A (0-1) GOAL PROGRAMMING APPROACH FOR SCHEDULING THE TOUR OF A MARKETING EXECUTIVE

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ABSTRACT

This paper addresses the problem of scheduling the tour of a marketing executive (ME) of a large electronics manufacturing company in India. In this problem, the ME has to visit a number of customers in a given planning period. As each customer has different quantum of business transactions with the company, the ME has to visit each customer a pre-specified number of times (usually proportional to the level of business transactions) in the planning period. In addition, the ME has to maintain an appropriate time interval between consecutive visits to a customer. Within the planning period, the ME has to pay regular full-day visits to his head office. In addition, as per company policies, upper and lower bounds on the number of customers to be visited per day are imposed. The scheduling (a personnel scheduling) problem taken up in this study seems to be quite different from the various personnel scheduling problems addressed in the literature. This type of personnel scheduling problem can be observed in many other situations such as periodical visits of inspection officers, tour of politicians during election campaigns, schedule of mobile courts, schedule of mobile stalls in various areas, etc. In this paper the tour scheduling problem of the ME is modeled using (0-1) goal programming (GP). The (0-1) GP model for the data provided from the company for one month has 802 constraints and 1167 binary variables. The model is solved using LINDO software package. The model takes less than a minute (on a 1.50 MHz Pentium machine with 128 MB RAM) to get a solution of the non-pre-emptive version and about 6 days for the pre-emptive version. The main contribution is in problem identification and development of the mathematical model for scheduling the tour of a marketing executive.

Author Keywords: Scheduling, Tour of a marketing executive; Goal programming

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1. Introduction

Efficient utilization of manpower has always been a key concern in organizations. This is one of the most important means to achieve gains in productivity. Because of its importance, considerable effort has been devoted to tackling various personnel-scheduling problems in the literature. Personnel scheduling is concerned with the determination of appropriate workforce requirements, workforce allocation and workforce duty assignments for an organization in order to meet internal and external requirements. This involves allocating people (personnel) to timeslots and possibly locations. Not surprisingly, personnel scheduling has been the subject of much investigation in the literature over the past 30 years with at least one survey article for every decade [Baker (1976), Tien and Kamiyama (1982), Bedworth and Bailey (1987), Bechtold et al. (1991), Ernst et al. (2004), Alfares (2004)]. Because the problem environment differs from one case to another, personnel scheduling problem has been applied to a variety of applications in the literature.

In this paper, we consider the problem of scheduling the tour of a marketing executive of a large electronics manufacturing company in India. Based on our observations of this problem in the company and the various personnel scheduling problems addressed in the literature, we felt that this problem differs significantly compared with many other personnel scheduling problems addressed so far in the literature. This type of personnel scheduling problem can be observed in many other situations such as periodical visits of inspection officers, tour of politicians during election campaigns, schedule of mobile courts, schedule of mobile stalls in various areas, etc. In this paper, a (0-1) goal programming is proposed for modeling the tour scheduling of marketing executive.

The paper is organized as follows: Section 2 presents the problem statement and assumptions. Section 3 provides a related review for the problem. Section 4 describes the development of a mathematical model for the problem stated in section 2. Section 5 presents an application of the model to the data from the company. Finally section 6 presents some concluding remarks and directions for future work.

2. Problem Statement

The problem of tour scheduling of a marketing executive (ME) of a company may be stated as follows. We are given a set of regions $\boldsymbol{R} = \{r_1, r_2, \ldots r_m\}$ having a number of customers in a city. Each region $\boldsymbol{r_i}$ is covered by one marketing executive. The ME assigned to each region has to visit periodically all the customers clustered in the region for continuously increasing the business interactions between the customers and the company. The number of effective working days for ME in a given planning period is accounted after excluding the holidays of the company and the days in which the ME has to make full-day visits to head-office. For each ME, the head-office visit-days varies, except the last visit, in the planning period. All the marketing executives assemble at the head-office during their last head-office visit towards the end of planning period for a common discussion on the business strategy. Accordingly, for every planning period and for every ME, the set of days not scheduled for customer visits is $\boldsymbol{M}$ = {holidays for the company, holidays for individual customers, days for full-day visits to head-office}.

Each region has a set of customers $\boldsymbol{C} = \{c_1, c_2, \ldots c_n\}$ and each customer has different level of business transactions with the company. Accordingly, based on the business transactions with the company, the customers are classified as A-type, B-type and C-type, which is similar to ABC-inventory classification. Thus class A customers have a highest level of business transaction in the company, followed by Class B and C customers. As per the policy of the company, the number of visits made by the ME to a customer is directly proportional to the customer's level of business transaction. That is, the ME should visit class A customer more number of times in a given planning period compared to the number of visits to class B and C customers. Thus, if ME has to visit each A-type customers N_A times, each B-type customers N_B times and each C-type customers N_C times in the planning period then $N_A > N_B > N_C$. As per the policy on each customer's number-of-visits, the company puts a condition that the ME has to maintain an appropriate time-interval between the consecutive visits of any customer in the planning period. The time-interval between the consecutive visits is a function of effective number of working days available for the ME in the planning period and number of required visits to a customer. In addition to the time-interval condition, the company specifies upper and lower bounds on the number of customer to be visited per day.

As the company divides logistically their customers in the city into a multiple regions and one ME is assigned to each region for the continuous and efficient development of their business with customers, in this paper, we are addressing the scheduling of the tour of a single ME.

<u>Assumptions</u>

- There are no restrictions/limitations in moving from one customer to another.
- The time and cost of traveling from one customer to another is not explicitly incorporated.
- The working hours and pattern (if any) remain the same for both customer and ME of the company.
- The emergency requirement of any customer is not addressed.
- The policy decisions of the management of the customers such as type of customer, number of visits of a customer, etc., do not change during the planning period.

- Natural calamities are not accounted for in the solution development.
- The model specifies the customers to be visited by the ME on any working day, but does not specify the sequencing of the customers.
- The total number of visits required by all the customers in the planning period should be less than or equal to the total number of trips expected to be made by the ME in the planning period.

3. Related Work

Personnel or staff or tour scheduling problems have been studied for many years as they contribute to the improvement of the overall performance of a system in terms of quality of service to the customer and cost to the organization. These problems involve the allocation of staff to timeslots and possibly locations. These scheduling problems cover many areas, such as the tour scheduling problem in a post office setting (Ritzman et al. 1976; Bard et al. 2003), scheduling personnel in a newspaper publishing environment (Gopalakrishnan et al. 1993), the transportation staff scheduling (Wren and Wren, 1995), scheduling of cashiers in a supermarket (Melachrinoudis and Olafsson, 1995), nurse rostering problem (Dowsland, 1998; Burke et al, 2001;), audit staff scheduling (Dodin et al. 1998), educational institute staff scheduling (Schaerf, 1999), airline crew-scheduling (Emden-Weinert and Proksch, 1999), scheduling a sales summit (Cowling et al., 2000), scheduling of laboratory personnel (Boyd and Savory, 2001) and scheduling pharmaceutical sales representatives (Hertel and Gautam, 2004). However, the scheduling of the visits of a ME (a tour scheduling) problem taken up in this study seems to be significantly different from the various personnel scheduling problems addressed in the literature.

Given the wide variety of tour scheduling problems, different approaches including mathematical programming and computational approaches have been employed in solving them.

The various employee tour-scheduling approaches in the literature have many different objectives and assumptions, and therefore a wide variety of mathematical formulation approaches such as set covering, goal programming, and implicit modeling. The first integer linear programming formulation was proposed by Dantzig (1954) using set covering approach. Recently, Alfares (2004) classified the tour scheduling approaches into ten categories and presented a brief literature review as well as compared the tour scheduling techniques.

The problem of designing the schedule of visits of a ME subject to the constraints imposed by the company is solved in this paper by expressing it as a (0-1) goal programming. Goal programming (GP) has received a great deal of attention among optimization techniques in personnel scheduling as it attempts to address multiple objectives simultaneously such as maximizing utilization of full-time staff, minimizing understaffing and overstaffing costs, minimizing payroll costs, as well as minimizing deviations from desired staffing requirements, customer special requests, staff preferences, and staff special requests [example: Azaiez and Sharif (2005), Easton and Rossin (1996), Brusco and Johns (1995), Trivedi (1981)]. Furthermore, the goal programming appears to be an appropriate, powerful, and flexible technique for decision analysis of the troubled modern decision maker who is burdened with achieving multiple conflicting objectives under complex environmental constraints [Schniederjans (1995), Tamiz, et al. (1998), and Aouni and Kettani (2001)].

4. Methodology

4.1. Goal Programming

The roots of Goal Programming (GP) lie in a paper by Charnes et al. (1955), which deals with executive compensation methods. A more explicit definition is given by Charnes and Cooper (1961), in which the term Goal Programming is first used. GP is a powerful technique since it can handle multiple objectives. Unlike Linear Programming, the GP model does not optimize (maximize/minimize) the objectives directly. Instead, it attempts to minimize the deviations between the desired goals and the realized results. Also, these goals must be prioritized in a hierarchy of importance. The over and under achievements of goals is measured in GP using the so called deviation variables. A commonly used generalized model for goal programming is as follows (Kwak et al. 1991):

$$\text{Min} \quad \sum_{i}^{k} P_i(w_i^+ d_i^+ + w_i^- d_i^-)$$

s.t

$$C^1X + d_1^+ - d_1^- = t_1$$

$$\vdots$$

$$C^kX + d_k^+ - d_k^- = t_k$$

$$X \in S$$

$$X,\ d_k^+,\ d_k^- \geq 0$$

in which S is the feasible region; P_i is the preemptive factor/priority level assigned to each relevant goal in rank order (i.e. $P_1 > P_2 > P_k$), C^iX is the i^{th} goal criterion function, and t_i are the target values of the k goal criteria. The variables d_i^+ and d_i^- are the deviational variables, which measure achievements below and above goal. The w_i^+ and w_i^- are relative importance weights attached to the underachievement and overachievement deviational variables.

The constraints involved in a GP model are broadly grouped into (i) hard constraints and (ii) soft constraints. Hard constraints are constraints that cannot be violated. For instance, the constraint that the ME can only be present at one place at one time is a hard constraint. Soft constraints are constraint that can be violated and the solution may still be acceptable. For instance, the expected time interval between two consecutive visits of a customer by the ME can be violated marginally. But we must be able to know how far we can bend a soft constraint. A common way to manage soft constraints is to assign goals to each of them, to associate deviational variables representing over and under achievements of the respective goals, and to minimize the sum of these deviational variables in the objective function.

The advantage of GP is that multiple objectives can be incorporated into a model that can be solved using conventional (single objective) optimization software. A major disadvantage of GP is that it requires about the decision maker's preference among objective *a priori* in the form of priority levels, importance weights, and goal target values.

4.2 *Development of (0-1) GP model for scheduling the visits of a marketing executive*

<u>Notation</u>

i stands for Customer i

j stands for Day j, j = 1, 2, …, N.

N = Number of days in the planning period

I = Maximum number of customers in the cluster (Without loss of generality, let us assume that the first I_A customers are Class A customers, the next I_B customers are Class B customers, and the next I_C customers are Class C customers. Thus, $I_A + I_B + I_C = I$.)

N_A = Number of days the ME should visit Class A customer in a given period

N_B = Number of days the ME should visit Class B customer in a given period

N_C = Number of days the ME should visit Class C customer in a given period

T_A = Time-interval between consecutive visits by the ME to Class A customers
= Integer value of the ratio (N/N_A)

T_B = Time-interval between consecutive visits by the ME to Class B customers
= Integer value of the ratio (N/N_B)

T_C = Time-interval between consecutive visits by the ME to Class C customers
= Integer value of the ratio (N/N_C)

M = {Holidays for the company, Holidays for the individual customers, Days in which the ME has to make a full-day visits to head-office}

MinVisit = Minimum number of Customers the ME should visit every day

MaxVisit = Maximum number of Customers the ME should visit every day

Decision variable: x_{ij} = 1 if the ME visits Customer i on Day j; 0 otherwise

Soft constraints

As per the policies of the Company, the ME is required to visit different classes of customers at a certain frequency. Thus, approximately one visit is required for Class A customers for every L_A+1 working days (Constraint 1). Similar constraints (2 and 3) can be written for Class B and Class C customers.

$$\sum_{k=0}^{T_A} x_{i,j+k} \approx 1,\ i = 1,2,\cdots I_A,\ j = 1,2,\cdots N - T_A,\ j \notin \mathrm{M} \tag{1}$$

$$\sum_{k=0}^{T_B} x_{i,j+k} \approx 1,\ i = I_A + 1, I_A + 2,\cdots I_B,\ j = 1,2,\cdots N - T_B,\ j \notin \mathrm{M} \tag{2}$$

$$\sum_{k=0}^{T_C} x_{i,j+k} \approx 1,\ i = I_B + 1, I_B + 2,\cdots I_C,\ j = 1,2,\cdots N - T_C,\ j \notin \mathrm{M} \tag{3}$$

Hard constraints

Constraints 4-6 below are used to ensure that the ME makes the required number of visits per planning period for different classes of customers as specified by the Company.

$$x_{i,1} + x_{i,2} + \cdots + x_{i,N} = N_A,\ i = 1,2,\cdots I_A \tag{4}$$

$$x_{i,1} + x_{i,2} + \cdots + x_{i,N} = N_B,\ i = I_A + 1, I_A + 2,\cdots I_B \tag{5}$$

$$x_{i,1} + x_{i,2} + \cdots + x_{i,N} = N_C,\ i = I_B + 1, I_B + 2,\cdots I_C \tag{6}$$

The ME should visit a minimum number of customers on any single working day (Constraint 7)

$$\sum_{i=1}^{I} x_{i,j} \geq MinVisit,\ j = 1,2,\cdots N,\ j \notin M \tag{7}$$

The ME should not visit more than a maximum number of customers on any single working day (Constraint 8)

$$\sum_{i=1}^{I} x_{i,j} \leq MaxVisit,\ j = 1,2,\cdots N,\ j \notin M \tag{8}$$

With this upper limit, the maximum number of visits that can be scheduled for a ME in a planning period is equal to [(N – number of days in M) * MaxVisit].

The following set of constraints, (9-11) are required as supplement to the soft constraints (1-3) specified earlier. Because of the approximate nature of the constraints (1-3), there is a possibility that the visits by the ME to the same customer may be scheduled frequently (for example on two consecutive days), and hard constraints (9-11) are written to overcome this possibility. The "less than" sign is needed in these constraints as these constraints, when specified as equality constraints, can violate the required number of visits (Constraints 4-6) in certain cases.

$$\sum_{k=0}^{T_A-1} x_{i,j+k} \leq 1,\ i = 1,2,\cdots I_A,\ j = 1,2,\cdots N - T_A + 1 \tag{9}$$

$$\sum_{k=0}^{T_B-1} x_{i,j+k} \leq 1,\ i = I_A + 1, I_A + 2,\cdots I_B,\ j = 1,2,\cdots N - T_B + 1 \tag{10}$$

$$\sum_{k=0}^{T_C-1} x_{i,j+k} \leq 1,\ i = I_B + 1, I_B + 2,\cdots I_C,\ j = 1,2,\cdots N - T_C + 1 \tag{11}$$

Formulating goals

Three goals are needed in the model to incorporate the importance structure of the three classes of Customers.

Goal 1: It minimizes the sum of deviational variables corresponding to the soft Constraint 1 (approximately one visit to Class A customers for every L_A +1 working days).

$$\sum_{k=0}^{T_A} x_{i,j+k} + d_{i,j}^{+} - d_{i,j}^{-} = 1, \; i = 1,2,\cdots I_A, \; j = 1,2,\cdots N - T_A, \; j \notin \mathrm{M} \tag{12}$$

Goal 2: It minimizes the sum of deviational variables corresponding to the soft Constraint 2 (Class B customers).

$$\sum_{k=0}^{T_B} x_{i,j+k} + d_{i,j}^{+} - d_{i,j}^{-} = 1, \; i = I_A + 1, I_A + 2, \cdots I_B, \; j = 1,2,\cdots N - T_B, \; j \notin \mathrm{M} \tag{13}$$

Goal 3: It minimizes the sum of deviational variables corresponding to the soft Constraint 3 (Class C customers).

$$\sum_{k=0}^{T_C} x_{i,j+k} + d_{i,j}^{+} - d_{i,j}^{-} = 1, \; i = I_B + 1, I_B + 2, \cdots I_C, \; j = 1,2,\cdots N - T_C, \; j \notin \mathrm{M} \tag{14}$$

Assigning Importance Weights

Importance levels of Goals 1, 2 and 3 can be assigned as per the company policy. In general, identifying the importance levels in GP is a complicated exercise. Several additional methods such as Analytical Hierarchy Process (Ramanathan and Ganesh, 1995) have been employed for deriving the importance levels. However, in this paper, identifying importance levels is relatively straight forward as the company has a clear policy of assigning importance to its customers. As stated earlier, Class A customers are the most important and hence Goal 1 should have the highest level of importance. Importance level decreases to Class B and to Class C customers. Class C customers are the least important and hence Goal 3 should have the lowest level of importance. Goal 2 has an importance level that is between those of Goals 1 and 3.

GP objective function

In GP for the problem addressed here, two different ways of specifying importance level are available – pre-emptive and non-preemptive (Schniederjans, 1995). Both the ways have been attempted in this study.

Pre-emptive GP: In pre-emptive GP, priority levels P_1, P_2 and P_3 are assigned to Goals 1, 2 and 3 respectively. By definition, P_1 is higher than P_2 by an order of magnitude, and P_2 is higher than P_3 by an order of magnitude, that is, $P_1 >>> P_2$, and $P_2 >>> P_3$. When such pre-emptive priorities are assigned to the goals, the GP objective function can be written as follows. The objective function minimizes the weighted sum of deviational variables corresponding to the goals.

$$\text{Minimize} \quad P_1\left(\sum_{i=1}^{I_A}\sum_{j=1}^{N-T_A}\left(d_{i,j}^{+}+d_{i,j}^{-}\right)\right)+P_2\left(\sum_{i=I_A+1}^{I_B}\sum_{j=1}^{N-T_B}\left(d_{i,j}^{+}+d_{i,j}^{-}\right)\right)+P_3\left(\sum_{i=I_B+1}^{I_C}\sum_{j=1}^{N-T_C}\left(d_{i,j}^{+}+d_{i,j}^{-}\right)\right) \qquad (15)$$

When this objective function is used the GP is solved in stages. In the first stage, the model is solved for optimizing the first level priority goals. The solution obtained is added as a constraint to the original constraints and the problem is solved again by optimizing the second priority goals and so on. If the deviational variables can be reduced to zero, the goals are satisfied exactly.

Non-pre-emptive GP: In non-pre-emptive GP, the importance levels of the goals are not pre-emptive but comparable to each other. Their magnitude gives implicit trade-off information about the achievements in terms of different goals. For example, if w_1, w_2 and w_3 are the importance weights assigned to Goals 1, 2 and 3 respectively, and if $w_1 = 4$, $w_2 = 2$ and $w_3 =1$, then a unit increase in the value of a deviational variable of Goal 1 is considered equivalent to an increase of 2 in the value of deviational variable of Goal 2 and to an increase of four in the value of deviational variable of Goal 3. With the importance weights w_1, w_2 and w_3, the GP objective function can be written as follows.

$$\text{Minimize } \left(w_1 \times \sum_{i=1}^{I_A} \sum_{j=1}^{N-T_A} \left(d_{i,j}^{+} + d_{i,j}^{-} \right) \right) + \left(w_2 \times \sum_{i=I_A+1}^{I_B} \sum_{j=1}^{N-T_B} \left(d_{i,j}^{+} + d_{i,j}^{-} \right) \right) + \left(w_3 \times \sum_{i=I_B+1}^{I_C} \sum_{j=1}^{N-T_C} \left(d_{i,j}^{+} + d_{i,j}^{-} \right) \right) \tag{16}$$

The full goal programming model: The full goal programming incorporates the objective functions, soft constraints and hard constraints specified earlier. Thus the pre-emptive GP model has Objective Function (14) and 11 Constraints (4-14). The non-preemptive GP model has Objective Function (16) and 11 Constraints (4-14). These full models are presented in the Appendix 1.

5. Application and Results

In this section, the (0-1) GP model proposed in the previous section is solved based on the data from the company. The following data, shown in Table 1, are used in the (0-1) GP model.

- *Customer data*: customer code and the number of visits required by the customer
- *Planning horizon data*: number of days in the planning period (= one month), name and starting day of the month

- *Set of days in which the ME is not scheduled to visit customers*: {{Holidays for the company}, {Holidays for individual customers}, {General holidays}, {Days in which the ME has to make a full-day visit to head-office}}
- *Constraints on number of customers to be visited by ME per day*: minimum and/or maximum number of expected visits by the ME

For data presented in Table 1, the planning horizon is one month, the name of the month is January, the starting day of the month is 2, the set of days in which the ME is not scheduled to visit customers, M = {{2, 9, 16, 23, 30} (holidays for the company), {14} (general holidays), {4, 11, 18, 29} (days in which the ME has to make a full-day visit to head-office)}, and the minimum and maximum customers to be visited per day by the ME is 4 and 6 respectively. Note that holidays for individual customers vary depending upon the customer and is specified in Table 1.

The software LINDO (version 5), an acronym for Linear Interactive Discrete Optimizer (Schrage, 1991) has been used to solve the (0-1) GP model developed in this paper in a 1.50 MHz Pentium IV Machine with 128 MB RAM.

For non-preemptive (0-1) GP model, we used two different weighting schemes. In the first scheme, the weights are chosen relatively close to each other as in $w_1 = 3$, $w_2 = 2$ and $w_3 = 1$. In this case, more trade-off among the achievements of deviational variables of the three goals are possible, compared to the other weighting scheme, which had if $w_1 = 25$, $w_2 = 10$ and $w_3 = 1$. This second weighting scheme is chosen to compare the results of the non-preemptive GP model with those of the preemptive (0-1) GP model. The preemptive (0-1) GP model can be solved (a) in stages using an appropriate LINDO command and (b) using the Lexico-optimization command 'GLEX' of LINDO. Accordingly, four versions of (0-1) GP model for the company data are solved using the software LINDO. The (0-1) GP model for the data provided from the company for one month has 802 constraints and 1167 (0-1) variables.

The detailed schedule of the tour of a ME obtained for the company data with the weighting scheme, "w_1 = 25, w_2 = 10 and w_3 =1" is presented in Table 2. A cross (x) in a cell in the table represents that the ME is scheduled to visit the customer represented by the corresponding row on the day represented by the corresponding column. The last row shows that the restrictions on the maximum and minimum number of visits for each day have been followed. Similarly, the last column shows that the restrictions on the number of visits required for the customer in the planning period have been followed. As mentioned earlier, the preemptive version yielded the same results, but the non-preemptive version with weights relatively close to each other resulted in more number of violations for B type customers and less number of violations for C type customers.

The comparison of the solution in all the four versions of the (0-1) GP model for the company data in terms of (a) number violations of time-interval between consecutive visits of each type of customers and (b) computational time are obtained and presented in Table 3. The non-preemptive version with weights close to each other resulted in more violations for B type customers and lesser violations for C type customers (first row of the table) compared to the other non-preemptive weighting scheme (second row) and the preemptive version (third row). For the company data, the weighting scheme, "w_1 = 25, w_2 = 10 and w_3 =1" in the (0-1) GP model resulted the same scheduling of the tour of a ME as resulted in preemptive version of (0-1) GP. It can be observed form Table 3 that computationally the non-preemptive (0-1) GP is simpler to solve than preemptive version.

6. Conclusion

Personnel scheduling problems are becoming increasingly important as business become more competitive, service oriented and cost conscious in the global environment. One such scheduling problem encountered by a large electronics manufacturing company in India, but has not been adequately addressed in the literature so far, is discussed in this paper. For the problem defined in this paper a (0-1) goal-programming model is developed and applied using data from the company.

The (0-1) GP model considers customers' closing days, their expected level of business-interactions with the company, the executive's (a) weekly holidays, (b) holidays for individual customers, (c) general holidays (if any), and (d) routine head-office full day visits in the planning period, and, the company's requirement of minimum and maximum visits per day. The main contribution of this paper is in problem identification and development of an appropriate mathematical model for scheduling the tour of a marketing executive. Furthermore, the company data used for demonstrating the (0-1) GP model indicated that an appropriate weighting scheme for non-preemptive version is computationally simpler compared to the preemptive version in obtaining an efficient and fast solution for scheduling the tour of the ME.

An immediate extension of this problem could be linking appropriately this model with the standard mathematical model for traveling salesman problem (TSP). Using the model for TSP, we could get an optimal sequence for daily tour of ME as the size of the TSP in the company problem is only 6 visiting-points [=maximum visits per day by ME]. The current version of the (0-1) GP model could be appropriately expanded to simultaneously schedule the visits of more ME's and to cover more regions. In that case the model could become large with multiple thousands of binary variables and may become computationally intractable. Hence another future work is to explore the possibility to develop other solution approaches such as simple heuristics or meta-heuristics, to tackle the problem, as solving a very large size problem using (0-1) GP may become computationally intractable. Efforts are now underway to develop a few simple heuristic approaches for the scheduling of the tour of ME. When more approaches become available, it would be interesting to develop decision support systems (DSS) to compare their performance and to evaluate their suitability when applied in different operational environments, including more feasible schedules, managers' partial schedules, shorter/longer planning horizons and more type of customers. The DSS could be more user friendly with appropriate menu structure so that the manager can use the model without the knowledge of the optimization tools involved.

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APPENDIX 1: The Complete Non-preemptive (0-1) Goal Programming Model

Non-preemptive 0-1 goal programming model

$$\text{Minimize } \left(w_1 \times \sum_{i=1}^{I_A} \sum_{j=1}^{N-T_A} \left(d_{i,j}^{+} + d_{i,j}^{-}\right)\right) + \left(w_2 \times \sum_{i=I_A+1}^{I_B} \sum_{j=1}^{N-T_B} \left(d_{i,j}^{+} + d_{i,j}^{-}\right)\right) + \left(w_3 \times \sum_{i=I_B+1}^{I_C} \sum_{j=1}^{N-T_C} \left(d_{i,j}^{+} + d_{i,j}^{-}\right)\right)$$

Subject to

$$\sum_{k=0}^{T_A} x_{i,j+k} + d_{i,j}^{+} - d_{i,j}^{-} = 1,\ i = 1,2,\cdots I_A,\ j = 1,2,\cdots N - T_A,\ j \notin \mathrm{M} \quad \text{(Approximately one visit for } T_A + 1 \text{ working days)}$$

$$\sum_{k=0}^{T_B} x_{i,j+k} + d_{i,j}^{+} - d_{i,j}^{-} = 1,\ i = I_A + 1, I_A + 2, \cdots I_B,\ j = 1,2,\cdots N - T_B,\ j \notin \mathrm{M} \quad \text{(Approximately one visit for } T_B + 1 \text{ working days)}$$

$$\sum_{k=0}^{T_C} x_{i,j+k} + d_{i,j}^{+} - d_{i,j}^{-} = 1,\ i = I_B + 1, I_B + 2, \cdots I_C,\ j = 1,2,\cdots N - T_C,\ j \notin \mathrm{M} \quad \text{(Approximately one visit for } T_C + 1 \text{ working days)}$$

$$x_{i,1} + x_{i,2} + \cdots + x_{i,N} = N_A,\ i = 1,2,\cdots I_A \quad \text{(Required number of visits to Class } A \text{ Customers)}$$

$$x_{i,1} + x_{i,2} + \cdots + x_{i,N} = N_B,\ i = I_A + 1, I_A + 2, \cdots I_B \quad \text{(Required number of visits to Class } B \text{ Customers)}$$

$$x_{i,1} + x_{i,2} + \cdots + x_{i,N} = N_C,\ i = I_B + 1, I_B + 2, \cdots I_C \quad \text{(Required number of visits to Class } C \text{ Customers)}$$

$$\sum_{i=1}^{I} x_{i,j} \geq MinVisit,\ j = 1,2,\cdots N,\ j \notin M$$

$$\sum_{i=1}^{I} x_{i,j} \leq MaxVisit,\ j = 1,2,\cdots N,\ j \notin M$$

$$\sum_{k=0}^{T_A - 1} x_{i,j+k} \leq 1,\ i = 1,2,\cdots I_A,\ j = 1,2,\cdots N - T_A + 1 \quad \text{(Permissible violation in } T_A\text{)}$$

$$\sum_{k=0}^{T_B - 1} x_{i,j+k} \leq 1,\ i = I_A + 1, I_A + 2, \cdots I_B,\ j = 1,2,\cdots N - T_B + 1 \quad \text{(Permissible violation in } T_B\text{)}$$

$$\sum_{k=0}^{T_C - 1} x_{i,j+k} \leq 1,\ i = I_B + 1, I_B + 2, \cdots I_C,\ j = 1,2,\cdots N - T_C + 1 \quad \text{(Permissible violation in } T_C\text{)}$$

APPENDIX 1 (Contd.): The Complete Pre-emptive (0-1) Goal Programming Models

Pre-emptive 0-1 goal programming model

Minimize $P_1\left(\sum_{i=1}^{I_A}\sum_{j=1}^{N-T_A}\left(d_{i,j}^{+}+d_{i,j}^{-}\right)\right)+P_2\left(\sum_{i=I_A+1}^{I_B}\sum_{j=1}^{N-T_B}\left(d_{i,j}^{+}+d_{i,j}^{-}\right)\right)+P_3\left(\sum_{i=I_B+1}^{I_C}\sum_{j=1}^{N-T_C}\left(d_{i,j}^{+}+d_{i,j}^{-}\right)\right)$

Subject to

$\sum_{k=0}^{T_A} x_{i,j+k} + d_{i,j}^{+} - d_{i,j}^{-} = 1,\ i=1,2,\cdots I_A,\ j=1,2,\cdots N-T_A,\ j\notin \mathrm{M}$ (Approximately one visit for T_A+1 working days)

$\sum_{k=0}^{T_B} x_{i,j+k} + d_{i,j}^{+} - d_{i,j}^{-} = 1,\ i=I_A+1, I_A+2,\cdots I_B,\ j=1,2,\cdots N-T_B,\ j\notin \mathrm{M}$ (Approximately one visit for T_B+1 working days)

$\sum_{k=0}^{T_C} x_{i,j+k} + d_{i,j}^{+} - d_{i,j}^{-} = 1,\ i=I_B+1, I_B+2,\cdots I_C,\ j=1,2,\cdots N-T_C,\ j\notin \mathrm{M}$ (Approximately one visit for T_C+1 working days)

$x_{i,1}+x_{i,2}+\cdots+x_{i,N}=N_A,\ i=1,2,\cdots I_A$ (Required number of visits to Class A Customers)

$x_{i,1}+x_{i,2}+\cdots+x_{i,N}=N_B,\ i=I_A+1, I_A+2,\cdots I_B$ (Required number of visits to Class B Customers)

$x_{i,1}+x_{i,2}+\cdots+x_{i,N}=N_C,\ i=I_B+1, I_B+2,\cdots I_C$ (Required number of visits to Class C Customers)

$\sum_{i=1}^{I} x_{i,j} \geq MinVisit,\ j=1,2,\cdots N,\ j\notin M$

$\sum_{i=1}^{I} x_{i,j} \leq MaxVisit,\ j=1,2,\cdots N,\ j\notin M$

$\sum_{k=0}^{T_A-1} x_{i,j+k} \leq 1,\ i=1,2,\cdots I_A,\ j=1,2,\cdots N-T_A+1$ (Permissible violation in T_A)

$\sum_{k=0}^{T_B-1} x_{i,j+k} \leq 1,\ i=I_A+1, I_A+2,\cdots I_B,\ j=1,2,\cdots N-T_B+1$ (Permissible violation in T_B)

$\sum_{k=0}^{T_C-1} x_{i,j+k} \leq 1,\ i=I_B+1, I_B+2,\cdots I_C,\ j=1,2,\cdots N-T_C+1$ (Permissible violation in T_C)

Appendix 2: Computational complexity – the solution status using LINDO over 15 days

: glex
LP OPTIMUM FOUND AT STEP 1782
OBJECTIVE VALUE = 4.00000000

NEW INTEGER SOLUTION OF 4.00000000 AT BRANCH 3 PIVOT 3608
BOUND ON OPTIMUM: 4.000000
ENUMERATION COMPLETE. BRANCHES= 3 PIVOTS= 3608

LAST INTEGER SOLUTION IS THE BEST FOUND
RE-INSTALLING BEST SOLUTION...

LP OPTIMUM FOUND AT STEP 26019
OBJECTIVE VALUE = 15.0000000

NEW INTEGER SOLUTION OF 15.0000000 AT BRANCH 0 PIVOT 57585
BOUND ON OPTIMUM: 15.00000
ENUMERATION COMPLETE. BRANCHES= 0 PIVOTS= 57585

LAST INTEGER SOLUTION IS THE BEST FOUND
RE-INSTALLING BEST SOLUTION...

[about 2 minutes]

PIVOT LIMIT OF 5633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 40000000

PIVOT LIMIT OF 45633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 40000000

PIVOT LIMIT OF 85633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 80000000

LP OPTIMUM FOUND AT STEP*******†
OBJECTIVE VALUE = 40.4999924

PIVOT LIMIT OF 165633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 100000000

PIVOT LIMIT OF 265633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 100000000

PIVOT LIMIT OF 365633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 100000000

PIVOT LIMIT OF 465633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 100000000

PIVOT LIMIT OF 565633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 100000000

PIVOT LIMIT OF 665633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 100000000

PIVOT LIMIT OF 765633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 100000000

PIVOT LIMIT OF 865633616 EXCEEDED. HOW MANY MORE ALLOWED?
? 200000000

PIVOT LIMIT OF **1065633616** EXCEEDED. HOW MANY MORE ALLOWED?
? 100000000

Terminated after 15 days

† These symbols represent that the number of LP iterations have exceeded one million.

Table 1: Customer Details

'A' type customers

Sl. No.	1	2	3
Customer Code	C10	C11	C09
# Visits required	8	8	8
Customer-Closure-Day	Nil	{3,10,17,24,31}	Nil

'B' type customers

Sl. No.	1	2	3	4	5	6	7	8	9
Customer Code	C01	C03	C25	C31	C24	C23	C32	C27	C05
# Visits required	6	6	6	6	6	6	6	6	6
Customer-Closure-Day	{5,12,19,26}	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil

'C' type customers

Sl. No.	1	2	3	4	5	6	7	8	9
Customer Code	C26	C02	C21	C22	C06	C07	C39	C08	C30
# Visits required	4	4	4	4	4	4	4	4	4
Customer-Closure-Day	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil

Table 2: Tour schedule of the Marketing Executive obtained using the non-preemptive version of (0-1) Goal Programming Model. See Appendix I for the Model. (w_1 = 25, w_2 = 10 and w_3 =1)

Customer	Tour Schedule of the Marketing Executive obtained using (0-1) GP model, Customer wise (row) and Day wise (column)																														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	# visits
C10 (8)		S		H	x			x	S		H	x		G	x	S		H		x			S	x		x			H	S	x	8
C11 (8)		S		H	x		x		S		H	x		G	x	S		H	x		x		S		x			x	H	S		8
C09 (8)		S	x	H		x		x	S		H		x	G		S		H	x			x	S			x		x	H	S		8
C01 (6)		S	x	H				x	S		H			G	x	S		H			x		S		x				H	S	x	6
C03 (6)		S		H		x			S	x	H			G	x	S		H		x			S	x				x	H	S		6
C25 (6)	x	S		H		x			S		H	x		G		S		H	x			x	S				x		H	S		6
C31 (6)		S		H	x				S	x	H			G		S	x	H				x	S				x		H	S	x	6
C24 (6)	x	S		H			x		S		H		x	G		S		H		x			S	x				x	H	S		6
C23 (6)		S		H	x				S	x	H			G		S	x	H				x	S			x			H	S	x	6
C32 (6)	x	S		H		x			S		H	x		G		S	x	H				x	S			x			H	S		6
C27 (6)		S	x	H				x	S		H			G	x	S		H		x			S	x			x		H	S		6
C05 (6)		S	x	H				x	S		H		x	G		S		H		x			S	x				x	H	S		6
C26 (4)	x	S		H					S	x	H			G		S		H		x			S				x		H	S		4
C02 (4)		S		H				x	S		H			G		S		H	x				S			x			H	S	x	4
C21 (4)	x	S		H			x		S		H			G		S	x	H					S		x				H	S		4
C22 (4)		S		H	x				S		H		x	G		S		H			x		S					x	H	S		4
C06 (4)		S	x	H					S		H	x		G		S		H			x		S				x		H	S		4
C07 (4)		S		H		x			S		H			G	x	S		H			x		S			x			H	S		4
C39 (4)		S		H	x				S		H		x	G		S		H				x	S						H	S	x	4
C08 (4)	x	S		H			x		S		H			G		S	x	H					S		x				H	S		4
C30 (4)		S	x	H					S		H	x		G		S		H			x		S				x		H	S		4
# visits	6		6		6	5	4	6		4		6	5		6		5		4	6	6	6		5	4	6	6	6			6	

S – Sunday, G – General-Holiday, H – Head-Office-Visit-day

Table 3: The computational complexity in getting optimal solution using the proposed (0-1) GP model

Importance level – (0-1) GP	Customer type wise, the **number of violations** in "Time-interval between consecutive visits"			**Computational Complexity** (in getting optimal solution; 1.50 MHz P4 machine with 128 MB RAM)	
	A	B	C	Time	# Iterations
Non-Preemptive with weights 3, 2, 1 respectively for A, B and C type Customers	4	12	24	About 2 minutes	3606
Non-Preemptive with weights 25, 10, 1 respectively for A, B and C type Customers	4	11	26	About 2 minutes	101117
Preemptive without using the LINDO option "GLEX"	4	11	26	About 6 days	About 3 millions[#]
Preemptive by using the LINDO option "GLEX"	Even allowing the computer to run for 15 days, we could not get the final optimal solution. The computational complexity is shown (empirically) in the Appendix 2.				

[#] The package LINDO does not print the number of iteration beyond 7 digits in the final output. Hence, we have specified the number of iterations as "About 3 million"