# Optimising Nurse Schedules at a Community Health Centre

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**Abstract**

We present a new scheduling approach to improve access to care at a community health centre serving marginalised clients with complex biopsychosocial needs. In order to meet the specific care needs of clients, the centre provides a diverse range of services on a booked and walk-in basis, and it is important that clients are seen in a timely manner. We developed a mixed integer linear programming model to identify combinations of nurse shifts that maximise time spent with clients. Key performance indicators were evaluated using a discrete event simulation model. Optimisation aligns schedules to demand, leading to fewer clients who leave without being seen due to an extended wait. This increases the number of clients receiving care by up to 9 per week in our results, without compromising wait times. Furthermore, the optimised schedules have essentially no coverage gaps, which improves access to triage and urgent care. Strategically aligning nurse shifts to demand is an effective approach to better meet client needs without increasing total nurse staffing levels in a community health centre context.

*Keywords:* Nurse schedule optimization, Primary health care, Access to care, Health equity, Mixed integer linear programming, Discrete event simulation

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## 1. Introduction

Marginalised people often experience barriers to accessing health care [1, 2, 3, 4, 5]. The Provincial Health Services Authority of British Columbia, Canada highlighted improving the availability

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*Abbreviations*: VCH, Vancouver Coastal Health; OAT, Opioid Agonist Therapy; CA, Clinical Assistant; SW, Social Worker; MRP, Most Responsible Practitioner.

of community-based primary care as one way to increase health equity [6]. In Vancouver, the local health authority Vancouver Coastal Health (VCH) owns and operates a network of inner-city community health centres to meet the needs of individuals with complex biopsychosocial needs who cannot access fee-for-service primary care.

Our project was conducted in partnership with a community health centre in this network. The centre offers a diverse range of services, including mental health, substance use, youth health, home health, and speech therapy services. Services are available both by appointment and on a walk-in basis. Managing service capacity and access to care are major operational concerns at the centre. The complex care needs of the clients, and wide range of services offered, present challenges for improving operations and access to care.

Staff members, managers, and the centre director worked closely with our team to analyse operations. Our partners identified nurse scheduling as an important factor influencing client access to care, specifically for core primary care services including booked nursing appointments, adult walk-in nursing services, triage, and opioid agonist therapy (OAT). An important indicator of access is walk-in wait times, especially for clients with complex biopsychosocial needs. The goal of this project is to identify weekly nurse shift combinations that better meet client needs, while maintaining coverage, total nurse hours, and client wait times.

We developed a three-stage approach to nurse scheduling at the community health centre. Firstly, a mixed integer linear programming (MILP) model identifies optimal weekly combinations of nurse shifts using existing total nurse hours. Secondly, a staff variability heuristic accounts for weekly fluctuations in total nurse hours. Lastly, a discrete event simulation (DES) model evaluates the improvement in client-centred key performance indicators, including wait times, for the weekly optimised schedules. The optimisation and simulation model parameters were primarily estimated using data from the electronic medical record (EMR) database. Two seasonal profiles of client demand were obtained from four weeks of client visit data, two from summer and two from winter.

Our approach to improving access to care through optimal nurse shift scheduling provides a new perspective on improving operations in outpatient facilities. Previous analysis of clinics serving both scheduled and unscheduled clients have focused on optimising the appointment schedule in the context of ambient demand [7, 8, 9]. Our scheduling-based approach is motivated by the diverse services and complex care needs at the centre.

## 2. Literature Review

Operations research analysis to improve efficiency and access to care at primary care clinics has largely focused on improvements to appointment scheduling [10, 11, 12]. Designing optimal appointment systems for clinics which serve both scheduled and walk-in clients can present challenges because of the need to consider client wait times. Simulation studies combined with heuristics are often used to address the complexities of this problem [13, 14, 15, 16]. Alternatively, an iterative queuing theory approach has been used for a CT-scan facility with scheduled and walk-in clients [8].

Open access appointment systems, in which a portion of appointment slots are reserved for same-day appointments, is one approach to improving access to care for community clinics [17, 9, 18]. Incorporating pre-booked, open access, and walk-in clients into an appointment optimisation model is computationally complex. One approach is to use discrete event simulation to evaluate candidate appointment schedules as a "black box" function, with optimisation done using a heuristic method, such as a tabu search [7] or a genetic algorithm [9].

Optimisation of appointment systems is usually considered separately from resource scheduling in outpatient clinics. In clinics offering specialised services, an integrated approach is preferable, in which appointments and walk-in demand are matched to resource scheduling. Discrete event simulation has been used to study the performance of combined appointment and resource allocation systems in a hospital emergency department [19], hypothetical clinics with seasonal walk-in demand [20], and an ambulatory care unit at a cancer agency [21].

Nurse scheduling, or the *nurse rostering problem*, has been extensively studied in acute care settings [22, 23, 24]. In the community care context, a staffing model has been developed for a network of family planning clinics [25]. The application of schedule optimisation outside of healthcare settings includes scheduling telephone operators [26], police patrols [27] and retail service [28].

One of the first papers to formulate nurse rostering as an integer programming problem is [29]. This approach has been extended to meet the needs of various healthcare facilities. Nurse rostering typically combines selecting optimal shifts and assigning these shifts to individual nurses [30, 31, 32, 33, 34, 35]. This allows for the consideration of nurse preferences and collective agreement requirements, including limitations on consecutive working days, workload, or minimum time between shifts. Some studies optimise schedules to improve staff satisfaction [31, 34, 36, 37] and others minimise costs [38, 31, 35, 28, 27]. Other studies use multi-objective or goal programming approaches to incorporate various goals [39, 40, 37]. The complex set of constraints for realistic hospital nurse scheduling has motivated increasingly sophisticated algorithms, which combine integer programming methods with heuristic search techniques. Approaches include network programming [36], generalised column generation [31], tabu search [34], variable neighbourhood search [33, 41], simulated annealing [42], and genetic algorithms [32].

The academic literature on the nurse rostering problem has largely focused on developing new optimisation techniques for simplified problems that do not consider the wider operational environment of the healthcare facility [43]. This approach is often successful for acute care facilities; however, community health centres are a much more fluid environment [44]. The approaches to nurse rostering discussed above are not directly applicable to this community health centre, where a diverse team delivers a broad range of services to a marginalised client population with complex care needs. We are unaware of previous applications of mathematical programming to nurse scheduling at a community health centre for improving access to care.

## 3. A Community Health Centre Context

Our approach to nurse scheduling at a community health centre was informed by the centre's context and the priorities of its management. Multiple meetings with staff and management were held to gain an understanding of their goals for improving operations and of client flow at the centre. A member of our team spent two days shadowing different staff at the centre to further understand operations. Subsection 3.1 discusses the goals for our project which are informed by these meetings, and how they are different from existing literature. Subsection 3.2 describes business process diagrams of client flow and health centre operations.

### *3.1. Project Goals*

Our project goals were chosen in collaboration with the centre management team and reflect the distinct community health centre context. The overarching goal for this project is to develop a new approach to nurse scheduling that can better meet client needs. The core of our approach is an optimisation model, which determines combinations of nurse shifts to maximise the time that nurses spend with clients. Optimisation preserves total nurse hours, motivated by the management team's desire to leave the existing operating budget unchanged. This model constrains schedules to have at least one nurse on duty whenever the centre is open, in order to provide timely triage to potentially urgent clients. The management team identified wait times as an important performance indicator, especially in the context of clients with complex biopsychosocial needs, and the centre aims to see walk-in clients within an hour of arrival. Our approach incorporates a simulation model which evaluates the impact of the new schedule on wait times and whether clients leave without being seen. The goals for this project reflect a distinct community health centre context and motivate a novel methodology.

### *3.2. Client Flow and Services Offered*

In collaboration with the health centre leadership team, we produced business process diagrams for client flow through core primary care services, including booked appointments, adult walk-ins, and opioid agonist therapy (OAT). These diagrams guided the development of the optimisation and simulation models described in Section 5.

After registration by a clinical assistant (CA), clients are seen by members of the core primary care team, including registered nurses (RNs), licensed practical nurses (LPNs), social workers (SWs), general practitioners (GPs), and nurse practitioners (NPs)—the latter two serving as most responsible practitioners (MRPs). The primary care centre is open from 8:30 to 20:30 on Monday to Friday and from 10:00 to 18:00 on Saturday and Sunday.

Weekday morning operating hours are reserved for booked appointments. Figure 1 shows the client flow for booked appointments. Registered clients are booked for 30 minutes. New clients are booked for one hour, to allow time for registration. Booked appointments with a nurse are scheduled specifically with an RN or an LPN.

Only urgent walk-in clients are seen during weekday mornings, because these hours are reserved for booked appointments. The client flow for these clients is shown in Figure 2. A triage nurse will assess whether a client is urgent, and urgent clients will be seen in the next available appointment slot or will be requested to return during the afternoon walk-in period.

Figure 3 shows client flows for weekday afternoon and weekend walk-in visits. On weekdays, walk-in clients can receive adult primary care services from 13:15 to 20:30, with registration from 12:45 to 19:00. On Saturday and Sunday, walk-in clients can register for and receive adult primary care services from 10:00 to 18:00. Walk-in clients needing a nurse can be seen by either an RN or LPN.

Opioid agonist therapy (OAT) services are provided daily, on a walk-in basis from 13:15 to 16:30, with registration from 12:45 to 15:00. Clients receiving OAT are seen by both an MRP and a nurse (either an RN or LPN).

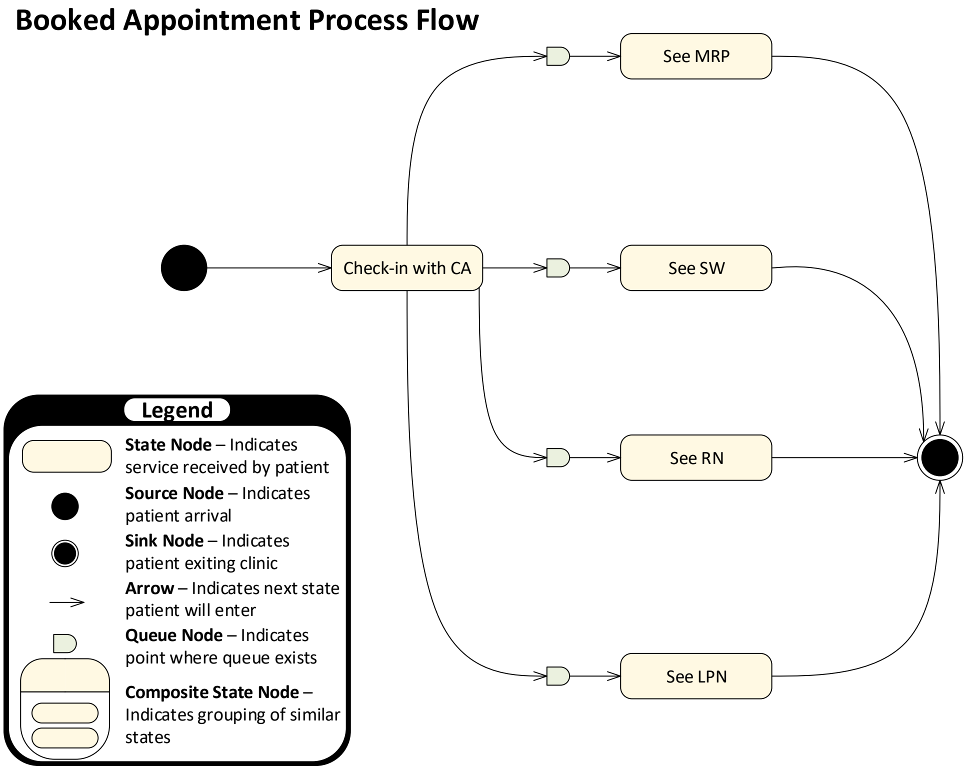



Figure 1: Client flow for booked appointments. Clients check-in with a clinical assistant (CA). The other service nodes are social worker (SW), most responsible practitioner (MRP), opioid agonist therapy (OAT), registered nurse (RN), and licensed practical nurse (LPN).

Clients identified as potentially urgent by the CA when they check-in are referred for triage. The centre does not usually have a dedicated nurse assigned to triage duties, except when triage demand is high. A nurse will typically interrupt current duties as expeditiously as possible to triage a newly arrived client.

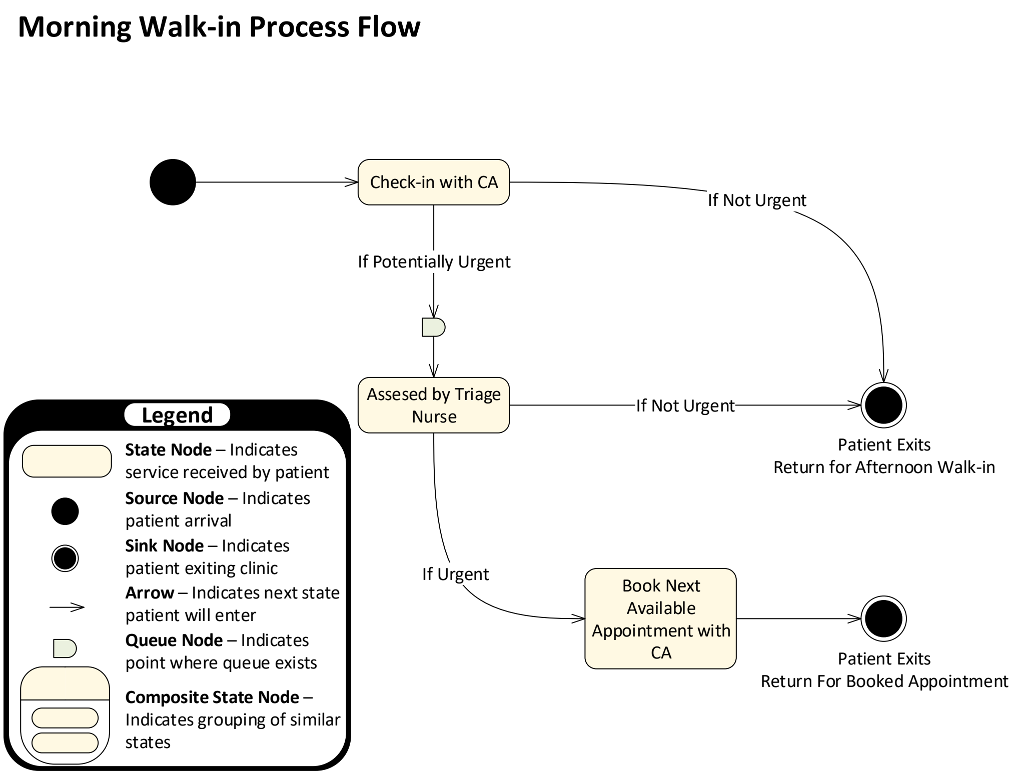



Figure 2: Client flow for morning walk-ins on weekdays. Clients check-in with a clinical assistant (CA). The other service nodes are social worker (SW), most responsible practitioner (MRP), opioid agonist therapy (OAT), registered nurse (RN), and licensed practical nurse (LPN).

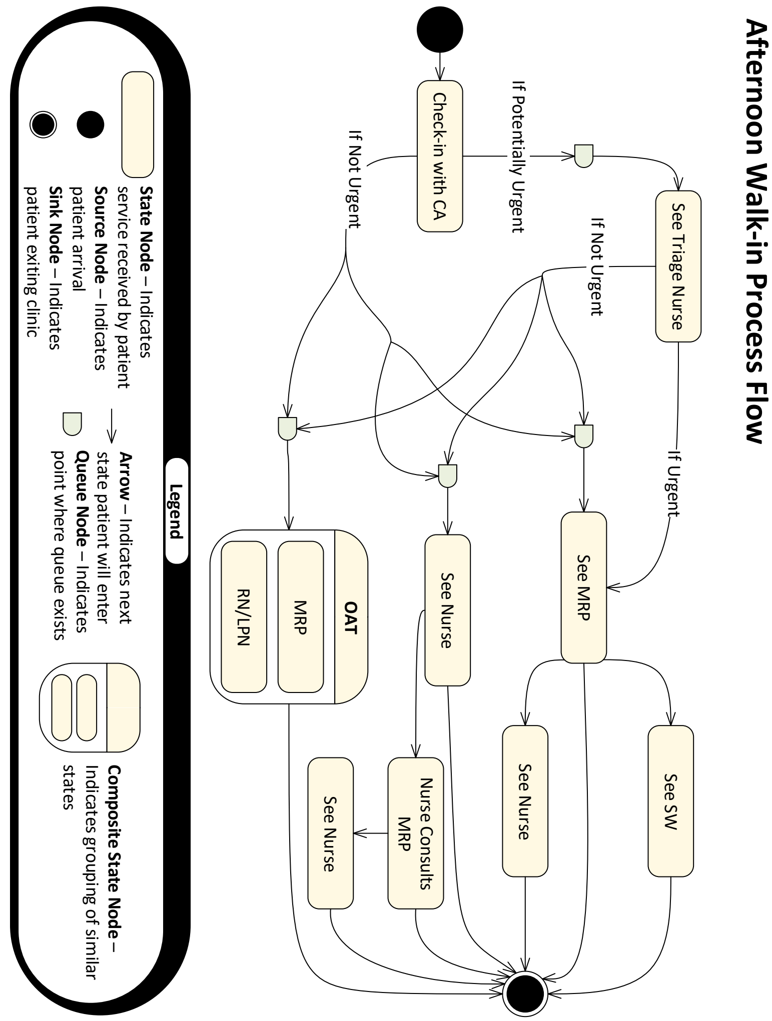


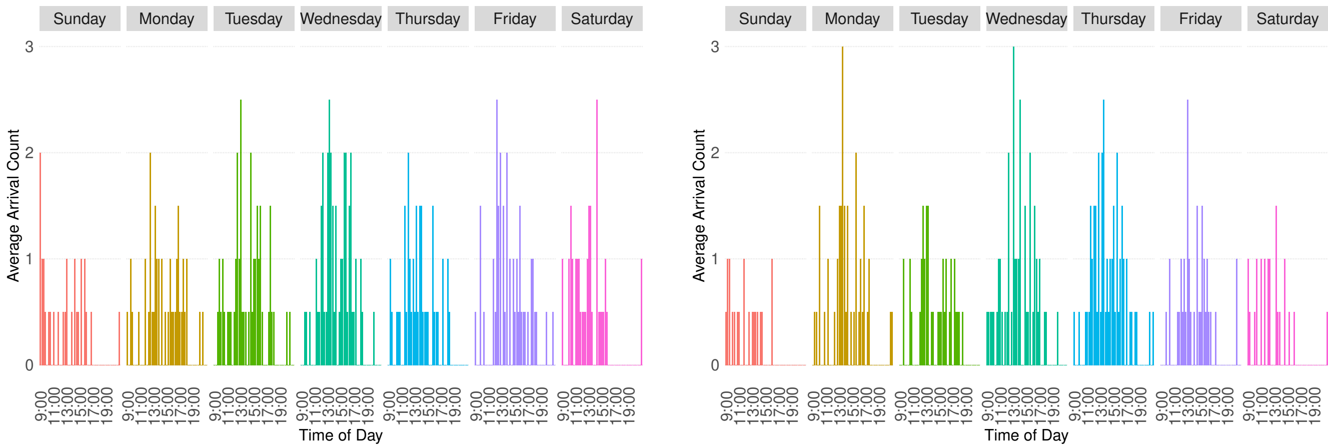

Figure 3: Client flow for weekday afternoon and weekend walk-ins. Clients check-in with a clinical assistant (CA). The other service nodes are social worker (SW), most responsible practitioner (MRP), opioid agonist therapy (OAT), registered nurse (RN), and licensed practical nurse (LPN).

## 4. Data Analysis and Parameter Estimation

Electronic medical record (EMR) data was the primary source of data used to inform model structure and estimate model parameters for the schedule optimisation and simulation models. Staff schedules and information for each appointment slot over four weeks were analysed to produce two seasonal demand profiles. Data from July 16$^{th}$ to 29$^{th}$ 2017 were used to produce a summer profile and data from November 26$^{th}$ to December 9$^{th}$ 2017 were used to produce a winter profile. The two profiles allowed us to capture seasonality in client needs, such as seasonal illnesses. These weeks were chosen to have diverse volumes of client visits and to not contain or be immediately after statutory holidays. Some parameters, for example service times, were fit using all weeks of data. Information not available through the EMR was estimated through consultations with the centre leadership team or published sources.

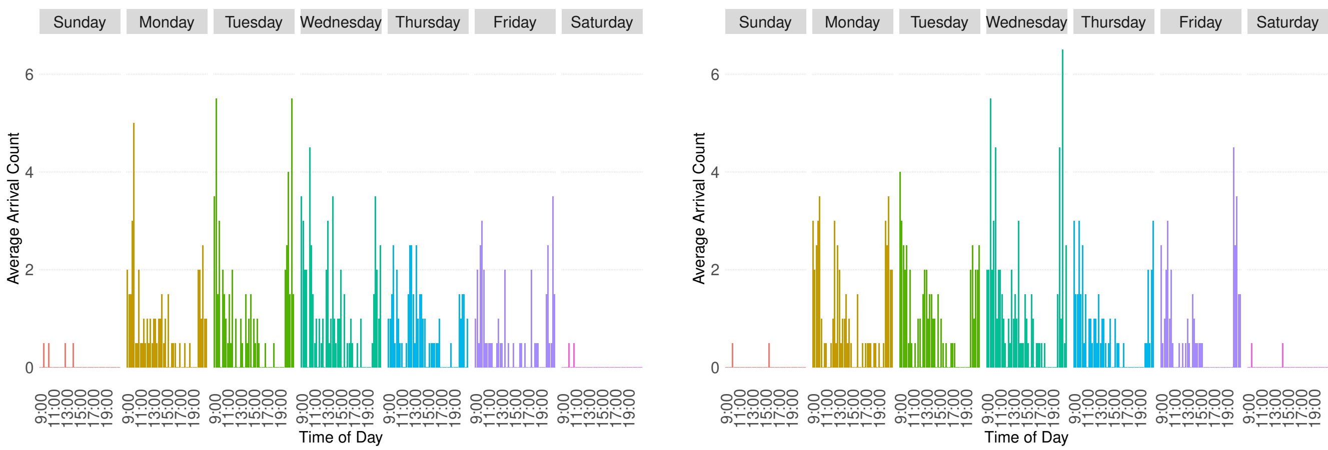
### *4.1. Arrival Rates*

We estimated the expected number of clients arriving in each 15-minute interval, based on the number of check-ins in the data, for each season, week, and service type. Figures 4, 5, and 6 show the seasonal average profiles for walk-in, booked, and OAT services. These numbers take into account all clients who check in for booked appointments or walk-in services, regardless of whether they see a nurse or a physician. The demand profiles are generally higher during the week than on weekends, and typically peak mid-day. The total average demand is higher in the two weeks of summer data than in the winter ones.



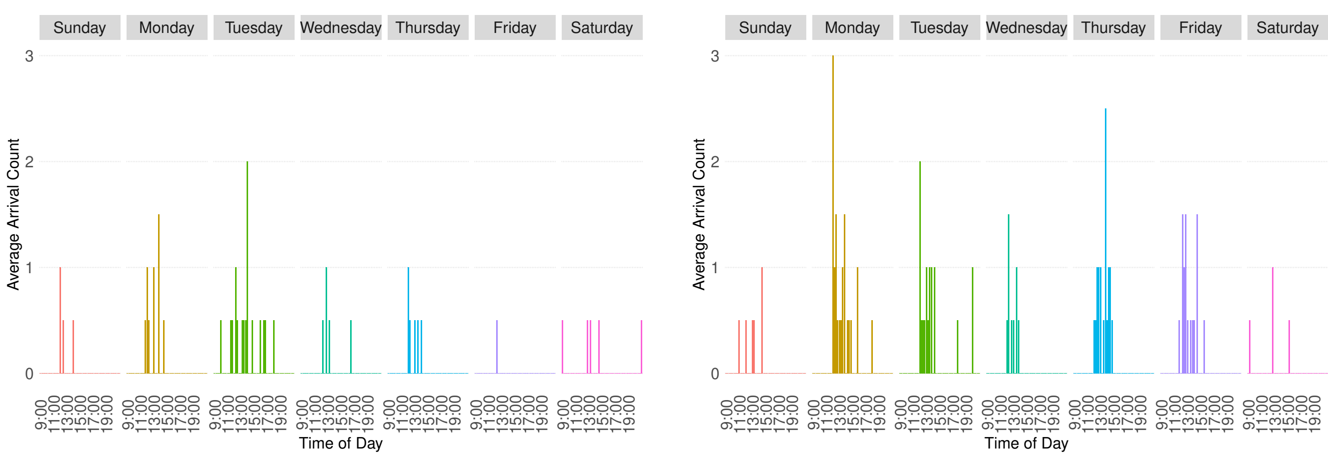

(a) Summer (b) Winter

Figure 4: Walk-in client expected arrivals (non-OAT), in 15-minute intervals.




(a) Summer (b) Winter

Figure 5: Booked client expected demand, in 15-minute intervals.

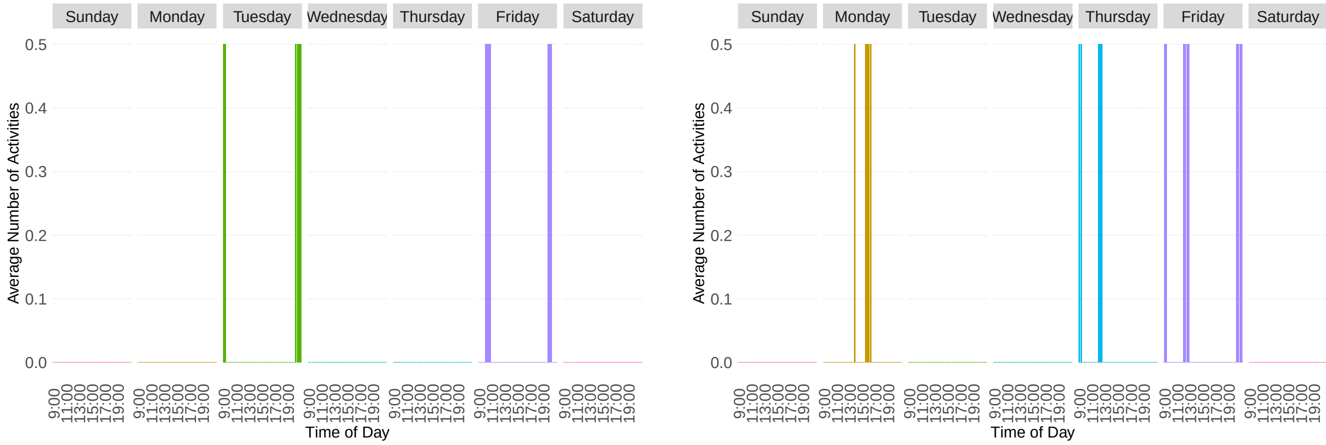



(a) Summer (b) Winter

Figure 6: OAT walk-in client expected arrivals, in 15-minute intervals.

### 4.2. External Nurse Activities

External nurse activities, including home visits, outreach, and other activities outside of the health centre location, were also included in the data. As seen in Figure 7, external activities are generally scheduled in specific time slots on specific days.




(a) Summer

(b) Winter

Figure 7: Home visit, outreach visit, and other external activities, in 15-minute intervals.

### *4.3. Percentage of Clients Seeing a Nurse*

We estimated the percentage of clients seeing a nurse, for each seasonal profile and service type, based on the proportion of appointments with nurses in the data (Table 1). The percentage of nursing walk-in appointments is higher in the summer weeks, while the percentage of nursing OAT appointments is higher in the winter weeks. Booked appointments are scheduled with specific providers so we stratified the data by RN or LPN. The combined percentage of booked appointments with RNs and LPNs does not change significantly between the summer and winter weeks.

Table 1: Proportion of clients requiring a nurse, by service.

| **Description** | **Summer** | **Winter** |
|---|---|---|
| Non-OAT walk-in demand for Nurses | 53.0% | 48.8% |
| OAT demand for Nurses | 4.1 % | 12.0% |
| Booked appointment demand for RNs | 14.3% | 19.4% |
| Booked appointment demand for LPNs | 10.7% | 5.8% |

### *4.4. Nurse-Client Service Time*

We used the recorded start and end times for each client visit in the EMR to estimate the nurse-client service time for each booked, walk-in, and OAT nursing appointment. The management team expressed concern that the recorded end times may be unreliable, as providers may leave files open long after clients leave. In order to mitigate this potential bias, we incorporated the recorded start times for consecutive clients with the same provider, and used the earlier of the recorded end and the recorded start of the next client. We also ignored service times that were substantially longer than their scheduled time slot. The EMR contained some visits which started and ended at the same time. Centre staff advised that these are more likely due to incomplete logging by providers

Table 2: Mean and standard deviation (SD) of the fitted service time distributions for booked nursing appointments, walk-in nursing, and OAT.

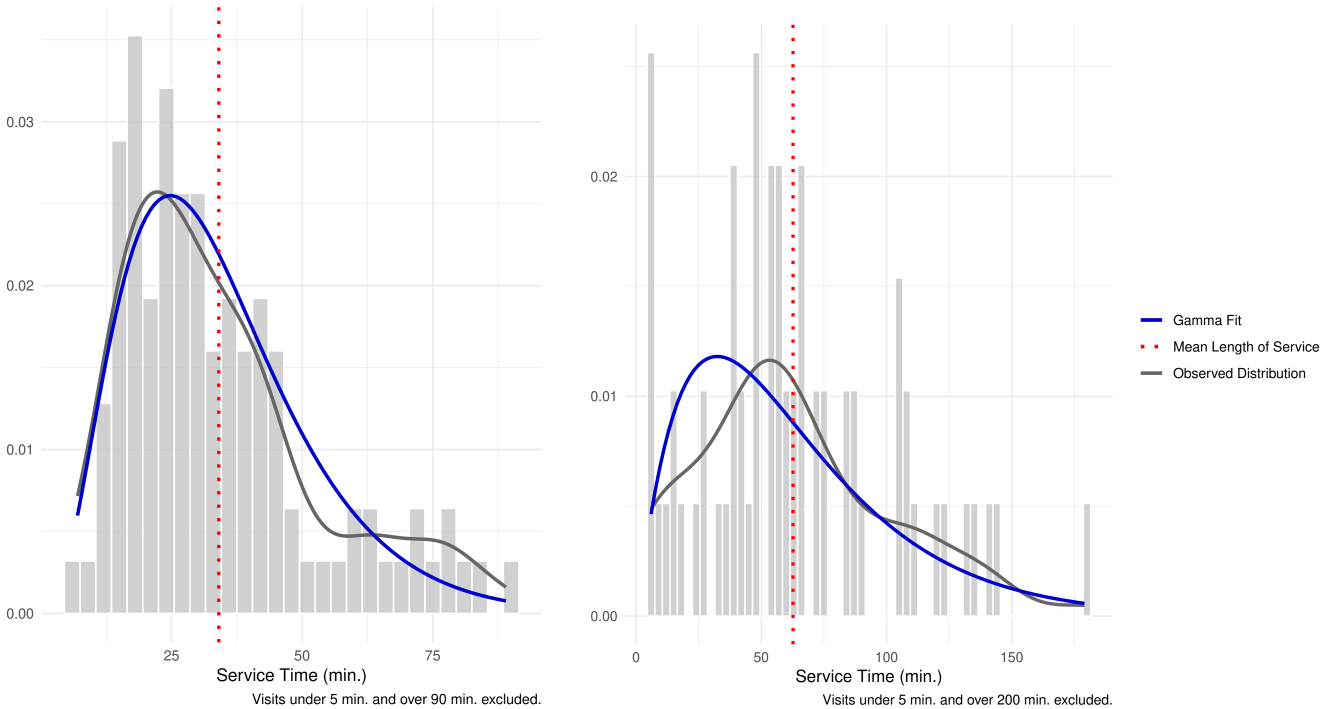
| **Service** | **Number of Visits** | **Overall Mean** [minutes] | **Length Type** | **Percentage of Visits** | **Time** [minutes] **Mean (SD)**. |
|---|---|---|---|---|---|
| | | | Service $< 5$ | 5.8% | 2.5 |
| Booked | 180 | 42.5 | Scheduled $\leq 45$ | 55.0% | 34.0 (17.8) |
| | | | Scheduled $> 45$ | 34.4% | 62.7 (43.5) |
| | | | Service $\leq 5$ | 12.7% | 2.0 |
| Walk-in | 242 | 30.8 | Scheduled $\leq 45$ | 73.0% | 32.2 (17.7) |
| | | | Scheduled $> 45$ | 7.7% | 64.1 (31.1) |
| | | | Service $\leq 5$ | 3.2% | 3.7 |
| OAT | 123 | 27.6 | Scheduled $\leq 45$ | 90.4% | 27.2 (15.3) |
| | | | Scheduled $> 45$ | 4.8% | 50.7 (24.9) |

than actual zero-length visits. We observed some short service times under 5 minutes in the data and assumed that these correspond to actual service times for health care needs that could be dealt with quickly.

We used the estimated service times from the data to estimate a nurse-client service time distribution for each nursing service type (booked, walk-in, OAT). The length of time that a client spends with a provider is presumed to related to the length of the scheduled time slot. We subdivided the data up into three length-type groups as follows: (1) short visits under 5 minutes, regardless of the scheduled length; (2) visits over 5 minutes scheduled under 45 minutes; (2) visits over 5 minutes scheduled over 45 minutes. We disregarded visits from length-type group (2) with a service time over 90 minutes, and visits from length-type group (3) with service time over 200 minutes. We fit a separate service time distribution for each length-type group then used a mixture distribution based on the proportion of visits in each group.

Commonly used probability distributions for fitting the duration of client visits are exponential, gamma, lognormal, and Weibull distributions. We chose to use a gamma distribution, because it reasonably represents services formed by a sequence of smaller tasks.

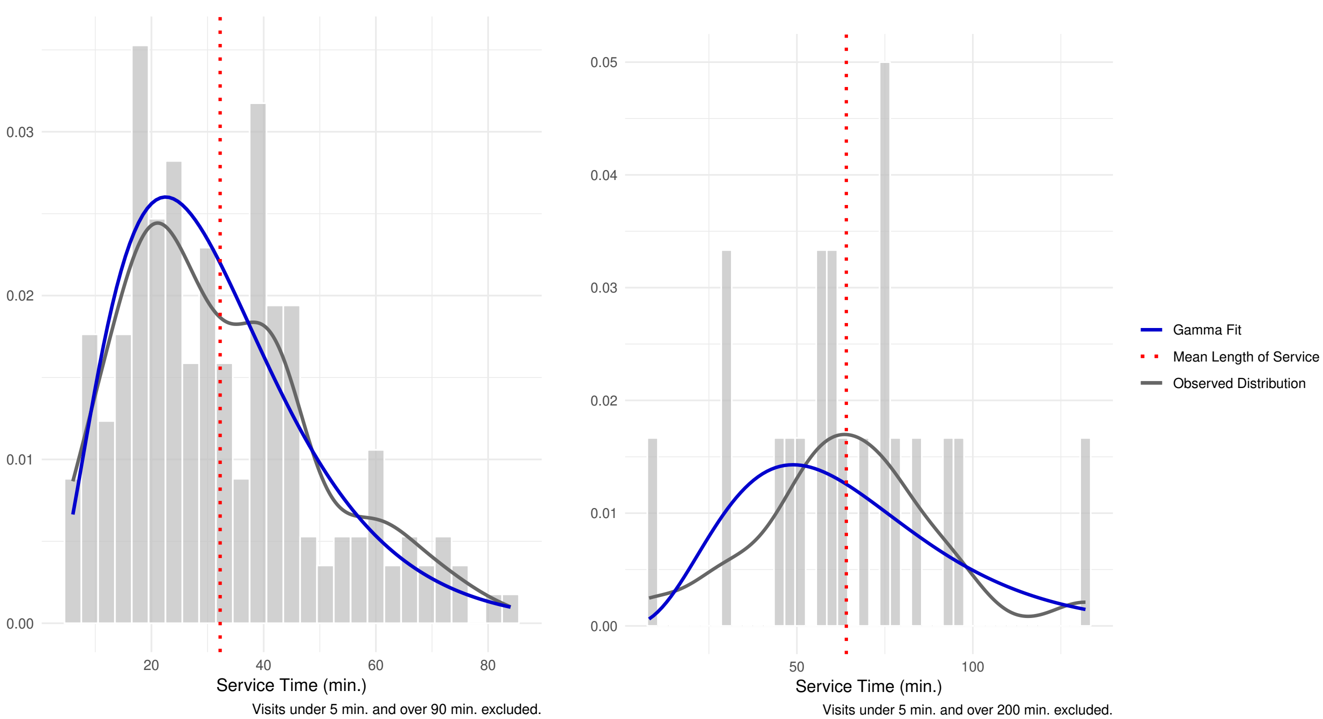
For length-type group (1), we modelled service time as a constant set to the mean of group (1) service times in the data. The second and third length-type groups were each fit to gamma distributions, using the function 'fitdistr' in the R package 'MASS', which uses maximum likelihood estimation. Figures 8, 9, and 10 show histograms of service times and the gamma distribution fits for booked nursing, walk-in nursing, and OAT services, respectively. The "Observed Distribution" lines are smoothed versions of the histograms, calculated as kernel density estimates in R. Service time statistics are given in Table 2.




(a) Scheduled for 0 to 45 minutes

(b) Scheduled for 45 to 200 minutes

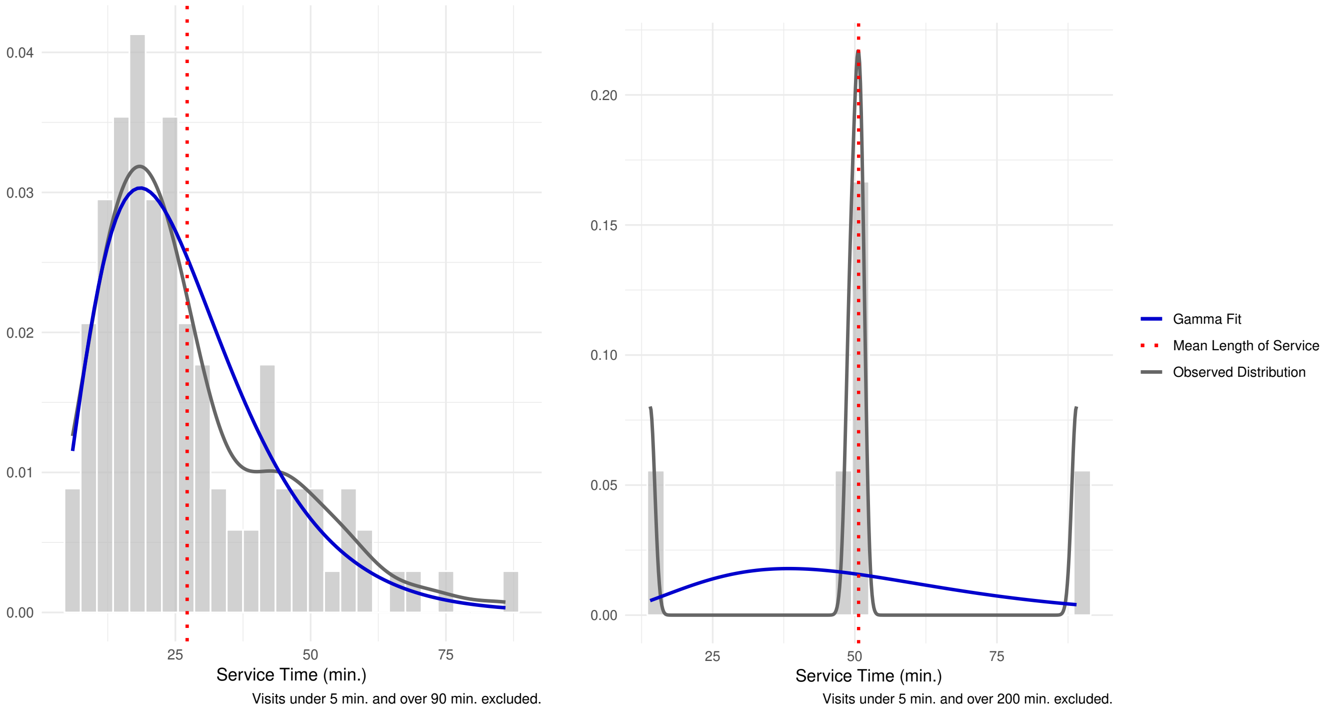
Figure 8: Observed and fitted distributions of service times for booked appointments with nurses. Bin sizes are 3 minutes. Both the gamma distribution fit to the service time data and an empirical distribution fit are shown.




(a) Scheduled for 0 to 45 minutes

(b) Scheduled for 45 to 200 minutes

Figure 9: Observed and fitted distributions of service times for walk-in visits with nurses. Bin sizes are 3 minutes. Both the gamma distribution fit to the service time data and an empirical distribution fit are shown.




(a) Scheduled for 0 to 45 minutes

(b) Scheduled for 45 to 200 minutes

Figure 10: Observed and fitted distributions of service times for booked OAT appointments. Bin sizes are 3 minutes. Both the gamma distribution fit to the service time data and an empirical distribution fit are shown.

### *4.5. Triage*

The decision to refer a client to triage is made by the clinical assistant at registration; however, the EMR does not contain triage data. The percentages of client visits in our data with an urgent label are recorded in Table 3. We used these estimates as the best available proxy for the percentage of clients requiring triage.

The data does not provide any information on the length of time required for triage. A study in an emergency department estimated a mean triage time of 3.3 minutes (with a range of 0.5 to 11.1 minutes) [45]. We used this distribution as a proxy for triage time because we have not found published estimates for triage in a community health centre setting. In order to fit a gamma distribution to this mean and range we assumed that the range values represent the $5^{\text{th}}$ and $95^{\text{th}}$ percentiles of the distribution. We fit the shape parameter by minimising the mean squared relative error in these two percentiles, given a distribution mean of 3.3 minutes. This optimisation used the 'optim' function in R which implements the Nelder-Mead algorithm. The fitted gamma distribution has a mean of 3.3 minutes and a standard deviation of 3.5 minutes.

Table 3: Percentage of clients labelled as urgent, by service type.

| **Service** | **Percentage Urgent** |
|---|---|
| Walk-in | 0.15% |
| OAT | 0.53 % |
| Booked appointments | 4.79% |

## 5. Description of the Models

We designed a three-step process for nurse scheduling to improve access to care at a community health centre. The first step uses a mixed integer linear programming (MILP) model to obtain nurse shift combinations that maximise expected nurse-client time while preserving total nurse hours, and maintaining baseline coverage. The optimisation model was applied separately to summer and winter demand profiles, to give two seasonal optimal schedules. Fluctuations in staff hours between weeks are addressed by applying a staff variability heuristic which makes minimal schedule changes. The heuristic was applied to produce four weekly optimised schedules with comparable hours to the original schedules. A discrete event simulation (DES) model was employed to evaluate the impact of the optimised schedules on key performance indicators for all four weeks. This section describes our modelling approach in the following order: nurse staffing rules, the optimisation model, the staff variability heuristic, and the simulation model.

### *5.1. Nurse Staffing Rules*

Data on nurse shifts during the four weeks we considered were obtained from the EMR. Information about nurse scheduling policy was provided by the centre staff. The MILP model works within the following scheduling policies, which are not always followed by nurse shifts in the data.

*Shift length.* The MILP model finds a scheduling solution with only 8- and 8.5-hour shifts. The EMR contains instances of longer and shorter shifts, which are not allowed in the MILP model.

*Breaks.* Each nurse shift has a 1-hour lunch and administrative break, and two 15-minute breaks. The MILP model evenly distributes these breaks throughout each shift. Specifically, the 1-hour break occurs 3.5 hours into a shift, the first 15-minute break occurs 2 hours into a shift, and the second 15-minute break occurs 5 hours 45 minutes or 6 hours into a shift for 8-hour and 8.5-hour shifts respectively.

*Administrative duties.* Nurses perform 30 minutes of administrative duties at the beginning and end of their shift. All nurses attend a staff huddle from 13:00 to 13:15. If this huddle occurs during a break or during administrative time, then additional time is added to accommodate all three activities in individual nurse schedules.

### *5.2. Schedule Optimisation Model*

We developed a new MILP model to find combinations of RN and LPN shifts that maximise expected nurse-client time, while preserving total paid nurse hours and having at least one nurse on duty when the centre is open. We applied the MILP model to produce two seasonal optimal weekly schedules based on seasonal demand profiles. This subsection describes the MILP model overall structure, parameters and notation, and equations and implementation.

#### *5.2.1. Structural Overview*

The typical approach to nurse rostering obtains schedules based on required nurse staffing levels within each time interval [46, 26]. A common approach is to use queuing theory [26] to obtain these levels based on the minimal staff required to meet service performance goals in each interval. The carry over of unmet demand into subsequent intervals poses challenges, which can be complicated to address [47, 27]. Regardless of the larger optimisation problem, these queuing theory approaches view service performance as a constraint and minimizing staffing levels as an objective. Our context motivates a different model structure, because we wish to improve service delivery while preserving total staff hours.

We formulated an MILP model which directly uses forecasted demand for nurse-client contact, instead of translating it into nurse levels. The model estimates the expected nurse-client contact time for each schedule, directly accounting for carryover demand. The expected demand in each interval is the expected number of clients multiplied by mean service time, plus unmet demand from previous intervals. Capturing demand as time is more accurate than translating into integer nurse levels, especially in our context where demand has high hourly and daily variation. Available nurse time is the number of on-duty nurses multiplied by interval length. Expected nurse-client time is the minimum of available nurse time and expected client demand, accounting for carryover demand.

#### *5.2.2. Notation and Parameters*

This subsection describes the notation and parameters used in the MILP model. The index sets in the model are listed in Table 4 and parameter notation and values are listed in Table 5. The model considers multiple types of services, listed in Table 6, which are categorised by needing

Table 4: Index sets.

| Symbol | Description | Values | Table |
|---|---|---|---|
| $K$ | nurse types | $\{RN, LPN\}$ | NA |
| $D$ | days | $\{1, ..., 7\}$ | NA |
| $S$ | shift options | $\{1, 2, ..., 10\}$ | 7 |
| $L$ | standard shift lengths | $\{8, 8.5\}$ | |
| $R$ | shift-day combinations | $\{1, 2, ..., \lvert D\rvert \cdot \lvert S\rvert\}$ | NA |
| $R_l$ | shift-day combinations of $l$-hour shifts, $\forall l \in L$ | subset of $R$ | NA |
| $P$ | all services | {1,2,3,4,5} | 6 |
| $P_k$ | services which need a type $k \in K$ nurse | $P_{RN} = \{2\}$ <br> $P_{LPN} = \{3\}$ | 6 |
| $P_{gen}$ | services that can use any nurse | $\{1, 4, 5\}$ | 6 |
| $T$ | time intervals | $\{1, 2, ...\}$ | 5 |

an RN, an LPN or either. The MILP model uses two different weekly parameter profiles from summer and winter weeks. The expected number of clients in each 15-minute interval of a week is based on average client-registration from two weeks of data, using visits from all provider types. The expected demand for nurses is obtained by multiplying this by the percentages in Table 1. External nurse activities are also averaged over seasonal demand profiles. The model assumes that demand is exogenous and does not depend on staff schedule. EMR data showed some client visits for services outside of service type delivery hours. For example, booked appointments were sometimes scheduled in the afternoon. The model considers all demand, regardless of normal service delivery hours. Mean service time is based on the distribution in Table 2 fit using all weeks of data. This assumes that service time depends only on the care required by the client and is independent of the season, time of day, or nurse type.

Table 5: MILP model parameters.

| Parameter | Definition | Value | Source |
|---|---|---|---|
| $\eta_{k,l}$ | number of nurses of type $k$ assigned to shifts of length $l$ | Table 8 | schedule data |
| $\tau$ | time interval length | 15 minutes | |
| $\mu_p$ | mean nurse-client time for service $p$ | Table 2 and Subsection 4.5 | EMR data |
| $d_{t,p}$ | expected number of clients for service type $p$ in interval $t$ | Figures 4 and 5 | EMR data |
| $g_t$ | expected number of external activities in interval $t$ | Figure 7 | EMR data |

Table 6: Services considered, with nurse type and index.

| Index | Service | Nurse Type(s) |
|---|---|---|
| 1 | triage | RN or LPN |
| 2 | booked RN appointments | RN |
| 3 | booked LPN appointments | LPN |
| 4 | walk-in nursing | RN or LPN |
| 5 | OAT | RN or LPN |

Model shifts are selected from the options shown in Table 7, which come from both the centre's

Table 7: Nurse shifts considered by the model.

| **Start** | **End** | **Length** [hours] |
|---|---|---|
| 8:00 | 16:00 | 8 |
| 8:30 | 16:30 | 8 |
| 8:30 | 17:00 | 8.5 |
| 9:00 | 17:00 | 8 |
| 9:00 | 17:30 | 8.5 |
| 9:30 | 18:00 | 8.5 |
| 10:00 | 18:00 | 8 |
| 10:00 | 18:30 | 8.5 |
| 10:30 | 18:30 | 8 |
| 11:30 | 19:30 | 8 |
| 12:00 | 20:00 | 8 |
| 12:00 | 20:30 | 8.5 |
| 12:15 | 20:45 | 8 |
| 12:30 | 20:30 | 8 |
| 13:00 | 21:00 | 8 |

Table 8: Total nurse hours, by season and type.

| | **Summer** | | **Winter** | |
|---|---|---|---|---|
| | **RN** | **LPN** | **RN** | **LPN** |
| 8-hour shifts in the model | 14 | 2 | 27 | 0 |
| 8.5-hour shifts in the model | 6 | 6 | 0 | 8 |
| total paid hours in the model | 153 | 63 | 202.5 | 64 |
| Maximum weekly paid hours in data | 153 | 63 | 202.5 | 64.5 |

nurse scheduling policy and data. Total nurse hours are preserved by specifying a priori the number of shifts of each length and nurse type, given in Table 8.The original schedules had different total hours in each week and we chose to optimise using a total number of shifts set to approximately match the maximum total weekly hours for each season and nurse type. A nurse staffing variability heuristic, described in Subsection 5.3 is used to reduce shifts in each week to account for fluctuations in staffing. The data had many shifts of non-standard length, thus it was not always possible to match total hours using 8- and 8.5-hour shifts, and we found the closest underestimates.

The MILP model utilises several indicator parameters. The binary indicator $c_{t,r}$ is defined to be 1 if time interval $t$ is a client service time of nurse shift $r$ and 0 if it is a break or administrative time interval, incorporating all breaks. The indicator $\tilde{c}_{t,r}$ is defined analogously, except that 15-minute breaks are treated as on-duty time. The indicator $O_t$ is defined to be 1 if the the clinic is open in time interval $t$ and it is not a staff huddle time, and 0 otherwise. The indicator $e_{t_1,t_2}$ is defined to be 1 if client demand from time interval $t_1$ is allowed to carry over to time interval $t_2$, and 0 otherwise. This implements an implicit carryover limit, which is set to 60 minutes, enabling the model to both capture carryover demand and align schedules with demand patterns. It is convenient to define the binary indicator

$$f_{t_1,t_2} = \begin{cases} e_{t_1,t_2}\,, & \text{for } t_1 \neq t_2 \\ 0\,, & \text{for } t_1 = t_2 \end{cases}$$

which distinguishes between carryover and current demand.

### *5.2.3. MILP Formulation*

This subsection describes the MILP model formulation, including the variables, objective function, constraints, and implementation. The MILP model varies the number of nurses assigned to each shift and uses auxiliary variables to capture nurse-client time. The number of nurses of type $k$ assigned to shift $r$ is denoted by the non-negative integer decision variable $x_{r,k}\,,\ \forall r \in R\,, \forall k \in K$. Nurse-client time for multiple services are represented by two groups of continuous variables: one for services which are nurse-type specific and one for services which are not. The expected nurse-client time for services requiring nurse-type $k$ during time interval $t$ is represented by the non-negative continuous variable $y_{t,k}\,,\ \forall t \in T\,, \forall k \in K$, and $y_t$ is defined similarly for services requiring any nurse type.

The model objective function, to be maximised, is the total expected nurse-client time,

$$\left(\sum_{k\in K}\sum_{t\in T} y_{t,k}\right) + \left(\sum_{t\in T} y_t\right)\,. \tag{1}$$

The model constraints are detailed below.

1. *Total nurse shifts must be preserved, by nurse and shift type:*

$$\sum_{r\in R_l} x_{r,k} \leq \eta_{k,l}\,,\ \forall k \in K\,, \forall l \in L \tag{2}$$

2. *Nurse-client time must not exceed available nurse time, in each interval:*

$$y_{t,k} \leq \tau \sum_{r\in R} c_{t,r} x_{r,k}\,,\ \forall t \in T\,, \forall k \in K \tag{3}$$

$$y_t \leq \tau \sum_{k\in K}\sum_{r\in R} c_{t,r} x_{r,k} - \sum_{k\in K} y_{t,k}\,,\ \forall t \in T \tag{4}$$

Equation (3) is for nurse-type specific services. Equation (4) is for non-specific services, with time spent in specific services subtracted from availability.

3. *Nurse-client time must not exceed client demand, in each interval:*

$$y_{t,k} \leq \sum_{q \in T} e_{q,t} \Big( \tau g_q + \sum_{p \in P_k} \mu_p d_{q,p} \Big) - \sum_{q \in T} f_{q,t} y_{q,k} \,, \ \forall t \in T \,, \forall k \in K \tag{5}$$

$$y_t \leq \sum_{q \in T} e_{q,t} \Big( \tau g_q + \sum_{p \in P_{gen}} \mu_p d_{q,p} \Big) - \sum_{q \in T} f_{q,t} y_q \,, \ \forall t \in T \tag{6}$$

Equation (5) is for nurse-type specific services and equation (6) is for non-specific services. Client demand includes unmet demand from previous intervals, within a time limit implemented by the indicators $e_{q,t}$ and $f_{q,t}$.

4. *At least one nurse must be on-duty when the centre is open:*

$$\sum_{k \in K} \sum_{r \in R} \tilde{c}_{t,r} x_{r,k} \geq \lceil 1 + g_t \rceil \, O_t \,, \ \forall t \in T \tag{7}$$

Here $\lceil \cdot \rceil$ denotes the ceiling function. This constraint does not consider 15-minute breaks, because we assume that nurses will accommodate urgent triage within their break schedule. The constraint is increased by $g_t$ during external activities.

This MILP model is solved using the 'Model.optimise()' function in Gurobi.

*5.3. Variability in Staffing*

We developed a staffing variability heuristic to account for fluctuations in total nurse hours from week to week. Rather than re-optimise the schedule for each week, the MILP model develops baseline optimal schedules using total weekly nurse hours set to a seasonal maximum. Then our heuristic is applied to remove shifts and produce four weekly schedules with comparable total paid nurse hours to the data. This comports with how operational planning is done at the clinic, where a new baseline schedule is not constructed on a weekly basis. The ability to respond to changes in staffing levels is important for practical nurse rostering algorithms [43].

The staff variability heuristic selects shifts to remove from the baseline schedule so that minimal coverage gaps are produced. It considers scheduled external nurse activities, but does not use any other demand data. The number of shifts to remove is identified based on the difference in total paid hours between weeks, broken down by length of shift and nurse-type. Because only 8- and 8.5-hour shifts are considered, the number of paid hours does not necessarily match the original schedules, and the closest underestimate is used. The algorithm for removing shifts is given below.

It is iterated until the required number of shifts is removed, first for 8-hour shifts and then for 8.5-hour shifts.

1. Identify the set of shifts of the desired length and nurse-type, which, if removed, would generate the minimal number of intervals with no nurse on-duty. This is based on constraint (7) of the MILP model, which considers external activities but not 15-minute breaks.
2. For this set of shifts, identify the subset which have maximal overlap with other shifts in the schedule. This overlap is calculated by summing, over time intervals in the shift, the number of other concurrent shifts.
3. If the resulting subset contains a single shift, then remove it. Otherwise, remove an arbitrary shift from the subset.
4. Return to step 1 and repeat until the required number of shifts have been removed.

### *5.4. Simulation Model*

A discrete event simulation (DES) model was developed to evaluate the eight weekly schedules in terms of client-centred key performance indicators and compare the original and optimised schedules. Wait times are of particular importance to clients with complex biopsychosocial needs, and the centre tries to see clients within an hour. The DES model estimates the number of arriving clients seen within an hour, the number of clients who leave without being seen due to an extended wait, and total time spent with clients in a week.

The DES model simulates the flow of walk-in, OAT, and booked nursing clients in the community health centre. It captures client arrival, potential triage, waiting, and nursing visit time. We model client arrivals as non-homogeneous Poisson processes, with rates varying by time of day, day of week, and season. Client arrivals are assumed to be independent of each other and of the nurse schedule. Arrival rates are piecewise constant, based on the number of clients registering in each 15-minute interval from the EMR data. These arrival rates include visits with all staff types so that triage time for non-nursing visits can be considered. The arrival processes are simulated by thinning a homogeneous Poisson process [48] with time-dependent probabilities. With the constant probabilities given in Table 3, arriving clients require triage. Afterwards, all client visits not requiring a nurse are removed from the simulation with constant seasonal probability, from Table 1. The service distributions and arrival processes used in the DES model are summarised in Table 9.

Clients are seen by nurses on a first-come-first-serve basis, within each service type. Booked appointments have higher priority than walk-in and OAT services. Potentially urgent clients re-

Table 9: Probability distributions and stochastic processes used in the simulation model.

| Quantity | Service(s) | Distribution/Process | Description |
|---|---|---|---|
| Arrival process | walk-in, OAT, booked | non-homogeneous Poisson | Subsection 4.1 |
| Service time | walk-in, OAT, booked | mixed gamma | Table 2 |
| Service time | triage | gamma | Subsection 4.5 |

quiring triage go through a higher priority service stream. Higher priority clients are seen sooner but do not preempt clients already being seen by a nurse, because the centre does not operate as an emergency department. Service priorities are recorded in Table 10.

The simulation model does not differentiate between RNs and LPNs, but rather has a single pool of scheduled nurses. External nurse activities are incorporated by reducing nurse availability during the corresponding times. The model interrupts client service if the associated nurse goes on break or ends their shift, and clients wait for the next available nurse to complete their service. This simplification of clinic operations ensures that the schedule is followed in the simulation and improves the accuracy of schedule comparison.

Nurse-client service times are modelled using the mixed gamma distributions described in Table 2. Time spent in triage follows a gamma distribution with parameters given in Subsection 4.5.

Table 10: Priority of services in the simulation model, with a lower number meaning higher priority.

| Service | Priority |
|---|---|
| Urgent walk-in/booked nursing, OAT | 1 |
| Triage | 2 |
| Booked nursing | 3 |
| Walk-in nursing, OAT | 4 |

Clients timeout and leave the simulation after 180 minutes of combined waiting time, which includes triage wait, service wait, and pause time. The incorporation of a wait limit is informed by staff experiences of clients leaving without being seen after an extended wait. It was challenging to calibrate the wait limit, because of incomplete data on unseen clients. In the simulation, as the wait limit becomes shorter than 180 minutes, there is a sharp and unrealistic rise in the number of clients who timeout and are not seen.

We implemented the DES model using AnyLogic modelling software. See Appendix A for a model diagram. We simulated each of the four weeks 1380 times, for both the original and optimised schedules. For each simulated week, we measured the number of clients seen within an hour, clients seen, clients unseen, and total nurse-client time. We found the mean and standard deviation of these numbers across all simulated weeks for each schedule. These simulations were run in series, because weeks are independent due to the wait limit.

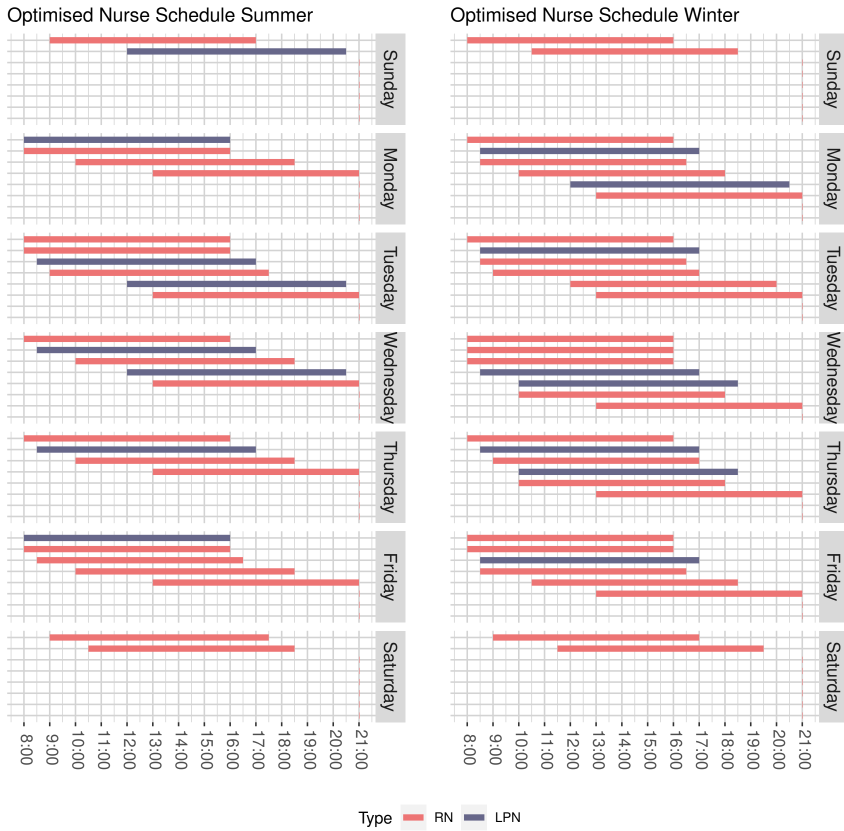



Figure 11: The optimal baseline nurse schedules for summer and winter. Breaks are not illustrated.

## 6. Results

The optimisation model described in Subsection 5.2 produced two seasonal optimal schedules, one for summer and one for winter, displayed in Figure 11. The staff variability heuristic from Subsection 5.3 was applied to each seasonal optimal schedule to yield four weekly optimised schedules with comparable paid hours to the original schedules. Figure 12 compares the original and optimised schedules for the first summer week. The optimised schedule for this week has more nurses on Friday and has slightly fewer nurses on Monday and Wednesday. Shift start times are more staggered; short and long shifts are eliminated because only standard 8-hour and 8.5-hour shifts are considered. Schedules for the other three weeks are discussed in Appendix B.

Table 11 shows schedule metrics measured within the MILP model. The optimised schedules have slightly fewer paid hours than the original schedules, although active hours (which exclude admin, break and staff meetings) may be higher. Coverage gaps are measured both with and without 15-minute breaks, because the optimisation model doesn't consider 15-minute breaks in its coverage constraints. When not considering 15-minute breaks, the optimised schedules have almost no coverage gaps, whereas the original schedules have 18 to 64 intervals per week with no on-duty

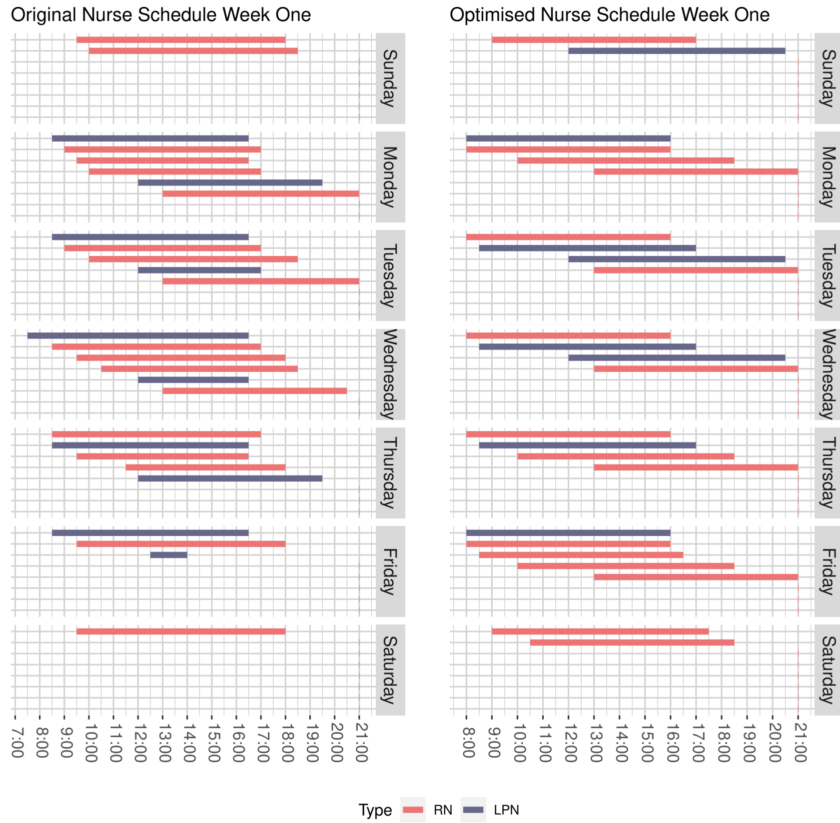



Figure 12: Comparison of the original and optimised nurse schedules for the first summer week. Breaks are not illustrated.

nurse.

Key performance indicators, evaluated by the simulation model, are broken down by service type. Indicators for booked appointments are shown in Table 13; indicators for walk-in and OAT are in Table 12. In the simulation, the optimised schedule increases nurse-client time by 0.9 to 6.1 hours per week. This breaks down to an increase of 0.4 to 5.1 hours for walk-in/OAT clients and an increase of 0.5 to 1.3 hours for booked clients. The number of clients seen increases by 1.3 to 8.8 per week, with walk-in/OAT clients seen increasing by 0.6 to 8.1 per week and booked clients seen increasing by 0.6 to 1.5 per week. Within each week, the demand profile is the same between the original and optimised schedules, so these increases do not come from an increase in the number of clients arriving at the clinic. For most weeks, the number of clients seen within an hour increases. For some weeks it decreases; however, we caution that wait time comparisons need to be interpreted in the light of more clients being seen. Our simulation also does not consider appointment scheduling, which can impact booked appointment arrival and wait times.

Table 11: Schedule outcome measures for original and optimised schedules. Weeks 1 and 2 are summer weeks and weeks 3 and 4 are winter weeks.

| **Outcome Measure per Week** | **Week** | **Schedule** | | **Change** |
|---|---|---|---|---|
| | | **Original** | **Optimised** | |
| Paid nurse hours | 1 | 197.0 | 192.5 | −4.5 |
| | 2 | 199.0 | 192.5 | −6.5 |
| | 3 | 265.5 | 259.0 | −6.5 |
| | 4 | 246.0 | 242.5 | −3.5 |
| Active nurse hours (not on break, admin, or staff meeting) | 1 | 135.8 | 136.3 | 0.5 |
| | 2 | 137.3 | 136.3 | −1.0 |
| | 3 | 183.3 | 182.5 | −0.8 |
| | 4 | 165.3 | 170.5 | 5.3 |
| Number of uncovered 15 min intervals (considering 15 min breaks) | 1 | 43 | 10 | −33 |
| | 2 | 39 | 11 | −28 |
| | 3 | 25 | 10 | −15 |
| | 4 | 70 | 11 | −59 |
| Number of uncovered 15 min intervals (not considering 15 min breaks) | 1 | 38 | 1 | −37 |
| | 2 | 34 | 0 | −34 |
| | 3 | 18 | 0 | −18 |
| | 4 | 64 | 0 | −64 |

Table 12: Key performance indicators (KPI) for walk-in and OAT clients, for original and optimised schedules. Weeks 1 and 2 are summer weeks and weeks 3 and 4 are winter weeks. The standard error of the mean is denoted by SE.

| **KPI per Week** | **Week** | **Schedule** | | | | | |
|---|---|---|---|---|---|---|---|
| | | **Original** | | **Optimised** | | **Change** | |
| | | **Mean** | **SE** | **Mean** | **SE** | **Absolute** | **Percent** |
| Time spent with clients (hours) | 1 | 36.34 | 0.13 | 39.61 | 0.14 | 3.27 | (8.99%) |
| | 2 | 41.01 | 0.14 | 43.16 | 0.14 | 2.15 | (5.25%) |
| | 3 | 31.94 | 0.13 | 32.36 | 0.13 | 0.42 | (1.30%) |
| | 4 | 36.79 | 0.14 | 41.87 | 0.15 | 5.07 | (13.8%) |
| Number of clients seen | 1 | 72.27 | 0.22 | 78.65 | 0.23 | 6.38 | (8.83%) |
| | 2 | 81.52 | 0.23 | 85.61 | 0.23 | 4.09 | (5.01%) |
| | 3 | 63.65 | 0.22 | 64.23 | 0.21 | 0.58 | (0.91%) |
| | 4 | 74.77 | 0.23 | 82.83 | 0.24 | 8.06 | (10.8%) |
| Number of clients not seen | 1 | 11.64 | 0.13 | 5.49 | 0.12 | −6.15 | (-52.8%) |
| | 2 | 11.56 | 0.13 | 7.89 | 0.13 | −3.66 | (-31.7%) |
| | 3 | 2.54 | 0.05 | 2.63 | 0.05 | 0.09 | (4%) |
| | 4 | 11.39 | 0.11 | 3.60 | 0.07 | −7.79 | (-68.4%) |
| Number of clients seen within an hour | 1 | 61.74 | 0.22 | 62.31 | 0.26 | 0.57 | (0.92%) |
| | 2 | 69.16 | 0.24 | 70.19 | 0.25 | 1.03 | (1.49%) |
| | 3 | 59.67 | 0.21 | 59.57 | 0.20 | −0.10 | (-0.17%) |
| | 4 | 71.87 | 0.23 | 74.92 | 0.24 | 3.05 | (4.25 %) |

Table 13: Key performance indicators (KPI) for booked appointments, for original and optimised schedules. Weeks 1 and 2 are summer weeks and weeks 3 and 4 are winter weeks. The standard error of the mean is denoted by SE.

| **KPI per Week** | **Week** | **Schedule** | | | | | |
|---|---|---|---|---|---|---|---|
| | | **Original** | | **Optimised** | | **Change** | |
| | | **Mean** | **SE** | **Mean** | **SE** | **Absolute** | **Percent** |
| Time spent with clients (hours) | 1 | 37.38 | 0.17 | 37.61 | 0.16 | 0.23 | (0.61%) |
| | 2 | 37.29 | 0.17 | 38.59 | 0.17 | 1.30 | (3.47%) |
| | 3 | 40.75 | 0.18 | 41.25 | 0.18 | 0.51 | (1.2%) |
| | 4 | 40.38 | 0.18 | 41.38 | 0.18 | 1.00 | (2.47%) |
| Number of clients seen | 1 | 52.84 | 0.19 | 53.43 | 0.18 | 0.58 | (1.1%) |
| | 2 | 52.96 | 0.18 | 54.49 | 0.20 | 1.53 | (2.89%) |
| | 3 | 57.46 | 0.20 | 58.07 | 0.20 | 0.61 | (1.1%) |
| | 4 | 57.56 | 0.21 | 58.31 | 0.20 | 0.75 | (1.3%) |
| Number of clients not seen | 1 | 2.03 | 0.05 | 1.93 | 0.06 | $-0.10$ | (-4.9%) |
| | 2 | 3.45 | 0.06 | 2.32 | 0.05 | $-1.13$ | (-33.8%) |
| | 3 | 0.77 | 0.03 | 0.61 | 0.02 | $-0.16$ | (-21%) |
| | 4 | 1.86 | 0.04 | 1.21 | 0.04 | $-0.66$ | (-35%) |
| Number of clients seen within an hour | 1 | 45.03 | 0.17 | 42.21 | 0.17 | $-2.82$ | (-6.25%) |
| | 2 | 44.96 | 0.17 | 45.36 | 0.17 | 0.40 | (0.89%) |
| | 3 | 54.22 | 0.19 | 55.63 | 0.19 | 1.57 | (2.89%) |
| | 4 | 56.04 | 0.20 | 53.62 | 0.19 | $-2.43$ | (-4.33%) |

## 7. Discussion

We developed a new approach to nurse scheduling for a community health centre, which serves clients with complex biopsychosocial needs. Our model is tailored to the urban community clinic context, where nurse scheduling approaches from acute care settings are not directly applicable. Our new scheduling approach addresses key service delivery concerns that are common in inner-city community health centres.

Our schedule optimisation model strategically aligns nurse shifts to better meet client arrivals, which can result in fewer clients leaving prior to receiving care due to long wait times. In our simulations, the optimised schedules increased the number of clients receiving care by up to 9 per week. This improvement is important for clients navigating complex health issues, who need timely care to maintain stability. Clients who are not able to receive timely care at the centre may have their health deteriorate, or go to the emergency department and receive care less informed by their medical history. Our approach to schedule optimisation improves access to care without additional nurse hours.

The community health centre aims to provide timely care by ensuring clients are seen within one hour of arrival. The increase in clients receiving care under our optimised schedules could potentially increase congestion and wait times. However, simulation wait times for walk-in and OAT clients were not significantly impacted. Wait times for booked clients slightly increased in some weeks; however, this could be addressed by adjusting scheduled appointment times. Overall, there is still improved service access, because more booked clients receive care in our simulations.

The original schedules implemented varied shift lengths to address demand peaks. However, our optimised schedules meet demand by staggering standard-length shifts, which may benefit the clinic by reducing overtime pay and call-in costs. Staggered nurse shifts have been previously studied in emergency departments [49, 50], and our analysis demonstrates that they merit consideration in primary care.

Having at least one nurse on duty during opening hours is necessary for triage and providing timely care to urgent cases. Our schedule optimisation model requires nurse coverage to be maintained during opening hours. Even when week-to-week variation in staffing reduces the number of nurse shifts, our staff variability heuristic minimises coverage gaps in the modified schedules. For example, only a single 15-minute gap in nurse coverage occurs in our optimised schedules, whereas the original schedules, with more total nurse hours, have numerous coverage gaps. Our scheduling approach could potentially help the centre to better meet urgent client need.

We now discuss some of the limitations of our scheduling approach that arise from model simplifications and incomplete historical data. In practice, changes to staff schedules may influence client arrivals and appointment times. This interaction was not considered in our model and it should be taken into account when interpreting wait times estimated from our simulation. Our results are based on client arrival data, which may underestimate true demand, because it does not capture preferences or clients who do not check-in due to full capacity. We were limited to developing bi-seasonal schedules, because only four weeks of data were available. With additional data, our approach could be used to determine detailed seasonal schedules capturing monthly variation and holidays.

Future developments of our optimisation approach could incorporate other provider types, team-based care, and other services at the centre. Additional model constraints could be added to address staff preferences and other scheduling factors. Integrating an appointment system into our staff scheduling approach could account for the interaction between schedules and demand.

## 8. Conclusions

We developed a new nurse schedule optimisation approach for an inner-city community health centre in Vancouver, Canada, which serves clients with complex biopsychosocial needs. Timely care access is important for maintaining continuity of care for chronic conditions and addressing urgent medical, addiction, and mental health issues. Our simulation results demonstrate that strategically aligning nurse shifts can effectively improve timely care provision at the centre, without increasing total staff hours. Our approach can improve triage and urgent care provision by maintaining a baseline level of staffing throughout the day. Furthermore, only standard shift lengths are used in our staffing solution and demand peaks are addressed by staggering shifts.

Ongoing collaboration with stakeholders at the community health centre can inform successful implementation and realisation of these benefits. Our approach to nurse scheduling could be applied to other primary care clinics, especially those which offer a broad range of services to clients with complex health needs.

## Acknowledgements

We thank the community health centre leadership team—especially Nicole LeMire, Stewart Williams, Poornima Nedungadi, and Susan Lim—who collaborated on this project and provided valuable insight into the centre's operations. We thank Jaime Kirschner for providing feedback on the frequency of triage, and Poornima Nedungadi and Nicole Roberge for providing insight on clients who leave without being seen. Jaime Kirschner facilitated S.L.Z. shadowing at the community health centre in order to understand the operational flow and context. We express gratitude towards the entire staff team at the centre for their support.

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### Declarations of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Appendix A. Simulation Model

Figure A.13 shows a graphic of the simulation model, which was implemented in the AnyLogic simulation software. Three source nodes generate clients, which are thinned multiple times (by diamond choice nodes) and then flow through dark blue service blocks where they queue for then spend time with a nurse before leaving the clinic.

### Appendix B. Optimized Schedules for Remaining Weeks

Tables B.14, B.15, and B.16 display the original and optimised schedules for weeks 2, 3, and 4, respectively. Across all weeks the optimised schedules are more staggered, with coverage more evenly distributed during the day and evening. They are also more spread out across different days in the week.

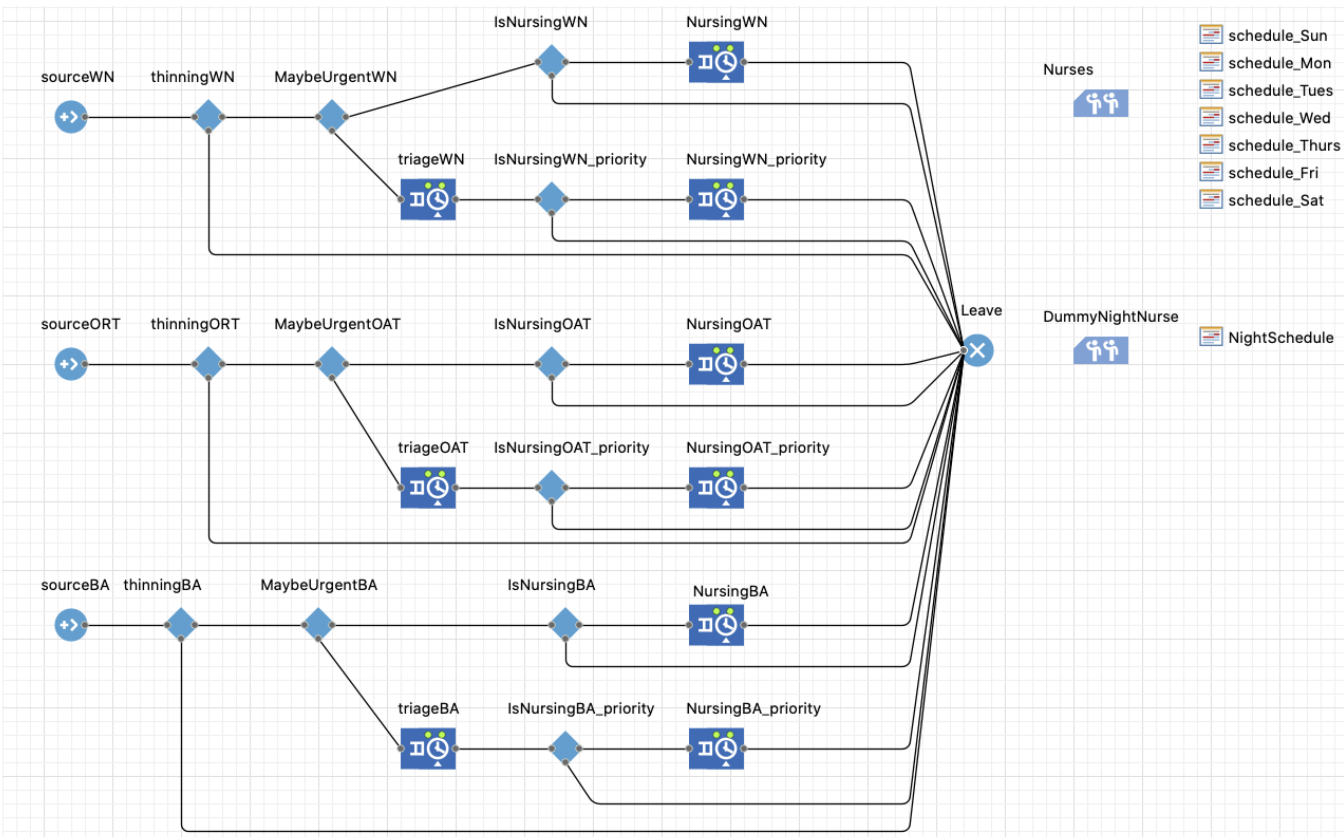


Figure A.13: Simulation model in AnyLogic. There are three streams for walk-in (WN), OAT, and booked appointments (BA), each with a regular and urgent sub-stream.

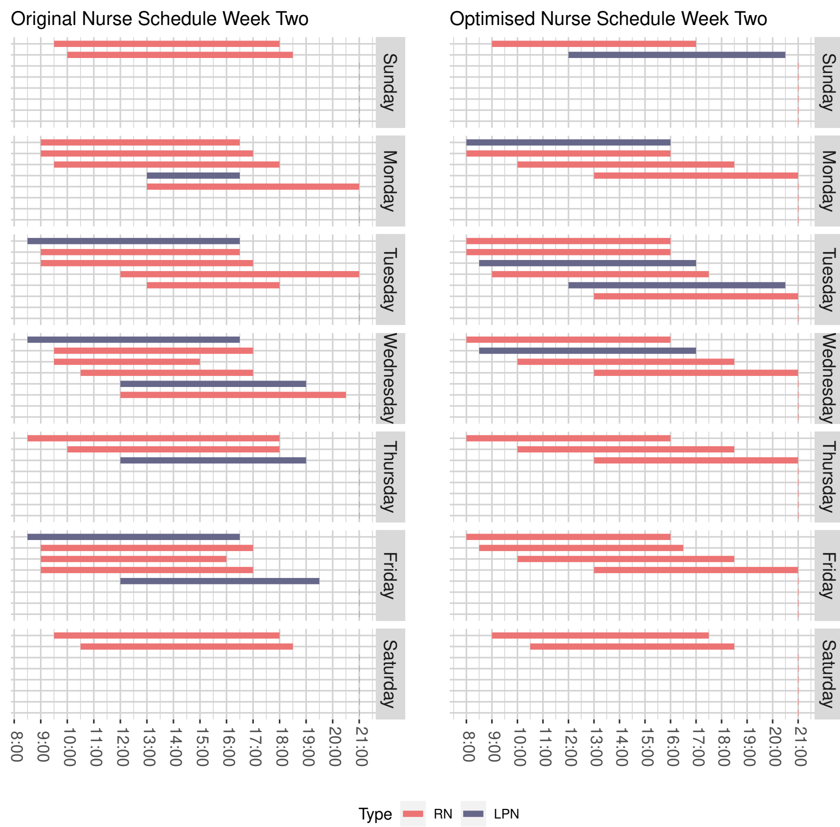


Figure B.14: Comparison of the original and optimised nurse schedule for the first summer week.

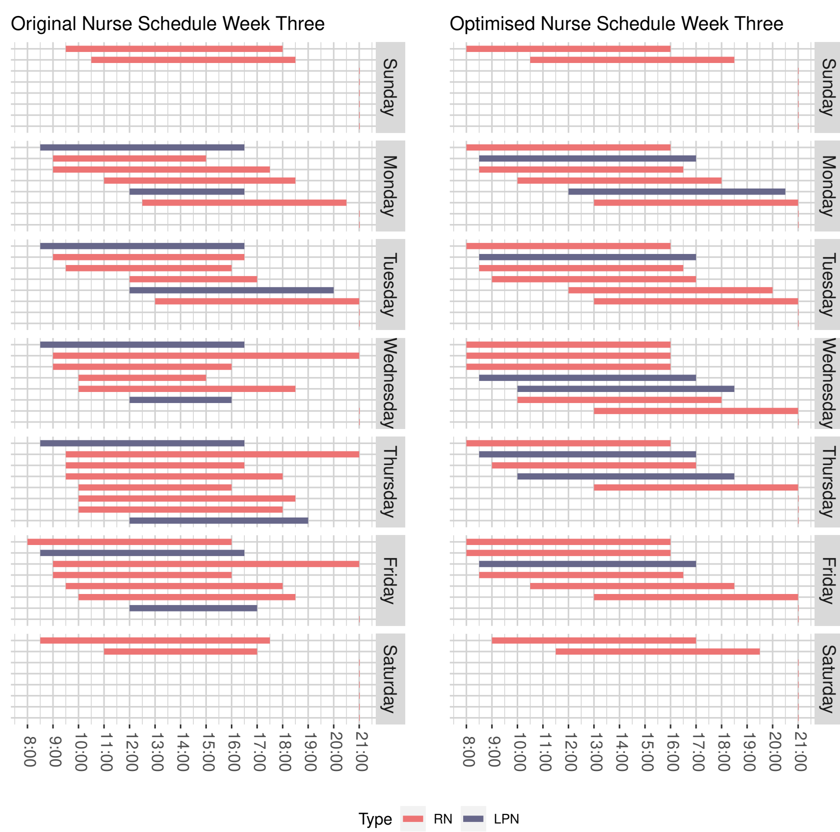


Figure B.15: Comparison of the original and optimised nurse schedule for the first summer week.

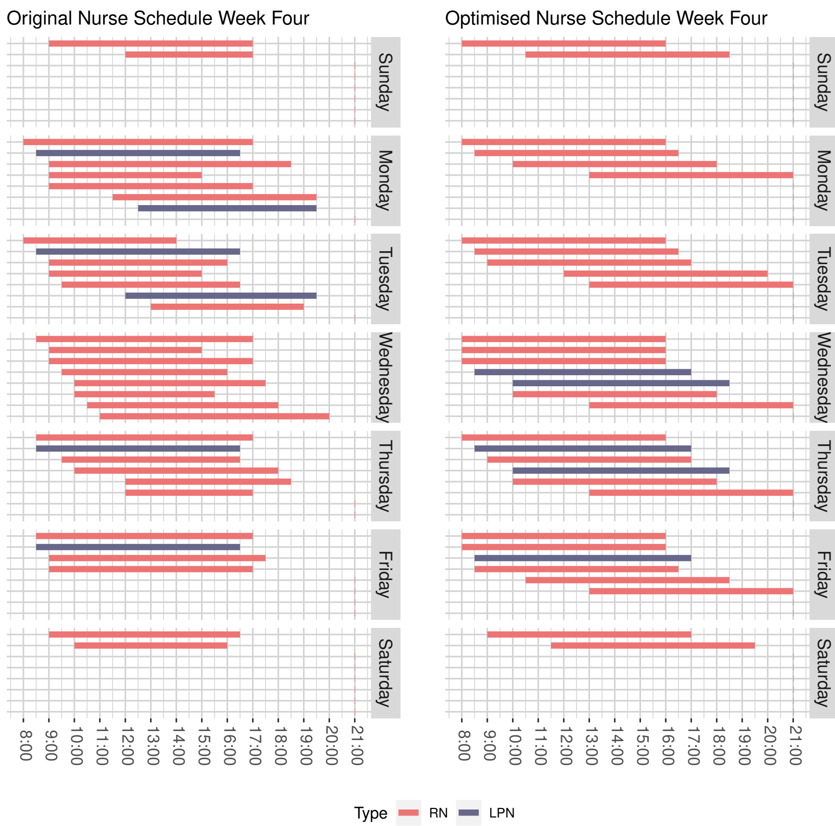


Figure B.16: Comparison of the original and optimised nurse schedule for the first summer week.

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