Robust Discrete Optimization

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Abstract

We propose an approach to address data uncertainty for discrete optimization problems that allows controlling the degree of conservatism of the solution, and is computationally tractable both practically and theoretically. When both the cost coefficients and the data in the constraints of an integer programming problem are subject to uncertainty, we propose a robust integer programming problem of moderately larger size that allows to control the degree of conservatism of the solution in terms of probabilistic bounds on constraint violation. When only the cost coefficients are subject to uncertainty and the problem is a $0-1$ discrete optimization problem on n variables, then we solve the robust counterpart by solving $n+1$ instances of the original problem. Thus, the robust counterpart of a polynomially solvable $0-1$ discrete optimization problem remains polynomially solvable. Moreover, we show that the robust counterpart of an NP-hard α-approximable $0-1$ discrete optimization problem, remains α-approximable.

1 Introduction

Addressing data uncertainty in mathematical programming models has long been recognized as a central problem in optimization. There are two principal methods that have been proposed to address data uncertainty over the years: (a) stochastic programming, and (b) robust optimization.

As early as the mid 1950s, Dantzig [7] introduced stochastic programming as an approach to model data uncertainty by assuming scenarios for the data occurring with different probabilities. The two main difficulties with such an approach are: (a) Knowing the exact distribution for the data, and thus enumerating scenarios that capture this distribution is rarely satisfied in practice, and (b) the size of the resulting optimization model increases drastically as a function of the number of scenarios, which poses substantial computational challenges.

In recent years a body of literature is developing under the name of robust optimization, in which we optimize against the worst instances that might arise by using a min-max objective. Mulvey et al. [12] present an approach that integrates goal programming formulations with scenario-based description of the problem data. Soyster, in the early 1970s, [13] proposes a linear optimization model to construct a solution that is feasible for all input data such that each uncertain input data can take any value from an interval. This approach, however, tends to find solutions that are over-conservative. Ben-Tal and Nemirovski [2, 3, 4] and El-Ghaoui et al. [9, 10] address the over-conservatism of robust solutions by allowing the uncertainty sets for the

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data to be ellipsoids, and propose efficient algorithms to solve convex optimization problems under data uncertainty. However, as the resulting robust formulations involve conic quadratic problems (see [3]), such methods cannot be directly applied to discrete optimization.

In this research we propose a new approach for robust linear optimization that retains the advantages of the linear framework of Soyster [13]. More importantly, our approach offers full control on the degree of conservatism for every constraint. We protect against violation of constraint i deterministically, when only a prespecified number Γ_i of the coefficients changes, that is we guarantee that the solution is feasible if less than Γ_i uncertain coefficients change. Moreover, we provide a probabilistic guarantee that even if more than Γ_i change, then the robust solution will be feasible with high probability. In the process we prove a new, to the best of our knowledge, tight bound on sums of symmetrically distributed random variables. In this way, the proposed framework is at least as flexible than the one proposed by Ben-Tal and Nemirovski [2, 3, 4] and El-Ghaoui et al. [9, 10] and possibly more. Unlike these approaches, the robust counterparts we propose are linear optimization problems, and thus our approach readily generalizes to discrete optimization problems.

Specifically for discrete optimization problems, Kouvelis and Yu [11] propose a framework for robust discrete optimization, which seeks to find a solution that minimizes the worst case performance under a set of scenarios for the data. Unfortunately, under their approach, the robust counterpart of many polynomially solvable discrete optimization problems becomes *NP-hard.* A related objective is the minimax-regret approach, which seeks to minimize the worst case loss in objective value that may occur. Again, under the minimax-regret notion of robustness, many of the polynomially solvable discrete optimization problems become NP-hard. Under the minimax-regret robustness approach, Averbakh [1] showed that polynomial solvability is preserved for a specific discrete optimization problem (optimization over a uniform matroid) when each cost coefficient can vary within an interval (interval representation of uncertainty); however, the approach does not seem to generalize to other discrete optimization problems.

Our goal in this paper is to propose an approach to address data uncertainty for discrete optimization problems that has the following features:

(a) It allows to control the degree of conservatism of the solution;

(b) It is computationally tractable both practically and theoretically.

Specifically, our contributions include:

(a) When both the cost coefficients and the data in the constraints of an integer programming problem are subject to uncertainty, we propose a robust integer programming problem of moderately larger size that allows to control the degree of conservatism of the solution in terms of probabilistic bounds on constraint violation.

(b) When only the cost coefficients are subject to uncertainty and the problem is a $0-1$ discrete optimization problem on n variables, then we solve the robust counterpart by solving $n+1$ nominal problems. Thus, we show that the robust counterpart of a polynomially solvable $0-1$ discrete optimization problem remains polynomially solvable. In particular, robust matching, spanning tree, shortest path, matroid intersection, etc. are polynomially solvable. Moreover, we show that the robust counterpart of an NP-hard α-approximable $0-1$ discrete optimization problem, remains α-approximable.

Structure of the paper. In Section 2, we present the general framework and formulation of robust discrete optimization problems. We also show that the proposed robust formulation has attractive probabilistic and deterministic guarantees. In Section 3, we propose an efficient algorithm for solving robust combinatorial optimization problems. In Section 4, we show that the robust counterpart of an NP-hard $0-1$ α-approximable discrete optimization problem remains α-approximable.

In Section 5, we present some experimental findings relating to the computation speed and the quality of robust solutions. Finally, Section 6 contains some remarks with respect to the practical applicability of the proposed methods.

2 Robust Formulation of Discrete Optimization Problems

Let $\boldsymbol{c}$, $\boldsymbol{l}$, $\boldsymbol{u}$ be n-vectors, let $\boldsymbol{A}$ be an $m \times n$ matrix, and $\boldsymbol{b}$ be an m-vector. We consider the following nominal mixed integer programming (MIP) on a set of n variables, the first k of which are integers:

$$\begin{aligned} \min \quad & \boldsymbol{c}'\boldsymbol{x} \\ \text{s.t.} \quad & \boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{b} \\ & \boldsymbol{l} \leq \boldsymbol{x} \leq \boldsymbol{u} \\ & x_i \in \mathcal{Z}, \qquad i = 1, \ldots, k, \end{aligned} \tag{1}$$

We assume without loss of generality that data uncertainty affects only the elements of the matrix $\boldsymbol{A}$ and $\boldsymbol{c}$, but not the vector $\boldsymbol{b}$, since in this case we can introduce a new variable x_{n+1}, and write $\boldsymbol{A}\boldsymbol{x} - \boldsymbol{b}x_{n+1} \leq \boldsymbol{0}$, $\boldsymbol{l} \leq \boldsymbol{x} \leq \boldsymbol{u}, 1 \leq x_{n+1} \leq 1$, thus augmenting $\boldsymbol{A}$ to include $\boldsymbol{b}$.

In typical applications, we have reasonable estimates for the mean value of the coefficients a_{ij} and its range $\hat{a}_{ij}$. We feel that it is unlikely that we know the exact distribution of these coefficients. Similarly, we have estimates for the cost coefficients c_j and an estimate of its range d_j. Specifically, the model of data uncertainty we consider is as follows:

Model of Data Uncertainty U:

(a) **(Uncertainty for matrix $\boldsymbol{A}$)**: Let $J_i, i = 1, \ldots, m$ be the set of coefficients of row i of $\boldsymbol{A}$ that are subject to uncertainty. Each entry a_{ij}, $j \in J_i$ is modelled as independent, symmetric and bounded random variable (but with unknown distribution) $\tilde{a}_{ij}, j \in J_i$ that takes values in $[a_{ij} - \hat{a}_{ij}, a_{ij} + \hat{a}_{ij}]$.

(b) **(Uncertainty for cost vector $\boldsymbol{c}$)**: Let J_0 be the set of coefficients in $\boldsymbol{c}$ that are subject to uncertainty. Each entry c_j, $j \in J_0$ takes values in $[c_j, c_j + d_j]$, where d_j represents the deviation from the nominal cost coefficient, c_j.

Note that the only assumption that we place on the distribution of the coefficients a_{ij} is that it is symmetric.

2.1 Robust MIP Formulation

For robustness purposes, for every i, we introduce a number Γ_i, $i = 0, 1, \ldots, m$ that takes values in the interval $[0, |J_i|]$. Γ_0 is assumed to be integer, while Γ_i, $i = 1, \ldots, m$ are not necessarily integers.

The role of the parameter Γ_i in the constraints is to adjust the robustness of the proposed method against the level of conservativeness of the solution. Consider the ith constraint of the nominal problem $\boldsymbol{a}_i'\boldsymbol{x} \leq b_i$. Let J_i be the set of coefficients a_{ij}, $j \in J_i$ that are subject to parameter uncertainty, i.e., $\tilde{a}_{ij}$, $j \in J_i$ independently takes values according to a symmetric distribution with mean equal to the nominal value a_{ij} in the interval $[a_{ij} - \hat{a}_{ij}, a_{ij} + \hat{a}_{ij}]$. Speaking intuitively, it is unlikely that all of the a_{ij}, $j \in J_i$ will change. Our goal is to be protected against all cases that up to $\lfloor \Gamma_i \rfloor$ of these coefficients are allowed to change, and one coefficient a_{it} changes from $(\Gamma_i - \lfloor \Gamma_i \rfloor)\hat{a}_{it}$. In other words, we stipulate that nature will be restricted in its behavior, in that only a subset of the coefficients will change in order to adversely affect the solution. We will then guarantee that if nature behaves like this then the robust solution will be feasible deterministically. We will also show that, essentially because the distributions we allow are symmetric, even if more than $\lfloor \Gamma_i \rfloor$ change, then the robust solution will be feasible with very high probability. Hence, we call Γ_i the protection level for the ith constraint.

The parameter Γ_0 orchestrating the level of robustness in the objective serves a different purpose from those parameters in the constraints, as it does not affect the feasibility of the problem. We are interested in finding an optimal solution that optimizes against all scenarios under which a number Γ_0 of the cost coefficients can vary in such a way as to maximally influence the objective. If $\Gamma_0 = 0$, we completely ignore the influence of the cost deviations, while if $\Gamma_0 = |J_0|$, we are considering all possible cost deviations, which is indeed most conservative. In general a higher value of Γ_0 increases the level of robustness at the expense of higher nominal cost.

Specifically, the proposed robust counterpart of Problem (1) is as follows:

$$\begin{aligned} \min \quad & \boldsymbol{c}'\boldsymbol{x} + \max_{\{S_0|\ S_0 \subseteq J_0, |S_0| = \Gamma_0\}} \left\{ \sum_{j \in S_0} d_j |x_j| \right\} \\ \text{s.t.} \quad & \sum_j a_{ij} x_j + \max_{\{S_i \cup \{t_i\}|\ S_i \subseteq J_i, |S_i| = \lfloor \Gamma_i \rfloor, t_i \in J_i \setminus S_i\}} \\ & \left\{ \sum_{j \in S_i} \hat{a}_{ij} |x_j| + (\Gamma_i - \lfloor \Gamma_i \rfloor) \hat{a}_{it_i} |x_{t_i}| \right\} \le b_i, \quad \forall i \\ & \boldsymbol{l} \le \boldsymbol{x} \le \boldsymbol{u} \\ & x_i \in \mathcal{Z}, \qquad \forall i = 1, \ldots k. \end{aligned} \tag{2}$$

Problem (2) can be reformulated as another MIP.

Theorem 1 *Problem (2) has an equivalent MIP formulation as follows:*

$$\begin{aligned} \min \quad & \boldsymbol{c}'\boldsymbol{x} + z_0 \Gamma_0 + \textstyle\sum_{j \in J_0} p_{0j} \\ \text{s.t.} \quad & \sum_j a_{ij} x_j + z_i \Gamma_i + \sum_{j \in J_i} p_{ij} \le b_i & \forall i \\ & z_0 + p_{0j} \ge d_j y_j & \forall j \in J_0 \\ & z_i + p_{ij} \ge \hat{a}_{ij} y_j & \forall i \ne 0, j \in J_i \\ & p_{ij} \ge 0 & \forall i, j \in J_i \\ & y_j \ge 0 & \forall j \\ & z_i \ge 0 & \forall i \\ & -y_j \le x_j \le y_j & \forall j \\ & l_j \le x_j \le u_j & \forall j \\ & x_i \in \mathcal{Z} & i = 1, \ldots, k. \end{aligned} \tag{3}$$

While the original Problem (1) involves n variables and m constraints, its robust counterpart Problem (3) has $2n + m + l$ variables, where $l = \sum_{i=0}^{m} |J_i|$ is the number of uncertain coefficients, and $2n + m + l$ constraints.

As we discussed, if less than $\lfloor \Gamma_i \rfloor$ coefficients a_{ij}, $j \in J_i$ participating in the ith constraint vary, then the robust solution will be feasible deterministically. We next show that even if more than $\lfloor \Gamma_i \rfloor$ change, then the robust solution will be feasible with very high probability.

Theorem 2 *Let $\boldsymbol{x}^*$ be an optimal solution of Problem (3).* **(a)** *Suppose that the data in matrix $\boldsymbol{A}$ are subject to the model of data uncertainty U, the probability that the ith constraint is violated satisfies:*

$$\begin{aligned} & \Pr\left(\textstyle\sum_j \tilde{a}_{ij} x_j^* > b_i \right) \le B(n, \Gamma_i) \\ & = \tfrac{1}{2^n} \left\{ (1 - \mu) \textstyle\sum_{l = \lfloor \nu \rfloor}^{n} \binom{n}{l} + \mu \sum_{l = \lfloor \nu \rfloor + 1}^{n} \binom{n}{l} \right\}, \end{aligned} \tag{4}$$

where $n = |J_i|$, $\nu = \frac{\Gamma_i + n}{2}$ and $\mu = \nu - \lfloor \nu \rfloor$. Moreover, the bound is tight.
(b) *For $\Gamma_i = \theta \sqrt{n}$,*

$$\lim_{n \to \infty} B(n, \Gamma_i) = 1 - \Phi(\theta), \tag{5}$$

where

$$\Phi(\theta) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\theta} \exp\left(-\frac{y^2}{2} \right) dy$$

is the cumulative distribution function of a standard normal.

Remarks:
(a) The bound (4) is independent of $\boldsymbol{x}^*$.
(b) Eq. (5) is a formal asymptotic theorem that applies when $\Gamma_i = \theta\sqrt{n}$. We can use the De Moivre-Laplace approximation of the Binomial distribution to obtain the approximation

$$B(n, \Gamma_i) \approx 1 - \Phi\left(\frac{\Gamma_i - 1}{\sqrt{n}} \right), \tag{6}$$

that applies, even when Γ_i does not scale as $\theta\sqrt{n}$.
(c) We make no theoretical claims regarding suboptimality given that we made no probabilistic assumptions on the cost coefficients. In Section 5.1, we apply these bounds in the context of the zero-one knapsack problem.

Note that in order to guarantee that the probability that the ith constraint is violated is less than 1%, we need to select Γ_i such that $\frac{\Gamma_i - 1}{\sqrt{n}} \approx 2.326$. Table 1 illustrates the choice of Γ_i as a function of $|J_i|$ so that the probability of violating the constraint is less than 1%. For $|J_i| = 200$, we need to use $\Gamma_i = 33.89$, i.e., only 17% of the number of uncertain data, to guarantee

$\lvert J_i \rvert$	Γ_i
5	5
10	8.3565
100	24.263
200	33.899

Table 1: Choice of Γ_i as a function of $|J_i|$ so that the probability of constraint violation is less than 1%.

violation probability of less than 1%. For constraints with fewer number of uncertain data such as $|J_i| = 5$, it is necessary to ensure full protection. Therefore, for constraints with large number of uncertain data, the proposed approach is capable of delivering less conservative solutions compared to having full protection.

3 Robust Combinatorial Optimization

Combinatorial optimization is an important class of discrete optimization whose decision variables are binary, that is $\boldsymbol{x} \in \{0,1\}^n$. Let X be the set of feasible $0-1$ vectors representing the set of feasible solutions. The nominal combinatorial optimization problem is:

$$\begin{aligned} \min \quad & \boldsymbol{c}'\boldsymbol{x} \\ \text{s.t.} \quad & \boldsymbol{x} \in X. \end{aligned} \tag{7}$$

We are interested in the class of problems where each entry $\tilde{c}_j,\ j \in J \subseteq N = \{1, 2, \dots, n\}$ takes values in $[c_j, c_j + d_j]$, $c_j \geq 0, j \in N$ and $d_j > 0, j \in J$. We would like to find a solution $\boldsymbol{x} \in X$ that minimizes the maximum cost $\boldsymbol{c}'\boldsymbol{x}$ such that Γ of the $|J| = r$ coefficients $\tilde{c}_j$ are allowed to change:

$$\begin{aligned} Z^* = \quad \min \quad & \boldsymbol{c}'\boldsymbol{x} + \max_{\{S|\ S \subseteq J, |S| = \Gamma\}} \sum_{j \in S} d_j x_j \\ \text{s.t.} \quad & \boldsymbol{x} \in X, \end{aligned} \tag{8}$$

Without loss of generality, we let $J = \{1, \dots, r\}$ and the indices are sorted such that $d_1 \geq d_2 \geq \dots \geq d_n$. Examples of such problems include the shortest path, the minimum spanning tree, the minimum assignment, the travelling salesman, the vehicle routing and matroid intersection problems. Data uncertainty in the context of the vehicle routing problem for example, captures the variability of travel times in some of links of the network.

In the context of scenario based uncertainty, finding an optimally robust solution involves solving the problem (for the case that only two scenarios for the cost vectors $\boldsymbol{c_1}$, $\boldsymbol{c_2}$ are known):

$$\begin{aligned} \min \quad & \max(\boldsymbol{c_1}'\boldsymbol{x}, \boldsymbol{c_2}'\boldsymbol{x}) \\ \text{s.t.} \quad & \boldsymbol{x} \in X. \end{aligned}$$

For many classical combinatorial problems (for example the shortest path problem), finding such a robust solution is NP-hard, even if minimizing $\boldsymbol{c_i}'\boldsymbol{x}$ subject to $\boldsymbol{x} \in X$ is polynomially solvable (Kouvelis and Yu [11]).

Clearly the robust counterpart of an NP-hard combinatorial optimization problem is NP-hard. We next show that surprisingly, the robust counterpart of a polynomially solvable combinatorial optimization problem is also polynomially solvable.

3.1 Algorithm for Robust Combinatorial Optimization Problems

In this section, we show that we can solve Problem (8) by solving at most $n+1$ nominal problems $\min \boldsymbol{f}_i'\boldsymbol{x}$, subject to $\boldsymbol{x} \in X$, for $i = 1, \dots, n+1$.

Theorem 3 *Problem (8) can be solved by solving the $n+1$ nominal problems:*

$$Z^* = \min_{l=1,\dots,n+1} G^l, \tag{9}$$

where for $l = 1, \dots, n+1$:

$$\begin{aligned} G^l = \Gamma d_l + \min \quad & \left(\boldsymbol{c}'\boldsymbol{x} + \sum_{j=1}^{l} (d_j - d_l)\, x_j \right) \\ \text{subject to} \quad & \boldsymbol{x} \in X. \end{aligned} \tag{10}$$

Theorem 3 leads to the following algorithm.

Algorithm A

1. For $l = 1, \ldots, n+1$ solve the $n+1$ nominal problems Eqs. (10):

$$G^l = \Gamma d_l + \min_{\mathbf{x} \in X} \left(\boldsymbol{c}'\boldsymbol{x} + \sum_{j=1}^{l} (d_j - d_l) x_j \right),$$

and let $\boldsymbol{x}^l$ be an optimal solution of the corresponding problem.

2. Let $l^* = \arg \min_{l=1,\ldots,n+1} G^l$.

3. $Z^* = G^{l^*}$; $\boldsymbol{x}^* = \boldsymbol{x}^{l^*}$.

Note that Z^l is not in general equal to G^l. If f is the number of distinct values among $d_1, \ldots, d_n$, then it is clear that Algorithm A solves $f+1$ nominal problems, since if $d_l = d_{l+1}$, then $G^l = G^{l+1}$. In particular, if all $d_j = d$ for all $j = 1, \ldots, n$, then Algorithm A solves only two nominal problems. Thus, if τ is the time to solve one nominal problem, Algorithm A solves the robust counterpart in $(f+1)\tau$ time, thus preserving the polynomial solvability of the nominal problem. In particular, Theorem 3 implies that the robust counterpart of many classical 0-1 combinatorial optimization problems like the minimum spanning tree, the minimum assignment, minimum matching, shortest path and matroid intersection, are polynomially solvable.

4 Approximation Algorithms

In this section, we show that if the nominal combinatorial optimization problem (7) has an α-approximation polynomial time algorithm, then the robust counterpart Problem (8) with optimal solution value Z^* is also α-approximable. Specifically, we assume that there exists a polynomial time Algorithm H for the nominal problem (7), that returns a solution with an objective Z_H: $Z \leq Z_H \leq \alpha Z$, $\alpha \geq 1$.

The proposed algorithm for the robust Problem (8) is to utilize Algorithm H in Algorithm A, instead of solving the nominal instances exactly. The proposed algorithm is as follows:

Algorithm B

1. For $l = 1, \ldots, n+1$ find an α-approximate solution $\boldsymbol{x}_H^l$ using Algorithm H for the nominal problem:

$$G^l - \Gamma d_l = \min_{\mathbf{x} \in X} \left(\boldsymbol{c}'\boldsymbol{x} + \sum_{j=1}^{l} (d_j - d_l) x_j \right). \quad (11)$$

2. For $l = 1, \ldots, n+1$, let

$$Z_H^l = \boldsymbol{c}'\boldsymbol{x}_H^l + \max_{\{S \mid \, S \subseteq N, |S| \leq \Gamma\}} \sum_{j \in S} d_j (\boldsymbol{x}_H^l)_j.$$

3. Let $l^* = \arg \min_{l=1,\ldots,n+1} Z_H^l$.

4. $Z_B = Z_H^{l^*}$; $\boldsymbol{x}^B = \boldsymbol{x}_H^{l^*}$.

Theorem 4 *Algorithm B yields a solution $\boldsymbol{x}^B$ with an objective value Z_B that satisfies:*

$$Z^* \leq \; Z_B \leq \; \alpha Z^*.$$

Note that Algorithm A is a special case of Algorithm B for $\alpha = 1$. Note that it is critical to have an α-approximation algorithm for all nominal instances (11). In particular, if the nominal problem is the travelling salesman problem under triangle inequality, which can be approximated within $\alpha = 3/2$, Algorithm B is not an α-approximation algorithm for the robust counterpart, as the instances (11) may not satisfy the triangle inequality.

5 Experimental Results

In this section we consider concrete discrete optimization problems and solve the robust counterparts.

5.1 The Robust Knapsack Problem

The zero-one nominal knapsack problem is:

$$\begin{array}{rl} \max & \sum_{i \in N} c_i x_i \\ \text{s.t.} & \sum_{i \in N} w_i x_i \leq b \\ & \boldsymbol{x} \in \{0,1\}^n. \end{array}$$

We assume that the weights $\tilde{w}_i$ are uncertain, independently distributed and follow symmetric distributions in

Γ	Violation Prob.	Optimal Val.	Reduction
0	0.5	5592	0%
2.8	4.49×10^{-1}	5585	0.13%
36.8	5.71×10^{-3}	5506	1.54%
82.0	5.04×10^{-9}	5408	3.29%
200	0	5283	5.50%

Table 2: Robust Knapsack Solutions.

$[w_i - \delta_i, w_i + \delta_i]$. The objective value vector $\boldsymbol{c}$ is not subject to data uncertainty. An application of this problem is to maximize the total value of goods to be loaded on a cargo that has strict weight restrictions. The weight of the individual item is assumed to be uncertain, independent of other weights and follows a symmetric distribution. In our robust model, we want to maximize the total value of the goods but allowing a maximum of 1% chance of constraint violation. Problem (2) is as follows:

$$\begin{aligned} \max \quad & \sum_{i \in N} c_i x_i \\ \text{s.t.} \quad & \sum_{i \in N} w_i x_i + \max_{\{S \cup \{t\} \mid \, S \subseteq N, |S| = \lfloor \Gamma \rfloor, t \in N \setminus S\}} \\ & \left\{ \sum_{j \in S} \delta_j x_j + (\Gamma - \lfloor \Gamma \rfloor) \delta_t x_t \right\} \leq b \\ & \boldsymbol{x} \in \{0,1\}^n. \end{aligned}$$

For this experiment, we solve Problem (3) using CPLEX 7.0 for a random knapsack problem of size, $|N| = 200$. We set the capacity limit, b to 4000, the nominal weight, w_i being randomly chosen from the set $\{20, \ldots, 29\}$ and the cost c_i randomly chosen from the set $\{16, \ldots, 77\}$. We set the weight uncertainty δ_i to equal 10% of the nominal weight. The time to solve the robust discrete problems to optimality using CPLEX 7.0 on a Pentium II 400 PC ranges from 0.05 to 50 seconds.

Under zero protection level, $\Gamma = 0$, the optimal value is $5,592$. However, with full protection, $\Gamma = 200$, the optimal value is reduced by 5.5% to $5,283$. In Table 2, we present a sample of the objective function value and the probability bound of constraint violation computed from Eq. (4). It is interesting to note that the optimal value is marginally affected when we increase the protection level. For instance, to have a probability guarantee of at most 0.57% chance of constraint violation, we only reduce the objective by 1.54%. It appears that in this example we do not heavily penalize the objective function value in order to protect ourselves against constraint violation.

5.2 Robust Sorting

We consider the problem of minimizing the total cost of selecting k items out of a set of n items that can be expressed as the following integer programming problem:

$$\begin{aligned} \min \quad & \sum_{i \in N} c_i x_i \\ \text{s.t.} \quad & \sum_{i \in N} x_i = k, \quad \boldsymbol{x} \in \{0,1\}^n. \end{aligned} \tag{12}$$

In this problem, the cost components are subjected to uncertainty. If the model is deterministic, we can easily solve the problem in $O(n \log n)$ by sorting the costs in ascending order and choosing the first k items. However, under the influence of data uncertainty, we will illustrate empirically that the deterministic model could lead to large deviations when the cost components are subject to uncertainty. Under our proposed Problem (8), we solve the following problem,

$$\begin{aligned} Z^*(\Gamma) = \quad \min \quad & \boldsymbol{c'x} + \max_{\{S \mid \, S \subseteq J, |S| = \Gamma\}} \sum_{j \in S} d_j x_j \\ \text{s.t.} \quad & \sum_{i \in N} x_i = k \\ & \boldsymbol{x} \in \{0,1\}^n. \end{aligned} \tag{13}$$

We experiment with a problem of size $|N| = 200$ and $k = 100$. The cost and deviation components, c_j and d_j are uniformly distributed in $[50, 200]$ and $[20, 200]$ respectively. Since only k items will be selected, the robust solution for $\Gamma > k$ is the same as when $\Gamma = k$. Hence, Γ takes integral values from $[0, k]$. By varying Γ, we will illustrate empirically that we can control the deviation of the objective value under the influence of cost uncertainty.

Γ	$\bar{Z}(\Gamma)$	% $\bar{Z}(\Gamma)$	$\sigma(\Gamma)$	% $\sigma(\Gamma)$
0	8822	0 %	501.0	0.0 %
20	8923	1.145 %	471.9	-5.8 %
40	9627	9.125 %	396.3	-20.9 %
60	10146	15.00 %	365.7	-27.0 %
80	10619	20.37 %	342.5	-31.6 %
100	10619	20.37 %	340.1	-32.1 %

Table 3: Influence of Γ on $\bar{Z}(\Gamma)$ and $\sigma(\Gamma)$.

We solve Problem (13) in two ways. First using Algorithm A, and second solving Problem (3):

$$\begin{aligned}
\min \quad & \boldsymbol{c}'\boldsymbol{x} + z\Gamma + \sum_{j\in N} p_j \\
\text{s.t.} \quad & z + p_j \geq d_j x_j \qquad \forall j \in N \\
& \sum_{i\in N} x_i = k \\
& z \geq 0,\ p_j \geq 0,\ \boldsymbol{x} \in \{0,1\}^n.
\end{aligned} \tag{14}$$

Algorithm A was able to find the robust solution for all $\Gamma \in \{0, \ldots k\}$ in less than a second. The typical running time using CPLEX 7.0 to solve Problem (14) for only one of the Γ ranges from 30 to 80 minutes, which underscores the effectiveness of Algorithm A.

We let $\boldsymbol{x}(\Gamma)$ be an optimal solution to the robust model, with parameter Γ and define $\bar{Z}(\Gamma) = \boldsymbol{c}'\boldsymbol{x}(\Gamma)$ as the nominal cost in the absence of any cost deviations. To analyze the robustness of the solution, we simulate the distribution of the objective by subjecting the cost components to random perturbations. Under the simulation, each cost component independently deviates with probability ρ from the nominal value c_j to $c_j + d_j$. In Table 3, we report $\bar{Z}(\Gamma)$ and the standard deviation $\sigma(\Gamma)$ found in the simulation for $\rho = 0.2$.

Table 3 suggests that as we increase Γ, the standard deviation of the objective, $\sigma(\Gamma)$ decreases, implying that the robustness of the solution increases, and $\bar{Z}(\Gamma)$ increases. Varying Γ we can find the tradeoff between the variability of the objective and the increase in nominal cost.

5.3 The Robust Shortest Path Problem

The shortest path problem surfaces in many important problems and has a wide range of applications from logistics planning to telecommunications. In these applications, the arc costs are estimated and subjected to uncertainty. Using Dijkstra's algorithm [8], the shortest path problem can be solved in $O(|\mathcal{N}|^2)$, while Algorithm A runs in $O(|\mathcal{A}||\mathcal{N}|^2)$. In order to test the performance of Algorithm A, we construct a randomly generated digraph with $|\mathcal{N}| = 300$ and $|\mathcal{A}| = 1475$ as shown in Figure 1. The starting node, s is at the origin $(0,0)$ and the terminal node t is placed in coordinate $(1,1)$. The nominal arc cost, c_{ij} equals to the Euclidean distance between the adjacent nodes $\{i,j\}$ and the arc cost deviation, d_{ij} is set to γc_{ij}, where γ is uniformly distributed in $[0,8]$. Hence, some of the arcs have cost deviations of at most eight times of their nominal values. Using Algorithm A (calling Dijkstra's algorithm $|\mathcal{A}|+1$ times), we solve for the complete set of robust shortest paths (for various Γ's), which are drawn in bold in Figure 1.

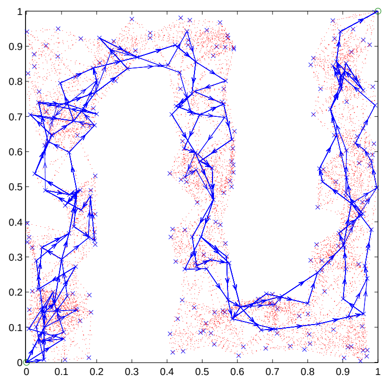

Figure 1: Randomly generated digraph and the set of robust shortest $\{s,t\}$ paths for various Γ values.

We simulate the distribution of the path cost by subjecting the arc cost to random perturbations. In each instance of the simulation, every arc (i,j) has cost that is independently perturbed, with probability ρ, from its nominal value c_{ij} to $c_{ij} + d_{ij}$. Setting $\rho = 0.1$, we generate 20,000 random scenarios and plot the distributions of the path cost for $\Gamma = 0, 3, 6$ and 10, which are shown in Figure 2. We observe that as Γ increases, the nominal

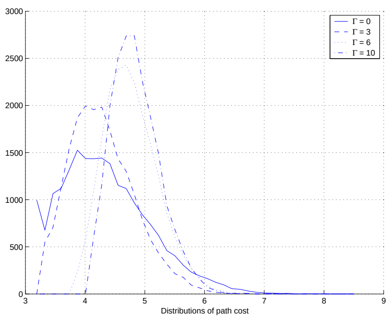

Figure 2: Influence of Γ on the distribution of path cost for $\rho = 0.1$.

path cost also increases, while cost variability decreases.

6 Conclusions

Unlike all other approaches that create robust solutions for combinatorial optimization problems, the proposed approach retains the complexity of the nominal problem or its approximability guarantee and offers the modeler the capability to control the tradeoff between cost and robustness by varying a single parameter Γ. For arbitrary discrete optimization problems, the increase in problem size is still moderate, and thus the proposed approach has the potential of being practically useful.

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