Working Paper

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Foreword

Many practical decision problems have more than one aspect with a high complexity. Current decision support methodologies do not provide standard tools for handling such combined complexities. The present paper shows that it is really possible to find good approaches for such problems by treating the case of scheduling programs for a television network. In this scheduling problem one finds a combination of types of complexities which is quite common, namely, the basic process to be scheduled is complex, but also the preference structure is complex and the data related to the preference have to estimated. The paper demonstrates a balanced and practical approach for this combination of complexities. It is very likely that a similiar approach would work for several other problems.

OPTIMAL PRIME–TIME TELEVISION NETWORK SCHEDULING

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ABSTRACT

This paper introduces SPOT (Scheduling of Programs Optimally for Television), an analytical model for optimal prime-time TV program scheduling. Due in part to the advent of new cable TV channels, the competition for viewer ratings has intensified substantially in recent years, and the revenues of the major networks have not kept pace with the costs of the programs. As profit margins decrease, the networks seek to improve their viewer ratings with innovative scheduling strategies. Our SPOT models for scheduling network programs combine predicted ratings for different combinations of prime-time schedules with a novel, mixed-integer, generalized network flow, mathematical programming model, which, when solved, provides an optimal schedule. In addition to historical performance, subjective inputs from actual network managers were used as input to the network flow optimization model. The optimization model is flexible. It can utilize the managers' input and maximize profit (instead of ratings) by considering not only the revenue potential but also the costs of the shows. Moreover, SPOT can describe the scheduling problem over any time period (e.g., day, week, month, season), and designate certain shows to, and restrict them from, given time slots. The methodology of SPOT is illustrated using data obtained from a cable network during the first quarter of *1990*. The optimization model produces solutions which would have generated an increase of approximately *2* percent in overall profitability, representing over *$12* million annually for a typical network with an average Nielsen rating of 18. SPOT not only produces more profitable TV schedules for this network, but also provides valuable general insights into the development of mixed programming strategies for improving future schedules.

Optimal Prime-Time Television Network Scheduling

1. INTRODUCTION

In the last decade, the television industry in the U.S. has seen tremendous changes which have dramatically affected its operations. Not too long ago, the three major networks (ABC, CBS and NBC) routinely captured over ninety percent of the viewing audience during prime-time, but in recent years their combined share has decreased to about sixty percent of the viewers. Meanwhile, network program costs escalated from about $*200,000* for an hour of prime-time in *1971* to over $*1* million today. For example, in 1991 NBC ordered the ninth season of *Night Court* at $*1.5* million for each of the *22* half-hour episodes for the *1991-1992* season. Hence, as costs have increased and competition stiffened, the profitability of prime-time programming has declined.

The advertising revenues of the TV networks are linked directly to the size of the audience delivered to the advertiser. The number of viewers of a show is measured using ratings provided by the old Nielsen meters or the new Peoplemeters (Webster and Lichty 1991, p. 17). With billions of dollars being spent on TV advertising, and $*9.6* billion spent on network TV advertising in *1989* alone, a swing of only one rating point translates into a loss or gain of millions of dollars in advertising revenues for the network. The outlook in terms of the total viewing audience is not very encouraging for the three major networks, as their average ratings are gradually shrinking. Krugman and Rust (1987) expect this trend to continue, projecting the combined ratings of the major networks to fall to about fifty-four percent by the year *2000*.

In sum, the competitive ratings arena has essentially become a game where the gain of one network could mean big losses for another [1]. There has never been a more urgent need to schedule prime-time TV programs carefully to maximize the network's ratings or profits. To complicate the scheduling task, the success or failure of a given show not only depends on the contents, characteristics, and cost of that show, but also on the show against which it is placed.

[1] Ted Danzig, the Editor of Advertising Age in an interview on McNeil-Lehrer Newshour, September 1989.

Though little published information exists on the use of analytical models to aid scheduling in the television industry, there has been some pioneering work in the management science literature on scheduling models using ratings data by Gensch and Shaman (1980), Horen (1980) and Henry and Rinne (1984a, 1984b); and the research by Rust and Echambadi (1989), which uses individual level viewing choice data. The current work attempts to extend this body of research by presenting SPOT (*Scheduling of Programs Optimally for Television*), analytical models for optimal prime-time TV program scheduling. These models combine predicted ratings with a novel, mixed-integer, generalized network-based flow, mathematical programming model, to provide an optimal schedule. Apart from the unique network flow-based model, SPOT is flexible in that it can utilize the managers' expert inputs, and can maximize profit (instead of just TV ratings), by considering not only the revenue potential, but also the costs of the shows. The models are illustrated using data obtained from a cable network.

The remainder of the paper is organized as follows. In Section 2, we review the literature on scheduling strategies and models, and summarize the contributions of our research. In Section 3, the SPOT methodology is introduced and justified, including both regression-based and judgmental data estimation, and the mathematical programming, network-based flow model used in SPOT to assign shows to time slots. The results of applying SPOT to a cable TV network and a discussion of model validation issues are presented in Section 4, followed by computational tests in Section 5 and potential model extensions in Section 6. The paper ends with a summary and conclusions in Section 7.

2. LITERATURE REVIEW

2.1. Scheduling Strategies

Among the most commonly used scheduling strategies is the "lead-in" placement strategy which relies on the strength of the preceding program to boost the ratings of a newly introduced, or a weaker program, following it. Empirical evidence supporting such a strategy has been reported in the pioneering work by Ehrenberg and Goodhardt (1969), Goodhardt and Ehrenberg (1969) and Goodhardt, Ehrenberg and Collins (1975). Further evidence confirming the effectiveness of a lead-in scheduling strategy has been found by Headen, Klompmaker and Rust (1979), Henry and Rinne

(1984), Horen (1980), Tiedge and Ksobiech (1986) and Webster (1985). A variant of the lead-in strategy considers the carry-over effects of sequences of more than two programs. The lead-in effect of one program can be viewed as the "lead-out" effect of the previous program. Taking the lead-in lead-out effects of three consecutive programs is often called a "hammocking" or "sandwiching" strategy.

Gantz and Zohoori (1982) found that viewers appear willing to structure their lives around television preferences, and that viewing behavior is sensitive to changes in the television schedule. Their study identified the time at which the show is aired and the contents of the program as the most important factors affecting TV viewers' behavior. Hence, a television station's program schedule has a critical impact on the type and the size of the audience it attracts, and the task of designing an effective schedule is a crucial component of a network programmer's responsibility. The programmer must not only acquire an inventory of programs, but also design a weekly schedule which places the available shows in the appropriate time slots in a manner which attracts as large an audience as possible. Head (1985, p. 27) describes the task of scheduling the programs of a station, cable or network as "... a singularly difficult process." Read (1976, p. 72) refers to broadcast television scheduling as an "arcane, crafty, and indeed, crucial" operation. With the increasingly rapid changes that are shaping the industry, scheduling has become more crucial and challenging today than at any time in the past.

It is not surprising that Michael Dann, a veteran network program executive and consultant, stated that "... where a show is placed is infinitely more important than the content of the show." (*New York Times*, February 26, 1989, p. 42). Therefore, it appears that optimal prime-time program scheduling is a powerful and important means for networks to realize an acceptable profit level.

2.2. Scheduling Models

There is little published evidence that formal and systematic approaches are used to guide this process. Rather, network programmers often rely on heuristics and subjective judgments. The program scheduling task as currently practiced appears to draw largely on past experience, instinct and guesswork. Stipp and Schiavone (1990) report that to gather information about how to best schedule their programs, NBC asks potential viewers whether they would watch a particular show if it were aired at the same time slots as competitors' shows. This kind of scheduling research technique is usually referred to as "competitives." The information from sample surveys and viewer questionnaires is then used to implement a scheduling strategy aimed at attaining high ratings.

Analytical research on scheduling network programs includes the work based on aggregate ratings data by Gensch and Shaman (1980), Horen (1980) and Henry and Rinne (1984), and the research by Rust and Echambadi (1989), using individual level viewing choice data. Gensch and Shaman (1980) use a trigonometric time-series approach to predict aggregate audience viewing for different days, times and seasons. The predicted audience values are then used to develop four different network share models to apportion the total market share of the three major television networks. Each of these network share models is based on specific assumptions about the strength of program loyalties, and the manner in which TV viewers form viewing preferences. Even though their model only takes into account the seasonality of the time-series data and does not consider the content of the program itself, Gensch and Shaman's (1980) predictions are highly accurate. Based on the findings of Gensch and Shaman (1980), Rust and Alpert (1984) hypothesize that television viewing may be conceptualized as a two-stage choice process: in the first stage the individual decides whether or not to watch TV, and in the second stage selects which program to watch.

Several approaches have been proposed to model this second stage of viewing choice behavior at the individual level. Rust (1986) provides a comprehensive review of viewing choice models. Using an economic utility approach, Lehmann (1971) relates program type and production quality to preference for television shows. Darmon (1976) uses both channel loyalty and program type to predict individual viewing choice. Zufryden (1973) views program selection as a dynamic process, and uses a linear learning model formulation in which the current choice behavior is a function of previous viewing choice decisions.

To date, the most comprehensive individual viewing choice model proposed is Rust and Alpert's (1984) audience flow model. This research uses Luce's (1959) choice axiom to estimate utilities for television programs based on segment-wise preferences for program type and audience flow. "Audience flow" records include data regarding the status of the TV set, in addition to information on whether the set is on or off at a given time, whether the TV remains tuned to the same channel during a given program, and whether the program is ongoing or just starting. Rust and Alpert (1984) found the audience flow model very accurate in predicting individual viewing choices, with correct predictions about *76* percent of the time.

Henry and Rinne (1984) investigate the effectiveness of several commonly used scheduling strategies such as "blunting" and "counterprogramming," and suggest several options for scheduling programs during the week in relation to the competition.[2] However, the Henry and Rinne study does not provide a model or method that can be used to schedule television programs.

Rust and Echambadi (1989) develop a heuristic method for scheduling a television network's programs. Their approach differs from the previous methods, in that they explicitly incorporate individual viewing choice by extending the audience flow model developed by Rust and Alpert (1984). Their heuristic, which maximizes the network's share of audience, produces program schedules, with substantially improved viewership over the original schedules. The flexibility of the model permits one to use an objective function other than audience share, and consider managerial constraints like slotting a particular show for a particular time or having certain programs appear only after *9:00* p.m.

Gensch and Shaman (1980) strongly suggest that models which incorporate expert opinions should be developed. The insights of practitioners in areas such as audience demographics, program content and competition should be extremely critical in determining not only the accuracy but also the successful implementation of those models.

Horen (1980) provides an explicit two-stage model to develop program schedules. This model defines multiple, half-hour program segments. Longer shows are divided into "program-

[2] Horen (1980) defines the "counterprogramming" strategy as scheduling programs in a given time slot which are of a different type than the programs offered by the competing networks in that time slot. A network using this strategy would place a show that appeals to one specific audience (say, women between the ages of *18-45*) against a competing network's program which is aimed at a different audience (for example, men between the ages of *45-60*). "Blunting," is the opposite of counterprogramming. A network applying this strategy seeks to schedule "strength against strength," offering a program with similar or greater appeal to the same target audience as its competitor's program at a given time slot. Tiedge and Ksobiech (1987) found that in the past, counterprogramming has been used more widely than blunting. Based on an analysis of prime-time programs in the period 1963-1984, they found that pure blunting was used only *1.4* percent of the time, while pure counterprogramming accounted for over *60* percent of the scheduling strategies.

parts," with ratings detailed for each program-part. In the first stage, Horen (1980) uses past rating information of the three major TV networks to predict ratings for each class of programs and each prime time slot by means of linear regression. In the second stage, a mathematical programming model is used to determine a potential schedule which maximizes the ratings.

However, a schedule which simply maximizes ratings may not be optimal for the network. The costs of shows differ dramatically, and as a result, it is possible that inexpensive shows are highly profitable, even though their ratings are lower than those of other more costly shows.[3] In SPOT, we take into account both the revenues and costs associated with each show, providing a more accurate indicator of the show's contribution to the network's profit. Moreover, SPOT will address the hypothesis that by using historical data or ratings for the existing schedule, an expert can better estimate how well a show will fare in each time slot. Judgmental estimates by experts may very well be more accurate than those found through forecasting by regression.

The contribution of this paper is the introduction of a novel, flexible, network-based flow model that analytically describes the difficult problem of scheduling of television programs optimally. We demonstrate that this approach is superior to that proposed by Horen (1980) in terms of computational effort and flexibility of the schedules. The flexibility of SPOT is demonstrated by its ability to incorporate show costs and revenues, rather than simply ratings, to incorporate either regression forecasts or expert judgments, the ability to assign certain shows to and restrict others from specific time slots, and the ability to handle lead-in effects directly.

3. METHODOLOGY OF SPOT

3.1. Modeling Framework

The modeling framework of SPOT is based in part on the work of Horen (1980). The basic assumptions made in Horen's mathematical programming model are (1) other networks' schedules

[3] Several recent reports in the media suggest that some networks do use a strategy to maximize *profit*. The placement of a low cost news feature *48 Hours* by CBS against the immensely successful, but expensive *The Cosby Show* of NBC is a prime example. Other networks are trying similar strategies, illustrating that with escalating program costs, maximizing *ratings* may no longer be optimal. ABC was the only one of the three major networks to earn a profit during 1991-92 season, even though it ranked third based on Nielsen's ratings. Its success is mainly attributed to a strategy of programming and scheduling shows to maximize profit rather than just ratings (*Business Week*, April 20, 1992). Hence, it appears useful to build a scheduling model which considers the profit potential of each show at any time slot.

remain fixed, and (2) the network's objective is to maximize its total expected ratings. Horen's model is a generalization of the classical assignment model, but it is neither a pure network nor a generalized network flow problem. Some of the shows last more than one program part (one half-hour), necessitating the use of complicating constraints which require combinatorial problem solving methods. Further, Horen does not explicitly address a variety of desired model features, such as, having more show durations than the time slots allow, assigning of a particular show to a particular time slot; assigning of a set of shows to a set of time slots; assigning of a sequence of shows to a set of time slots and restricting shows from certain time slots. The lead-in effects are approximated by linear costs to avoid a quadratic objective function.

Similar to Horen (1980), the modeling framework of SPOT consists of two stages. The first stage uses either a *regression model* based on past profit data (from past ratings and costs of shows) (for SPOT-REG), or a *judgmental analysis* (for SPOT-EC) to predict the potential performance of each show at alternative time slots. Predictor variables in the regression model include show type, duration of the show, relative attractiveness of the show, day and time the show is televised.

In SPOT-EC, the Analytic Hierarchy Process (AHP) is used to obtain the manager's judgments or assessments of the relative importance of each of the critical variables. This results in relative performance values for each combination of show and time slot, which in turn serve as a prediction of how well a particular show would do at each particular time slot. In the process of determining the judgmental forecasts, the manager has access to the past performance data of each show.

The advantage of incorporating judgmental factors is that it enables one to explicitly consider qualitative and conceptual factors which may affect program ratings. It may be difficult or impossible to include such factors in a regression modeling framework. By offering the option of using either regression or judgmental inputs, SPOT provides considerably greater flexibility than previous modeling efforts. It also provides an opportunity to compare these two approaches, and, as discussed in Section 4.2, determine which appears to give more accurate rating predictions. The regression forecasting model and judgmental forecasting model are discussed in more detail in Sections 3.3 and 3.4, respectively.

The projections from either the SPOT-REG or the SPOT-EC analysis are then used as inputs into the second stage of SPOT. In this stage, a generalized, mixed-integer, network-based flow model is used to determine the optimal program schedule given the inputs from the first stage. The general modeling process is outlined in Figure 1. The model components of stage 2 are discussed in detail in Section 3.5.

Figures 1 and 2 About Here

3.2. Data

The data used were provided by a major cable network, and represent actual programming utilized by this network during the first quarter of *1990*. For confidentiality, this cable network is not identified and the data are disguised, but the numbers are representative. Each week during this quarter (for 13 weeks), the network aired *26* different half-hour and hour-long shows in the *8-11* p.m. prime-time period, Monday through Sunday. The data provide information on show characteristics, each show's relative attractiveness to the network's audience, as measured by the manager's judgment,[4] the cost of each show, each show's TV ratings, and the cost per thousand (CPM) charged to the advertisers for commercial time during each show.

On average, during this quarter, there were *10* half-hour shows, *16* hour shows of *6* show types to fill the 42 half-hours of prime-time slots every week. Using the data, our regression model was employed to predict net profit objective values for the allowable combinations of shows and time slots. Based on our discussion with the Program Director, the following assumptions were made:

1. The model encompasses half-hour time slots from *8:00* p.m. to *11:00* p.m., over all seven days of the week.
2. Shows have durations of one half-hour (*1* program-part) or one hour (2 program parts).
3. Two program-part shows may only start at *8:00*, *9:00* or *10:00* p.m.

[4] The Program Director at the network was asked to evaluate each show that was telecast during the first quarter of 1990 in terms of its perceived attractiveness to the audience on 1 to 10 scale, with 10 being most attractive and 1 being least attractive. Eliciting evaluations post-hoc poses some potential concerns in terms of memory and accuracy. However, similar judgments have been used by Dacin and Smith (1994), Reddy, Holak and Bhat (1994) and Smith and Park (1992).

4. The seven *best* shows, as identified by the network manager, are one hour in length, and must be scheduled at *9:00* p.m., every night.[5]

5. Lead-in effects are negligible.

In consultation with the network managers, the shows are classified into six homogeneous types, based on their general characteristics. These show types are identified by the following symbols: *A, H, L, N, P* and *S*. The full description of these categories is not given to maintain confidentiality. A typical week's schedule of the network during the first quarter of *1990* is presented in Figure 2.

Before proceeding with the forecasting model used to predict viewer ratings, the general relationships between the revenues during the first quarter of *1990* and several key show characteristics are presented graphically in Figure 3.

Figure 3 About Here

Figure 3 indicates that for this cable network, the *H* and *S* type shows tend to perform the best in generating revenues. Moreover, hour-long shows do substantially better than half-hour programs, Tuesdays and Saturdays are the best days in terms of revenues, while the *9:00* p.m. and *10:00* p.m. time slots tend to generate more revenues than other prime-time slots.

As discussed above, the SPOT profit forecasts can be estimated in two ways. Initially, we present SPOT-REG, followed by an outline of SPOT-EC.

3.3. Regression Forecasts (SPOT-REG)

At the aggregate level, regression models have been used in the past in forecasting TV ratings. Horen (1980) uses a linear regression model but did not explicitly incorporate characteristics of the television shows. Henry and Rinne (1984a) use a logit model to predict ratings with show characteristics as predictors of ratings, but do not address the issue of optimal scheduling of television

[5] As *9.00* p.m. slot is the most desirable prime-time slot, the *best* shows with the greatest audience appeal and potentially highest ratings are scheduled at this time slot. Seven shows were identified as fulfilling these requirements by the Program Director.

shows. Neither of these models dealt with the issue of cost of shows. We propose a richer, aggregate forecasting model which not only explicitly incorporates the show characteristics, day and time characteristics, but also managerial perceptions of the relative attractiveness of each of the television shows.

$$Y_{i,t} = \beta_0 + \sum_{l} \beta_l^A A_i^l + \sum_{j} \beta_j^S S_i^j + \sum_{k} \beta_k^D D_i^k + \sum_{m} \beta_m^T T_i^m + \sum_{p} \beta_p^R R_i^p + \varepsilon_{i,t} \quad (1)$$

where Y_{it} is the rating of show i in time slot t, A_i^l is a measure of the relative perceived attractiveness of show i of type l, measured on a ten point scale, while S_i^j, D_i^k and T_i^m are zero-one variables which equal one if, and only if, show i is of type j, scheduled on day k (Monday through Sunday), in time slot m (half-hour slot between *8* and *10:30* p.m.), respectively. The binary variable R_i^p equals zero if, and only if, the duration of show i is one half-hour, and one if the show lasts one full hour, and ε_{it} is the residual term.

The time-series data on 26 shows over 13 weeks were pooled to estimate the model presented here. Pooling of this data may be considered a problem if the shows may be considered a source of heterogeneity. As we are using show and day and time characteristic variables in the model for the differences, pooling is not a concern (Parsons and Vanden Abeele 1981). However, the Lagrange Multiplier (LM) test (Breusch and Pagan 1979) indicates the presence of heteroskedasticity. As a result, applying ordinary least squares (OLS) will produce unbiased but inefficient estimates (Belsley 1973), necessitating the use of the generalized least squares (GLS) procedure (Greene 1993; Draper and Smith 1981; Montgomery and Peck 1982) to estimate the model. More details on the effects of using different estimation procedures on the outcomes of the SPOT and Horen models are discussed in Section 5.

The model estimates using both OLS and GLS are presented in Table 1. The explanatory power of the model is good, as reflected by an adjusted R^2 of *0.926* and *0.943* for OLS and GLS, respectively. Perceived show attractiveness is positive and significant, indicating it to be strong determinant of ratings and, in turn, on revenue. Show duration is also positive and significant, so that one-hour shows generate significantly more revenue per half hour than half-hour shows. Overall, as expected the GLS procedure provides a slightly better R^2 and the parameter estimates have smaller standard errors. The current model is only a main effects model, and some interaction effects could be added to improve the predictions. However, adding selected interaction terms to the model improved the R^2 only marginally.[6] In other contexts, if the main effects do not predict well, it may be necessary to include interaction terms selectively. This, and other model validation issues, will be addressed in Section 5. Other enhancements could be made to the model, for instance by including audience characteristics. The estimates from this model are used to project revenues for shows at various time slots, and as inputs into the optimization component of SPOT-REG.

Table 1 About Here

3.4. Judgmental Forecasts (SPOT-EC)

The utilization of management science models by managers is limited in practice. Alluding to the lack of application of these models, Little (1970, B-466) describes the practice as "... a pallid picture of promise," identifying the absence of communication between manager and model as the key element for such lack of implementation. The attempt here, in developing a judgmental model, is to involve the manager directly in the modeling process by asking for his/her expert inputs. Thus, the manager is an integral part of the model. This is achieved by incorporating managers' judgments on the relative importance of the various aspects of the TV shows (*e.g.*, show type, show attractiveness, duration, time of day, day of the week, etc.), to generate forecasts which can supplement and validate the regression forecasts discussed in the previous section. In addition to getting management directly involved in the process, judgmental forecasts also reflect aspects of the decision problem which cannot be captured by the quantitative information used in obtaining regression forecasts.

Judgmental estimates of the relative importance of assigning shows to certain time slots can be obtained using any preference elicitation method, as long as the resulting importance measures are based on a ratio scale. In SPOT-EC, the "absolute judgment" mode of the Expert Choice (1992) software implementation of the Analytic Hierarchy Process (AHP) developed by Thomas Saaty

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[6] For example, of the 30 show type x day interactions, only 10 were significant, with an increase in the adjusted R^2 to .935 in the case of OLS and to 0.946 in the case of GLS. Moreover, the addition of these interactions has caused a severe collinearity problem. As the main effects model has accounted for a substantial variance, and due to the problems caused by multicollinearity, interaction terms were not included.

(1980, 1986) is used for this purpose. The relative importance judgments can be based on revenue and profit, but it is also possible to include other relevant factors. The AHP has recently emerged as an extremely useful tool in analyzing complex business decision problems, and has proven particularly helpful in determining priority scores and preference rankings of the decision alternatives. Applications of the AHP in combination with optimization techniques include general mathematical programming (Bard 1986; Harker 1986; Liberatore 1987; Stam and Kuula 1991), and network analysis (Sinuany-Stern 1984). The AHP has also been applied successfully in marketing, notably by Wind and Douglas (1981) and Wind and Saaty (1980).

For several reasons, we have opted to use the absolute judgment approach of the AHP in SPOT-EC, rather than the relative judgment mode, in order to avoid the rank reversal problem in the AHP (Dyer 1990a, 1990b), because it facilitates an easier evaluation of large numbers of program combinations, and because the analysis and evaluation of new shows is straightforward. Note that, in contrast, it may be difficult to accurately predict profits or TV ratings for new shows using any regression-based model, because no "hard" historical data exist on these shows. In the AHP analysis, no such hard data are needed; only the manager's subjective judgments.

Therefore, the absolute judgment approach of the AHP appears to have potential advantages over the regression based approach, and should certainly prove useful to the network program scheduler as an additional decision support tool. Since SPOT-EC yields ratio scale results, these can serve as the input - in the same way as regression estimates - into the network-based flow model analysis, which, as described in Section 3.5, determines the optimal scheduling of shows to time slots.

Figure 4 and Table 2 About Here

In Figure 4, we show an AHP hierarchy with the five factors (criteria) that affect the profit contribution of each program-time slot combination: show type, show attractiveness, day of the week, time slot, and show duration. The numerical values in the figure reflect the relative importance judgments of the criteria and of the different categories for each criterion made by the network scheduling expert. In our case, the expert judged each of the five factors equally important in terms of impact on profit, implying weights of *0.20*, which need not be the case in general. Table 2 illustrates the overall relative importance of twelve different representative show assignments (alternatives *01* through *12*) to various time slots and days-of-the-week for our example. Once the structure of the scoring spreadsheet in Table 2 has been set up, it is easy for the manager to evaluate any combination of show-time slot assignment, existing or new, by selecting the appropriate categories of the five factors.

3.5. Generalized Network Flow Model for TV Scheduling

We now discuss stage 2 of the SPOT methodology: the development of a mixed-integer, generalized network flow model that accurately describes the TV scheduling problem structure. A network is a graphical representation of a flow problem. By defining the problem as a network, it can be visualized and stated mathematically, facilitating model and problem analysis, efficient solution, managerial understanding and more readily acceptance of the problem by non-analysts. In fact, pure network flow problems can be solved up to *100* to *200* times faster by network programming algorithm implementations than by standard linear programming ones (Aronson 1989). Generalized network flow problems can be solved *10* to *20* times faster than by standard linear programming methods. Mainly due to compact, graphical problem representation and optimization procedures, network algorithms can solve much larger problems than can be solved by more general optimization techniques.

We adopt the definition of integer, one half-hour "program-parts" for shows longer than one half-hour (Horen 1980). A complication for all TV scheduling models is that shows extend over multiple, consecutive time slots, which destroys the pure network structure of the model. The program-parts determine values of arc multipliers for our generalized network structure to enforce these conditions. In addition, we introduce some simple side constraints to speed up the optimization substantially. The simultaneous treatment in SPOT of both half-hour and hour or longer shows within a network-based flow formulation is a novel modeling contribution.

The model is related to that of an assignment problem with some intermediate nodes and arcs with multipliers. The supply-to-demand arcs indicate the scheduling of a single program-part show.

In SPOT-REG, their arc objective values are the individual show's estimated net profit defined by *profit = revenue - cost*; in SPOT-EC, the individual show's estimated scores based on managerial experience obtained through the AHP. If required, it is possible to use show ratings. The supplies to intermediate node arcs indicate scheduling a multiple program-part show. Its multiplier equals the number of half-hour program-parts of the show. The intermediate node to demand arcs split the multiple program-parts of shows into the requisite, consecutive half-hour time slots. We next introduce the notation and terminology necessary to describe the mathematical formulation of the network flow problem.

Let N be the set of nodes and A the set of arcs consisting of ordered pairs of nodes (i, j), $i, j \in N$. The network is defined by $[N, A]$. Let $N_i^+ \subset N$ be the set of "to" nodes $j \in N$ for which $(i, j) \in A$, and $N_i^- \subset N$ the set of "from" nodes $i \in N$ for which $(i, j) \in A$. With each arc (i, j), we associate a flow x_{ij}, a contribution to the objective function per unit flow c_{ij}, a multiplier α_{ij}, a flow capacity u_{ij}, and a lower bound of zero.

Furthermore, let K be the maximum number of program-parts of all shows under consideration, denote the set of all supply nodes corresponding to K program part shows ($k = 1$ for half-hour shows, $k = 2$ for hour shows, *etc.*), by S^k, $k = 1, ..., K$; I^k be the set of intermediate nodes for time slots of k program-part durations, for $k = 2, ..., K$; and let demand node T_j represent the j-th time slot to be filled for $j = 1, ,,,, J$.

The time slot nodes are grouped into set T. The show nodes are supplies that have requirements of $+1$, the intermediate nodes are transshipment nodes, and the time slot nodes are demands with requirements of -1. To balance the network to enforce feasibility, if the number of program-parts (P) exceeds the number of time slots to be filled (D), a dummy demand node (T_d) having requirement - (P - D) is added to the network. If $D > P$, then a dummy show, corresponding to unknown television shows to be added into the line-up at a later date, with a requirement of $D - P$ program-parts is added. To match the shows with appropriate, consecutive time slots, a *time slot group* G^k is defined as a set of sets of consecutive time slots that may be filled by a show with a duration of k program-parts, $k = 2, ..., K$. There is equal flow through each of the arcs in such a time-slot group, which requires a simple side constraint set to be included in the problem.

The integer, generalized network-based flow SPOT TV scheduling model may be described as:

$$\text{(I) Maximize } z = \sum_{i \in S^1} \sum_{j \in T \cup \{T_d\}} c_{ij} x_{ij} + \sum_{k=2}^{K} \sum_{i \in S^k} c_{i,T_d} x_{i,T_d} + \sum_{k=2}^{K} \sum_{i \in S^k} \sum_{j \in I^k} c_{ij} x_{ij}, \qquad (2)$$

subject to:

$$\sum_{j \in T \cup \{T_d\}} x_{ij} = +1, \; i \in S^1, \qquad (3)$$

$$\sum_{j \in I^k \cup \{T_d\}} x_{ij} = +1, \; i \in S^k \,; \; k = 2, \ldots\ldots, K, \qquad (4)$$

$$\sum_{j \in G_i^k} x_{ij} - \sum_{j \in S^k} k\, x_{ji} = 0, \quad i \in I^k \,; \; k = 2, \ldots\ldots, K, \qquad (5)$$

$$- \sum_{j \in S^1} x_{ji} - \sum_{k=2}^{K} \sum_{j \in I^k \,/\, i \in G^k} x_{ji} = -1, \; i \in T, \qquad (6)$$

$$- \sum_{k=1}^{K} k \sum_{j \in S^k} x_{j,T_d} = r_{T_d}, \qquad (7)$$

$$x_{ij} - x_{ih} = 0, \; i \in I^k; \; k = 2, \ldots, K; \; j, h \in G^k, \; h = j + 1, \qquad (8)$$

$$x_{ij} \in \{0, 1\}, \; (i, j) \in A. \qquad (9)$$

The first term of (2) represents the contribution to the objective of the half-hour shows; the second term is for the half-hour show arcs linked to the dummy node; the third term is for the multiple time slot shows. Constraints (3)-(7) are the conservation of flow constraints. Constraint set (8) tightens the linear programming relaxation, forcing equal flow on the arcs from intermediate to time slot nodes. There are only $|G^k| - 1$ such constraints for every set G^k. Constraint set (9) enforces the binary condition on all arcs. Because the requirements of the supplies are all $+1$, the multipliers are defined by show duration, and the demand node requirements are all -1, so that no explicit statement of arc flow capacities is needed; the model defaults to a *0, 1* (binary) problem. See Figure 5 for the graphical representation of an example problem.

Figure 5 About Here

The SPOT integer, generalized network flow model is a difficult, NP-hard (Nemhauser and Woolsey 1988) combinatorial problem. However, if all shows and time slots have equal duration, or if certain other simplifications occur (*e.g.*, all half hour shows are of the same type and quality), then SPOT becomes an easily solved, pure assignment problem. Though this rarely occurs in practice, the SPOT model describing the third quarter data of *1990* for the cable network was transformed into a pure assignment problem. The SPOT model, when solved, provides an optimal schedule given the profit projections based on either inputs from SPOT-REG or SPOT-EC. It is possible just to use TV audience rating estimates, but, as previously noted, there is a weakness when show costs are not included. High ratings for an expensive show may not be as desirable as lower ratings for a modestly priced show in terms of the contribution to the overall net profitability of the television network. Further, a schedule that maximizes net profit also maximizes ratings but not vice versa.

3.6. Lead-in Effects

Lead-in effects complicate the structure of the generalized network somewhat, introducing either nonlinearities or approximations in the objective function as in Horen (1980), which leads to a quadratic cost function, or by including additional, non-network side constraints. Let x_{ij} represent the assignment of show i to a time slot or intermediate node j; let x_{pq} represent the assignment of show p to the next available time slot or intermediate node q; and let c_{ipj} represent the pairwise contribution to the objective when show i starting in time slot j precedes show p in the next starting time slot q. Then the quadratic term $c_{ipj}\, x_{ij}\, x_{pq}$ must be included in the objective (2) for every relevant pair of shows in every relevant pair of consecutive time slots. The model then becomes related to the quadratic assignment problem (see Aronson 1986). However, the following set of side constraints and additional linear objective function terms can be introduced to avoid creating a nonlinear, integer programming problem:

$$z_{ipj} \leq 0.5(x_{ij} + x_{pq}), \quad \text{all relevant } (i, j), (p, q) \text{ assignments,} \tag{10}$$

$$z_{ipj} \geq x_{ij} + x_{pq} - 1, \quad \text{all relevant } (i, j), (p, q) \text{ assignments,} \tag{11}$$

$$z_{ipj} \in \{0, 1\}. \tag{12}$$

The linear term $c_{ipj}\, z_{ipj}$ is added to the objective (2) for every relevant pair of shows in every relevant pair of consecutive time slots. See Aronson and Klein (1989) and Klein and Aronson (1991) for a similar modification to a model describing MIS development. Aronson and Klein (1989) and Klein and Aronson (1991) implicitly bundle the constraints into precedence definitions in an implicit enumeration method. Since we are interested in solving (1) - (9) directly for TV scheduling, (10) - (12) can be used explicitly. As long as there are only a few pairs of shows for which lead-in is important, these side constraints will prove effective.[7] If there are many, then data estimation for each pair of shows in each time slot may prove difficult, if not impossible to perform.

Until now, no one has attempted to explicitly define lead-in directly and accurately into their scheduling models, probably due to its complexity. The novel approach of Aronson and Klein (1989) and Klein and Aronson (1991), though not well known in the scheduling literature, produces an exact, linear, but complex, characterization of lead-in effects.

4. RESULTS

Figure 5 illustrates the network-flow representation of our example problem, taken from the weekly prime-time schedule for the first quarter of 1990 provided by the Program Director of the cable television network. The existing set of shows and the network-based flow model defined in (I) were used to determine optimal schedules for different objective functions.

Specialized methods can be developed for solving SPOT. However, typically more than 10% of the SPOT model rows are non-network due to the presence of a mixture of one-hour and half-hour shows (or other show lengths), it is ineffective to use an integer, generalized network with side constraints code (see Aronson 1989). In several computational experiments, comparing the specialized integer, generalized network with side constraints code developed by Adolphson (1989)

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[7] According to the Program Director of the cable network, only a limited number of pairs of shows' lead-in effects must be typically considered, among others because many of the revenue or ratings estimates would not be sufficiently accurate.

with the computationally robust Linear INteractive, and Discrete Optimizer, HyperLINDO (Schrage 1991a, 1991b), we found that for the particular type of problem in our application, HyperLINDO yielded faster and more accurate solutions, on average. None of the problems took over 2 seconds to solve. Therefore, in our analysis we used HyperLINDO on an IBM PC compatible computer with an Intel 80486 processor at 66 MHz. In our tests, we omitted lead-in effects. We used net profit OLS (NO) and GLS (NG) estimates from the regression formula (1) to generate weekly SPOT models for the first quarter of 1990. We further tested models with ratings generated from OLS (RO) and GLS (RG) regression formulas, and an AHP / Expert Choice (EC) generated model. For each of these five models, three progressively tighter cases are investigated: (1) restrict the time slots at 9:00 p.m. to any of the hour-long shows; (2) restrict the time slots at 9:00 p.m. to only the seven best hour-long shows on any given day; and (3) fix the schedule so that the seven best hour-long shows are scheduled at 9:00 p.m. on their given days in the actual schedule for the first quarter of 1990. We also substitute the Base or actual schedule solution into each objective function category, yielding the objective value of the actual schedule. We shall call this Case 4.

For Case 1, the complete SPOT network model has a total of 76 nodes and 14 side constraints. Of the 798 arcs or variables, only 644 arcs are used because only hour-long shows may be scheduled at 9:00 p.m. By back substitution of the variables in the side constraints, the problem size was reduced to 76 rows and 630 variables, of which 336 are explicitly declared as integer. For Case 2, further arc elimination yielded a problem size of 76 rows and 469 columns (175 integer). For Case 3, the problem size could be reduced further to 62 rows and 420 columns (120 integer).

4.1 SPOT-REG Results - Net Profit (NO and NG)

The weekly net profit of the actual Base solution appears in Table 3 for comparative purposes. All computational runs took less than two CPU seconds to solve. The objective values found for all twenty cases, and the value of the Base schedule are shown in Table 3a. Table 3b indicates the difference (degradation) from the optimal value.

Table 3 About Here

From Table 3a, we see that the weekly operating cost, revenue and net profit for the Base schedule are $3,180,000, $9,500,310 and $6,320,310 respectively.

The objective values of the net profit models (NO and NG) progressively degrade as the models become more restrictive. Consider column 1 (NO), for the Net Profit SPOT models with objective coefficients generated from OLS. The optimal NO solution (with a profit of $6,448,263) only scheduled 4 of the best shows at 9:00 p.m., and none on their designated days as in the Base schedule. When the restriction that only the best hour shows are allowed to be scheduled at 9:00 p.m. (Case 2), still none of the best shows were scheduled on the same day as in the Base schedule. The objective value of Case 2 dropped slightly from the optimal value of $6,448,263, by a mere $197 per week (only $10,244 per year) or 0.003%, to $6,448,066. In Case 3, for which the best shows are locked into their respective days and time slots, the objective value degrades by $21,288 or 0.330%, to $6,426,975. The Case 3 optimal solution is $119,799 or 1.858% better than Case 4, the Base schedule using the regression coefficients. Finally, the optimal solution yields net profits that are about 2% higher ($127,953) than the Base schedule.

The increase in net profit for Case 1 and Case 2 over the Base schedule may initially not appear to be much of an improvement, but one should remember that this increase in profit is obtained without incurring any additional costs. On an annual basis this increase translates to over $12 million, in higher net profit for a big 3 network with a Nielsen rating of about 18 which is substantial in an industry where the profit margins are dwindling due to increased competition.[8] Similar SPOT regression models developed for the second and third quarter data for 1990 yielded comparable results.

Interestingly, the optimal solution for the first quarter data props up weak second half-hour time slots, especially in the 10:30 time slot, by always scheduling one hour shows at the 10:00 time slot. In each of the Case 1-3 model solutions, all of the 10 half-hour shows were scheduled at 8:00 and 8:30 p.m. All of the Net Profit OLS (NO) schedules used Monday and Saturday as the evenings to schedule one-hour shows at 8:00 p.m., boosting ratings at 8:30, while the NG schedules used the

[8] Cumulative profits of the three major networks which were a healthy $800 million in 1984 shrunk to $400 million by 1988 (Auletta 1991).

one-hour shows on Thursday and Friday evenings. See Figure 6 for a revenue breakdown by time slot and day.

Figures 6 and 7 About Here

Inspecting past data, it was evident that the 10:30 p.m. slot is indeed weak. By scheduling a half-hour show at 10:00 p.m., the audience is given an option to turn off the television or switch to some other channel. By scheduling an hour-long show at 10:00 p.m., the network is able to hold on to a larger portion of the audience. This is precisely the strategy that the Program Director followed for the second and third quarters of 1990. The optimal solutions also verified the Program Director's opinion about which seven of the shows were the best (most profitable) to air from 9:00 - 10:00 p.m., since the optimal Case 2 net profit solution for the NO model degraded by only $197 per week.

Compared with the Base schedule (Figure 2), the schedule obtained through SPOT (Figure 7) improves the profit at the weaker time slot (10:00 p.m.) and on the weaker days (certainly for Wednesday, Thursday and Friday). Further, the use of the 8:00 and 8:30 p.m. time slots for all the half-hour shows indicates a trade-off between propping up the 10:30 time slots and maintaining audience early in the evening. This redistribution of profit illustrates that the model maximizes the schedule over the entire week, rather than concentrating on any particular time slot, or day.

Comparable results are obtained for the Net Profit GLS model (NG). When moving from the optimum (Case 1) to Case 2, the objective value decreases by $1229 (.019%) per week, whereas the decrease for Cases 3 and 4 are 0.364% and 1.730%, respectively. The percentage difference between the Base Case solution for the NG model is somewhat less than that for the NO model, 1.348% ($86,378 per week). The number of the best shows that are scheduled at 9:00 p.m. for Case 1 is 2, with none on their designated days, which is worse than the 4 shows scheduled for the NO schedule. For NG Case 2, none of the best shows were scheduled on their designated days. The fact that moving from Case 1 to Case 2 results in only a minimal decrease in the objective value for both the NO and NG models indicates that the Program Director's opinion on which shows were the seven best is fairly accurate.

For both the OLS and GLS Net Profit models, the increased profit over the Base solution exceeds $600,000 per week, or over $6.2 million per year.

4.2 SPOT-REG Results - Ratings (RO and RG)

We modified the regression formula (1) to produce weekly ratings estimates, on a half-hour basis, to a SPOT model. The ratings models, RO for OLS and RG for GLS, were designed to maximize the total weekly ratings for the network, considering one-half hour ratings values per time slot, and were also solved by HyperLINDO. The results are reported in Tables 3a and 3b. Interestingly, Cases 1 - 3 have the same objective value each for the RO and RG models; the objective function value did not degrade as the problem became more restrictive. Thus, the 7 best shows yield the highest ratings when restricted by time slot and by day. In all 6 models, the 10:00 p.m. time slot contained only one-hour shows, again propping up the 10:30 time slot, but the days for which the 8:00 p.m. time slot contained one-hour shows varied, depending upon whether or not a 'best' show was available to boost the ratings. It should be noted that a ratings maximization approach is equivalent to maximizing revenues, so that more options exist to boost weak half-hour time slots with hour shows than in the case of maximizing net profit. The Base schedule regression objective value degraded from that of the optimum ratings models (Case 1) by 0.679% for the RO model and 0.623% for the RG model. This translates to a ratings boost of over 0.6% per week (on average, for every half-hour time slot) for simply shuffling the weekly prime-time line-up. The ratings models also varied more widely than the net profit models, in terms of the evenings at which a one-hour show was scheduled in the 8:00 p.m. time slot.

4.3 SPOT-EC Results - AHP / Expert Choice

The use of expert judgmental forecasts on the show portfolio for the first quarter of 1990 are next examined. We set up the AHP / Expert Choice scoring method as described in Section 3.4, and shown in Figure 4. The scores resulting from the preference analysis are used as objective function coefficients of the SPOT-EC model. The optimal objective function value of 23.140 (in Table 3a) represents the sum of AHP scores associated with show-time combinations selected in the optimal schedule shown in Figure 8. Cases 2 and 3 yielded solutions for which the objective values were near-optimal (see Tables 3a and 3b), When using the AHP / Expert Choice relative importance coefficients, the Base solution (Case 4) had an objective value of 22.913 which was 0.981% worse than the optimum. However, the results for the AHP / Expert Choice (EC) model solutions are better than those for the Net Profit OLS solutions, and comparable to those of the Net Profit GLS schedules. The objective value percentage decrease from the optimum to the Base solution is a bit less than the net profit GLS case. As for the NO and NG models, some improvement (about 1%) can be attained over the Base schedule by simply rescheduling the existing line up. In Case 1, the EC models scheduled one-hour shows at 8:00 p.m. on Wednesday and Friday; in Case 2 on Wednesday and Thursday; and in Case 3 on Wednesday and Saturday.

Figure 8 About Here

It is interesting that in Case 1, EC selected 5 out of the 7 best shows to be scheduled at 9:00 p.m., with 1 on the same day as the Base solution. In comparison, the NO optimum selected only 4, with none on their designated days; the NG Case 1 solution selected only 2 of the best shows, and neither on their Base schedule day; RO used 2 and RG used 3 of the best shows at 9:00 p.m. in their respective Case 1 solutions. Thus, we found that the EC solutions best reflected the Program Director's preferences in the placement of the 7 best shows. This result is not surprising, in that the Program Director's judgment was used in developing the objective function coefficients.

4.4 Comparison of SPOT Model Results

Summarizing the scheduling aspects of the various models, the identification and fixed scheduling of the 7 best shows did not impact severely upon the objective value for the optimal schedule obtained for each model. However, scheduling half-hour shows during the relatively weak 10:30 p.m. time slot does. The common factor of all models was that the optimal schedules did prop up the relatively weak 10:30 p.m. time slots by scheduling only hour-long shows at 10:00 p.m. all week. The Base schedule has half-hour shows during the Wednesday through Friday 10:00 and 10:30 p.m. time slots, and during the Monday and Wednesday 8:00 and 8:30 p.m. time slots. Inspecting the various optimal schedules in detail, we found that for two days per week, all schedules filled the 8:00 p.m. - 9:00 p.m. slot with a one-hour show, considering the 8:30 p.m. time slot a write-off.

The EC optimal schedule had more (5) of the best hour-long shows scheduled at 9:00 p.m., and one on its designated day, followed by the NO model with 4 at 9:00 p.m., none on its designated day, while for NG these figures were 2 and 0. Though not a net profit optimizer, the EC model best captured the Program Director's judgments about which he considered to be his best shows. In terms of the two net profit models, the EC solution yielded objective values that were within 0.893% of the optimum objective value for NO; and within 0.901% for NG, both comparable to the results of the RO and RG ratings models.

It is also interesting to analyze how each model's optimal schedule and the Base schedule compare when using the objective function measures of the other models. In Table 4a, we show a cross comparison of the objective values corresponding to the six weekly SPOT models: Base, NO, NG, RO, RG and EC. There is a row and column corresponding to each of the six models. In the first column, we show the objective values of the Base schedule. For the remaining columns, the diagonal element is the objective value to its optimal Case 1 SPOT schedule (corresponding to the least restrictive models), shown in Table 3. In each column, of the first row, Base, we show the objective value obtained when inserting the Base schedule directly into the column's model's objective function (NO through EC), i.e., the value of the actual schedule, using the regression-generated coefficients. The objective values in rows 2 through 6 are found by inserting the model row's optimal schedule into the column's model. For example, inserting the optimal schedule found when solving the ratings GLS (RG) model (row 5, column 5), into the objective function of the net profit GLS (NG) model yields the value of 6,374,944 in row 5, column 3

We validate the model by first considering the direct improvement of the weekly Net Profit models over the Base (actual) schedule. As a baseline measure, we observe from Table 4a that the NO objective with the Base solution is only $8,154 (0.129%) larger than the Base solution value of $6,320,310, while for NG model, the value is less by only $24,427 (0.386%). Based on this small variation, the generated objective function coefficients of the models are reasonable estimates. Similar results hold for the ratings models. We cannot compare the base schedule data to AHP / Expert Choice model, but the confirmatory evidence presented earlier indicates consistency with the Program Director's judgments.

Furthermore, Table 4a shows that the Case 1 optimal solution to the NO model is \$127,953 (2.024%) larger than that of the Base solution, while the optimal NO solution in the NG model yields a weekly increase in objective value of \$78,559 (1.243%). When considering the other situation, the optimal NG solution was \$86,378 (1.367%) larger than the Base schedule's weekly value, and substituting it into the NO model, we obtain a weekly increase in net profit of \$113,674 (1.799%). Regardless of which of the two net profit optimal solutions we choose, we obtain a minimum increase in weekly net profit of over 1.2% per week, simply by rescheduling the shows. The ratings and EC model optima, when substituted into the Net Profit models, increase the weekly objective function value by between 1.1% to 1.4%, translating to between \$1.5 and \$3.6 million per year.

For the remainder of our comparisons in this section, we shall use the regression estimates for the Base schedule. In Tables 4b and 4c, we show the improvement in the objective value over the Base schedule. In all cases, the optimal solution increase ranges from just under 1%, to about 2%.

Table 4 About Here

Consider the Net Profit OLS model. The net profit models are most sensitive to the different optimal schedules. They do yield optimal ratings. However, the non-optimal ratings models do not yield optimal net profits (or overall revenue). That is to say, both net profit models, both ratings models and the EC model schedules, when substituted into both of the ratings models (RO and RG) yield optimal ratings values. However, each ratings model's optimal solution, when applied to both of the net profit models (NO and NG) yield sub-optimal solutions for which the objective is still better than that of the base schedule. For the EC model, the other optimal model schedules yield objective values that are slightly worse (about 0.22 or 0.960%) than that of the base schedule (22.913), while the optimum EC schedule is 0.991% or 0.227 better than that of the base schedule value of 23.140.

The optimal NO model value of \$6,448,263 is \$119,799 or 1.893% better than the value of the weekly base schedule of \$6,328,464. The NG optimal schedule produces change in the objective value within 5% of the change due to using the optimal NO schedule. Even the two optimal ratings and the AHP / Expert Choice schedules improve the net profit (NO) by between 0.996 and 1.289% over the base schedule. Comparable results are obtained for the NG model.

The results for the EC values are consistent with the Program Director's opinions and with the results obtained from the net profit regression-based objective. The consistency of the solutions and their objective values found by using both expertise and regression confirm the validity of the final schedule and adds credence to the application of our network-based analytical approach.

5. COMPUTATIONAL STUDY

In this section, we study the extent to which the regression models are robust with respect to variation in the data. Additionally, we analyze the impact of this variability on the results of the SPOT and Horen optimization models, both in terms of net profit and computational performance. Weekly fluctuations in the viewership, as reflected by the ratings, offer a challenge to the programming executive. Typically, over a quarter, our TV network has experienced a variation in ratings of about five percent. Wide variation in ratings may influence the regression estimates, and as a consequence may affect the results of the optimization, potentially leading to sub-optimal program schedules. Another issue of interest is to investigate how the model estimates are affected by heteroskedasticity in the data. To this purpose, we estimate all of the models using ordinary least squares (OLS) and generalized least squares (GLS) procedures. GLS takes into account the presence of heteroskedasticity, while the simpler OLS is preferred if the data are homoskedastic.

As the actual variance in ratings during the Fall 1990 quarter was about five percent about the mean show ratings, we conduct Monte-Carlo simulation experiments with 2, 5, and 10 percent variation in ratings, reflecting the low, moderate and high end of ratings fluctuations. Each data condition is replicated 10 times, so that the total number of data sets generated is 30, the number of regression models to be estimated is 60 (30 OLS and 30 GLS models), and the number of optimization runs is 120 (60 each for SPOT and Horen). Obviously, the typical fluctuations may be different for other applications. Moreover, in general the fluctuations may differ by show, but we chose to vary the ratings uniformly across all shows. This simulation design will provide us with the magnitude of effects and a general sense of direction due to variation in the ratings.

5.1 Parameter Estimates

The summary of OLS and GLS regression parameter estimates for different degrees of rating variation is presented in Table 5. As one would expect, the predictive power of the model as reflected by the R^2 improves with lower variability in ratings. Models with only 2% variation have an R^2 of about 96%, which is about 3-12% higher, on average, than the 10% variation models. That the explanatory power of GLS models appears to be slightly worse than the OLS models. Very few of the OLS and GLS parameter estimates differed substantially, as indicated by the root mean squared difference computed for each set of estimates.

Tables 5, 6a and 6b About Here

The OLS and GLS estimates were used as input into SPOT and Horen's model. Three key performance measures of output from SPOT and Horen's model are monitored -- computational performance, as measured by CPU time and number of pivots; and solution quality, as measured by predicted net profit (or ratings).[9] Table 6a provides the mean performance measures and their standard deviations, for SPOT and Horen model, when optimizing for net profit. Table 6b provides the corresponding results when optimizing for ratings. Obviously, as both SPOT and Horen's model solve to optimality, these methods will always yield identical predicted net profit (ratings) figures when using the same objective function values. However, the results presented in Table 6 suggest that in all cases, SPOT outperforms Horen's model in terms of solution time and pivot count. The average improvement of SPOT over Horen ranges from 25-48% in CPU solution time, and from 37-53% in pivot count.

5.2 Effects on Model Choice

Analysis of variance was used to ascertain whether the optimization model (SPOT and Horen), the estimation procedure (OLS and GLS) and the variance in ratings (2%, 5%, and 10%) significantly affect the three key measures of performance. Tables 7a and 7b provide the ANOVA results when optimizing for net profit and ratings, respectively. The main effects of estimation method and variance in ratings have a significant effect on the optimal objective value, be it ratings or net profit, with a slightly lower objective value when using GLS estimates, and slightly higher with increased variance in ratings. There also appears to be a significant interaction effect of estimation and variance

[9] Solution CPU time and Pivot count are standard measures found in the literature to indicate the comparative effectiveness of the model and the efficiency of the method used to solve them.

on the net profit. However, this effect was insignificant in the case of ratings. In the case of net profit, significant main effects of estimation and model are evidenced on the solution time and pivot count. The results in Table 7a and 7b confirm that SPOT consistently outperforms Horen's model on these measures. Using GLS estimates consistently produce faster optimization. Variance in ratings fail to have any significant impact on solution time or pivot count. None of the interaction effects are significant.

Tables 7a and 7b About Here

Summarizing the most interesting finding of this part of our simulations, the computational performance of SPOT is systematically better than that of Horen's model, both in terms of CPU solution time and the number of pivots needed to optimize the prime time network program schedule.

5.3 Solution Quality

In Table 8, we compare the improvement in solution quality, within the framework of our simulation experiment, between the Base schedule and the optimal schedule recommended by SPOT. Comparing the net profit figures in Table 8, we see that the schedules recommended by SPOT would have yielded significant improvements ($p < .01$ level) in profit to the cable network). The mean improvement is over 2%, with larger improvements as the variance in ratings increases. An improvement of 2% amounts to an increase in profit of over $12 million on an annual basis for a typical network with an average Nielsen rating of 18.

Table 8 About Here

5.4 Qualitative Comparison of Simulation Results

In Section 5.3, we establish that SPOT's computational performance is consistently better than Horen's. As would be expected, their optimal values are not different if the models use the same objective function values. However, it is interesting to know whether the schedules produced by the models differ significantly. We examine this issue by means of three measures of similarity: first, similarity in terms of scheduling the hour and half-hour shows; second, we verify whether similar show types (A, H, N, S, P etc.) are allocated in the same time slot by both methods; third, we check if a specific show (A1, or P2 etc.) is allocated to the same time slot is used. This last measure provides the closeness of the match between the schedules.

This qualitative examination shows that the schedules produced by both models are very similar when optimizing for net profit. On the first two measure, there is a 100% correspondence between the schedules produced by both models. None of the schedules allocate half-hour shows after 9 p.m., and no differences in the scheduling of show type are evident. Typically, the differences in schedule are in terms of the particular shows of a given show type that are allocated to the time slot. For example, if SPOT schedules the half-hour shows P1 and P2 (of show type P) on Wednesday at 8.30 p.m. and Monday at 8.30 p.m., respectively, Horen's model might assign P1 to Monday at 8.30 p.m. and P2 to Wednesday at 8.30 p.m. A close examination of such patterns suggests that in all instances, the switching is between shows that are "equivalent" in terms of cost, perceived attractiveness, and duration. Even so, between 20 to 26 out of 26 possible time slots (77% to 100%) are identically allocated by both models.

The optimal ratings schedules differ more than the net profit schedules. Although the allocation of half-hour and hour-long shows is identical in all cases, matches at the show type level are found in only 4 to 9 out of 26 possible time slots (15 to 35%), and in 0 to 4 out of 26 time slots at the specific show level. It appears that schedules generating the same weekly ratings can be quite different.

6. MODEL EXTENSIONS

One of SPOT's attractive features is that it can readily be customized and adapted to a wide variety of real-life applications. Here, we summarize some extensions, generalizations and simplifications that are relevant and useful in practice. The general model can easily accommodate shows of any duration. It can cover complete or portions of days, weeks, months, quarters, seasons, and even years, by defining the node and arc sets accordingly. When appropriate, the model can be simplified by omitting nodes and arcs, leading to more efficient solution. For example, when specific time slots must contain shows of a specific length, arcs linking shows with different program-parts to them may be omitted because such assignments are prohibited, as for the *9:00* to *10:00* p.m. time slots in our test case. Furthermore, when shows with a unique number of program-parts must be assigned to certain time slots, the corresponding multiple time slot demand nodes may be omitted by placing their demand requirements directly on their corresponding intermediate nodes. When certain shows are restricted to certain sets of time slots, the arcs linking them to other time slots, and the arcs linking other shows to these time slots are omitted, along with the appropriate sets of intermediate nodes. When considering a full day schedule, some shows may be restricted to certain sets of time slots (early evening, late evening, *etc.*), depending on the target market population. Accordingly, unneeded arcs and nodes may be omitted.

In terms of the tactical and operational use of SPOT models, additional restrictions can be accommodated by augmenting the constraint set of the formulation. These restrictions can include blocks of shows that must be chosen or not, due to contractual agreements, the assignment of blocks of shows to several consecutive blocks of time slots, and the restriction of shows to be assigned, or not to be assigned in designated sequences, because of content and time of day. In all these cases, the basic network model structure is unchanged.

Other applications of the model include scheduling movies on (cable) movie channels, non prime-time TV scheduling, the use of the model by independent and small networks for local programming, and the scheduling of news segments within a newscast, where the "benefit" or rate of return varies over time as the currency and impact of the story changes. Likewise, the sequencing and scheduling of guests on a talk show or acts on a variety show may be accomplished by SPOT using the expertise of the scheduler.

Expanded and more general model variations could include multi-week, dynamic network-based models (Aronson 1989); dynamic whole season models with mid-season replacements; consideration of summer replacements versus re-runs; handling more shows than time slots; insertion of specials to replace existing shows; and occasional variation of the line-up (temporary and permanent show/time slot reassignments). Future directions could include the development of specialized algorithms and implementations that utilize the structure of the model efficiently and the use of the model in a Decision Support System with a visual representation of the SPOT model and its solution. Future research should concentrate on advanced model variations that include the development of a competitive equilibrium model, and the incorporation of precedence rules and their effects.

7. SUMMARY AND CONCLUSIONS

Scheduling the inventory and proposed purchase of TV programs is a major task of programming executives at television networks and stations. These managers often accomplish this arduous task with a combination of common sense, intuition and experience. Scheduling, therefore, is often considered an art. Proper scheduling can make or break a network or TV station in terms of its overall profitability. Effective scheduling is therefore crucial to a network's long-term survival. Recent research efforts (Gensch and Shaman 1980; Horen 1980; Rust and Echambadi 1989) have added more scientific rigor to the scheduling task. The attempt here is to further discussion in this direction by incorporating more "science" into the decision making process. It is realized that the "art" of scheduling is essential, and the SPOT model acts as a *synergistic tool in evaluating the quality of the decisions made.* SPOT assists the manager in the evaluation of alternative scheduling strategies, and in gaining greater insight into the potential outcomes and strategies, thus helping make more informed and effective decisions.

SPOT utilizes historical data to project potential performance of shows at various time slots based on show, day and time characteristics. An integral part of the model is the incorporation of expert judgment in show evaluations. The regression forecasting model can act as a catalyst in building the judgmental evaluations, but the judgmental factors are not limited to quantitative considerations. The input into the optimization portion of the SPOT model are provided either by forecasting or by the AHP model.

SPOT allows the programming executive to perform sensitivity analysis on existing and proposed schedules by examining the effects of juggling the line-up via model modification. More importantly, SPOT allows the programming executive to move away from relying purely on historical and estimated show ratings, and instead move toward considering network profitability. In general, the model implicitly accommodates the fact that the cost of a show depends on the expected ratings from its time slot(s), which directly affects net profit, because ratings, as well as revenues and costs (and thus net profit) vary depending on when the show is scheduled. Through the use of net profit, SPOT recognizes the marginal value of rescheduling a low cost show from a low revenue time slot to a high revenue time slot.

Using the generalized network-based model component of SPOT to describe the problem of TV scheduling is novel, and its structure in itself represents a contribution to the field of TV program scheduling. The model yields better solutions than existing ones, utilizes the expertise of the Program Director, and can be extended in a number of ways. Further, the objective is flexible, and can accommodate a number of alternative measures such as revenues, net profits, rating points, or some ranking indicating the quality of assignments in determining the total program schedule. By utilizing the SPOT conceptual model, a television network can develop more effective schedules and hence maintain a competitive advantage in its programming.

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Table 1

Parameter Estimates of the Regression Model

	OLS Estimates		GLS Estimates	
Perceived Attractiveness	0.113	(0.003)***	0.109	(0.003)***
Duration	0.131	(0.015)***	0.126	(0.013)***
Show Type				
A	-0.013	(0.032) ns	-0.027	(0.027) ns
S	-0.005	(0.027) ns	0.006	(0.021) ns
N	-0.024	(0.028) ns	-0.015	(0.021) ns
H	-0.079	(0.034)**	-0.102	(0.026)***
P	-0.045	(0.036) ns	-0.096	(0.026)***
Day				
Monday	0.026	(0.018) ns	0.009	(0.016) ns
Tuesday	-0.028	(0.021) ns	-0.045	(0.020)*
Wednesday	0.037	(0.012) ns	-0.008	(0.017) ns
Thursday	-0.009	(0.016) ns	-0.053	(0.012)***
Friday	-0.090	(0.021)***	-0.092	(0.017)***
Saturday	-0.091	(0.021)***	-0.085	(0.023)***
Time of Day				
8 p.m.	0.014	(0.021) ns	-0.046	(0.015)**
8.30 p.m.	0.032	(0.028) ns	0.008	(0.018) ns
9 p.m.	0.104	(0.021)***	0.045	(0.017)**
10 p.m.	0.074	(0.015)***	0.046	(0.010)***
Intercept	0.241	(0.035)***	0.334	(0.028)***
Adjusted R^2	.926		.943	
Sample Size	338		338	

Standard errors of the estimates in parentheses.
*** Significant at $p < .001$ level.
** Significant at $p < .01$ level.
* Significant at $p < .05$ level.
ns Not significant.

Table 2

AHP Results of a Sample of Potential Show Placements

Alternative	Show Type	Day of the Week	Time	Show Duration	Attractiveness	Total Rating
01	S	Monday	*8:00* p.m.	Half Hour	7	0.530
02	S	Sunday	*10:00* p.m.	Full Hour	5	0.555
03	N	Tuesday	*8:30* p.m.	Half Hour	4	0.462
04	N	Saturday	*9:00* p.m.	Full Hour	7	0.685
05	A	Wednesday	*10:00* p.m.	Half Hour	6	0.413
06	A	Friday	*10:30* p.m.	Half Hour	6	0.326
07	H	Tuesday	*8:00* p.m.	Half Hour	5	0.529
08	H	Saturday	*8:30* p.m.	Half Hour	5	0.443
09	P	Monday	*10:00* p.m.	Half Hour	3	0.416
10	P	Thursday	*9:00* p.m.	Full Hour	4	0.555
11	L	Wednesday	*8:00* p.m.	Full Hour	3	0.525
12	L	Friday	*10:00* p.m.	Full Hour	3	0.577

Table 3
Optimal Solutions for the SPOT Models

Table 3a: Optimal Objective Values for the Solutions: SPOT Models of Net Profit, Ratings and AHP/Expert Choice

Case #	1 NO	2 NG	3 RO	4 RG	5 EC
Optimum 1	$6,448,263	$6,406,688	40.77193	40.62851	23.140
2	$6,448,066	$6,405,459	40.77193	40.62851	23.138
3	$6,426,975	$6,383,343	40.77193	40.62851	23.134
4	$6,328,464	$6,295,883	40.49508	40.37522	22.913
(Actual)Base 5	$6,320,310	$6,320,310			
Cost:	$3,180,000				
Total Revenue:	$9,500,310				

Table 3b: Difference in Objective Value from that of the Optimum:

Case #	1 NO	2 NG	3 RO	4 RG	5 EC
Optimum 1	$0	$0	0.00000	0.00000	0.000
2	$197	$1,229	0.00000	0.00000	0.002
3	$21,288	$23,345	0.00000	0.00000	0.006
4	$119,799	$110,805	0.27685	0.25329	0.227
(Actual) Base 5	$127,953	$86,378			

Optimal Solutions for the SPOT Models of Net Profit OLS Regression (NO), Net Profit GLS Regression (NG), Ratings OLS Regression (RO), Ratings GLS Regression (RG), and Expert Choice (EC). Five cases are examined: (1) Optimal Schedules with hour-long shows only at 9:00 p.m.; (2) Optimal Schedules with the 7 best (hour-long) shows scheduled at 9:00 p.m.; (3) Optimal Schedules with the 7 best (hour-long) shows scheduled at 9:00 p.m. on their designated days; (4) the objective values for the Actual Schedule for the cable network in the first quarter of 1990 using the regression objective coefficient values. Case (5) is the Base Case or Actual Schedule's objective value.

Table 4
Comparison of SPOT-REG and SPOT-EC Results

Table 4a : Optimal Solutions (Diagonals) and Cross Solutions: Computation of Objective Values for Optimal Solutions into Alternate Objective Functions.

	Solution into Model					
		NET PROFIT		RATINGS		EXPERT CHOICE
	1	2	3	4	5	6
Model	BASE	NO	NG	RO	RG	EC
1 BASE	6,320,310	6,328,464	6,295,883	40.49508	40.37522	22.913
2 Net Profit OLS (NO)	-	6,448,263	6,398,869	40.77193	40.62851	22.693
3 Net Profit GLS (NG)	-	6,433,984	6,406,688	40.77193	40.62851	22.693
4 Ratings OLS (RO)	-	6,389,625	6,350,353	40.77193	40.62851	22.693
5 Ratings GLS (RG)	-	6,410,021	6,374,944	40.77193	40.62851	22.692
6 Expert Choice (EC)	-	6,390,709	6,348,968	40.77193	40.62851	23.140

Table 4b: Improvement in the Objective over the Base Regression Solution (1st Row).

	Solution into Model					
		NET PROFIT		RATINGS		EXPERT CHOICE
	1	2	3	4	5	6
Model	BASE	NO	NG	RO	RG	EC
1 BASE	N/A	0	0	0.00000	0.00000	0.000
2 Net Profit OLS (NO)	-	119,799	102,986	0.27685	0.25329	-0.220
3 Net Profit GLS (NG)	-	105,520	110,805	0.27685	0.25329	-0.220
4 Ratings OLS (RO)	-	61,161	54,470	0.27685	0.25329	-0.220
5 Ratings GLS (RG)	-	81,557	79,061	0.27685	0.25329	-0.221
6 Expert Choice (EC)	-	62,245	53,085	0.27685	0.25329	0.227

Table 4c: Percent (%) Improvement in the Objective over the Base Regression Solution (1st Row).

	Solution into Model					
		NET PROFIT		RATINGS		EXPERT CHOICE
	1	2	3	4	5	6
Model	BASE	NO	NG	RO	RG	EC
1 BASE	N/A	0.000%	0.000%	0.000%	0.000%	0.000%
2 Net Profit OLS (NO)	-	1.893%	1.636%	0.684%	0.627%	-0.960%
3 Net Profit GLS (NG)	-	1.667%	1.760%	0.684%	0.627%	-0.960%
4 Ratings OLS (RO)	-	0.966%	0.865%	0.684%	0.627%	-0.960%
5 Ratings GLS (RG)	-	1.289%	1.256%	0.684%	0.627%	-0.965%
6 Expert Choice (EC)	-	0.984%	0.843%	0.684%	0.627%	0.991%

Table 5

Mean Parameter Estimates of the Regression Model

	OLS-2%	GLS-2%		OLS-5%	GLS-5%		OLS-10%	GLS-10%	
	MEAN	MEAN	RMSD*	MEAN	MEAN	RMSD	MEAN	MEAN	RMSD
Perc. Attract.	0.1085	0.1023	0.0062	0.1086	0.1060	0.0027	0.1085	0.1071	0.0016
Duration	0.1258	0.1329	0.0078	0.1259	0.1222	0.0049	0.1177	0.1210	0.0079
S	-0.0327	-0.0107	0.0223	-0.0256	-0.0116	0.0150	-0.0237	-0.0107	0.0154
N	-0.0435	-0.0140	0.0300	-0.0409	-0.0249	0.0173	-0.0450	-0.0364	0.0119
A	-0.0429	-0.0449	0.0052	-0.0343	-0.0388	0.0087	-0.0294	-0.0288	0.0040
H	-0.0954	-0.1215	0.0268	-0.0872	-0.0981	0.0154	-0.0918	-0.1048	0.0149
P	-0.0711	-0.1298	0.0590	-0.0683	-0.0987	0.0332	-0.0657	-0.0942	0.0301
Mon	0.0399	0.0419	0.0039	0.0329	0.0157	0.0174	0.0156	0.0013	0.0167
Tue	-0.0365	-0.0350	0.0052	-0.0307	-0.0438		-0.0447	-0.0568	0.0139
Wed	0.0365	-0.0003	0.0372	0.0379	-0.0050	0.0431	0.0133	-0.0074	0.0355
Thu	0.0076	-0.0312	0.0389	0.0086	-0.0308	0.0394	0.0023	-0.0309	0.0359
Fri	-0.0936	-0.0774	0.0168	-0.0925	-0.0765	0.0730	-0.1108	-0.1162	0.0114
Sat	-0.0783	-0.0611	0.0174	-0.0785	-0.0746	0.0170	-0.0758	-0.1016	0.0548
8 p.m.	0.0056	-0.0911	0.0969	0.0072	-0.0417	0.0517	0.0126	-0.0314	0.0447
8.30 p.m.	0.0471	-0.0295	0.0768	0.0551	0.0149	0.0408	0.0538	0.0165	0.0383
9 p.m.	0.1120	0.0174	0.0949	0.1118	0.0573	0.0553	0.1199	0.0724	0.0488
10 p.m.	0.0886	0.0258	0.0630	0.0920	0.0559	0.0364	0.0925	0.0688	0.0258
Intercept	0.2801	0.3870	0.1070	0.2730	0.3481	0.0761	0.2917	0.3487	0.0593
R^2	0.9630	0.9789	0.016	0.9330	0.9417	0.009	0.8430	0.8543	0.013
Adj. R^2	0.9611	0.9778	0.017	0.9294	0.9386	0.010	0.8347	0.8466	0.014

* RMSD = Root Mean Squared Difference of the estimated coefficients, across the 10 replications

Table 6a

Means and Standard Deviations of Objective Value (Net Profit), Solution CPU Time (seconds), and Pivot Count

Variance In Ratings		OLS HOREN	OLS SPOT	% Impr.**	GLS HOREN	GLS SPOT	% Impr.
2%	Obj. Val	6,477,566.6* (15,394.50)	6,477,566.6 (15,394.50)	------	6,385,107.7 (17,149.04)	6,385,107.7 (17,149.04)	------
	Soln. Time	2.677 (.799)	1.937 (.161)	37.7%	2.273 (.134)	1.876 (.170)	21.2%
	Pivot Count	347 (23.3)	254 (17.0)	36.6%	328 (17.1)	250 (21.0)	31.2%
5%	Obj. Val	6,489,261.3 (29,826.09)	6,489,261.3 (29,826.09)	------	6,457,213.3 (40,304.92)	6,457,213.3 (40,304.92)	------
	Soln. Time	2.390 (.113)	2.012 (.118)	18.8%	2.335 (.141)	1.856 (.137)	25.8%
	Pivot Count	345 (14.7)	260 (14.9)	32.7%	339 (18.0)	240 (18.3)	41.2%
10%	Obj. Val	6,514,625.8 (106,604.30)	6,514,625.8 (106,604.30)	------	6,489,743.1 (52,840.90)	6,489,743.1 (52,840.90)	------
	Soln. Time	2.530 (.380)	2.000 (.230)	26.5%	2.420 (.244)	1.840 (.118)	31.5%
	Pivot Count	353 (29.7)	251 (17.2)	40.6%	343 (19.4)	243 (16.7)	41.1%
TOTAL							
	Obj. Val	6,493,100.4 (62,044.20)	6,493,100.4 (62,044.20)	------	6,442,444.8 (58,185.40)	6,442,444.8 (58,185.40)	------
	Soln. Time	2.532 (.532)	1.983 (.177)	27.7%	2.340 (.187)	1.858 (.145)	24.2%
	Pivot Count	348 (23.3)	254 (16.8)	37.0%	336 (19.2)	244 (19.3)	37.7%

* Figures in parentheses are standard deviations.
** Percentage improvement of SPOT over Horen's model.

Table 6b

Means and Standard Deviations of Objective Value (Ratings), Solution CPU Time (seconds), and Pivot Count

Variance In Ratings		OLS HOREN	OLS SPOT	% Impr.**	GLS HOREN	GLS SPOT	% Impr.
2%	Obj. Val	40.886* (0.064)	40.886 (0.064)	------	40.499 (.074)	40.499 (.074)	------
	Soln. Time	1.518 (.417)	1.121 (.322)	40.5%	1.586 (.360)	1.036 (.213)	59.1%
	Pivot Count	175 (24.7)	114 (12.1)	55.1%	179 (19.6)	114 (10.6)	57.4%
5%	Obj. Val	40.939 (0.128)	40.939 (0.128)	------	40.840 (.186)	40.840 (.186)	------
	Soln. Time	1.625 (.345)	1.121 (.270)	52.6%	1.791 (.597)	1.237 (.237)	51.4%
	Pivot Count	178 (11.7)	116 (10.1)	55.3%	187 (30.4)	121 (11.4)	55.5%
10%	Obj. Val	41.050 (.401)	41.050 (.401)	------	40.912 (.194)	40.912 (.194)	------
	Soln. Time	1.562 (.326)	1.158 (.184)	37.2%	1.467 (.098)	1.174 (.361)	32.2%
	Pivot Count	172 (12.2)	118 (7.33)	46.5%	174 (8.0)	119 (10.9)	46.5%
TOTAL							
	Obj. Val	40.960 (.255)	40.960 (.255)	------	40.750 (.242)	40.750 (.242)	------
	Soln. Time	1.568 (.367)	1.133 (.270)	43.4%	1.615 (.428)	1.149 (.291)	47.6%
	Pivot Count	175 (17.5)	116 (10.2)	52.3%	180 (22.1)	118 (11.3)	53.2%

* Figures in parentheses are standard deviations.
** Percentage improvement of SPOT over Horen's model.

Table 7a

Analysis of Variance Results (Maximizing Net Profits): Effect of Model, Estimation and Variance

	Dependent Variable		
	Objective Value	Soln. Time	Pivots
Main Effects	F-Value	F-Value	F-Value
A. MODEL (SPOT or Horen)	------	78.57***	600.26***
B. Estimation (OLS or GLS)	27.51***	7.37**	8.35**
C. Variance (2%, 5% or 10%)	17.92***	0.03^{ns}	0.14^{ns}
Interactions			
A x B	------	0.03^{ns}	0.04^{ns}
A x C	------	0.06^{ns}	1.32^{ns}
B x C	4.98**	0.04^{ns}	0.09^{ns}
A x B x C	------	0.15^{ns}	1.33^{ns}

* Significant at p < .05 level.
** Significant at p < .01 level.
*** Significant at p < .001 level.

^{ns} Not significant

Table 7b

Analysis of Variance Results (Maximizing Ratings): Effect of Model, Estimation and Variance

	Dependent Variable		
	Objective Value	Soln. Time	Pivots
Main Effects	F-Value	F-Value	F-Value
A. MODEL (SPOT or Horen)	------	601.46***	1278.57***
B. Estimation (OLS or GLS)	17.23***	9.48**	9.79**
C. Variance (2%, 5% or 10%)	19.65***	4.68**	2.19^{ns}
Interactions			
A x B	------	13.46***	18.87***
A x C	------	4.49**	3.32*
B x C	2.93ns	1.77^{ns}	0.57^{ns}
A x B x C	------	0.06^{ns}	1.02^{ns}

* Significant at p < .05 level.
** Significant at p < .01 level.
*** Significant at p < .001 level.

^{ns} Not significant

Table 8

Improvement in Average Net Profit Due to the Optimized SPOT Schedule Over the Network Base Schedule

OLS

	Network	SPOT	Improv.	% Improv.
2%	6,327,096.9	6,477,566.6	150,469.7**	2.38%
	(15,130.99)	(15,394.50)	(4,351.21)	(.07)
5%	6,334,083.2	6,489,261.3	155,178.1**	2.45%
	(29,820.30)	(29,826.09)	(8,813.49)	(.14)
10%	6,366,579.6	6,514,625.8	148,046.2*	2.33%
	(102,233.50)	(106,604.30)	(15,013.60)	(.23)
ALL	6,341,759.2	6,493,100.4	151,341.2**	2.39%
	(60,203.50)	(62,044.20)	(10,221.3)	(.16)

GLS

	Network	SPOT	Improv.	% Improv.
2%	6,261,619.4	6,385,107.7	123,488.3**	1.97%
	(17,725.72)	(17,149.04)	(3,010.63)	(.05)
5%	6,325,404.6	6,457,213.3	131,808.7**	2.09%
	(57,730.85)	(40,304.92)	(21,397.79)	(.35)
10%	6,347,343.9	6,489,743.1	142,399.2**	2.24%
	(49,588.80)	(52,840.90)	(27,855.10)	(.44)
ALL	6,310,218.4	6,442,444.8	132,226.3**	2.10%
	(56,954.10)	(58,185.40)	(20,793.70)	(.33)

* Significant at $p < .01$ level.

** Significant at $p < .001$ level.

Figures in parentheses are standard deviations.

Figure 1

SPOT (Scheduling of Programs Optimally for Television) Model

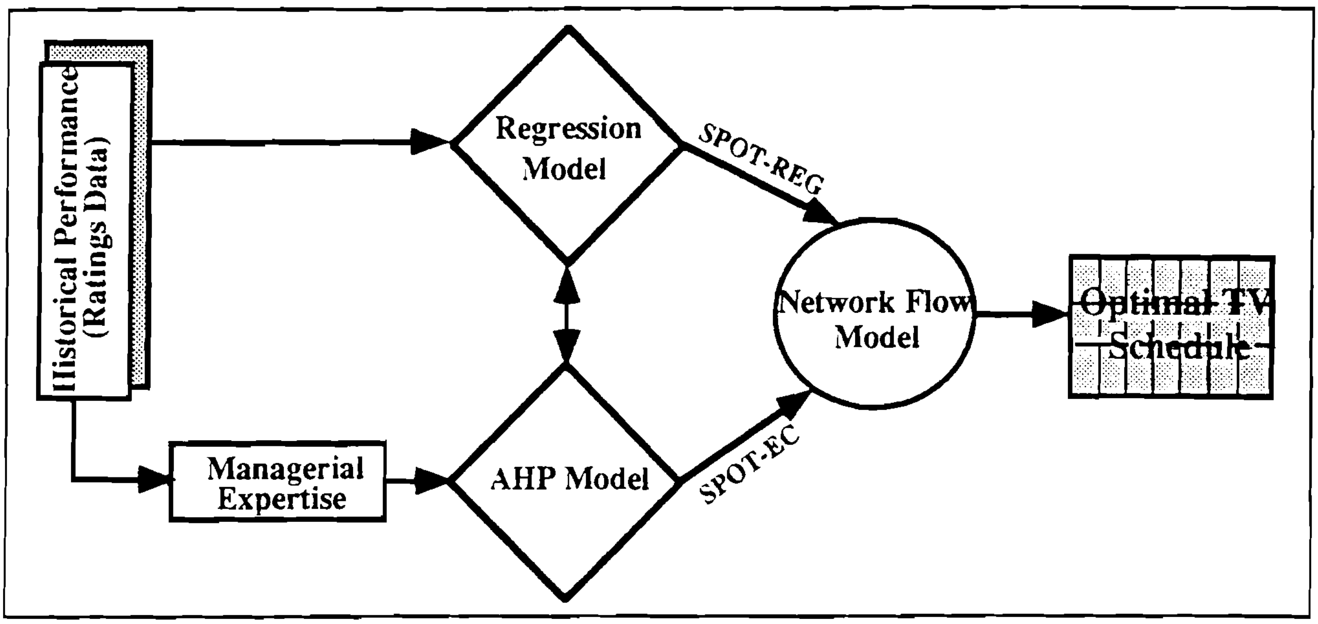


Figure 2

TV Network's Original (Base) Schedule During the First Quarter, 1990

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
8:00	S1	L1	N1	N6	N7	A2	N8
8:30	A1		N2				
9:00	N5	S2	H4	S3	H5	H6	N9
9:30							
10:00	P3	H3	H1	N3	P1	H7	N10
10:30			H2	N4	P2		

Total Cost/Week = $3,180,000

Total Net Operating Profit = $ 6,320,310

Total Revenue = $ 9,500,310

Figure 3

TV Show Characteristics and Revenue

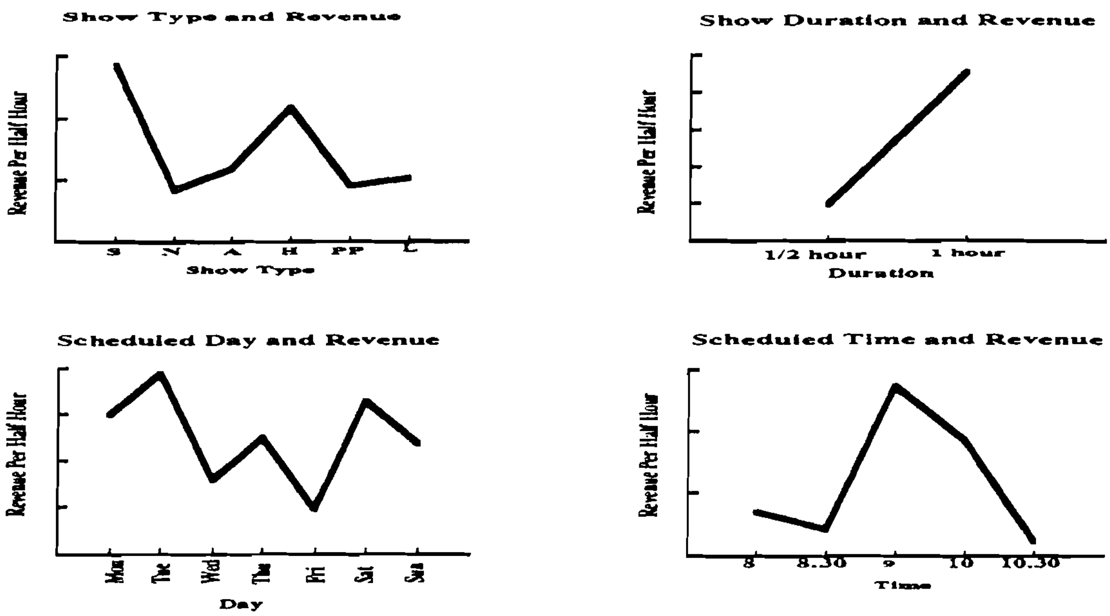


Figure 4

AHP Model (Using Expert Choice)

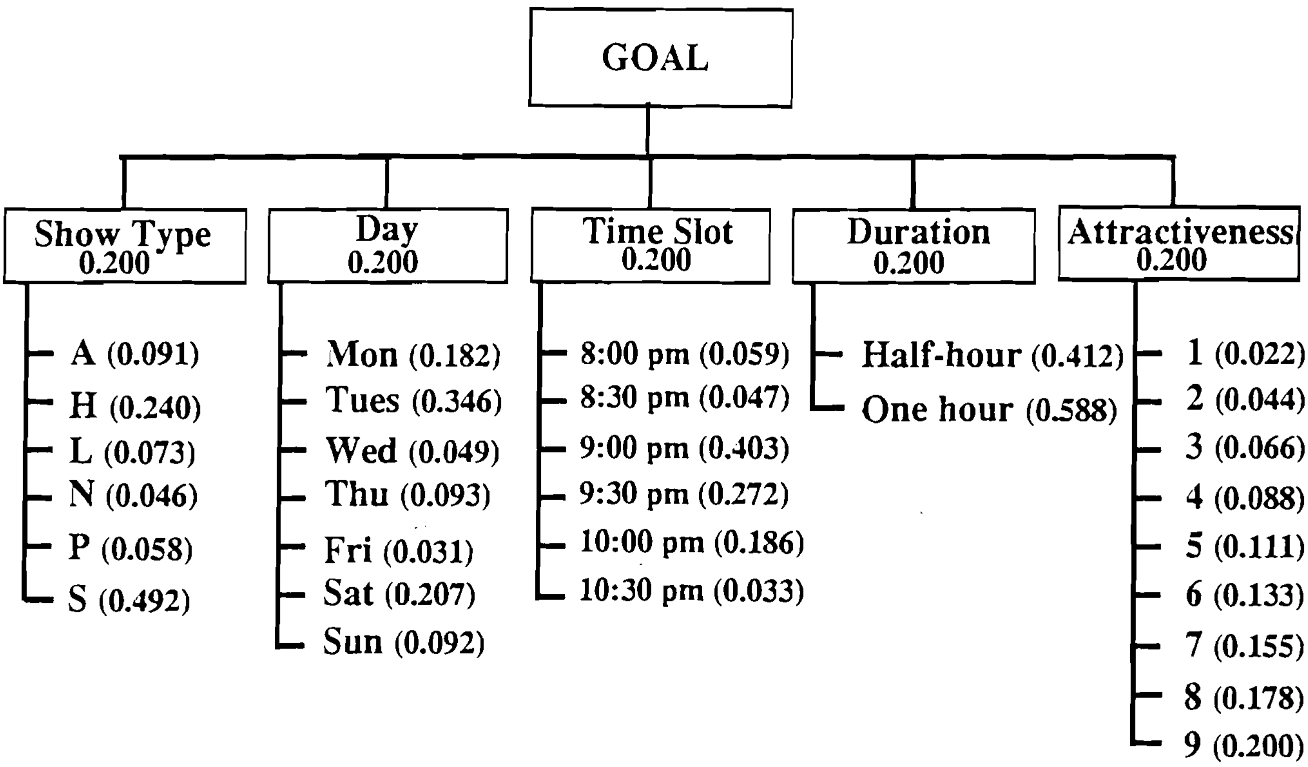
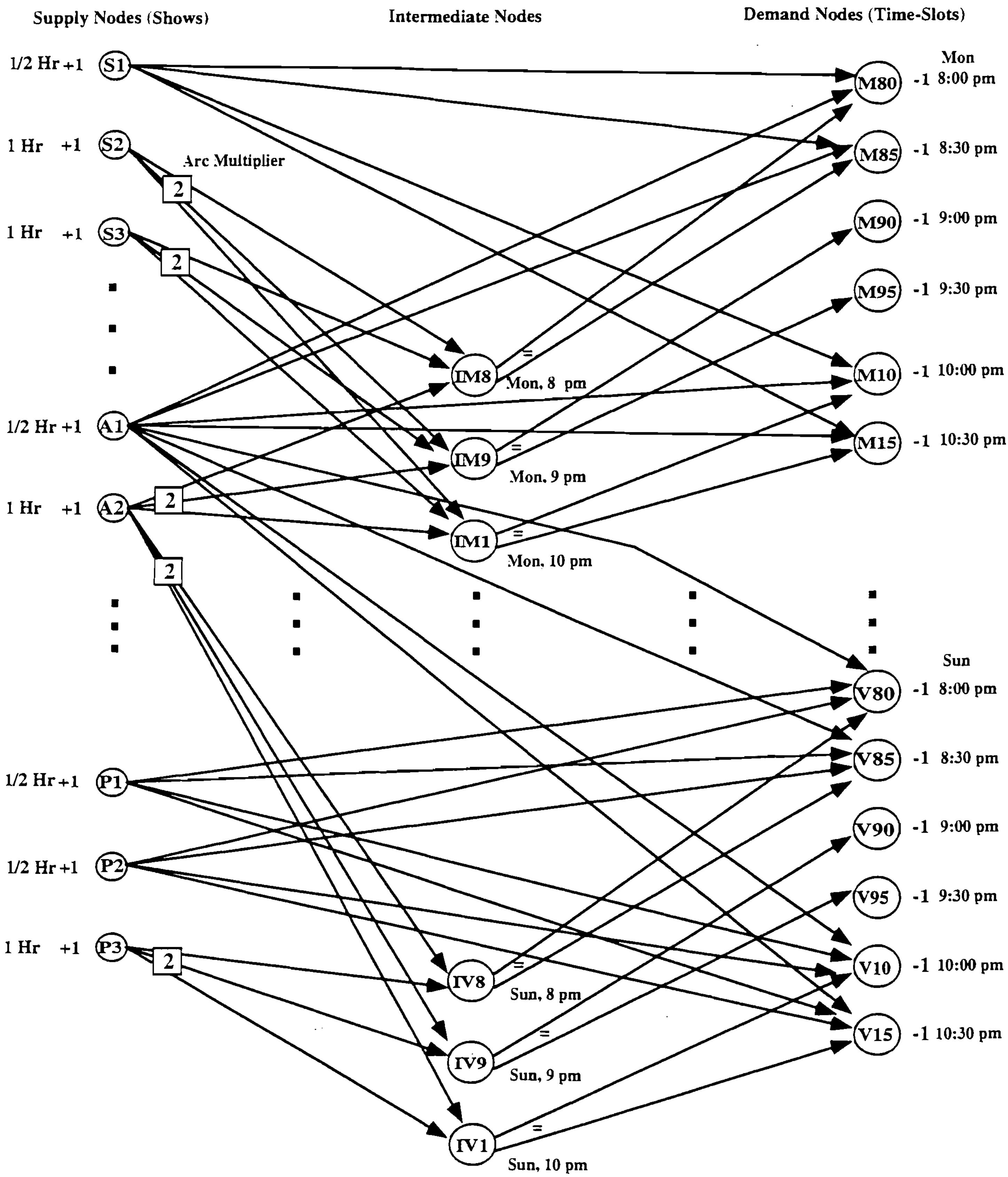


Figure 5

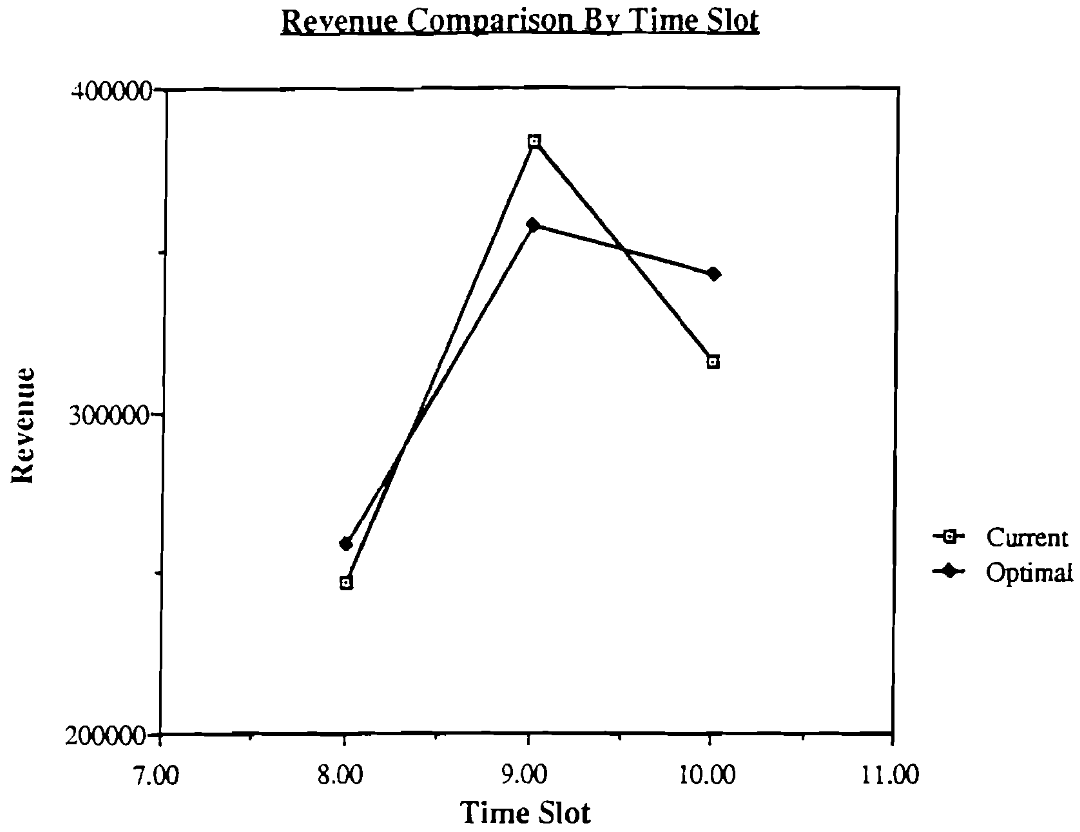
Mixed-Integer, Generalized Network Flow Model for the Cable Network (First Quarter 1990)



Not all arcs and nodes are shown for clarity.

= indicates a side constraint forcing equal flow through the 2 surrounding arcs.

Figure 6


Revenue Comparison By Time Slot
400000
300000
200000
Revenue
7.00
8.00
9.00
10.00
11.00
Time Slot
Current
Optimal

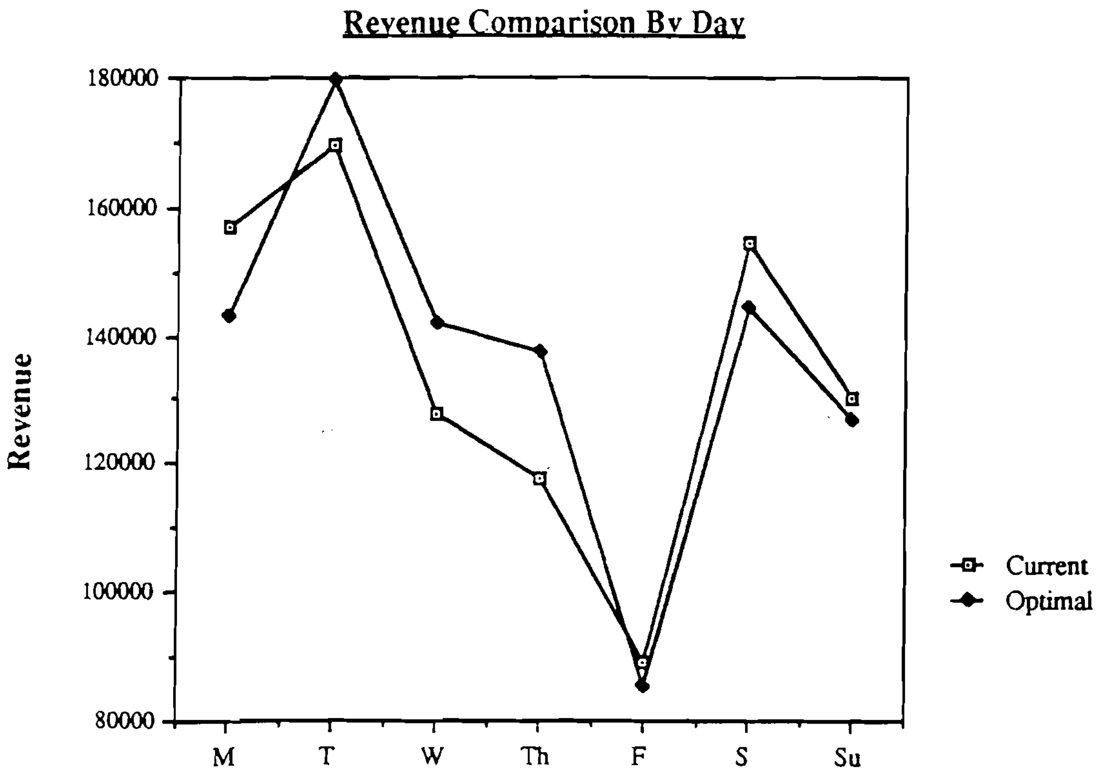

Revenue Comparison By Day
180000
160000
140000
120000
100000
80000
Revenue
M
T
W
Th
F
S
Su
Current
Optimal

Figure 7

SPOT Optimal Schedule (Net Profit/OLS) for First Quarter 1990 (Case 1)

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
8:00	N9	N3	P1	N1	A1	N7	H1
8:30		N4	P2	S1	N2		H2
9:00	S3*	H4*	S2*	H3	N8	N5*	P3
9:30							
10:00	H5	N10	A2	L1	H7	N6	H6
10:30							

Total Cost/Week = $3,180,000

Total Net Operating Profit = $ 6,448,263
Total Revenue = $ 9,628,263

* Indicates a 'best' show at 9:00 pm.

Figure 8

SPOT Optimal Schedule (AHP/Expert Choice) for First Quarter 1990 (Case 1)

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
8:00	H2	A1	N6	P2	S2	H1	P1
8:30	N2	N4		N1		N3	S1
9:00	S3*	N5*	A2	H4*	N10	H5*	N9*
9:30							
10:00	L1	H3	P3	H7	H7	N8	H6
10:30							

Total Cost/Week = $3,180,000

Objective Value = 23.14
Total Net Operating Profit = $ 6,390,709
Total Revenue = $ 9,570,709

* Indicates a 'best' show at 9:00 pm.