The Maturation of the Science of Media Selection

Roger J. Calantone and Ulrike de Brentani-Todorovic

Journal of the Academy of Marketing Science 1981; 9; 490
DOI: 10.1177/009207038100900411

The Maturation of the Science of Media Selection*

Roger J. Calantone, Ph.D.
and
Ulrike de Brentani-Todorovic, M.B.A.
McGill University

INTRODUCTION

This paper traces the historical development of models in the field of media scheduling. It shows how the process of decision-making in the area of marketing has, over the years, become increasingly more explicit, objective and sophisticated. It describes, in some detail, the models which have dominated certain stages of development over the past twenty-five years and provides a more general discussion of the less sophisticated methods that were in use during the preceding period. It shows how many of the limitations of the earlier models were slowly eliminated through the continuous improvement of analytical methods, measurement techniques and data availability, and above all, through the improved ability to conceptualize and understand increasingly more sophisticated models by theorists and practitioners in the field of advertising and marketing. Overall, we will describe the evolution in terms of the development of a science to maturity.

*This paper was invited and has not been subject to our blind review process.

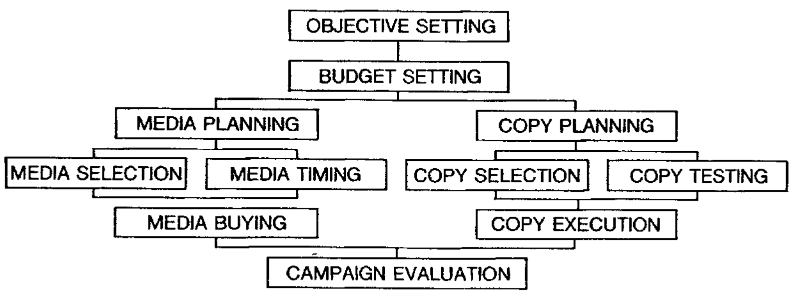
 Journal of the Academy of Marketing Science
Fall, 1981, Vol. 9, No. 4, 490-524
0092-0703/81/0903—0490 $2.00

Media Scheduling as part of the Advertising Plan

Media scheduling or planning is an integral part of the advertising plan. It involves the selection of advertising vehicles, the number of advertisements to be placed in each of these, and the timing of their insertions. Chandon (6), in a chart describing campaign planning, clearly depicts the position of media planning within the framework of the advertising campaign.

Exhibit I points out the specific tasks involved in media scheduling (planning) and shows how this function is related to the elements of budget setting and copy strategy within the campaign planning process.

EXHIBIT I
CAMPAIGN PLANNING



Media planning has attracted a larger number and a greater variation of model building efforts than any other single problem in marketing (12). It is easy to conclude that this is so when we look at the nature of media scheduling. Each year over 27 billion dollars is spent on the 8 major media in the United States alone (6). Given such huge expenditures, not only are economic criteria such as minimum costs and maximum efficiency bound to be applied, but also, ways are found to help make superior scheduling decisions offer major opportunities for cost savings. Furthermore, both the complexity and the very large volume of information that is available for effective media decisions are important characteristics leading to model building. Modeling efforts can vary from simply trying to digest some of this data volume to making major efforts in simulating relationships at a very detailed level. As such, the objectives of the models can vary from merely providing new information (i.e., digesting raw data that can aid in the media decision-making process) to actually making the final scheduling decision.

History of Media Scheduling Models: A Summary

The need for media data and models to aid in media decision-making has long been recognized. The first marketing research department in the United States was established over sixty-five years ago by Charles C. Parlin at the Saturday Evening Post, and the first systematic measure of circulation of printed media was started in 1914 with the creation of the Audit Bureau of Circulation. It was 1937 when the first media research based on the concept of exposure (rather than circulation) was performed (6).

The very early media "models," developed and used in the period from about 1910 to 1960, tended to be quite simplistic. Most were qualitative and subjective and only slowly over the years began to include quantitative elements.

It was not until the introduction of television in the fifties and the ensuing competition with established media that a vast increase in the volume of media data and exposure studies occurred. This information volume together with the introduction and development of operations research techniques and computer facilities triggered the first mathematical media scheduling models at the beginning of the sixties.

The period spanning the early to late sixties can be seen as a stage of exploration and rapid growth, marked by a proliferation of all sorts of mathematical models, many exhibiting different approaches and various techniques of analysis. Moreover, this period saw a substantial increase in model sophistication. That is, media models made fewer unacceptable simplifying assumptions and increasingly strove towards a better representation of reality.

The last decade (1969-1979) has exhibited much less in the line of new model building and much more in terms of model reevaluation and expansion. If we look at this historical development of media scheduling models in Thomas Kuhn's terms, this stage might be referred to as a certain level of "maturity" in the "science," one that features a more esoteric type of research involving "restrospective reflections" and "theory articulation." In contrast, the previous two stages could be labelled as periods of "crisis" and "revolution" (13).

In summary, although there is some overlap between the various periods, the historical development of media scheduling models can be described in terms of four reasonably distinct stages of growth:

1) the Pre-mathematical Era (pre-sixties)
2) Introduction to Mathematical Models (1960-1963)
3) Stage of Exploration and Growth (1963-1969)
4) Period of Reevaluation and Synthesis (1969-1979)

Before discussing the models associated with each of these historical periods, a review of some of the major concepts and definitions pertinent to media scheduling models follows.

THE PRE-MATHEMATICAL ERA (PRE-1960)

The pre-mathematical era spans a term from about 1900 to 1960. During the early part of this period, the media scheduling decision tended to be less complex and of less economic importance since not only were the media classes more limited in number but also the use of advertising as a major promotional tool was much less extensive. During this early period, media specialists tended to use highly subjective models based on "expert judgment" in addition to some arithmetic models based on circulation data and cost of media. Such simple models as cost per thousand tended to dominate the scene.

As advertising increased in importance as a promotional tool and as more sophisticated media information became available, the media selection process became increasingly more complex. Also, in 1938, the first exposure studies were performed thus changing the emphasis from circulation count to audience measures. The latter part of this pre-mathematical period, therefore, was marked by an increasing effort on the part of advertising executives to find models which would simplify the media scheduling function and provide an aid in making better decisions.

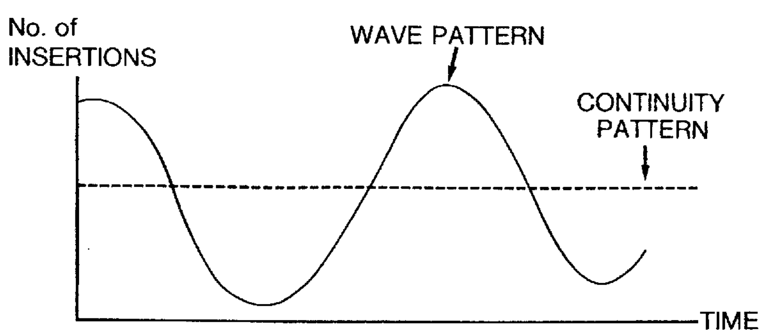
Qualitative Models

In some cases, the media scheduling "model" tended to be only implicit. For example, the size of the advertising budget and therefore, the method or "model" by which it was set, in many cases would implicitly, although in only the roughest manner, determine the type of media classes and/or vehicles that could be used.

Other qualitative media models were/are based on specific theories of consumer response to advertising and on the concepts of reach, frequency and continuity. The Wave Theory Model involves a sacrifice in continuity of advertising in order to build up coverage and frequency within specified periods of time. For example, with a given budget, an advertiser might concentrate a strong campaign into a relatively short period gaining coverage (reach) and/or frequency, and then stop advertising for a while in the hope that the carry-over effect would be adequate to cover the next period. At a later stage, the advertiser would begin the process again. Exhibit II provides a schematic representaton of this theory (5). As is evident from this model it does little towards making specific recommendations regarding the media classes and vehicles to use nor is it very explicit in spelling out the actual time periods involved.

EXHIBIT II

WAVE THEORY MODEL - QUALITATIVE



The Media Dominance Model is another qualitative and very subjective model based on the theory that concentration in any one medium or media vehicle will eventually bring diminishing returns. Therefore, an advertiser should move from one medium or media vehicle to another building up an "optimum" level of coverage and frequency in each (5). Although this model would tell the media specialists something about how long advertisements should run in individual media classes or vehicles, the exact number of insertions and the specific vehicles to use are left to "expert judgment."

An opposing qualitative media model is the Media Concentration Model based on the theory that if a medium or a certain vehicle is to be effective in exposing advertisements, it must be used on a continuous basis in spite of the fact that this may cause less breadth in media classes and therefore, less coverage (5). Again the decision of which media classes/vehicles to use, and to what degree, must be determined by "expert judgment."

Quantitative Models

As already mentioned, in the very early stage of the pre-mathematical period, quantitative models entailed circulation counts and very simple cost analyses. It was not until 1938 that major media research based on the concept of exposure shifted "the emphasis from counting the number of physical media units to counting the number of individuals entering into contact with the media" (6, p. 3). As the emphasis shifted from circulation to exposure and as a larger volume of media information became available, media experts showed increasing interest in developing more quantitative models.

Besides the more traditional cost-per-thousand type of models, several explicit models based on the concepts of reach and frequency of exposure were developed. Depending on the advertising objectives, such models could be used to maximize either reach or frequency or some combination of the two. For example: total exposure, reach and frequency could be modeled in a number of ways depending on the type of information available (16, 12):

Equation 1: $T = \sum_{i=1}^{I} A_i N_i$

where T = Total Exposure
A_i = Number of persons exposed to an insertion in medium i (i = 1, 2, . . . I)
N_i = Number of insertions in medium i on a specific period of time

Equation 2: $WT = \sum_{i=1}^{I} \sum_{j=1}^{J} A_{ij} W_j N_i$

where WT = Weighted Total Exposure
A_{ij} = number of persons in market segment j exposed to an insertion in medium i
W_j = Weight reflecting segment effect

Equation 3: $T = R \cdot F$

where R = the reach or number of persons exposed to one or more of the insertions
F = the frequency with which, on average, each person is exposed to the insertions.

Equation 4: $F = \frac{T}{R}$

Equation 5: $R = A_1 + A_2 - A_{12}$

where A_{12} = duplication; i.e., the number of persons exposed to an insertion in medium 1 and 2

Equation 6: Agostini's Formula (1961)

$$R = \left(\frac{1}{K(D/A) + 1}\right) A$$

where R = total reach
A = total number of persons in the audience of media vehicles 1, 2, . . . I
D = total of all pairwise duplicated audiences
K = constant

In the case of all but one (equation 5 involves only two media vehicles and would quickly become computationally unfeasible in cases of more than four) of the above equations (models), information was/is generally easily available. Using these formulae, the media expert could, for example, choose a schedule that maximizes reach. This might be appropriate in the early stages of a campaign when a minimal awareness in all segments is desired (16). However, using such a simple model creates problems. The model implicitly assumes that only the first exposures are relevant. Moreover, no effort is made to distinguish the type of exposure in different market segments nor is forgetting accounted for (3).

Maximizing frequency, on the other hand, may be appropriate in the later stages of a campaign when repeated exposure is needed to actually bring about purchasing behavior (16). Needless to say, the oversimplicity of the model again creates problems. In this case, the breadth of exposure, as well as the segment effect and forgetting are ignored and the very unrealistic assumption is made that each exposure has equal value. More often, a model was created to maximize some combination of reach and frequency such as a weighted combination of the two (see, for example, equation 2) or a model that maximized reach/frequency with some frequency/reach constraint (3).

With such simple quantitative models available to the media decision-maker during this pre-mathematical era, it is clear that most media decisions even those based on one or more of the arithmetic models, had to be substantially tempered by "experienced judgment" to account for the many qualitative and quantitative factors not included in the models.

INTRODUCTION TO MATHEMATICAL MODELS (1960-1963)

In 1961, mathematical programming was first applied to the media scheduling problem. The development of linear programming by G.B. Dantzig in 1947, the expansion of computer facilities during the fifties, and the continually increasing volumes of market and media data all together culminated in this first really major attempt to model quantitatively the media decision-making process.

The introduction of the first major media selection models using linear programming (L.P. models) by Young and Rubicam (Y & R) and Batten, Barton, Durstine and Osborne (B, B, D & O) in 1961 was a highly publicized event. It was greeted with much excitement since it represented a major step forward over existing techniques for allocating media budgets. At the same time, L.P. models created a great deal of confusion since the exaggerated claims of the advertising agencies using them and the demands of clients for similar services from other agencies brought to the fore the question among practitioners and theorists as to which method (computer or traditional) was, in fact, better (8,3,4).

The Linear Programming Model

Linear programming is a mathematical tool that can be used to allocate a scarce resource among several alternative uses to attain the best possible value of some stated criterion function. The criterion function of a model is a rule used to assign values to the results of alternative solutions to the problem. By looking at the assigned values generated by the criterion function, the model can rank the alternative solutions and hence specify which is the best solution. As such, linear programming is an optimizing technique using a specific algorithm (e.g., simplex method) to determine the best solution.

Linear programming, in its application to media scheduling, treats the advertising budget as the scarce resource and views the various T.V. shows, magazines and newspapers, etc., as the alternative means of using this budget allocation. The best combination of media options is then determined by some effectiveness criterion. The effectiveness criterion is generally one that has as an objective, for example, getting the most weighted advertising units for a given budget or incurring the least cost for a given level of weighted advertising units. The weighting in the criterion function is really quite subjective and represents an attempt to account for such factors as variations in the audience, in the prestige of different vehicles, in the different exposure values of particular ad forms and so forth. The final selection of media vehicles is constrained by the budget size, minimum and maximum allowable use of specific media vehicles and classes, and types of ad form permitted (8).

The B.B.D. & O. model so widely publicized in 1961 is a good example of these very early L.P. models. It attempted to maximize total exposure value of a media schedule. Its criterion (or objective) function included the desired number of units of each media vehicle multiplied by its exposure value (subjective weighting of estimated numerical exposure). That is:

Objective Function

$$\text{Maximize} \rightarrow E = e_1X_1 + e_2X_2 + \ldots e_IX_I$$

or

$$E = \sum_{i=1}^{I} e_iX_i$$

Subject to: budget, environmental and copy form constraints,

where: E = Total weighted exposure value
e_i = Exposure value (weight) of media vehicle i ($i = 1, 2, \ldots I$)
X_i = Number of units of media vehicle i to be used.

Limitations of L.P. Models

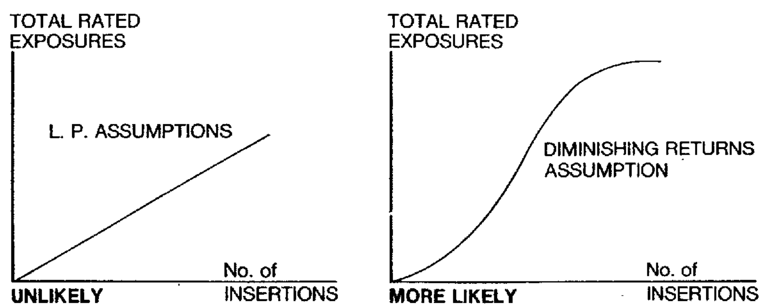
The success of L.P. models was very limited and initially highly overrated. Kotler (12) summarizes the most important limitations as follows:

1) L.P. models assume that repeat exposures have a constant effect.
2) L.P. models assume constant media costs (no discounts).
3) They cannot handle the problem of audience duplication.
4) They do not specify timing of ads.
5) They often require poor or non-existent data.

Of these limitations the key weakness is the linearity assumption. Such variables as discounts, estimates of audience duplication and value of repeated exposures are known or believed by media experts to be non-linear functions (8). For example, the assumption that all rated exposure values are constant is not logical. First, it is unreasonable to assume that, for example, a third exposure to one individual has the same value as the first exposure to another individual. Second, to assume that all additional repeat exposures to the same individual have equal value is very much in conflict with the generally accepted theory of diminishing returns. As shown in Exhibit III, it is much more likely that for any one person, as the number of exposures to insertions increases, the value of such exposure tends eventually to decrease (16).

EXHIBIT III

DIMINISHING RETURNS OF REPEATED EXPOSURES



In spite of the limitations that were characteristic of the early L.P. models, these attempts at modeling the media-selection function in in explicit and quantitative terms were extremely important. They set the stage for a great deal of creativity in model building, which eventually led to the much more sophisticated and practical models of the present decade.

STAGE OF EXPLORATION AND GROWTH (1963-1969)

The period from 1963 to 1969 was characterized by creativity and criticism: criticism, because the early L.P. models had been overrated in terms of their usefulness in media scheduling yet had been found to have many obvious flaws; creativity, because an increasing number of persons, sophisticated both in quantitative approach to marketing in general and to media scheduling in particular, turned their attention to the problem. This led to important efforts: 1) to save the L.P. approach by finding ways to handle some of its basic limitations; and 2) to apply other mathematical techniques that were more elegant in their approach to the media scheduling problem.

Since, during this period, models of all types were being developed, we will sort by class of model and then, within each group, trace the historical development that occurred. Media scheduling models can be classified either as optimizing or as non-optimizing models with various sub-categories in each group. A discussion follows of optimizing models and the various L.P. model revisions that took place.

Linear Programming Models

The single most important flaw in simple linear programming is its linearity assumption. The response function (i.e., total exposure value) is not, as is suggested, a linear function of the number of insertions. Instead, it tends to be a curvalinear function which at one point starts exhibiting diminishing returns (see Exhibit III). To deal with this reality, M.L. Godfrey (in 1962) and D. B. Brown together with M.R. Warshaw (in 1965) showed that if total exposure can be seen in terms of a concave function (diminishing returns throughout), then by splitting this curve into equivalent linear segments, an optimum media schedule could be determined through Piecewise-Linear Programming (16). That is, each straight line segment is analysed separately by the L.P. technique. The best solutions for each segment are then compared and the best of these is selected as the optimum solution for the entire curve (8).

Also in 1965, S. Stash showed that scheduling aspects could be applied to the L.P. model by adding a time suscript to each set of media insertions. Similarly, preliminary copy consideration could be added to the L.P. model via a subscript to reflect size or colour (16).

In spite of these improvements, problems remained. The concavity requirement of the Piecewise-Linear Programming technique, although realistic for parts of the response function is generally not applicable to the entire curve. Usually exposure value is seen as something that initially increases with the number of insertions and only after some point begins to bring diminishing returns (i.e., S-curve, See Exhibit III). Moreover, assuming that the exposure function could presumably be seen in non-linear terms, this still left the constraints (such as discounts, estimates of audience duplications and value of repeat exposures), which are known or believed by media experts to be non-linear, as straight-line functions (8).

The most recent improvement of the basic L.P. approach to media selection was published in an article by Charne, Cooper, DeVoe, Learner and Reinecke in 1968. L.P. II (as this second generation L.P. approach is often referred to) uses the concept of "goal programming" whereby the program seeks to minimize the distance from stated goals. The deviations are weighted so that some goals can be given preference over others. The objective function is as follows:

$$\text{Minimize} \rightarrow Z = W_1(u^+ + u^-) + W_2(v^+ + v^-)$$

where: Z = distance from stated goals
W_1 = importance of goal i (i = 1, 2, . . . n)
$(u^+ + u^-)$ = positive and negative variances from first goal
$(v^+ + v^-)$ = positive and negative variances from second goal.

L.P. II is an improvement over the earlier L.P. models in that it attempts to separate individuals into different market segments (i.e., segment effect) via the use of a frequency distribution in place of the customary single value for average exposure frequency. It also attempts to deal with the problem of optimizing interrelated goals for advertising schedules by evaluating the tradeoffs between interrelated and interdependent advertising goals (8).

Although goal programming offers some improvements (but even this may be questioned, since according to Gensch, much of the model must be accepted on faith (8)), important limitations remain. Duplication is not accounted for realistically; the model is completely dependent on the goals set by managers (these may not necessarily be optimal); and the integer nature of insertions (i.e., L.P. solutions are often fractional) are not explicitly considered (16). W.I. Zangwill (in 1965) did attempt to overcome the problem of fractional L.P. solutions via integer programming, but the relevant algorithms as well as the entire L.P. II approach at present, is still computationally and practically unfeasible (16, 8). As a result, the L.P. model, even in its extended form, is generally not applied to the media selection problem today.

Dynamic Programming

Dynamic programming is an optimizing technique whose main approach to solving a complex problem is to divide it into a sequence of smaller problems, called "stages." The stages are solved, one at a time, starting with the last stage in the decision sequence. A number of variables determine the quality of alternative decisions at each stage. This quality is given a numerical value called the "reward" of that stage. The effect that the decision that was reached in a particular stage will have on the status or "states" of all the previous stages is taken into account before the decision in that stage is made. Therefore, the state of each stage depends on: 1) the variables that determine the reward of the stage; and 2) the decisions made in all previous stages.

Dynamic programming can be applied to the media scheduling problem by interpreting the time periods over which the schedule is to run as the various "stages" and where the variables that affect the "reward" of each stage would include, for example, vehicle cost, number of vehicles available, value of successive exposures, values of different advertising formats and values of different market segments. The objective function of a dynamic programming media selection problem would be:

$$\text{Maximize} \rightarrow \sum_{i=1}^{t} R_i \text{ given that } R_i = f(s_i, d_i)$$

where: R_i = Reward of the process in stage (time period) i ($i = 1, 2, \ldots t$)
s_i = Process state of stage i
d_i = Decision made at stage i

The dynamic programming algorithm is a "brute force technique" that takes into account all possible combinations of decisions and then selects the best alternative. By selecting the best decision in the last stage and then working backwards, the number of combinations that must be directly examined is substantially reduced (8).

In 1960, Richard Maffei first used this approach to solve a media scheduling problem of allocating a given advertising budget among three media in a test market. This went by almost unnoticed since it was very small and quite unrealistic.

Probably the best known and certainly the dynamic programming model most often referred to in the literature is MEDIAC. It was developed by John Little and Leonard Lodish in 1966 and later extended and changed to a heuristic program. (I shall refer to the 1966 version as MEDIAC I and the extended 1969 version as MEDIAC II.)

MEDIAC I uses sales as the criterion for a media schedule. The sales results of a schedule are defined as the sum of the sales in each of a number of market segments over a number of time periods. The sales in each segment, in turn, depend on the number of persons in the segment, their sales potential and the level of advertising exposure in the segment. The *sales response function* is non-linear exhibiting diminishing returns to the *exposure value per capita*. The exposure value per capita is seen as the principal determinant of sales and reflects the sales effect of a media schedule. The exposure value per capita is subject to change over time since it takes in decay (forgetting) and the cumulative effect of additional exposures (carry-over).

EXHIBIT IV

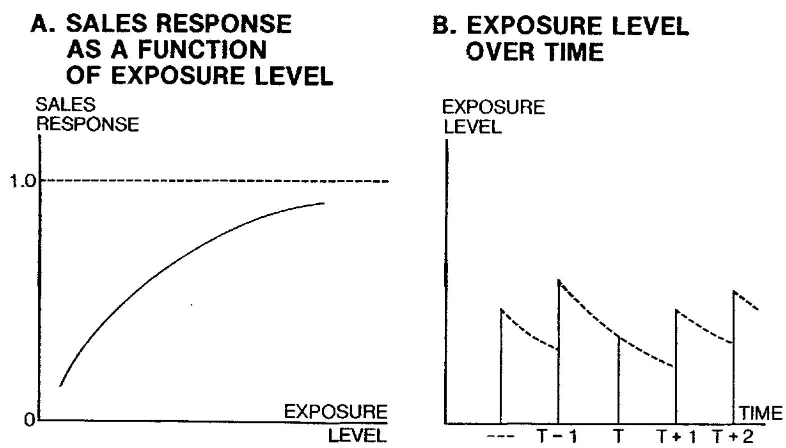


Exhibit IV presents hypothetical curves depicting the sales response function and the exposure level as described in MEDIAC I.

The mathematical programming problem in MEDIAC I is to maximize al sales over the planning period subject to budget and media restrictions. The objective function is to find the media insertion schedule that will:

$$\text{Maximize} \rightarrow \begin{matrix}\text{Total Sales}\\ \text{for the year}\end{matrix} = \sum_{i=1}^{s} \sum_{t=1}^{t} n_i q_{it} f(y_{it})$$

where: n_i = Number of people in market segment i (i = 1, 2, . . . S)

q_{it} = Sales potential of a person in segment i in time period t (t = 1, 2, . . . T)

$f(y_{it}) = r_{it}$ = % of sales potential of market segment i that is realized in period t.

Subject to: 1) Current Exposure Value Constraint

$$Y_{it} = \alpha Y_{i,t-1} + \sum_{j=1}^{N} k_{ijt} e_{ij} x_{jt}$$

where: y_{it} = exposure level of average individual in market segment i in time period t

α = % of ad remembered from one period to next

k_{ijt} = expected number of exposures produced in market segment i by one insertion in media vehicle j in time period t

e_{ij} = exposure value of one exposure in media vehicle j to a person in segment i

x_{jt} = number of insertions in media vehicle j in time period t

2) Lower and Upper Media Usage Constraints

$$\ell_{jt} \le x_{jt} \le u_{jt}$$

where: ℓ_{jt} = least number of insertions in media vehicle j in time t

u_{jt} = most number of insertions in media vehicle j in time t

3) Budget and Nonnegativity Constraints

$$\sum_{j=1}^{N} \sum_{t=1}^{T} c_{jt} x_{jt} \le B \text{ and } x_{jt}, y_{it} \ge 0$$

where: c_{jt} = cost of one insertion in media vehicle j in time t

Little and Lodish make a number of assumptions and these are the basis of the most important weaknesses in MEDIAC I. First, the model is limited to four time periods since the nature of dynamic programming in combination with the storage capacity of computers does not permit longer time spans. For similar reasons, the model assumes that only one media class (magazines) and only fifteen vehicles are relevant. These are not very practical assumptions considering the length of most major advertising campaigns and the number of media classes and vehicles actually available. In addition, although the model does try to take into account a limited number of different market segments, each of these is assumed to be homogeneous. Not only are individuals in any one segment seen as homogeneous with regard to their sales potential but also in terms of their exposure value, exposure efficiency, retention of advertisement and their probability of media usage. This is highly unrealistic and one would question whether segmentation of this type has any value at all in accounting for the segment effect (8).

Another very important and highly unrealistic part of the model is the assumption that sales are a function of advertising exposure alone. Factors such as price, product quality, product availability, competitive behavior and environmental factors are basically ignored (8). Presumably the advertising executive is expected to build these factors into her/his subjective estimate of the response function. Furthermore, the model assumes that the sales potential of each segment is fixed and cannot be influenced by the primary demand stimulating nature of advertising. These assumptions are particularly upsetting since this is a dynamic model covering several time periods.

Finally, the inability of MEDIAC I to handle the discounted cost structure of advertising media purchasing places an additional strain on the model (8).

To summarize, dynamic programming is an improvement over linear programming in that it permits curvalinear relationships and introduces the concept of real time into the model. At the same time, it does not seem to have the capacity to select a media package that considers simultaneously all of the leading media vehicles. Present (1979) computers simply do not have the storage and computational capacity to handle a large scale problem with the degree of complexity found in a realistic media scheduling system. The method requires constraints (in the number of variables and interactions) that simplify the problem to where it tends to distort reality.

Up until now, the discussion of mathematical media scheduling models has involved those that use various optimizing approaches. That is, each model has a definite procedure or algorithm by which it can predict the "best" media schedule from the various alternatives under evaluation. The chief task of the model builder using one of these approaches is to define the real world problem in terms of the requirements and limitations of the specific algorithm. An obvious danger with such an approach is that the model builder tends to get carried away with the mathematics and, in the process, distorts reality in order to meet the constraints of the model.

Non-optimizing models differ from the optimizing approach in two important ways: 1) they attempt to find a "good" solution to the problem (rather than the best); and 2) they are much more flexible in their representation of reality. In the case of non-optimizing models, the model-builder attempts to identify the relevant variables and quantify the relationships between these without modifying reality excessively to fit a specific solution algorithm. As such, non-optimizing models are much more able to use data about individuals in all their complexity (i.e., fewer simplifying assumptions are required).

Non-optimizing mathematical media scheduling models fall into two basic groups: 1) heuristic models and 2) simulation models. Both types permit manipulation of the variable and/or relationships in order to infer possible outcomes and both lead to only "close-to-optimum" rather than "optimum" solutions. The chronological development of these models occurred concurrently with the more advanced L.P. models just described.

Heuristic Programming

Early Heuristic Models

Some of the earliest attempts at heuristic programming of the media scheduling function were British efforts to deal with problems arising at British European Airways. These models were much more explicit in their treatment of exposure probabilities and individual response to exposure than those concurrently developed in the U.S.

Lee and Burkart, British authors, in 1960, were the first authors to formulate mathematically the media problem in a really meaningful fashion. In their model, they clearly differentiated between the exposure criterion of frequency and reach and developed mathematical relationships for these. In this first model, they attempted to maximize the frequency of the campaign via a heuristic rule of purchasing advertising in an inverse proportion to the square of the cost per thousand. At the same time, maximization of reach was attempted under the assumption that the square of the proportion of the target group readership for a medium, divided by the cost of an insertion, was equivalent for all media (16).

In 1962, Lee expanded the 1960 model by showing that since it was generally impossible to maximize both reach and frequency criteria simultaneously, it would be more realistic to maximize one criterion subject to restrictions in the other. Lee stressed the difference between the two criteria and explored the implications of maximizing either (16).

In 1963, Taylor proposed graphical heuristic procedures to derive solutions to the exposure problems formulated by Lee and Burkart. Through his method, both the number and size of insertions for each medium could be determined by finding the point (graphically) where the marginal returns of the last insertion equaled the cost of insertion for each medium. In the same year, Lee developed an approach that considered the dynamic nature of the media problem. By introducing into the model a mathematical rule to account for forgetting, Lee reformulated the problem as "one of determining the media schedule that would maintain at least a specified total awareness for each day of the campaign at the minimum cost" (16, p. 142).

In 1966, D.M. Ellis modified Lee and Burkart's problem formulation to include a more complete probabilistic response function by assuming different probabilities of exposure for different people in the target group. Marc, in 1968, used panel data to determine individual readership probabilities and thus made the model more realistic (8, 16).

The final key equation of the Lee and Burkart model was (8):

$$R = Q \sum_r W_r I_r$$

where: R = response function indicating how positively the target population responds to a given media schedule
Q = Value indicating effectiveness of formats used
W = Weighting factor measuring proportional response from those people who have received r impacts (frequency) and who form proportion I_r of target population
I_r = Proportion of target population who have received r impacts

The initial Lee and Burkart formulation and the various mathematical expressions that supported its objective function required making several assumptions. The degree to which these assumptions were realistic determined the quality of the model. The initial assumptions include the following (8):

1) The attention value of an advertising form is solely a function of an ad size (ignoring such variables as use of colour, ad position, and uniqueness, etc.)

2) In estimating audience duplication between media vehicles, the authors assumed independence in readership (i.e. randomness) among various vehicles (thus ignoring empirical evidence that showed definite viewing and reading patterns).
3) The readership probability of various issues of a specific media vehicle is independent; (again ignoring a definite vehicle reading/viewing patterns over time).
4) The probability of ad recognition is independent of previous exposures; (thus ignoring all recognition patterns).
5) Sales is solely a function of the number of ad exposures a given individual receives; (thus ignoring other important marketing mix and environmental factors).

A subset of these five basic assumptions tends to be found in all media selection models. The extent to which they have been eliminated in any one formulation, greatly determines the quality and realism of that model. In the Lee and Burkart model, all five assumptions were present in the initial version (1960). However, the work performed (by the authors noted) to improve and extend the model in the period from 1962 to 1968 plus the increasingly more sophisticated data available, contributed substantially to making the model more useful and realistic.

Iterative Heuristic Models

Iteration models in media selection are in widespread use both in Europe and in North America. It is a technique that constructs a media schedule in steps. It brings vehicles into the solution one at a time selecting the one with the highest value first. The list is then examined and the vehicle with the next highest value is selected. This process is repeated until enough media vehicles have been scheduled to exhaust the budget. Generally, after each selection, the values of the remaining vehicles are re-computed and any duplication in the values of the remaining vehicles is subtracted. This re-computing ensures that only vehicles with the largest unduplicated value are chosen. The mathematical technique used in this approach is called "iteration," meaning that successive solutions are reached, each moving closer to optimum. Although iteration tends to move towards an optimum solution, it is not an optimizing technique since it does not use an algorithm which guarantees the best solution out of all possible alternatives (8).

One of the first iteration models used was developed by Young and Rubicam in 1963 and is known as "high assay." Other users include J. Walter Thompson (U.S. agency), Standard Rate and Data Services (U.S., in 1964), Mather and S.H. Benson (both British agencies, in 1965 and 1966 respectively). Since these models or expanded versions of their original formulation, are presently still in use and are treated by the respective agencies as trade secrets, it is impossible to provide the details of any one of these models. However, the basic structure of an iteration advertising media selection model can be observed in the flow chart in Exhibit V.

There are certain advantages to using the iterative approach. First, not only does it select media vehicles but it simultaneously develops a schedule. Second, it does attempt to deal with the duplication problem and it takes into account media discounts. Finally by breaking the market down into subgroups, it tries to include the segment effect in the media plan.

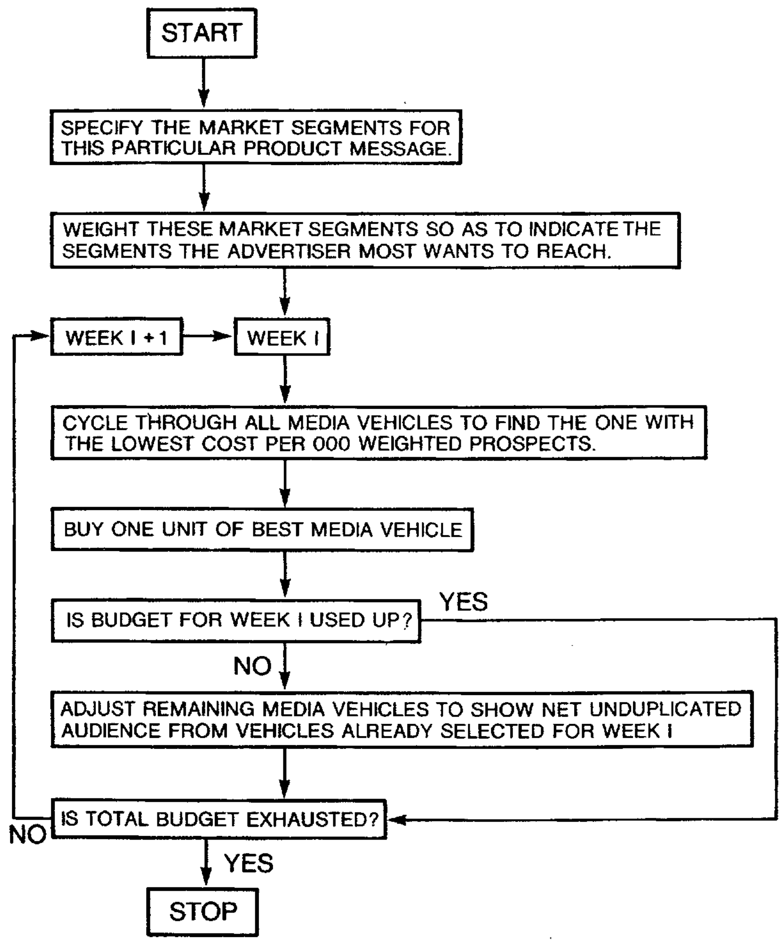
Iteration models also have several limitations. The models often do not reach an optimal solution (although this is, of course, true of all heuristic models) and tend more towards short-run, instead of the long-run, optimum. The criterion function generally is rather limited in that it is often based on rather simplistic measures. Finally, the model does not take into account the effects of time on retention; that is, it ignores forgetting and the carry-over effect (8).

Other Heuristic Models

Two other well-known (that is, well-described in the literature) heuristic media planning models, both developed by David A. Aaker in 1968, include POMSIS and ADMOD I. (Since Aaker published an expanded version of the latter model in 1975, I shall refer to the 1968 verion as ADMOD I and the 1975 version as ADMOD II). It is essential to point out at this stage that these are not the only heuristic models in use during this period. As a matter of a fact, from what is known, neither versions of ADMOD have ever been applied. However, given the secrecy on the part of advertising agencies regarding the details of models actually in use, it is difficult, if not impossible, to include these models as part of the discussion presented here.

EXHIBIT V

BASIC STRUCTURE OF AN ITERATION ADVERTISING MEDIA SELECTION MODEL FLOW CHART



(Source: Dennis H. Gensch, Advertising Planning: Mathematical Models in Advertising Media Planning(Amsterdam, Elsevier Scientific, 1973), p. 48.)

POMSIS is a heuristic model applicable only to industrial media selection. By limiting the model in this way and considering only industrial journals, Aaker avoids many of the complexities and data requirements characteristic primarily of the consumer advertising media scheduling problem.

In POMSIS, Aaker directly attacks the problem of how to evaluate multiple exposures to ads by disaggregating the exposure function to the level of the individual. POMSIS divides the relevant population into mutually exclusive and exhaustive segments and a sample of at least 100 to 200 individuals is taken from each segment. These samples provide both the exposure and the readership probabilities. The objective function is as follows (8):

$$\text{Maximize} \rightarrow TEE = \sum_{i=1}^{n} WE_i$$

$$\text{Given that} \rightarrow WE_i = \sum_{j=1}^{m} P_{ij}\, W_{1ij}\, W_{2ij}\, W_{3ij}\, W_{4ij}$$

where: TEE = Total effectiveness of exposures for a particular media schedule

WE_i = Weighted exposures for individual i (i = 1, 2, . . . N; N = total number of individuals).

P_{ij} = Probability that individual i will receive an exposure from journal j.

W_{2ij} = Individual weights; importance of market segment of which individual is a member.

W_{3ij} = Vehicle weights; editorial climate of journal

W_{4ij} = Advertising form weights; individual actually exposed to the ad in that journal.

The above formulation states that the total effectiveness exposure for a particular media schedule is the sum of all weighted individual exposures in each of the market segments. The fact that the probabilities are multiplied by, rather than added to, each of the four weights implies that they repesent variables that are not independent of each other. In order to maximize TEE, POMSIS uses a selection heuristic, similar to iteration, that adds insertions incrementally until the budget constraint is reached (8).

POMSIS is well suited for the industrial market since limiting media vehicles to journals and defining mutually exclusive market segments can be tolerated here. Through its system of weights and its disaggregation of exposure, it accounts for the various effects (e.g. segment effect, media option source effect, etc.) that impinge on a media schedule. At the same time, a number of problems prevail, particularly regarding the method of obaining exposure probabilities. Obtaining these for each campaign would involve substantial time delays and expense; and such sampling data would require validation and regular updating. An important theoretical limitation of the model concerns its static nature. It does not deal with the dynamic nature of media scheduling by completely ignoring the concept of carry-over effect (8).

ADMOD I uses the same approach as POMSIS in evaluating multiple exposures by operating at the individual level (i.e. disaggregate) through the use of sample populations. Moreover, it is similar to most media models in that exposure value is at the basis of its objective function. However, instead of leaving it to the manager to relate exposure implicitly to some marketing objective or connecting it explicitly to sales response, as in the case of MEDIAC, ADMOD I provides for such a relationship within the framework of the model but does not specify its precise nature. Instead, for each campaign, ADMOD I might focus on a different consumer cognitive change or decision that the advertising is attempting to precipitate and will select that schedule which will maximize the total present value generated (3).

The purpose of the objective function in ADMOD I is to attach a value (expected value that has been discounted over time) to a media insertion schedule based on exposure of ads to the individual. Its precise formulation is as follows (3):

$$\text{Maximize} \rightarrow V = \sum_{s} N_s/n_s \sum_{i \varepsilon s} W_s \sum_{z_i} a_s(z_i) f(z_i)$$

Subject to: $C_j X_j \leq B$ and $\ell_j \leq x_j u_j$

where: V = Total expected value generated by insertion schedule
N_s = Number of individuals in the total markets
n_s = Number of individuals in the market segment
w_s = Present value of obtaining a certain result from a member in segment s
$a_s(z_i)$ = Repetition function

a_s = probability that advertising campaign was successful in market segment s

z_i = Number of exposures (based on probability that individual i will be exposed to media option j, i.e., p_{ij}).

c_j = Cost of insertion in vehicle j

x_j = Number of insertions of media option j

B = Budget size

ℓ_j = Minimum number of insertions of media option j

u_j = Maximum number of insertions of media option j

Advantages of ADMOD I include its attempt to account for: 1) exposure probabilities at the individual level, 2) the segment and media option source (very subjective) effect, 3) the relationship of exposure to a specific but flexible marketing objective, and 4) time, via the repetition function. However, there are several limitations. Although segments are brought into the model, these are asumed to be homogeneous in regard to, for example, repetition and forgetting. The model excludes any reference to the many environmental and non-advertising variables that can have an impact on exposure and on the probability of advertisement success. In fact, the probability of success is seen as a function of the number of exposures only.

The second major class of non-optimizing models involves a micro-analytic simulation approach. "Simulation models attempt to ascribe personal probabilities of exposure to a large sample of simulated individuals, in order to reproduce as well as possible the observed reading (viewing) patterns" (6, p. 32). The logical structure of such model is not predetermined or constrained by the requirements of a mathematical formula (algorithm) used for the purpose of selecting the best alternative on the basis of some specified criteria. Instead, simulation permits the model builder substantial freedom in specifying the logical structure of the model. Therefore, by giving up the elegance of a model which optimizes a very simplified version of the problem, the media specialist gains a flexibility which allows for much more complex and realistic formulations of the problem (8).

As in the case of any other class of models, simulation also has its drawbacks. First, although the model can evaluate media schedules, it is left entirely up to the decision-maker to make the final selection. That is, simulation does not perform the function of choosing the optimum or near-optimum solution (unless the model is extended and includes such a heuristic as is true of more recent models). Second, in a number of cases (e.g. C.A.M., to be discussed) simulation models output a measure of effectiveness which cannot be compared to any of the more conventional measures. This makes it very difficult to judge schedule effectiveness and to relate explicitly or implicitly this measure to a specific advertising or marketing goal. Finally, the majority of simulation models (excluding C.A.M. and SCAL, to be discussed) are characterized by a general lack of reported empirical validation (of the simulated behavioral patterns) (6, 8). This, of course, places an important burden on the part of model-builders to prove that such simulations are indeed useful and realistic.

Simulmatics

"Simulmatics" was developed by Simulmatics Corporation and advocated for use in media scheduling as early as 1961. It is one of the best known simulation models in the industry, although one that was never adopted. Simulmatics is based on an imaginary population representing an accurate national sample of 2,994 individuals. This sample is properly distributed with regard to both demographic and economic characteristics and provides for each individual social attributes and media habits (8).

The computer simulation cycles through the entire population of 2,994 individuals hour by hour through a day, week, month or year as the client's needs dictate. The exact evaluation program varies from medium to medium. For television, for example, the program starts with an initial estimate of the probability that an individual will be exposed to a given program at a given time. This initial exposure probability is then modified by functions representing habit formations in T.V. viewing, saturation with given shows and competitions from other shows. It was even claimed that the model could simulate the decision-making process that individuals undergo when faced with a choice between T.V. shows (8).

Besides the fact that in 1961 advertising theory was not sufficiently developed to permit as abstract a model as Simulmatics, advertising agencies did not use the model for a number of reasons. They knew that clients would demand some evidence that the imaginary sample really did correspond to the national audience. Also, it was impossible to determine to what degree the interrelations programmed into the imaginary sample would become dated over time. And how sure could agencies be that such relationships would, in fact, be updated by Simulmatics Corporation? Finally, simulmatics could not really justify many of the functions it proposed using to represent such things as habit formation, saturation and competition in media vehicles. Although Simulmatics Corporation did offer to make the model less abstract and more valid, it was never adopted by advertising agencies (8).

In spite of its failure in practical terms, Simulmatics represents an important milestone in media modelling. It encouraged the development of a large number of other attempts at simulating the media selection problems; models that were less abstract, more realistic and that avoided some of the pitfalls inherent in Simulmatics. In fact, simulation is an important method of modelling the media planning process that is in actual use by advertising agencies today.

C.A.M. and SCAL Simulation Models

The British C.A.M. and the French SCAL simulation are the only two models in this class that have had adequate empirical validation. This fact has made much more credible within the advertising industry and has probably been an important factor in their practical application by advertising agencies.

C.A.M. became operational in 1964 and was based on two years of research by Beale, Hughes and Broadbent of the London Press Exchange. The model is in use today and influences the spending of over ten million pounds per year.

C.A.M. attempts to simulate the process by which T.V. and magazine ads reach individuals. It starts by acquiring and combining viewing and reading data for a certain time period. A target population for a message is then selected and weighted in three different ways. First, a set of weights is developed to determine the perception value (i.e. expected impact of ad viewer). Next, to account for the difference in advertising impact due to time of day, day of week and type of publication, a series of selectivity weights are used. Third, to determine the ad's usefulness (effects on person), impact weights are created. The objective of the model is to describe how an advertising campaign affects the defined target population.

That is, to determine the campaign's "Impression Value" or its PRI (i.e., the Probability of Receiving an Impression) for each individual. That is:

$$PRI - P_{ij}\ W_p\ W_s\ W_I$$

where: P_{ij} = Adjusted probability of seeing the media vehicle for each individual
W_p = Perception weights
W_s = Selectivity weights
W_I = Impact weights

Once PRI has been determined for each individual, an impression distribution can be obtained. Another series of weights applied to this impression distribution produces one number, the Schedule Effectiveness Value, by which the entire schedule can be evaluated (8).

Important characteristics of C.A.M. are its empirical validation and its attempt to combine all judgements involved in evaluating a media package into a logical flow sequence. As already noted, its unitary (one number) output, although convenient, presents problems in that it is not comparable to any conventional effectiveness criterion. Also, it is generally agreed that its present method of combining reading and viewing data leaves something to be desired (8).

SCAL is a model simulating the media scheduling process that was developed by Bertier and deJeu, and has been in operation in French advertising agencies since 1967. It is limited to magazine print media and is based on data from a survey of some 2,000 individuals. Using a model of individual behavior, SCAL simulates a person's reading patterns over time via a Monte Carlo process. The survey data on which the model is based is checked regularly via validating panels (8).

SCAL is an improvement over C.A.M. and Simulmatics because it introduces the actual timing of ads into the decision process and because it uses a validating panel to check on reading habit predictions (8).

AD-ME-SIM MODEL

In 1969, Gensch developed a simulation model, AD-ME-SIM, that attempts to incorporate the multi-dimensional individual differences found in any defined market segment into the media decision model. In order to perform this simulation AD-ME-SIM requires a number of data and judgmental inputs. First, a proposed media plan and schedule is required together with four sets of weights to account for: (1) effectiveness of different media, (ii) effectiveness of alternative media options, (iii) the value of different patterns of exposure frequency, and (iv) the value of an exposure to different types of persons in the target population. Next, a list of media cost and volume discounts is required; and finally, data from the Brand Rating Research Corporation is put in showing the reading and viewing patterns over time of a real sample of people (9).

As output, AD-ME-SIM provides information on five different evaluation criteria. First, the model provides an estimate of the unduplicated audience of the various media vehicles in the schedule (i.e., vehicle reach). Second, vehicle reach is adjusted by the media option weights to determine the number of individuals reached by the various commercials presented in these media vehicles (i.e., commercial reach). Vehicle frequency and commercial frequency estimates are determined in a similar manner. Finally, the model outputs an appraisal of "Impact Units." These represent an abstract number that describes the impact that the given media schedule is estimated to have on the target population. With this array of five outputs, the media decision-maker has several criteria with which to evaluate a media schedule. As an option, a heuristic program can be introduced to aid in finding a good media schedule (9).

Although the Gensch model was developed and tested on major products in conjunction with J. Walter Thompson, advertising agency, it has never actually been applied to a media scheduling situation. What is an important step forward, is the amalgamation of the detail and flexibility provided by simulation and the near-optimal selection procedure provided by the heuristics. The fact that it is limited to the television and magazine media classes, and that it produces five different evaluation criteria values tend to be drawbacks in that they make the model less realistic and less convenient to use.

Other Simulation Models

The models covered in this paper are by no means the only ones published or in use today. Several others remain unpublished and are used by advertising agencies. This is true particularly in the case of European and British agencies where simulation (at least the published models) seems to have taken a much stronger hold.

Stage of Exploration and Growth: Summary

Considering the changes that took place during the period from the early sixties to 1969, one could conclude that by the end of this decade, the state-of-the-art of media model building had altered radically. It has moved from a rather simplistic and naive stage of development to an extremely detailed and complex setting. Many different approaches had been applied to the media planning progrlem and had produced some reasonably viable and many not-so-viable alternative formulations. However, many problems remained. Practically all models, including those that had actually been applied, still had important limitations which required attention. For example all models, to a greater or lesser extent, were limited in regard to the type of audience data available, in accounting for segment and media option source effect, in acquiring appropriate intermedia information and advertising exposure data. Furthermore, all models still needed substantial effort in developing realistic response functions that took into account, in an objective and explicit manner, the many environmental and non-advertising variables that influenced the effectiveness of an advertising campaign.

PERIOD OF REEVALUATION AND SYNTHESIS

The onset of the seventies marked the end of the uninterrupted growth that was so characteristic of the previous decade. A review of the literature from 1969 to 1979 shows that very few really new models or approaches in the area of media selection were being developed during this period. Instead, some authors were reevaluating and expanding their earlier formulations while others concentrated on analysing the details of previously developed models.

If, for the moment, we again view the development of media planning models as a field of interest that is maturing towards the stage of a "science," then in Kuhn's terms, one could conclude that it has very possibly reached the early stages of what he refers to as a "normal science" (13). That this stage of maturity is not that far removed is signified by the fact that much of the current research is at a much more esoteric level; that it is published in highly specialized journals; and that it is increasingly concerned with "mopping up the details" (13) type of inquiries.

By the end of the sixties it was clear that a definite trend towards either heuristic or simulation models was underway with the former model type having greater popularity in the U.S. while the latter found more acceptance in Britain and Europe. Increasingly, model builders were interested in models that programmed their view of reality and incorporated much of the complexity involved in the media selection process.

In 1970, Gensch published an article that very clearly expressed the need for future research in the area of model details. He states here that "model builders tend to stress the functional relationships within a model, going into considerable detail in regard to its mathematical properties, and then leave it to the model *user* to fill in the blanks regarding media weights" (10, p. 216). The accuracy and usefulness of any quantitative model is, after all, as much influenced by the quality of the media weights as it is by the correctness of the mathematical relationship. Gensch therefore suggests research to answer such questions as: 1) what are the most common media weights, 2) what factors should be considered in determining the value of specified media weights; and 3) what are some ways of measuring the influence of each relevant factor (10).

Re-evaluation and Improvement of Heuristic Models

In 1969, Little and Lodish brought out an improved version of their 1966 dynamic programming model. Although the new model (MEDIAC II) maintained the same basic structure, it incorporated a number of changes that helped to eliminate some of the weaknesses described concerning MEDIAC I. First, by basing the exposure level of individuals in the various segments, not on an overall average, but instead on the moments of a probability distribution, the authors have helped to eliminate some of the distortion due to aggregation. Second, changing the selection mechanism from a dynamic optimizing approach to a heuristic permits a much more realistic number of media vehicles, media classes and market segments. Third, MEDIAC II attempts to account for the effects of duplication, although even in this improved version, the effort leaves much to be desired. Finally, changing the model to a conversational, on-line, time-sharing program makes it more practical for potential users (14).

In 1973, Zufryden developed a model that incorporate much the same territory as does MEDIAC II in that it accounts for: market segments, size and sales potential of each segment, media costs and budget constraints, time and probability of ad exposure, carry-over and forgetting effects, diminishing returns and saturation effects of total advertising exposures, and individual response and purchase behavior. Also, as in MEDIAC II, Zufryden's model directly relates the media schedule's exposure effectiveness to the sales response function. However, instead of leaving it up to the manager to estimate such a relationship on a subjective "expert judgment" basis, Zufryden develops a stochastic model based on actual purchase behavior (18). If the stochastic relationship between exposure value and sales response is truly representative of consumer behavior, then this development has helped to eliminate an important weakness in the MEDIAC model.

In 1975, Aaker published an expanded version of the ADMOD model (i.e., I shall refer to it as ADMOD II). It attempts to account for the interdependencies between the media selection function and the other two management decision areas within the advertising planning framework (see Exhibit I). In addition to the media schedule, ADMOD II simultaneously addresses the budget decision and the copy platform. Its goal is to select a budget level, a copy approach and a media insertion schedule to maximize the objective function (1).

In 1976, Srinivasan in one respect followed the Aaker lead in proposing a method that simultaneously determines advertising budgets as well as media plans. A more important contribution, however, derives from his attempt to apply a viable optimizing method to a multiperiod media scheduling problem. (Previous methods were computationally not feasible beyond three to four periods — see MEDIAC I). The author shows that under certain conditions a multi-period problem can be decomposed into a sequence of simple one-period problems. Then, by determining "correction factors" to account for the carry-over effects, the optimum media schedule can be found. Furthermore, to deal with multiperiod problems that do not meet the decomposition conditions, Srinivasan develops a heuristic which he shows to be an improvement over that used in MEDIAC II and which will reach very close to optimal solutions (17).

A recently published article in the field of media selection models is one by Headen, Klompmaker and Teel in 1977. These authors do not develop a media scheduling model per se but instead present an improved method of accurately predicting audience exposure patterns that would be generated by a given advertising schedule. Since recent emphasis, both in the ADMOD and the MEDIAC models has focused on the complete frequency distribution of exposure (instead of just average reach and frequency). This new approach should be particularly useful in increasing the accuracy of their solutions (11).

Further Development of Simulation Models

Simulation models, at least those published, have found greater acceptance in Britain and Europe than in the U.S. A number of models were developed there in the sixties and early seventies and are still in use today. The only major ongoing effort in the U.S. regarding simulation media models is COMPASS. In 1965, ten U.S. advertising agencies banded together under the advisory services of the Diebold consulting firm to develop this joint project. Presently it is not yet operational. Apparently many of the problems that would define a meaningful single evaluation criterion, find a method leading to "the" optimal solution, and obtain updatable empirical measurements for the many interrelations among variables that are generally ignored, have not yet been solved (3).

The Future

It is clear from the foregoing that media scheduling models still must undergo substantial refinements before they can be expected to reach the levels of accuracy and realism that is required by advertisers. Nevertheless, it is also clear from this chronological discussion, that in less than twenty years media models have moved from a state where they comprised a set of very simplistic arithmetic operations to one where they include highly sophisticated mathematical formulations. If future research continues to focus on "cleaning up" the details of the most feasible models, it is very possible that, to an increasing degree, the media scheduling function will be carried out by these models.

At the same time, it is important to remember that advertising involves people, competitors, products, and a changing environment. Above all, it calls for creativity and innovativeness and it is highly unlikely that any mathematical model, no matter how elegant, can ever find effective solutions to the media selection problem, let alone the entire advertising question. But, if to an increasing degree, the analytical details can be handled by a computer that is endowed with a really good model, advertising executives can spend more time and energy on these creative aspects and hence altogether make much more effective advertising decisions.

REFERENCES

1. Aaker, David A., "ADMOD: An Advertising Decision Model", *Journal of Marketing Research*, Vol. XII (February 1975), pp. 37-45.
2. ————, "A Probabilistic Approach to Industrial Media Selection", *Journal of Advertising Research*, Vol. 8, (September 1968).
3. ————, and John G. Myers, *Advertising Management*, Englewood Cliffs, N.J., Prentice-Hall, Inc., 1975.
4. Barbon, Roger, *Media in Advertising* (New York, McGraw Hill, 1964).
5. Brown, Lyndon O., Richard S. Lessler and William M. Weilbacher, *Advertising Media: Creative Planning in Media Selection*, (New York, Ronald Press, 1957).
6. Chandon, Jean-Louis Jose, *A Comparative Study of Media Exposure Models*, Unpublished Ph.D. Thesis (Northwestern University, 1976).
7. Duffy, Ben, *Advertising Media and Markets*, (New York, Prentice-Hall Inc., 1939).
8. Gensch, Dennis H., *Advertising Planning: Mathematical Models in Advertising Media Planning*, (Amsterdam, Elsevier Scientific, 1973).
9. ————, "A Computer Simulation Model for Selecting Advertising Schedules", *Journal of Marketing Research*, Vol. VI (May 1969), pp. 203-214.
10. ————, "Media Factors: A Review Article", *Journal of Marketing Research*, Vol. VII (May 1970), pp. 215-25.
11. Headen, Robert S., Jay E. Klompmaker and Jesse E. Teel, Jr., "Predicting Audience Exposure to Spot T.V. Advertising Schedules", *Journal of Marketing Research*, Vol. XIV (February 1977), pp. 1-9.
12. Kotler, Philip. *Marketing Decision Making: A Model Building Approach*, (New York, Galt, Rinehart and Winston, 1971).

13. Kuhn, Thomas S. *The Structure of Scientific Revolutions*, 2nd Ed., enlarged, (Chicago, University of Chicago Pres, 1970.
14. Little, John D.C. and Leonard M. Lodish, "A Media Planning Calculus", *Operations Research*, Vol. 17 (Jan.-Feb. 1969), pp. 1-35.
15. ————, "A Media Selection Model and its Optimization by Dynamic Programming", *Industrial Management Review*, Vol. 8, (Fall 1966), pp. 15-23.
16. Montgomery, David B. and Glen L. Urban, *Management Science in Marketing*, (Englewood Cliffs, New Jersey, Prentice-Hall, 1969).
17. Srinivasan, V., "Decomposition of a Multi-Period Media Scheduling Model in Terms of Single Period Equivalents", *Management Science*, Vol. 23, (December: 1976), pp. 349-360.
18. Zufryden, Fred S., "Media Schedulings: A Stochastic Dynamic Model Approach", *Management Science*, Vol. 19, No. 12 (August 1973), pp. 1395-1406.

ABOUT THE AUTHORS

ROGER J. CALANTONE, Ph.D., received his doctorate from the University of Massachusetts, Amherst. Currently he is Associate Professor of Marketing and Management Science at McGill University, Montreal, Quebec. He is a member of AMS, AMA, ASA, and TIMS. His major work has appeared in *Management Science*, the *Journal of the Academy of Marketing Science*, the *Journal of Development Economics*, the *Journal of Marketing*, the *Journal of Marketing Research* and elsewhere.

ULRIKE DE BRENTANI-TODOROVIC is a Ph.D. student in Marketing at McGill University, Montreal, Quebec. She received her B.Com. and M.B.A. at Concordia University where she is Assistant Professor of Marketing. She is a member of AMS and AMA. Her main areas of research interest are industrial marketing and new product screening.