

**Developing a Pathologists' Monthly Assignment Schedule: A Case Study at the
Department of Pathology and Laboratory Medicine of The Ottawa Hospital**

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Abstract

In the Department of Pathology and Laboratory Medicine, at the beginning of each month, the clinical managers use expert knowledge to assign pathologists to expected daily specimens based on the criteria of workload restrictions, clinical sub-specialties, and availability. Since the size of the pathologists' assignment problem is large, finding a feasible assignment manually is a very time-consuming process that takes a number of iterations over a number of days to complete. Moreover, every time there is a need to make a revision, a new assignment needs to be developed taking into account all the above criteria. The goal of this research is to develop an optimization model and a decision support tool that will help with monthly staffing of pathologists based on the criteria outlined above. The developed model is rooted in the classical operations research assignment problem and it is extended to account for the following requirements: each pathologist should be assigned to a similar specimen type throughout a week; for a given pathologist, there should be a rotation of the specimen types between the weeks; and the clinical managers' preferences in terms of assigning a particular specimen type to a particular pathologist on a specific day need to be considered. A monthly assignment model covering 36 pathologists and 26 specimen types was solved using IBM ILOG CPLEX Optimization Studio. It is embedded in a decision support tool that helps clinical managers to make staffing decisions. The decision support tool has been validated using data from The Ottawa Hospital (TOH).

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Chapter 1: Introduction

1.1 Background and motivations

Pathology is an area of medicine where pathologists provide expertise to help diagnose the nature of disease based on specimens taken from patients' organs [1]. For each specimen a number of activities at different levels (macroscopic, microscopic and molecular) are performed to provide accurate diagnosis. The type and number of these activities depend on the type of specimen (e.g. specimen taken from a patient's liver or breast) that in turn is determined by clinical practice [2]. The processing of each type of specimen draws on personnel (laboratory staff and pathologists) and equipment resources. Since pathologists have different sub-specialties, each type of specimen can be examined only by a qualified pathologist with the appropriate sub-specialty. Therefore, assigning pathologists to different types of specimens subject to existing constraints such as pathologists' availability and workload restrictions is a challenge that clinical directors and managers in pathology laboratories have to deal with on a regular basis. Since an inappropriate assignment leads to a loss of time and resources, managers put a lot of effort into finding feasible solutions for this problem. As the number of specimens to be assessed grows, the time spent on creating the pathologists' assignment schedule increases creating a need for a computer-aided scheduling support tool [3]. In this thesis we describe the research behind the development of a decision support tool and optimization model that was developed in collaboration with the clinical managers and pathologists from the Department of Pathology and Laboratory Medicine (DPLM) at The Ottawa Hospital (TOH).

There are typically three steps in scheduling pathologists at a pathology laboratory. The first step is to forecast the daily arrivals of specimens of different types requiring diagnosis for the entire planning period (e.g., a month). The second step is to translate this information into a daily resource requirement (i.e. number of pathologists required to diagnose all cases of each type of specimen each day). The third step is to assign pathologists to the specimen types based on the daily resource requirement.

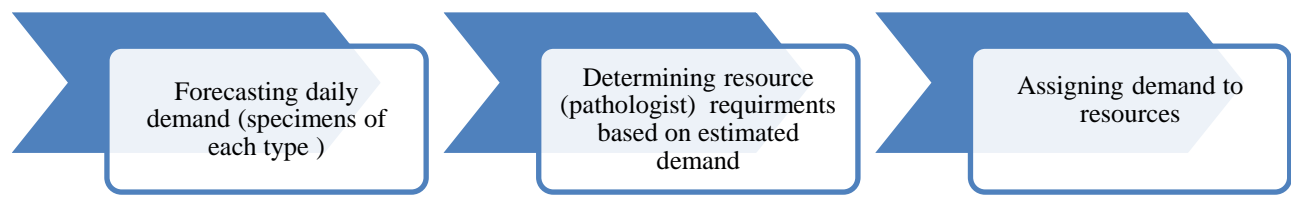


Figure 1.Steps in scheduling pathologists

In the first and second steps, the expected workload of pathologists for each specialty is determined based on the level of complexity of each type of specimen and the expected number of that type of specimen. What constitutes an efficient workload for different sub-specialties has been widely studied during the last few decades. Researchers (Cheung et al (2014) [25], G.A. Meijer et al (2009) [2], R. Mounq (2010) [4]) have proposed a number of different methods and guidelines to find the approximate number of specimens that can be analyzed efficiently by each pathologist per day (pathologist’s workload). This helps to find how many pathologists are required to assess all the daily specimens of each type based on the estimated forecast. The Canadian Association of Pathologists (CAP-ACP) developed guidelines that “allow pathologist workforce planning and benchmarks to be established for a reasonable, practical, and safe workload” [4].

In the third step, managers assign pathologists to the specimens based on the daily resource requirements determined in the first and second step, the pathologists' availability and their expertise. Considering the number of pathologist's sub-specialties and pathologists' availability, there are many possibilities in assigning daily specimens to the pathologists. Therefore, a question arises as to what is the best schedule derived from this assignment problem and what are the relevant criteria for determining the best assignment? While the importance of the assignment problem for the efficient use of pathology resources is acknowledged, no formal model has been developed to find the optimal policy of assigning daily specimens to pathologists. In this thesis we fill this gap by proposing a formal assignment problem model to facilitate the process of scheduling pathologists in a pathology department.

To avoid any ambiguity, we define the terms we use in this paper as the following.

- Pathology requests, cases, specimens, specimen type

Pathology requests are recoded as "cases" with each case involving the analysis of one or more specimens that are processed and further subdivided into slides. We are not concerned with the process of creating the slides from a specimen but want to stress that each specimen may include (depending on its type) anywhere from 3 to over 200 slides that need to be examined by a pathologist. The specimens of different types can be diagnosed by pathologists with specific sub-specialties (described below). In this research we make a simplifying assumption that the specimens of similar type that require pathologist with a given sub-specialty are grouped together, thus the relationship between sub-specialty and specimen type is a 1:1 relationship.

- Specialty, sub- specialty

In general, specimens are categorized into three main areas:

- Autopsy: samples taken from deceased patients
- Cytology: single cells (smear, fluid, brush, discharge, aspirate)
- Surgical pathology: tissue/s or organ/s (biopsy, excision, resection)-not necessarily from surgery, can be medical (endoscopic), from clinic (dermatology) or radiology department

Each main specialty is divided into its own sub-specialties. Specimens are categorized based on the sub-specialties and all the daily specimens of each type are assigned to one or more pathologists (depending on workload restrictions) who are specialized in assessing that particular type of specimen. Each pathologist usually has a number of sub-specialties and therefore is specialized in assessing a number of specimen types.

- Service weights

The proportion of a full day's workload for a pathologist required to complete the expected daily demand of a specimen type is called the "service weight" of the given specimen type. Service weights are clearly stochastic variables that depend on the number of specimens arriving in a day, the amount of time it will take to assess all slides of a given type of specimen in a day (including the level of diagnostic complexity) and the skill level of each pathologist. However, these service weights are estimated using pre-determined values that are different for each specimen type and that represent the expected amount of time (measured usually in days) for a pathologist to complete all demand to diagnose specimens of a given type for that day. These estimations are established in the first and second steps of the scheduling process presented in Figure 1. For example, a service weight of 1.0 for neuropathology specimen indicates that in order to meet the expected daily demand for the

diagnosis of neuropathology specimens, one pathologist needs to be assigned. There is no agreement in the literature (nor in clinical practice) as to how the service weights ought to be determined but such discussion is beyond the scope of our research. Clinical managers at the Department of Pathology and laboratory Medicine (DPLM) at The Ottawa Hospital (our collaborating hospital) rely on weights that are based on the L4E indicator [26] used in a number of Canadian and American laboratories to establish pathologists' workload.

1.2 Research question

In a pathology department, at the beginning of each month, the clinical managers use a heuristic approach to assign the estimated daily demand for diagnosing specimens of different types to the pathologists based on pre-defined criteria. Since the size of the pathologists' assignment problem is large in most clinical settings, finding a feasible solution manually represents a very time-consuming process and can take a number of iterations over a number of hours to complete. Moreover, every time there is a need to revise the assignment, the process must be re-started. Furthermore, the manual scheduling approaches do not ensure that the resulting schedule is an optimal one satisfying all the pre-defined requirements as much as possible. Thus, in order to develop an optimal assignment of pathologists to specimen types (a schedule) we define the following research questions:

- *What makes a good pathology schedule and what constitutes an optimal assignment?*
- *Considering the factors that make a good pathology schedule, what is the optimal assignment that matches the specimen types (based on the service weights) with the available pathologists respecting each pathologist's expertise and workload restrictions?*

The objectives of this research were addressed in a two-fold manner. First, we identified factors that constitute a good schedule and developed, in consultation with the managers from DPML, an optimization model for the pathologists' assignment problem. Second, we embedded the model in an easy-to-use decision support tool for clinical. The tool allows the managers to manipulate and revise the assignment schedule in order to assess a number of scheduling scenarios or consider special cases.

1.3 Problem Definition

In a pathology laboratory, when diagnostic requests translated into an assessment of specimens are received from operating rooms and clinics, these requests go through an accession process that entails receiving, labelling, and entering data on the specimen into the Laboratory Information System. After this step, all of the specimens must undergo the gross-embed-cut process before they can be mounted, stained and cover slipped [5]. Once this step is completed, specimens are 'batched' and 'distributed' in the form of stained slides, meaning that they are categorized based on their type and then they are assigned to pathologists for their diagnosis. The specimens are assigned to the pathologists based on the following requirements:

- *Pathologist's sub-specialty*: Each pathologist can assess only those specimens that are within his/her area of clinical expertise.
- *Pathologist's availability*: Due to a number of clinical and non-clinical duties, each pathologist's availability needs to be assessed on a daily and weekly basis. We measure availability in a given week using "full time equivalent (FTE)" fraction (i.e. for a pathologist working full time in a given week $FTE = 1$). The weekly availability rate is practically

stable for each pathologist over a month. However, pathologists might not work on some days in a month due to training, teaching, etc. These absences change, thus the number of available pathologists varies from day to day, but this variation is largely known in advance.

- *The service weight:* As was explained earlier, the fraction of “full day” required to assess all the estimated specimens of a given type is defined as the service weight of that type of specimen.

The above requirements define what we call “hard requirements” as they need to be satisfied by any assignment schedule. However, there are a number of “performance criteria” that should be considered when a reasonable assignment schedule is created. These criteria determine the performance of a schedule based on what have been defined as a good schedule in a pathology department. The following are some of the most important performance criteria that pathology departments take into account:

- *Consistent assignment in a week:* It is desirable that a pathologist remains on the same sub-specialty for an entire week. The advantage of this is that it allows him/her to manage the variability in specimen load from day-to-day while maintaining complexity of the assessment relatively stable. For example, if we assume that it is preferred for a pathology laboratory to assign a single specimen type to a pathologist within a week and specimen types of X and Y are within the areas of expertise of both pathologist 1 and 2, the first schedule presented in Figure 2 is preferred to the third schedule as the pathologists are assigned to the same specimen types consistently throughout the week.
- *Rotation of the specimen types between the weeks:* In order to maintain the clinical skills required by a sub-specialty, each pathologist should regularly rotate through the diagnosis of

each type of specimen that falls within her/his area of expertise. Thus, in the example, the first schedule is preferred over the second one.

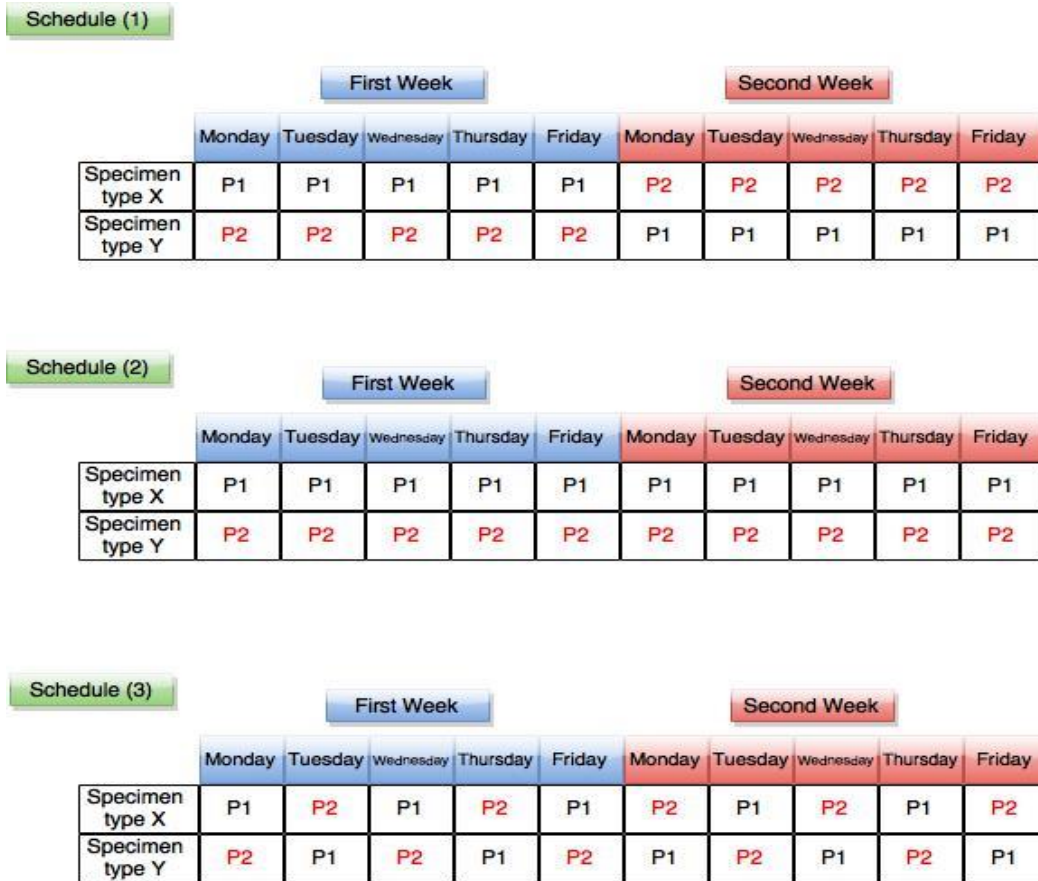


Figure 2.Examples of the assignment schedules

- Unassigned specimen types:* Due to vacations and other absences, it is not always possible to cover every sub-specialty on every day to the degree that is desirable. Thus it is important to determine which types of specimens will not be assigned for diagnosis, if necessary. For instance, full coverage for one sub-specialty might require three pathologists. Faced with insufficient resources, the department may choose to reduce that coverage to two pathologists as a first step. Also, the demand for some types of specimens is quite low, so when there is a shortage of resources the department may decide to assign

the given specimen types to the pathologists only on some days of a week rather than for a full week. Therefore there are some weights that determine which types of specimens should be definitely assigned to the pathologists and the remaining are assigned last and only if resource is available. The specimen types which are not assigned are called “unassigned specimen types”. It is desirable to have as less unassigned specimen type as possible.

Balancing pathologists’ workloads, maximizing pathologists’ preferences in terms of assigning their “preferred” specimen types and minimizing pathologists’ overtime are some other potential requirements that can be considered. However, we do not consider these requirements here because they are not as important for the clinical manager at DPLM.

The next section provides a review of research using the assignment problem in healthcare and other industries. This is followed by a description of the analytics model in Section 3. The decision support tool is described in the Implementation section. In the Results section we use the data from DPLM in order to compare the assignment schedules developed by our model with those used by DPLM. The paper ends with concluding remarks.

Chapter 2: Literature review

The majority of papers dealing with the pathologist assignment problem is focused on the pathologist workload measurement and what is the best way to determine the service weight for each type of specimen. To the best of our knowledge this is the first research that looks into the optimal assignment of pathologists to the specimen types in order to create a monthly pathologists’ schedule.

The pathologist assignment problem can be considered as a type of staff assignment problem. The staff assignment problem is an optimization problem that aims to find an optimal arrangement of n available staff to m positions or tasks in a system. During the last few decades, researchers have developed a number of assignment models for various settings such as industrial systems, educational institutions and healthcare organizations to help decision makers in assigning tasks to resources (including human resources and equipment).

Ernst *et al* [9] have reviewed research on staff scheduling and have classified this problem into six different categories: “demand modelling”, “days off scheduling”, “shift scheduling”, “line of work construction”, “task assignment” and “staff assignment”. They analyzed the applications of the staff scheduling problems in various settings such as transportation systems [10, 11], call centers [12, 13], healthcare systems [14, 15] (discussed later), manufacturing [16, 17] etc. The authors state that “optimised staff schedules can provide enormous benefits, but require carefully implemented decision support systems”.

2.1 Industrial assignment problems

The assignment problem of the pathology workforce is similar to task/demand assignment problem in industrial settings. Assigning specimen types to pathologists with different sub-specialties is comparable to the assignment of different types of tasks to multi-skilled employees or assigning demand to different members of a workforce. There is a substantial amount of research on the staff assignment problem in industry [9] with the representative examples discussed below.

Cheng *et al* [6] employ an optimization model to assign tasks to multi-skilled employees with different skill levels in a product development project. Considering the balance of employee’s

workload, the authors minimize the time to completion of the development project. While the duration of a task in a project is not certain, the researchers apply fuzzy numbers to increase the level of accuracy in the model. The model was applied it in a die design project for a car door.

Corominas *et al* [7] develop a non-linear Mixed Integer Program (MIP) model to address the problem of assigning project tasks to multi-skilled human resources. In this model the authors consider different priorities for assigning tasks to workers with different levels of skills. The objective of the assignment is to maximize the preferences of the assignments as well as to reach human capacity as close as possible.

Zhu *et al* [8] apply a stochastic MIP to address demand fluctuation in a multi- unit workforce planning problem. The problem is to find the optimal solution for assigning demand to different units of a workforce. The authors initially solve the problem based on deterministic demand and define different scenarios to determine how the optimal assignment changes if the demand changes. A two stage stochastic approach is used to analyze how the uncertain demand changes the optimal staff assignment policy. In the first stage, a decision is made about the number of workers who should be recruited while the demand is uncertain. In the second stage, the optimal policy about assigning demand to different units of a workforce is determined.

2.2 Healthcare assignment problems

A number of assignment models have been developed to improve the management of healthcare organizations [18]. The type of models developed depends on the type of organization and the specific characteristics of the problem [28]. Assigning nurses and physicians to shifts so staffing requirements are met, represents two of the most common problems. Jaumard *et al* [24] use a

linear programming model to solve a multi- objectives nurse scheduling problem. The model includes three different criteria - minimizing salary costs, maximizing the nurse preferences, and balancing the teams in terms of members' experience. The criteria have been included into a single objectives, with each weighted differently to reflect the importance of the component.

Punnakitikashem *et al* [29] have used a stochastic integer programming model to assign nurses to patients subject to the nurses' workload constraint. The model minimizes a non-decreasing piecewise linear convex function representing the overload penalty for nurses. The number of patients (demand) is considered as a fixed parameter that also includes the potentially unanticipated patients. The model was solved using data from Baylor Regional Medical Center in Grapevine, TX. (More articles about nurse scheduling are Ferland *et al* [30], Burke *et al* [27], Berrada *et al* [23])

Hertz *et al* [19] propose a MIP model to assign patients to the nurses who work for different health providers. In their study, the authors declare that demand fluctuation is one of the most important factors causing the imbalance in nurses' workload. Therefore, they attempt to balance a workload which includes the number of home visits that each nurse makes for each patient, the number of patients that a nurse is responsible to visit (case load), and the distance that nurses have to travel to visit patients.

Similarly, Lanzarone *et al* [20] use an linear programming model to optimize the home care staff assignment problem. The authors minimize the care providers' overtime penalty while balancing their workload. New demand is considered to be either deterministic or stochastic. The authors conclude that the impact of the variability in demand is negligible if some variability is allowed for the nurses' workload.

Errahout *et al* [18] assume a deterministic patient demand to develop a MIP model for the home care staff assignment problem. They take into account the nurses' qualifications, availabilities and capacities while balancing the nurses' workload.

Bertels *et al* [21] conducted a similar study but included a set of soft constraints such as patients' preferences and staff satisfaction to obtain more realistic assignments. Incorporation of soft constraints asked for using a combination of linear programming and meta-heuristics approach.

Yalcindag *et al* [22] applied a two-stage model to solve the home care assignment problem. The authors solve MIP model to find the optimal assignment of service providers under the assumption of deterministic patient demand. Then, they find the routes (sequence in which the patients are visited) for each provider according to the optimal solutions obtained in the first stage. Authors use Italian data to analyse the result of their model.

Literature review demonstrates that while assignment models were used in healthcare, to the best of our knowledge this research is the first attempt to develop the optimization model for developing assignment schedule in a pathology department. The proposed model is similar to those used by others but has a number of distinct features: it deals with a situation where each pathologist has multiple sub-specialties and explicitly considers the need for pathologists to rotate through the types of specimens in order to maintain the required skills in a given clinical sub-specialty.

Chapter 3: Model Development: A case study of the Department of Pathology and Laboratory Medicine at The Ottawa Hospital

3.1 Introduction to the DPLM

TOH is a teaching hospital affiliated with the University of Ottawa that provides inpatient and outpatient services on three campuses located in different parts of the city and organized into 28 departments. The DPLM is located on one of these campuses (General Hospital campus) and serves the entire TOH. It also receives specimens from community hospitals and from private pathology laboratories serving the City of Ottawa and surrounding areas. Each day about 200 specimens of differing types and complexity arrive from the operating rooms of TOH, the clinics affiliated with the hospital, the community hospitals, and from small laboratories. The 36 full time and part time pathologists working at the DPLM are salaried and their responsibilities, apart from clinical work include teaching and research that impact their availability in a given day, week, and month. These pathologists cover services spanning 26 sub-specialties (shown in Appendix).

The pathologists' assignment problem is large and complex and represents one of main challenges that the clinical managers at the DPLM have to deal with each month. In this research an optimization model has been developed with a goal of alleviating the load associated with developing the schedule. While the model presented here is based on the requirements provided by the DPLM, it can be ported with some modifications to any other pathology department.

3.2 Integer Programming

The development of the pathologists' assignment schedule is a decision-making problem that involves the analysis and assessment of a number of alternative schedules each with different characteristics. Considering the previous studies, this type of problem is commonly solved using

MIP or IP models that incorporate hard constraints as well as some performance criteria (goals of a problem). IP is a good method to solve daily assignment problems because it is efficient and easy to solve.

The IP model developed in this research includes a statement of the assumptions behind the model, a description of the decision variables and model parameters, a description of the components comprising the objective function of the model, and finally, a description of the constraints.

3.3 Assumptions

Most of the modeling assumptions discussed here were obtained from the managers of DPLM.

However they are common for academic hospitals.

- Number of daily demands for each type of specimen is constant and consequently the service weights of specimen types are constant.
- Standard FTE for a pathologist is based on 5 days a week (FTE=1); a pathologist who works less than 5 days a week (his/her FTE is less than 1) can be assigned to any days of a week unless s/he requests a particular working day. For example, a pathologist with a FTE of 0.6 can only work a maximum of 3 days in a week.
- A pathologist available on a given day works the full day. There is no partial workload during a day.
- Service weight of a specimen type depends only on the specimen (homogenous categories).
- All specimen types that can be diagnosed within the same sub-specialty have the same priority of processing. Demand is collected throughout the day and batched for diagnosis

the next day. Although each day there might be some rare cases that are urgent, those cases are assessed by on-call pathologists and thus are not considered here.

Model Structure

3.4 Decision Variables

The decision variables represent the unknown (to be determined by the solution of the model) daily assignments of the pathologists to specimen types for each day in the schedule. Based on a monthly assignment schedule of 20 business days on average (max 25 days as the DPLM does not work on the weekends and statutory holidays), and assuming there are 36 pathologists and 26 types of specimens, there are a maximum 23,400 possible daily assignment combinations (decision variables). However, after taking into account a number of soft requirements that required modeling with decision variables, the total number of decision variables in the model increases to 43,649.

The decision variables are as follows:

$$X_{ijt} = \begin{cases} 1, & \text{if pathologist } i \text{ is assigned to specimens of type } j \text{ on day } t \\ 0, & \text{otherwise.} \end{cases}$$

$$i=1,2,3,\dots,36 \quad j=1,2,3,\dots,26 \quad t=1,2,3,\dots,25$$

$$Y_{ijk} = \begin{cases} 1, & \text{if pathologist } i \text{ is given specimens of type } j \text{ in week } k \\ 0, & \text{otherwise.} \end{cases}$$

$$i=1,2,3,\dots,36 \quad j=1,2,3,\dots,26 \quad k=1,2,3,4,5$$

d_{jt} : auxiliary variables that are used to account for the unassigned specimen types on day t when there is not enough pathologists to satisfy all demand. In other words, we use these variables to count the number of unassigned specimen types.

β_{ij} : auxiliary variables used to keep track of the number of different types of specimens that have been assigned to each pathologist within a month. These variables help to incorporate a requirement that specimen types should be rotated between the pathologists so they maintain clinical expertise in each of their sub-specialties..

3.5 Parameters

We use seven types of parameters in the model:

- \mathbf{b}_i : **FTE** for each pathologist working full time has a value of 1 while for the part timer it can be any number between 0 and 1 (for example, for a pathologist working two out of five days a week, the value of his/her FTE is 0.4). Values for the b_i parameters were obtained from the DPLM.
- \mathbf{a}_j : The **service weights** a_j represent the resource requirement to diagnose all the daily demand of specimen type j (for example, $a_j = 3$ indicates that 3 FTEs are required to diagnose daily volume of specimen type j). Values for this parameter are derived from the workload determination system used at the DPLM.
- T_{it} : The **availability of a pathologist** on a given day is represented by a binary parameter with value 1 if the pathologist is available and 0 if the pathologist is unavailable. These

values change from month to month and reflect each pathologist's availability taking into account teaching/research obligations, vacations, leave, etc.

- S_{ij} : Binary parameter that represents which types of specimens are within **each pathologist's area of expertise**. (for example, when pathologist i is able to diagnose specimen type j then the value of this parameter is 1. It is 0 otherwise).
- γ_{ij} : Binary parameter that is used to represent pathologists' sub-specialties. Its value equals 1 if specimen type j belongs to one of the sub-specialties that pathologist i has to practice. This is not necessarily the same as S_{ij} as a pathologist may be able to diagnose a given type of specimen while not needing to practice that sub-specialty regularly.
- C_1, C_2, C_3 : Weights that reflect the relative importance of each component of the objective function (explained more in the next section)
- W_j : Weight of specimen type j that is used to indicate which types need to be assigned first in case of limited availability of pathologists with required sub-specialties. W_j can take values of 1 (least important), 2 or 3 (the most important). The specimen types with smaller value of W_j will have more "unassigned" specimen type than those with higher values.

3.6 Objective Function

The objective function establishes a performance measure for assignment schedules. In our model the objective function is created by combining the performance criteria outlined earlier (consistent assignment in a week, rotation of the specimen types between the weeks, unassigned specimen types). As the managers want to consider only one schedule for each month, we develop a single objective function with three components, each with a specific weight of importance that can be

assigned by a clinical manager. In our research, the values of the weights were determined experimentally so the resulting assignment schedule best matches the expectations of the managers.

The objective function is written as:

$$\min z = C_1 \sum_{i=1}^{36} \sum_{j=1}^{26} \sum_{k=1}^5 Y_{ijk} - C_2 \sum_{i=1}^{36} \sum_{j=1}^{26} \beta_{ij} + C_3 \sum_{j=1}^{26} \sum_{t=1}^{25} w_j d_{jt}$$

The first component penalizes assignment schedules each time a pathologist is given a different specimen type in the same week. The second component rewards assignment schedules every time a different specimen type (within a pathologist's area of expertise) is assigned to a pathologist. The third component penalizes assignment schedules for every unassigned specimen type. The weights C_1 , C_2 and C_3 are user-defined and reflect the relative importance of each of the three components.

3.7 Constraints

Model constraints include hard requirements as well as a number of constraints related to different components of the objective function to produce feasible daily assignments over 20 or 25 days. Our model has in total 52057 constraints, excluding binary and non-negativity constraints imposed on the decision variables. The constraints are outlined below.

- Constraints that track consistent assignment within a week (maximum 5 weeks within a month, 5 business days within a week):

$$\forall (i, j)$$

$$\sum_{t=1}^5 X_{ijt} \leq MY_{ij1}$$

$$\sum_{t=6}^{10} X_{ijt} \leq MY_{ij2}$$

$$\sum_{t=11}^{15} X_{ijt} \leq MY_{ij3}$$

$$\sum_{t=16}^{20} X_{ijt} \leq MY_{ij4}$$

$$\sum_{t=20}^{25} X_{ijt} \leq MY_{ij5}$$

Where M is a large number (in this particular case M should be greater than 5). Each time a new specimen type is assigned to a pathologist in a given week, the above constraints force a corresponding variable Y_{ijk} representing the fact that pathologist i was given specimen type j in week k to take the value 1. Ideally, we want a pathologist to be given only one specimen type in a week so there is only one corresponding Y_{ijk} that takes the value 1. The more $Y_{ijk} = 1$, the higher value of the first component of the objective function.

- Constraints tracking the rotation of the specimen types

$$\forall (i, j)$$

$$\sum_t \gamma_{ij} X_{ijt} \geq \beta_{ij}$$

$$\beta_{ij} \leq 5$$

The ideal schedule gives a week's (5 days) worth of one specimen type to a pathologist and then for that pathologist switches to a different specimen type for the subsequent week in order to rotate through his/her areas of expertise. The above set of constraints allows values of β_{ij} to be less than the number of days pathologist i is assigned specimen type j up to a maximum of 5 (representing a full week's worth for that specimen type). β_{ij} takes value 1 once specimen type j is assigned to pathologist i . Maximum number of β_{ij} for one specimen type and given pathologist is 5 meaning that if the model assign more than 5 times the same specimen type to the given pathologist, β_{ij} will not change. Higher values of β_{ij} decrease the value of objective function thus incentivizing the model to rotate between specimen types each week to allow for higher β_{ij} .

- Respecting resource availability

These constraints ensure that pathologist i does not work more than his/her FTE availability. The FTE fractions are measured per day using 0 to 1 scale, so values of b_i have to be multiplied by 5 in order to derive the number of days that each pathologist works per week (5 business days in a week). These constraints are repeated for each week of the month.

$\forall i$

$$\sum_{t=1}^5 \sum_{j=1}^{26} a_j X_{ijt} \leq 5b_i$$

$$\sum_{t=6}^{10} \sum_{j=1}^{26} a_j X_{ijt} \leq 5b_i$$

$$\sum_{t=11}^{15} \sum_{j=1}^{26} a_j X_{ijt} \leq 5b_i$$

$$\sum_{t=16}^{20} \sum_{j=1}^{26} a_j X_{ijt} \leq 5b_i$$

$$\sum_{t=20}^{25} \sum_{j=1}^{26} a_j X_{ijt} \leq 5b_i$$

- Daily workload

This set of constraints ensures that no pathologist in a given day can work up to full FTE is given more than a full day's work on any given day. The left hand side of each constraint, for a given pathologist and given day calculates the workload of each pathologist per day taking into account all assignment types assigned to that pathologist on that day. However, as we explain later, in some special situations managers overload some of the pathologists. We took this into account when

developing the decision support tool by allowing the FTE fraction to be set higher than 1 for individual pathologist if necessary.

$$\forall(i, t)$$

$$\sum_{j=1}^{26} a_j X_{ijt} \leq 1$$

- Unassigned specimen types

For a given specimen type on a given day, it can be either assigned to a pathologist or not. If it is not assigned, then X_{ijt} takes value 0 for all i and thus d_{jt} is forced to take on the value 1 for that specimen type and day combination. Thus d_{jt} counts the number of unassigned specimen types.

$$\forall(j, t)$$

$$\sum_{i=1}^{36} X_{ijt} + d_{jt} = 1$$

- Pathologists' availability

These constraints allow the manager to explicitly indicate what days a given pathologist is not available. If pathologist i is not available on day t , the associated variable $T_{it} = 0$ and therefore it is not possible to assign that pathologist any specimen type (because corresponding $X_{ijt} = 0$) on that day.

$$\forall(j, t)$$

$$X_{ijt} \leq T_{it}$$

- Sub-specialty coverage

These constraints allow the manager to explicitly indicate which types of specimens a pathologist is unable to analyze. If specimen type j is not within the area of expertise of pathologist i then $S_{ij} = 0$. This forces the associated X_{ijt} to be 0.

$$\forall(i, j)$$

$$X_{ijt} \leq S_{ij}$$

3.5. Solving the model

The model was solved by a version of Simplex algorithm (IP gap tolerance of 1.0E-6) being part of the IBM ILOG CPLEX Optimization Studio (version 12.6) running on a Dell T7600 desktop computer with Windows 7. On average it took between 7 to 10 minutes to obtain the optimal assignment schedule for a given month (the code of the model is shown in the Appendix).

Chapter 4: Results and Comparison

4.1 Selecting weights for objective function components

Generally, there might be many optimal schedules arising from the IP model depending on the weights assigned to each component of the objective function. Therefore, we need to determine an appropriate weight for each component to make sure the resulting schedule meets the expectations of the DPLM. For this purpose we defined the following metrics (M_i) associated with each component of the objective function:

- M_1 : Percentage of inconsistent assignments; this measures the consistency of assignments within a given week. It is calculated as the percentage of all assignments that are not consistent within a week divided by all the assignments in a month. For instance, the percentage of inconsistent assignments for the schedule given in Figure 3 is 25% (the inconsistent assignments are circled): two specimen types and 2 weeks implies total weekly assignments = $2 \times 2 = 4$ Total inconsistent assignments (circled) $M_1 = (1/4) \times 100 = 25\%$

	First Week					Second Week				
	Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday	Friday
Specimen type X	P1	P1	P1	P1	P1	P2	P2	P2	P2	P2
Specimen type Y	P2	P3	P2	P3	P2	P1	P1	P1	P1	P1

Figure 3. Example for inconsistent assignment

- M_2 : Percentage of missed rotations of specimen types. Each pathologist ought to assess the specimens that allow him/her to “cycle” through all sub-specialties within his/her area of expertise. This is accomplished by rotating what specimen type a pathologist is covering each week. Missed rotations are the number of sub-specialties within each pathologist’s

area of expertise that are not covered (pathologist has not been assigned relevant specimen type) in a given month divided by the total number of sub-specialties for each pathologist. This metric is aggregated over all pathologists to derive a single measure. It is important to note that it may not be possible to cover all sub-specialties for a given pathologist while still maintaining consistency within the week as some pathologists have 5 or more sub-specialties. Nevertheless, an assignment schedule that has less missed rotations is preferred.

- M3: Percentage of unassigned specimen types. In the schedule developed by the model we allow for some specimen types not to be assigned if there is not enough coverage by sub-specialty (volume of demand for a given specimen type exceeds available capacity). However, we clearly want to find a schedule where the total number of unassigned specimen types is as small as possible.

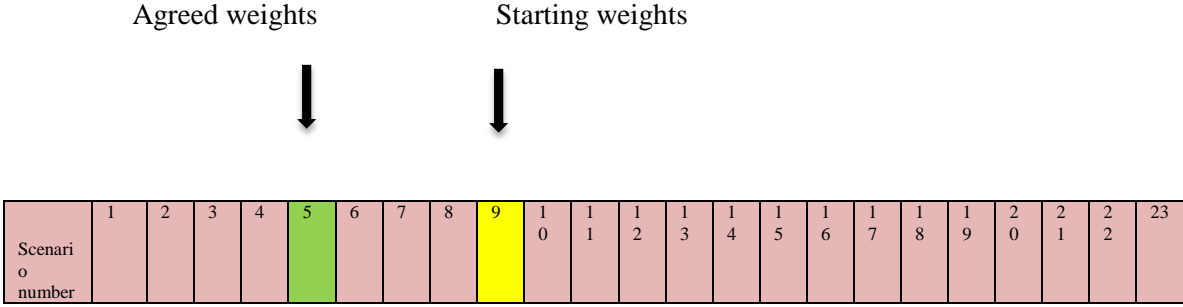
After defining the metrics, we ran the model for multiple scenarios characterized by different values of the weights each producing a different assignment schedule. Following discussions with the clinical managers at the DPLM we agreed upon the values $C1=15$, $C2=1$, and $C3=100$ ($C1$, $C2$, $C3$ are the weights for objective function components) to be used when using the model. The third component of the objective function has significantly higher weight as the most important criterion of the clinical manager is to have as few unassigned specimen types as possible. Therefore, the weight should be high enough so that we achieve almost as good a result as we would if it was the only criterion (extreme scenario). Then, there is a trade-off between the first and the second components of the objective function as consistency within a week makes it harder or even sometimes impossible to rotate through all a pathologist's sub-specialties. Therefore, we need to find weights that provide a good balance for that trade-off. To determine this balance, we first ran

the model with each component of the objective function separately in order to determine the optimal schedule. Table 1 shows the values of the metrics for the problem where each component represents the only objective:

EXTREME Scenarios			
C1	1	0	0
C2	0	1	0
C3	0	0	1
M1	0%	81%	83%
M2	35%	7%	9%
M3	16.3%	10.5%	0.6%

Table 1. Extreme scenarios run for single component objective function

Table 2 shows results when the model was run for 23 different combinations of the weighting scheme (running the model for more scenarios does not improve the results). The best value for the “unassigned specimen types” metric was 0.6% (meaning that only 0.6% of specimen types were not assigned over the month). Therefore, we fixed the value of C3 at 100 (the starting value) and tried to determine the best trade-off between C2 and C1 values while ensuring that the unassigned specimen metric does not deviate greatly from 0.6% (all the other parameters in the model such as availabilities, skill sets and etc. are fixed). C2 is then set to 1 and C1 is varied as all that matters is the ratio between C1 and C2. After showing the results of the scenarios with various values for C1, we settled on one that best fit the objectives of the clinical managers.



C1	2	5	8	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	3	4	6	90
C2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C3	10	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M1	14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	12
	%	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	%
		%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
M2	15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	17
	%	5	8	8	5	6	6	6	7	7	6	6	6	6	8	6	6	6	6	6	6	6	%
		%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
M3	0.6	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.
	%	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	%
		%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%

Table 2. Different scenarios to determine the weights of different components of the objective function

It is important to stress here that values of the weights can be determined externally by the managers to reflect any possible preferences that they might have.

It is worth mentioning here that normalizing the weights based on the potential values for each component of the objective function did not have any significant effect on the results. This is because the ranges of values for each component of the objective function are very similar.

4.2 Validation

The model was validated by comparing assignment schedules developed by the DPML managers with those created by the model. The results summarized in Table 3 show that the model is effective in developing an assignment schedule according to the three metrics described earlier. Results given in Table 3 compare the assignment schedules generated by the model for the months of October and November 2014 against the schedules that were developed manually for those months and implemented in the DPLM.

Period	Inconsistent assignments (M1)	Missed rotation (M2)	Unassigned specimen types (M3)
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	IP model	Manual assignment schedule	IP model	Manual assignment schedule	IP model	Manual assignment schedule
October 2014	14%	50%	17%	14%	1.5%	0.8%
November 2014	12%	44%	15%	16%	0.6%	0.1%

Table 3. Comparison of automatic and manual assignment schedule for October and November 2014.

Looking at the results we note that the model consistently outperforms the manually developed assignment schedule when considering the M1 measure. The difference between the model results and the manual schedule on M2 measure is negligible indicating that the model quite accurately reflects actual practice. In terms of the M3 measure, while it would appear that the manual assignment outperforms the model, this is because the clinical managers sometimes break the rules and overload some pathologists in order to have less unassigned specimen types. (For instance, in the manual schedule provided by a clinical manager at DPLM for October and November 2015, some of the pathologists are overloaded up to 2 FTE). However, the model can produce a starting schedule for the clinical manager that allows to manually assign the unassigned specimen types by overloading some of the pathologists. The decision support tool that we have developed allows the clinical manager to experiment with potential overloads by defining the workload restriction for each pathologist on each day individually.

Chapter 5: Implementation: Automatic Pathologists' Scheduler (APS)

The most challenging part of applied research involves the use of the theoretical models in everyday practice. This is especially true for optimization models where the application often requires a

knowledge set that is outside the expertise of managers. This is why these models are often embedded as a part of a larger computer system that in a sense simplifies what the user needs to know about the model (Ernst *et al* [9]). This is certainly the case with IP model we have developed and thus it was embedded into a stand-alone scheduling tool named the *Automatic Pathologists' Scheduler* (APS) that helps managers to manipulate model parameters and to explore different scenarios.

Responding to the user request that the interface should have a “spreadsheet – like” feel, we embedded the model within a customized Microsoft Excel platform. The platform integrates the optimization model and the Microsoft Excel spreadsheet using a number of macros. The APS has a hierarchical structure with a main menu (see Figure 4) that allows the managers to access the different functions of the tool.

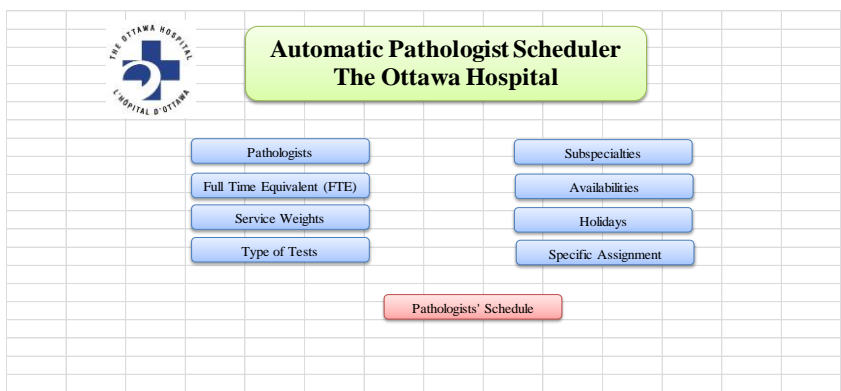


Figure 4. Main Menu for the APS system

In order to use the APS tool, the manager needs to enter the values of the parameters required by the model. These parameters can be categorized into:

- Dynamic parameters: the values of these parameters have to be updated every month before solving the model. They include information about the holidays in a given month, pathologists' availability and specific "hard-wired" assignments that assign a pathologist to a specific specimen type on a given day.
- Static parameters: the values of these parameters are updated infrequently (or do not need to be updated at all). They include the roster of pathologists working in the division, the list of sub-specialties, the FTE fraction for each pathologist, the weight of different components of the objective function, the maximum workload restriction (explained later) and the service weights.

5.1 APS Functionality

The APS tool has the built-in functionality to allow for extended editing and control of the development of assignment schedules. This functionality includes:

- Editing: revising values of all parameters such as service weights of specimen types, pathologists' roster (adding a new pathologist or removing one), or pathologists' FTE. Figures 5 and 6 are examples of the data entry sheets in APS that allow the managers to update the pathologists' areas of expertise (1: if the specimen type is within the area of expertise of a pathologist, otherwise 0) and availabilities (1: if the given pathologist is available on the given day, otherwise 0).

Pathologists' Specialties	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
FS-Neuro Civic	0	0	0	0	0	0	0	0	0	0
FS general	1	1	1	1	1	1	1	0	1	1
FS Civic	0	0	1	0	1	0	1	1	0	0
BREAST 1	0	0	0	0	0	0	0	0	1	0
BREAST 2	0	0	0	0	0	0	0	0	1	0
CARDIAC	0	0	1	0	0	0	1	0	0	0
CYTO 1A	0	0	0	0	0	1	0	0	1	1
FS-Riv/CYTO 2	0	0	0	0	0	1	0	0	1	1

Figure 5.Pathologists' sub-specialties sheet in the APS system

Availability	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
6-Apr	1	1	1	1	1	1	1	0	1	1
7-Apr	1	1	1	1	1	1	1	0	1	1
8-Apr	1	0	1	1	1	1	1	0	1	1
9-Apr	1	0	1	1	1	1	1	0	1	1
10-Apr	1	0	1	1	0	1	1	0	1	1
13-Apr	1	1	1	1	1	1	0	1	1	1
14-Apr	1	1	1	1	1	1	0	1	1	1
15-Apr	1	1	1	1	1	1	0	1	1	1
16-Apr	1	1	1	1	1	1	0	1	1	1
17-Apr	1	1	1	1	1	1	0	1	1	1

Figure 6.Pathologists' availability sheet in the APS system

- Editing workload restriction: in the model there is a daily limit on assigning specimens to the pathologists to avoid overloading the pathologists. In practice, when there are not enough pathologists available on a given day, the clinical managers break this rule and overload some of them as often some types of specimen take less time to diagnose than what has been defined by the service weights. Moreover, some of the pathologists are faster in diagnosing some types of specimens than others. To accommodate that in the APS tool we defined the workload restriction for each pathologist and for each day as a parameter that can be externally manipulated by the manager.

- Blanks: in the model all types of specimens are assigned to the pathologists for each day. In practice, some types of specimens do not need to be assigned in a day. For instance, Hemorrhage (Heme) is a type of specimen that needs to be assigned only two or three days a week (depending on the availability of pathologists) because of the low volume of this specimen type. To accommodate that in the APS tool we provided a data sheet for the managers to enter the days and the type of specimens that do not need to be filled by the pathologists. Therefore, the model does not need to assign any pathologist to these specimen types on particular days. These unfilled cells are called “Blanks”. Figure 7 shows the data sheet in the APS that allows the managers to specify holidays of a month and “Blanks” (holiday - in this case April 6 - and blanks are shown by 0).

Holiday and Blanks	6-Apr	7-Apr	8-Apr	9-Apr	10-Apr	13-Apr	14-Apr	15-Apr	16-Apr	17-Apr
FS-Neuro Civic	0	1	1	1	1	1	1	1	1	1
FS general	0	0	0	0	0	0	0	0	0	0
FS Civic	0	1	1	1	1	1	1	1	1	1
BREAST 1	0	1	1	1	1	1	1	1	1	1
BREAST 2	0	1	1	1	1	1	1	1	1	1
CARDIAC	0	1	1	1	1	0	1	1	1	1
CYTO 1A	0	1	1	1	1	1	1	1	1	1
FS-Riv/CYTO 2	0	1	1	1	1	1	1	1	1	1

Figure 7. Holidays and Blanks sheet in the APS system

- Optimization control: the tool allows the manager to experiment with different values for the weights associated with the components of the objective function. The purpose of this functionality is to provide the manager with the ability to develop different assignment schedules depending on the changing importance of each component of the objective function.
- Schedule analysis: a separate spreadsheet interface for analyzing the schedule allows the managers to evaluate and revise the schedule, if needed.

5.2 Specific Assignment

The APS tool allows a manager with no knowledge of modeling to manipulate model parameters and experiment with the modeling scenarios. However, when there is a need to change the structure of the optimization model (add/revise constraints, revise decision variables or revise objective function), such a change requires an analyst who is knowledgeable with regards to the modeling. Currently the clinical managers in DPLM adjust the criteria for selecting the assignment schedule as needed. These adjustments should be taken into account when a schedule is produced. The following are some examples of situations that cannot be handled by the APS tool as they require expert knowledge:

- In practice there are some substitutions of the pathologists that takes place when a large number of pathologists with a given sub-specialty is not available. For instance, if pathologist P1 is unavailable then pathologist P2 will be overloaded and she/he will be given pathologist P1's responsibilities. There is no specific rule for these kinds of substitutions and thus APS is not useful here.
- According to the requirements, the model is developed in such a way that the same specimen types are assigned to a pathologist for a whole week and then rotated between the pathologists during a month. However, there are some types of specimens that can be diagnosed by a large number of pathologists. In these cases, the assignment schedule produced by the model will rotate the specimen types only between 4 or 5 (depending on the number of weeks in the scheduling month) pathologists during one month. The other pathologists capable to do the diagnosis of this specimen type will have "missed rotations". To solve this problem in practice the managers ensure that in the schedule for the next

month those pathologists who had a “missed rotation” are given priority when considering the assignment to those specimen types. Considering that currently the model develops an assignment schedule for one month at a time, addressing this situation will require expanding the model to schedule multiple months at a time.

- From the optimization perspective, part-time pathologists constitute a problem. This is because the model attempts to meet the requirements of the consistent assignment of specimen types within a week as much as possible. Therefore it chooses not to assign part time pathologists to any type of test as such assignment conflicts with the “Consistent assignment in a week” requirement. For instance, if pathologist P1 has an FTE = 1 while pathologist P2 works only part of a week ($FTE < 1$) and both of them are capable of diagnosing specimen type A, the optimal assignment schedule will include pathologist P1 diagnosing specimen type A because by assigning this specimen type to the part time pathologist will increase the value of the first component of the objective function and therefore produce a schedule that is not optimal.

To adjust the APS tool to account for the above situations, we added a function called “Specific Assignment”. It allows the managers to assign a specific type of specimen to a specific pathologist on a given day so that the model uses these assignments as a starting point and then produces a schedule that includes these assignments and, from that starting point, best meets the objective. This functionality helps the managers to address the problem of “missed rotations” and “part-timers” as it enables them to force the model to assign the missed rotations from previous month in the current scheduling month or to give the part-timers sufficient work.

5.3 APS Output

The output produced by the APS tool is illustrated in Figure 8 (only a section of the spreadsheet is presented). The assignment schedule is organized by the days in a month (columns), types of the specimens (coded with the abbreviations used in the DPLM and represented as the rows), and labels associated with individual pathologists (cell values). In the original schedule the cell values include pathologists’ initials, but for privacy concerns they are replaced here with P# labels. The dash (-) on the schedule indicates a non-business day. As an example pathologist P14 is assigned all cardiac specimen types from April 7 to April 10. Starting on April 13 this type of specimen is assigned to pathologist P5 (until April 17, inclusive). In the schedule, two separate rows have been allocated to breast specimens (indicated by “Breast1” and “Breast2” labels) as historically two pathologists are required to analyze all daily breast specimen requests – meaning that breast type specimen is subdivided into two groups corresponding to a daily workload of one pathologist each.

Date	6-Apr	7-Apr	8-Apr	9-Apr	10-Apr	13-Apr	14-Apr	15-Apr	16-Apr	17-Apr	20-Apr	21-Apr	22-Apr	23-Apr	24-Apr	27-Apr	28-Apr	29-Apr	30-Apr	1-May
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
FS-Neuro Civic	-	P1	P1	P1	P1	P2	P2	P2	P2	P2	P3	P3	P3	P3	P3	P4	P4	P4	P4	P4
FS Civic	-	P5	P5	P5	P5	P6	P6	P6	P6	P6	P7	P7	P7	P7	P7	P8	P8	P8	P8	P8
BREAST 1	-	P10	P10	P10	P10	P11	P11	P11	P11	P11	P12	P12	P12	P12	P12	P13	P13	P13	P13	P13
BREAST 2	-	P11	P11	P11	P11	P10	P10	P10	P10	P10	P11	P11	P11	P11	P11	P12	P12	P12	P12	P12
CARDIAC	-	P14	P14	P14	P14	P5	P5	P5	P5	P5	P6	P6	P6	P6	P6	P14	P14	P14	P14	P14
CYTO 1A	-	P15	P15	P15	P15	P16	P16	P16	P16	P16	P17	P17	P17	P17	P17	P18	P18	P18	P18	P18
FS-Riv/CYTO 2	-	P16	P16	P16	P16	P18	P18	P18	P18	P18	P15	P15	P15	P15	P15	P17	P17	P17	P17	P17
DERM/DIF	-	P17	P17	P17	P17	P17	P17	P17	P17	P17	P16	P16	P16	P16	P16	P19	P19	P19	P19	P19
GI star	-	P20	P20	P20	P20	P15	P15	P15	P15	P15	P19	P19	P19	P19	P19	P5	P5	P5	P5	P5
GI no star 1	-	P19	P19	P19	P19	P19	P19	P19	P19	P19	P2	P2	P11	P11	P11	P10	P10	P10	P10	P10

Figure 8. Sample output from the APS tool

There are commercial scheduling systems such as Q-Genda (Corporation: Q-genda), Field Service Management (Corporation: FieldAware) and ScheduleLabs (Corporation: MapleWood Software) designed to develop an assignment schedule for health systems. However these systems are mostly concerned with implementing the existing scheduling practice in terms of rules rather than developing the optimal assignment schedule that the APS tool creates. In other words, because of

the way that schedules are created by commercial systems, the proposed assignment is truly just meets the expressed requirements and potentially can be further improved. Furthermore, these commercial systems are generally targeted at a specific area (for instance, nurse scheduling) and cannot be easily ported to other domains.

Chapter 6: Conclusions

In this research we have developed an optimization model to help the clinical managers at pathology department to assign specimen types to pathologists automatically. To achieve this goal we firstly tried to find the criteria which make a good pathology schedule at a pathology laboratory. The criteria include the following requirement: each pathologist should be assigned to a similar specimen type throughout a week; for a given pathologist, there should be a rotation of the specimen types between the weeks; and the clinical managers' preferences in terms of assigning a particular specimen type to a particular pathologist on a specific day need to be considered. Then, according to the criteria, we developed a IP model which takes into account all the scheduling requirements such as respecting the pathologists' availability, area of expertise, workload restriction, service weights of different specimen types and so on. In order to solve the developed model we designed the APS system that helps clinical managers of the Pathology departments to develop a monthly assignment schedule in a simple way. Providing the clinical managers with such an easy to use support tool has value for a number of reasons. First, the APS system helps to create the optimal assignment schedule very quickly. Secondly, the proposed schedule can be used by the managers to either make additional adjustments taking into account intrinsic requirements or to create a number of scenarios considering different staffing possibilities, demand levels, etc. Finally,

the APS system gives flexibility in establishing and revising all model parameters to reflect for example a sudden change in the pathologists' availability.

While the APS tool was created for DPLM at TOH and using data from that division, it can be customized and ported to different pathology departments provided that there is data to revise the model's parameters.

A possible extension for the model is to relax the assumptions of constant demand (solve a stochastic model). Over a one month planning horizon the variability in demand might create significant effects on the optimal solution. Therefore, by developing a forecasting model the daily demand generated by the surgeries and clinics can be predicted according to historical data. TOH schedules its Operating Rooms using block schedules. In a block scheduling system, blocks of time are reserved for surgical specialties in a repeatable fashion. Each day the scheduled surgeries generate specific pathology requests. Since the types and the amount of specimens produced by each type of surgery can be forecasted based on data, daily pathology requests received from the surgeries can be predicted as well.

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Appendix

Categories of specimen types (sub-specialties) in DPLM are shown in figure 9. This research focuses on the specimen types which are shown in blue.

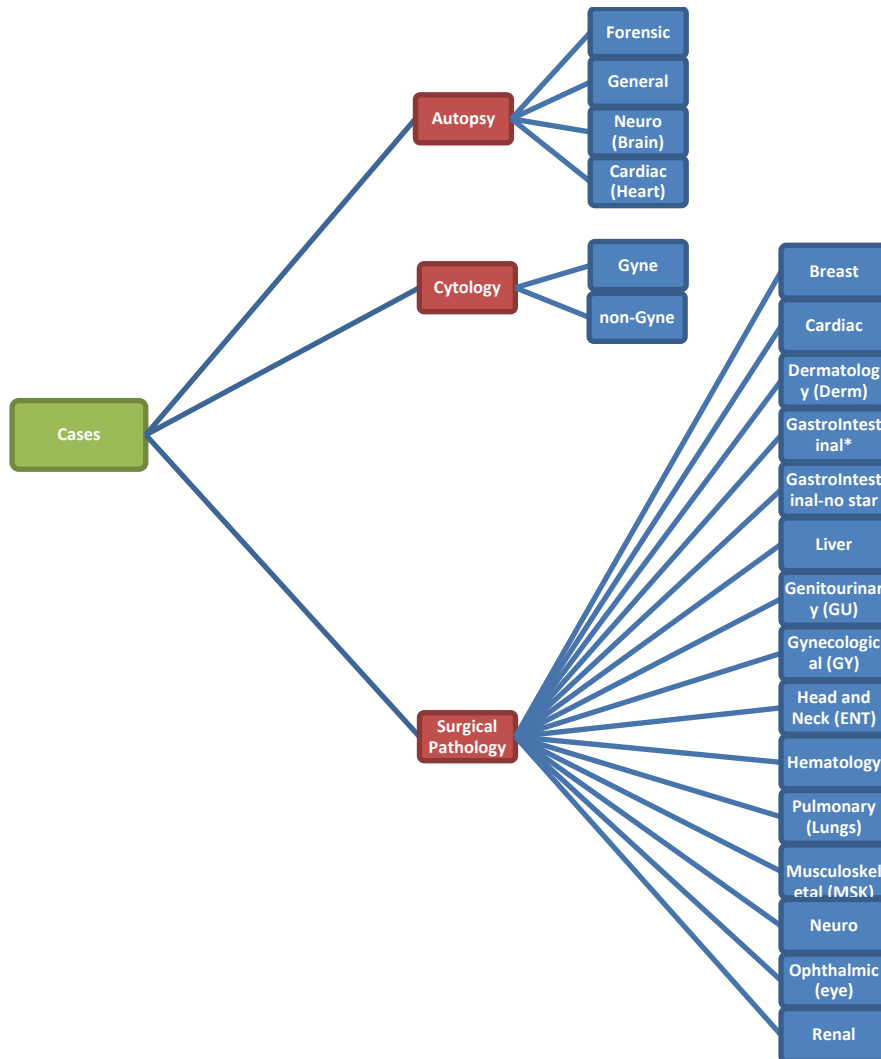


Figure 9. Categories of specimen types (sub-specialties) in DPLM

Programming Code of the Model

Each model to be solved using CPLEX IDE has two main parts: the first part allows coding all the variables, objective function and constraints, and the second part exists to add the parameters of the model. The parameters can be read from an external file including Excel spreadsheet and the results can also be written into an external file. Following is the code of IP model discussed in the text.

First part:

```
{string} Pathologists =...;
{string} Tests =...;
{int} Days =...;
{int} Weeks={1,2,3,4,5};

float ServiceWeight [Tests] =...;
float FTEfraction [Pathologists] =...;
int Weight [Pathologists]=...;
int Preferences [Pathologists][Tests]=...;
int Blanks [Days][Tests]=...;
int Vacations [Pathologists][Days] =...;
int Specialties [Pathologists][Tests]=...;

dvar int WeeklyAssignment[Pathologists][Tests][Weeks] in 0..1;
dvar int PathologistAssignment[Days][Tests][Pathologists] in 0..1;
dvar int WeeklyRotation[Pathologists][Tests];

minimize

sum(d in Days, t in Tests, p in Pathologists)1000*Weight[p]*PathologistAssignment[d][t][p]+
sum (t in Tests, p in Pathologists, w in Weeks)150*WeeklyAssignment[p][t][w]-
sum(p in Pathologists, t in Tests)10*WeeklyRotation[p][t];

subject to {

forall (t in Tests, p in Pathologists)
  WeeklyRotationConstraints1:
  sum (d in Days)Preferences[p][t]*PathologistAssignment[d][t][p]>=WeeklyRotation[p][t];
forall (t in Tests, p in Pathologists)
  WeeklyRotationConstraints2:
  WeeklyRotation[p][t]<=5;

forall (p in Pathologists, t in Tests)
  WeeklyAssignmentConstraint1:
```

```

    sum (d in 1..5) PathologistAssignment[d][t][p]<= 100000*WeeklyAssignment[p][t][1];
forall (p in Pathologists, t in Tests)
    WeeklyAssignmentConstraint2:
    sum (d in 6..10) PathologistAssignment[d][t][p]<= 100000*WeeklyAssignment[p][t][2];
forall (p in Pathologists, t in Tests)
    WeeklyAssignmentConstraint3:
    sum (d in 11..15) PathologistAssignment[d][t][p]<= 100000*WeeklyAssignment[p][t][3];
forall (p in Pathologists, t in Tests)
    WeeklyAssignmentConstraint4:
    sum (d in 16..20) PathologistAssignment[d][t][p]<= 100000*WeeklyAssignment[p][t][4];
forall (p in Pathologists, t in Tests)
    WeeklyAssignmentConstraint5:
    sum (d in 21..25) PathologistAssignment[d][t][p]<= 100000*WeeklyAssignment[p][t][5];

forall (p in Pathologists)
    ResourceConstraints1:
    sum (t in Tests, d in 1..5)
        ServiceWeight[t]*PathologistAssignment[d][t][p] <= 5* FTEfraction [p]*1;
forall (p in Pathologists)
    ResourceConstraints2:
    sum (t in Tests, d in 6..10)
        ServiceWeight[t]*PathologistAssignment[d][t][p] <= 5* FTEfraction [p]*1;
forall (p in Pathologists)
    ResourceConstraints3:
    sum (t in Tests, d in 11..15)
        ServiceWeight[t]*PathologistAssignment[d][t][p] <= 5* FTEfraction [p]*1;
forall (p in Pathologists)
    ResourceConstraints4:
    sum (t in Tests, d in 16..20)
        ServiceWeight[t]*PathologistAssignment[d][t][p] <= 5* FTEfraction [p]*1;
forall (p in Pathologists)
    ResourceConstraints5:
    sum (t in Tests, d in 21..25)
        ServiceWeight[t]*PathologistAssignment[d][t][p] <= 5* FTEfraction [p]*1;

forall (p in Pathologists, d in Days)
    EachDayAssignmentConstraints:
    sum(t in Tests)
        ServiceWeight[t]*PathologistAssignment[d][t][p] <= 1;

forall (t in Tests, d in Days)
    EachDayRequestsConstraints:
    sum(p in Pathologists)
        PathologistAssignment[d][t][p]==Blanks[d][t];

forall ( p in Pathologists, t in Tests, d in Days : Vacations [p][d] ==0 )
    PathologistVacationConstraints:
        PathologistAssignment [d][t][p] ==0;

forall ( p in Pathologists, t in Tests, d in Days : Specialties [p][t] ==0 )
    PathologistSpecialtiesConstraints:
        PathologistAssignment [d][t][p] ==0;

}

```

```
tuple someTuple{
int Days;
string Tests;
string Pathologists;
int value;
}
{someTuple} someSet = {<d,t,p, PathologistAssignment[d][t][p]> | d in Days, t in Tests,p in Pathologists };
```

Second Part:

```
SheetConnection sheet("test9.xlsx");
Pathologists from SheetRead (sheet, "Pathologists");
Tests from SheetRead (sheet, "Tests");
Days from SheetRead (sheet, "Days");
ServiceWeight from SheetRead (sheet, "ServiceWeight");
FTEfraction from SheetRead (sheet, "FTE_Fraction");
Weight from SheetRead (sheet, "Weight1");
Preferences from SheetRead (sheet, "Preference");
Blanks from SheetRead (sheet, "Blanks");
Vacations from SheetRead (sheet, "Vacations");
Specialties from SheetRead (sheet, "Specialties");
someSet to SheetWrite (sheet, "Sheet6!B2:E35201");
```