THE STOCHASTIC SCOUTING PROBLEM

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ABSTRACT

Efficiently scouting talented sports players is of key importance in the commercially oriented sports world. Besides being able to recognize talent, it is important to plan the scouting activities given the available time, in order to maximize the potential for scouting talented players. This problem relates to the orienteering problem. In reality, not only are the times required to travel between schools and the times required to scout at these schools uncertain, but also the potential of the sports players is yet to be determined by the scout. The approaches found in the literature do not model all these uncertainties simultaneously. Therefore, we will introduce the stochastic version of the scouting planning problem by extending an existing approach to fit the practical features of this problem. We illustrate the benefits of this new approach using a case study.

KEYWORDS. Sports scouting problem, Orienteering problem, uncertainty, stochastic programming

Main area: OA - Other applications in OR, MP- Mathematical Programming

1. Introduction

Due to the increasing commercialization of sports, huge amounts of money are involved in the transfer of players. Consequently, sport scouting or headhunting is an important issue in human resources sport management. As such, research has been conducted in order to develop systems that can effectively support scouting decisions. In a team sport context, wherein the aim is to find new team members to fill open positions and/or to enhance the quality of the team, Boon and Sierksma (2003) and Sierksma (2006) have developed a decision support system to help football coaches and managers to assess the potential or actual contributions of particular players to their teams. This approach supports not only scouting and purchasing new players but also team selection decisions. Cooper et al. (2008) showed that a Data Envelopment Analysis can be used to develop performance indices of basketball players. Their approach to basketball enables the assessment of players according to a previously specified profile. On the other hand, Papić et al. (2009) present a fuzzy expert system for scouting and evaluating young sport talents. Based on the knowledge of several human sports experts, various motoric skills tests, morphologic characteristics measurements and functional tests, this system helps to identify a talented youngster and to select the most appropriated sport for him/her.

The above research focusses mainly on how to scout talented sports players individually or in a team context. Another facet of the scouting problem corresponds to the planning of the scouting activities in the most effective way. Butt and Cavalier (1994) were the first to explore this problem and focused on the scouting planning of high school football players. They consider the high school scouting approach wherein high school campuses in a given area will be visited. Usually, the time available for scouting is insufficient to visit all schools in the area. Therefore the goal is to visit a subset of the schools, which maximizes the potential for scouting future players. The authors model this problem as an Orienteering Problem (OP).

The OP is a generalization of the well-known Traveling Salesman Problem (TSP). It is defined on a graph where a profit is associated to each node and a cost is associated to each arc. Contrary to the TSP, the OP does not require all nodes to be visited. The aim of the OP is to find a maximum profit tour, starting and ending at a depot location, where the total cost of the arcs selected in the tour does not exceed some predefined cost limit. The scouting problem corresponds to an OP wherein the nodes represent the schools and the associated profit value corresponds to the scouting potential of the school in terms of talented players. The costs of the arcs represent the travel times between the schools, combined with the time required for scouting at each school. The scout needs to leave and return to the college campus, represented by the depot location, within a desired time limit, which is modeled as the total cost limit in the OP.

In the model of Butt and Cavalier (1994) all parameters are assumed to be deterministic. In reality however, the travel times, the times required to scout, as well as the scouting potential of the schools are uncertain. Therefore, the solution to the deterministic OP might turn out to be infeasible or suboptimal in reality. Although research has been conducted on how to incorporate uncertainty in the OP already in the modeling stage, none of the approaches fits the special case of our 'Stochastic Scouting Problem' (SSP). The existing research incorporates uncertainty either only in the travel and visiting times of the OP, or only in the profit values. To better model the SSP, we extend one of the models of Evers at al. (2012b) by including profit uncertainty. We adjust the model by assuming that the visiting times are influenced by the actual profit realizations. That is, when observing the sports players at a school, the scout may decide to leave earlier or stay longer than planned, depending on the potential of the players. This approach fits the SSP best with regard to the way uncertainty is handled, as we will discuss in the next section.

This paper is structured as follows. In the next section we will provide some background on models that incorporate uncertainty in the OP and we will discuss their suitability to the SSP, which we will formally introduce in Section 3. In Section 4 we will describe the solution approach we applied to the SSP and we will illustrate its application in Section 5. We will conclude in Section 6.

2. Orienteering problems under uncertainty

The deterministic OP has been well studied in the literature. Although in most practical applications some or all of the parameters are uncertain, the amount of research on uncertain variants of the OP is limited. In this section we will discuss how the SSP relates to the existing variants of the OP. The two main approaches to incorporate uncertainty in an optimization problem are stochastic programming and robust optimization. Most of the uncertain variants of the OP use a stochastic programming approach, where the uncertain parameters are assumed to follow a predefined probability distribution. Robust optimization, on the other hand, uses more general assumptions on the behavior of the uncertain parameters, like interval uncertainty. We will use the term 'visiting time' to define the time spent at a node, which in applications of the OP may represent service time (like the unloading time of a truck), or like in case of the SSP, the time required to scout sports players at a school.

In most uncertain variants of the OP, uncertainty is considered only in the travel and visiting times and not in the profit values (Teng et al. (2004), Tang and Miller-Hooks (2005), Campbell et al. (2011), Evers et al. (2012a) and Evers et al. (2012b)). In many applications of the OP it is indeed reasonable to assume that profit values are deterministic. Ilhan et al. (2007) on the other hand, provide examples of applications of the OP where it seems more appropriate to assume that profit values are uncertain while travel and visiting times are deterministic. For the SSP however, travel and visiting times, as well as the profit values are uncertain, as we will discuss in the next section.

Regarding the way to incorporate uncertainty in an OP, we distinguish between three approaches used in the literature. Both Teng et al. (2004) and Campbell et al. (2011) penalize the objective function when travel and visiting time realizations are such that the tour cannot be finished within the time limit. As a penalty, Teng et al. (2004) use the amount of time in excess of the time limit to represent the cost associated to overtime paid to drivers, while Campbell et al. (2011) penalize the nodes in the planned tour that cannot be visited, representing a loss in customer goodwill. For the SSP both penalties do not seem suitable, since the scout might decide to return to college campus before completing the planned tour to meet the time limit. Loss in goodwill indeed plays a role in a customer - service provider relation, but this does not reflect the aim of the scout who focuses only on maximizing the scouted player potential.

The second approach to incorporate uncertainty in an OP, is by balancing the probability of satisfying the time limit constraint under travel and visiting time uncertainty, against the profit that will be obtained in all feasible cases. This can be done by chance constraints (Tang and Miller-Hooks (2005)) or by a robust optimization approach (Evers et al. (2102a)). These approaches are appealing when feasibility of the initial plan plays an important role, like in military missions or when trying to meet service level agreements with customers. A drawback of these approaches however, is that they do not take into account the effect of infeasibility on the realized objective function value. For example, when the last node of the planned tour has a high profit, this high profit will not be obtained when realizations of travel and visiting times from previous nodes turned out to be higher than accounted for.

The third approach overcomes the issue just mentioned. The Two Stage Orienteering problem (TSOP) by Evers et al. (2012b), explicitly models the effect of not reaching one or more of the final nodes in the planned tour due to travel and visiting time uncertainty. The TSOP is a two stage stochastic model, where the first stage decision is the construction of a tour and the so-called 'second stage cost' is the expected unobtainable profit, based on predefined travel and visiting time distributions. In determining this second stage cost, the TSOP takes into account that one should return to the depot within the time limit. The objective of the TSOP is to maximize the total profit of the first stage tour minus the expected second stage cost. A similar objective is suitable for the SSP, since feasibility of the initial plan does not play an important role and maximizing the expected value of the profit (potential of the players) is the scout's aim. To model the SSP, we will extend the TSOP first by including profit uncertainty, and secondly by introducing a relation between the actual profit realization and the visiting time realization. This relation models the scout's decision on when to leave the school, depending on the level of the sports players he/she observes.

3. The stochastic scouting problem

In this section we will give a formal problem description of the Stochastic Scouting Problem (SSP). In Section 3.1 we will first provide the formulation of the deterministic OP used by Evers et al. (2012b) while in Section 3.2 we will present the SSP model.

3.1 The Orienteering Problem

Consider a graph $G(N^+,A)$ where $N^+ = N \cup \{0\}$ represents the set of schools N combined with the college campus $\{0\}$ from where the scout will start his/her tour. To each school $i \in N$ we associate a profit value p_i, representing the expected potential to scout talented sports players at school i. To each arc $(i,j) \in A$ we associate a parameter t_{ij} representing the travel time from school i to school j and to each node $i \in N$ we associate a visiting time parameter v_i representing the time required to scout at school i. The total time limit, wherein the scout should finish the scouting tour, is denoted by T. We introduce the decision variables x_{ij}, which are assigned the value 1 in case arc (i,j) is selected in the tour and 0 otherwise. We use an auxiliary variable u_i to denote the position of node i in the tour. Based on these definitions, a Mixed Integer Programming (MIP) formulation of the scouting problem in a deterministic setting is the following:

(OP)
$$\max \sum_{i \in N} p_i \sum_{j \in N^+ \setminus \{i\}} x_{ij}, \tag{1}$$

Subject to

$$\sum_{i \in N} x_{0i} = \sum_{i \in N} x_{i0} = 1, \tag{2}$$

$$\sum_{i \in N^+ \setminus \{j\}} x_{ij} = \sum_{i \in N^+ \setminus \{j\}} x_{ji} \leq 1 \qquad \forall j \in N, \tag{3}$$

$$\sum_{(i,j) \in A} (t_{ij} + v_j) x_{ij} \leq T, \tag{4}$$

$$u_i - u_j + 1 \leq (1 - x_{ij})|N| \qquad \forall i, j \in N, \tag{5}$$

$$1 \leq u_i \leq |N| \qquad \forall i \in N, \tag{6}$$

$$x_{ij} \in \{0,1\} \qquad \forall (i, j) \in A. \tag{7}$$

Constraint (2) guarantees that the tour starts and ends at the depot. Constraints (3) are the flow conservation constraints and ensure that a node is visited at most once. Constraint (4) is the capacity constraint. Finally, Constraints (5) prevent the construction of subtours.

3.2 The Stochastic Scouting Problem

The scouting problem can be modeled as an OP only when parameters t_{ij}, v_i and p_i are deterministic. However, in reality all these parameters are uncertain and therefore SSP will incorporate uncertainty in the modeling stage. Before the actual visit to the schools, the scout has only estimates about the potential of the sports talents (i.e. the profit values) at each school. If the scout would have been certain about their potential beforehand, the scouting process would not have been necessary in the first place. Regarding the travel times of the SSP, unpredictable traffic causes uncertainty in the travel time between schools. Similarly, the visiting time or scouting time at a school is also uncertain. Furthermore, for the SSP the uncertainty in the profit values will influence the visiting times, i.e. depending on the scout's observations the scout can decide how long to stay at the school. For example, when the scout encounters a player with a very high potential, the scout might want to stay longer and talk with the player about the future possibilities. On the other hand, the scout is likely to leave earlier than planned in case he/she observes players of low potential. This extra source of uncertainty cannot be fully captured in the TSOP model of Evers et al. (2012b) and therefore, a relation between the realization of the scouting potential value at a specific school and the scouting time at the school will now be taken into consideration. We model this relation and the inherent uncertainty of the scouting times by $v_i = f(p_i,\varepsilon_i)$, where ε_i represents a random deviation in the scouting time, independent from the realization of the scouting potential. Function $f(\cdot)$ can be derived using historical data on previous scouting tours. We assume p_i, t_{ij} and ε_i to follow a certain predefined probability distribution. Given the definitions provided in Section 3.1, we define the SSP-objective as follows:

(SSP-Objective)
$$\max E_{t,p,\varepsilon}\left(\sum_{i\in N} p_i \sum_{j\in N^+\setminus\{i\}} x_{ij} - g\big(x,t,f(p,\varepsilon)\big)\right), \tag{8}$$

where $g(x,t,v)$ is a function that expresses the sum of the values of the scouting potential of the schools in the tour described by x that cannot be visited as a result of a given vector of travel time realizations t and a given vector of scouting time realizations v. The function $E_{t,p,\varepsilon}(\cdot)$ corresponds to the expected scouting potential to be obtained, based on the probability distributions of the travel times t, the profit values p and associated influence on the scouting time and the inherent visiting time uncertainty ε.

To formulate the complete SSP model, SSP-Objective (8) should be combined with Constraints (2) and (3) and Constraints (5) to (7). Note that the time limit Constraint (4) is not included in this model. When travel and visiting times are uncertain, it will depend on the actual realizations of the travel and visiting times whether or not Constraint (4) will be satisfied. Therefore, the SSP captures the expected effect of the actual travel and visiting time realizations on the total profit value to be obtained by the second term within the expected value function of (8). Note that this formulation will produce planned tours that are long, since a tour will not be optimal as long as nodes exist that have a strictly positive probability of being reached, and since adding one of those nodes to the tour increases the objective value given by (8).

Concluding, the first stage decision boils down to constructing a tour before the actual travel and visiting time realizations are known. However, this first stage decision is based on the expected effect that the realizations in the second stage will have on the profit value to be obtained.

4. Sample average approximation

Sample Average Approximation (SAA) is a well-known solution approach in stochastic programming (Norkin et al. (1998), Mak et al. (1999), Kleywegt et al. (2001)). It uses random samples of data realizations generated by Monte Carlo simulation to approximate upper and lower bounds on the objective value of the associated stochastic optimization problem. We will now discuss how SAA can be used to provide an approximation of the solution to the SSP.

To apply SAA to the SSP we will construct a set of scenarios S. These scenarios will be used to estimate the SSP-Objective (8). For each scenario $s\in S$ we draw one realization $t_{ij}^{\,s}$ for every arc $(i,j)\in A$, as well as one realization $p_i^{\,s}$ and $\varepsilon_i^{\,s}$ for every node $i\in N$, based on the associated probability distributions. The total profit value that will be obtained for one specific scenario, for a given tour described by x, can be calculated using a linearization proposed by Evers et al. (2012b). In that linearization a decision variable $y_i^{\,tv}$ was introduced, assigned the value 1 in case node i belongs to the planned tour, described by x, and it cannot be reached due to the scenario specific travel and visiting time realizations t and v. Using this linearization, the SAA objective function of the SSP now becomes:

(SAA-SSP-Objective) $$\max \frac{1}{|S|}\sum_{s\in S}\left(\sum_{i\in N} p_i^s \sum_{j\in N^+\setminus\{i\}} x_{ij} - \sum_{i\in N} p_i^s y_i^{t^s f(p^s,\varepsilon^s)}\right). \quad (9)$$

The constraints of the SAA-SSP model are Constraints (2) and (3) and (5) to (7), which are related to the first-stage problem: constructing a tour before the realizations of the uncertain parameters are known. Additionally, for each scenario the second stage problem can be solved by the linearization proposed by Evers et al. (2012b) yielding the scenario specific solutions y_i^{tv}. In this second stage problem, the scenario specific travel and visiting time realizations are used to determine for how long the planned tour can be continued, and consequently which of the nodes in the planned tour cannot be visited and thus will get assigned the value y_i^{tv}=1.

The resulting SAA-SSP model is a large MIP, which aims to find the maximum total estimated expected profit, which is the average of the first-stage profit reduced by the second-stage cost over all predefined scenarios. Thus, the resulting tour is based on the expected profit, resulting from the realizations of travel and visiting times, as well as the realizations from the profit values (and their effect on the visiting time realizations), estimated by the samples generated in the SAA procedure.

5. Case study

In this section we will report the results of a case study to illustrate the purpose of the SSP model and to compare the results of the SSP to two alternative models: the OP where travel and scouting times as well as the scouting potentials are modeled as deterministic values and the a TSOP approach where uncertainty only in travel times and visiting times is taken into account.

5.1 Data

For this case study we use the first eight nodes from the benchmark data set ‘Tsiligirides problem 2’ (Tsiligirides 1984). In this data set the nodes are positioned in a rectangular area of 15 by 15 units. The profit values associated to the nodes are 10, 15, 15, 20, 20, 20, 20 and 30. These profit values represent the expected scouting potential of the schools in our case study.

Since the original data set does not contain data uncertainty, additional settings regarding the uncertainty in the travel times will be used as described in Evers et al. (2012b). To represent the expected value of the travel times, we use the Euclidean distance between the nodes. The travel time uncertainty will follow a uniform distribution. Such a distribution helps illustrating the effect of very uncertain situations with respect to the kind of realizations that one can expect. Note that other distributions could also be tested easily by the SAA solution approach. The bounds of the uniform distribution were determined by taking a 15 percent deviation from the expected travel time.

For scouting potential uncertainty, we use a uniform distribution as well. The bounds of the associated interval however, are constructed differently. The uncertainty in the scouting potential cannot only be represented via an equal deviation from the expected scouting potential for every school. For two schools with the same expected scouting potential, historical data could indicate that the deviation from this expected level is larger for one school than the other. In constructing the size of the uncertainty interval, we first consider a 20 percent deviation from the expected scouting potential for each school. Additionally, to model the variation in the size of the uncertainty intervals between schools, we add a random element to each school individually. This random element is drawn from a uniform distribution defined between 0 and 80 percent of the expected scouting potential. Note that in this way the maximum deviation from the expected scouting potential could turn out to be 100 percent.

Finally, the function describing the relation between the realized scouting potential and the realized scouting time needs to be defined. We like to stress that in applications of this model, this relation should be derived based on empirical data. For illustrational purposes we use the following simple linear relation between the scouting potential and the scouting time, combined with an additional random term:

$$v_i = f\left(p_i, \varepsilon_i\right) = 2 + 0.2 p_i + \varepsilon_i .$$

where the random term ε_i follows a uniform distribution within $\left[-0.15 f(\overline{p_i}, 0); 0.15 f(\overline{p_i}, 0)\right]$. Finally, we set the time limit for the tour to be performed by the scout at 40 time units.

5.2 Experiments

To solve the SSP for the data instance just described, we implemented the SAA solution procedure in Java and performed the optimization with CPLEX 12.1. The MIP is constructed based on $|S|=8$ scenarios. Note that the solution found by the SAA procedure gives an approximation of the SSP objective. That is, the SAA-SSP Objective (9) is an estimation of the real SSP Objective (8). Therefore, in order to better estimate the SSP objective, the resulting SAA tour was evaluated over 10,000 scenarios, independent from the 8 scenarios previously defined to find the solution. Since the SAA solution is feasible for the SSP, but not necessarily optimal, the estimated objective value derived in this way provides an estimate of a lower bound on the actual SSP solution. This whole procedure of solving an MIP based on 8 scenarios and evaluating the associated solution based on 10,000 scenarios was repeated for 10 runs and we will report the best estimated lower bound of the SSP solution found in these 10 runs.

We will compare the SAA solution of the SSP both to the solution of the deterministic OP, and to the solution of a TSOP approach to this problem. For the OP, no uncertainty is taken into account and all parameters are defined by the expected values of the distributions described in the previous subsection. Since in the standard OP and the TSOP a relation between scouting potential and scouting time is not taken into account, we consider the same expected scouting times for all schools. This expected scouting time corresponds to the average scouting time over all schools based on our data assumptions used for the SSP. For the TSOP we take travel and visiting time uncertainty into account and disregard profit uncertainty. Similar to the SSP, in the TSOP we consider uniformly distributed travel times, with bounds set at 15 percent deviation from the expected value. For the scouting time uncertainty in the TSOP, we take a uniform distribution as well, bounded by a 15 percent deviation from the overall expected scouting time. To solve the TSOP, the same SAA solution approach is used as described for the SSP.

When taking the expected value of all parameters in an optimization problem, the resulting solution will use the available capacity to the highest extend possible. In the case of the deterministic OP, this means that the expected duration of the resulting tour is likely to almost fully use the total available time. When evaluating the resulting deterministic solution under data uncertainty, the tour might therefore often turn out to be infeasible. In those cases, this implies that the scout will return to the college campus before he/she has visited all schools in the planned tour. Consequently some of the planned scouting potential will not be obtained. The SSP and the TSOP tours on the other hand, explicitly take into account the effect of not reaching one or more of the final nodes in the planned tour due to travel and visiting time uncertainty.

Similar to the SSP tours evaluation, we will use 10,000 scenarios to evaluate the OP tour and the TSOP tour, and we will report the average unobtainable scouting potential value due to the realizations of the uncertain parameters. We will refer to the average unobtainable scouting potential value over all scenarios as the ‘profit shortage’. On the other hand, we will also consider the situation where low realizations result in left-over time at the end of the deterministic tour. In that case we consider the possibility of adding schools after the final school of the initial tour according to the agile strategy described by Evers et al. (2012a). We will refer to the average of this additionally obtained scouting potential value over all scenarios as ‘profit surplus’. Note that such a surplus will not be attained for the solution of the SSP and the TSOP, due to its problem formulation. Recall that adding schools to an existing solution does not decrease the objective value of the TSOP and the SSP and therefore the resulting tours will be relatively long. To compare the results fairly, we use the same 10,000 scenarios to evaluate each solution.

5.3 Results

Table 1 contains the results for the best SSP tour and the best TSOP tour found in the associated 10 SAA runs, as well as the results for the tour found by the deterministic OP. The three models each result in a different tour. The 'average total profit' value denotes the average scouting potential of all schools in the tour over the 10,000 scenarios. However, due to the uncertainty, not all schools in these tours can be visited in every scenario. The resulting average scouting potential of the schools that could not be visited is reported in the next column 'profit shortage'. As mentioned in the previous subsection, for the deterministic OP tour, we include the possibility of extending the tour with additional schools if possible. The average additional scouting potential obtained in that way is given in the column 'profit surplus'. The 'expected profit' is the result of the average profit of all schools in the tour, reduced by the profit shortage, and increased by the profit surplus.

	Tour (by index)	**Expected profit**	**Average total profit**	**Profit shortage**	**Profit surplus**
OP tour	3,2,4,5	72.88	79.81	9.31	2.38
TSOP tour	1,2,3,5,6	73.50	94.85	21.36	0
SSP tour	1,2,4,5,6,8	77.78	99.86	22.08	0

Table 1: results for the SSP, the TSOP and the deterministic tour, evaluated over the same 10,000 scenarios of realizations of the uncertain parameters, rounded to two decimals.

As shown in Table 1, the average profit value of the SSP tour and the TSOP tour is quite large compared to the average profit value of the OP tour. This can be explained by the SPP and TSOP problem formulations that yield tours with a relatively large number of schools. Therefore, the sum of the simulated values of the scouting potential of these schools is higher than for the tour obtained for the deterministic OP. This effect is to some extent corrected by the profit shortage. But still, the expected scouting potential of the SSP tour far exceeds the expected scouting potential of the other two tours, since it takes into account all uncertainties of the problem, the relation between these uncertainties, and the effect that these uncertainties have on to eventual scouting potential to be obtained.

Furthermore, the average tour duration of the OP tour is 39.81. As expected, this deterministic solution turned out to be very close to the available capacity of 40 units. Consequently, in 47% of all scenarios the scouting potential value of one or more of the schools of the planned tour turned out to be unobtainable due to a large realized tour duration.

Concluding, this case study illustrates the benefits the SSP formulation over the use of either a deterministic or a TSOP approach by incorporating the effect of uncertainty in travel and scouting times as well as in the values of the scouting potential, already in the modeling stage.

6. Conclusions

Sport scouting is an important issue in human resources sport management. In this paper we addressed the planning of the scouting tour in the most effective way. The deterministic approach to this problem corresponds to the Orienteering Problem (OP). However, in reality several uncertainties play a role. Not only are the times required to travel between schools and the times required to scout uncertain, but also the potential of the sports players is yet to be determined by the scout. Therefore, we introduce a more realistic extension of the OP: the Stochastic Scouting Problem (SSP). Since previous research on related problems focusses only on incorporating uncertainty either in the travel and visiting times or in the values that would model the scouting potential of the schools, we developed a separate approach to fit the reality of the SSP, based on one of the available models from the literature: the Two-Stage Orienteering problem (TSOP). Our model of the SSP not only considers uncertainty in all of the input parameters of the problem, but it also takes into account a relation between the potential of the sports player at a school and the remaining time that the scout will stay at the school. Using a case study we show that this model performs much better than a deterministic model and a TSOP approach with respect to the expected scouting potential that will be achieved.

This model is also suitable to other applications, like the tourist tour planning problem. In this problem a tourist encounters uncertain travel times between sightseeing locations, and the satisfaction that the tourist will get from visiting the locations, is uncertain beforehand as well. In this example it is also reasonable to assume that a relation exists between profit value and visiting time. When a sightseeing location is more beautiful than the tourist expected, the tourist might decide to stay at the location longer than planned.

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