CHAPTER 2
SURVEY OF LITERATURE

2.0. Introduction

The use of formal methods in advertising decision is of recent origin. The efforts in this direction started in 1961 with the pioneering work done by Balten, Barton, Durstine and Osborne, a major advertising agency in U.S.A. Many papers have been written since then on the application of quantitative methods in media planning. This work has been done mostly in U.S.A and Europe. Unfortunately none of the approaches that have been published deals directly with the selection problems in the medium of cinema. This is for the obvious reason that cinema is not a major advertising medium in the western countries. Also, as we shall show later, it so happens that the methodologies developed and reported so far cannot be directly used for the resolution of the problem outlined in Chapter one.

The main purpose of this chapter is to highlight the reasons for our having to develop an entirely new methodology for the problem of cinema planning. The review of the literature is done keeping this purpose in view. We, therefore, do not present a very detailed review of all the published literature on this subject. This is for the simple reason that
many excellent reviews are available to a reader who is interested in a review of the work done on this problem. Not much purpose will be served by our repeating the reviews which have already appeared.

2.1. Review of Important Papers:
From the study of published literature on this subject three approaches are discernible. The first approach seeks to maximize the exposure value in the given target segment. In this approach, linear programming has been used to achieve the desired maximization/objectives. Descriptions of this approach are found in Day\(^{9}\), Buzzel\(^{6}\), Kotler\(^{25}\), Engel & Warshaw\(^{11}\), Wilson\(^{44}\) and Bass and Lonsdale\(^{5}\).

The second approach centres around the use of reach and frequency in the resolution of the media planning problems. In this approach, given a plan, it is evaluated in terms of the reach and frequency it achieves or if a plan is not available but it is required to be prepared, then it is prepared so as to achieve the minimum level of reach and frequency at the lowest cost. This approach has been used by Mote\(^{38}\), Jain\(^{22}\), Lee\(^{31}\), Methrington\(^{37}\), Agostini\(^{4}\), Landis\(^{30}\), Engelman\(^{12}\), Kwerel\(^{29}\), Greene\(^{16}\), Krugman\(^{28}\), Friedman\(^{14}\), Kamin\(^{24}\), Headen et al.\(^{18}\) Caffyn & Sagovsky\(^{7}\), and Charenes et al.\(^{8}\).
In the third approach the media vehicles (media options) are chosen so as to maximize response. The important papers in this category are by Little and Lodish(35), Zangwill(47), Jain (22), David Aaker(2), Jagpal et.al (23), and Horsky(20).

For an excellent review of literature encompassing all the three approaches, readers are referred to Dennis(10), Aaker & Myres(1), Little and Lodish(35), Jain A.K. (22) and Mote and Kalyani Rangarajan(39).

In the following sections we present in brief the main characteristics of these three approaches:

2.2. Approach 1:

A typical formulation in this approach is given below:

Let

$A_{ij}$ denote audience of $j$th media vehicle in the $i$th target audience group $i = 1, 2, \ldots, s$

$j = 1, 2, \ldots, m$

$W_{ij}$ denote the effectiveness weight of media vehicle $j$ for a single individual in target audience $i$. $i = 1, 2, \ldots, s$

$j = 1, 2, \ldots, m$
\( e_j \) denote the weighted exposure value of a single insertion in vehicle \( j \), \( j = 1, 2, \ldots, m \).

\( x_j \) denote the number of insertions to be taken in media vehicle \( j \), \( j = 1, 2, \ldots, m \).

\( c_j \) denote the cost of buying one insertion in media vehicle \( j \), \( j = 1, 2, \ldots, m \).

\( N_j \) denote the minimum number of insertions to be bought in media vehicle \( j \), \( j = 1, 2, \ldots, m \).

\( K_j \) denote the maximum number of insertions which could be bought in media vehicle \( j \), \( j = 1, 2, \ldots, m \).

\( B \) denote the total budget available.

Define \( e_j = \sum_i A_{ij} W_{ij} \) \ldots (2.2.1).

The linear programming problem is then formulated as

\[
\text{Maximize } \sum_{j=1}^{m} e_j x_j \quad \ldots \ldots \quad (2.2.2)
\]

Subject to \( \sum_{j=1}^{m} c_j x_j \leq B \) \ldots (2.2.3) (Total budget constraint)

\( x_j \geq N_j \) \ldots (2.2.4) (Lower limit on number of insertions to be put in media vehicle \( j \), \( j = 1, 2, \ldots, m \)).
\[ x_j \leq K_j \quad (2.2.5) \]  
(Maximum number of insertions which could be put in media vehicle \(j\), \(j = 1, 2, \ldots, m\)).

and

\[ x_j \geq 0 \quad (2.2.6) \]  
(Number of insertions to be put in all the media vehicles to be non-negative, \(j = 1, 2, \ldots, m\)).

The limitations of this approach have been pointed out by Little & Lodish\(^{(35)}\), Kotler\(^{(25)}\) and Jain A.K.\(^{(22)}\).

In addition to the limitations stressed by the above authors, the limitation from the point of our problem is that this approach requires the use of data that are not available. It should be noticed that \(e_j\), the component of the objective function, requires the knowledge of \(A_{ij}\) and \(W_{ij}\). The value of \(A_{ij}\) in our context corresponds to the number of people from the target audience \(i\) visiting \(j\) th theatre week combination. This is so because in the context of planning in cinema medium a vehicle corresponds to a theatre week combination. Such data are not readily available.
2.3. Approach 2

In the second approach we shall briefly state some of the important works done.

2.3.1. Clarion-Mote Model:

A pioneering effort in India in the field of mathematical model for media planning has been the development of a model by the Clarion Advertising Services Ltd. in consultation with Dr. Mote. The model used the NRS I data effectively to develop a minimum cost press media plan in order to achieve the minimum reach and frequency in several target audience groups.

The formulation of the problem is shown below:

Parameters:

\(r_{ij}\) denotes readership of \(j^{th}\) publication in the \(i^{th}\) stratum.

\(c_{ijk}\) denotes common readership of \(j^{th}\) and \(k^{th}\) publication in the \(i^{th}\) stratum.

\(L_j\) denotes minimum number of insertions in the \(j^{th}\) publication if included.

\(K_j\) denotes maximum number of insertions possible in the \(j^{th}\) publication.

\(c_j\) denotes cost per insertion in \(j^{th}\) publication.
R_j denotes minimum desired reach in the i-th stratum,
\[ R_j > 0 \]

\( f_i \) denotes minimum average frequency desired per member of the i-th stratum reached by a media plan,
\[ f_i > 0. \]

n denotes the number of strata.
m denotes the number of publications.

**Decision Variable:**

\[ x_j = \begin{cases} 
1 & \text{if the } j \text{-th publication is included in the media plan.} \\
0 & \text{Otherwise} 
\end{cases} \]

\[ y_j = \text{Number of insertions in the } j \text{-th publication.} \]

Minimize
\[ \sum_{j=1}^{m} c_j y_j \quad \ldots (2.3.1.1) \]

subject to

\[ \sum_{j=1}^{m} r_{ij} x_j - \sum_{j<k} c_{ijk} x_j x_k \geq R_i, \quad i = 1, 2, \ldots, n \]
\[ \ldots (2.3.1.2) \quad \text{(Constraint on reach)} \]

\[ \sum_{j=1}^{m} \frac{r_{ij} y_j}{\sum_{j<k} c_{ijk} x_j x_k} \geq f_i, \quad i = 1, 2, \ldots, n \]
\[ \ldots (2.3.1.3) \quad \text{(Constraint on frequency)} \]
\[ y_j - \ell_j x_j \geq 0 \quad \text{for} \quad j = 1, 2, \ldots, m \quad (2.3.1.4) \]
\[ y_j \leq \ell_j \quad \text{for} \quad j = 1, 2, \ldots, m \]
\[ x_j \leq 1, \quad j = 1, 2, \ldots, m \quad (2.3.1.5) \]

\( x_j \) and \( y_j \) are non-negative integers.

2.3.2. Minimum Reach and Frequency Model (MRF): 

The Clarion-Mote model ignored higher overlaps among media vehicles, for the lack of data. As a result a major limitation of the model was that it under-estimated the reach in the target audience group. To overcome this difficulty, Jain developed lower and upper bounds on the reach using only the available data on readership of publications and common readership of the publications. These bounds are sharper than the ones obtained by Kwerel (29). He then reduced the formulation to that of Clarion-Mote model, where the reach obtained by a media plan in a target audience group was taken as its lower bound in the group. This method reduced the problem of under-estimating the reach.

Both the Clarion-Mote and the MRF models require the \( r_{ij} \)'s - the readership of \( j \)th vehicle (publication) in the \( i \)th target audience. In our context this corresponds to the number of visits to the \( j \)th theatre week combination (vehicle) by the \( i \)th target audience, which is not available.
Moreover, the models stated above need the pair-wise duplication data between the two vehicles i and j which are also not available in our situation. None of the above models gives the complete OTS distribution.

The approach developed by us gives the complete OTS distribution.

2.3.3. Lee's Model:

Lee essentially follows the approach of reach and frequency in the selection of publications. He introduces a refinement in the computation of reach and frequency. The refinement is in terms of computing the probability of a person noticing the advertisement in a given publication, given that he is in the audience of that publication.

The use of his model also requires the knowledge of the probability that a person is the reader of different publications (vehicles). In our context this would mean that we should know the probability of a person in the target audience visiting the different theatre week combinations. These data are not readily available. In addition, Lee makes the assumption of pair-wise independence between publications (vehicles).
For example, if for an individual the probabilities of being in the audience of publications $i_1$ and $i_2$ are $p_{i_1}$ and $p_{i_2}$ respectively, then the probability of his being in the audience common to both of these publications is assumed to be $p_{i_1} \times p_{i_2}$. In our context this assumption is certainly not valid because the probability of a person visiting $i$ and $j$th theatre week combinations is not the product of probabilities of visiting $j$th theatre week combination and the probability of visiting $i$th theatre week combination.

2.3.4. Beta Binomial Methods:

Recent research has centred on methods that yield the complete distribution of audience exposure. In the literature this is achieved by fitting theoretical distribution to actual audience exposure data covering a small number of media vehicles and then by using the theoretical distribution to predict the audience exposure pattern for schedules for a large number of vehicles.

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The paper states explicitly only the assumption of pair-wise independence. To derive the results in the paper stated, however, the assumption of mutual independence is required.
These methods are used for press and TV. For press, the methods used are to generate OTS distribution by getting the probability of exposure of an individual based on survey data and then to use binominal or Monte Carlo methods.

For TV, Friedman\(^{(14)}\) reported that the compound probability distribution namely the negative Binomial can be used to compute the reach and frequency of a TV advertising plan. Later Headen et al.\(^{(18)}\) developed a Beta Binomial model for audience exposure to TV. We will briefly state below the underlying model of the Beta Binomial:

Let \(n\) - be the number of spots in the schedule.  
\(r\) - be the number of spots in the schedule seen by household \(0 \leq r \leq n\).  
\(p\) - be the probability of exposure to a spot in the schedule for a given household  
\(f_b(r|n,p)\) - be the binomial distribution given \(n\) and \(p\)  
\(r = 0, 1, 2, \ldots \ n\).

The Binomial distribution determines the probability that a given household will be exposed once, twice \ldots \ldots \ldots \ n\) times to a schedule.
But the potential audience is composed of many households. Hence the parameter \( p \) varies from household to household over the heterogeneous population and therefore becomes a random variable \( p^* \) which is assumed to be independent over households. This random variable follows a Beta distribution with parameters \( a \) and \( b \) and the density function 
\[
\beta\left(p^* | a, b\right).
\]

Therefore the proportion of audience that will be exposed exactly once, \( \ldots n \) times is determined by compounding the Beta distribution with the Binomial.

The Beta Binomial distribution is characterized by the two parameters \( a \) and \( b \).

\[
f_{BBD}(r) = \int_0^1 f_b(r | n, p^*) \beta(p^* | a, b) \, dp^*
\]

Let \( p_1 \) is the average probability of exposure to the specific set of spots contained in the schedule.

Let \( p_{ij} \) be the \( i \) th household's probability of exposure to spot \( j \), \( 1 \leq j \leq n \) then
\[
p_1 = \frac{\sum_{j=1}^n p_{ij}}{n}.
\]

Estimates of \( a \) and \( b \) are determined through the methods of moments. (That is, through the mean and variance of the empirical distribution. Of course, sometimes information about the variance of the empirical distribution may not be available, in which case it is obtained through regression methods).
This methodology is not applicable mainly for the reason that the data generated in our problem will not follow the Bernoulli process. This can be illustrated with the help of a simple example. Suppose that the advertiser has a list of $M$ candidate theatres from which he has decided to select $T$ theatres in which to screen the advertisement. Let us consider for the sake of simplicity a planning horizon of one week. Here $T$ stands for the number of trials equivalent to $n$ spots in the TV model.

The Advertiser wishes to know the proportion of the target audience that will visit the $T$ theatres he has selected at least once. Let us assume that a person who does visit a theatre in a week does not have any particular preference of choosing the theatre he visits. The only condition is that he will not visit the same theatre more than once a week. \(^{12}\)

With these data now we see that

$$\text{the probability}\left\{\text{any one of M theatres} \mid \text{he has made a visit}\right\} = \frac{1}{M}$$

\(^{12}\)This assumption made in the cinema planning model is discussed in Chapter 3.
the probability\{ \text{he selects anyone theatre} \mid \text{he has already made a visit to a particular theatre} \} = \frac{1}{M-1}

Since the unconditional and conditional probabilities are not the same, it follows that trials are not independent. Therefore, the Beta Binomial approach does not fit in our context.

2.4. Third Approach:

2.4.1. MEDIAC (Model by Little and Lodish) (35):

The model is based on the foundations stated below:

a. Sales potential and media habits are not uniform in the entire population. It is, however, possible to segment (stratify) the population into groups so that within a group the sales potential and media habits are similar but differ substantially between groups.

b. The population is assumed to be divided into different segments based on some criteria such as sex, education or lifestyle.

c. An advertising schedule creates an exposure \{e_{ij}\}. Exposure means that a person has perceived the presence of the advertisement. The effect of the exposure on a
person in a segment differs not only from one media class to another but also differs from one vehicle to another in the same media class.

For example, the advertiser may believe that the effect that an advertisement in 'Life' may have on a person would be different from the effect that the advertisement in 'Look' may have on the same person. This belief, it is assumed, can be quantified. Thus, \( e_{ij} \) will give the exposure value of an advertisement in the \( j \)th media vehicle to a person in the \( i \)th segment.

d. The response of individuals in a market segment increases with the exposure level, but with diminishing returns at high level.

The mathematical reasoning developed in the model is discussed below:

Notations Used:

\[
x_{jt} = \begin{cases} 
1 & \text{if an advertisement is placed in vehicle } j \text{ in time period } t \\
& \text{(This is a decision variable)} \\
0 & \text{otherwise.}
\end{cases}
\]

\( j = 1, 2, \ldots, M, \quad t = 1, 2, \ldots, T. \)
\[
\begin{align*}
\begin{array}{l}
\text{If the person in segment } i \text{ is exposed to an advertisement in media vehicle } j \text{ in period } t, \\
\text{Then } z_{ijt} = \begin{cases} 
1 & \text{if } \text{exposure} \\
0 & \text{otherwise.}
\end{cases}
\end{array}
\end{align*}
\]

The probability distribution of \( z_{ijt} \) is determined by media exposure probabilities and whether or not an advertisement is placed.

\( e_{ij} \) denotes the exposure value in media vehicle \( j \) going to a person in market segment \( i \).

\[
\sum_{j=1}^{M} e_{ij} z_{ijt} \text{ is the increase in exposure level of a particular individual in market segment } i \text{ in the period } t.
\]

\( y_{it} \) denotes exposure level of a particular individual in market segment \( i \) in time \( t \)

\[
y_{it} = a y_{it-1} + \sum_{j=1}^{M} e_{ij} z_{ijt}, \text{ where } a \text{ is a memory constant.}
\]

\[
\text{(2.4.1.1)}
\]

\( n_i \) denotes the number of people in the market segment \( i \),

and \( w_{it} \) denotes the sales potential of a person in segment \( i \) in time period \( t \).

The equation (2.4.1.1) will reduce to

\[
y_{it} = \sum_{s=-\infty}^{t} \sum_{j=1}^{M} a^{t-s} e_{ij} z_{ij},
\]

by taking infinite past period.
Having developed an expression for exposure level of a particular individual, the authors develop the response function. The response from an individual belonging to a segment at a given point of time is his sales potential. Let \( r(y_{it}) \) denote the response generated in time period \( t \) from an individual belonging to the \( i \)th segment who has received \( y_{it} \) level of exposure. Total response is the sum of individual responses over the entire time span under consideration. It is obvious that the total response is a random variable since \( y_{it} \) is a random variable having a density function \( f_{it}(\cdot) \). Therefore, total expected market response

\[
R = \sum \sum n_{i} w_{it} E \{ r(y_{it}) \}.
\]

The choice of function \( r(y) \) is left to the user's judgement. In this paper the authors have used an exponential function which is of the form

\[
r(y) = r_{0} + a(1 - e^{-by}) \quad 0 \leq y < \infty \quad .... (2.4.1.2)
\]

where \( r_{0}, a \) and \( b \) are non-negative constants specific to the product.

The reason for this choice is that the graph of this function increases at a decreasing rate.
The authors have then expanded the function \( r(y) \) through Taylor's series around the expected value of \( y_{it} \). Note that such an expansion is valid only if variables \( y_{it} \) are continuous. In this case for \( y_{it} \) to be continuous, \( e_{ij} \) must be continuous.

For the ease of exposition, dropping the subscripts for time and segment and using the Taylor's expansion, we obtain

\[
\begin{align*}
r(y) &= r(\mu) + \sum_{k=1}^{n-1} \frac{1}{k!} r^{(k)}(\mu) (y - \mu)^k \\
&\quad + \frac{1}{n!} r^{(n)}(y_1) (y - \mu)^n \\
\end{align*}
\]

where \( r^{(k)}(\mu) \) is the \( k \)th derivative of \( r(y) \) evaluated at \( y = \mu \) and \( y_1 \) is some value between \( y \) and \( \mu \).

By taking expectation

\[
\begin{align*}
\mathbb{E}(r) &= r(\mu) + \sum_{k=2}^{n-1} \frac{1}{k!} r^{(k)}(\mu) \mu_k + \\
&\quad + \frac{1}{n!} \mathbb{E} \left\{ r^{(n)}(y_1) (y - \mu)^n \right\} \\
\end{align*}
\]

Recalling \( \mu = \mathbb{E}(y) = \text{Mean of } y \)

\[
\mu_n = \mathbb{E} \left\{ (y - \mu)^n \right\} = \text{n th moment of } y \text{ about the mean.}
\]

The authors then express the moments of distribution of exposure level in terms of media decisions, \( x_{ijt} \) and the
probability of a person in the target audience exposed to individual and pair options.

The equation (2.4.1.4) can be re-written as

\[ E(r) = r(u) + \frac{1}{2} (\mathbb{E}(u))_2 + \sum_{k=3}^{n-1} \frac{(k)}{k!} \mu_k \]

\[ + \frac{1}{n!} E\{ r^n(y) - (y - \mu)^n \} \quad \cdots \quad (2.4.1.5). \]

Since \( y = \Sigma e_j z_j \)

\[ \mathbb{E}(y) = \mu = \Sigma e_j \mathbb{E}(z_j) \]

\[ z_j = \begin{cases} x_j & \text{if the person is in the audience of } j \text{ th option.} \\ 0 & \text{Otherwise} \end{cases} \quad \cdots \quad (2.4.1.6) \]

Hence \( p(z_j) = x_j p_j \quad \cdots \quad (2.4.1.7) \)

\[ \mathbb{E}(y) = \mu = \Sigma e_j x_j p_j. \]

\[ \mathbb{V}(y) = \mu_2 = \Sigma e_j^2 V(z_j) + 2 \Sigma e_j e_k \text{Cov}(z_j, z_k). \]

From (2.4.1.6) it follows that

\[ V(z_j) = x_j^2 p_j - x_j^2 p_j^2 \]

\[ = x_j^2 p_j (1 - p_j) \]

\[ = x_j p_j (1 - p_j)^2 \quad \text{since } x_j = 0 \text{ or } 1. \]

Similarly \( \text{Cov}(z_j, z_k) = x_j x_k (p_{jk} - p_j p_k). \)
Substituting these values in (2.4.1.5). We have

\[ E(r) = r \left( \sum j e_j p_j \right) + \frac{\sigma^2}{2} \left[ \left( \sum j e_j p_j \right)^2 \right] \left( \sum j e_j^2 x_j p_j (1 - p_j) \right) + 2 \sum \sum e_j e_k x_j x_k (p_{jk} - p_j p_k) \right] + \sum_{k=3}^{n-1} \frac{r_k(\mu)}{k!} \mu_k + \ldots \]

Now it can be seen that to compute \( \mu_k \) we need \( p_{j_1 j_2 \ldots j_k} \) where \( p_{j_1 j_2 \ldots j_k} \) denote the probability that a person belongs to the common audience of \( j_1, j_2, \ldots, j_k \) vehicles. Little and Lodish have done some empirical work to relate the lower moments and higher moments and thereby generating the higher moments, which are used in the expression of (2.4.1.5).

By substituting the response function used by authors given in (2.4.1.2) in (2.4.1.5) we get

\[ E(r) = \sigma_0 + a (1 - e^{-b_\mu}) + a e^{-b_\mu} \left\{ -\frac{1}{k!} b_{2_\mu} + \frac{1}{6} b^3_{3_\mu} \right\} \]

(They have ignored moments from 4th onwards, as they become very small).

Therefore MEDIAC boils down to a mathematical programming problem in which the expected response is maximized subject to the budget constraint.

\[ \text{Max} \sum \sum E \{ r(y_{it}) \} \]
The major problem in this model is the formulation of the response function.

Formulation of the sales response as a function of exposure level of an individual is not convincing. This is so because the method of construction is not based on the currently accepted reasoning that shows how advertising leads people to take the desired action. The currently accepted theory is that advertising leads people to take the desired action by moving them through a series of states.

First, advertising creates awareness, then comprehension and finally conviction which in turn leads to action. The more appropriate way to construct the response function would have been to show how the exposure values will change the transition probabilities of persons in different segments. For instance, it would have been more appropriate to relate the exposure level with the transition probabilities. To be more specific let $p_{i,s_1,s_2}$ denote the probability of a person belonging to the $i^{th}$ segment moving from state $s_1$ to $s_2$ if he has received unit level of exposure. Here states $s_1$ and $s_2$ refer to the states mentioned earlier, namely, awareness and conviction. It would have been more appropriate to
assess these transition probabilities and then work out the probability of a person being in a state of readiness to try. Such an approach was attempted by Jain, A. K. (22) and we believe that the manner of constructing such a response function would be more meaningful. It can be argued that the ideal approach to the problem of response function would be through the construction of these transition probabilities. This ideal, however, cannot be achieved in practice because of the difficulties involved in assessing the transition probabilities and because of the computation involved even in measuring the response that a media schedule will generate. The computational difficulty in optimization would be of a very high order. Therefore, the approach adopted in MEDIAC is the next best approach to the problem of selection of a media plan so as to maximize the expected response.

This argument is not convincing because the current practice of preparing a plan so as to achieve a minimum level of reach and frequency can also be considered as a simplification of the main problem of preparing plans so as to maximize the response. The minimum reach and frequency approach is based on the premise that a person needs minimal level of exposures to enable him to comprehend the message and to be convinced about it.
This is the reasoning why an advertiser wants to know the entire probability distribution of exposure per person. The reasoning behind using minimum reach is to ensure that for the desired response at least a minimum number of people are exposed to the message.

It therefore cannot be claimed that the approach used in MEDIAC for media selection is superior to the one currently being followed. At least in the existing approach, the advertiser has before him a complete probability distribution of exposure per person and has the flexibility to exercise his judgement regarding the response that will be generated from such an exposure pattern. This flexibility is denied to him in MEDIAC where he would have with him only the mean and variance of the exposure distribution.

In MEDIAC, unless \( e_{ij} \)’s (exposure level) are assumed to be continuous, the response function falls in the category of a step function and hence not differentiable.

In such a case use of Taylor’s series as done by the authors is not permissible. Moreover, to estimate the expected sales response it is necessary to obtain higher overlaps among media vehicles. We also need to know the probability of a person being exposed to both media options \( j \) and \( k \).
The authors have used some empirical studies to estimate $p_{112}$, $p_{1123}$, etc.

To adopt this model in the Indian situation, similar studies will have to be conducted. Such studies are very expensive to carry out. However, looking to the limitations of this model, implementation of this model in the Indian context does not seem to be promising.

2.5. Conclusion:

Thus from the above discussion it will be clear that all the three approaches require data regarding the probability of a person in the target audience being in the audience of either one or more vehicles. These data are not readily available in the case of cinema, the problem of interest to us. NRS II reports only the data on the cinema going habits of people belonging to different sexes, age groups, income groups, education groups, and population strata. It does not provide data regarding the manner in which the visits are distributed among the different theatres.

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Cinema going habits means the frequency of visits to theatres in a period, say one year.
The data provided in MRS II for the medium of cinema are sharply contrasted with the data for the press medium. MRS II provides data on the profile of readership for each of the 370 publications. Specifically for each of the publications it reports data about the number of people who read an 'average issue' and belonging to different sexes, different income groups and having different educational background. It also provides data about the common readership of two publications and the frequency with which different issues of a publication are read by a person. Such complete data are not available for the medium of cinema.

Unfortunately it is not possible to compile such data. In India there are approximately 3000 theatres spread over the length and breadth of the sub-continent. To compile data about the profile of the audience visiting the theatres is next to impossible. Hence, to a planner dealing with the planning problem in the medium of cinema, the need for a methodology that will generate the complete data with the help of the limited information provided on the cinema going habits of the people is paramount.

The argument we have put forth so far in support of developing a newer approach for cinema planning would be acceptable in part to almost all readers. Even the strong
proponents of the response function approach will be in agreement with the need for developing a methodology that will, starting from the incomplete information of the movie going habits of persons, generate complete data on the probability of a person visiting different theatre week combinations.

This group, however, may not be in agreement with the reach and frequency approach that we have used. Their view would be that we should have used the approach of maximizing the response in situations where the planner was interested in preparing an optimal plan. In those situations, where the interest was limited to evaluation of a given plan, the evaluation should have been done in terms of the response rather than reach and frequency.

Seemingly there are two advantages of doing so. First, if the planner is interested in preparing the optimal plan then the response function approach avoids the difficulty of deciding the minimum level of reach and frequency inherent in the reach and frequency approach. It might be recalled that in the preparation of an optimal plan using the reach and frequency approach the planner is required to specify the minimal level of reach and frequency that he wishes to achieve. Admittedly this is not an easy task.
Second, the approach of maximising response does not require the complete distribution of exposures. Such a distribution is required for reach and frequency approach.

The main reason for departing from the response approach is because of dissatisfaction with the method of constructing the response function discussed in Section 2.4.1. We would readily agree with the view that the main purpose of advertising is to maximize the proportion of people who will take the desired action. We, however, strongly believe that the method of setting a functional relationship between the advertising effort and the proportion of people who will take the desired action as a result of the advertising effort must be consistent with the currently accepted theory that explains how advertising works. Existing methods of construction of response function do not meet this test.

We, therefore, came to the conclusion that until a satisfactory method is found to construct a response function it would be better to provide the user the reach and a complete distribution of exposure that will be generated by the plan and leave it to his judgement the task of assessing the response that will be generated by the plan.
The literature did not provide us with any methodology that could be used for solving the cinema planning problem. We, therefore, examined some of the practices currently followed in the practising world. In practice the preparation of an optimal plan is rarely attempted. At the best, a given plan is evaluated in terms of gross OTS it generates in the target audience. The formula for computing gross OTS is as follows:

\[
\text{Gross OTS} = \text{Number of persons in the target group visiting a theatre in an average week} \times \text{Number of screening weeks selected.}
\]

where the number of persons in the target group visiting a theatre in an average week = (average occupancy per show) \times (average capacity per theatre per show) \times (Number of shows per week) \times (proportion of the target group in the audience of a show).

This approach has the apparent advantage of simplicity of computation and using the data that might be easy to obtain. It can be argued that the data pertaining to average occupancy per theatre and average capacity per theatre might be easy to obtain at least in major towns of interest.

In our view these advantages are more apparent than real. There are three reasons for this assertion. First, the data on the proportion of the target group in the
audience of a show are not easy to obtain. To obtain these data it is necessary to assess the theatre-going habits of the target group. The moment such an assessment is required, the advantage of easy availability of data is lost. Second, gross OTS achieved by a plan is not the only feature of interest. The planner wishes to know the reach achieved by the plan and the pattern of OTS distribution. Finally, this method masks the assumption under which such a formula will give the gross OTS.

Therefore, for the resolution of the problem we decided to develop a more general approach that will start with the data on theatre-going habits of the target audience and end by providing for a given plan, the reach it will achieve and distribution of OTS that it will generate. Such a methodology will automatically provide a base for preparation of an optimal plan if the planner desires to prepare a plan which is optimal, according to a chosen criterion.

In developing this approach we have strived to keep a balance between fidelity and practicality. It is possible to make the problem very complex so that it resembles the live situation very closely. This is, however, done at a cost. The difficulties involved in obtaining judgements and data
required for the solution of such a complex problem and the computational effort involved in processing the data and judgements are so great that it is impracticable to find a solution within the available resources. On the other hand the temptation to simplify the problem to overcome these difficulties is so strong that sometimes the problem that is solved does not even remotely resemble the problem faced. We have strived to avoid both these extremes.