Beyond Effective Frequency: Evaluating Media Schedules Using Frequency Value Planning

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ABSTRACT

The practice of effective frequency planning (EFP) presents an enormous paradox. On one hand, research suggests that it is used by the majority of media planners. On the other hand, it also suggests that the method makes little sense. This paper discusses possible reasons for the paradox and offers frequency value planning (FVP) as a practical solution. It discusses the steps involved in implementing the frequency value method, the practical problems involved, and approaches to overcoming them. Finally, it uses the logic of the frequency value model to suggest practical areas for future research.

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There is some uncertainty over the roots of the effective reach and frequency concept. However, there is no question regarding the enormous popularity it has achieved as an approach to media planning. In the years following the publication of Naples' (1979) classic book on the subject, it has become standard industry doctrine. According to a survey by Kreshel, Lancaster and Toomey (1985), 86.2% of advertising agencies use effective reach as a major criterion in media planning. Leckenby and Kim (1994) found 68.3% of media planners in the top 100 U. S. agencies used effective reach compared to 59.3% usage in 1982. While the actual estimations vary according to the methodology used, it is clear that effective reach is widely used by the advertising industry.

For purposes of discussion, we can use effective reach, effective frequency, and effective reach and frequency interchangeably. Effective frequency generally refers to the average number of vehicle exposures (often called opportunities to see, or OTS) required to effectively expose the average audience member to an advertising message. Effective reach is the number (or percentage) of a particular target population who is exposed at this level. Effective reach and frequency refers to the concept of using these measures in media planning. For convenience, we will use the term effective frequency planning (EFP) to represent the process through which media planners put effective reach and frequency into practice. This is generally done by seeking to maximize effective reach within a particular budget constraint, subject, of course, to other media planning and buying factors.

Given the popularity of EFP within the advertising industry, it is no wonder that recent criticisms of the concept have met with a storm of controversy. But the criticisms are persuasive. Cannon and Riordan (1994) reviewed the literature and argued that the overwhelming weight of evidence suggests that the underlying assumptions behind the process are simply not valid.

Their conclusion was reflected in the general tone of an ARF symposium on effective frequency (ARF 1994), where leading-edge practitioners discussed emerging issues regarding effective reach and frequency.

The essence of the argument revolves around the shape of the advertising response curve. For effective frequency to be valid, advertising must be subject to a threshold effect, reflected in an S-shaped advertising response curve (Stankey 1989). But research suggests that, in actual advertising situations, response curves tend to be concave, characterized by continually diminishing returns (Simon and Arndt 1980; Schultz and Block 1986; Zielske 1986).

Consider the enormous paradox this situation presents: Leading-edge media experts agree that effective frequency planning (EFP) -- a planning doctrine espoused by the majority of industry practitioners -- makes no sense! The experts not only agree that the process is based on faulty premises, but that it leads those who use it to develop inefficient media plans and schedules. By implication, they agree that this costs the industry millions of dollars in wasted advertising every year.

This paper is based on two key assumptions: First, the paradox is valid. Advertisers are in fact wasting millions of dollars each year through inefficient media planning. Second, there must be a reason behind the paradox, and unless we can identify the reason and address it, the situation is not likely to change.

The paper begins by articulating several possible reasons for the EFP paradox. It then addresses these reasons by outlining frequency value planning, or for convenience, (FVP) as a practical, and more theoretically sound, media planning procedure that achieves effective frequency goals. It gives an example of FVP using a hypothetical product and media schedule. Finally, it discusses key areas where further research is necessary to improve FVP.

ROOTS OF THE PLANNING PARADOX

We see three reasons for the popularity of EFP: (1) Dissatisfaction with the conventional reach and average frequency criteria it replaced; (2) Face validity; and (3) Some initial encouraging research findings.

Dissatisfaction with Conventional Reach and Average Frequency Criteria

First, when EFP was introduced it appeared to be much more attractive than average reach and frequency planning, the alternative it replaced. In order to understand this, consider the evolution of media planning in an historical context. In the early 1960s, media planning was still struggling with the basic concepts of quantitative media analysis. This was reflected in the earliest issues of the *Journal of Advertising Research* which formulas for estimating reach and frequency played a prominent role (Agostini 1961; Bower 1963; Caffyn and Sagovsky 1963; Kuhn 1963; Marc 1963; Hofmans 1966; and Claycamp and McClelland 1968). Prior to the advent of these formulas, media planners were dependent on raw media weight as a basis for planning. Reach and average frequency were superior in that they addressed two key elements of media strategy -- how many people are exposed, and how much advertising these people received.

The notion of reach and average frequency is flawed by the fact that many different patterns of media exposure that might result in the same reach and average frequency. With the advent of computer, planners were able to begin working with frequency distributions -- estimations of not only how many people were reached, but how many were reached with various levels of exposure. This stimulated an on-going stream of research in the development and evaluation of models for estimating exposure frequency distributions (Metheringham 1964; Green and Stock 1967; Liebman and Lee 1974; Beardon, Haden, Klompmaker and Teel 1981;

Leckenby and Kishi 1982; Rust and Leone 1984; Leckenby and Boyd 1984; Leckenby and Kishi 1984; Leckenby and Rice 1985; Danaher 1988; 1989, 1991; 1992, Leckenby and Hong 1998, Kim and Leckenby 2000).

With the advent of personal computers, and the corresponding drop in the cost of computations, frequency distribution began attracting much greater attention among media planners and theorists. In the early 1980s, the popular advertising literature was filled with discussions of why frequency distributions should be used instead of simple reach and average frequency analysis.

The problem was what to do with frequency distributions? Agencies needed a simple approach that could be implemented by relatively low-level planning staffers. Some visionary organizations, such as Foote, Cone and Belding Communications, developed sophisticated planning systems (Wray 1985). But the greater concensus seemed to be that these involved too many assumptions, and that their comprehensive nature would encourage planners (unjustifiably) to “rely on the numbers” instead of using their own professional judgment.

In this environment, a simple rule such as 3+ reach appeared very attractive. At worst, it represented a great improvement over simple reach and average frequency. It gave planners an index of how well their plans met frequency objectives, while still allowing for professional judgment in the development and evaluation of plans. Over time, effective frequency became an integral part of media planning culture and procedures. People were trained and on-going systems developed to assess effective reach and frequency. In this environment, abandoning EFP would be understandably difficult, even when it proved to be misleading for most media planning situations.

Face Validity

The primary theoretical justification for effective reach and frequency is the notion of a communication threshold. That is, a certain level of exposure is needed to break into people's awareness and capture their attention, to effectively reach them. Notions such as Webers Law (Aaker and Myers 1982, pp. 248-9) suggest that there is a critical ratio of message strength to ambient "noise" is intuitively appealing. If the level of advertising exposure falls below a critical level, the message will not be perceived by consumers. This is consistent with the logic of "pulsing" the market, as suggested by the classic Budweiser studies (Ackoff and Emshoff 1975). Pavlou and Stewart (2000) suggest that threshold effects not only exist, but that they are likely to become more important as new media focus on more demanding types of consumer response.

Perhaps even more important than the attention given to advertising thresholds by theorists is the fact that virtually everyone has had personal experience with advertising messages that did not "sink in" until the second or third exposure. When it comes time to act on one's convictions, media planners are no different than anyone else. Abstract scientific evidence will rarely prove as credible as conclusions drawn from personal experience, and effective reach appeared to fit personal experience.

Krugman (1972; 1977) captured the imagination of the industry with his three-exposure theory, which described an intuitively appealing sequence of consumer responses to television advertising that appeared to be consistent with a communication threshold. He suggested that the first exposure causes consumers to ask, "What is it?" The second causes them to ask, "What of it?" The third exposure is both a reminder and the beginning of disengagement.

Krugman's theory did not necessarily imply a need for three, or even two, physical advertising exposures, but only a series of mental steps in message processing. These might take place in conjunction with a series of advertising exposures, in response to a single exposure, or perhaps be triggered by a single exposure, but take place in the theater of one's mind at some other time and place (Cannon and Goldring 1986).

Krugman's actual theory was not as relevant as how it was interpreted by proponents of effective reach and frequency. Proponents defined effectiveness to be "a minimum of three confirmed vehicle exposures to an individual member of the target group over an agreed-upon period of time" (Murray and Jennings 1992, p. 37). The magic number "three" came to be a commonly accepted industry standard (Lancaster, Kreshel and Harris 1986). This was an interesting interpretation, considering Krugman's research involved forced ad exposure combined with eye-movement or brain wave measures. There is a big difference between three ad exposures and three exposures to a media vehicle.

Encouraging Research

Given the need for a simple planning approach that considered frequency distribution, and given a predisposition to accept the notion of effective reach and frequency on the basis of face validity, planners were ready to accept findings supporting this position. The notion of a communication, or exposure, threshold had already received apparent empirical support from Ackoff and Emshoff's (1975) Budweiser studies. When Naples (1979) presented McDonald's 1971 study in his book, *Effective Frequency*, there was very little incentive to question the validity of its interpretation. Its apparent support of EFP made it an ideal reference to use when presenting the new planning paradigm to clients.

FREQUENCY VALUE PLANNING

In response to their criticism of EFP, Cannon and Riordan (1994) suggest that optimal frequency planning (OFP) might be superior approach. It seeks to assign a value to each level of advertising exposure and then select a schedule with the highest value.

In practice, selecting a schedule with the highest value among those considered does not guarantee that the schedule will be *optimal*, since it does not consider all possible schedules. Nor do Cannon and Riordan suggest any guidelines for constructing schedules that are likely to be optimal. In this sense, OFP is probably not an ideal term for the successor to EFP. However, the basic concept appears to be valid.

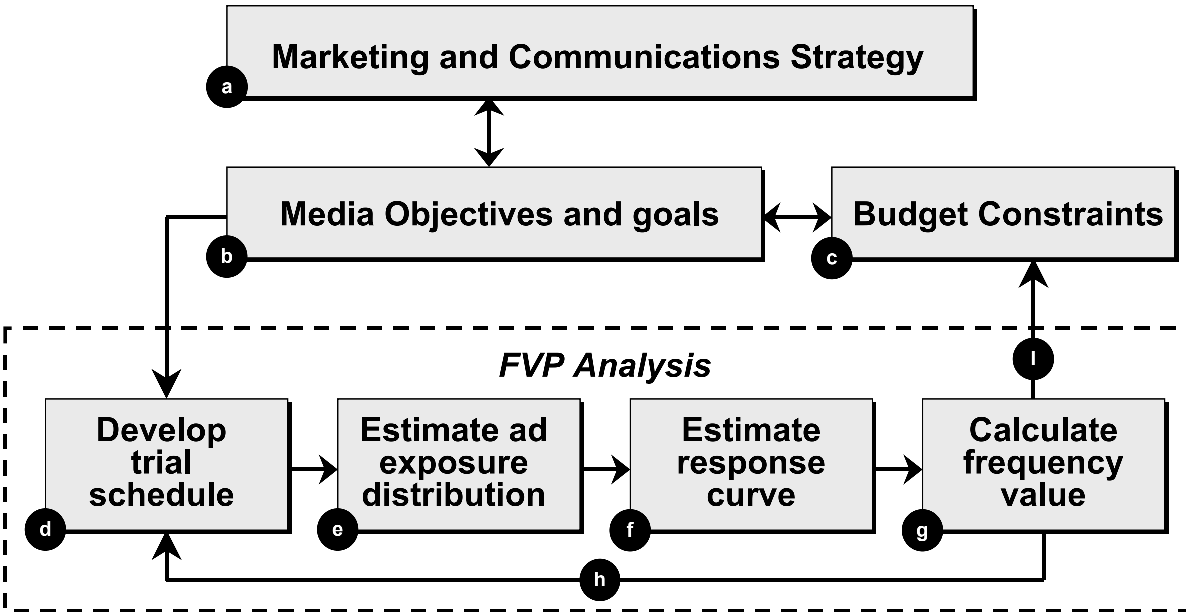
In place of optimal frequency planning, we will suggest the term, frequency value planning (FVP). Instead of assuming that advertising is ineffective until it reaches a particular threshold level, as is the case with EFP, it suggests that every level of advertising exposure has some probability of impact on consumers. By assigning these probabilities, or exposure values, to each level of a campaign's frequency distribution, planners can estimate the campaign's total impact. This, in turn, enables the planner to design and test various schedules to find one that best meets campaign objectives. Exhibit 1 summarizes the FVP process.

Media Objectives and Goals

FVP begins in the way conventional media planning systems begin, with marketing and communications strategy (box a) yielding a set of quantitative media objectives (box b). Consistent with the classic DAGMAR approach (Colley 1961), these objectives involve specific levels of consumer response. The response might range from brand awareness to actual purchase behavior.

Exhibit 1:

The Frequency Value Planning Process



According to the DAGMAR approach, advertising is generally given the task of communicating rather than closing a sale. The measurement of advertising response should be consistent with the task given to the advertising campaign. This is especially important in the context of modern intregrated marketing communications (IMC) campaigns. While different media have always played different roles in a campaign, IMC suggests that we need to be more systematic in the way we allocate tasks (Schultz and Kitchen 1997; Kitchen and Schultz 1999), and by implication, measure advertising effects. Furthermore, the fact that campaigns allocate different budgets to each of the constituent advertising programs suggests that these effects should have a monetary value to the advertiser. For instance, if an advertiser were willing to invest $1 million in a television advertising program that is expected to create brand awareness among 50% of market members, we might infer that the value of each percentage point of awareness is ($1,500,000/50=) $30,000.

Achieving a desired advertising response, of course, depends on more than just media. The message content and execution both play crucial roles. However, FVP assumes that the message and execution are already fixed, and the purpose of the planning process is to deliver this message in a way as cost-effective as possible. The media objective, and by extension, the effectiveness with which it is achieved, is measured by what percentage of the target market responds in the desired manner. In our previous example, this was brand awareness.

Budget Contraints

The advertising budget is usually not considered part of the media planning process, because it is normally established by the client, separate from the advertising agency, and certainly separately from the agencies media department. Nevertheles, there is usually interaction (as suggested by the arrows connecting boxes b and c in Exhibit 1). The is necessarily the case, because the budget determines the extent to which media objectives can be achieved, or using Colley's (1961) terminology, the extent to which specific advertising goals can be achieved.

In order to establish both the budget and advertising goals, planners must estimate the relationship between advertising and advertising response, or what is commonly known as the advertising response curve. A number of studies have addressed this topic over the years. Unfortunately, the work has been largely judgmental, with relatively little rigorous classificational research or testing of theorized relationships.

Cannon (1987) reviewed the literature and developed 27 theoretical propositions regarding the relative need for increased level of exposure. Foote & Belding Communications (FCB) took a similar approach (Ostrow 1982; Wray 1985). While the FCB propositions were not anchored in specific studies found in the literature, they represented a comprehensive effort by advertising practitioners who were seeking to develop a valid, workable system for estimating advertising response, addressing marketing factors, copy factors, and media factors.

One of the advantages of the FVP process is that it provides metrics for determining how good the budget is, based on other assumptions that are incorporated into the planning model. At very least, it helps advertisers be internally consistent in their decisions. The line labeled “i” Exhibit 1 suggests that the FVP process may indicate a need to reconsider the budget, and hence, the advertising goals, as a result of the analysis.

Developing a Trial Schedule

The first step in the actual FVP analysis is to construct a trial media schedule (box d in Exhibit 1) to represent the media program, much as a planner would when using a conventional EFP system. The only difference is that the planner is working against a different criterion. An effective reach schedule of 3+ means the planner will try to place ads in vehicles that have relatively high audience overlap if they have relatively few GRPs with which to work.

In contrast, if the planner were working against a frequency value criterion the plan would generally seek to minimize duplication and extend reach as much as possible (Ephron 1995; Jones 1995). This is because the advertising response curve is typically concave, characterized by continually diminishing returns (Simon and Arndt 1980; Schultz and Block 1986). Therefore, lower levels of frequency deliver relatively higher value to the schedule.

This is not to say that frequency is unimportant, only that, if there is a trade-off, reach will take priority. Again, we see the effect of the budget constraint. If a budget constrained program requires relatively high frequency, conventional media planning tends to limit the scope fo the campaign to ensure that advertising reaches the necessary “threshold” of frequency. However, if the advertising response curve is truly concave, FVP provides a compelling argument for abandoning this practice. At the same time, it can also provide a cogent rationale for increasing the budget, as we will see later in our discussion.

Estimating the Advertising Exposure Distribution

Box d in Exhibit 1 indicates that the next step in FVP analysis is the development of an advertising exposure distribution for the trial schedule. We noted earlier that one of the most significant developments in the area of quantitative media planning has been the development of mathematical models for estimating frequency distribution. These are based on estimates of the probability that a given person will be exposed to a media vehicle, or the probability of OTS. However, there is no reason these models cannot be applied to advertising exposure as well. One need only define the media vehicle more narrowly, as the actual ad rather than the medium in which it was delivered. Thus, the probability of exposure to a particular page of a magazine, rather than to the magazine itself, would be the input into the frequency distribution model. The result is a distribution indicating what percentge of a target population is likely to be exposed once, twice, three times, and so forth to an actual ad.

The literature suggests that sequential aggregation methods provide what is perhaps the most practical tool for estimating the distribution since, they strike a balance between theoretical grounding, accuracy and speed of computation (Lee 1988; Rice and Leckenby 1986). Such methods are also inherent in some proprietary packages used by media planners (Lancaster 1993; Liebman and Lee 1974).

Within the larger class of sequential aggregation models, a simple, but powerful, approach is called MSAD (Morgenzstern Sequential Aggregation Distribution) and is based upon a reach formula developed by Morgenzstern (Lee, 1988). It has proved to be a very accurate model when used for magazine and television schedules (Rice and Leckenby, 1986). In sequential aggregation procedures, the vehicle frequency distribution of the first two vehicles is computed first; these are then viewed as a composite, single vehicle to be combined with the next vehicle in the media schedule. The resulting distribution is viewed as that of the second composite vehicle to be combined with the fourth vehicle. This procedure continues until all vehicles in the schedule have been integrated into one final vehicle exposure distribution.

Again, any frequency distribution model will accept advetising exposure instead OTS data, so developing a frequency distribution for advertising versus vehicle exposures does not present any inherent problem. The question is how to estimate the probability of advertising exposure needed as input for the models. A considerable literature exists regarding the general subject, but very little has been written to provide practical guidance in making the necessary estimates. This explains why most media planning models have relied on OTS rather than advertising exposure, notwithstanding the nearly universal acceptance of the criticisms of this approach.

We will argue that, regardless of how difficult the process of estimation, or how inaccurate the estimates, the issue cannot be ignored. Cannon and Riordan (1994) suggest that it was a failure to consider the problem of advertising exposure that caused the industry to misinterpret McDonald’s classic brand switching study (Naples 1979), thus setting the stage for the costly media planning paradox referred to earlier in this paper. Their analysis suggests that even the crudest estimates of advertising exposure rates would have unmasked the problem, and helped head off a decade and a half of misguided industry effort. The fact is that we know advertising exposure rates are substantially lower than vehicle exposure rates. To ignore the fact is analogous to financial executives ignoring the time value of money, simply because they have no accurate way to predict future interest rates.

The literature suggests two basic approaches for making the necessary estimations. One is *norming*. Given the prominence of television and magazine media, we will use these two media as examples in our discussion. *Norming* draws on empirical studies of the ratio between advertising and vehicle exposure to develop adjustment factors for vehicle exposure data. For instance, if a television program has a projected rating of 10.0, and past data suggest that 50% of viewers are exposed to advertising in similar programs, the projected advertising exposure would be an effective rating of (10.0 x .50 =) 5.0.

Research based on actual observations of television audience members found eyes-on-screen time averaged 32.8% for commercials compared to 62.3% for programs (Krugman, Cameron and White 1995), suggesting that advertising exposure would be only (32.8/62.3=) 52% of OTS. ... Perhaps the best estimate is given by Abernethy's (1990) detailed review of observational and survey studies. He estimates 32% television commercial avoidance, or 68% advertising exposure.

An average figure, such as Abernethy's 68% exposure, might be used as a basis for the FVP model. However, a better approach would be to develop different estimates, based on the nature of the media vehicle, accounting for differences in the opportunities audience members have to physically avoid the ads by leaving the room, “zapping,” and so forth (Abernethy 1991). For instance, Bearden, Headen, Klompmaker and Teel (1981) reviewed studies addressing attention levels for daytime television, noting that they varied between 20% and 50% of program ratings. In prime time, attention levels were reported at 76% of program ratings for station-break and 84% for in-program commercials. In practice, a planner would adjust the average exposure estimates up or down, depending on whether an ad was placed in daytime or primetime television, in a station-break or in a program.

A similar approach might be used in magazine advertising. Roper Starch publishes data from a host of different magazines, indicating what percentage of readers “noted” seeing ads, “associated” the ads with their sponsors, and “read most” in its *Adnorms* service. The service breaks these down by magazine and product category. As with television, these scores may be adjusted upwards or downwards to reflect the effect of different environmental factors, such as the advertising’s position within a magazine, differences between magazines, differences across product categories, and so forth.

The second approach is *modeling*. For instance, Cannon (1982) developed a regression model to predict magazine exposure rates, based on the similarity of values reflected in the editorial environment of the magazine versus those reflected in ads themselves. While this method was designed to account for the specific effects of editorial environment, a similar approach might be taken to predict the more general effects of ad size and placement, color versus black and white, etc. Philport (1993) discusses the factors that might be used to estimate magazine exposure. Donthu, Cherian and Bhargava (1993) discuss the factors that might be used to estimate exposure rates in outdoor advertising. In a different kind of approach, Gensch (1970, 1973) discusses a general set of media factors that might determine exposure effectiveness across a number of different media.

Estimating the Advertising Response Curve

An advertising exposure distribution has little value without knowing the response values associated with each level of exposure. For instance, suppose you are evaluating your campaign in terms of “message recognition.” Having estimated the advertising frequency distribution (box e), you need to know the degree of “message recognition” that will be achieved by each level of exposure (box f). We may think of response value as a type of conditional probability. That is, how likely are consumers to recognize the advertising message, given 0, 1, 2, 3 and so forth exposures? If we plot these response probabilities, they form an advertising response curve.

As we have noted, the shape of the curve will typically be concave. That is, response to increasing levels of advertising exposure is characterized by continually diminishing returns. True, one might conceive of an S-shaped curve, where response is characterized by increasing returns, at least in the beginning of a campaign. Incremental response to a second or third advertising exposure would be greater than the response to the first... But still, the response would be relatively low until the advertising exposures reach a "threshold" level, at which point they begin to deliver rapidly increasing returns (Ackoff and Emshoff .1975; Pavlou and Stewart 2000). The increasing returns continue to a point of inflection, followed by diminishing returns. The FVP model will accommodate any pattern of advertising response, whether concave or S-shaped.

The concave curve can be represented by the formula shown in equation [1]. (Note that mathematical functions are shown in spreadsheet notation).

$$R_I = R_\infty * (1 - exp(- a - b * i)) \qquad [1]$$

where

R_I = *Advertising response value to i exposures*
R_∞ = *Maximum response value, or the response to infinite exposures*
a = *Parameter representing the Y-intercept, or the response to zero exposures*
b = *Parameter representing the slope of the curve*
i = *the number of advertising exposures*

Note that the equation has three key parameters: R_∞, *a* and *b*. R_∞ and *a* can be estimated directly. *b* can be determined by using equation [2] with an estimate of the response value to the first advertising exposure (i.e. R_1, or the value of R where i=1).

$$b = -\ln(1 - R_1 / R_\infty) \quad [2]$$

We can develop a corresponding formula for the S-shaped curve. This is shown in equation [3].

$$R_i = R_\infty / (1 - \exp(a + b * i)) \quad [3]$$

The parameters *a* and *b* do not have the same meaning for the S-shaped curve as for the concave curve, and the curve is mathematically undefined for zero exposures. Nevertheless, the formula provides a practical tool for estimating an S-shaped pattern of response. Again, it can be estimated from three points, such as the advertising response to one exposure, response to an "effective" level of exposures, and the maximum level of anticipated response. Given the popularity of the three-exposure criterion in EFP, three provides a convenient point to estimate. The formulas for estimating a and b are shown in equations [4] and [5].

$$a = 3 * (\ln(R_\infty / R_1 - 1) - \ln(R_\infty / R_3 - 1) / 2 \quad [4]$$

$$b = \mathrm{Ln}(R_\infty / R_3 - 1) - a \quad [5]$$

The rationale for using a mathematical curve rests in the fact that advertising response is not capricious. It operates according to principles. If the principle is diminishing returns, as we have suggested through the concave curve, the incremental response value of advertising must be lower for each subsequent exposure. How much lower depends on the situation, which, in turn, is reflected in the slope and magnitude of the curve. If you experiment with different values, you will find that there is virtually no variation in the way you can plot hypothetical response values without violating the principle of diminishing returns, given an initial level of response (response level with zero advertising exposures), a minimum response (response to one exposure), and a maximum response (response to an infinite number of exposures). These values are determined by the mathematics of the curve.

As an illustration of how this might work, consider the guidelines developed at Foote, Cone & Belding (Exhibit 2) for establishing maxima and minima, based on the kind of objective a campaign is designed to achieve. For instance, it suggests that undemanding tasks, such as message recognition or brand awareness, can be achieved for 85% to 95% of the population, whereas demanding objectives, such as purchase behavior, tend to have maximum from 10-25%.

Exhibit 2:
Typical Maximum and Minimum Response Values for Different Kinds of Objectives

Type of Objective	Typical Maximum Range	Typical Minimum Range
Message recognition	85-95%	5-35%
Brand awareness	85-95%	3-25%
Message recall	70-80%	2-25%
Brand attitude	30-45%	0-5%
Purchase behavior	10-25%	0-5%

In order to estimate the actual minimum and maximum, a planner can select values on the high or low end of the range, depending on the campaign's relative need for exposure frequency. Ostrow (1982) suggests a number of factors that might be used to help estimate this need (see Exhibit 3). In order the use the framework, the planner must weight the various factors according to their relevance, and then rate them according to the degree to which they characterize the advertising situation.

Exhibit 3:
Factors that Affect the Need for More (+) or Less (-) Frequency

Marketing Factors	Copy Factors	Media Factors
Established brands (-)	Complex copy (+)	High clutter (+)
High market share (-)	Unique copy (-)	Compatible environment (+)
Dominant brand in market (-)	New copy (+)	High attentiveness (-)
High brand loyalty (-)	Image type copy (+)	Pulsed or flighted (+)
Long purchase cycle (-)	Many kinds of messages (+)	Few media used (-)
Product used daily (+)	High copy wearout (-)	Repeated ad exposure (-)
Heavy spending category (+)	Small ad units (+)	
Special targets (+)		

Adapted from Joseph W. Ostrow, "Setting Effective Frequency Levels," *Effective Frequency: The State of the Art*... New York: Advertising Research Foundation, Key Issues Workshop, 1982, pp. 89-102.

Exhibit 4 illustrates a response-curve parameter evaluation using Ostrow's example. Consider a campaign featuring the thirteen characteristics shown in column 1. Column 2 contains an index of relative importance of the factors, derived by distributing 100 points among them. The resulting allocation can be taken as the percentage of total importance given to each factor. Column 3 represents a rating of the advertising situation relative to each factor, using a +1 to -1 scale. Column 4 represents the weighted rating of the situation. The sum, at the bottom of Column 4, provides a net rating. A high rating places the maximum response at the low end and the minimum response at the high end of the range.

Exhibit 4:
An Example of How Situational Factors Might Be Used to Adjust Maximum and Minimum Response Values

Column 1: Factors Determining Response Value	Column 2: Weight	Column 3: Rating	Column 4: Net Value
New Product	...10	+ .8	+ .08
High competitive market	...10	-1.0	- .10
Short purchase cycle	.05	- .6	- .03
Less well known brand	.10	+ .8	+ .08
Product used daily	.05	0	0
Ad copy complex	...10	- .4	- .04
Unique copy*	.05	- .8	- .04
Large copy units*	...10	- .6	- .06
High clutter	...10	- .8	- .08
Media environment compatible with category*	...10	- .6	- .06

Continuous advertising*	...05	- .6	- .03
Many media used	...05	- .6	- .03
Many opportunities for repetition*	.05	- .4	- .02
Weighted Average (response value adjustment)			- ...33

* Items that are reverse scored to reflect the item's effect on the need for frequency.

To illustrate this approach, if message recognition were the objective in Exhibit 4, the maximum response range would be between 85% and 95%. A weighted average response of zero would call for a maximum response value of 90% (halfway between the 85%-95% range). A weighted average of +1 would mean a maximum response value of 85%. A weighted average of -1 would mean a maximum response of 95%.

Looking now at the lower range (5%-35%), a weighted average of zero would represent a minimum response of 20%. A weighted average of +1 would represent a minimum response value of 5%, a weighted average of -1 a value of 35%. The minimum response value would be the response to a single ad exposure.

The actual value adjustment was -.33, suggesting a maximum response of (90% + .33*5% =) 91.65% and a minimum value of (20% + .33*15% =) 24.95%. Assuming a no-exposure response value of zero, and applying the values to equations [1] and [2], the resulting response curve is shown in Exhibit 5. Exhibit 5 also shows an S-shaped advertising response curve, assuming that the 24.95% minimum requires three exposures and (somewhat arbitarily) that the response to a single exposure is 10.00%. A lower one-exposure response value produces a curve that reaches its maximum value with fewer exposures. For instance, a single-exposure response of 5% yields a curve that reaches 46.64% with four exposures, and 91.38% with ten exposures.

Exhibit 5:
An Example of an Estimated Advertising Response Curve

Advertising Exposures	Message Recognition Response (Assuming Concave Curve)	Message Recognition Response (Assuming S-Curve)
0	00.00%	Undefined
1	24.95%	5.00%
2	43.11%	11.74%
3	56.32%	24.95%
4	65.94%	44.71%
5	72.94%	64.89%
6	78.035	78.87%
7	81.74%	86.17%
8	84.44%	89.42%
9	86.40%	90.76%
10	87.83%	91.30%

Calculating Frequency Value

Box g in Exhibit 1 represents the final stage of the FVP process. In order to see how this works, consider a schedule that yields a frequency distribution such as the one shown in column b of Exhibit 6. If 38.35% of the target market is exposed to one ad in a campaign (as is the case for Schedule A in Exhibit 6), and the probability of a given audience member recognizing the message after a single exposure is 24.95%, the "message recognition" response value for the one-advertisement exposure group would be (.3835 x .2495 =) 9.57%. If the probability of message recognition after two exposures were 32.65%, the value for the two-exposure group would be (.3265 x .4311 =) 14.08%. In essence, we are developing a weighted average of the various response curve values (from column d), weighting each level of response by the percentage of the target population exposed (column b). The total frequency value of the schedule is shown in column e, 32.07%. In other words, we estimate that 32.07% of the target market will respond with message awareness as a result of the media schedule.

Exhibit 6:
Estimating Frequency Value

Number. of Exposures (a)	Schedule A Distribution (b)	Schedule B Distribution (c)	Avertising Response Curve (d)	Schedule A Frequency Value (e)	Schedule B Frequency Value (f)	Schedule A (GRPs) (g)	Schedule B (GRPs) (h)
0	15.00%	40.00%	0.00%	0.00%	0.00%	0.00	0.00
1	38.35%	10.50%	24.95%	9.57%	2.62%	38.35	10.50
2	32.67%	11.11%	43.11%	14.08%	4.79%	65.34	22.22
3	9.79%	16.59%	56.32%	5.51%	9.34%	29.37	49.77
4	2.50%	12.00%	65.94%	1.65%	7.91%	10.00	48.00
5	1.25%	5.81%	72.94%	0.91%	4.24%	6.25	29.05
6	0.40%	2.76%	78.03%	0.31%	2.15%	3.60	16.56
7	0.03%	1.02%	81.74%	0.02%	0.83%	0.21	7.14
8	0.01%	0.15%	84.44%	0.01%	0.13%	0.08	1.20
9	0.00%	0.04%	86.40%	0.00%	0.03%	0.00	0.36
10	0.00%	0.02%	87.83%	0.00%	0.02%	0.00	0.20
Total	100.0%	100.0%	N/A	32.07%	32.07%	152.0*	185.0*

* NoteThese are "effective GRPs," based on advertising exposure versus OTS.

The significance of frequency value becomes more obvious when we compare the media Schedule A (column b) with Schedule B (column c). We see from the bottom of columns e and f that they both have the same frequency value, 32.07%. However, when we compare the effective freach, Schedule B appears to be much superior. By investing in more GRPs (185 versus 152) and using multiple ads in the same media vehicles to sacrifice reach for frequency, the plan achieves an effective (3+) reach of 38.39%. By contrast, Schedule A uses media vehicles with very low target market audience duplication. Its effective (3+) reach is only 13.98%. While Schedule B is roughly 40% more expensive (due to the higher GRPs), conventional EFP suggests that it is (38.39%/13.98=) 2.75 times as effective! While Schedules A and B represent extreme cases that would be very hard to duplicate in actual media planning situations, they clearly illustrate the issues addressed by FVP versus EFP.

FVP offers several useful metrics for evaluating alternative schedules.

1. ***Total frequency value (TFV)***... As we have seen, the core metric for FVP analysis is the total frequency value (TFV) of a schedule, which is the total response (stated as a percentage, or a response probability) of the target population. In the previous example, both schedules yielded a total frequency value of 32.07%, as shown at the bottom of columns e and f. This means that both schedules would result in an estimated 32.07% message recognition by target market members by the end of the campaign.
2. ***Frequency value per GRP (VPG)***. Frequency value per GRP (VPG) is simply total frequency value divided by the number of GRPs required to achieve it. It is a measure of media efficiency, indicating the probability that any given media vehicle exposure will result in the kind of audience response desired in the campaign. In the example of Schedules A and B, the VPG of Schedule A is (32.07/152=) 21.10% versus (32.07/185=) 17.33% for Schedule B. Note, however, that the "GRPs" from which these were calculated (the bottom of columns g and h) are based on advertising exposure, not vehicle exposure (OTS). If half of the vehicle exposures result in advertising exposure, then the actual VPG is probably around half these numbers.
3. ***Total monetary value (TMV)***. Total monetary value (TMV) is a variant of total frequency value (TFV), indicating how much the frequency of a schedule is worth. We noted earlier that we should be able to infer the value per point (VPP) of advertising response by simply dividing the advertising budget by the percentage level of response it is expected to achieve. For instance, if the company were willing to invest $1,500,000 to create 50% message recognition within the target market, the VPP would be ($1,500,000/50=) $30,000. TMV for both Schedule A and Schedule B would be (32.07% x $30,000 =) $962,100. As long as this is higher than the projected cost of the campaign, the campaign will generate a profit.

4. ***Cost/efficiency per point (CEP)***. The cost/efficiency per point (CEP) addresses the efficiency with which advertising money is being spent... It looks at the total cost of advertising divided by schedule efficiency (VPG). If the cost per GRP for Schedules A and B were $6,000, CEP would be ($6,000/.2110=) $28,436 and ($6,000/.1733=) $34,622 respectively. Given a VPP of $30,000, Schedule A pays out, but Schedule B does not. CEP, then, can also be used to evaluate the profitability of a campaign.

The metrics provide tools for making the comparisons suggested by lines *i* and *h* in Exhibit 1. Line *i* suggests that planners may negotiate for higher budgets if they can demonstrate that a higher budget would yield attractive returns. This would happen when total monentary value (TMV) is much greater than the cost of a proposed schedule. Similarly, when the cost/efficiency per point (CEP) is less than the economic value per point (VPP) we get the same result.. Line *h* indicates that planners will compare different schedules in an effort to find one that delivers total frequency value (TFV) that is close to established targets. They will also compare schedules in search of one that maximizes value per GRP (VPG).

SUMMARY AND CONCLUSIONS

The purpose of this paper has been to describe a new media planning system – frequency value planning. In order to put the system in perspective, it sought to outline the history of effective reach and frequency, with the hope of explaining the media planning paradox -- the fact that effective frequency planning (EFP) is seriously flawed, and yet it is widely used among media planners. Frequency value planning (FVP) presents a simple and powerful alternatives to EFP. For all its flaws, EFP was the first practical method for incorporating media distribution data into the media planning process. The need for such a method still exists, and

EFP will likely continue to be practiced until a better planning approach takes its place. Hence, the need for FVP

Note that FVP is appropriate to its time. While the concept is simple, the method is relatively complicated. It has always been within the grasp of mainframe computers, but planners were justifiably reluctant to base their planning on systems they could not understand or access directly without working through an expert. This, combined with the many assumptions embedded within a frequency value model, interfered with its acceptance. Now, with the proliferation of powerful personal computers, spreadsheets, and other highly sophisticated analytical software, planners have become much more technologically sophisticated. Furthermore, the fact that media planning models can be installed and/or accessed on a local computer means that planners are able to experiment in greater depth with the tools they use. In the case of a frequency value model, they can become familiar not only with how it works, but how sensitive it is to variations in assumptions. This makes the model much less threatening and more useful in the hands of media planners.

Note that the system described in this paper represents only a stage in the ongoing development of FVP. Many of the measures are relatively crude and may serve as an impetus for future research. Indeed, a final purpose of this paper is to draw on the logic of the FVP model to suggest productive areas for future research:

- **General advertising exposure norms**. As noted in our review, some research has been done. However, so far, research has yet to fully address even the crudest norms for various kinds of media and media options. At very least, we should have exposure norms for different kinds of media, modified for major options (embedded versus station-break commercials, daytime versus prime-time television, etc.). So far, research in this area has tended to be spotty (addressing only some of the major media options) and limited to major media, such as television and magazines.

- **Principles and systems for estimating variations in exposure norms resulting from situational factors**. Situational factors might include dimensions such as the message, media context (editorial environment, physical or social setting of media exposure, layout and executional format, etc.), audience member knowledge and experience, interactive media/message effects, and the objectives of the campaign. At this point, we are just beginning to develop the most rudimentary model of how research in this area should be organized. What dimensions should it consider? What theoretical bases are relevant to the problem?
- **Advertising response functions**... Existing research suggests that advertising response functions are generally concave, characterized by continually diminishing returns. Traditional wisdom and some research suggests that they may also be S-shaped in form. Are there other forms as well? What functions and parameters best describe the response curves. In this paper, we used the efforts of Foote, Cone & Belding in the early 1980s to illustrate how one might go about establishing meaninful response functions. We need much more research in this area. This research needs to account for the effects of such things as prior consumer knowledge and advertising exposure, the effects of time between messages and campains, and segmentation effects.
- **Schedule value norms**. If relatively accurate standards can be developed and accepted for FVP, then we can begin to develop schedule value norms for different kinds of schedules. That is, what constitutes a "good" versus "bad" VPG for different kinds of advertising objectives?

- **Validation studies**... Validation studies would presumably address each part of the FVP model as it is developed. For instance, models for estimating the shape and position of an advertising response curve should clearly be tested against actual data, as should models for estimating advertising exposure, given media vehicle exposure. However, there is also a need for overall validation studies through which the value of a schedule would be matched against actual demonstrated advertising value.
- **Accounting for interaction effects across schedules**... In an era of integrated maketing communications, advertisers are putting more and more effort into developing synergy across media campaigns. Newspapers are being used to prime people to watch television programs; magazines are being used to promote Internet sites, and so forth. FVP addresses single media campaigns, but more work is needed to adapt it to address the synergystic effects of multiple media classes.

None of this is to diminish the significance of frequency value planning. In fact, it is a very practical system, even given our present state of knowledge – more so, at least than effective frequency planning. Our sugggestion, then is that we begin implementing FVP and work on improving it at the same time.

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