ARCHIVES OF ACOUSTICS
5, 2, 125-142 (1980)

LONG-TIME SPECTRA OF RADIO BROADCAST PROGRAMME SIGNALS*

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Long-time spectra of signals of different radio broadcast programmes have been measured using the method of sample superposition (superposing signals of statistically independent sections of programme signals, recorded on tape, interpreted by ensembles with instruments of similar character). Spectra of signals of different ensemble groups (set of ensembles of equal composition of interpreters), having equal probabilities of occurrences, are calculated. Using programme policy statistics of three different transmitted programmes, the probabilities of occurrence of different ensemble classes (sets of ensembles, composed according to a rule) are calculated. Using these probabilities, the long-time-weighted spectra of the signals of three different radio programmes and the averages of these spectra are computed. The values are only slightly dependent on programme policy. A definition of the spectrally equivalent programme signal and a network for forming it are given.

Introduction

The original aim of this work was to collect data published in the literature in order to construct a network with the aid of which it would be possible to simulate adequately the spectral properties of a long-time-average radio broadcast programme signal. Collecting the data, we found that there exists a considerable amount of information concerning speech sounds, see e.g. [1]-[8], and also concerning musical sounds, see e.g. [2], [9], [10]-[17], but the data are insufficient for defining an artificial signal which has a power spectral density similar to that of a long-time-averaged broadcast programme signal. We have therefore conducted some work to obtain new data. This paper gives only a brief introduction to the problem and some of the results achieved; a more comprehensive review will appear elsewhere.

* Presented March 02. 1976, at the 53rd Convention of the Audio Engineering Society, Zurich, Switzerland.

The understanding of long-time-averaged spectra

It is evident that short-time statistical properties of the programme signal depend mainly on two things:

(a) The kind of signal that is transmitted at the moment of the measurement (e.g. speech or different music pieces etc.).

(b) The kind of interpreters that are working together during the performance (e.g. soloists with their given instruments or a symphonic orchestra, etc.); more shortly: what is being played by whom. Therefore if meaningful results of the short-time-statistical properties of the programme signal are to be obtained, knowledge of this data is also needed.

In the case of the long-time-spectra of the programme signals there is an additional problem: it is clear that these depend more or less on the programme policy of the broadcasting institution: a transmitted programme consisting of serious music and another consisting of popular music, must have very clearly different spectral properties. Thus if we need a realistic picture of the long-time spectral properties of an "average" radio broadcast programme containing mixed programme items, measurements must be made over a time interval long enough to ensure that different typical kinds of signals, generated by different, typical kinds of interpreters occur with typical frequencies.

It is not difficult to see that it is practically impossible to make such measurements because the time interval needed would be too long. We have therefore chosen another way. Namely that if the spectral properties of typical kinds of signals generated by typical kinds of interpreters are known, and if the probabilities of occurrence of these signals over a long enough time are known then we can calculate the long-time-spectral properties of the programme signal. In other words: it is necessary to have an average over the programme signals generated by sound sources of typical interpreters interpreting typical kinds of programme items, weighted by the probabilities of occurrences of these interpretations. This has been done in three steps as follows.

The theoretical background of the method

In order to obtain meaningful results some general assumptions have been made for the signals measured [18]:

(a) The programme signals belonging to different programme items are sample functions of separable, weakly stationary stochastic processes having expected values equal to zero.

(b) These stochastic processes are completely independent and their power spectral density functions exist.

(c) These stochastic processes satisfy all the assumptions necessary to permit ergodicity of almost all of their first and second-order statistical properties, to be assumed.

(d) The duration of measurements of the sample functions is long enough to have a small statistical error but short enough to secure stationarity in the weak sense. (For probabilistic concepts see e.g. [19].) We assume that the programme signals considered fulfil all of these requirements.

We should emphasize that according to these assumptions we are considering the programme signal measurable over a long time, as a linear sum of sample functions of different stochastic processes, stationary in the weak sense and ergodic in their first and second-order properties. This means that we give, for example, to the speech waves of the different speakers, different sample functions, and these sample functions belong to different stochastic processes. The procedure used is the same for music, also. This point of view has a significance of a fundamental character and differs clearly from that used tacitly in the literature where for example speech, as a whole, has been considered as one stochastic process and the speech waves of individual speakers as sample functions of this process.

As a consequence of these assumptions it can be shown [18] that the sum of sample functions of equal length has the same first and second-order statistical properties (expected values, autocorrelation functions, powers, power spectral distributions) as a sample of a signal whose consecutive parts are the said sample functions added. This signal is then no other than the real programme signal having a total length that of the summands. Thus it does not matter whether the summing is performed mathematically or physically, by which we mean the simultaneous observation — measurement — of a set of sample functions of equal duration, belonging to different stochastic processes, i.e. belonging to different parts of programme signals of different programme items of equal length.

It is clear that each sample function has been generated by an ensemble, i.e. the nonempty set of interpreters coworking in generating the programme signal, corresponding to a given programme item. Consequently, each ensemble — which can be a single speaker or a large symphonic orchestra — has its typical sound generating instruments. These instruments are by no means identical but are similar in their sound generating properties as ensembles with the same composition of interpreters. We have thus defined an ensemble group as the set of ensembles having a nominally equal composition of interpreters. This "equality" cannot be seen too strictly: each symphonic orchestra is to be regarded belonging to the same ensemble group, in spite of a different composition in practice. If we now choose, for each ensemble of an ensemble group, different but typical programme material to be interpreted by their sound generating mechanisms, then the statistical properties of the simultaneously observed sample functions will be typical for the group.

Using this train of thought we can achieve data for each of the different ensemble groups. Now let us construct an upper level: we define a nonempty set of different ensemble groups as an ensemble class where the composition of the class follows a rule. This rule cannot be similar to those of the groups; it is better if we define it more or less according to the programme statistics available. The concept, shown by Table I, seems to be self explanatory. The statistical properties of a given ensemble class can be now calculated using the above mentioned assumptions simply by adding the sample functions. It should be noted that additivity is valid only for the expected values, the autocorrelation functions and the spectral properties but by no means for, for example, the long-time-averaged peak factor of the programme signal, which can be only measured. Although there is a possibility of estimating the least upper limit.

Thereafter if we have the statistics of the occurrence of different items in the programme transmitted, characterising the programme policy of the broadcast institution, we can calculate the weighted averages of the data of each ensemble classe, where the weights are the probabilities of occurrence of each ensemble classe in the statistics, collected over a long enough time interval.

It should be mentioned that the simultaneous observation i.e. the measurement of a set of superposed sample functions using sounds from different speakers was originated intuitively by TARNÓCZY [6]. Probably because of the lack of a sufficient theoretical basis he was of the opinion that this method, called by him the "speech chorus method", can only be used for speech sounds [11]. It is however clear that it is by no means necessary to restrict this ingenious method, which may perhaps better be called the "method of sample superposition", to speech sounds alone.

Method of measurement

In order to produce the superposed samples, i.e. to construct the programme signal of an ensemble group, we have chosen, for each group, six different two-minute long samples of typical programme items recorded on studio tapes. These six samples were subsequently simultaneously copied onto a single tape, using six studio tape recorders and a studio mixing desk, as shown in Fig. 1*a*.

This sixfold record has been cut into four equal parts. After simultaneous copying of these parts the record contained the superposition of 24 samples of practically independent programme signals. This record of $T = 30$ s duration was regarded as the programme signal of the ensemble group considered. A value of $T = 30$ s was chosen for the length because musical phrases have approximately this length or less. The sound generated by this record is like a noise; it is not possible to hear any kind of melody.

The spectral properties of this record have been analysed for rms and peak power using setup shown in Fig. 1*b*, first over the whole audio frequency range

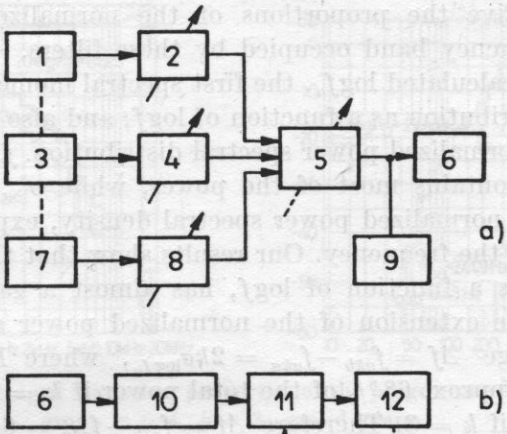

Fig. 1. a. Arrangement used for reconstructing the programme signal of an ensemble group.
b. Arrangement used for measuring the programme signal of an ensemble group
1 – 1st tape recorder STM 200/b, *2* – 1st line amplifier, *3* – kth tape recorder STM 200/b, *4* – kth line amplifier *5* – summing amplifier, *6* – tape recorder STM/b (in a)) or STM 10 (in b)), *7* – 6th tape recorder STM 200/b, *8* – 6th line amplifier, *9* – programme level meter, *10* – input transformator B-Kj Tl 0001, *11* – 1/3 oct. filter B-Kj 2112, *12* – level recorder B-Kj 2305

and thereafter in 26 different 1/3 octave bands, beginning at 50 Hz. The level recorder has been used as an integrating instrument, with a 50 dB potentiometer using 50 dB potentiometer-range, and a 20 Hz lower limiting frequency setting. The writing speed was 2 mm/s. These settings corresponded to an effective averaging time of approx. 12 s [20].

Evaluation of the results

The results of the measurements have been evaluated as level differences referred to the long-time averaged rms voltage level of the unfiltered signal. The level of this has been chosen as the 0 dB reference level. In each case we have calculated $20 \log \bar{K}_p = \bar{L}_p - \bar{L}_e$, where $\bar{K}$ is the long-time-averaged peak factor and $\bar{L}_p$ is the long-time-averaged peak voltage level referred to $\bar{L}_e = 0$ dB. Then, using the measured results, we have evaluated the values of $\bar{L}_e(f_m)$, $\bar{L}_p(f_m)$ and $20 \log \bar{K}_p(f_m)$ where $f_m (m = 1, 2, \ldots, 26)$ are the mid-band frequencies of the 1/3 octave filters, beginning at $f_1 = 50$ Hz.

Using these data we have calculated the values $10 \log N_l[h(f_{ln})]$ and $10 \log N_h[n(f_{hn})]$. The former is essentially $N_l[n(f_{ln})]$ the normalized power spectral distribution, expressed in dB, as a function of the frequency $f_{ln} (n = 1, 2, \ldots, 26)$. The latter is then $10 \log \{1 - N_l[n(f_{ln})]\}$, also expressed in dB, as a function of the frequency $f_{hn} (n = 1, 2, \ldots, 26)$. Identifying f_{ln} and f_{hn} as the last and first mid-band frequencies respectively of a low pass or high pass filter, composed of 1/3 filters with ideal cut-off, $10 \log N_l[n(f_{ln})]$, and

$10 \log N_h[n(f_{hn})]$ give the proportions of the normalized power, expressed in dB, in the frequency band occupied by these filters.

We have also calculated $\log f_a$, the first spectral moment of the normalized power spectral distribution as a function of $\log f$, and also $\sigma^2_{\log f_a}$, the variance, belonging to this normalized power spectral distribution. f_a gives the frequency whose neighbour contains most of the power, while $\sigma^2_{\log f_a}$ characterizes the "peakiness" of the normalized power spectral density, expressed as a function of the logarithm of the frequency. Our results show that the normalized power spectral density, as a function of $\log f$, has almost a gaussian shape. Using this assumption the extension of the normalized power spectral density, i.e. the frequency range $\Delta f = f_{akb} - f_{aka} = 2k\sigma_{\log f_a}$, where k is a nonnegative number, contains approx. 68 % of the total power if $k = 1$, and approx. 99 % of the total power if $k = 3$. Therefore $\Delta f = f_{a3b} - f_{a3a} = 6\sigma_{\log f_a}$ gives approximately the full frequency range occupied by the spectrum of the programme signal considered. Thereafter we have calculated n_a, frequency-weighted average of the normalized power spectral density; small values give correspondingly peaked spectral densities as a function of $\log f$.

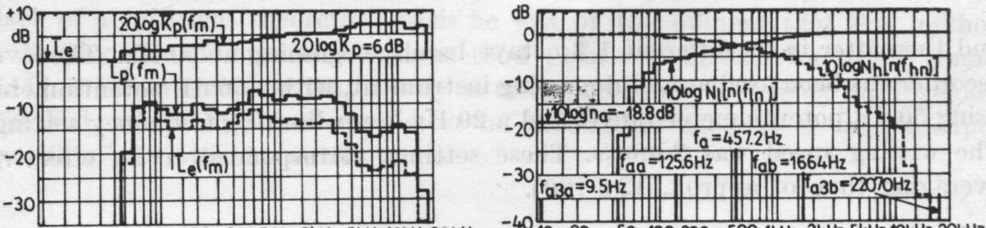

Fig. 2 a, b. Long-time-averaged statistical properties of the programme signal of the ensemble group $x = 3$, $y = 2$: pop group

Some results measured

In order to demonstrate some of the results achieved Figs. 2*a* and 2*b* show the long-time-averaged statistical properties of the ensemble group: a pop ensemble, $x = 3$, $y = 2$. This was one of the ensemble groups whose spectrum occupies the broadest frequency band. As Fig. 2*a* shows, $\bar{L}_e(f_m)$, the long-time-averaged rms level, shows only a variation of about 5 dB — as a function of f_m, the mid-band frequency of the 1/3 octave bands considered — over the range from 63 Hz to 3 kHz. Most of the power — indicated by Fig. 2*b* — lies near the first spectral moment $f_a = 457.2$ Hz. The frequency band occupied is very large: $\Delta f = f_{a3b} - f_{a3a} \approx 22$ kHz.

Figs. 3*a* and 3*b* show the results obtained for the ensemble group: grand piano, $x = 4$, $y = 3$. This has one of the most peaked spectra among the ensemble

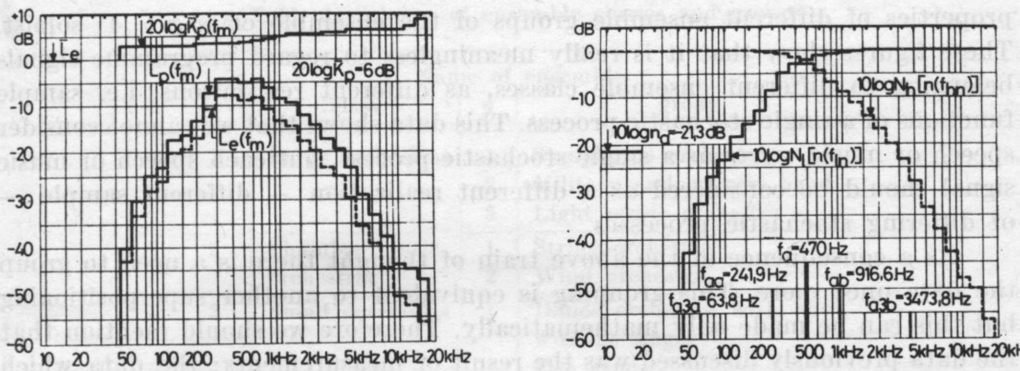

Fig. 3 a, b. Long-time-averaged statistical properties of the programme signal of the ensemble group $x = 4$, $y = 3$: grand piano

groups considered, as can be seen from Table I. The extension of the normalized power spectral density shown by Δf, $\Delta f = f_{a3b} - f_{a3a} \approx 3400$ Hz, is considerably narrower than that of the pop group.

The question arises whether or not the data achieved for a given group is really characteristic of the properties of the group considered? In some cases the measurements were repeated using other programme materials for composing the programme signal of the group. The results were quite similar: there being no more than 2 dB deviation in the levels obtained. This shows that the method of "sample superposition" is useful and adequate for obtaining characteristic results.

In order to show why broad spreadings in the results obtained for different ensemble groups exist, the reader is referred to see Figs. 4a and 4b, where $J[\cdot]$ denotes the interval occupied by the characteristics considered. We should mention that this large spreading has been caused mostly by the very different

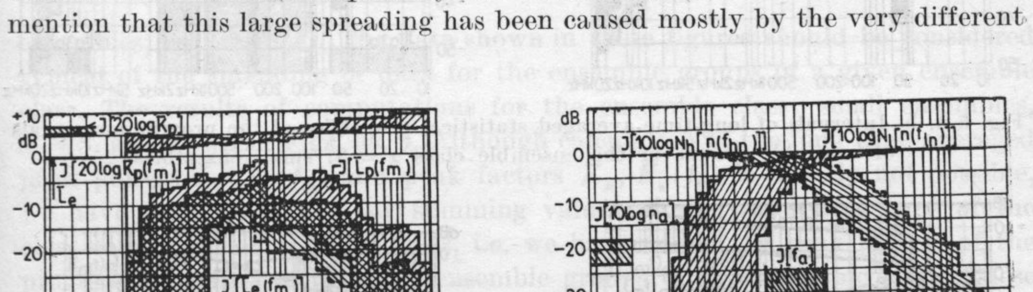

Fig. 4 a, b. Intervals of long-time-averaged statistical properties of the programme signals of all the ensemble groups considered (see Table 1) properties of different ensemble groups of the ensemble class $x = 4$: soloist. These figures show that it is really meaningless to regard programme signals belonging to different ensemble classes, as different realizations, i.e. sample functions of a single stochastic process. This data shows that we cannot consider speech or music waves as a single stochastic process, but each speech or music signal should be considered as a different realization — different sample — of differing stochastic processes.

As a consequence of the above train of thought there is a need to group the data once more. This grouping is equivalent to another superpositioning but this can be made only mathematically. Therefore we should mention that the data previously discussed was the result of measurements; the data which will be shown subsequently is the result of computation.

Selected computed results

As a result of the assumptions made, we can calculate the programme signal of each ensemble class. The necessity for this can be seen in Figs. 5*a* and 5*b*, which show the intervals occupied by the different data obtained for the different ensemble groups $y = 1, 2, 3, 4$ of the ensemble class $x = 3$ (small

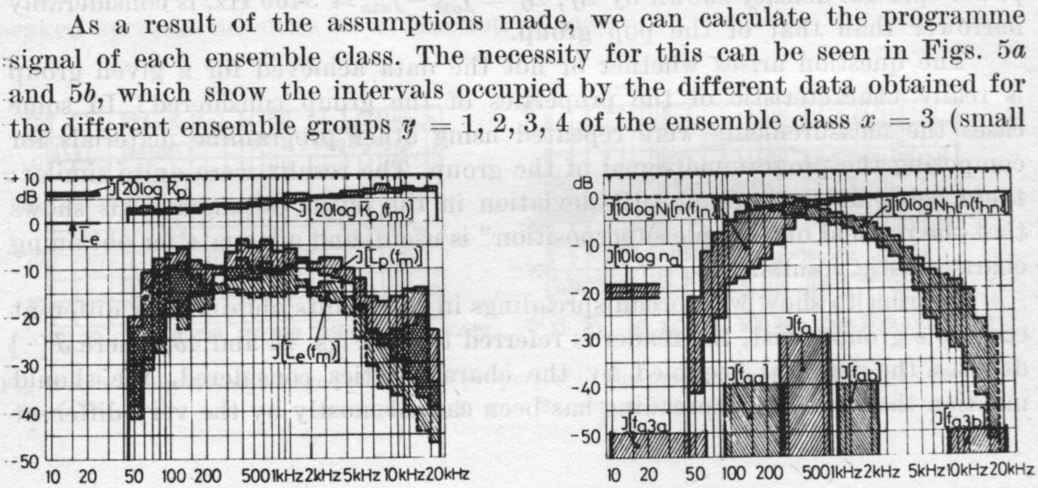

Fig. 5 a, b. Intervals of long-time-averaged statistical properties of the programme signals of ensemble groups of the ensemble class $x = 3$: small ensembles

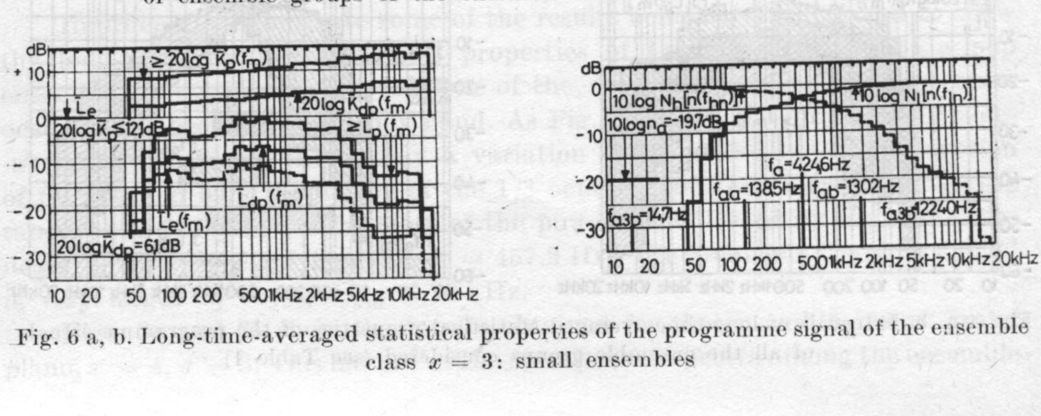

Fig. 6 a, b. Long-time-averaged statistical properties of the programme signal of the ensemble class $x = 3$: small ensembles

Table 1. Scheme of ensemble classes and groups

x	Name of ensemble class	y	group
1	Large orchestras	1	Symphonic orchestra
		2	Military and concert band
		3	Light music orchestra
2	Chamber music orchestras	1	String orchestra
		2	Wind orchestra
3	Small ensembles	1	Dance orchestra with and without singer
		2	Pop group
		3	Jazz ensemble
		4	Folk ensemble
4	Soloists	1	Violin
		2	Violoncello
		3	Grand piano
		4	Cemballon
		5	Organ
		6	Violin with grand piano
		7	Wind instr. with grand piano
		8	Singer with grand piano
5	Stage ensembles	1	Ensemble for opera
		2	Ensemble for operette
6	Mixed singing choirs		
7	Voices	1	Male voice
		2	Female voice
		3	Radio drama

ensembles, see Table 1). The data shown in these figures should be considered typical of the spreading of data for the ensemble groups of a given ensemble class. The results of computations for the ensemble class: small ensembles, $x = 3$, are shown in Figs. 6*a*, *b*. Although calculation of the long-time-averaged peak powers $\bar{L}_p$, $\bar{L}_p(f_m)$ and peak factors $\bar{K}_p$, $\bar{K}_p(f_m)$ is strictly not possible, we have calculated these by summing values of the different groups of the class considered on a linear basis, i.e. we have added the peak powers of the programme signals of different ensemble groups of the ensemble class. These values are indexed by dp. The maximum peak powers and peak factors are marked by $\geqslant$ before the abbreviations. Other marks have the same meaning as before. Fig. 6*b* shows that the first spectral moment of the programme signal of this ensemble class is at $f_a \approx 425$ Hz and the frequency band occupied by the spectrum of the programme signal of this class is approximately $\Delta f \approx 12.26$ Hz.

We have also calculated data belonging to each of the ensemble classes of Table 1. The differences between the data from the ensemble classes were then considerably smaller than the data from different ensemble groups as a consequence of the averaging, but large enough to indicate that they are characteristic of the properties of the programme signal of the ensemble class considered.

The weighted programme signal

The next step was the collection of the statistical data on the occurrences of different programme items in different radio broadcast programmes. Data was found [21] for different quarters of different years, denoted by k. Naturally, this data had been originally collected for an other purpose, so that it was necessary to perform some transformation before using it. The method of transformation and the method of calculation of the probability ${}_xW_k$, of the occurrence of a given ensemble class in a given quarter of year k, are shown in Table 2. This validates our method of grouping ensemble groups into ensemble classes according to the classification in Table 1.

Table 2. Method of calculation of ${}_xW_k$, the probability of occurrence of different encemble classes in a given quarter of a year k

x	${}_xW_k$
1	(programme time of symphonic music + military or concert bands + light music + 1/3 of the presentation of popular education) · (full programme time)$^{-1}$
2	(programme time of chamber music + 1/3 of the presentation of popular education) · (full programme time)$^{-1}$
3	(programme time of dance music + pop music + jazz music + folk music + morning musical programmes) · (full programme time)$^{-1}$
4	(programme time of solos + songs) · (full programme time)$^{-1}$
5	(programme time of operas + operettas + parts of them + 1/3 of the presentation of popular education) · (full programme time)$^{-1}$
6	Mixed singing choirs (programme time of choruses + mass songs) × × (full programme time)$^{-1}$
7	$1-\sum_{x=1}^{6} {}_xW$

There were only two sorts of programmes which were somewhat outside our method of grouping, namely the presentation of popular education and morning musical programmes. However, the second dealt with music, played by large or chamber orchestras, or by some kind of stage ensembles, interconnected with some speech of much shorter duration. We have therefore divided this programme time into three equal parts and these have then been added to the programme times of the above mentioned ensemble classes. The morning musical programmes correspond in their contents — apart form the short periods of speech connecting the music — with those of the pieces interpreted by small ensembles.

In Hungary three different radio programmes are broadcast. Taking this in account we have collected data and have calculated the weighted long-time-spectral properties for each of these different radio broadcast programmes and also their averages. Fig. 7 shows the probability of occurrence of the different ensemble classes,

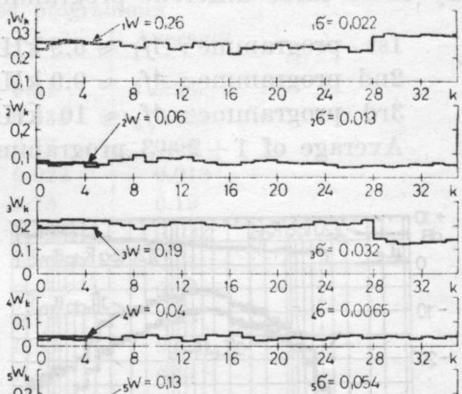

Fig. 7. Rounded probabilities of occurrences of different ensemble classes, $_xW_k$, as a function of the quarter year k, beginning at 1965. The data is the average from three different programmes. $_xW$ are averages over k and $_x\sigma$ are the standard deviations of the occurrences $_xW_k$, averaged over the three different programmes, of the ensemble class x

rent ensemble classes, $_xW_k$, $x = 1, \ldots, 7$, as a function of k, the index for a quarter of a year, beginnning at 1965. This data is the result of an averaging over the probabilities of occurrences of the three different programmes. Fig. 7 shows $_x\sigma$, the standard deviations of occurrence of each of the ensemble classes of these programmes, and time averaged data. It is clear that the probability of occurrence of different ensemble classes is quite uniform as a function of k, i.e. time, showing stability of the programme policy of the broadcast institution.

It is also interesting to analyse the mean values $_xW$ and standard deviations $_x\sigma$ of probability of occurrence of the different ensemble classes in the different transmitted programmes, as shown in Table III. The last column of the table gives the averages of the three different transmitted programmes, which are also shown in Fig. 7. The deviations between the mean probabilities $_xW$ obtained for the different programmes are not too severe.

Using these mean values, $_xW$, we have calculated the weighted averages of the programme signals of different ensemble classes, on a linear basis for each transmitted programme, called the programme signal of transmitted programme 1, 2, or 3, by adding the probability — weighted powers. The weights here physically correspond to power gains. It is interesting to note that in spite of the fact that the differences between the spectral values obtained for the three different programmes are not larger than 2 dB, as shown in Figs. 8*a*, 8*b*, there are considerable differences between the frequency ranges occupied by these three different programmes:

1st programme: $\Delta f_1 \approx 6.9$ kHz, $f_{a1} \approx 452$ Hz;
2nd programme: $\Delta f_2 \approx 9.0$ kHz, $f_{a2} \approx 470$ Hz;
3rd programme: $\Delta f_3 \approx 10$ kHz, $f_{a3} \approx 512$ Hz.
Average of 1 + 2 + 3 programmes: f_{mean} 9.2 kHz, $fa_{\text{mean}} \approx 477$ Hz.

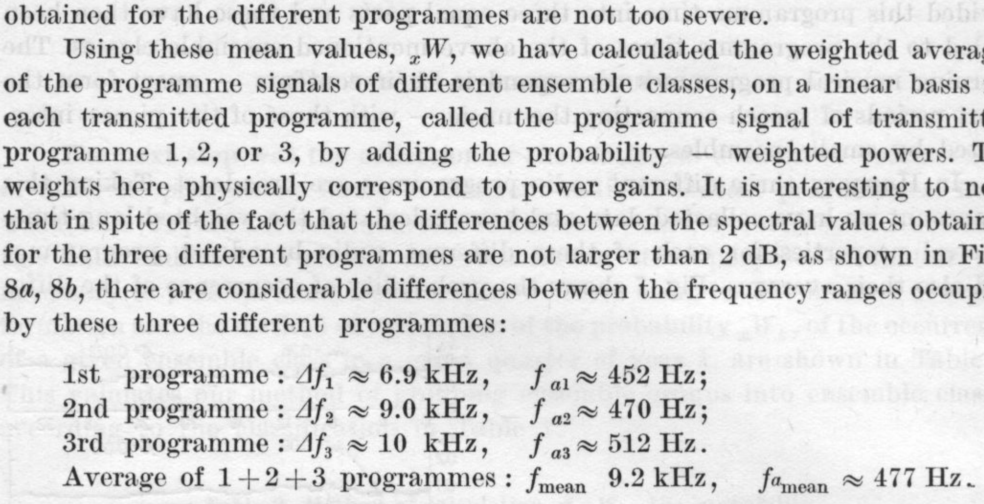

Fig. 8 a, b. Intervals of long-time-averaged statistical properties of programme signals weighted by $_xW$, the rounded mean probability of occurrence of different ensemble classes, averaged over the three different transmitted programmes. Values of the weights are given in Table III

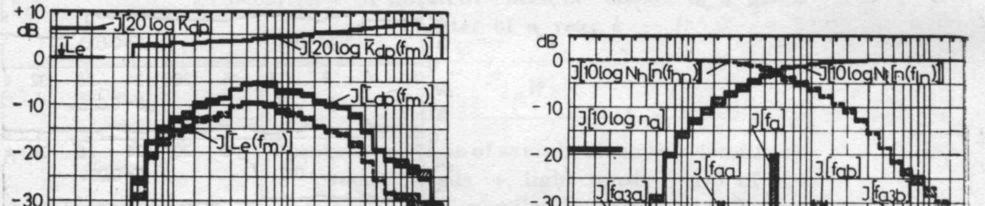

Fig. 9 a, b. Statistical properties of the long-time-averaged programme signal

Taking the data of Table 3 into consideration we can say generally that the bandwidth Δf of a programme signal is particularly dependent on the probability of music occurring rather than speech, i.e. of the ratio $_7W(1-{_7W})^{-1}$. The smaller this ratio is, approximately, the wider will be the bandwidth Δf. There is also another interesting consequence: a diminution of this ratio causes a growth of the first spectral moment f_a.

Thus it is evidently possible to define a hypothetical programme in which the probability of the occurrence of different ensemble classes are the averages of the values obtained for these three different programmes. The mean values of these averages are given in the last column of Table 3. Using these average

Table 3. Rounded mean probabilities, $_xW$, and standard deviations $_x\sigma$, of the occurrence $_xW_k$, of different ensemble classes in different transmitted programmes

$_xW$ / $_x\sigma$	Marks of transmitted programmes			
	No. 1	No. 2	No. 3	Averages
$_1W$	0.20	0.26	0.31	0.26
$_1\sigma$	0.043	0.039	0.035	0.022
$_2W$	0.03	0.04	0.12	0.06
$_2\sigma$	0.0064	0.0096	0.028	0.013
$_3W$	0.23	0.21	0.15	0.19
$_3\sigma$	0.052	0.047	0.035	0.032
$_4W$	0.02	0.03	0.06	0.04
$_4\sigma$	0.005	0.0044	0.016	0.0065
$_5W$	0.10	0.11	0.18	0.13
$_5\sigma$	0.014	0.015	0.03	0.054
$_6W$	0.01	0.01	0.02	0.01
$_6\sigma$	0.0025	0.003	0.011	0.0035
$_7W$	0.41	0.34	0.16	0.31
$_7\sigma$	0.036	0.041	0.054	0.037

values for weights, we have calculated the weighted long-time-averaged statistical properties in the same manner as discussed above. The results are shown in Figs. 9*a*, 9*b*. These are really averages in all respects because we have first averaged in a given ensemble group, using 24 independent samples of the programme signals, characteristic of the ensemble group considered; then we have averaged data between ensemble groups and thereafter we have weighted these averaged values with an averaged programme statistics where the last averaging procedure has been made using data from 34 quarter years and from three different transmitted programmes. Our procedure therefore justifies calling the data obtained the long-time programme signal.

We should mention that calculating the weighted average values, regarding the probability of occurrence of different ensemble classes as equal, we obtain results having only small (one or two dB) differences from the values weighted by the different or by the average programme statistics. Thus in general most of the spectral properties of the long-time-averaged programme signal are quite insensitive to the probability of occurrence of our ensemble classes. This is clearly a consequence of our using a considerable number of ensemble classes.

Spectrally equivalent programme signal

It is now possible to construct a spectrally equivalent programme signal, by which we mean the output of a linear, passive or active network fed by random noise of gaussian probability distribution and of constant power spectral density in the frequency range of at least 31.5 Hz-16,000 Hz, where the frequency response of the network corresponds within close limits to the power spectral density of the long-time-averaged programme signal.

We have therefore calculated $\bar{L}_e(f)$, the power spectral density level of the long-time programme signal integrated power density level $\bar{L}_e(f_m)$, shown in Fig. 9*a*, simply by subtracting $10 \log \Delta f_m$, where Δf_m is the power bandwidth of the 1/3 octave bandwidth filter of mid-band frequency f_m. In order to obtain a filter as simple as possible, we have chosen for the tolerance limits of the spectral density function, the upper and lower curves drawn by the thin lines of Fig. 10. The calculated power spectral density level $\bar{L}_e(f)$ lies

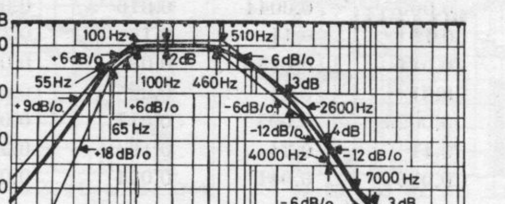

Fig. 10. Tolerance band of the spectrally equivalent programme signal. The curve drawn with a thick line is the power spectral density of a white noise signal weighted by the network of Fig. 11

approximately in the middle of this tolerance band. The curve drawn with a thick line on this figure shows the measured frequency response of the network shown in Fig. 11. Our tolerance band appears to be broad enough to have a simple network but also narrow enough to obtain practically a close approximation to the spectral density level of the long-time programme signal. The output of the network, fed by white noise, measured by using an 1/3 octave band-pass filter of Brüel & Kjaer Type 2112 is shown in Fig. 11. The results obtained for the 1/3 octave band levels in the bands from 63 Hz to 12.5 kHz had midfrequency deviations of no more than 2 dB, referred to the levels $\bar{L}_e(f_m)$, shown in Fig. 9. Taking into consideration that the tolerance band of Fig. 10 contains all the results obtained for the three different programmes, as well as for the case of an equally weighted case, there seems to be no reason to make this tolerance band narrower.

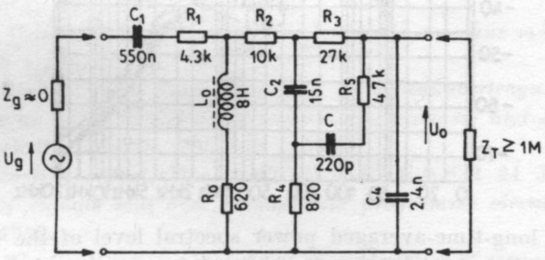

Fig. 11. A weighting network, fed by white noise, to obtain the spectrally equivalent programme signal. All component values are of tolerances of $\pm 1\%$. The power spectral density of the output signal of the network is shown by Fig. 10, thick line

Discussion

It is very interesting to compare our result expressed as a power spectral level to those existing in the literature. Fig. 12 shows (with a thick curve) our results and the thin lines are the proposed limits of the tolerance band. We have drawn data published in [13], Fig. 5, for two different programmes, measured and calculated taking into account the daily statistics of different kinds of programmes. Fig. 12 also shows the results of [14] Fig. 9. These have been obtained by measuring representative samples of normal broadcasting programme items (classical and light music, jazz and speech) having a duration proportional to their relative occurrence in the daily transmitted programme.

As Fig. 18 shows there is satisfactory agreement between the different results in the frequency range of 50 Hz - 3 kHz but outside this range, the data shows quite large deviations (particularly that taken from [14], Fig. 9). This is very probably due to the small nummer of programme items as well as to the measurement and evaluation procedures used. The data given by [13], Fig. 5, shows, over the whole frequency range for which it has been published, i.e. from 40 Hz - 8 kHz, good agreement with our data.

Unfortunately we have not found any other data published in the literature. Our results, and the data presented concerning the spectrally equivalent programme signal seem therefore to provide a solid base for future investigations.

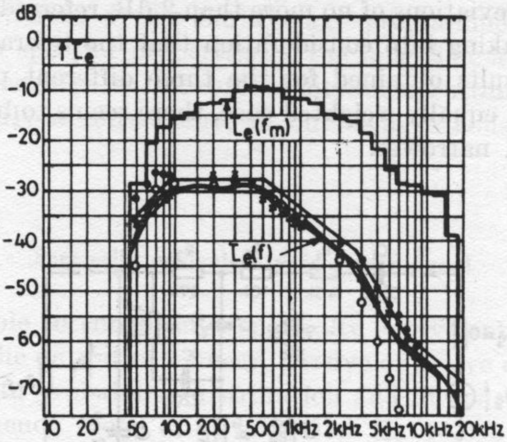

Fig. 12. $\bar{L}_e(f_m)$, the long-time-averaged power spectral level of the long-time programme signal, integrated in 1/3 octave bands of mid-band frequencies of $\bar{L}_e(f_m)$, the long-time-averaged power spectrum level of the long-time programme signal, both referred to $\bar{L}_e$, the long-time-averaged power of the unfiltered long-time programme signal. Points and circles are results of other investigations (see text)
× — data for transmitted programme No. 1, ● — data for another transmitted programme No. 2 Both are averaged for one day, After [12], Fig. 5, ○ — data of a transmitted programme signal, calculated for a year. After [14], Fig. 9. The thin curves border the tolerance band proposed for the spectrally equivalent programme signal

Acknowledgment. During this work, the writer has been encouraged by Mr. András Hartai, Technical Director of Elektroakusztikai Gyár, as well as by Mr Gábor Heckenast, Technical Director of Hungarian Radio. Thanks are also due to Mr. Tibor Szávai for writing the computer programme, to Miss Rozalia Szabó for drawing the figures, and to Mr Sándor Steinbach who mixed and edited the tapes used.

The editor wishes to express his gratitude to Prof. T. Tarnóczy for his assistance in preparing this paper for publication.

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Received on September 6, 1979.