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In a time series analysis of prime time network television viewing data a weekly trigonometric regression model is used to predict the total network viewing for specific times on specific days of the year. These predictions are very accurate. Four network share models, each based on different assumptions about how the activity of television viewing interacts with nonviewing activities and the strength of program loyalties, are used to allocate the total network prediction to specific program predictions. The predictions of the network share model are compared with the highly accurate published predictions of an expert who explained his predictions on the basis of demographic and program content considerations. The predictions of the network share models, which do not utilize demographic or program content information, compare reasonably well with the expert judgment predictions. The authors suggest how demographic, program content, and competitive bridging information would be incorporated within the framework provided by the time series models to produce advanced network scheduling models.

Models of Competitive Television Ratings

Members of the advertising industry know the tremendous economic impact of television ratings. Millions of dollars are at stake because advertising rates, particularly spot television rates, are a direct function of network ratings. Also, the network television programs available to the public are generally determined by ratings. Given the economic and social implications of television ratings, the lack of published research in this area is surprising. Because advertising time is generally purchased prior to actual presentation, practitioners must have some method of predicting future ratings. Conversations with network schedulers and researchers in several major corporations in the United States indicate that research is being done in this area. Unfortunately, this research is viewed as proprietary. From our discussions it is clear that *program content* is the dominant variable in most of the proprietary models that predict program ratings. In the few published empirical articles on television viewing, mainly the static models of factor analysis (Ehrenberg 1968; Frank, Becknell, and Clokey 1971; Gensch and Ranganathan 1974; Swanson 1967; Wells 1969) and multidimensional scaling (Farley and Bowman 1972; Lehmann 1971) are used to analyze and predict television ratings in terms of program content.

The purpose of this article is to put into the public domain a predictive method based on time series analysis. Though the method described does not use program content information in predicting future program ratings, this information can and should be incorporated within the basic structure of the time series model. We believe the time series approach should be viewed as a first stage analysis that establishes the constraints or bounds within which sophisticated program content analysis would proceed. Thus we view our study as complementing rather than competing with much of the current proprietary research effort in the industry. To the best of our knowledge no reports have been published of attempts by other authors to analyze television viewing patterns over time.

The first section of our article briefly describes a trigonometric regression approach that provides accurate predictions of the total network viewing audience by time of day and day of the year. Our research approach is analogous to estimating total industry sales

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The findings and conclusions are the sole responsibility of the authors and are not necessarily endorsed by the A. C. Nielsen Company.

Journal of Marketing Research
Vol. XVII (August 1980), 307–15

and then developing network brand share models to apportion the total. Thus with the trigonometric regression model providing reasonable estimates of the total network viewing, the emphasis of the article is on the development of network share models. A set of four network share models built on different behavioral assumptions about the formation of viewing preferences and the strength of program loyalties is applied to the empirical data.

In the second section we apply the four models to predict the ratings of new competitive combinations of existing programs. In the third section we apply the four models to competitive situations involving the introduction of a new program. A set of predictions for individual programs in the general time period of our data was made by an experienced practitioner and published in *Television Magazine*. These predictions are presented simply to indicate that the network share models we analyze, which do not incorporate program content information, compare rather well with predictions reflecting an expert's opinion of the viewing trends, wearout factors, and the competitive interactions of the various program sets.

Finally, we recognize that the type of data we analyze is rather crude for the purpose of building a sophisticated network share model. The principal shortcoming of the Nielsen data used is that they do not relate individuals to programs, but simply measure viewing by any or all members of the household. A previous study indicates that demographically defined groups of individuals have significant differences in their preference for various types of program content (Gensch and Ranganathan 1974). In the last section of the article we discuss the development of a more sophisticated network share model utilizing individual viewing data and program content influences in conjunction with the basic modeling approach.

TIME SERIES ANALYSIS

The data analyzed are estimates of network television viewing as reported in the Nielsen Television Index. The analysis is restricted to certain prime time evening viewing segments, specifically, the six 15-minute periods beginning on the hour and the half-hour and extending from 7:30 p.m. to 10:15 p.m. A designated time refers to the time at which a program is telecast in the Eastern Time Zone. Throughout the article the six quarter-hour time slots are labeled by their starting times, 1930, 2000, 2030, 2100, 2130, and 2200. The time series studied at each quarter hour consist of the sum of the three network ratings. The period spanned by the data is November 7, 1966 to August 24, 1969 totaling 1,022 days or 146 weeks.

Plotting the data reveals almost three annual cycles for the 2.8 years of data. However, an annual cosine curve would not fit these annual cycles because the peaks, high viewing months, are considerably broader than the troughs. This pattern of data suggests that a linear combination of cosine curves such as found in a trigonometric regression approach would provide a reasonable and interpretable time series model; see Anderson (1971, Chapter 4) for a more technical discussion of why the trigonometric regression approach is suggested for the type of data set described here. Trigonometric regression models use different length cycles as independent variables. Thus a predicted value is a linear combination of various length cycles. Readers not familiar with this form of time series regression and its advantages over the lagged variable approach should see Parsons and Henry (1972) for a marketing-related discussion of trigonometric regression.

The following weekly trigonometric equation was fit to the data.

$$y_t = \alpha + \beta t + \sum_{j=1}^{6}\left(\gamma_j \cos\frac{2\pi jt}{52} + \delta_j \sin\frac{2\pi jt}{52}\right) + e_t,\ t \in T \tag{1}$$

y_t denotes the value on day t and t ranges from 1 to 146. The e_t variables are assumed to have mean 0, variance α^2, and be uncorrelated. T in equation 1 is a subset of $\{1,2, \ldots, 146\}$. The model, consisting of the annual and five harmonics, was run for each day of the week at each of the six time periods producing 42 regression runs. The harmonics of the annual cycle represent cycles of shorter length such as the semiannual, quarterly, etc. The number of harmonics was a subjective judgment by the authors based on visual inspection of the time series plots. Results of the analysis, given hereafter, and a spectral analysis of the residuals, detailed in a supporting paper (Gensch and Shaman 1979), suggest the subjective judgment is reasonable and appropriate. The R^2 values for the trigonometric models listed in Table 1 indicate that the annual and its harmonics explain a very high proportion of the variation in total network viewing.

The annual component is by far the most significant variable in the models. The annual accounts for more than 85% of the variation at 1930, but the proportion

Table 1

R^2 VALUES RESULTING FROM TRIGONOMETRIC REGRESSION MODELS

	Hour					
Day	*1930*	*2000*	*2030*	*2100*	*2130*	*2200*
Monday	.9407	.9389	.9116	.8942	.8370	.7535
Tuesday	.9267	.9112	.9020	.8695	.7180	.6317
Wednesday	.9239	.9207	.9450	.9138	.8308	.7191
Thursday	.9095	.9238	.9236	.8983	.8295	.8802
Friday	.9392	.9376	.9288	.8983	.8749	.8233
Saturday	.9423	.9325	.9444	.9252	.8909	.8300
Sunday	.9408	.9509	.9371	.9182	.8992	.7827

declines sharply in the late evening to 50% at 2130 and 44% at 2200. One explanation for the declining strength of the annual component over the evening time slots is the annual variation in daylight at a given time period. The early evening hours (1930–2100) vary considerably in the daylight-darkness relationship, but the late evening hours, 2130 to 2300, are dark during almost the entire year. One cannot precisely track the daylight-darkness influence in the Nielsen data because the Nielsen ratings aggregate the viewing across the entire nation into one rating. Varied degrees of daylight are present in different parts of the country at a given time period. In addition there was not a uniform period of daylight saving time across all states during the data collection period.

It seems reasonable to assume that during the daylight segment of the annual cycle, warmer weather prevails and is accompanied by more outdoor activity. This assumption implies that total network viewing is more a function of alternative activities than a function of cumulative program content, a conclusion further substantiated by the fact that the peak for the annual component occurs between January 9th and 11th for each of the series analyzed. This is important information in that the dominant component of the trigonometric model, the annual, does not seem to be in phase with the program content cycle in American network scheduling. The new program season starts in September. One would expect that if program content were the primary driving force underlying total network viewing, the peak of the viewing year would occur sometime in late September or in October, when viewers have a relatively fresh set of programs to view. The new programs are generally promoted by the networks and the older programs remaining from the last programming season are generally the more popular ones.

Spectral analysis of the residuals does not reveal any other cycles of importance beyond the components of the trigonometric model. The full details of the time series analysis summarized here are given by Gensch and Shaman (1979).

As with any statistical model no causation is implied by the good predictive fits. Furthermore, the predictive results used in the network share model can be expected to be very good, provided that the total network viewing pattern continues to have the strong seasonal pattern. The relative strength of the annual in relation to the seasonal presence or absence of daylight may have important behavioral implications. Our interpretation is that total television viewing is strongly influenced by the availability of nontelevision viewing activities. If nontelevision activities and not program content considerations determine the size of total network viewing, the behavioral assumptions about how viewers determine when they will watch television may require a subtle change. In predictive models dominated by program content considerations it is generally assumed that individuals first determine their first programs and then organize their other activities to permit viewing whenever those programs are shown. The results of the trigonometric regression analysis suggest that individuals first decide whether they are interested in watching television at a given time and *then* select one of the programs on the basis of competitive program content.

SCHEDULING EXISTING PROGRAMS INTO NEW TIME PERIODS

Broadly defined, network scheduling decisions cover two basic cases, (1) the movement of an existing program into a new weekly time period, thus presenting a different competitive environment, and (2) the introduction of a completely new program.

During the 2.8-year time frame of our data there are 18 cases in which an existing or previously shown program changed time period and went into competition with two other previously shown network programs, excluding movies (Appendix A). Numerous other existing programs were moved during the 2.8-year time frame, but are not shown in Appendix A because they went into competition with either at least one new program or a movie. New competitive situations involving movies are not included in the study because the week-to-week variability associated with movies tends to be higher than that associated with sequential episodes of the same program series. Existing programs moving into competition with movies should be treated separately. The average ratings of programs are predicted for 15-minute segments beginning on the hour and the half hour. Six of the moved programs were hour-long shows. The prediction of total network viewing generated by the trigonometric regression model must now be allocated among the networks. The prediction serves as a *benchmark* from which network share models may proceed.

Four methods of predicting network share, each implying a different behavioral model of television viewing, are applied to the data. The methods differ in the manner by which the individual programs are assigned fractions of the benchmark. The fractions are determined by examining past ratings of the three individual programs which compete as a new set and past ratings of the program(s) which was (were) replaced in a given time segment. In each case four weeks of ratings prior to the realignment are used to calculate proportions for individual programs. Ratings for each program by 15-minute segments are averaged over the four weeks. From these averages each program's proportion of the total network viewing audience is calculated. Table 2 illustrates these calculations. The proportion for *Time Tunnel*, the program which replaced *Green Hornet*, is .22150. This value was obtained in the same fashion from four weeks of ratings in *Time Tunnel's* previous competitive alignment.

Table 2
ILLUSTRATION OF CALCULATION OF NETWORK VIEWING PROPORTIONS FOR PRIOR WEEKS' DATA FOR SET 1, FRIDAY, 7:30–7:45 p.m., RATINGS OF PROGRAMS SHOWN

Prior date	*Green Hornet*	*Wild Wild West*	*Tarzan*
6/2/67	9.0	11.9	11.1
6/16/67	7.0	10.8	9.8
6/30/67	5.7	10.3	10.2
7/7/67	6.7	12.4	9.1
Average of ratings	7.1	11.35	10.05
Proportion	.24912	.39825	.35263

We first investigated the period two through five weeks prior to the introduction of a new competitive alignment for each of the three programs in that alignment and for the replaced show(s). If during one of these previous weeks the programs appeared opposite their regular series competition, the ratings for that week are used. The ratings are not used if any of the three regularly scheduled series was pre-empted, e.g., replaced by special telecasts. In some cases, it was necessary to backtrack several months to accumulate the appropriate four prior weeks. Thus some judgment was exercised in the choice of the previous ratings used to determine the proportions. The general guideline was to select previous competitive situations which remained relatively stable from week to week.

The proportions described heretofore are used to derive fractions, and the product of a fraction and a benchmark value is a predicted rating for an individual program. Four methods of prediction are considered.

1. The proportions for the three programs in the new competitive situation are normalized to sum to 1. These normalized values define the fractions by which to multiply the benchmarks. In the example in Table 2, the proportions .22150, .39825, .35263 are normalized to .22779, .40956, .36265.
2. The fractions are taken to be the proportions in method 1 prior to normalization, .22150, .39825, .35263 in the example.
3. The proportion for each replaced program is used for the program moved to the corresponding position in the new alignment. These proportions already add to 1. In the cited example, the values are .24912, .39825, .35263.
4. The fractions are obtained by forming the average of the method 1 and method 3 fractions. In the example the values are 1/2 (.22779, .40956, .36265) + 1/2 (.24912, .39825, .35263) = .23846, .40390, .35764.

Each of the methods 1, 2, and 3 represents an extreme point on a behavioral dimension underlying viewer choice. Method 4 is presented as an example of a compromise between two of the extreme positions by combining two basic assumptions. One assumption is that over time individuals tend to develop a preference for one of the programs in a given time slot, and program loyalty or preference of varying strength is established. That is, the viewing of individual programs is not a random event. The second assumption is that individuals only occasionally reorganize their nontelevision viewing activities to follow specific programs into time periods they do not currently use for viewing. Moreover, one observes empirically that programs which move into a different time slot tend, on average, to have a higher normalized proportion (from method 1) than the programs they replace. Thus, method 1 may tend to overestimate moved programs and underestimate unmoved programs. Method 3, which is based on the assumption that unmoved programs have loyal viewing audiences, implies that a popular moved program will fail to attract additional viewers in significant numbers from the holdover programs. In practice this approach seems, on average, to underestimate moved programs and overestimate unmoved programs. Method 4 recognizes these considerations. Under this method a moved program's rating depends on both its previous popularity in another time slot and the rating of the program it is replacing. The equal weighting we use works reasonably well on our data and is meant to be illustrative. Obviously, a more sophisticated version of a network scheduling model would vary the weights to take into account the wearout factors associated with the unmoved programs and the relative preferences by demographic segments for the current program in relation to the unmoved programs. In this manner the weights to be assigned in method 4 could be estimated for each particular case, thus taking into account more information and presumably improving the predictive accuracy.

Ratings of individual programs for each of the competitive alignments shown in Appendix A were predicted for four weeks by each of the methods. In each case the four weeks selected began with the introduction of the new alignment. Tables 3–5 are statistical summaries. A residual value is an actual

Table 3
AVERAGE ABSOLUTE PREDICTION ERROR
(average over four dates, three networks)

	Method			
	1	*2*	*3*	*4*
Programs moved (88 predictions)	2.06	2.56	1.90	1.72
Programs not moved (128 predictions)	1.74	1.91	1.91	1.69
All programs (216 predictions)	1.87	2.18	1.91	1.70

Table 4
ALGEBRAIC SIGNS OF PREDICTION ERRORS
(total number of positive and negative signs)

	Method							
	1		2		3		4	
Sign	+	−	+	−	+	−	+	−
Programs moved	45	43	34	54	58	30	47	41
Programs not moved	74	54	55	73	55	73	68	60
All programs	119	97	89	127	113	103	115	101

rating minus a predicted rating. In terms of the average absolute prediction error, method 1 provides more accurate predictions than method 2. This finding is consistent with the underlying process suggested by the time series analysis, that total network viewing is not a function of aggregate program content. Table 4 clearly shows that on average method 1 tends to underestimate unmoved programs, and method 3 tends to overestimate them. Hence method 4 seems designed to estimate unmoved programs fairly well. Table 5, which shows the distributions of the absolute prediction error, indicates that, on balance, method 4 works best with the given data. Method 2 is clearly poorest and 1 and 3 are approximately comparable.

The methods yield some large residuals. Several of these occur in sets 8, 9, and 12. In two of these cases a program with high ratings against relatively weak competition was moved into a time slot to compete against stronger competition. In the third case one of the unmoved programs lost its appeal and its share of audience was considerably lower than predicted. This program appears to be one that audiences tired of, and it was dropped from the schedule soon after the prediction period.

A more sophisticated model that would take demographic factors, relative competition, and wearout factors into consideration in estimating the weights used in method 4 would lead to better predictive results than those reported here. However, it is noteworthy that all of the methods, with the possible exception of 2, provide reasonable estimates of comparable quality when aggregate statistics are viewed (e.g., Table 5).

NON-NETWORK VIEWING

Finally, before shifting attention to new program predictions, one should consider the role of non-network viewing in predicting the ratings for network programs. Perusal of non-network ratings indicates these time series values range from less than a single rating point to just under 10 rating points during prime time hours. The low values tend to occur in winter months when network ratings are high and the high values occur in summer months when networks offer repeat and replacement series. There is some evidence that the non-network programming is capable of gaining and losing viewers in sufficient numbers to partly justify use of fractions that do not sum to 1. As an example, on Monday, November 4, 1968, election eve, all three networks offered only paid political advertising during most of the evening. Differences between total network viewing and fits by the trigonometric regression models were as much as −16. Yet the comparable differences for total television viewing did not exceed −6. In fact, non-network viewing that evening during the quarter hour periods beginning at 7:30, 8:00, ..., 9:30 was 15.1, 12.5, 18.3, 17.1, and 13.7, respectively. Thus, non-network offerings do allow some flexibility in the size of the pie the networks may slice. Because in this data set most moved programs happened to be shifted primarily during the fall and winter months, mostly in conjunction with

Table 5
CUMULATIVE PERCENTAGE OF ABSOLUTE PREDICTION ERRORS WITHIN RANGES

	Programs moved				*Programs not moved*				*All programs*			
Absolute prediction error less than	*Method*				*Method*				*Method*			
	1	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*
1	28.4	22.7	30.7	31.8	36.7	35.9	35.9	39.8	33.3	30.6	33.8	36.6
2	54.5	45.5	62.5	67.0	66.4	62.5	62.5	67.2	61.6	55.6	62.5	67.1
3	73.9	65.9	81.8	85.2	81.3	81.3	81.3	79.7	78.2	75.0	81.5	81.9
4	88.6	75.0	92.0	94.3	93.0	85.9	85.9	90.6	91.2	81.5	88.4	92.1
5	95.5	83.0	97.7	98.9	98.4	94.5	94.5	99.2	97.2	89.8	95.8	99.1
6	100.0	95.5	98.9	98.9	100.0	100.0	100.0	100.0	100.0	98.1	99.5	99.5
7		98.9	98.9	100.0						99.5	99.5	100.0
8		100.0	100.0							100.0	100.0	

a new television viewing season, the normalized approaches tended to give better predictive results than a non-normalized method. However, for predictions made during summer months or in periods in which there is considerable non-network viewing a non-normalized approach (such as method 2) might be an improvement. One should also consider the fact that there has been an increase in non-network viewing over that reported during the 1966–1969 period.

SCHEDULING NEW PROGRAMS

Among the most difficult problems faced by network schedulers is prediction of ratings when a new program series is introduced. Within our data are 21 sets in which a new program series is introduced into competition against two unmoved programs previously shown. Sets containing movies were not selected. The new programs are listed in Appendix B. Because nine of the new programs cited span one-hour time periods for the available data, there are actually 30 competitive sets to consider.

The same guidelines as employed in the preceding section are used to select the four previous weeks of ratings to determine proportions. As before, ratings of individual programs are predicted for four weeks. Again the four different models of network share are considered, each corresponding to a different way of assigning fractions of the benchmarks to individual programs. The methods are:

1. The normalized method whereby prior ratings influence the allocation but not the size of the network viewing audience. For new programs the value .31000 is used for the proportion of "prior ratings." This is approximately the average network share for the first 10 competitive situations listed in Appendix B. In the example in Table 2, if *Green Hornet* is to be replaced by a new program, the proportions .31000, .39825, .35263 are normalized to .29221, .37540, .33239.
2. The non-normalized method whereby aggregate prior ratings influence both the size and allocation of the total network audience. The fractions are taken to be the proportions in method 1 prior to normalization, .31000, .39825, .35263 in the example.
3. The time slot method whereby the proportion for the new program is taken to be the proportion of the replaced program.
4. The combined prior rating allocation and time slot method. The fractions are the average of the method 1 and method 3 fractions, 1/2 (.29221, .37540, .33239) + 1/2 (.24912, .39825, .35263) = .27066, .38682, .34251 in the example.

In practice the proportion for a new program could be computed as a moving average of all new programs introduced in the past year or two. Program content and other competitive influences also could be used to determine the proportion for an individual new program. It should be emphasized again that the methods we illustrate are somewhat crude, because they do not incorporate program content information. This issue is discussed further in the next section.

Table 6
AVERAGE ABSOLUTE PREDICTION ERROR
(average of four dates, three networks)

	Method			
	1	*2*	*3*	*4*
New programs (80 predictions)	2.57	2.52	2.94	2.70
Holdover programs (160 predictions)	1.60	1.78	1.78	1.66
All programs (240 predictions)	1.93	2.03	2.17	2.00

Results of the predictions for situations involving new programs are summarized in Tables 6–8. The last 20 competitive situations listed in Appendix B (sets 8–21) are predicted. For the data sets predicted, method 1 is best in terms of aggregate average absolute error, and method 4 is second best. None of the four methods tends to underpredict or overpredict much, according to Table 7. Finally, Table 8 displays few noticeable differences among the methods. These results are as expected. Method 2 uses the mean value for predicting new program ratings and as expected the mean value provides the most accurate estimate of new programs. Method 1 normalizes the new program prediction of .3100 to take into account the relative strength of the two unmoved programs. Thus method 1 does better on predicting the unmoved programs. Obviously, a prediction method for new program sets which combines the method 1 predictions of unmoved programs with the mean estimate of .3100 for new programs outperforms the four basic methods. This procedure for predicting new program sets, labeled method 5 in Table 8, uses the mean value prediction for new programs and takes into account the competitive strength of the existing programs. In general the aggregate predictions for new program sets are approximately the same as for moved program sets with 67% of the ratings predicted correctly within two rating points and 80% of the predictions correct to within three rating points.

Table 7
ALGEBRAIC SIGNS OF PREDICTION ERRORS
(total number of positive and negative signs)

Method	A		B		C		D	
Sign	+	−	+	−	+	−	+	−
New programs	38	42	36	44	44	36	40	40
Holdover programs	83	77	80	80	80	80	86	74
All programs	121	119	116	124	124	116	126	114

Table 8

CUMULATIVE PERCENTAGE OF ABSOLUTE PREDICTION ERRORS WITHIN RANGES

Absolute prediction error less than	*New programs*				*Holdover programs*				*All programs*				
	Method				*Method*				*Method*				
	1	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*5*
1	28.8	27.5	26.2	25.0	40.0	37.5	37.5	38.1	36.2	34.2	33.8	33.8	36.0
2	45.0	55.0	48.8	47.5	70.0	66.2	66.2	71.9	61.7	62.5	60.4	63.8	67.8
3	58.8	68.8	63.8	63.8	84.4	80.6	80.6	85.6	75.8	76.7	75.0	78.3	81.2
4	80.0	76.2	71.2	77.5	93.8	90.0	90.0	90.6	89.2	85.4	83.8	86.2	90.6
5	86.2	81.2	77.5	87.5	97.5	96.2	96.2	97.5	93.8	91.2	90.0	94.2	93.5
6	92.5	90.0	85.0	92.5	100.0	98.1	98.1	99.4	97.5	95.4	93.8	97.1	97.5
7	97.5	98.8	90.0	95.0		98.8	98.8	100.0	99.2	98.8	95.8	98.3	99.6
8	100.0	100.0	93.8	96.2		100.0	100.0		100.0	100.0	97.9	98.8	100.0
9			96.2	100.0							98.8	100.0	
10			100.0								100.0		

It is difficult to find published predictions on a program-by-program basis with which to compare the error distributions in Tables 5 and 8. With the aid of the library research department at NBC we were able to find a set of predictions for programs in the general time period of our data. Predictions for the 1965–1966 television season were made by Stuart Gray, at the time director of broadcast research for MacManus, John, & Adams, and were published in the September 1965 issue of *Television Magazine*. Actual ratings subsequently were reported in the March 1966 issue. Gray's predictions reflect an expert's opinion of the viewing trends, wearout factors, and competitive interactions of the various program sets. He explains his predictions in terms of those concepts as they relate to various demographic groups. A direct comparison of Gray's results with those we are reporting requires care and qualification, as the types of ratings being predicted differ in several ways. First, Gray predicted the average rating for each program for the entire three-month period—October, November, and December—rather than ratings on individual days. Moreover, Gray predicted the average rating for the entire duration of a show, whether 30, 60, or 90 minutes. In contrast, the predictions we report are applicable only to 15-minute time segments. Because the aggregate method used in reporting Gray's results enables the user to smooth or average out the random errors associated with both the week-to-week fluctuations and variations from one 15-minute time segment to the next, one would expect Gray's error distribution to be more dispersed if he were predicting the ratings of programs at specific 15-minute intervals on specific dates.

Table 9 shows the cumulative distribution of Gray's absolute prediction errors as determined from the March 1966 issue of *Television Magazine*.

Gray predicted 98 programs. The sets of programs in Table 9 were selected to be as directly comparable as possible with those in Tables 5 and 8. The second column contains all 34 new programs introduced. Only nine new programs were introduced against two holdover programs, a sample which we considered too small. Thus there is more variety in the competitive mix (in terms of other new programs, movies, and moved existing programs) facing the new programs reported in Table 9 than in the mix facing the new programs in Table 8. There were 27 moved programs, existing programs moved into a new competitive time slot, and 37 holdover programs, existing programs staying in same time slot; their cumulative predictions are summarized in the next two columns, respectively. The last column summarizes the predictions for all 98 programs. The television trade magazine which analyzed Gray's predictions commented that his work produced a very accurate set of predictions. "He called so much of the schedule so accurately, he left little to explain in the way of where he went wrong."

The four benchmark methods compare reasonably well with the estimates based on expert opinion. The

Table 9

CUMULATIVE PERCENTAGES OF GRAY'S ABSOLUTE PREDICTION ERRORS

Average absolute prediction error	*New programs (n = 34)*	*Moved programs (n = 27)*	*Holdover programs (n = 37)*	*Total (n = 98)*
0– .9	32.4	29.6	51.4	39.8
1.0–1.9	52.9	59.2	78.4	64.3
2.0–2.9	61.8	77.7	83.8	74.5
3.0–3.9	70.6	85.1	89.2	81.6
4.0–4.9	88.2	100.0	91.9	92.9
5.0–5.9	91.2		94.6	94.9
6.0–6.9	94.1		97.3	96.9
7.0–7.9	97.1		97.3	98.0
8.0–8.9	100.0		97.3	99.0
9.0–9.9			100.0	100.0

purpose of presenting Gray's predictions is simply to indicate that the benchmark predictions provide reasonably accurate sets of predictions. We do not intend to imply that any purely statistical method provides better predictions than expert judgment. As previously noted, comparisons are tenuous because of differences in how the errors were tabulated. Furthermore, there might have been other experts whose unpublished predictions were more accurate than Gray's. The point of the comparison is to emphasize that the crude network share models based on benchmark estimates which do not involve expert opinion or content analysis do provide reasonable predictions. We contend that benchmark estimates derived from time series models can provide a framework within which expert opinions on program content and life cycles can be incorporated to provide predictions superior to those based solely on the statistical model or solely upon expert opinion.

FUTURE DEVELOPMENTS IN PREDICTION OF TELEVISION PROGRAM RATINGS

A major conclusion that emerges from time series study of prime time television viewing is that levels of total network viewing show considerable stability. This fact may be exploited to predict the ratings of three competing network series programs. The methods we illustrate are based on total household viewing data. To bring program content into the prediction model the use of individual viewing data rather than total household viewing data would be desirable. A previous study (Gensch and Ranganathan 1974) has shown that segments of the population, defined in terms of either demographic factors or past purchasing histories, have statistically significant mean differences in their preferences for various *types* of television programs. Since 1970 several national data sources, including American Research Bureau, Target Group Index, and A. C. Nielsen audience composition have provided time series viewing data by individual rather than household. Program content preferences are more meaningfully incorporated into a network share model in terms of individuals. The individual viewing data also permit greater freedom in formation of relevant market or viewing segments. Analysis of viewing segments, such as those based on age, sex, occupation, and education, should be helpful in attempting to improve the basic time series predictions illustrated in this article.

Certain competitive effects, if taken into account, would probably improve the predictions. One is the lead-in influence generated by the program shown on the same network in the immediately preceding time slot. Another is the bridging situation which arises when programs differ in length. A bridging situation occurred when *Walt Disney's World of Color*, a highly rated hour-long program, began at 7:30 p.m. and competitive hour-long programs began at 8:00 p.m. on the other two networks. A half-hour program followed *Disney*, and then the highly rated program *Bonanza* started on the same network at 9:00 p.m. It is unlikely that many *Disney* viewers switched channels at 8:00, and thus at 8:30 they faced the choice among the three networks of viewing a half-hour program or of switching to the middle of hour-long programs. Thus the competitive sequencing of programs of different duration can generate influences that are somewhat independent of program conent.

CONCLUSION

A time series analysis of prime time Nielsen viewing data provides very accurate predictions of total network viewing. The size of the total network audience appears to be more a function of calendar factors, possibly related to warm weather activities, than a function of aggregate program content. Four network share models are examined as methods of allocating the total network audience among the three networks. The models represent different assumptions about the influence of prior program and network ratings. A model for combining various influences is suggested and reasons why it provides a better empirical fit than the network share models emphasizing a single influence are presented. The empirical results of the network share models compare rather well with the highly regarded predictions of an industry practitioner.

Finally, we contend that predictions derived from network share models provide a framework within which expert opinions should be incorporated. In particular, the insights of practitioners about demographic and wearout factors, bridging situations, and program content should be utilized. A model which uses individual viewing data and incorporates the expert insights within the predictive framework of the network share model should produce a truly sophisticated program prediction. Its predictive capabilities should be superior to those of either the strict statistical models describe here or the expert judgment approach which lacks an explicit model.

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APPENDIX A
LIST OF MOVED PROGRAMS

Set	*Moved program*	*Network*	*New time slot*	*Day of week*	*Date of move*
1	*Time Tunnel*	ABC	7:30–8:30	Friday	7/21/67
2	*My Three Sons*	CBS	8:30–9:00	Saturday	9/9/67
3	*The Avengers*	ABC	7:30–8:30	Wednesday	1/10/68
4	*The Saint*	NBC	7:30–8:30	Saturday	2/17/68
5	*I Dream of Jeannie*	NBC	7:30–8:00	Monday	9/16/68
	The Avengers	ABC	7:30–8:00	Monday	9/23/68
6	*High Chapparal*	NBC	7:30–8:30	Friday	9/20/68
	Operation Entertainment	ABC	7:30–8:30	Friday	9/27/68
7	*Get Smart*	NBC	8:00–8:30	Saturday	9/21/68
8	*Jonathan Winters*	CBS	8:00–8:30	Thursday	1/9/69
	That Girl	ABC	8:00–8:30	Thursday	2/6/69
9	*The Prisoner*	CBS	8:00–9:00	Thursday	5/29/69
10	*Tarzan*	CBS	7:30–8:30	Wednesday	6/4/69
11	*Let's Make a Deal*	ABC	7:30–8:00	Friday	5/30/69
12	*Guns of Will Sonnett*	ABC	8:30–9:00	Monday	6/9/69

APPENDIX B
LIST OF NEW PROGRAMS

Set	*New program*	*Network*	*Day of week*	*Time slot*	*Date of introduction*
1	*Coronet Blue*	CBS	Monday	10:00–10:30	5/29/67
2	*Away We Go*	CBS	Saturday	7:30–8:30	6/3/67
3	*Malibu U.*	ABC	Friday	8:30–9:00	7/21/67
4	*Custer*	ABC	Wednesday	7:30–8:30	9/6/67
5	*Second Hundred Years*	ABC	Wednesday	8:30–9:00	9/6/67
6	*Off to See the Wizard*	ABC	Friday	7:30–8:30	9/8/67
7	*Gentle Ben*	CBS	Sunday	7:30–8:00	9/10/67
8	*Mothers-In-Law*	NBC	Sunday	8:30–9:00	9/10/67
9	*Maya*	NBC	Saturday	7:30–8:30	9/16/67
10	*Laugh-In*	NBC	Monday	8:00–9:00	1/22/68
11	*Dream House*	ABC	Wednesday	8:30–9:00	3/27/68
12	*The Prisoner*	CBS	Saturday	7:30–8:30	6/1/68
13	*The Champions*	NBC	Monday	8:00–9:00	6/10/68
14	*Showcase '68*	NBC	Tuesday	8:00–8:30	6/11/68
15	*Julia*	NBC	Tuesday	8:30–9:00	9/17/68
16	*Adam 12*	NBC	Saturday	7:30–8:00	9/21/68
17	*The Ghost and Mrs. Muir*	NBC	Saturday	8:30–9:00	9/21/68
18	*This Is Tom Jones*	ABC	Friday	7:30–8:30	2/7/69
19	*Generation Gap*	ABC	Friday	8:30–9:00	2/7/69
20	*Animal World*	CBS	Thursday	7:30–8:00	5/1/69
21	*John Davidson Show*	ABC	Friday	8:00–9:00	5/30/69