Recoverable Robust Single Machine Scheduling with Budgeted Uncertainty

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Abstract

This paper considers a recoverable robust single-machine scheduling problem under continuous budgeted uncertainty with the objective of minimising the total flow time. In this setting, a decision-maker must determine a first-stage schedule subject to the uncertain job processing times, and then following the realisation of these processing times, can swap the positions of up to $\Delta$ disjoint pairs of jobs to obtain a second-stage schedule.

We first formulate this scheduling problem using a general recoverable robust framework, before we examine the incremental subproblem in further detail. We prove a general result for max-weight matching problems, showing that for edge weights of a specific form, the matching polytope can be fully characterised by polynomially many constraints. We use this result to derive a matching-based compact formulation for the full problem. Further analysis of the incremental problem leads to an additional assignment-based compact formulation. Computational results compare the relative strengths of the three compact models we propose.

Keywords: scheduling; robust optimization; recoverable robustness; budgeted uncertainty

1. Introduction

We consider a scheduling problem where $n$ jobs must be scheduled on a single machine without preemption, such that the total flow time, i.e. the sum of completion times, is minimised. This problem is denoted as $1||\sum C_i$ under the $\alpha|\beta|\gamma$ scheduling problem notation introduced by Graham et al. (1979). In practice, job processing times are

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often subject to uncertainty, and when this is the case it is important to find robust solutions that account for this uncertainty. In this paper, we propose a recoverable robust approach (Liebchen et al., 2009) to this uncertain single machine scheduling problem. In this recoverable robust setting, we determine a full solution in a first-stage, before an adversarial player chooses a worst-case scenario of processing times from an uncertainty set, and then in response to this, we allow the first-stage solution to be adjusted in a limited way.

The deterministic single machine scheduling problem (SMSP) is one of the simplest and most studied scheduling problems, and can be solved easily in $O(n \log n)$ time by ordering the jobs according to non-decreasing processing times, i.e. by using the shortest processing time (SPT) rule. However, despite the simplicity of the nominal problem, the robust problem has been shown to be NP-hard for even the most basic uncertainty sets (Daniels and Kouvelis, 1995).

In fact, the majority of research to date regarding robust single machine scheduling has been concerned with the presentation of complexity results for a number of different SMSPs. First discussed by Daniels and Kouvelis (1995), Kouvelis and Yu (1997) and Yang and Yu (2002), these papers study the problem with the total flow time objective, and show that it is NP-hard even in the case of two discrete scenarios, for min-max, regret and relative regret robustness. Robust single machine scheduling for discrete uncertain scenarios has been examined extensively. Aloulou and Della Croce (2008) present algorithmic and complexity results for a number of different SMSPs under min-max robustness. Aissi et al. (2011) show that the problem of minimising the number of late jobs in the worst-case scenario, where processing times are known, but due dates are uncertain is NP-hard. Zhao et al. (2010) consider the objective of minimising the weighted sum of completion times in the worst-case scenario, and propose a cutting-plane algorithm to solve the problem. Mastrolilli et al. (2013) study this same problem and show that no polynomial-time approximation scheme exist for the unweighted version. Kasperski and Zieliński (2016) apply the ordered weighted averaging (OWA) criterion, of which classical robustness is a special case, to a number of different SMSPs under discrete uncertainty. The consideration of SMSPs under novel optimality criteria has been continued most recently by Kasperski and Zieliński (2019), where a number of complexity results are presented for the SMSP with the value at risk (VaR) and conditional value at risk (CVaR) criteria.

Robust single machine scheduling in the context of interval uncertainty has also received considerable attention. Daniels and Kouvelis (1995) address interval uncertainty, and describe some dominance relations between the jobs in an optimal schedule based on their processing time intervals. Kasperski (2005) considers an SMSP with precedence constraints, and where the regret of the maximum lateness of a job is to be minimised. A polynomial-time algorithm is presented. Lebedev and Averbakh (2006) show that the SMSP with the total flow time objective is NP-hard in the case of regret robustness. Montemanni (2007) present a mixed-integer program (MIP) for this same problem, and use it to solve instances involving up to 45 jobs. Kasperski and Zieliński (2008) also consider this problem, and show that it is 2-approximable when the corresponding deterministic problem is polynomially solvable. Lu et al. (2012) present an SMSP with
uncertain job processing and setup times, show this problem is NP-hard, and design a simulated annealing-based algorithm to solve larger instances. Chang et al. (2017) apply distributional robustness to an SMSP, and make use of information about the mean and covariance of the job processing times to minimise the worst-case CVaR. Most recently, Fridman et al. (2020) consider an SMSP with uncertain job processing times and develop polynomial algorithms for solving the min-max regret problem under certain classes of cost functions. For a survey of robust single-machine scheduling in the context of both discrete and interval uncertainty, see Kasperski and Zielinski (2014).

A criticism of classical robustness is that the solutions is provides are overly conservative and hedge against extreme worst-case scenarios that are very unlikely to occur in practice. To reduce the level of conservatism, in this paper we consider a restriction to interval uncertainty introduced by Bertsimas and Sim (2004), known as budgeted uncertainty. Under budgeted uncertainty, the number of jobs that can simultaneously achieve their worst-case processing times is restricted. Robust single machine scheduling under budgeted uncertainty was first considered by Lu et al. (2014), who present an MIP and heuristic to solve the problem. Following this, Tadayon and Smith (2015) study different versions of the min-max robust SMSP under three different uncertainty sets, including a budgeted uncertainty set. Recently, Bougeret et al. (2019) present complexity results and approximation algorithms for a number of different min-max robust scheduling problems under budgeted uncertainty.

To the best of our knowledge, this paper is the first to solve a single-machine scheduling problem in a recoverable robust setting. However, recoverable robustness has had recent application to a number of closely related matching, assignment and scheduling problems. Fischer et al. (2020) consider a recoverable robust assignment problem, in which two perfect matchings of minimum costs must be chosen, subject to these matchings having at least \(k\) edges in common. If the cost of the second matching is evaluated in the worst-case scenario, we arrive in the setting of recoverable robustness as we consider it in this paper. Hardness results are presented, and a polynomial-time algorithm is developed for the restricted case in which one cost function is Monge. Regarding project scheduling, Bendotti et al. (2019) introduce the so-called anchor-robust project scheduling problem in which a baseline schedule is designed under the problem uncertainty, such that the largest possible subset of jobs have their starting times unchanged following the realisation of the activity processing times. This problem is shown to be NP-hard even for budgeted uncertainty. In a series of papers Bruni et al. (2017, 2018); Bold and Goerigk (2020), a two-stage resource-constrained project scheduling problem with budgeted uncertainty is introduced and solved.

The contributions of this paper are as follows. In Section 2 we formally define the recoverable robust scheduling problem that we consider in this paper. In Section 3 we present a general result that enables the construction of compact formulations for a wide range of recoverable robust problems, and apply this in the context the scheduling problem at hand. We then analyse the stages of the recoverable robust scheduling problem in detail and show that the incremental problem can be solved using a simple linear programming formulation in Section 4. To this end, we prove a general result for max-weight matching problems, arguing that odd-cycle constraints are not required in problems with
weights of a specific form. This formulation of the incremental problem then leads to an alternative matching-based compact problem formulation. Additionally, we transfer the matching result to an assignment-based formulation for the incremental problem, which results in a third compact model. In Section 5, computational experiments are presented, showing the benefits of a recourse action, the effects of the uncertainty on the model, and the strength of the assignment-based formulation. Finally, some concluding remarks and potential directions for future research are given in Section 6.

2. Problem definition

We consider a single machine scheduling problem with the objective of minimising the sum of completion times. Given a set of jobs $N = \{1, \ldots, n\}$ with processing times $p = (p_1, \ldots, p_n)$, we aim to find a schedule, i.e. an ordering of the jobs $i \in N$, that minimises the sum of completion times. This nominal problem is denoted by $1||\sum C_i$ under the $\alpha|\beta|\gamma$ scheduling problem notation introduced by Graham et al. (1979). Recall that this problem is easy to solve; the shortest processing time (SPT) rule of sorting jobs by non-decreasing processing times results in an optimal schedule. This problem can be modelled as the following assignment problem with non-general costs:

$$\min \sum_{i \in N} \sum_{j \in N} p_i(n + 1 - j)x_{ij}$$  \hspace{1cm} (1)

$$\text{s.t.} \sum_{i \in N} x_{ij} = 1 \quad \forall j \in N$$  \hspace{1cm} (2)

$$\sum_{j \in N} x_{ij} = 1 \quad \forall i \in N$$  \hspace{1cm} (3)

$$x_{ij} \in \{0, 1\} \quad \forall i, j \in N,$$  \hspace{1cm} (4)

where $x_{ij} = 1$ if job $i$ is scheduled in position $j$, and $x_{ij} = 0$ otherwise.

We assume the job processing times $p_i, i \in N$ are uncertain, but are known to lie within a given uncertainty set $U$. In this paper, we specifically consider the continuous budgeted uncertainty set introduced by Bertsimas and Sim (2004):

$$U = \left\{ p \in \mathbb{R}_+^n : p_i = \hat{p}_i + \delta_i\bar{p}_i, \sum_{i \in N} \delta_i \leq \Gamma, \delta_i \in [0, 1], i \in N \right\}.$$

Each job $i \in N$ has a nominal processing time given by $\hat{p}_i$, but can have a processing time delay of up to $\bar{p}_i$. To prevent unrealistically pessimistic worst-case outcomes, we assume that at most $\Gamma$ jobs can simultaneously reach their maximum delays, i.e., an adversarial player has a budget on the total amount of relative delay that they can allocate to the jobs.

We consider this uncertain single machine scheduling problem in the context of a two-stage decision process, where, having decided on a first-stage schedule $x$ under the problem uncertainty, the decision-maker is given the opportunity to react to the
realisation of the uncertain data by choosing up to \( \Delta \) distinct pairs of jobs and swapping their positions, to obtain a second-stage schedule \( y \).

This recoverable robust problem can be written as follows:

\[
\min_{x \in \mathcal{X}} \max_{p \in \mathcal{U}} \min_{y \in \mathcal{X}(x)} \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}} p_i (n + 1 - j) y_{ij},
\]

where \( \mathcal{X} = \{ x \in \{0, 1\}^{n \times n} : (2), (3) \} \) is the set of feasible schedules, and \( \mathcal{X}(x) \subseteq \mathcal{X} \) is the set of feasible second-stage assignments given \( x \). That is,

\[
\mathcal{X}(x) = \{ y \in \mathcal{X} : d(x, y) \leq \Delta \},
\]

where \( d(x, y) \) is the minimum number of pairwise distinct swaps required to transform \( x \) into \( y \), if this number exists; otherwise, we set it to \( \infty \). Observe that the value \( d(x, y) \) can be calculated using the following approach. Let \( E_x \) be the edges chosen by \( x \) in the corresponding bipartite graph, oriented towards the right, and let \( E_y \) be the edges chosen by \( y \), oriented towards the left, i.e. \((j, i) \in E_y \) corresponds to assigning job \( i \) to position \( j \). If and only if the edges \( E_x \cup E_y \) decompose into 2-cycles and 4-cycles, we have \( d(x, y) < \infty \), in which case \( d(x, y) \) is equal to the number of 4-cycles. This is because a 2-cycle corresponds to a job with an unchanged position, whilst 4-cycles represent a swap of positions of two jobs. An example is given in Figure 1.

![Jobs, i Positions, j](image)

Figure 1.: An example first and second-stage solution. The first-stage assignment is given by the solid arcs oriented towards the right, and corresponds to the schedule \((1,2,4,5,3)\). The second-stage assignment is given by the dashed arcs oriented towards the left, and corresponds to the schedule \((1,4,2,3,5)\). There are two 4-cycles corresponding to the switching of positions of jobs 2 and 4, and 3 and 5. Hence \( d(x, y) = 2 \).

We define the adversarial and incremental problems of (RRS) as follows. Given both a first-stage solution \( x \in \mathcal{X} \) and a scenario \( p \in \mathcal{U} \), the incremental problem consists of
finding the best possible second-stage solution \( y \in \mathcal{X}(x) \). That is,

\[
\text{Inc}(x, p) = \min_{y \in \mathcal{X}(x)} \sum_{i \in N} \sum_{j \in N} p_i (n + 1 - j) y_{ij}.
\]

The adversarial problem is to find a worst-case scenario \( p \in \mathcal{U} \) for a given first-stage schedule \( x \in \mathcal{X} \). That is,

\[
\text{Adv}(x) = \max_{p \in \mathcal{U}} \min_{y \in \mathcal{X}(x)} \sum_{i \in N} \sum_{j \in N} p_i (n + 1 - j) y_{ij} = \max_{p \in \mathcal{U}} \text{Inc}(x, p).
\]

Finally, note that in problem (RRS) we aim to minimise the worst-case costs of the resulting recovery solutions. If the first-stage costs are also relevant, all the results presented in this paper can be adjusted trivially.

### 3. A general model for recoverable robustness

In this section we present a general model for recoverable robust optimisation problems, and apply this method to the uncertain single machine scheduling problem (RRS). Our approach is to determine a first-stage solution \( x \in \mathcal{X} \) as well as a finite set of candidate recovery solutions \( y^1, \ldots, y^K \in \mathcal{X}(x) \).

The following result shows that \( K = n^2 + 1 \) is sufficient to guarantee that this approach provides an exact solution to the problem.

**Theorem 1.** Let a recoverable robust problem of the form

\[
\min_{x \in \mathcal{X}} \max_{c \in \mathcal{U}} \min_{y \in \mathcal{X}(x)} f(y, c)
\]

be given, where \( \mathcal{X}, \mathcal{X}(x) \subseteq \{0,1\}^n \), \( \mathcal{U} \) is a compact convex set, \( f \) is linear in \( y \), and concave in \( c \). Then this problem is equivalent to

\[
\min_{x \in \mathcal{X}} \min_{y \in \mathcal{X}(x)} \max_{c \in \mathcal{U}} \min_{i=1}^{n+1} f(y^{(i)}, c).
\]

**Proof.** The idea of the proof is similar to models developed for \( K \)-adaptability (see Hanasusanto et al. (2015, Theorem 1) and Buchheim and Kurtz (2017, Corollary 1)). Using Carathéodory’s theorem and the minimax theorem, we have that

\[
\min_{x \in \mathcal{X}} \min_{y \in \mathcal{X}(x)} f(y, c) = \min_{x \in \mathcal{X}} \max_{y \in \mathcal{X}(x)} \min_{c \in \mathcal{U}} f(y, c)
\]

\[
= \min_{x \in \mathcal{X}} \min_{y \in \mathcal{X}(x)} \max_{c \in \mathcal{U}} f(y, c)
\]

\[
= \min_{x \in \mathcal{X}} \min_{y \in \mathcal{X}(x)} \max_{c \in \mathcal{U}} f(y, c)
\]

\[
= \min_{x \in \mathcal{X}} \min_{y \in \mathcal{X}(x)} \max_{c \in \mathcal{U}} f(y^{(i)}, c)
\]
This approach can be used to derive a compact formulation to the uncertain single machine scheduling problem (RRS). To this end, we first consider the inner selection problem, given a first-stage solution $x$ and set of recovery solutions $y^{1}, \ldots, y^{K}$, and a scenario $p$. This is given by

$$\min \sum_{k=1}^{K} \left( \sum_{i \in N} \sum_{j \in N} p_i (n+1-j)y_{ij}^k \right) \lambda_k$$

s.t. $\sum_{k=1}^{K} \lambda_k = 1$

$$\lambda_k \geq 0 \quad \forall k \in \{1, \ldots, K\}.$$

The problem of finding the worst-case scenario for the choice of first-stage solution $x$ and recovery solutions $y^{1}, \ldots, y^{K}$ is therefore:

$$\max t$$

s.t. $t \leq \sum_{i \in N} \sum_{j \in N} (\hat{p}_i + p_i \delta_i) (n+1-j)y_{ij}^k \quad \forall k \in \{1, \ldots, K\}$

$$\sum_{i \in N} \delta_i \leq \Gamma$$

$0 \leq \delta_i \leq 1 \quad \forall i \in N.$

Dualizing this problem then gives the following formulation for (RRS):

$$\min \sum_{k=1}^{K} \left( \sum_{i \in N} \sum_{j \in N} \hat{p}_i (n+1-j)y_{ij}^k \right) \mu_k + \Gamma \pi + \sum_{i \in N} \rho_i$$

s.t. $\sum_{k=1}^{K} \mu_k = 1$

$$\pi + \rho_i \geq \sum_{k=1}^{K} \left( \sum_{j \in N} p_i (n+1-j)y_{ij}^k \right) \mu_k \quad \forall i \in N.$$
\[ d(x, y^k) \leq \Delta \quad \forall k \in \{1, \ldots, K\} \]
\[ x \in \mathcal{X} \]
\[ y^k \in \mathcal{X} \quad \forall k \in \{1, \ldots, K\}. \]

We now model the distance \( d(x, y^k) \). Let \( z^k_{ij} \) denote the whether or not jobs \( i \) and \( j \) have swapped positions in recovery solution \( y^k \), relative to the first-stage schedule \( x \). In this case, we have that

\[ y^k_{ij} = \sum_{\ell \in N} z^k_{i\ell} x_{\ell j}. \]

Hence, \( y^k \) can be removed from the model, and replaced by \( z^k \) with the inclusion of the following constraints:

\[ \sum_{j \in N} z^k_{ij} = 1 \quad \forall i \in N, k \in \{1, \ldots, K\} \]
\[ \sum_{i \in N} z^k_{ij} = 1 \quad \forall j \in N, k \in \{1, \ldots, K\} \]
\[ z^k_{ij} = z^k_{ji} \quad \forall i, j \in N, k \in \{1, \ldots, K\} \]
\[ \sum_{i \in N} z^k_{ii} \geq n - 2\Delta \quad \forall k \in \{1, \ldots, K\}. \]

To arrive at a mixed-integer linear program, the products \( z^k_{i\ell} x_{\ell j} \mu_k \) need to be linearised using standard techniques. The full linearised formulation is shown in Appendix B.1.

### 4. Complexity of subproblems and compact formulations

In this section, examine the incremental and adversarial problems of (RRS) in more detail, with the objective of deriving additional compact formulations.

#### 4.1. Matching-based formulation

We first consider a matching-based formulation for the incremental problem. For the ease of presentation, we assume for now that \( x_{ii} = 1 \) for all \( i \in N \), i.e. the first-stage solution is a horizontal matching. Supposing that the positions of jobs \( i \) and \( j \) are switched in the recovery schedule, the reduction in cost of making this switch is given by

\[ p_i(n + 1 - i) + p_j(n + 1 - j) - p_i(n + 1 - j) - p_j(n + 1 - j) = (p_i - p_j)(j - i). \]

Letting \( y_{ij} \) indicate whether or not jobs \( i \) and \( j \) swap positions in the schedule, the incremental problem can be formulated as:

\[
\min \sum_{i \in N} p_i(n + 1 - i) - \sum_{e = (i, j) \in E} (p_i - p_j)(j - i)y_e \tag{5}
\]
\[
\begin{align*}
    \text{s.t.} & \quad \sum_{e \in \partial(i)} y_e \leq 1 \quad \forall i \in N \quad (6) \\
    & \quad \sum_{e \in E} y_e \leq \Delta \quad (7) \\
    & \quad y_e \in \{0, 1\} \quad \forall e \in E, \quad (8)
\end{align*}
\]

where \( E = \{i, j : i, j \in N, i \neq j\} \) is the set of unique swaps, and \( \partial(i) \) is the set of edges incident to vertex \( i \). This is a cardinality-constrained matching problem on a complete graph with one node for each job \( i \in N \).

We examine this matching-based formulation in further detail. First, consider the maximum weight matching problem on a general graph \( G = (V, E) \). This problem can be formulated as the following linear program:

\[
\begin{align*}
    \text{max} & \quad \sum_{e \in E} w_e x_e \quad (9) \\
    \text{s.t.} & \quad \sum_{e \in \partial(i)} x_e \leq 1 \quad \forall i \in V \quad (10) \\
    & \quad \sum_{e \in E(U)} x_e \leq \frac{|U| - 1}{2} \quad \forall U \subseteq V, |U| \text{ odd} \quad (11) \\
    & \quad x_e \geq 0 \quad \forall e \in E, \quad (12)
\end{align*}
\]

where \( E(U) \) is the set of edges in the subgraph induced on \( U \). Edmonds (1965) showed that constraints (11), known as odd-cycle constraints or blossom constraints, are required to fully characterise the matching polytope.

In the following theorem, we show that for a matching problem with the same cost structure as (5), odd-cycle constraints are not required.

**Theorem 2.** For any \( a, b \in \mathbb{R}^{|V|}_+ \), the problem

\[
\begin{align*}
    \text{max} & \quad \sum_{e=(i,j) \in E} (a_i - a_j)(b_i - b_j)x_e \quad (13) \\
    \text{s.t.} & \quad \sum_{e \in \partial(i)} x_e \leq 1 \quad \forall i \in V \quad (14) \\
    & \quad x_e \geq 0 \quad \forall e \in E \quad (15)
\end{align*}
\]

has an optimal solution with \( x_e \in \{0, 1\} \) for all \( e \in E \).

**Proof.** Schrijver (2003, Theorem 30.2, page 522) states that each vertex of the matching polytope described by (14) and (15) is half-integer, i.e. \( x_e \in \{0, \frac{1}{2}, 1\} \) for all \( e \in E \) in an optimal solution. Additionally, as observed by Balinski (1965), the vertices of the matching polytope can be partitioned into a matching \( M \), where \( x_e = 1 \) for each \( e \in M \), and a set of 1/2-fractional cycles of odd length, where \( x_e = \frac{1}{2} \) for each e in the odd cycles. Hence, we can restrict our attention only to 1/2-fractional odd cycles, and show that there is an optimal solution where such cycles do not exist.
Suppose we are given an optimal solution containing a 1/2-fractional odd cycle, consisting of edges \( C = \{e_{i_1,i_2}, e_{i_2,i_3}, \ldots, e_{i_{q-1},i_q}, e_{i_q,i_1}\} \), with weights given by \( w_{ij} = (a_i - a_j)(b_i - b_j) \). Without loss of generality, we assume an orientation in the cycle, where edges are directed as \((i_j, i_{j+1})\) for \( j = 1, \ldots, q \), where \( i_{q+1} = i_1 \).

Note that if \( w_e \leq 0 \) for some edge \( e \), it can be removed from \( E \), as such an edge will never be selected in an optimal matching. Hence, we may assume that \( w_e > 0 \) for all \( e \in C \). Since \( w_{ij} = (a_i - a_j)(b_i - b_j) > 0 \) for all \( e_{ij} \in C \), \( (a_i - a_j) \) and \( (b_i - b_j) \) must have the same sign. That is, either \( a_i > a_j \) and \( b_i > b_j \), in which case we refer to \( e_{ij} \) as a decreasing edge, or \( a_i < a_j \) and \( b_i < b_j \), in which case we refer to \( e_{ij} \) as an increasing edge.

We show that there is an optimal 1/2-fractional cycle that alternates between increasing and decreasing edges. Suppose that there are \( p < q \) consecutive decreasing edges in \( C, e_{j_1,j_2}, e_{j_2,j_3}, \ldots, e_{j_{p-1},j_p} \), i.e. \( a_{j_1} > a_{j_2} > \cdots > a_{j_p} \) and \( b_{j_1} > b_{j_2} > \cdots > b_{j_p} \). In this case

\[
\begin{align*}
w_{j_1,j_p} &= (a_{j_1} - a_{j_p})(b_{j_1} - b_{j_p}) \\
&= \left( (a_{j_1} - a_{j_2}) + (a_{j_2} - a_{j_3}) + \cdots + (a_{j_{p-1}} - a_{j_p}) \right) \\
&\quad \cdot \left( (b_{j_1} - b_{j_2}) + (b_{j_2} - b_{j_3}) + \cdots + (b_{j_{p-1}} - b_{j_p}) \right) \\
&= w_{j_1,j_2} + w_{j_2,j_3} + \cdots + w_{j_{p-1},j_p} + (a_{j_1} - a_{j_2}) \left( (b_{j_2} - b_{j_3}) + \cdots + (b_{j_{p-1}} - b_{j_p}) \right) \\
&\quad + (a_{j_2} - a_{j_3}) \left( (b_{j_1} - b_{j_2}) + \cdots + (b_{j_{p-1}} - b_{j_p}) \right) \\
&\quad + \cdots \\
&\quad + (a_{j_{p-1}} - a_{j_p}) \left( (b_{j_1} - b_{j_2}) + \cdots + (b_{j_{p-2}} - b_{j_{p-1}}) \right) \\
&> w_{j_1,j_2} + w_{j_2,j_3} + \cdots + w_{j_{p-1},j_p},
\end{align*}
\]

which means that replacing the \( p \) consecutive decreasing edges in \( C \) by the edge \( e_{j_1,j_p} \) would lead to an even better objective value (see Figure 2 for an illustration). The same argument can be used to show that there also cannot be \( p \) consecutive increasing edges in an optimal 1/2-fractional cycle.

We have thus constructed an optimal 1/2-fractional cycle that strictly alternates between increasing and decreasing edges. Clearly, this is only possible if \( q \) is even. As a 1/2-fractional even cycle is a convex combination of two feasible matchings, there hence exists an optimal solution without any 1/2-fractional cycles. \( \Box \)

The following result, presented in Schrijver (2003) (Corollary 18.10a, page 331), states that the integrality of the vertices of the matching polytope is unaffected by the addition of a cardinality constraint.

**Theorem 3.** Let \( G = (V, E) \) be an undirected graph and let \( k, l \in \mathbb{Z}_+ \) with \( k \leq l \). Then the convex hull of the incidence vectors of matchings \( M \) satisfying \( k \leq |M| \leq l \) is equal to the set of those vectors \( x \) in the matching polytope of \( G \) satisfying \( k \leq 1^\top x \leq l \).
Figure 2.: An example of a 1/2-fractional cycle involving $q = 5$ nodes. Up and down arrows indicate increasing and decreasing edges respectively. It is optimal to replace the two consecutive decreasing edges $(3,4)$ and $(4,5)$ with the dashed edge $(3,5)$, i.e. $w_{35} > w_{34} + w_{45}$.

This result, in combination with Theorem 2, provides us with the following corollary:

**Corollary 4.** For any $a, b \in \mathbb{R}_+^{|V|}$, the problem

\[
\max \sum_{e=(i,j) \in E} (a_i - a_j)(b_i - b_j)x_e
\]

s.t.

\[
\sum_{e \in \delta(i)} x_e \leq 1 \quad \forall i \in V
\]

\[
\sum_{e \in E} x_e \leq \Delta
\]

\[
x_e \geq 0 \quad \forall e \in E
\]

has an optimal solution with $x_e \in \{0, 1\}$ for all $e \in E$.

Hence, given a first-stage solution $x$ and scenario $p$, we can formulate the incremental problem a linear program with polynomially many constraints. We use this result to derive a compact formulation for the full uncertain single machine scheduling problem (RRS).

We begin by formulating the incremental problem Inc($x, p$) according to Corollary 4. Note that we now consider a general first-stage assignment that is not necessarily horizontal, and therefore introduce terms $\sum_{\ell \in N} x_{i\ell}$ to track the position in which job $i$ is scheduled in the first-stage schedule. We fix an arbitrary orientation of edges, using $E = \{(i,j) \in N \times N : i < j\}$ in the following.

\[
\min \sum_{i \in N} p_i \left( n + 1 - \sum_{\ell \in N} x_{i\ell} \right) - \sum_{(i,j) \in E} (p_i - p_j) \left( \sum_{\ell \in N} x_{j\ell} - \sum_{\ell \in N} x_{i\ell} \right) y_{ij}
\]
\[
\begin{align*}
\text{s.t. } & \sum_{(i,j) \in E} y_{ij} + \sum_{(j,i) \in E} y_{ij} \leq 1 & \forall i \in N \\
& \sum_{(i,j) \in E} y_{ij} \leq \Delta \\
& y_{ij} \geq 0 & \forall (i,j) \in E.
\end{align*}
\]

Taking the dual of this, we get the following formulation for the adversarial problem \text{Adv}(x):\

\[
\begin{align*}
\text{max} & \sum_{i \in N} (\hat{p}_i + \delta_i \bar{p}_i) \left( n + 1 - \sum_{\ell \in N} x_{i\ell} \right) - \sum_{i \in N} \alpha_i - \gamma \Delta \\
\text{s.t. } & \alpha_i + \alpha_j + \gamma \geq \left( (\hat{p}_i + \delta_i \bar{p}_i) - (\hat{p}_j + \delta_j \bar{p}_j) \right) \left( \sum_{\ell \in N} x_{j\ell} - \sum_{\ell \in N} x_{i\ell} \right) & \forall (i,j) \in E \\
& \sum_{i \in N} \delta_i \leq \Gamma \\
& 0 \leq \delta_i \leq 1 & \forall i \in N \\
& \alpha_i \geq 0 & \forall i \in N \\
& \gamma \geq 0.
\end{align*}
\]

Since this is a linear program, we immediately obtain following result:

**Corollary 5.** *The adversarial problem can be solved in polynomial time.*

Finally, dualising the above adversarial formulation, we get the following compact formulation for problem (RRS):

\[
\begin{align*}
\text{min} & \sum_{i \in N} \bar{p}_i \left( n + 1 - \sum_{\ell \in N} x_{i\ell} \right) \\
& + \sum_{(i,j) \in E} (\hat{p}_j - \hat{p}_i) \left( \sum_{\ell \in N} x_{j\ell} - \sum_{\ell \in N} x_{i\ell} \right) y_{ij} + \Gamma \pi + \sum_{i \in N} \rho_i & (20) \\
\text{s.t. } & \rho_i + \pi + \sum_{(i,j) \in E} \bar{p}_i \left( \sum_{\ell \in N} x_{j\ell} - \sum_{\ell \in N} x_{i\ell} \right) y_{ij} \\
& \geq \sum_{(j,i) \in E} \bar{p}_j \left( \sum_{\ell \in N} x_{j\ell} - \sum_{\ell \in N} x_{i\ell} \right) y_{ij} \geq \bar{p}_i \left( n + 1 - \sum_{\ell \in N} x_{i\ell} \right) & \forall i \in N & (21) \\
& \sum_{(i,j) \in E} y_{ij} + \sum_{(j,i) \in E} y_{ij} \leq 1 & \forall i \in N & (22) \\
& \sum_{(i,j) \in E} y_{ij} \leq \Delta & (23)
\end{align*}
\]
\[ \sum_{i \in N} x_{ij} = 1 \quad \forall j \in N \] (24)
\[ \sum_{j \in N} x_{ij} = 1 \quad \forall i \in N \] (25)
\[ \rho_i \geq 0 \quad \forall i \in N \] (26)
\[ \pi \geq 0 \] (27)
\[ y_{ij} \geq 0 \quad \forall (i,j) \in E \] (28)
\[ x_{ij} \in \{0,1\} \quad \forall i,j \in N. \] (29)

Upon linearising the quadratic \( x_{i\ell} y_{ij} \) terms, this model becomes a mixed-integer linear program. The fully linearised model is presented in full in Appendix B.2.

4.2. Assignment-based formulation

We now consider an alternative formulation for the incremental problem. Again, for the purposes of examining the incremental problem, we initially consider the first-stage schedule to be a horizontal assignment, i.e. \( x_{ii} = 1 \) for all \( i \in N \). By letting variables \( y_{ij} \) represent a second-stage assignment, we can formulate the incremental problem as follows:

\[
\min \sum_{i \in N} \sum_{j \in N} p_i (n + 1 - j) y_{ij} \tag{30}
\]
\[
\text{s.t.} \quad \sum_{i \in N} y_{ij} = 1 \quad \forall j \in N \tag{31}
\]
\[
\sum_{j \in N} y_{ij} = 1 \quad \forall i \in N \tag{32}
\]
\[
y_{ij} = y_{ji} \quad \forall i,j \in N \tag{33}
\]
\[
\sum_{i \in N} y_{ii} \geq n - 2\Delta \tag{34}
\]
\[
y_{ij} \in \{0,1\} \quad \forall i,j \in N. \tag{35}
\]

Constraints (33) and (34) ensure that the second-stage assignment is a feasible recovery to the first-stage solution, that is, the second-stage assignment is constructed by swapping the first-stage positions of up to \( \Delta \) disjoint pairs of jobs. Note that this is a level-constrained symmetric perfect matching problem, which can be solved in polynomial time (Thomas, 2015, Theorem 2.28).

We show that problem (30)-(35) can be solved as a linear program as a result of its non-general cost structure. As the proof is technical and based on a reduction to the corresponding maximum weight matching problem, it is omitted here and can be found in Appendix A.

**Theorem 6.** For any \( a, b \in \mathbb{R}_+^n \), the problem

\[
\min \sum_{i \in N} \sum_{j \in N} a_i b_j y_{ij} \tag{36}
\]
has an optimal solution with $y_{ij} \in \{0, 1\}$ for all $i, j \in N$.

We now use this result to find an assignment-based formulation for (RRS). We first write the incremental problem in the form given by (36)-(38). Since we are now considering the case where $x$ is not necessarily a horizontal matching, we rearrange the indices accordingly.

$$
\min \sum_{i \in N} \sum_{j \in N} p_i (n + 1 - \sum_{\ell \in N} x_{j\ell}) y_{ij}
$$

s.t.

$$
\sum_{i \in N} y_{ij} = 1 \quad \forall j \in N
$$

$$
\sum_{j \in N} y_{ij} = 1 \quad \forall i \in N
$$

$$
y_{ij} = y_{ji} \quad \forall i, j \in N
$$

$$
\sum_{i \in N} y_{ii} \geq n - 2\Delta
$$

$$
y_{ij} \geq 0 \quad \forall i, j \in N.
$$

Taking the dual of this, the adversarial problem can be formulated in the following way:

$$
\max \sum_{i \in N} (\alpha_i + \beta_i) + (n - 2\Delta)\tau
$$

s.t.

$$
\alpha_j + \beta_i + \gamma_{ij} \leq (n + 1 - \sum_{\ell \in N} x_{j\ell})(\hat{p}_i + \bar{p}_i\delta_i) \quad \forall i, j \in N : i < j
$$

$$
\alpha_j + \beta_i - \gamma_{ji} \leq (n + 1 - \sum_{\ell \in N} x_{j\ell})(\hat{p}_i + \bar{p}_i\delta_i) \quad \forall i, j \in N : i > j
$$

$$
\alpha_i + \beta_i + \tau \leq (n + 1 - \sum_{\ell \in N} x_{j\ell})(\hat{p}_i + \bar{p}_i\delta_i) \quad \forall i \in N
$$

$$
\sum_{i \in N} \delta_i \leq \Gamma
$$

$$
\delta_i \leq 1 \quad \forall i \in N
$$

$$
\tau \geq 0.
$$

Finally, we dualise this adversarial formulation to derive the following formulation for the recoverable problem:

$$
\min \sum_{i \in N} \sum_{j \in N} (n + 1 - \sum_{\ell \in N} x_{j\ell}) \hat{p}_i y_{ij} + \Gamma \pi + \sum_{i \in N} \rho_i
$$

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As before, products \( x_{ij}y_{ij} \) can be linearized using standard techniques. The resulting mixed-integer linear program can be found in Appendix B.3.

5. Computational experiments

This section presents and compares results from solving the three compact models introduced in this paper, as well as three additional heuristic solution methods. Before introducing these heuristics and examining their performance, we comment on the test instances and computational hardware used for these experiments.

Instances have been generated by randomly sampling both \( \bar{p}_i \) and \( ar{p}_i \) from the set \( \{1, 2, \ldots, 100\} \). 20 instances of sizes \( n \in \{10, 15, 20\} \) have been generated, resulting in a total of 60 deterministic test instances. For each deterministic instance, three uncertain instances have been generated by setting \( \Gamma \in \{3, 5, 7\} \), resulting in a total of 180 uncertain instances. These instances, as well as the complete results data, can be found at https://github.com/boldm1/RR-single-machine-scheduling.

All methods have been run on 4 cores of a 2.30GHz Intel Xeon CPU, limited to 16GB RAM. The exact models have been solved using Gurobi 9.0.1, with a time limit of 10 minutes.

5.1. Heuristics

The three heuristic methods we consider are as follows:

1. **Sorting.** Obtain a schedule by ordering the jobs \( i \in N \) according to non-decreasing \( \hat{p}_i + \bar{p}_i \), i.e. a schedule that performs best in the worst-case scenario when \( \Gamma = n \), and evaluate by solving \( \text{Adv}(x) \).

2. **Max-min.** Solve the max-min problem

\[
\max_{p \in \mathcal{P}} \min_{x \in \mathcal{X}} \sum_{i \in N} \sum_{j \in N} p_i (n + 1 - j) x_{ij}
\]
to obtain a worst-case scenario $p \in U$. Find a schedule $x$ that performs best in this worst-case scenario and evaluate by solving $\text{Adv}(x)$.

3. **Min-max.** Solve the problem without recourse, i.e. with $\Delta = 0$.

Each heuristic method has been used to find a feasible solution to all 180 uncertain test instances. Figure 3 shows the cumulative percentage of instances solved by each of the heuristics to within a given gap to the best solution found by any method, including the exact models, which have been solved with $\Delta = 2$. It is clear from this plot that min-max is the strongest of the three proposed heuristics, solving all 180 instances to within 3.2% of the best solution. This gap increases to 8.8% for sorting, whilst max-min solves all but one instance to within 15%. The average of these gaps across all instances for min-max, sorting and max-min are 0.9%, 3.1% and 4.1% respectively.

Given its strong performance, we propose using min-max to provide a warm-start solution to the exact models. The benefits of this are assessed in the next section.

![Figure 3: Cumulative percentage of instances solved to within a given gap of the best known solution.](image)

**5.2. Exact models**

We now examine the results of solving the three exact models proposed in this paper and their warm-start variants. The 180 uncertain instances have been solved by each model and its warm-start variant for $\Delta \in \{0, 1, 2, 3\}$. Note that the general model has been implemented with $K = 2$. This has been chosen to make the general model as
computationally efficient to solve as possible, whilst actually still providing an advantage
over the min-max model, i.e. for $K = 1$ the general model corresponds to the min-max
model.

Tables 1 and 2 compare the performance of these exact models for different values of $\Gamma$
and $\Delta$ respectively. For each set of 20 instances with the same combination of instance
parameters, Tables 1 and 2 report the following:

- **time** - Average CPU time (secs) required to solve the instances that were solved
to optimality within the time limit.

- **LBgap** - Average gap (%) between the best objective bound and the best known
feasible solution found by any method, over the instances not solved to optimality
within the time limit.

- **UBgap** - Average gap (%) between the best feasible solution found within the time
limit and the best known feasible solution found by any method, over the instances
not solved to optimality within the time limit.

- **#solv** - Number of instances solved to optimality within the time limit.

From Tables 1 and 2, it is clear that the general model is by far the weakest of the
three proposed models. Other than for $\Delta = 0$, no instances are solved to optimality. The
general model is able to find near-optimal feasible solutions, but fails to begin closing
the optimality gap in most instances. The matching-based model improves considerably
on the general model, whilst the assignment model is the strongest performing of the
three exact models, solving the most number of instances to optimality and having the
smallest gaps over those instances that cannot be solved to optimality. The addition of
a warm-start solution is clearly beneficial only for the assignment-based model, where
the addition solves more instances to optimality in less time.

From Table 1 it can be seen that instances tend to become harder to solve as $\Gamma$
increases. From Table 2 we see that, unsurprisingly, instances are easiest to solve
to solve when $\Delta = 0$ (this corresponds to solving the min-max model). Interestingly
however, instances are most difficult when $\Delta = 1$, and become easier to solve as the
number of recovery swaps allowed $\Delta$ increases, i.e. the second stage-solution becomes
less constrained by the first-stage solution.

Figure 4 shows performance profiles (Dolan and Moré, 2002) of the relative solution
times of the matching and assignment-based models and their warm-start variants, for
different instance sizes. The general model and its warm-start variant is excluded from
these plots given its poor performance. A performance profile is a graphical comparison
of the performance ratios. The performance ratio of model $m \in \mathcal{M}$ for instance $i \in \mathcal{I}$ is
defined as

$$p_{im} = \frac{t_{im}}{\min_{m \in \mathcal{M}} t_{im}},$$

where $t_{im}$ is the time required to solve instance $i$ using model $m$. If model $m$ fails to find
an optimal solution to instance $i$ within the given time-limit, then $p_{im} = P$, for some
| $n$ | $\Gamma$ | $\Delta$ | time | LBgap | UBgap | #solv |
|-----|---------|---------|------|-------|-------|-------|
| 10  | 3       | 2       | -100.0 | 0.2   | 0     | -100.0 | 0.2   | 0     |
| 10  | 5       | 2       | -100.0 | 0.1   | 0     | -100.0 | 0.1   | 0     |
| 10  | 7       | 2       | -100.0 | 0.1   | 0     | -100.0 | 0.0   | 0     |
| 15  | 3       | 2       | -100.0 | 0.4   | 0     | -100.0 | 0.3   | 0     |
| 15  | 5       | 2       | -100.0 | 0.6   | 0     | -100.0 | 0.3   | 0     |
| 15  | 7       | 2       | -100.0 | 0.4   | 0     | -100.0 | 0.3   | 0     |
| 20  | 3       | 2       | -100.0 | 0.8   | 0     | -100.0 | 0.3   | 0     |
| 20  | 5       | 2       | -100.0 | 0.9   | 0     | -100.0 | 0.4   | 0     |
| 20  | 7       | 2       | -100.0 | 1.2   | 0     | -100.0 | 0.5   | 0     |

| $n$ | $\Gamma$ | $\Delta$ | time | LBgap | UBgap | #solv |
|-----|---------|---------|------|-------|-------|-------|
| 10  | 3       | 2       | 2.6  | -     | -     | 20    |
| 10  | 5       | 2       | 4.1  | -     | -     | 20    |
| 10  | 7       | 2       | 2.1  | -     | -     | 20    |
| 15  | 3       | 2       | 110.9 | 0.0  | 0.0  | 19    |
| 15  | 5       | 2       | 132.4 | 0.2  | 0.0  | 17    |
| 15  | 7       | 2       | 111.7 | 0.2  | 0.0  | 16    |
| 20  | 3       | 2       | 540.7 | 0.9  | 0.0  | 3     |
| 20  | 5       | 2       | 598.6 | 0.5  | 0.0  | 1     |
| 20  | 7       | 2       | -    | 0.5   | 0.0  | 0     |

Table 1.: Comparison of the three exact models proposed in this paper and their warm-start variants, for different values of $\Gamma$. 

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| \(n\) | \(\Gamma\) | \(\Delta\) | General | General + warm-start |
|-----|-----|---|---|---|
|     |     |     | \(\text{time}\) & \(\text{LBgap}\) & \(\text{UBgap}\) & \#solv | \(\text{time}\) & \(\text{LBgap}\) & \(\text{UBgap}\) & \#solv |
| 10  | 7   | 0  | 0.3  & - & - & 20 | 0.3 & - & - & 20 |
| 10  | 7   | 1  | 100.0 & 0.0 & 0 & - | 100.0 & 0.0 & 0 & - |
| 10  | 7   | 2  | 100.0 & 0.1 & 0 & - | 100.0 & 0.0 & 0 & - |
| 10  | 7   | 3  | 100.0 & 0.0 & 0 & - | 100.0 & 0.0 & 0 & - |
| 15  | 7   | 0  | 3.3  & - & - & 20 | 3.0 & - & - & 20 |
| 15  | 7   | 1  | 100.0 & 0.4 & 0 & - | 100.0 & 0.3 & 0 & - |
| 15  | 7   | 2  | 100.0 & 0.4 & 0 & - | 100.0 & 0.3 & 0 & - |
| 15  | 7   | 3  | 100.0 & 0.5 & 0 & - | 100.0 & 0.3 & 0 & - |
| 20  | 7   | 0  | 69.5 & 0.8 & 0.0 & 18 | 81.1 & 0.9 & 0.0 & 18 |
| 20  | 7   | 1  | 100.0 & 1.1 & 0 & - | 100.0 & 0.7 & 0 & - |
| 20  | 7   | 2  | 100.0 & 1.2 & 0 & - | 100.0 & 0.5 & 0 & - |
| 20  | 7   | 3  | 100.0 & 1.6 & 0 & - | 100.0 & 0.5 & 0 & - |

| \(n\) | \(\Gamma\) | \(\Delta\) | Matching | Matching + warm-start |
|-----|-----|---|---|---|
|     |     |     | \(\text{time}\) & \(\text{LBgap}\) & \(\text{UBgap}\) & \#solv | \(\text{time}\) & \(\text{LBgap}\) & \(\text{UBgap}\) & \#solv |
| 10  | 7   | 0  | 0  & - & - & 20 | 0.0 & - & - & 20 |
| 10  | 7   | 1  | 2.1 & - & - & 20 | 2.2 & - & - & 20 |
| 10  | 7   | 2  | 2.1 & - & - & 20 | 3.4 & - & - & 20 |
| 10  | 7   | 3  | 5.3 & - & - & 20 | 5.9 & - & - & 20 |
| 15  | 7   | 0  | 0.2 & - & - & 20 | 0.2 & - & - & 20 |
| 15  | 7   | 1  | 207 & 0.2 & 0.0 & 11 | 162.7 & 0.2 & 0.0 & 12 |
| 15  | 7   | 2  | 111.7 & 0.2 & 0.0 & 16 | 97.6 & 0.2 & 0.0 & 16 |
| 15  | 7   | 3  | 66.1 & 0.2 & 0.0 & 17 | 72.7 & 0.2 & 0.0 & 16 |
| 20  | 7   | 0  | 1.6 & - & - & 20 | 1.6 & - & - & 20 |
| 20  | 7   | 1  | 0.9 & - & - & 20 | - 0.9 & 0.0 & 0  |
| 20  | 7   | 2  | 0.5 & - & - & 20 | - 0.5 & 0.0 & 0  |
| 20  | 7   | 3  | 395.3 & 0.3 & 0.0 & 8  | 490.9 & 0.3 & 0.0 & 8  |

| \(n\) | \(\Gamma\) | \(\Delta\) | Assignment | Assignment + warm-start |
|-----|-----|---|---|---|
|     |     |     | \(\text{time}\) & \(\text{LBgap}\) & \(\text{UBgap}\) & \#solv | \(\text{time}\) & \(\text{LBgap}\) & \(\text{UBgap}\) & \#solv |
| 10  | 7   | 0  | 0.0 & - & - & 20 | 0.0 & - & - & 20 |
| 10  | 7   | 1  | 2.8 & - & - & 20 | 2.0 & - & - & 20 |
| 10  | 7   | 2  | 3.4 & - & - & 20 | 3.0 & - & - & 20 |
| 10  | 7   | 3  | 5.7 & - & - & 20 | 4.1 & - & - & 20 |
| 15  | 7   | 0  | 0.2 & - & - & 20 | 0.1 & - & - & 20 |
| 15  | 7   | 1  | 71.1 & 0.0 & 0.0 & 19 | 86.8 & - & - & 20 |
| 15  | 7   | 2  | 59.1 & - & - & 20 | 64.3 & - & - & 20 |
| 15  | 7   | 3  | 42.4 & - & - & 20 | 50.3 & - & - & 20 |
| 20  | 7   | 0  | 1.5 & - & - & 20 | 1.3 & - & - & 20 |
| 20  | 7   | 1  | 433.5 & 0.4 & 0.0 & 2  | 523.5 & 0.3 & 0.0 & 6  |
| 20  | 7   | 2  | 445.5 & 0.0 & 0.0 & 19 | 321.3 & - & - & 20 |
| 20  | 7   | 3  | 435.2 & 0.3 & 0.0 & 19 | 312.0 & - & - & 20 |

Table 2.: Comparison of the three exact models proposed in this paper and their warm-start variants, for different values of \(\Delta\).
$P > \max_{i,m} r_{im}$. The performance profile of model $m \in \mathcal{M}$ is then defined to be the function

$$\rho_m(\tau) = \frac{|\{p_{im} \leq \tau : i \in I\}|}{|I|},$$

that is, the probability that model $m$ is within a factor $\tau$ of the best performing model. The performance profiles in Figure 4 have been plotted on the log-scale for clarity.

The top-left performance profile in Figure 4 includes data from all instances, whilst the three other performance profiles consider the three sizes of instance separately. We see that for $n = 10$, the matching-based model performs slightly better than the assignment-based model, however the inclusion of a warm-start does not seem to improve the matching model. For $n = 15$ and $n = 20$ however, the assignment model is stronger than the matching model. The benefits of a warm-start solution become most apparent when solving the largest instances, where a warm-start increases both solution times and the number of instances solved to optimality of both the matching and assignment model.

Figure 4.: Performance profiles of relative solution times for different instance sizes.
5.3. Model parameters

We now examine the impact of the model parameters $\Gamma$ and $\Delta$ on the objective value. For each set of instances, Tables 3 and 4 report the average objective value of the best known feasible solutions found by any method for different values of $\Gamma$ and $\Delta$ respectively, as well as the relative percentage difference in this average from the sets of instances where $\Gamma = 3$ and $\Delta = 0$, respectively.

The results in Table 3 show that, as we would expect, increasing the $\Gamma$ increases the average objective value in a concave manner. Table 4 shows that the inclusion of a second-stage recourse solution provides an improvement in objective value. However we also see that beyond $\Delta = 1$, increasing $\Delta$ provides little additional benefit. That is, the vast majority of the benefit of allowing a recourse solution can be captured by allowing just a single swap to the first-stage schedule. However, it is important to note the effect of having been limited to instances sizes of 20 and less by the computational intensity of solving the proposed exact models. We expect that for larger instance sizes, a less restricted and more powerful recourse action, i.e. increasing $\Delta$, would become more advantageous. Additionally, for a discrete budgeted uncertainty set where $\delta_i \in \{0, 1\}$ for each $i \in N$, we might expect the benefits of increasing $\Delta$ to be more apparent, since in this case the adversary is unable to spread the delay across multiple jobs in an attempt to preempt the recourse response, as is currently the case under the continuous budgeted uncertainty set that we consider. The impact of discrete budgeted uncertainty is an interesting possibility for future research on this problem.

| $n$ | $\Gamma$ | $\Delta$ | avg. best | %diff. |
|-----|-----------|-----------|------------|--------|
| 10  | 3         | 2         | 3946.5     | 0.0    |
| 10  | 5         | 2         | 4578.0     | 14.1   |
| 10  | 7         | 2         | 5053.0     | 22.1   |
| 15  | 3         | 2         | 7164.9     | 0.0    |
| 15  | 5         | 2         | 8177.5     | 12.7   |
| 15  | 7         | 2         | 9002.1     | 20.7   |
| 20  | 3         | 2         | 11814.3    | 0.0    |
| 20  | 5         | 2         | 13317.8    | 11.5   |
| 20  | 7         | 2         | 14582.5    | 19.3   |

Table 3.: The effects of increasing $\Gamma$ on the average objective value of the best known solution.

| $n$ | $\Gamma$ | $\Delta$ | avg. best | %diff. |
|-----|-----------|-----------|------------|--------|
| 10  | 7         | 0         | 5079.7     | 0.0    |
| 10  | 7         | 1         | 5053.0     | -0.5   |
| 10  | 7         | 2         | 5053.0     | -0.5   |
| 10  | 7         | 3         | 5053.0     | -0.5   |
| 15  | 7         | 0         | 9093.8     | 0.0    |
| 15  | 7         | 1         | 9002.2     | -1.0   |
| 15  | 7         | 2         | 9002.1     | -1.0   |
| 15  | 7         | 3         | 9002.1     | -1.0   |
| 20  | 7         | 0         | 14735.6    | 0.0    |
| 20  | 7         | 1         | 14583.7    | -1.0   |
| 20  | 7         | 2         | 14582.5    | -1.0   |
| 20  | 7         | 3         | 14582.5    | -1.0   |

Table 4.: The effects of increasing $\Delta$ on the average objective value of the best known solution.
6. Conclusions

This paper has introduced a recoverable robust model for the single machine scheduling problem with the total flow time criterion. A general result that allows for the construction of compact formulations for a wide range of recoverable robust problems has been presented, and this approach has been applied to the specific scheduling problem we consider. We have analysed the incremental problem of the robust scheduling problem in detail in an attempt to develop further, more tailored and effective compact formulations for this problem. Specifically, we have proved that matching problems with edge weights of the form of (13) have integral solutions, and therefore the inclusion of the odd-cycle constraints of the standard matching polytope is unnecessary. This result allows us to derive a matching-based compact formulation for the full recoverable robust single machine scheduling problem. In addition to this matching-based formulation of the incremental, we have also presented a symmetric assignment-based formulation, to which we can transfer the integral matching result and derive a third compact model for this problem. Computational results show that this assignment-based model is clearly the strongest of the three exact models.

There remain a number of promising directions in which future research on this problem can develop. Firstly, in this work we have considered a limited recourse action of allowing $\Delta$ disjoint swaps to be made to the first-stage schedule. Other measures of distance between the first and second-stage solution are certainly possible and worth investigating, especially if the restriction that the swapped pairs be disjoint could be relaxed, and interchanges between the positions of three or more jobs simultaneously can be factored into a recourse action. Another obvious avenue for future research is the analysis of this problem in the context of uncertainty sets different from budgeted uncertainty. Given the vast number of different objective criteria that have been used for single-machine scheduling problems and the unique properties of each, it would be interesting and worthwhile to investigate the application of this recoverable robust model to some of these. As a final suggestion, given the limited size of instance that have been solved by the exact models we propose, an accurate and effective heuristic approach for solving large-scale instances of this problem would certainly be a valuable development.

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A. Omitted proof

Proof of Theorem 6. Let an instance $I$ of problem (36)-(38) be given, and define

$$P = \{ y \in \mathbb{R}^{n \times n} : (31) - (34) \}.$$  

To solve $I$, we construct a graph with a single node for each job $i \in N$, where an edge between nodes $i$ and $j$ indicates that jobs $i$ and $j$ swap their positions from the first-stage schedule. Since edges correspond to unique swaps, the set of edges in this graph is given by $E = \{ (i, j) : i, j \in N, j > i \}$. The weight of an edge $(i, j)$ in this graph is equal to the reduction in objective cost from making the corresponding swap, i.e. $a_i b_i + a_j b_j - a_i b_j - a_j b_i = (a_i - a_j)(b_i - b_j)$. We aim to choose up to $\Delta$ edges from this graph to maximise the reduction in objective cost. That is, given $I$, we construct an instance $J$ of the following cardinality-constrained matching problem:

$$\min \sum_{i \in N} a_i b_i - \sum_{(i,j) \in E} (a_i - a_j)(b_i - b_j)z_{ij}$$  

s.t. $$\sum_{(i,j) \in E} z_{ij} + \sum_{(j,i) \in E} z_{ij} \leq 1 \quad \forall i \in N$$  

$$\sum_{(i,j) \in E} z_{ij} \leq \Delta \quad \forall (i, j) \in E.$$  

As stated in Corollary 4, this problem has an integral optimal solution. Hence, letting $P' = \{ z \in \mathbb{R}^{\left| E \right|} : (40) - (42) \}$, we construct mappings $\phi : P \to P'$ and $\phi^{-1} : P' \to P$ which preserve objective value and integrality, showing problems $I$ and $J$ are indeed equivalent. To this end, we define $\phi(y) = z$ by $z_{ij} = y_{ij}$ for all $(i, j) \in E$. Observe that

$$\text{obj}_J(y) = \sum_{i \in N} \sum_{j \in N} a_i b_j y_{ij}$$
Conversely, we define $\phi^{-1}(z) = y$ with $y_{ij} = y_{ji} = z_{ij}$ for each $(i, j) \in E$, and $y_{ii} = (1 - \sum_{j \in N : j > i} z_{ij})(1 - \sum_{j \in N : j < i} z_{ji})$ for each $i \in N$. Then

$$
\text{obj}_j(z) = \sum_{i \in N} a_i b_i - \sum_{(i, j) \in E} (a_i - a_j)(b_i - b_j)z_{ij}
$$

$$
= \sum_{i \in N} a_i b_i - \sum_{i \in N} \sum_{j \in N : j > i} a_i b_i + a_j b_j z_{ij} + \sum_{i \in N} \sum_{j \in N : j < i} (a_i b_j + a_j b_i)z_{ij}
$$

$$
= \sum_{i \in N} a_i b_i - \sum_{i \in N} \sum_{j \in N : j > i} a_i b_i \sum_{j \in N : j > i} z_{ij} - \sum_{i \in N} a_i b_i \sum_{j \in N : j < i} z_{ji}
$$

$$
+ \sum_{i \in N} a_i b_i \sum_{j \in N : j < i} z_{ij} \sum_{j \in N : j < i} z_{ji} + \sum_{i \in N} \sum_{j \in N : j > i} (a_i b_j + a_j b_i)z_{ij}
$$

$$
= \sum_{i \in N} a_i b_i \left(1 - \sum_{j \in N : j > i} z_{ij}\right) \left(1 - \sum_{j \in N : j < i} z_{ji}\right) + \sum_{i \in N} \sum_{j \in N : j > i} (a_i b_j + a_j b_i)z_{ij}
$$

$$
= \sum_{i \in N} a_i b_i y_{ii} + \sum_{i \in N} \sum_{j \in N : j > i} a_i b_j y_{ij} + \sum_{i \in N} \sum_{j \in N : j > i} a_j b_i y_{ji}
$$

$$
= \sum_{i \in N} a_i b_i y_{ii} + \sum_{i \in N} \sum_{j \in N : j \neq i} a_i b_j y_{ij}
$$

$$
= \text{obj}_j(y).
$$
Therefore \( \min_{y \in P} \text{obj}(y) = \min_{z \in P'} \text{obj}(z) \). Since problem (16)-(19) has an optimal integral solution, there must also be an optimal integral solution to \( I \) via the mapping \( \phi^{-1} \), proving the claim.

\[ \Box \]

**B. Complete formulations**

**B.1. General model**

The complete linear compact formulation for the general recoverable robust model presented in Section 3 is as follows:

\[
\begin{align*}
\text{min} & \quad \sum_{k=1}^{K} \sum_{i \in N} \sum_{j \in N} \hat{p}_i (n + 1 - j) h^k_{ij} + \Gamma \pi + \sum_{i \in N} \rho_i \\
\text{s.t.} & \quad \sum_{k=1}^{K} \mu_k = 1 \\
& \quad \pi + \rho_i \geq \sum_{k=1}^{K} \left( \sum_{j \in N} \hat{p}_i (n + 1 - j) y^k_{ij} \right) \mu_k \quad \forall \ i \in N \\
& \quad \sum_{j \in N} z^k_{ij} = 1 \quad \forall \ i \in N, \ k \in \{1, \ldots, K\} \\
& \quad \sum_{i \in N} z^k_{ij} = 1 \quad \forall \ j \in N, \ k \in \{1, \ldots, K\} \\
& \quad z^k_{ij} = z^k_{ji} \quad \forall \ i, j \in N, \ k \in \{1, \ldots, K\} \\
& \quad \sum_{i \in N} z^k_{ii} \geq n - 2\Delta, \quad k \in \{1, \ldots, K\} \\
& \quad \sum_{j \in N} x_{ij} = 1 \quad \forall \ i \in N \\
& \quad \sum_{i \in N} x_{ij} = 1 \quad \forall \ j \in N \\
& \quad w^k_{ij} \leq z^k_{il} \quad \forall \ i, j, l \in N, \ k \in \{1, \ldots, K\} \\
& \quad w^k_{ij} \leq x_{lj} \quad \forall \ i, j, l \in N, \ k \in \{1, \ldots, K\} \\
& \quad w^k_{ij} \geq z^k_{il} + x_{lj} - 1 \quad \forall \ i, j, l \in N, \ k \in \{1, \ldots, K\} \\
& \quad h^k_{ij} \leq w^k_{ij} \quad \forall \ i, j, l \in N, \ k \in \{1, \ldots, K\} \\
& \quad h^k_{ij} \leq \mu_k \quad \forall \ i, j, l \in N, \ k \in \{1, \ldots, K\} \\
& \quad h^k_{ij} \leq \mu_k + w^k_{ij} - 1 \quad \forall \ i, j, l \in N, \ k \in \{1, \ldots, K\} \\
& \quad w^k_{ij} \geq 0 \quad \forall \ i, j, l \in N, \ k \in \{1, \ldots, K\} \\
& \quad h^k_{ij} \geq 0 \quad \forall \ i, j, l \in N, \ k \in \{1, \ldots, K\} \\
& \quad \rho_i \geq 0 \quad \forall \ i \in N
\end{align*}
\]

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\[ \pi \geq 0 \]
\[ y_{ij} \geq 0 \quad \forall (i, j) \in E \]
\[ x_{ij} \in \{0, 1\} \quad \forall i, j \in N. \]

### B.2. Matching-based model

The fully-linearised formulation of the matching-based model presented in Section 4.1 is as follows:

\[
\begin{align*}
\min \sum_{i \in N} \hat{p}_i \left( n + 1 - \sum_{\ell \in N} x_{i\ell} \right) \\
+ \sum_{(i, j) \in E} \left( \hat{p}_j \sum_{\ell \in N} v_{ij\ell} - \hat{p}_j \sum_{\ell \in N} u_{ij\ell} - \hat{p}_i \sum_{\ell \in N} v_{ij\ell} + \hat{p}_i \sum_{\ell \in N} u_{ij\ell} \right) + \Gamma \pi + \sum_{i \in N} \rho_i \\
\text{s.t.} \quad \rho_i + \pi + \sum_{(i, j) \in E} \hat{p}_i \left( \sum_{\ell \in N} v_{ij\ell} - \sum_{\ell \in N} u_{ij\ell} \right) \\
- \sum_{(j, i) \in E} \hat{p}_j \left( \sum_{\ell \in N} v_{ij\ell} - \sum_{\ell \in N} u_{ij\ell} \right) \geq \hat{p}_i \left( n + 1 - \sum_{\ell \in N} x_{i\ell} \right) \quad \forall i \in N \\
\sum_{(i, j) \in E} y_{ij} + \sum_{(j, i) \in E} y_{ij} \leq 1 \\
\sum_{(i, j) \in E} y_{ij} \leq \Delta \\
\sum_{i \in N} x_{ij} = 1 \\
\sum_{j \in N} x_{ij} = 1 \\
u_{ij\ell} \leq x_{i\ell} \quad \forall (i, j, \ell) \in E \\
u_{ij\ell} \leq y_{ij} \quad \forall (i, j, \ell) \in E \\
u_{ij\ell} \geq y_{ij} + x_{i\ell} - 1 \quad \forall (i, j, \ell) \in E \\
v_{ij\ell} \leq x_{j\ell} \quad \forall (i, j, \ell) \in E \\
v_{ij\ell} \leq y_{ij} \quad \forall (i, j, \ell) \in E \\
v_{ij\ell} \geq y_{ij} + x_{j\ell} - 1 \quad \forall (i, j, \ell) \in E \\
u_{ij\ell} \geq 0 \quad \forall (i, j, \ell) \in E \\
v_{ij\ell} \geq 0 \quad \forall (i, j, \ell) \in E \\
\rho_i \geq 0 \quad \forall i \in N \\
\pi \geq 0 \\
y_{ij} \geq 0 \quad \forall (i, j) \in E \\
x_{ij} \in \{0, 1\} \quad \forall i, j \in N.
\end{align*}
\]
B.3. Assignment-based model

The fully-linearised formulation of the assignment-based model derived in Section 4.2 is as follows:

\[
\begin{align*}
\min & \sum_{i \in N} \sum_{j \in N} \left( \hat{p}_i (n + 1) y_{ij} - \hat{p}_i \sum_{\ell \in N} w_{ij\ell} \right) + \Gamma \pi + \sum_{i \in N} \rho_i \\
\text{s.t.} & \sum_{i \in N} y_{ij} = 1 \quad \forall j \in N \\
& \sum_{j \in N} y_{ij} = 1 \quad \forall i \in N \\
& y_{ij} = y_{ji} \quad \forall i, j \in N \\
& \sum_{i \in N} y_{ii} \geq n - 2\Delta \\
& \pi + \rho_i \geq \sum_{j \in N} (n + 1 - \sum_{\ell \in N} x_{i\ell}) \hat{p}_i y_{ij} \quad \forall i \in N \\
& w_{ij\ell} \leq x_{j\ell} \quad \forall i, j, \ell \in N \\
& w_{ij\ell} \leq y_{ij} \quad \forall i, j, \ell \in N \\
& w_{ij\ell} \geq y_{ij} + x_{j\ell} - 1 \quad \forall i, j, \ell \in N \\
& w_{ij\ell} \geq 0 \quad \forall i, j, \ell \in N \\
& \rho_i \geq 0 \quad \forall i \in N \\
& \pi \geq 0 \\
& y_{ij} \geq 0 \quad \forall i, j \in N \\
& x_{ij} \in \{0, 1\} \quad \forall i, j \in N.
\end{align*}
\]