Histopathology laboratory operations analysis and improvement

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Abstract

Histopathology laboratories aim to deliver high quality diagnoses based on patient tissue samples. Indicators for quality are the accuracy of the diagnoses and the diagnostic turnaround times. However, challenges exist regarding employee workload and turnaround times in the histopathology laboratory. This paper proposes a decomposed planning and scheduling method for the histopathology laboratory using (mixed) integer linear programming ((M)ILP) to improve the spread of workload and reduce the diagnostic turnaround times. First, the batching problem is considered, in which batch completion times are equally divided over the day to spread the workload. This reduces the peaks of physical work available in the laboratory. Thereafter, the remaining processes are scheduled to minimize the tardiness of orders. Preliminary results show that using this decomposition method, the peaks in histopathology workload in UMC Utrecht, a large university medical center in the Netherlands, are potentially reduced with up to 50% by better spreading the workload over the day. Furthermore, turnaround times are potentially reduced with up to 20% compared to current practices.

1 Introduction

The histopathology and anatomic pathology laboratories consist of a sequence of labor intensive processes. Therefore, resources and personnel in the laboratories should be used effectively (Buesa, 2009). However, challenges exist regarding turnaround times and employee workload (Muirhead et al., 2010). In this study we aim to reduce the peaks in workload for histopathology technicians, while ensuring turnaround times within the required norms (see Stotler et al., 2012; Buesa, 2004), by analyzing planning and scheduling solutions for histopathology resources. This is particularly relevant for patients awaiting a cancer diagnosis, since a long lead time of pathology processes may lead to emotional and physical distress (Paul et al., 2012).
Histopathology processes are complex processes (Brown, 2004). The process can be divided into five main steps: grossing, tissue processing, embedding, sectioning and staining, and examination. This system of processes can be defined as a multi-stage, multiproduct flow shop, in which all specimens go through a predefined order of stages in which only their parameter values vary, as known from the process industry (Harjunkoski et al. 2014; Méndez et al., 2006; Gupta and Karimi, 2003). All stages consist of several single-unit parallel processors, except for the tissue processing stage. Here, batch processors are to be scheduled with large processing times compared to the other stages.

The multi-stage, multiproduct flow shop planning and scheduling is a difficult problem to solve, due to the large amount of solutions (Prasad and Maravelias, 2008). Frequently used exact approaches to solve these problems are Mixed-Integer Linear Programming (MILP) and Mixed-Integer Non-Linear Programming (MINLP). Many approaches consider batch size and batch scheduling decisions separately, for complexity reasons. A few approaches exist that combine batch size, batch assignment, and batch sequencing decisions (Prasad and Maravelias, 2008). However, these approaches only allow for very small instances, with limited number of resources and orders (Harjunkoski and Grossmann, 2002). For real life settings, with more orders to be scheduled, heuristics are used.

The lead-time optimization of histopathology laboratory processes requires a system-wide approach. Existing approaches consist of lean or rapid improvement events focusing on operational bottlenecks, and trial-and-error experimentation with interventions on the operational level of control (i.e., Brown, 2004). Other work focusses on optimizing tissue processing machines (i.e., Vernon, 2005). In this research we aim to integrally optimize histopathology processes by considering all resources involved, and addressing the tactical level of control in addition to the operational (Hans et al., 2012). More specifically, at a tactical level we optimize the batch completion times in order to spread the workload, and at an operational level we reschedule the orders in the histopathology laboratory such that the tardiness of orders is minimized. For both problems we use an (M)ILP approach.

The remainder of this paper is organized as follows. Section 2 gives a description of the histopathology laboratory. In Section 3, we define the problem, and give the mathematical formulation of the problem. Section 4 presents preliminary results of the application of our method in an academic histopathology laboratory. Section 5 ends with conclusions, discussion, and opportunities for further research.

## 2 Histopathology processes

The histopathology process can be divided into five main steps: grossing, tissue processing, embedding, sectioning and staining, and examination, as shown in Figure 1. Depending on the size and the moment of arrival of a tissue sample, tissue becomes available for the grossing stage immediately, or the next day. Information on tissue arrival is unknown.
In the grossing stage, tissues are trimmed in representative parts by a technician, and put into cassettes. In the automated tissue processing stage, the tissue in these cassettes is fixated and dehydrated using various chemicals. This process takes up to 12 hours depending on the tissue size. After tissue processing, the tissues are embedded in paraffin wax by a technician, to be sectioned in very thin sections (+/- 4µ) by another technician. When these sections are put on slides, the slides receive a staining using an automated stainer, which is required for the residents and pathologists to subsequently examine the slides under the microscope or using digital examination.

In many academic hospitals in the Netherlands, the tissue processing is regularly done in batches during the night, due to the large processing time of the conventional tissue processors. By overnight tissue processing, turnaround times are unnecessarily increased with one night. Currently, schedules of pathologists and technicians accommodate this delay for diagnosis, by facilitating the overnight tissue processing (Vernon, 2005). This results in batch processing throughout all stages of the histopathology laboratory. The implications of overnight tissue processing for the diagnostic workload in the histopathology laboratory are a buzzy environment in the morning, with lower work pressure in the afternoon (Buesa, 2009). However, when introducing tissue processing during the day, specific activities, such as sectioning, will shift from the early morning towards the afternoon (Vernon, 2005), which has consequences for the spread of workload over the day.

As a case study we consider the histopathology laboratory of the department of Pathology of University Medical Center Utrecht (UMCU). UMCU is a 1042 bed academic hospital which is committed to patient care, research, and education. In UMCU’s department of Pathology there are several laboratories, such as the histopathology laboratory, the immunochemistry laboratory, the DNA-laboratory, and cytology. The histopathology laboratory evaluates tissue of close to 30.000 patients each year, resulting in the examination of some 140,000 slides each year.

3 Problem description

This study considers the scheduling of histopathology processes, using a decomposed, two-phase approach, since exact approaches to solve the batching and the scheduling problem simultaneously, only allow for very small instances, with limited number of resources, batches, and orders (Harjunkoski and Grossmann, 2002). First, batching moments are determined to minimize the workload. This is called the batching problem (Section 3.1). Second, orders
are scheduled for all resources to minimize the tardiness, given the start times of batches from the first phase. This is called the *scheduling problem* (Section 3.2). To solve the batching and scheduling problem we propose two (M)ILP models. Furthermore, we use an approximation method for solving larger instances of the scheduling problem.

3.1 Batch problem

The batching problem focuses on scheduling tissue processing batches on multiple machines (tissue processors) aiming to minimize the workload for employees. This problem is considered separately, since the tissue processors experience very high processing times compared to the remaining processes, and since they are the only batch processors in the system. The expected duration of the batches might differ, but is known. All batches can be processed on all machines, and preemption is not allowed. The moment that a batch is finished is referred to as batch completion moment (BCM). The interval between two subsequent BCMS is defined as the batch completion interval (BCI): see Figure 2. The length of the BCIs depends on the assignment, sequence, and timing of the batches.

In this research, we aim to spread the BCMS over the day, such that peaks in workload in the subsequent stages are minimized. Consider a set of B batches (b=1,…,B). We then maximize the minimum batch completion interval:

\[
\text{max} \min_{b \in B} BCI_b.
\]

Under our objective, the workload is most effectively divided over the day when all batches contain the same number of slides, i.e., lead to the same workload in subsequent stages. In practice, if two batches of the same batch type are scheduled within a small time frame, only a few new arrivals have occurred, and thus the workload resulting from the second batch will be small compared to the workload resulting from the first batch. Therefore, the time between the completion of subsequent batches of the same type should be maximized. Consider a set of T batch types (t=1,…,T), with for each batch type t a corresponding set of batches B_t (B_t \subseteq B). This gives a second objective: \(\text{max} \sum_{t \in T} \min_{b \in B_t} \{BCI_{b,t}\}\), where BCI_{b,t} equals the interval between two subsequent BCMS of the same batch type, which is minimized for all batch types.

To determine the maximum minimum BCI, we formulated an ILP that not only decides upon the batch sequencing on each machine and the batch timing (e.g. the completion time of all batches), as proposed in Van Essen et al. (2012), but also considers the batch-machine assignment. This way, we can determine the BCIs, using the sequence in which all batches are finished by taking the interval in between subsequent batches. We consider the following as given:

- A set of B batches \((b \in B)\);
- A set of T batch types \((t \in T)\), and each batch type t has its own set of batches \(B_t (B_t \subseteq B)\);
- A set of M machines \((m \in M)\), with known start time \(s\) and end time \(e\).
Considering the machine assignment, we introduce a binary variable \( X_{b,m} \):

\[
X_{b,m} = \begin{cases} 
1 & \text{if batch } b \text{ is scheduled on machine } m \\
0 & \text{otherwise}
\end{cases}
\]

Each batch \( b \in B \) should be assigned to exactly one machine \( m \in M \). This gives:

\[
\sum_m X_{b,m} = 1 \quad \forall b \in B \tag{1}
\]

Considering the batch sequencing on each machine, we define a position variable \( P_b \) indicating the overall completion position of a batch \( b \in B \), and we introduce a binary variable \( Y_{b,b'} \):

\[
Y_{b,b'} = \begin{cases} 
1 & \text{if batch } b \text{ is scheduled somewhere before batch } b' \\
0 & \text{otherwise}
\end{cases}
\]

The position of a batch \( b \in B \) equals one plus the number of batches scheduled before this batch. Furthermore, a batch \( b \in B \) is either scheduled before batch \( b' \in B \), or after batch \( b' \in B \). This gives:

\[
P_b = \sum_{b'} Y_{b,b'} + 1 \quad \forall b \in B \tag{2}
\]

\[
Y_{b,b'} + Y_{b',b} = 1 \quad \forall b,b' \in B, b < b' \tag{3}
\]

Since cycles in the positioning are not allowed, and no batch can be on the same position as one of its successors, we introduce the following big-M constraint:

\[
P_b \leq P_{b'} - 1 + BigM \cdot Y_{b,b'} \quad \forall b,b' \in B \tag{4}
\]

Now the batch assignment and sequencing are guaranteed, we consider the batch timing. The completion time \( C_b \) and starting time \( S_b \) of a batch \( b \in B \) depend on the processing time \( p_b \). This gives:

\[
C_b = S_b + p_b \quad \forall b \in B \tag{5}
\]

A batch \( b \in B \) can only start processing after the machines’ starting time \( s \) and should be finished before the end time \( e \). We consider the same start and end time for all machines, which gives:

\[
S_b \geq s \quad \forall b \in B \tag{6}
\]

\[
C_b \leq e \quad \forall b \in B \tag{7}
\]

The completion time and starting time of two successive batches scheduled on the same machine \( m \in M \), cannot overlap. This gives:

\[
C_b - BigM \cdot (1 - Y_{b,b'}) \leq S_{b'} + BigM \cdot (2 - X_{b,m} - X_{b',m}) \quad \forall b,b' \in B, m \in M \tag{8}
\]
Now the assignment, sequencing, and timing is assured, we can determine the batch completion intervals. Let the first objective, \( \min_{b \in \mathcal{B}} BC_{I_b} \), be represented by OBJ1, and the second objective, \( \min_{b \in \mathcal{T}} \{BC_{I_{bt}}\} \) be represented by OBJ2.

\[
OBJ1 \leq C_{b'} - C_b + \text{BigM} \times (1 - Y_{b,b'}) \quad \forall b, b' \in \mathcal{B}
\]  
\[
OBJ2_t \leq C_{b'} - C_b + \text{BigM} \times (1 - Y_{b,b'}) \quad \forall t \in \mathcal{T}, b, b' \in \mathcal{B}_t
\]

When necessary, one can include the start time of the interval as batch completion moment, which gives two additional constraints:

\[
OBJ1 \leq C_b - s \quad \forall b \in \mathcal{B}
\]  
\[
OBJ2_t \leq C_b - s \quad \forall t \in \mathcal{T}, b \in \mathcal{B}_t
\]

Furthermore, we can set a lower bound to the objective, since it cannot become negative:

\[
OBJ1 \geq 0
\]

The objective of the ILP is a weighted sum of the two objectives mentioned, i.e. maximize the minimum batch completion interval and maximize the minimum interval between the completions of two batches of the same type. This gives:

\[
\max(\alpha \times BC_{I} + \beta \sum_{t \in \mathcal{T}} BC_{I_t})
\]

### 3.2 Scheduling problem

The scheduling problem encompasses three decisions to minimize the tardiness of orders: The sequencing of orders, the timing of all processes, and the order assignment to resources.

We consider multiple stages and multiple resources per stage, as shown in Figure 1. Orders arrive to the system, with known target due dates. Furthermore, it is known which resources are allowed to be used to process which orders. Preemption of orders is not allowed, since it can cause contamination of specimens, which causes diagnostic errors.

To solve the scheduling problem to optimality we propose an extended MILP formulation of the problem of Gupta and Karimi (2003) that decides upon the order assignment to resources in each stage, order sequencing on each resource, and the order timing. We consider the following as given:

- A set of \( G \) stages (\( g \in G \)).
- A set of \( J \) resources (\( j \in J \)), and each stage \( s \) has its own set of resources \( J_s \).
- A set of \( B \) batches (\( b \in B \)), with known resource \( J_b \), and start times \( S_b \).
• A set of I different orders (corresponding to the incoming specimens) (i ∈ I), with known target due dates di, and known sets of resources J, and batches B, which are allowed to process this order.
• A set of T different order types (t ∈ T). Each order type t ∈ T has its own set of orders It, consisting of all orders of that type, and its own set of batches Bt (Bt ⊆ B).

The scheduling problem can be written as a MILP. The sequencing of orders in the non-batching stages can be modeled using adaptations to the constraints presented by Gupta and Karimi (2003). Furthermore, we need to decide upon the assignment of orders to batches and resources, and the timing of orders.

We define three binary variables Zij, ZFij, and Aij as follows:

\[
Z_{ij} = \begin{cases} 
1 & \text{if order } i \text{ is processed by unit } j \\
0 & \text{otherwise}
\end{cases}
\]

\[
ZF_{ij} = \begin{cases} 
1 & \text{if order } i \text{ is processed first by unit } j \\
0 & \text{otherwise}
\end{cases}
\]

\[
A_{ij,ig} = \begin{cases} 
1 & \text{if order } i \text{ is processed directly before order } i' \text{ in stage } g \\
0 & \text{otherwise}
\end{cases}
\]

First of all, each order needs to be assigned to exactly one resource in each stage, since an order has to be processed in each stage exactly once (15). From all orders assigned to an operating resource j, one order has to be processed first (16). Since not all resources have to be operating, the left hand side of constraint (16) can also be zero.

\[
\sum_{j \in J, g} Z_{ij} = 1 \quad \forall i, g \quad (15)
\]

\[
\sum_{i \in I, j} ZF_{ij} \leq 1 \quad \forall j \quad (16)
\]

Order i ∈ I can only be processed first on resource j ∈ J if it is assigned to that resource (17).

\[
Z_{ij} \geq ZF_{ij} \quad \forall i \in I_j \quad (17)
\]

An order cannot have more than one feasible predecessor and one feasible successor in each stage. Each order can be processed first on a specific resource, or it succeeds another order (18). Furthermore, orders cannot have more than one direct successor (19).

\[
\sum_{i \notin NC_{ig}} A_{i,j,ig} + \sum_{j \in J, g} ZF_{ij} = 1 \quad \forall i, g \quad (18)
\]

\[
\sum_{i \notin NC_{ig}} A_{i',j',g} \leq 1 \quad \forall t, g \quad (19)
\]

To assign resources to a specific resource j ∈ J, it should hold that successive orders i ∈ I and i' ∈ I cannot be processed by resources that cannot process them both, but should be processed by a single resource j ∈ J ∩ I ∩ I'.
The combination of constraints (20) and (21) performed best in the review of Gupta and Karimi (2003), and were therefore included in our model.

\[ A_{i,t',g} + A_{i',t,g} + \sum_{j \in J_{ig} \cap J_{i'}} Z_{ij} \leq 1 \quad \forall g, i, i' > i, (i, i') \in I_g, i' \notin N_{Ci} \] (20)

\[ Z_{i'} \leq Z_{ij} + 1 - A_{i,t',g} - A_{i',t,g} \quad \forall g, i, i' > i, (i, i') \in I_g, i' \notin N_{Ci} \] (21)

Now the order assignment and sequencing is accounted for, the start times of the orders should be set in each stage, as follows from the continuous time representation. Therefore, we define a decision variable \( S_{ig} \) as follows:

\[ S_{ig} = \text{start time at which order } i \text{ starts processing in stage } g \]

To assign an order to a batch in the batching stage, we need an indicator for an order to be assigned to a specific time slot. Therefore, we define variable \( Q_{i,j,b} \) as follows:

\[ Q_{i,j,b} = \begin{cases} 1 & \text{if order } i \text{ is processed in batch } b \text{ on unit } j \\ 0 & \text{otherwise} \end{cases} \]

An order \( i \in I \) can only start processing in the next stage, after order \( i \in I \) has finished processing in the previous stage, and is transported to the next stage. Therefore, stage sequencing constraints are introduced.

When a batch \( b \in B \) is selected in a batching stage, this batch should start processing after order \( i \in I \) has finished processing in the previous stage, and is transported to the batching stage (22).

\[ \sum_j \sum_b Q_{i,j,b} \cdot b_{ij} \geq S_{ig} + \sum_j (Z_{ij} \cdot (f_{ij} \cdot t_{ij} + tt_{ij})) \quad \forall i, g \in G^{batch} \] (22)

To start processing in a post-batch stage, all orders of the batch containing order \( i \) should be fully processed in the batching stage, and transported towards the post-batch stage (23), with \( n_{ig} \) defined as the next processing stage of order \( i \in I \), currently being processed in stage \( g \in G \).

\[ S_{ig'} \geq S_{ig} + \sum_j (Z_{ij} \cdot (tb_j + tt_{ij})) \quad \forall i, g \in G^{batch}, g' \in n_{ig} \] (23)

In the stage sequencing relation between two non-batching stages, order \( i \in I \) has to finish processing in stage \( g \in G \) and be transported to the next stage before starting in next stage (24). The stage dependent timing constraints are adapted from the timing constraint of Gupta and Karimi (2003) to take the increasing order size into account, and to correct for batching influences.

\[ S_{ig'} \geq S_{ig} + \sum_j (Z_{ij} \cdot (f_{ij} \cdot t_{ij} + tt_{ij})) \quad \forall i, g \notin G^{batch}, g' \in n_{ig} \] (24)

Not only relations between stages influence the timing of orders on processing resources, also the relation between orders should be taken into account.
In all non-batching stages, order $i' \in I$ can start processing on $j \in J$ after its predecessor order $i \in I$ is finished (25). This constraint is adapted from the constraint of Gupta and Karimi (2003) to take the increasing order size into account.

$$\text{BigM} \times (1 - A_{i,i',g}) + S_{i',g} \geq S_{ig} + \sum_{j \in J_{ig}} (Z_{ij} \times f_{ij} \times t_{ij}) \quad \forall g \not\in G^{batch}, i, i' \not\in NC_{ig} \ (25)$$

The timing of orders on resources is subject to some constraints. The first order $i \in I$ on resource $j \in J$ can only start processing after the release time of the resource (26). Furthermore, each order can only start processing after its release time (27). Setup times are not taken into account.

$$S_{ig} \geq \sum_{j \in J_{ig}} (ZF_{ij} \times URT_{j}) \quad \forall g, i \ (26)$$

$$S_{ig} \geq ORT_{i} \quad \forall i, g = 1 \ (27)$$

The assignment of orders to a specific batch on a specific resource, is subject to two constraints. First, all orders can only be assigned to one batch, which follows from constraint (28). Second, the corresponding batch starting time equals the order timing of order $i$ in stage $g$ (29).

$$\sum_{j} \sum_{b} Q_{ijb} = 1 \quad \forall i \ (28)$$

$$S_{ig} = \sum_{j} \sum_{b} Q_{ijb} \times b_{sb} \quad \forall i, g \not\in G^{batch} \ (29)$$

Orders can only start processing on resources when the resources are available. Since resources are unavailable during night-hours, we consider $D$ nights during the planning horizon. To indicate if order $i \in I$ is planned before or after a certain night $d \in D$, let $W_{d_{ig}}$ be an auxiliary binary variable defined as follows:

$$W_{d,i,j} = \begin{cases} 1 & \text{if order } i \text{ is processed after night } d \text{ on resource } j \\ 0 & \text{otherwise} \end{cases}$$

Processing of any order in any stage cannot start at moments it cannot be finished before the closing hours of the resource. Therefore, processing of an order $i \in I$ in stage $g \in G$ should start before or after the non-working moments (30) (31), which does not involve the transfer time. These constraints only holds for non-batching stages, since the batch processors in the histopathology laboratory model are able to work during night hours, when the process is started before the start of the night.

$$S_{ig} \leq \sum_{j \in J_{ig}} (Z_{ij} \times NW_{1d} - f_{ij} \times t_{ij}) + \text{BigM} \times W_{d_{ij}} \quad \forall d, g \not\in G^{batch}, i \in I_{g} \ (30)$$

$$S_{ig} \geq (NW_{2d} + URT_{j}) \times W_{d_{ij}} \quad \forall d, g \not\in G^{batch}, j \in J_{g}, i \ (31)$$

The objective is to minimize the weighted tardiness of all orders. Let us define $S_{di}$ as follows:

$$S_{di} = \text{delay of order } i$$
The tardiness of order \( i \in I \) equals the sum of the start time in last stage \((\bar{g} \in G)\), the transfer time of order \( i \in I \) in this stage, and the order factor times the processing time of order \( i \in I \) in this stage, which together equals the completion time of order \( i \in I \), minus the due date of this order \((\text{dd}_i)\) (32). This constraint is adapted from Gupta and Karimi (2003).

\[
S_{d_i} \geq [S_{i,g} + \sum_{j \in I_{i,g}} (Z_{ij} \times f_{ij} \times t_{ij} + tt_{ij})] - \text{dd}_i \quad \forall i, g \in \bar{g} \tag{32}
\]

Specific specimen types are more important to finish on time than others. Therefore, the orders are prioritized, by priority factor \( \delta_i \). This makes the objective to minimize the sum of the weighted tardiness (33).

\[
\text{minimize} \sum_{i \in I} (\delta_i \times S_{d_i}) \tag{33}
\]

Some additional constraints are proposed to increase the efficiency of the MILP. An upper bound on the order timing \( T_i \) can be given by the end time of the planning horizon \( H \). A better upper bound is derived when subtracting the processing time of order \( i \) in the final stage. Since the processing times are equal in all resources, the last resource is chosen for the upper bound determination. This results in constraint (34).

\[
S_{i,g} \leq H - (f_{ij} \times t_{ij} + tt_{ij}) \quad \forall g, i, j = 13 \tag{34}
\]

When an order cannot be processed by resource \( j \in J \), since it is not allowed to be processed by that resource (i.e. \( i \notin I_j \)), the order cannot be assigned to that resource (35).

\[
Z_{ij} = 0 \quad \forall j, i \notin I_j \tag{35}
\]

As mentioned, only small instances can be solved using the MILP, due to the large problem size of real life instances and the long computation time (Harjunkoski and Grossmann, 2002). Therefore, we propose a constructive heuristic based on several dispatching rules to find a feasible solution within reasonable time for real life instances (including up to 130 orders per time interval, 4 stages, and 13 resources). These dispatching rules include Earliest Due Date (EDD) and First In First Out (FIFO), since these are easy to implement in the histopathology practices and have shown to result in near optimal solutions (Haupt, 1988). In the remainder of this research, we will use EDD

4 Results

The histopathology laboratory of UMCU has provided real life data to evaluate the applicability and performance of the solution method. We consider 10 different problem instances based on historical data of 22,379 patients derived from January to December 2013. The instances differ in terms of number and type of orders. Each instance includes four order types, corresponding with large specimens (type 1), small specimens (including biopsies) (type 2), priority specimens (type 3), and external specimens (type 4).
The priority of the order type is reflected in their due date, as shown in Table 1. The turnaround time (TAT) targets per order type, and therefore the corresponding due dates, are set by hospital management, the Dutch government, and external parties, to ensure a timely diagnosis for all patients (Pathologie, 2013).

We consider two scenarios. First we consider the current situation, for which only the scheduling problem is solved. The batching problem is not solved since the batching moments are already known in the current situation. Second we consider the situation with the batching policy as derived from the batching model. In both scenarios we fix one batch of type 3, to 11:15 AM each day, due to hospital regulations.

All experiments are solved on a HP laptop personal computer with 2GB RAM, using CPLEX 12.6 in AIMMS 4.0.

<table>
<thead>
<tr>
<th>Order type</th>
<th>TAT target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Order type 1</td>
<td>90% diagnosed within 7 days</td>
</tr>
<tr>
<td>Order type 2</td>
<td>90% diagnosed within 5 days</td>
</tr>
<tr>
<td>Order type 3</td>
<td>80% diagnosed within 24 hours</td>
</tr>
<tr>
<td>Order type 4</td>
<td>90% diagnosed within 3 days</td>
</tr>
</tbody>
</table>

### 4.1 Current situation

In the current situation, all orders are processed in batches during the night, except for type 3 orders, which are processed on fixed moments during the morning, but only consist of a very small amount of orders (1-3 slides per batch). This results in a high workload during the morning, as shown in Figure 3 for one representative instance.

The overall TAT results are shown in Table 2. One can see that only a small percentage of type 2 and type 4 orders are ready before their due date. This is a direct result of tissue processing during the night, which leads to a one-day delay for all orders.

![Figure 3: Workload performance batching policy](image)

![Figure 4: Workload performance current situation](image)
### 4.2 Batching policy

In the batching policy, we consider four interventions, based on the number of batches per order type per day allowed: (2-3-1), (1-3-1), (2-2-1), (1-2-1). Order type 1 batches are omitted, since type 1 orders are technically restricted to be processed during the night.

Figure 4 shows the spread in workload for one representative instance, including 6 batches. The TAT results are shown in Table 2. All interventions showed improved results regarding their norms, but specific patient types experience reduced performance compared to the current situation, such as type 1 patients. However, the results show that the performance of an intervention depends on the timing of the batches, especially in relation to the underlying arrival patterns of orders.

<table>
<thead>
<tr>
<th>Intervention</th>
<th>1: Current situation</th>
<th>2:(3-1-1)</th>
<th>3:(2-1-1)</th>
<th>4:(2-2-1)</th>
<th>5:(3-2-1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type 1 patients on time</td>
<td>99.4%</td>
<td>93.9%</td>
<td>93.6%</td>
<td>93.4%</td>
<td>93.4%</td>
</tr>
<tr>
<td>Type 2 patients on time</td>
<td>54.6%</td>
<td>88.4%</td>
<td>91.7%</td>
<td>94.7%</td>
<td>97.0%</td>
</tr>
<tr>
<td>Type 3 patients on time</td>
<td>98.0%</td>
<td>97.4%</td>
<td>97.4%</td>
<td>98.0%</td>
<td>97.4%</td>
</tr>
<tr>
<td>Type 4 patients on time</td>
<td>84.5%</td>
<td>92.5%</td>
<td>90.9%</td>
<td>90.4%</td>
<td>88.7%</td>
</tr>
<tr>
<td>TAT (in hours)</td>
<td>25.77</td>
<td>21.00</td>
<td>20.96</td>
<td>21.29</td>
<td>20.12</td>
</tr>
</tbody>
</table>

### 5 Conclusion / Discussion

We have introduced a decomposed solution method to optimize and prospectively assess the planning and scheduling of batches and orders in the histopathology laboratory. The results show that the turnaround time, which is the main performance indicator, can be reduced by 20% through eliminating unnecessary waiting during the night hours. Furthermore, peaks in workload can be reduced by more than 50% by shifting a part of the pile of work from the morning towards the afternoon.

The batches under the solution approach are not always equally filled, which in specific cases may result in larger or smaller peaks in workload depending on the patient arrival pattern, especially since different arrival patterns are encountered over the day. Therefore, future work will be dedicated to analyze the effect of weighing the BCIs according to the arrival distribution of orders per order type during the corresponding BCI.

By fixing the batch starting times of specific batches, the corresponding orders in that batch are prioritized, since they have a higher chance of being processed at a favorable time. The analysis showed evidence that prioritizing specific order types increases the TAT performance of those orders. However, this occurs at expense of others. Further research will be executed to analyze this relation.

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1 (# order type 2 batches, # order type 3 batches, # order type 4 batches)
Based on this work, UMC Utrecht is currently implementing planning and control approaches in the histopathology laboratory regarding the planning and scheduling of tissue processing batches and stage one resources.

References


