the estimation of the weighting function. To obtain the estimate of the weighting function the orthogonal expansion and output error approach with minimum mean square criteria have been used. It has been shown that a PFM weighting function estimate does not require the apriori knowledge of input signal spectral density in order to find a suitable set of orthogonal functions.
As it follows from the proved theorem for the PFM estimation, the orthogonal functions should keep their orthogonal properties when the argument of these functions has an arbitrary shift.
For the PFM estimation one can use Rademacher and trigonometrical

functions. Nevertheless an auxiliary investigation could be attempted in order to find another set of orthogonal functions which satisfy the given condition.

Two different cases of PFM estimation of the weighting function have been considered. First when the process is excited by a PFC output signal and second when a PFC is used only for the observation. It has been established that in the first case the weighting function estimate is unbiased. In the second case the estimate has a bias, but for a sufficiently small interval between the pulses (or for a sufficiently high average frequency of the PFC) the bias is small and one can neglect it. It permits us to use the PFM estimation in those cases when an ordinary estimate based on regular time sampling is used.

The relationship between the PFM estimate of the weighting function coefficients and the emperical transfer function estimate has given an easier way to verify the obtained results. The simulation based on this relationship has shown that for arbitrary input signal or for unknown noise the variance of the PFM estimate can be smaller than the estimate with regular time quantization.

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APPENDICES

```
      PROGRAM IND1
      IMPLICIT REAL(A-Z)
C
C      ESTIMATION OF THE TRANSFER FUNCTION
C      FIRST ORDER MODEL
C      PULSE FREQUENCY OBSERVER
C      CORRELATION ANALYSIS
C
C      FS-average frequency of PFC
C      OM-circle frequency of input signal
C      G -coefficient of PFC sensetivity
C      file 'IND.DAT'collect the output data of program
C      Q -number of periods of input signal
C
      OPEN(3,FILE='INN.DAT')
      WRITE(*,4)
    4 FORMAT(1X,'Q=')
      READ(*,10) Q
      WRITE(*,5)
    5 FORMAT(1X,'FS=')
      READ(*,10) FS
   10 FORMAT(E10.4)
      WRITE(*,15)
   15 FORMAT(1X,'G=')
      READ(*,10) G
   25 WRITE(*,30)
   30 FORMAT(1X,'OM=')
      READ(*,10) OM
      TN=0
      SR=1
      SM=0
      TI=2*3.1415/OM*Q
      H=1/SQRT(OM**2+1)
      FH=-ATAN(OM)
   40 U=H*SIN(OM*TN+FH)
      TE=1/(FS+G*U)
      TN=TN+TE
      ER=COS(OM*TN)
      EM=SIN(OM*TN)
      SR=SR+ER
      SM=SM-EM
      IF (TN .LT. TI) THEN
         GOTO 40
      ELSE
         SN=SQRT(SR**2+SM**2)/(G*TI)*2
         F=ATAN(SM/SR)-1.57075
         WRITE(*,45)
   45    FORMAT(9X,'SN',14X,'H',15X,'F',15X,'FH')
         WRITE(*,50) SN,H,F,FH
         OO=0
```

```
      WRITE(3,51) OM,SN,H,OO
50    FORMAT(1X,4(E15.5,2X))
51    FORMAT(1X,3(E15.5,2X),F2.1)
      IF (OM .LT. 100) THEN
         GOTO 25
      ELSE
         GOTO 55
      END IF
    END IF
 55 END
```

```
      PROGRAM IND2
      IMPLICIT REAL(A-Z)
C
C      SPECTRA ANALISIS
C      HARMONIC SIGNAL
C      PULSE FREQUENCY OBSERVER
C
C
C      FS-average frequency of PFC
C      OM-circle frequency of signal
C      G -coefficient of PFC sensetivity
C      file 'IND.DAT'collect the output data of program
C      Q -number of periods of the  input siignal
C
      OPEN(3,FILE='IND.DAT')
      WRITE(*,5)
    5 FORMAT(1X,'OM=')
      READ(*,10) OM
      WRITE(*,6)
    6 FORMAT(1X,'Q=')
      READ(*,10) Q
   10 FORMAT(E10.4)
   25 WRITE(*,30)
   30 FORMAT(1X,'FS=')
      READ(*,10) FS
      G=FS/10
      DM=G/FS
   35 TN=0
      SR=1
      SM=0
      TI=2*3.1415/OM*Q
   40 U=SIN(OM*TN)
      TE=1/(FS+G*U)
      TN=TN+TE
      ER=COS(OM*TN)
      EM=SIN(OM*TN)
      SR=SR+ER
      SM=SM-EM
      IF (TN .LT. TI) THEN
         GOTO 40
      ELSE
         SN=SQRT(SR**2+SM**2)/(G*TI)
         F=ATAN(SM/SR)
         WRITE(*,45)
45       FORMAT(9X,'FS',14X,'DM',14X,'SN',14X,'F')
         WRITE(*,50) FS,DM,SN,F
         OO=0
         WRITE(3,51) FS,DM,SN,OO
50       FORMAT(1X,4(E15.5,2X))
51       FORMAT(1X,3(E15.5,2X),F2.1)
         IF (G .LT. (8*FS/10)) THEN
            G=G+FS/10
            DM=G/FS
            GOTO 35
```

```
        ELSE
            IF(FS.LT.100) THEN
            GOTO 25
            ELSE
            GOTO 55
            END IF
       END IF
     END IF
55   END
```

```
      PROGRAM IND3
      IMPLICIT REAL(A-Z)
C
C      ESTIMATION OF THE TRANSFER FUNCTION
C      FIRST ORDER MODEL
C      PULSE FREQUENCY OBSERVER
C      NOISE INTERRUPTION
C      CORRELATION ANALYSIS
C
C      FS-average frequency of PFC
C      OM-circle frequency of input signal
C      G -coefficient of PFC sensetivity
C      file 'IND.DAT'collect the output data of program
C      Q -number of periods of input signal
C      file 'F.MAT' consists the random numbers RR
C
      OPEN(3,FILE='INN.DAT')
      WRITE(*,4)
    4 FORMAT(1X,'Q=')
      READ(*,10) Q
      WRITE(*,5)
    5 FORMAT(1X,'FS=')
      READ(*,10) FS
   10 FORMAT(E10.4)
      WRITE(*,15)
   15 FORMAT(1X,'G=')
      READ(*,10) G
   25 WRITE(*,30)
   30 FORMAT(1X,'OM=')
      READ(*,10) OM
      OPEN(4,FILE='F.MAT')
      TN=0
      SR=1
      SM=0
      TI=2*3.1415/OM*Q
      H=1/SQRT(OM**2+1)
      FH=-ATAN(OM)
   40 U=SIN(OM*TN+FH)
      READ(4,41) RR
   41 FORMAT(3X,F7.5)
      R=U+RR
      TE=1/(FS+G*R)
      TN=TN+TE
      ER=COS(OM*TN)
      EM=SIN(OM*TN)
      SR=SR+ER
      SM=SM-EM
      IF (TN .LT. TI) THEN
         GOTO 40
      ELSE
         SN=H*SQRT(SR**2+SM**2)/(G*TI)*2
         F=ATAN(SM/SR)-1.57075
         WRITE(*,45)
  45     FORMAT(9X,'SN',14X,'H',15X,'F',15X,'FH')
         WRITE(*,50) SN,H,F,FH
         OO=0
```

```
       WRITE(3,51) OM,SN,H,OO
50     FORMAT(1X,4(E15.5,2X))
51     FORMAT(1X,3(E15.5,2X),F2.1)
       IF (OM .LT. 100) THEN
          CLOSE(4,STATUS='KEEP')
          GOTO 25
       ELSE
          GOTO 55
       END IF
     END IF
 55 END
```

```
      PROGRAM IND 4
      IMPLICIT REAL(A-Z)
C
C      ESTIMATION OF THE TRANSFER FUNCTION
C      FIRST ORDER MODEL
C      PULSE FREQUENCY OBSERVER
C      CORRELATION ANALYSIS
C
C      FS-average frequency of PFC
C      OM-circle frequency of input signal
C      G -coefficient of PFC sensetivity
C      file 'IND.DAT'collect the output data of program
C      Q -number of periods of input signal
C
      OPEN(3,FILE='INN.DAT')
      WRITE(*,4)
    4 FORMAT(1X,'Q=')
      READ(*,10) Q
      WRITE(*,5)
    5 FORMAT(1X,'FS=')
      READ(*,10) FS
   10 FORMAT(E10.4)
      WRITE(*,15)
   15 FORMAT(1X,'G=')
      READ(*,10) G
   25 WRITE(*,30)
   30 FORMAT(1X,'OM=')
      READ(*,10) OM
      TN=0
      SR=1
      SM=0
      TI=2*3.1415/OM*Q
      H=1/SQRT(OM**2+1)
      FH=-ATAN(OM)
   40 U=SIN(OM*TN+FH)
      TE=1/(FS+G*U)
      R1=0
      WRITE(3,41) U,TN,G,R1
   41 FORMAT(1X,3(E15.5,2X),F2.1)
      TN=TN+TE
      ER=COS(OM*TN)
      EM=SIN(OM*TN)
      SR=SR+ER
      SM=SM-EM
      IF (TN .LT. TI) THEN
         GOTO 40
      ELSE
         SN=H*SQRT(SR**2+SM**2)/(G*TI)*2
         F=ATAN(SM/SR)-1.57075
         WRITE(*,45)
  45     FORMAT(9X,'SN',14X,'H',15X,'F',15X,'FH')
         WRITE(*,50) SN,H,F,FH
         OO=0
```

```
      WRITE(3,51) OM,SN,H,OO
50    FORMAT(1X,4(E15.5,2X))
51    FORMAT(1X,3(E15.5,2X),F2.1)
      IF (OM .LT. 100) THEN
         GOTO 25
      ELSE
         GOTO 55
      END IF
    END IF
 55 END
```

```
      PROGRAM RTC
      IMPLICIT REAL(A-Z)
C
C      ESTIMATION OF THE TRANSFER FUNCTION
C      FIRST ORDER MODEL
C      REGULAR TIME QUANTIZATION
C      NOISE INTERRUPTION
C      CORRELATION ANALYSIS
C
C      FS-average frequency of PFC
C      OM-circle frequency of input signal
C      G -coefficient of PFC sensetivity
C      file 'IND.DAT'collect the output data of program
C      Q -number of periods of input signal
C      file 'F.MAT' consists the random numbers RR
C
      OPEN(3,FILE='INN.DAT')
      WRITE(*,4)
    4 FORMAT(1X,'Q=')
      READ(*,10) Q
      WRITE(*,5)
    5 FORMAT(1X,'FS=')
      READ(*,10) FS
   10 FORMAT(E10.4)
      DO 2 OM=0.1,100,0.1
      TN=0
      SR=1
      SM=0
      TI=2*3.1415/OM*Q
      H=1/SQRT(OM**2+1)
      FH=-ATAN(OM)
   40 U=SIN(OM*TN+FH)
      TE=1/FS
      TN=TN+TE
      ER=COS(OM*TN)*U*TE
      EM=SIN(OM*TN)*U*TE
      SR=SR+ER
      SM=SM-EM
      IF (TN .LT. TI) THEN
         GOTO 40
      ELSE
         SN=H*SQRT(SR**2+SM**2)/(TI)*2
         F=ATAN(SM/SR)-1.57075
         WRITE(*,45)
   45    FORMAT(9X,'SN',14X,'H',15X,'F',15X,'FH')
         WRITE(*,50) SN,H,F,FH
         OO=0
```

```
        WRITE(3,51) OM,SN,H,OO
50      FORMAT(1X,4(E15.5,2X))
51      FORMAT(1X,3(E15.5,2X),F2.1)
      END IF
   2 CONTINUE
  55 END
```

```
      PROGRAM IDNWF1
      IMPLICIT REAL (A-Z)
C
C     ESTIMATION OF THE COEFFICIENTS OF THE WEIGHTING FUNCTIONS
C     RECTANGULER INPUT SIGNAL
C     FIRST ORDER MODEL
C     PULSE FREQUENCY ANALYSIS
C     ANALITICAL DESISION FOR SYSTEM OUTPUT
C
C     DENOTIONS:
C     FS-AVERAGE FREQUENCY OF PFM,
C     OMU-FREQUENCY OF THE INPUT SIGNAL ,
C     N-NUMBER OF COEFFICIENTS OF WEIGHTING FUNCTIONS,
C     G-PFM COEFFICIENT,
C     Q-NUMBER OF THE PERIODS OF INPUT SIGNALS,
C     AR-REAL PART OF THE ESTIMATE(ARM-REAL PART TRUE VALUE OF COEFFICIE
C     AM-COMPLEX PART OF THE ESTIMATE(AMM-COMPLEX PART TRUE...),
C     AOM-ABSOLUTE VALUE OF THE ESTIMATE(MM-ABSOLUTE TRUE VALUE...)
C
      OPEN(3,FILE='IDN.DAT')
      WRITE(*,5)
    5 FORMAT(1X,'FS=')
      READ(*,10) FS
   10 FORMAT(E10.4)
      WRITE(*,15)
   15 FORMAT(1X,'OMU=')
      READ(*,10) OMU
      WRITE(*,35)
   35 FORMAT(1X,'N=')
      READ(*,10) N
      WRITE(*,36)
   36 FORMAT(1X,'G=')
      READ(*,10) G
      WRITE(*,37)
   37 FORMAT(1X,'Q=')
      READ(*,10) Q
      DO 1,K=1,N,2
      TN=0
      SR=0
      SM=0
      T=6.283/OMU
      TI=Q*T
   40 U=SIN(OMU*TN)
      IF (U.LT.0) THEN
         U=-1
      ELSE
         U=1
      END IF
```

```
      TE=1/(FS+G*U)
      TN=TN+TE
      ER=COS(OMU*K*TN)
      EM=SIN(OMU*K*TN)
      SR=SR+ER
      SM=SM-EM
      IF (TN.LT.TI) THEN
              GOTO 40
      ELSE
          SN=(SR**2+SM**2)
          R=4*Q/(1+(OMU*K)**2)
          M=4*Q/(OMU*K*(1+(OMU*K)**2))
          AR=G*(R*SR-M*SM)/SN
          AM=-G*(R*SM+M*SR)/SN
          AOM=SQRT(AR**2+AM**2)
          ARM=(1-EXP(-T))/(1+(OMU*K)**2)
          AMM=ARM*OMU*K
          MM=SQRT(ARM**2+AMM**2)
      END IF
      WRITE(*,45)
   45 FORMAT(9X,'K',14X,'AR',14X,'AM',15X,'AOM')
      WRITE(*,50) K,AR,AM,AOM
      O1=0
      WRITE(3,54) AR,AM,AOM,O1
   50 FORMAT(1X,4(E15.5,2X))
      WRITE(*,51)
   51 FORMAT(24X,'ARM',14X,'AMM',15X,'MM')
      WRITE(*,52) ARM,AMM,MM
      WRITE(3,54) ARM,AMM,MM,O1
   52 FORMAT(18X,3(E15.5,2X))
   54 FORMAT(1X,3(E15.5,2X),F2.1)
    1 CONTINUE
      END
```

```
      PROGRAM WF1N
      IMPLICIT REAL (A-Z)
C
C     ESTIMATION OF COEFFICIENTS OF WEIGHTING FUNCTIONS
C     PERIODIC INPUT SIGNAL
C     NOISE DISTURBANCE NN
C     FIRST ORDER MODEL
C     PULSE FREQUENCY ANALYSIS
C
C     DENOTIONS:
C     FS-AVERAGE VALUE OF FREQUENCY OF PFM,
C     OMU-FREQUENCY OF  THE INPUT SIGNAL OF PFM,
C     N-NUMBER OF COEFFICIENTS OF WEIGHTING FUNCTIONS,
C     G-PFM COEFFICIENT,
C     Q-NUMBER OF PERIODS OF INPUT SIGNALS (Q>11.),
C     AR-REAL PART OF THE ESTIMATE(ARM-REAL PART TRUE VALUE OF THE COEFF
C     AM-COMPLEX PART OF THE  ESTIMATE(AMM-COMPLEX PART..),
C     AOM-ABSOLUTE VALUE OF THE ESTIMATE(MM-ABSOLUTE VALUE..)
C
      OPEN(3,FILE='IDN.DAT')
      WRITE(*,5)
    5 FORMAT(1X,'FS=')
      READ(*,10) FS
   10 FORMAT(E10.4)
      WRITE(*,15)
   15 FORMAT(1X,'OMU=')
      READ(*,10) OMU
      WRITE(*,35)
   35 FORMAT(1X,'N=')
      READ(*,10) N
      WRITE(*,36)
   36 FORMAT(1X,'G=')
      READ(*,10) G
      WRITE(*,37)
   37 FORMAT(1X,'Q=')
      READ(*,10) Q
      DO 1,K=1,N,2
      TN=0
      YN=FS+.5
      SR=0
      SM=0
      SNR=0
      SNM=0
      T=6.283/OMU
      TI=Q*T
      OPEN(4,FILE='F.MAT')
   40 U=SIN(OMU*TN)
      IF (U.LT.0) THEN
         U=-1
      ELSE
         U=1
      END IF
```

```
      TE=1/(FS+G*U)
      F=OMU*K
      ER=COS(F*TN)
      EM=SIN(F*TN)
      NR=YN*EM/F
      NM=YN*ER/F
      YR1=COS(F*TE)-1
      YM1=SIN(F*TE)
      YNR=NR*YR1+NM*YM1
      YNM=-NR*YM1+NM*YR1
      READ(4,41) NN
   41 FORMAT(3X,F7.5)
      YN=YN*EXP(-TE)+1+NN/10
      TN=TN+TE
           SR=SR+ER
           SM=SM-EM
           SNR=SNR+YNR
           SNM=SNM+YNM
      IF (TN.LT.TI) THEN
                GOTO 40
      ELSE
           SN=(SR**2+SM**2)
           AR=(SR*SNR+SM*SNM)/SN
           AM=(SM*SNR-SR*SNM)/SN
           AOM=SQRT(AR**2+AM**2)
           ARM=(1-EXP(-T))/(1+(OMU*K)**2)
           AMM=ARM*OMU*K
           MM=SQRT(ARM**2+AMM**2)
      END IF
      WRITE(*,45)
   45 FORMAT(9X,'K',14X,'AR',14X,'AM',15X,'AOM')
      WRITE(*,50) K,AR,AM,AOM
   50 FORMAT(1X,4(E15.5,2X))
      O1=0
      WRITE(3,54) AR,AM,AOM,O1
      WRITE(*,51)
   51 FORMAT(24X,'ARM',14X,'AMM',15X,'MM')
      WRITE(*,52) ARM,AMM,MM
      WRITE(3,54) ARM,AMM,MM,O1
   52 FORMAT(18X,3(E15.5,2X))
   54 FORMAT(1X,3(E15.5,2X),F2.1)
      CLOSE(4,STATUS='KEEP')
    1 CONTINUE
      END
```

```
      PROGRAM RC1N
      IMPLICIT REAL (A-Z)
C
C     ESTIMATION OF COEFFICIENTS OF WEIGHTING FUNCTIONS
C     PERIODIC INPUT SIGNAL
C     NOISE DISTURBANCE
C     FIRST ORDER MODEL
C     REGULAR TIME QUANTIZATION
C
C     DENOTIONS:
C     FS-AVERAGE VALUE OF FREQUENCY OF PFM,
C     OMU-FREQUENCY OF  THE INPUT SIGNAL OF PFM,
C     N-NUMBER OF COEFFICIENTS OF WEIGHTING FUNCTIONS,
C     G-PFM COEFFICIENT,
C     Q-NUMBER OF PERIODS OF INPUT SIGNALS (Q>11.),
C     AR-REAL PART OF THE ESTIMATE(ARM-REAL PART TRUE VALUE OF THE COEFFI
C     AM-COMPLEX PART OF THE  ESTIMATE(AMM-COMPLEX PART..),
C     AOM-ABSOLUTE VALUE OF THE ESTIMATE(MM-ABSOLUTE VALUE..)
C
      OPEN(3,FILE='IDN.DAT')
      WRITE(*,5)
    5 FORMAT(1X,'FS=')
      READ(*,10) FS
   10 FORMAT(E10.4)
      WRITE(*,15)
   15 FORMAT(1X,'OMU=')
      READ(*,10) OMU
      WRITE(*,35)
   35 FORMAT(1X,'N=')
      READ(*,10) N
      WRITE(*,37)
   37 FORMAT(1X,'Q=')
      READ(*,10) Q
      DO 1,K=1,N,2
      OPEN(4,FILE='F.MAT')
      TN=0
      YN=0
      SR=0
      SM=0
      SNR=0
      SNM=0
      T=6.283/OMU
      TI=Q*T
   40 U=SIN(OMU*TN)
      IF (U.LT.0) THEN
         U=-1
      ELSE
         U=1
      END IF
```

```
      TE=1/FS
      F=OMU*K
      ER=COS(F*TN)*U*TE
      EM=SIN(F*TN)*U*TE
      NR=YN*SIN(F*TN)/F
      NM=YN*COS(F*TN)/F
      YR1=COS(F*TE)-1
      YM1=SIN(F*TE)
      YNR=NR*YR1+NM*YM1
      YNM=-NR*YM1+NM*YR1
      READ(4,41) NN
   41 FORMAT(3X,F7.5)
      YN=YN*EXP(-TE)+U*(1-EXP(-TE))+NN/10
      TN=TN+TE
          SR=SR+ER
          SM=SM-EM
          SNR=SNR+YNR
          SNM=SNM+YNM
      IF  (TN.LT.TI) THEN
              GOTO 40
      ELSE
          SN=(SR**2+SM**2)
          AR=(SR*SNR+SM*SNM)/SN
          AM=(SM*SNR-SR*SNM)/SN
          AOM=SQRT(AR**2+AM**2)
          ARM=(1-EXP(-T))/(1+(OMU*K)**2)
          AMM=ARM*OMU*K
          MM=SQRT(ARM**2+AMM**2)
      END IF
      WRITE(*,45)
   45 FORMAT(9X,'K',14X,'AR',14X,'AM',15X,'AOM')
      WRITE(*,50) K,AR,AM,AOM
   50 FORMAT(1X,4(E15.5,2X))
      O1=0
      WRITE(3,54) AR,AM,AOM,O1
      WRITE(*,51)
   51 FORMAT(24X,'ARM',14X,'AMM',15X,'MM')
      WRITE(*,52) ARM,AMM,MM
      WRITE(3,54) ARM,AMM,MM,O1
   52 FORMAT(18X,3(E15.5,2X))
   54 FORMAT(1X,3(E15.5,2X),F2.1)
      CLOSE(4,STATUS='KEEP')
    1 CONTINUE
      END
```

```
      PROGRAM WFN1
      IMPLICIT REAL (A-Z)
C
C     ESTIMATION OF COEFFICIENTS OF WEIGHTING FUNCTIONS
C     NOISE INPUT SIGNAL
C     FIRST ORDER MODEL
C     PULSE FREQUENCY ANALYSIS
C
C     DENOTIONS:
C     FS-AVERAGE VALUE OF FREQUENCY OF PFM,
C     OMU-FREQUENCY OF  THE INPUT SIGNAL OF PFM,
C     N-NUMBER OF COEFFICIENTS OF WEIGHTING FUNCTIONS,
C     G-PFM COEFFICIEN,
C     AR-REAL PART OF THE ESTIMATE(ARM-REAL PART TRUE VALUE OF THE COEFF
C     AM-COMPLEX PART OF THE  ESTIMATE(AMM-COMPLEX PART..),
C     AOM-ABSOLUTE VALUE OF THE ESTIMATE(MM-ABSOLUTE VALUE..)
C
      OPEN(3,FILE='IDN.DAT')
      WRITE(*,5)
    5 FORMAT(1X,'FS=')
      READ(*,10) FS
   10 FORMAT(E10.4)
      WRITE(*,15)
   15 FORMAT(1X,'OMU=')
      READ(*,10) OMU
      WRITE(*,35)
   35 FORMAT(1X,'N=')
      READ(*,10) N
      WRITE(*,36)
   36 FORMAT(1X,'G=')
      READ(*,10) G
      DO 1,K=1,N
      TN=0
      YN=FS+.5
      SR=0
      SM=0
      SNR=0
      SNM=0
      T=6.283/OMU
      OPEN(4,FILE='F.MAT')
   40 READ(4,41) U
   41 FORMAT(3X,F7.5)
```

```
      TE=1/(FS+G*U)
      F=OMU*K
      ER=COS(F*TN)
      EM=SIN(F*TN)
      NR=YN*EM/F
      NM=YN*ER/F
      YR1=COS(F*TE)-1
      YM1=SIN(F*TE)
      YNR=NR*YR1+NM*YM1
      YNM=-NR*YM1+NM*YR1
      YN=YN*EXP(-TE)+1
      TN=TN+TE
         SR=SR+ER
         SM=SM-EM
         SNR=SNR+YNR
         SNM=SNM+YNM
      IF  (TN.LT.T)  THEN
            GOTO 40
      ELSE
         SN=(SR**2+SM**2)
         AR=(SR*SNR+SM*SNM)/SN
         AM=(SM*SNR-SR*SNM)/SN
         AOM=SQRT(AR**2+AM**2)
         ARM=(1-EXP(-T))/(1+(OMU*K)**2)
         AMM=ARM*OMU*K
         MM=SQRT(ARM**2+AMM**2)
         RSN=SQRT(SN)
      END IF
      WRITE(*,45)
   45 FORMAT(9X,'K',14X,'RSN',14X,'AOM',15X,'MM')
      WRITE(*,50) K,RSN,AOM,MM
   50 FORMAT(1X,4(E15.5,2X))
      O1=0
      WRITE(3,54) RSN,AOM,MM,O1
   54 FORMAT(1X,3(E15.5,2X),F2.1)
      CLOSE(4,STATUS='KEEP')
    1 CONTINUE
      END
```

```
      PROGRAM RC2N
      IMPLICIT REAL (A-Z)
C
C     ESTIMATION OF COEFFICIENTS OF WEIGHTING FUNCTIONS
C     NOISE INPUT SIGNAL
C     FIRST ORDER MODEL
C     REGULAR TIME QUANTIZATION
C
C     DENOTIONS:
C     FS-AVERAGE VALUE OF FREQUENCY OF PFM,
C     OMU-FREQUENCY OF  THE INPUT SIGNAL OF PFM,
C     N-NUMBER OF COEFFICIENTS OF WEIGHTING FUNCTIONS,
C     G-PFM COEFFICIENT,
C     Q-NUMBER OF PERIODS OF INPUT SIGNALS (Q>11.),
C     AR-REAL PART OF THE ESTIMATE(ARM-REAL PART TRUE VALUE OF THE COEFFI
C     AM-COMPLEX PART OF THE  ESTIMATE(AMM-COMPLEX PART..),
C     AOM-ABSOLUTE VALUE OF THE ESTIMATE(MM-ABSOLUTE VALUE..)
C
      OPEN(3,FILE='IDN.DAT')
      WRITE(*,5)
    5 FORMAT(1X,'FS=')
      READ(*,10) FS
   10 FORMAT(E10.4)
      WRITE(*,15)
   15 FORMAT(1X,'OMU=')
      READ(*,10) OMU
      WRITE(*,35)
   35 FORMAT(1X,'N=')
      READ(*,10) N
      DO 1,K=1,N
      OPEN(4,FILE='F.MAT')
      TN=0
      YN=0
      SR=0
      SM=0
      SNR=0
      SNM=0
      T=6.283/OMU
   40 READ(4,41) U
```

```
      TE=1/FS
      F=OMU*K
      ER=COS(F*TN)*U*TE
      EM=SIN(F*TN)*U*TE
      NR=YN*SIN(F*TN)/F
      NM=YN*COS(F*TN)/F
      YR1=COS(F*TE)-1
      YM1=SIN(F*TE)
      YNR=NR*YR1+NM*YM1
      YNM=-NR*YM1+NM*YR1
   41 FORMAT(3X,F7.5)
      YN=YN*EXP(-TE)+U*(1-EXP(-TE))
      TN=TN+TE
           SR=SR+ER
           SM=SM-EM
           SNR=SNR+YNR
           SNM=SNM+YNM
      IF (TN.LT.T) THEN
                GOTO 40
      ELSE
           SN=(SR**2+SM**2)
           AR=(SR*SNR+SM*SNM)/SN
           AM=(SM*SNR-SR*SNM)/SN
           AOM=SQRT(AR**2+AM**2)
           ARM=(1-EXP(-T))/(1+(OMU*K)**2)
           AMM=ARM*OMU*K
           MM=SQRT(ARM**2+AMM**2)
      END IF
      WRITE(*,45)
   45 FORMAT(9X,'K',14X,'AR',14X,'AM',15X,'AOM')
      WRITE(*,50) K,AR,AM,AOM
   50 FORMAT(1X,4(E15.5,2X))
      O1=0
      WRITE(3,54) AR,AM,AOM,O1
      WRITE(*,51)
   51 FORMAT(24X,'ARM',14X,'AMM',15X,'MM')
      WRITE(*,52) ARM,AMM,MM
      WRITE(3,54) ARM,AMM,MM,O1
   52 FORMAT(18X,3(E15.5,2X))
   54 FORMAT(1X,3(E15.5,2X),F2.1)
      CLOSE(4,STATUS='KEEP')
    1 CONTINUE
      END
```

```
      PROGRAM IDNWF3
      IMPLICIT REAL (A-Z)
C
C     ESTIMATION OF COEFFICIENTS OF WEIGHTING FUNCTIONS
C     PERIODIC INPUT SIGNAL
C     FIRST ORDER MODEL
C     PULSE FREQUENCY ANALYSIS
C     PFC1-INPUT
C     PFC2-OUTPUT
C     ONLY PFM OBSERVATION
C
C     DENOTIONS:
C     FS-AVERAGE VALUE OF FREQUENCY OF PFM,
C     OMU-FREQUENCY OF  THE INPUT SIGNAL OF PFM,
C     N-NUMBER OF COEFFICIENTS OF WEIGHTING FUNCTIONS,
C     G-PFM COEFFICIENT,
C     Q-NUMBER OF PERIODS OF INPUT SIGNALS (Q>11.),
C     AR-REAL PART OF THE ESTIMATE(ARM-REAL PART TRUE VALUE OF THE COEFF
C     AM-COMPLEX PART OF THE  ESTIMATE(AMM-COMPLEX PART..),
C     AOM-ABSOLUTE VALUE OF THE ESTIMATE(MM-ABSOLUTE VALUE..)
C
      OPEN(3,FILE='IDN.DAT')
      WRITE(*,5)
    5 FORMAT(1X,'FS=')
      READ(*,10) FS
   10 FORMAT(E10.4)
      WRITE(*,15)
   15 FORMAT(1X,'OMU=')
      READ(*,10) OMU
      WRITE(*,35)
   35 FORMAT(1X,'N=')
      READ(*,10) N
      WRITE(*,36)
   36 FORMAT(1X,'G=')
      READ(*,10) G
      WRITE(*,37)
   37 FORMAT(1X,'Q=')
      READ(*,10) Q
      DO 1,K=1,N,2
      TN=0
      TN2=0
      YN=-1.
      SR=0
      SM=0
      SNR=0
      SNM=0
      TE=0.
      T=6.283/OMU
      TI=Q*T
   40 U=SIN(OMU*TN)
      YN=YN*EXP(-TE)
      IF (U.LT.0) THEN
         U=-1.
         YN=YN-(1-EXP(-TE))
      ELSE
         U=1.
         YN=YN+(1-EXP(-TE))
      END IF
```

```
      TE=1/(FS+G*U)
      ER=COS(OMU*K*TN)
      EM=SIN(OMU*K*TN)
      TE2=1/(FS+G*YN)
      YNR=COS(OMU*K*TN2)
      YNM=SIN(OMU*K*TN2)
      TN2=TN2+TE2
      TN=TN+TE
           SR=SR+ER
           SM=SM-EM
           SNR=SNR+YNR
           SNM=SNM-YNM
      IF (TN.LT.TI) THEN
                GOTO 40
      ELSE
           SN=(SR**2+SM**2)
           AR=(SR*SNR+SM*SNM)/SN
           AM=(SM*SNR-SR*SNM)/SN
           AOM=SQRT(AR**2+AM**2)
           ARM=(1-EXP(-T))/(1+(OMU*K)**2)
           AMM=ARM*OMU*K
           MM=SQRT(ARM**2+AMM**2)
      END IF
      WRITE(*,45)
   45 FORMAT(9X,'K',14X,'AR',14X,'AM',15X,'AOM')
      WRITE(*,50) K,AR,AM,AOM
   50 FORMAT(1X,4(E15.5,2X))
      O1=0
      WRITE(3,54) AR,AM,AOM,O1
      WRITE(*,51)
   51 FORMAT(24X,'ARM',14X,'AMM',15X,'MM')
      WRITE(*,52) ARM,AMM,MM
      WRITE(3,54) ARM,AMM,MM,O1
   52 FORMAT(18X,3(E15.5,2X))
   54 FORMAT(1X,3(E15.5,2X),F2.1)
    1 CONTINUE
      END
```

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