объединенный
институт
ядерных
исследований
дубна

E10-94-14

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COMPARISON OF THE NOISE DIAGNOSTICS SYSTEMS BASED ON THE PATTERN RECOGNITION AND DISCRIMINANT METHODS*

Submitted to «Annals of Nuclear Energy»

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*The work has partially been supported by Polish Grant KBN 8.S503.024.05

1994

Дзвинель В. и др. E10-94-14

Сравнение систем шумовой диагностики, основанных на методах распознавания образов и методе дискриминант

Сравниваются системы шумовой диагностики ядерных реакторов, основанные на методах распознавания образов и методе дискриминант. В качестве конкретного примера взяты системы анализа шумов реактора ИБР-2 (Дубна, Россия, кластерный анализ) и реакторов типа ВВЭР-440 (Ржеж, Чехия, алгоритм Пити). Анализируются чувствительность и достоверность распознавания различного рода искусственно вводимых возмущений мощности.

Работа выполнена в Лаборатории нейтронной физики им. И.М.Франка ОИЯИ.

Препринт Объединенного института ядерных исследований. Дубна, 1994

Dzwinel W. et al. E10-94-14

Comparison of the Noise Diagnostics Systems Based on the Pattern Recognition and Discriminant Methods

To clarify the features of two different reactor surveillance systems — the JINR Dubna system based on the cluster method, and the NRI Rez system, based on the Piety algorithm — the evaluation of artificial noise was carried out. After analysis of results of both sides finer differences are discussed.

The investigation has been performed at the Frank Laboratory of Neutron Physics, JINR.

Preprint of the Joint Institute for Nuclear Research. Dubna, 1994

1. Introduction

There are various surveillance methods used in working nuclear reactors which are based on the analysis of the reactor noise. These system projects lack the pure information about advantages of systems based on other surveillance principles. The task of this paper is to clarify the features of two different reactor surveillance systems – the JINR system, based on the cluster method of pattern recognition (KMPR) [1,2,3,4,5], and the NRI system, based on the Piety algorithm [6,7] (SAM). The principle of the comparison was as follows:

- both institutes should prepare test signals for the other one in such a way that test signals should contain unknown disturbances superimposed onto real reactor signals;
- the obtained test signals should be passed over to the other side for evaluation;
- the processed results should be discussed and published.

2.The data generation

The test data, as settled, has taken following formal form:

- reactor neutron flux was used as the base signal;
- the way of superimposing the signal can be arbitrary, even statistical zero;
- introduced signal disturbance could be arbitrary, but the same in the four successive data files;
- data must have the form of 154 binary MS-DOS [11] data files, every file with minimum 1024 time samples;
- every disturbance will cover 4 data files and 26 disturbances will be generated;
- 50 files without disturbance will be used as data base.

2.1. The JINR data

Following types of test signal sets of IBR-2 (Fast Pulsed Reactor: peak power = 1600 MW, pulses frequency = 5 1/s, pulse duration = 215 μs), were used:

- power noise data in various reactor conditions (see Table 1, No.16-18);
- power noise data with known periodical disturbances (see Table 1, No.19-22), which were introduced by computer controlled amplitude and frequency of the control rod movements with a small effectiveness;
- power noise data with artificial disturbance in the form of white noise, harmonic disturbance and exponential filter (Table 1).

The artificial disturbances were introduced according to the formula:

$$Q(t) = \mathbf{q} + q(t) * H_f + A' \cdot (1 + ran_1) \cdot \sin(2\pi f t) + B' \cdot ran_2, \qquad (1)$$

where

q(t), **q** = noise and mean value of neutron power; ran_1 , ran_2 = random quantities with uniform distribution in the ranges [-0.1,0.1] and [-1,1];
$A' = \mathbf{A} \cdot \mathbf{q}/\beta, \quad B' = \mathbf{B} \cdot \mathbf{q} \cdot \sqrt{12}/\beta$;
A = amplitude of harmonic disturbance;
B = standard deviation of white noise;
β = part of delated neutrons;
H_f = impulse response of exponential filter;
$*$ = convolution.

(Comment: With a small power change, the A and B values are equal to absolute change of reactivity in the units of ΔK/K.) Some characteristics of the disturbances are presented in Table 1. An example of the data spectrum is shown on Figure 1.

2.2. The NRI data

For data generation the AR-model of 50th order was used:

$$y_n = \sum_{i=1}^{50} a_i y^{n-i} + u_n,$$

where

a = AR-coefficients,
u_n = white noise.

This model was created as a result of the analysis of ex-core ionization chamber signal of the reactor of WWER-440 type at 100% power. Applying this approach implies greater flexibility because the signal generation was practically the filtration of white noise by a filter with transfer function the AR-model used. The white noise was generated by a random number generator [8]. The generated signal was then modified in the two frequency regions, typical for the reactor of WWER-440 type: at about 8.5 Hz and 25 Hz. The most changes were in the amplitude and frequency of the signal in this regions. In some cases the spectrum shape or standard deviation were changed, too (see Table 1). Example of the generated signal is on Fig.1.

2.3. The JINR extra data

While in general the power fluctuations of the IBR-2 reactor can be different from the data for the analysis proposed, the real spectra of the IBR-2 reactor were additionally used by the JINR side:

general number of spectra ... 82;
analysed time interval ... 2 years;
all spectra correspond to the normal reactor operation.

This work demonstrates the power of a determination of the spectra groups with quite different characteristics modelling thus real situation when it is necessary to determine different reactor operation states.

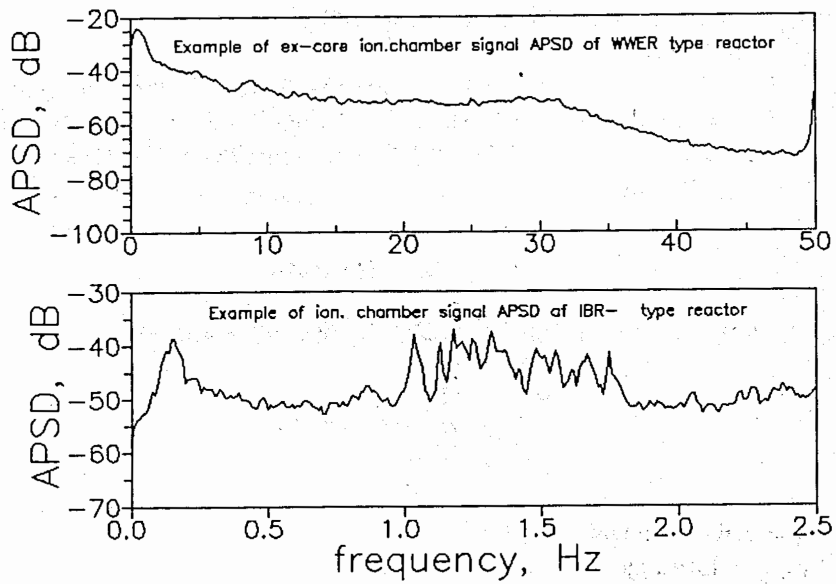

Fig.1: Example of generated signal

Table 1: The description of the modified signals

Disturb. No.	IBR - 2			WWER		
	A, 10^{-6}	B, 10^{-6}	f,Hz	amplit., dB	f, Hz	
0	0	5	0		8.69	25
1	1.5	5	2	-1	8.69	
2	1.5	5	2.05	+1	8.69	25
3	1.5	5	1.95			24
4	1.5	5	1.48		8.44	
5	1.5	5	0.9			25.5
6	2.0	5	0.9			
7	2.5	5	0.9			
8	3.0	5	0.9		9.69	
9	1.5	5	0.2			25.25
10	2.0	5	0.2		8.191	
11	3	5	0.2		7.69	
12	0	10	0			24.75
13	0	7.5	0			
14	2	5	1.3			26
15	3	5	1.3	+0.49	8.69	
16	data No.1				8.69	
17	data No.2			-0.5	8.69	25
18	data No.3				white noise	
19	6	exper. No.1	0.19			24.5
20	8	exper. No.2	0.061		8.94	
21	4	exper. No.3	0.81			
22	2	exper. No.4	0.81		white noise	
23	0	5	0		white noise	
24	0	20	0			
25	filter	5	0			
26	filter	10	0			

3. Short description of the surveillance methods used

3.1. The cluster method of pattern recognition - KMPR

A hierarchical algorithm of the cluster analysis MNN [9] was used for the pattern recognition. According to MNN, the i–th spectrum with n lines is considered as vector $\mathbf{X}_i$ of the n–th range, i.e. as one point in the n–dimensional Euclidean space. For every vector $\mathbf{X}_i$ in the Euclidean space R {dim (R) = n; $\mathbf{X}_i = (x_{i1}, x_{i2}, \ldots x_{in})$; i = 1,N; N = No. of vectors} there are two different distances determined.

The first: $S_{ij} = (X_i - X_j)^T(X_i - X_j)$ – the classical Euclidean distance.

The second: $mnv_{ij} = L_i(j) + L_j(i)$,

where $L_i(j)$ describes the place of the point X_j in the list of k_i neighbours of the point X_j, and is chosen according to distance S_{im}, where m =No. of neighbouring point and it is determined from the condition $S_{im} \leq R_{CUT}$. If the k_i of the closest neighbours, satisfying the condition, is different for every i–th point, the maximal mnv–distance is less or equal to

$mnv_{max} = \max_i(k_i) + \max_i(k_i - \max_i(k_i))$.

It means: $\forall i,j : 2 \leq mnv_{ij} \leq mnv_{max}$. That is in the MNN method the determining classification factor is the value of R_{CUT}. While the numerical characteristics of clusters, which evaluate the changes of difficult hyperstructures, give not always objective information about the process surveyd, an algorithm was developed for the transformation from n-D to 2-D or 3-D space. To do this, the method was used, as being the expansion of Neumann's conception [10]: If R is the Euclidean space with the dimension of n, i.e. $dim(R) = n, n' < n$ and the point in n-D space is described as $X_i = (x_{i1}, x_{i2}, \ldots x_{in})$; i = 1,N; N = No. of points, then for the conservation of the similarity of cluster structure $R_0 = \{x1; i = 1, N\}$(especially of the distance between the points x_{ij}) with the transform to the space of less dimensionality, according to [8] the following condition must be satisfied:

$$E(R, R_0') = minE(R, R'),$$

where

$$E(R, R') = \sum_{k<j}(S_{jk} - S'_{jk})^2 / \sum_{k<j} S_{jk}, \quad \sum = \sum_{j=2}^{N}\sum_{k=1}^{j-1}$$

and S_{jk}, S'_{jk} — the distances between j and k points in R and R' spaces.

3.2. The Piety method — SAM

NRI uses for surveillance of reactor and primary circuit Piety's algorithm [6] in own realization (System for Automative Monitoring - SAM) [7] for WWER type reactors. This algorithm is based on the simple mathematical operations over the quotient of two power spectral densities, one of which describes normal and the other current state of reactor. As a measure of reactor status, eight discriminants were selected. After computation, values of these discriminants are monitored. The limits are computed from the presumption about the character of input signal from given confidential intervals. The monitoring process has two phases: In the so called learning phase there are computed reference power spectral densities and limits for every operational state and every signal. Then in the monitoring phase values of the discriminants are monitored. The NRI realization of Piety's algorithm has the possibility of monitoring only some of the eight discriminants and of monitoring in 5 frequency ranges. The windowing, overlapping and averaging of spectra are arbitrary. The maximum number of monitored signals and sampling frequency depend on the type and number of A/D-converters.

4. The main results from identification of disturbances

4.1.1. The JINR results

The general scheme of analysis was as follows:

1. The formalized procedure of cluster analysis was performed over the whole massive of spectra, including the base spectra. The initial space dimensionality was 256.

2. The most informative frequencies were established by the entropy method.

3. The clusterization operation was repeated in regions of spectra with maximum information. The found disturbances were differentiated by the frequency symptoms.

4. Spectral analysis was carried out. Distinctive symptoms of disturbances were found.

As the formal symptom of data analysis correctness for point 1 the following condition was chosen: The number of clusters must not be greater than the number of allowed disturbances (< 26) plus one base data. Besides, all the spectra with one disturbance type must belong to the same cluster.

4.1.2. Identification of disturbed spectra of WWER-type reactor by the JINR method

It can be seen from Fig.2 that the cluster number change depends on the spectrum number of the input data. The distribution of the first eight clusters, concentrated from 256-D to 2-D space is presented on Fig. 3. Fig.4 shows projection of all the found clusters onto the two planes of 3-D space.

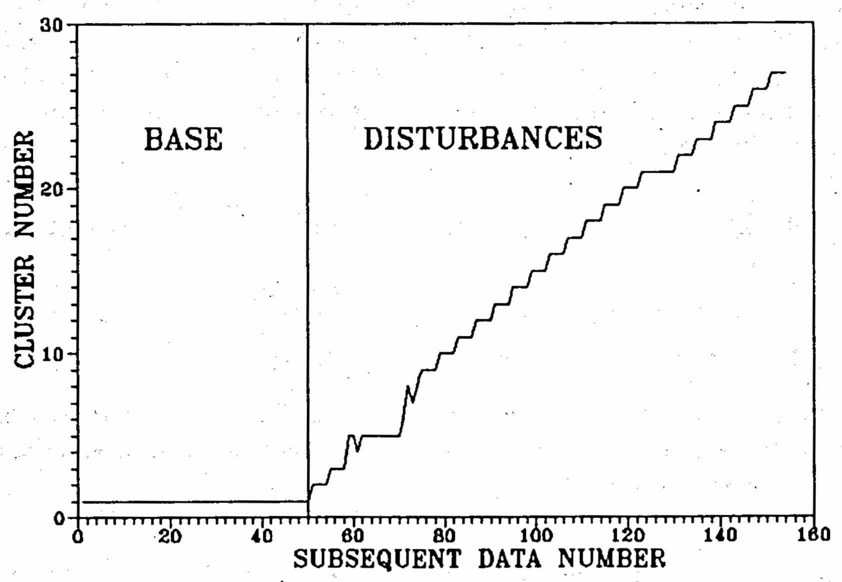

Fig.2: The change of the actual cluster number with subsequent spectrum number. Classification of 154 spectra within the full frequency range (256 coordinates)

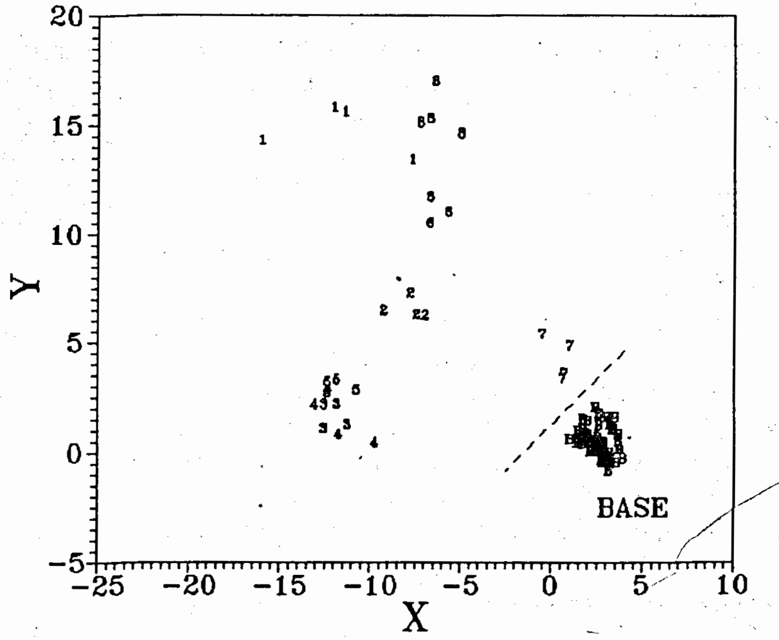

Fig.3: Example of the WWER type reactor power disturbance spectra distribution in the 2-D view

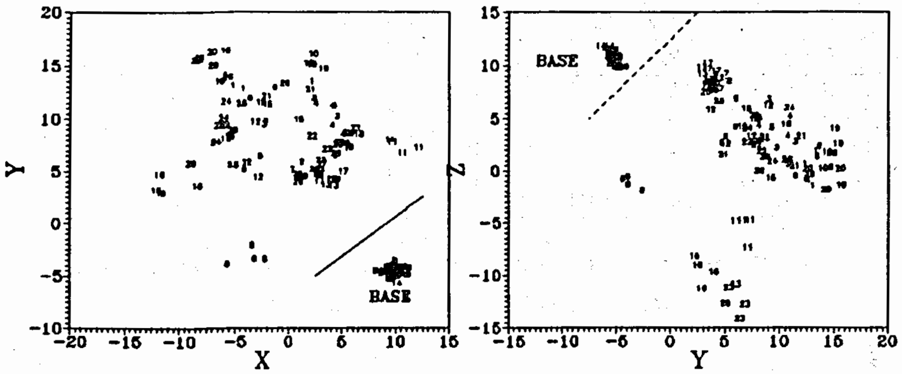

Fig.4: Projection of the all 154 WWER type reactor power disturbances spectra from 3-D view

It can be noted here that a great number of clusters (> 10) are not typical for the reactor diagnostics, because it is enough to analyse only the current state and a small number of predecessors (actual states). That is why the real situation is more easily overlooked as in this situation. According to the result of point 1 (see for example Fig.2) disturbances No. 3,4,5 and No. 19,20 are in two clusters and disturbance No. 6 was divided into three clusters. The case of the connection of the three disturbances in one cluster can be the following:

-Statistically identical disturbances;

-Disturbances lower than the level of the statistical noise;

-Disturbances lower than the sensitivity level of the system.

With the help of formalized analysis procedures applied to the system there were the regions of the most informative frequencies found (see Table 2). Disturbances No. 19 and 20 are **distinguished** in the frequency regions, which corresponds to the reality (see Table 1). Disturbances No. 3, 4, 5 are distinguished in frequency region No.4. But the observed differences are small and are on the limit of statistical significance.

Table 2: The regions with the most informative frequencies of spectra of WWER type reactor found by the entropy method

No.	frequency range, Hz	f,Hz
1	2.1 - 3.1	
2	4.1 - 5.7	
3	7.2 - 9.2	8.5
4	11.2 - 12.2	11.9
5	12.9 - 13.9	13.8
6	16.0 - 16.8	
7	18.2 - 21.1	
8	25.1 - 25.7	25.2
9	28.9 - 31.2	

Comment: Frequency **f** in the table marks the peaks, usually seen in the spectra of WWER-type reactors

4.1.3 Identification of disturbed spectra of IBR-2 reactor by the JINR method

The analysis scheme was the same as in the case of WWER-type reactor data. After the 1st analysis procedure there were 85% of disturbances found. Only the 1st small disturbance ($A = 1.5 \cdot 10^{-6} \Delta K/K$) with the base data and three disturbances with their neighbours joined the same cluster. As the most informative frequencies all the frequencies introduced into the signal were found (see Table 1). Some results of the analysis are on Fig. 5. By the procedure of clusterization of the normalized spectra

$$X = (X_i - X)/\sigma_i^2,$$

where i is the number of frequency interval, i = 1, 256, and X,σ_i = the mean value of X_i and standard deviation from the N spectra in the i–th frequency range, it was then easy to identify all the disturbances with the additional introduced peaks (0.2, 0.9, 1.48, 1.95 2.00, 2.05 Hz), i.e. all the introduced disturbances were found and identified.

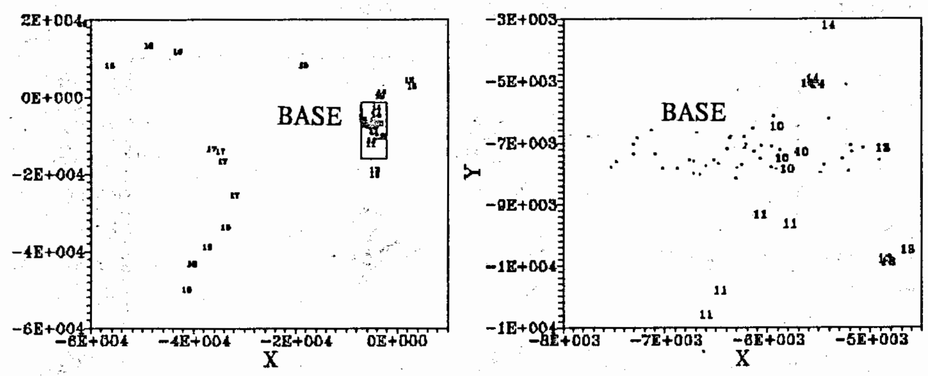

Fig.5: Distribution of the IBR - 2 reactor power disturbances in the 2-D view. The low intensity disturbances in the small box in the left part are in detail presented on the right

4.1.4 Identification of real spectra of IBR-2 reactor by the JINR method

This analysis is an example of the operational diagnostics procedure at the IBR-2 reactor. The current spectrum enters the data base and the analysis is performed over all the spectra or over some portion of the last – "actual" – spectra. The number of actual spectra depends on the history of the operation. The past spectra are forgotten, but they can be used for the analysis of slow trends. In this case all the spectra were analysed (82). Because the form of the spectra and their change in time are very complex on the IBR-2 reactor, there is analysis of any invariant to the noise change symptoms as the only way for finding anomaly states,for example the spectrum form ($X = X/\sigma^2$, X – input spectrum, σ^2 - variance) that was used in the current case. The distribution of spectra over the clusters in the 3-D space can be seen on Fig.6 . As seen from Fig.6, even in the 3-D space the six found clusters are well different. Note that with operational analysis the result can be optimal by the use of only the formalized procedures and that there is no necessity to use any data base.

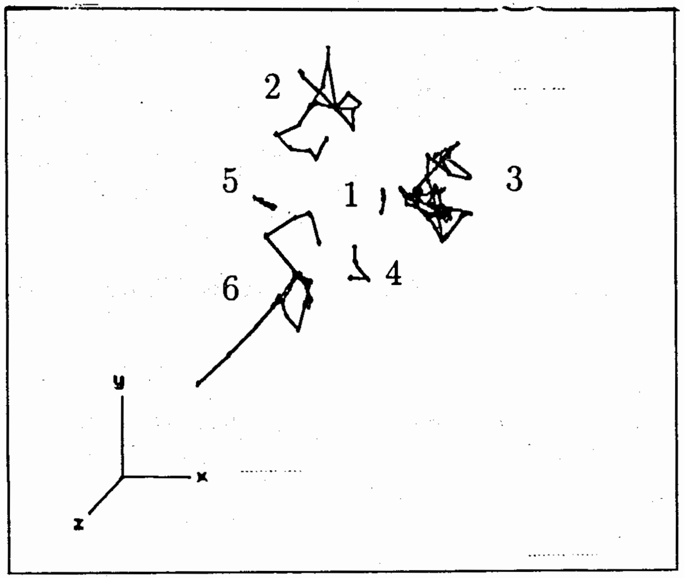

Fig.6: Spectra distribution of the real IBR-2 reactor power fluctuations in the 3-D view. The clusters are specified by numbers

4.2. The NRI results

The data analysis was performed in the iterative way: First, the system worked with the general parameters:
-confidential intervals were chosen for a probability of 0.1%;
-one frequency range, covering the whole frequency range, was used;
-all discriminants were switched on.
The results corrections were made after the first round analysis. Because the data character was very dissimilar and the number of data with one disturbance was limited, the averaging of spectral densities could not be optimal and the only way to do the analysis was to broaden the confidential intervals. Five frequency intervals for monitoring were chosen in the case of JINR data and three in the case of NRI data. All discriminants were constantly switched on.

5. Discussion of results

5.1. JINR side

The KMPR method is reliable in finding any disturbance type, i.e. either harmonic or white noise, if their amplitudes are greater than about $2 \cdot 10^{-6}$ (1dB) or the frequency shift is greater than 0.05-0.25 Hz. The amplitudes correspond to the reactivity change of about the same value. This is valid for the stable spectra form of WWER reactor type as well as for the more complex and unstable spectra of IBR-2 reactor type. The analysis of results shows also that the presence of reference data base is not necessary in the case of the KMPR method in contrast to the SAM method. Besides, the KMPR method allows one to see the results of analysis of all the data, i.e. gives a means for the monitoring of the operation of the reactor in time.

5.2. NRI side

Based on the analysis of results, the following features of both algorithms can be found:

1. The SAM algorithm has, in this case, sensitivity to the frequency shifts of about 0.5 Hz and to the amplitude shifts of about 1 dB. This feature is determined by the limited amount of data (4 files with 10240 samples);

2. The KMPR algorithm

   (a) has small sensitivity to the narrow peaks changes;

   (b) in some cases (e.g. normal state followed by anomalous one and then again by normal one) does not determine that the identified change has practically returned the state to a normal one and marks it as a new cluster (i.e. new state).

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Received by Publishing Department
on January 19, 1994.