Acuity-based nurse assignment and patient scheduling in oncology clinics*

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The oncology clinics use different nursing care delivery models to provide chemotherapy treatment to cancer patients. Functional and primary care delivery models are the most commonly used methods in the clinics. In functional care delivery model, patients are scheduled for a chemotherapy appointment without considering availabilities of individual nurses, and nurses are assigned to patients according to patient acuities, nursing skill, and patient mix on a given day after the appointment schedule is determined. Patients might be treated by different nurses on different days of their treatment. In primary care delivery model, each patient is assigned to a primary nurse, and the patients are scheduled to be seen by the same nurse every time they come to the clinic for treatment. However, these clinics might experience high variability in daily nurse workload due to treatment protocols that should be followed strictly. In that case, part-time nurses can be utilized to share the excess workload of the primary nurses. The aim of this study is to develop optimization methods to reduce the time spent for nurse assignment and patient scheduling in oncology clinics that use different nursing care delivery models. For the functional delivery model, a multiobjective optimization model with the objectives of minimizing patient waiting times and nurse overtime is proposed to solve the nurse assignment problem. For the primary care delivery model, another multiobjective optimization model with the objectives of minimizing total overtime and total excess workload is proposed to solve the patient scheduling problem. Spreadsheet-based optimization tools are developed for easy implementation. Computational results show that the proposed models provide multiple nondominated solutions, which can be used to determine the optimal staffing levels.

Key words: Chemotherapy, oncology, nurse assignment, patient scheduling, multiobjective optimization

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1. Introduction

Chemotherapy patient scheduling and nurse assignment are complex problems due to high variability in treatment durations and nursing care requirements. Nurses are the key resources that provide chemotherapy treatment in oncology clinics. They administer chemotherapy, manage side-effects

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of the drugs, educate patients about the treatment, and provide counseling [13]. Patients have different acuity levels and require different nursing times that depend on treatment protocols, patient health status, difficulty of vein access, and side effects of the drugs. Therefore, nurse workload during a shift depends on several factors including the number of patients assigned to the nurse, the acuities of those patients, their relative start times, and the additional tasks that should be performed by the nurses (i.e. triaging patient calls, documenting the treatment on patient's medical records, drawing blood from the patients who have PORT access, and mixing drugs). Nurse-to-patient assignment is an important task, because it affects daily nurse workload and patient flow. For example, when several acute patients are assigned to a nurse, it will cause patient waiting times, overtime, nurse burnout, and patient safety problems.

Besides nurse assignment, chemotherapy patient scheduling is another important task that affects patient flow and nurse workflow. For example, if too many patients are scheduled to arrive at the same time, their treatment might not start at the same time due to limited nurse availability. According to the ONS survey, 41% of the responding nurses were responsible for scheduling patients and 54% were fixing scheduling problems [9]. This shows the complexity of appointment scheduling in infusion clinics, because valuable nursing time is used for patient scheduling. Previous studies in nursing literature propose using scheduling templates and rules that are based on nursing or treatment times, but patient acuity is usually not considered while scheduling patients. There are studies that develop acuity systems for nurse staffing in oncology clinics, but they are not commonly used in oncology clinics due to the difficulty of determining the acuity levels for hundreds of treatment protocols. We believe patient acuity systems can estimate the nursing requirements for each patient more accurately. The integration of acuity systems, nurse workflow, and patient scheduling can provide better schedules that minimize patient waiting times and staff overtime, and balance workload for the nurses.

In oncology clinics, different nursing care delivery models are used for nurse assignment and patient scheduling. In functional care delivery model, nurses are assigned to a group of patients depending on patient mix in a given day. The patients may see different nurses every time they come to the clinic. In primary care delivery model, patients are assigned to a primary nurse and care is provided by the same primary nurse in each visit. In medical care delivery model, nurses assist the physicians as needed and carry out nursing aspects of medical care [9]. According to the Oncology Nursing Society Survey, functional and primary care delivery models are the most commonly used methods (40% use functional care delivery model and 39% use primary care model) in oncology clinics [9].

Our prior experience with oncology clinics also showed that different care delivery models are adopted according to several factors including the availability of skilled nurses in that area, staffing costs, patient satisfaction, and patient safety. In one clinic, functional care delivery model was used where nurses were assigned to patients at the beginning of the day. The patient-nurse assignment was performed by the charge nurse. Nurse working hours, skill levels, appointment times, and nurse workload were considered while assigning the nurses to patients. The nurse assignment process was taking 45-60 minutes every day. In another clinic, primary care delivery model was used. The patients were assigned to a primary nurse before their first treatment and they were scheduled to see the same nurse at every clinic visit throughout the treatment. However, since the chemotherapy treatment plans should be followed strictly, there were days at which workload was exceeding the primary nurse's capacity. On those days, the clinic was using other nurses with less workload or additional nurses to take the extra workload for safe administration of chemotherapy. In the third clinic, the main delivery model was functional care delivery model. However, at the nurse assignment phase, the nurses were assigned to pods to work as teams, and the charge nurse was trying to assign the same nurse who treated the patient previously while considering patient acuity levels, nurse working hours, appointment times, nurse workload, and pod assignments.

In this study, we focus on functional and primary care delivery models, and propose optimization methods to reduce the time spent for nurse assignment and patient scheduling. The aim is to determine the optimal number of nurses with the objectives of minimizing patient waiting times and nurse overtime in functional care delivery model and minimizing excess workload and nurse overtime in primary care delivery model.

In the remainder of this paper, a brief overview of the existing literature is provided in Section 2. The problem is defined with its underlying assumptions in Section 3. In Section 4, two multiobjective optimization models are proposed to solve the nurse assignment problem for the functional care delivery model, and the patient scheduling problem for the primary care model. A numerical example and spreadsheet based optimization tools are explained in the same section. Computational results along with managerial insights are discussed in Section 5, and concluding remarks are provided in Section 6.

2. Literature review

Nurse assignment:

In the operations research literature, there are several studies on personnel staffing and scheduling that use mathematical programming, constraint programming, and heuristics [1]. However, nurse assignment problem where patients are assigned to nurses based on their care needs is considered in a few studies. Mullinax and Lawley [12] developed a patient acuity tool and proposed an integer linear programming model to assign patients to nurses, and nurses to zones in a neonatal intensive care unit. Schaus et al. [20] solve the same problem using constraint programming. Rosenberger et al. [17] solve nurse-to-patient assignment by integer programming method to minimize excess workload on nurses in a hospital unit. Meanwhile, Punnakitikashem et al. [15, 16] proposed a stochastic programming approach that addresses the uncertainty and fluctuations in patient care, and differences in nursing skills in an inpatient unit. Sundaramoorthi et al. [23] build a simulation model driven by data mining to evaluate different nurse-to-patient assignment policies in a medical/surgical unit.

All of the existing studies solve the nurse assignment problem in inpatient settings. To the best of our knowledge, this is the first study that solves nurse assignment problem for a given patient mix and appointment schedule in an outpatient setting. The characteristics of the problem in outpatient setting different from the inpatient setting include: i) regular working hours in clinics (e.g. clinic opens at 7am, closes at 5pm), ii) dynamic patient arrivals and departures that depend on appointment schedules and treatment durations, and iii) the need for nursing time for the start of the treatment. Because of these characteristics, besides excess workload (a performance measure used in inpatient settings), we consider patient waiting times and staff overtime (performance measures considered in outpatient settings). In infusion clinics, nurse assignment problem is important to achieve a balanced workload for nurses. In practice, most nurse assignments are either based on judgment of the charge nurse or same number of patients are assigned to each nurse to provide similar caseload. However, it is difficult to achieve a balanced workload due to high variation in care needs of chemotherapy patients. Patient acuity systems can be used to accurately estimate the nursing needs. In nursing literature, there are studies that propose patient intensity/acuity tools in ambulatory oncology settings to establish appropriate staffing levels [5, 8, 25]. In this study, we consider patient acuities when assigning nurses to patients for a given schedule. We assume the acuity levels are already assigned to each regimen based on the number of agents, pre-medications, total treatment time, complexity of administration, and assessments required [2, 8].

Chemotherapy patient scheduling:

In oncology nursing literature, there are few studies about chemotherapy appointment scheduling [2, 3, 4, 6, 8, 10]. Most of them propose using scheduling templates or guidelines to reduce the complexity of the task for the schedulers [3, 8, 10]. For example, the number of patients that can be scheduled might be limited at certain hours due to nurse schedules, and working hours of other departments (i.e. laboratory, pharmacy for research drugs). The scheduling templates, which show the availability of nurses and chairs on a spreadsheet, can avoid scheduling of the patients when the resources are not available. There might be restrictions on the appointment times such as not scheduling long treatments in the afternoon to reduce overtime. The scheduling guidelines might also include the accurate calculation of appointment durations, especially when additional time is required for patients who need pre-medications, laboratory tests, or education. The scheduling templates and guidelines are shown to balance workload, reduce overtime, and improve on-time starts [2, 6]. However, they should be updated as patient mix changes, and generating a template is not an easy task in this complex environment with several treatment protocols.

In operations research literature, there are a few studies that propose optimization models to solve patient scheduling problem. Sevinc et al. [21] propose a multiple knapsack model to assign patients to infusion chairs. Sadki et al. [18] propose an integer programming model to determine oncologist and chemotherapy appointments with the objective of minimizing a weighted combination of patient waiting time and makespan (clinic total working time). The studies by Sevinc et al. [21] and Sadki et al. [18] assume nurses have enough capacity, and hence do not consider them in their models. Hahn-Goldberg et al. [7] consider pharmacy, nurse, and chair capacities, and propose a constraint programming model to create a template schedule without assigning patients to nurses.

Santibanez et al. [19], Turkcan et al. [24], and Shasha-ani [22] consider available nurse capacities and assign patients to nurses while scheduling patients. Turkcan et al. [24] consider patient acuities and nurse availabilities in their integer programming model that minimizes total completion time of all treatments. The proposed model assigns patients to nurses and chairs while determining the appointment times. Shashaani [22] extends the daily appointment scheduling model of Turkcan et al. [24] by incorporating patient preferences, staggered nurse schedules, and start time constraints (i.e. start after the completion of oncologist appointment). These two studies do not restrict the assignment of patients to specific nurses, and hence do not have to deal with the problem of excess workload for nurses. Santibanez et al. [19] consider nursing times in their multi-objective integer programming model with the objectives of satisfying patients' time preferences, pharmacy capacity, balancing workload between nurses, balancing workload of each nurse throughout the day and assigning clinical trial patients to specialized nurses. None of these models consider primary care delivery model, where patients have to be scheduled with their primary nurse. Our model considers a primary care delivery model, and addresses the problem of high variability in daily workload by minimizing the total excess workload.

Contributions of this study:

1. This is the first study that solves nurse assignment problem for a given patient mix and appointment schedule in an outpatient setting. Due to predetermined appointment schedules and staff schedules with fixed start and end times, timeliness is important in outpatient settings. The proposed multiobjective optimization model finds schedules that minimize total patient waiting time and clinic overtime simultaneously.

2. This is the first study that considers primary care delivery model in oncology clinics. The clinics, which use primary nurse model to improve continuity of care, might experience high variability in daily nurse workload due to treatment protocols. The proposed model finds several schedules that minimize total overtime and total excess workload simultaneously. The proposed model can be used as a decision making tool to determine the number of part-time nurses required when the workload is higher than the primary nurses' capacity.

3. The proposed methods can reduce the time spent for daily nurse assignment and patient scheduling tasks significantly. Two spreadsheet-based optimization tools, which use open-source optimization software (OpenSolver), are developed for easy implementation. The developed tools require minimal training and can be used as decision making tools to determine the optimal staffing levels required for safe chemotherapy treatment.

3. Problem definition

In this study, we consider patient scheduling and nurse assignment problems in outpatient oncology clinics using functional and primary care delivery modes, respectively. The notation that will be used throughout the paper can be seen in Table 1.

We consider outpatient oncology clinics where fixed start times and regular working hours are commonplace. The clinics set their regular working hours according to patient demand and volume, and availability of providers. The outpatient clinics might run from 7am to 5 pm, and provide longer hours on certain days of the week to accommodate patient demand (i.e. patients who work can come to the clinic after work). The day is divided into smaller time slots (i.e. 30 minutes) and patients are scheduled to arrive at the beginning of these pre-determined slots. The patient may need more than one slot according to the treatment duration and these time slots are blocked once the patient is scheduled.

We consider a single stage system where P patients are scheduled only for the infusion appointment. The laboratory tests and oncologist appointments that occur before the infusion appointment

Table 1 Notation

Parameters:	
S	Number of slots
P	Number of patients
D_i	Treatment duration of patient i
$\mathbf{N}$	Set of nurses
H_j^s, H_j^f	Work schedule (shift start and end times) of nurse j
L_i	Acuity level of patient i
K_j	Skill level of nurse j
n_{ij}	Takes value 1 if the skill level of nurse j is enough to treat patient i
M_j	Maximum acuity level for nurse j
A_i	Appointment time of patient i (for functional delivery model only)
Decision variables:	
y_{ijs}	Binary variable, 1 if patient i is treated by nurse j and the treatment starts at time slot s
t_i	Treatment start time of patient i (for functional delivery model only)
w_i	Waiting time of patient i (for functional delivery model only)
o_j	Overtime of nurse j
e_{js}	Excess workload of nurse j at time slot s (for primary care delivery model only)

are not considered. The pharmacy time for chemotherapy preparation is assumed to be included in the treatment duration (D_i). The treatment durations, which might range between 30 minutes and 8 hours, are assumed to be given. We assume punctual arrivals where patients come to the clinic for chemotherapy treatment at their appointment times.

Nurses are the key resources who administer chemo-therapy to patients. Based on clinic working hours, nurses might have different start times and end times. For example, a nurse with 8-hour schedule might start at 7am and work until 3pm, and another nurse with 10-hour schedule might start at 8am and work until 6pm. This type of nurse schedule (staggered nurse schedule) is commonly used in outpatient settings to adjust the availability of nurses according to changing demand throughout the day and provide flexible working hours for the nurses. We assume a staggered nurse schedule with H_j^s and H_j^f as the starting and ending time of working hours for nurse j. If the patients are still being treated or waiting for the treatment at the end of the shift, the nurse who provides the service will continue working to complete the treatment.

A nurse is assigned to multiple patients for administering the chemotherapy. The assignment is made based on nurse working hours, skill level of nurse, patient acuity, and maximum number of patients a nurse can simultaneously treat. Each patient has an acuity (L_i) level, which represents the complexity of the treatment and the nursing time required. Nurses are assigned to the patients based on their skill level (K_j). A nurse can be assigned to a patient only if her skill level is higher than the patient acuity ($n_{ij} = 1$). We assume a nurse can treat multiple patients at the same time. The maximum acuity level (M_j) defines how many patients a nurse can treat simultaneously. For

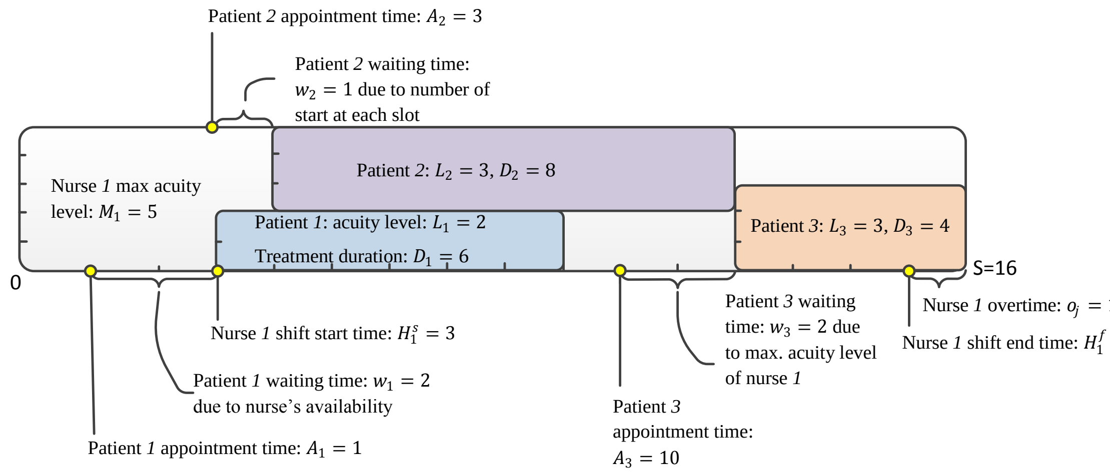


Figure 1 **Sample schedule**

instance, nurse j can treat patient p_1 and p_2 whose acuity levels are 2 and 3 at the same time if her maximum acuity level is greater than or equal to 5. We also assume a nurse can start at most one treatment in each slot.

A sample schedule with three patients and one nurse is provided in Figure 1 to clarify the notation. The skill level and maximum acuity level of the nurse are 3 and 5, respectively. The shift start and end times are 3 and 16. Even though the appointment time of the first patient is 1, the treatment cannot start until time 3 due to the shift start time of the nurse. Patient 2 has to wait until next time slot, because a nurse cannot have more than one treatment start in any time slot. Patient 3 is scheduled to arrive at slot 10. However, the treatment cannot start until slot 12 due to maximum acuity level of 5. That means, the nurse cannot take care of two patients with acuity level 3 at the same time.

4. Proposed optimization models

4.1. Functional care delivery model: Multiobjective optimization model for nurse assignment

We propose a multiobjective optimization model with the objectives of minimizing patient waiting time and nurse overtime. The proposed model assigns nurses to patients and determines the actual treatment start times of the patients. We assume patient schedules are given with appointment times (A_i), treatment durations (D_i) and acuity levels (L_i). The nurse work schedules (H_j^s, H_j^f), skill levels (K_j) and maximum acuity level a nurse can handle at any given slot (M_j) are also given.

Objectives: We consider objectives of minimizing total patient waiting time (O.1) and nurse overtime (O.2).

$$min \quad TWT = \sum_{i=1}^{P} w_i = \sum_{i=1}^{P} [t_i - A_i] = \sum_{i=1}^{P} \Big[\sum_{j \in \mathbf{N}} \sum_{s=1}^{S} (s-1) y_{ijs} - A_i \Big] \tag{O.1}$$

$$min \quad TOT = \sum_{j \in \mathbf{N}} o_j \tag{O.2}$$

Assignment constraints: The proposed model aims to allocate a nurse to each patient and determine the start time of the treatment. The decision variable y_{ijs} takes value 1 when nurse j is assigned to patient i and the treatment starts in time slot s. Constraint (1.a) ensures that each patient is assigned to only one nurse who has enough skill to treat the patient. The treatment can start after the nurse assigned to the patient starts working for the day and the patient arrives for his/her appointment ($s \geq \max\{A_i, H_j^s\} + 1$). Due to the intensity of tasks that should be performed at the beginning of the treatment, a nurse can start at most one treatment in any given slot, which is guaranteed by constraint (2.a).

$$\sum_{j \in \mathbf{N}} \sum_{s=\max\{A_i, H_j^s\}+1}^{S} (n_{ij} \times y_{ijs}) = 1 \qquad \forall i = 1 \cdots P \tag{1.a}$$

$$\sum_{i=1}^{P} (n_{ij} \times y_{ijs}) \leq 1 \qquad \forall j \in \mathbf{N}, s = \max\{A_i, H_j^s\} + 1 \cdots S \tag{2.a}$$

Acuity constraints: Nurses can treat limited number of patients simultaneously due to nursing requirements and safety issues. Constraint (3.a) makes sure the total acuity level of patients assigned to a nurse does not exceed the maximum acuity level.

$$\sum_{i=1}^{P} \sum_{u=max\{1, s-D_i+1\}}^{s} (n_{ij} \times L_i \times y_{iju}) \leq M_j \qquad \forall j \in \mathbf{N}, s = 1 \cdots S \tag{3.a}$$

Nurse overtime: Nurse overtime is the difference between the treatment completion time of the last patient assigned to the nurse and end of regular working hours for that nurse. Constraint (4.a) calculates the overtime for each nurse.

$$o_j \geq n_{ij} \times y_{ijs} \times (s + D_i - 1) - H_j^f \qquad \forall i = 1 \cdots P, j \in \mathbf{N}, s = 1 \cdots S \tag{4.a}$$

Non-negativity and integrality: The non-negativity (5.a) and integrality (6.a) constraints make sure all variables are non-negative and y_{ijs} is binary.

$$w_i, o_j \geq 0 \qquad \forall i = 1 \cdots P, j \in \mathbf{N} \tag{5.a}$$

$$y_{ijs} \in \{0,1\} \qquad \forall i = 1 \cdots P, j \in \mathbf{N}, s = 1 \cdots S \tag{6.a}$$

4.2. Primary care delivery model: Integer programming model for patient scheduling

We propose a multiobjective optimization model to solve the patient scheduling problem. We assume the primary nurse for each patient is known, and appointments are scheduled based on the primary nurse availability. The proposed integer programming model is as follows:

$$min \quad TOT = \sum_{j \in \mathbf{N}} o_j \tag{O.2}$$

$$TEW = \sum_{j \in \mathbf{N}} \sum_{s=1}^{S} e_{js} \tag{O.3}$$

$$st \quad \sum_{s=H^s_{r_i}+1}^{S} y_{i,r_i,s} = 1 \qquad \forall i = 1 \cdots P \tag{1.b}$$

$$\sum_{i=1}^{P} y_{ijs} \leq 1 \qquad \forall j \in \mathbf{N}, s = H^s_j + 1 \cdots S \tag{2.b}$$

$$\sum_{i=1}^{P} \sum_{u=max\{1, s-D_i+1\}}^{s} (L_i \times y_{iju}) \leq M_j + e_{js} \qquad \forall j \in \mathbf{N}, s = 1 \cdots S \tag{3.b}$$

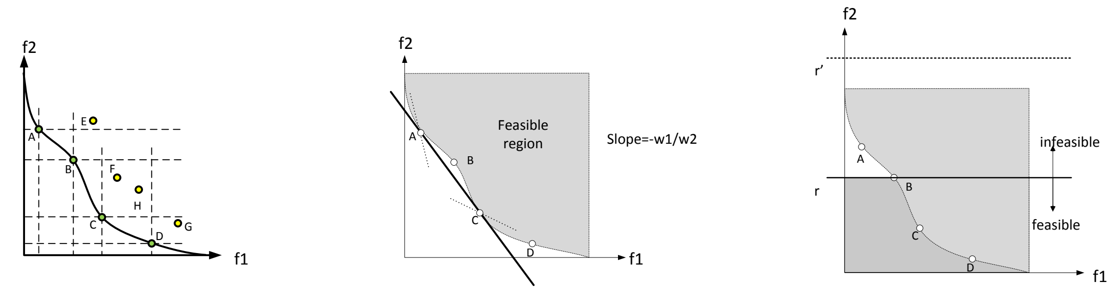
$$o_j \geq y_{ijs} \times (s + D_i - 1) - H^f_j \qquad \forall i = 1 \cdots P, j \in \mathbf{N}, s = 1 \cdots S \tag{4.b}$$

$$\sum_{j \in \mathbf{N}} e_{js} \leq E_s \qquad \forall s = 1 \cdots S \tag{5.b}$$

$$o_j \geq 0, e_{js} \geq 0 \qquad \forall j \in \mathbf{N}, s = 1 \cdots S \tag{6.b}$$

$$y_{ijs} \in \{0,1\} \qquad \forall i = 1 \cdots P, j \in \mathbf{N}, s = 1 \cdots S \tag{7.b}$$

The model determines the appointment times for all patients while minimizing the total excess workload (TEW) and total overtime (TOT) simultaneously. Different from the functional care delivery model, the patients can only be assigned to their primary nurse r_i (constraint 1.b), and the total workload assigned to each nurse at each slot can exceed the maximum acuity level (constraint 3.b). The decision variable e_{js} is added to the right-hand-side of constraint (3.b) to calculate the excess workload for each nurse at each slot. However, since high workload can cause patient safety problems, we assume part time nurses can be used to take the excess workload. Even though the proposed model does not assign patients to specific part-time nurses, it restricts the total



(a) (b) (c)

Figure 2 a) Pareto optimal set; b) Weighted sum method; c) ϵ-constraint method (adapted from [26])

excess workload at each slot (constraint 5.b), where the upper bound (E_s) is determined according to the maximum acuity level part-time nurses can handle. Similar to functional care delivery model, a nurse can start at most one treatment at each slot (constraint 2.b), and constraint (4.b) calculates the overtime for each nurse. Constraints (6.b) and (7.b) are non-negativity and integrality constraints for the proposed model.

The proposed nurse assignment and patient scheduling models have multiple objectives and our aim is to find the nondominated solution set that minimizes all objectives simultaneously. For a minimization problem, solution y is said to dominate y' if $f_i(y) \leq f_i(y')$ for all objectives ($i \in \{1, 2 \cdots n\}$) and $f_i(y) < f_i(y')$ for at least one objective i. In Figure 2.a, solutions A, B, C, and D form the nondominated solution set which minimizes both f_1 and f_2. The other solutions (E, F, G, and H) are dominated by the solutions in the nondominated solution set.

Different approaches are used to solve multiobjective optimization problems in the literature. The weighted sum method uses a weighted linear combination of the objectives and assigns different weight combinations to determine the set of nondominated solutions. The ϵ-constraint method converts $k-1$ of the k objectives into constraints and finds nondominated solutions by changing the right-hand-sides (upper bounds) of these constraints. Figures 2.b and 2.c show how each method works to find the nondominated solutions. We use ϵ-constraint method to solve our optimization problems. We convert the overtime objective into a constraint ($\sum_{j \in \mathbf{N}} o_j \leq \epsilon$), and then solve the models with different ϵ values to find the nondominated solutions. Figure 3 shows the algorithm used to generate all nondominated solutions for the functional care delivery model, where the objective is minimization of total waiting time. The algorithm for the primary care model uses the objective of minimization of total excess workload instead of total waiting time.

4.3. Numerical example

In this section, we will give a small numerical example to show the schedules generated by the proposed integer programming models. We consider 20 chemotherapy patients to be seen in one

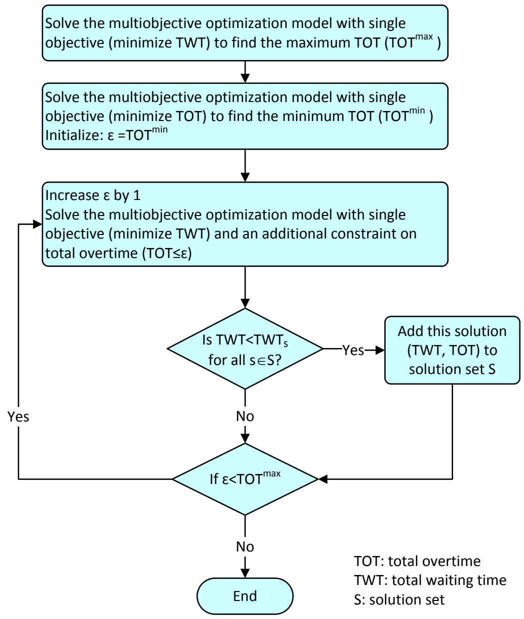


Figure 3 Algorithm based on ϵ-constraint approach to find nondominated solutions

Table 2 Numerical example data for nurse assignment model

Patient number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Appointment time	0	0	1	1	2	2	3	3	4	4	5	5	6	6	7	7	8	8	9	9
Appointment duration	9	5	6	7	4	4	3	4	5	3	4	6	1	5	7	9	8	6	7	5
Acuity level	3	2	2	1	3	1	1	2	3	2	2	3	2	1	2	2	3	2	3	1

Table 3 Nondominated solutions for nurse assignment model in functional care delivery model

Nondominated solution	Number of nurses	Objective function values		Waiting time per patient (slots) (min, average, max)	Overtime per nurse (slots) (min, average, max)
		Total waiting time (slots)	Total overtime (slots)		
1	3	14	3	0, 0.70, 6	0, 1.00, 2
2	3	16	1	0, 0.80, 6	0, 0.30, 1
3	4	3	1	0, 0.15, 1	0, 0.25, 1
4	4	4	0	0, 0.20, 4	0, 0.00, 0

day. The day is divided into 16 half-hour slots and treatment durations range from 1 to 9 slots (e.g. 30 minutes to 4.5 hours). The patient acuities range from 1 to 3. Table 2 shows the appointment times, durations and acuity levels for each patient. We assume there are at most 4 nurses scheduled for the day. Their skill levels are 3, 3, 2, and 2, and maximum acuity levels are 6, 5, 5, and 4, respectively. We consider an outpatient clinic with regular working hours from 8am (slot 0) to 4pm (slot 16). All nurses start working at time slot 0 and regular working hours end at slot 16.

Nurse assignment model:

First, we solve the proposed multiobjective optimization model with different staffing levels (3 and 4 nurses) to find the optimal nurse assignment and actual treatment start times. Table 3 shows the objective function values of the nondominated solutions found by ϵ-constraint approach. When there are three nurses, the nurse assignment model gives two nondominated solutions. The first solution gives total waiting time of 14 slots and total overtime of 3 slots. The second solution has higher waiting time (16 slots) and lower overtime (1 slot).

Table 3 also shows the minimum, average, maximum values for waiting time and overtime in the last two columns. These minimum and maximum values are presented to show the range of waiting time and overtime for individual patients and nurses, respectively. For the first nondominated solution, the average waiting time per patient is 0.7 slots, that is 21 minutes (14 slots $\times$ 30 minutes/slot / 20 patients = 21 minutes/patient). The minimum and maximum waiting times are 0 and 6 slots (0 and 180 minutes). The average overtime is 1 slot (30 minutes) per nurse (3 slots $\times$ 30 minutes/slot / 3 nurses = 30 minutes/nurse). The minimum and maximum overtime are 0 and 2 slots (0 and 60 minutes).

Even though patient waiting time and staff overtime are the most commonly used performance measures in appointment scheduling literature, other performance measures such as resource utilizations are also important in infusion clinics. Since nurse skill levels and maximum acuity levels that can be handled by each nurse differs, we use the following formula to calculate the nurse utilizations.

$$u_j = \frac{\sum_{i=1}^{P}\sum_{s=1}^{S}(y_{ijs} \times D_i \times L_i)}{(H_j^s - H_j^f) \times M_j}$$

The numerator calculates the total acuity for all patients assigned to a nurse and the denominator calculates the maximum acuity a nurse can handle during regular working hours. For nondominated solution 1, the nurse utilizations are 94%, 98% and 81% for nurses 1–3, respectively. For nondominated solution 4, the nurse utilizations are 86%, 60%, 69%, and 70%, for nurses 1–4, respectively.

The resource utilizations calculated using the above formula is an average value for the day and it does not show how the workload changes throughout the day. In order to see the workload variation throughout the day, we should look at the number of patients and total acuity assigned to each nurse in each time slot. Figure 4 shows the patients assigned to each nurse, treatment start times and durations for two nondominated solutions: nondominated solution 1 (3 nurses, 14

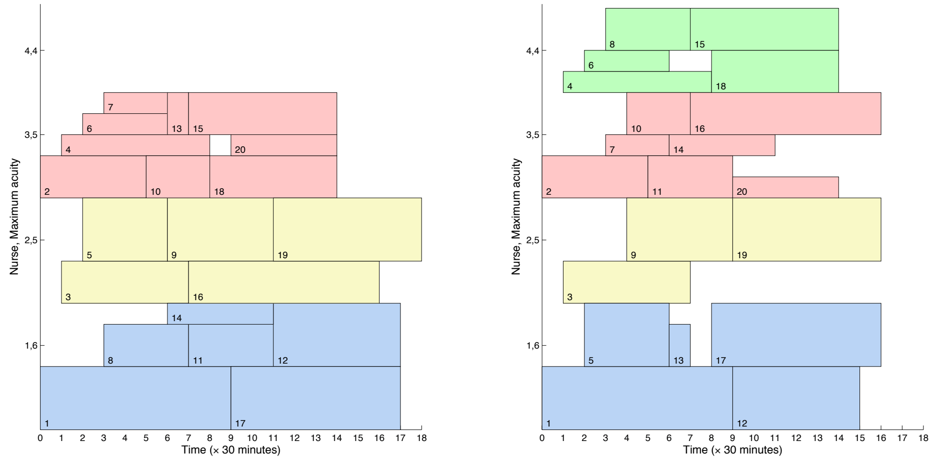


Figure 4 **(a) Nondominated solution 1 (Number of nurses = 3, total waiting time = 14, total overtime = 3), (b) Nondominated solution 4 (Number of nurses = 4, total waiting time = 4, total overtime = 0)**

waiting time, 3 overtime), and nondominated solution 4 (4 nurses, 4 waiting time, 0 overtime). In the figure, each patient appointment is represented with a rectangle where the width of the rectangle shows the treatment duration and the height shows the acuity of the treatment. The total acuity assigned to each nurse does not exceed the maximum acuity level. Patients with acuity level 3 cannot be assigned to nurses 3 and 4 whose skill levels are 2.

For nondominated solution 1, the number of patients assigned to nurses 1–3 are 6, 5, and 9, respectively. For nondominated solution 4, the number of patients assigned to nurses 1–4 are 5, 3, 7, and 5, respectively. In nondominated solution 1, nurses are utilized at their maximum capacity for most of the day (total acuity assigned to a nurse is equal to the maximum acuity level). There is also very low slack time, which might cause problems when there is high variability in treatment durations and nurses have breaks.

When the number of nurses increases, the waiting time and overtime decrease as expected. However, the cost of adding one nurse might be higher than the total waiting time and overtime costs. In that case, the decision maker can use another criterion that combines the cost of an additional nurse with patient waiting time and staff overtime costs to determine the optimal number of nurses. In order to calculate the total cost, we should determine the regular cost (c_r) of an additional nurse and overtime (c_o) cost of an existing full-time nurse per unit time. We also have to estimate the cost of waiting time (c_w) with respect to overtime and regular working time costs. When we know all these cost values, total cost can be calculated as ($c_w \times TWT$ + $c_o \times TOT$ + $c_r \times$ total regular working time). If the decrease in total waiting time cost ($c_w \times \Delta TWT$) and overtime cost ($c_o \times \Delta TOT$) is larger than the increase on regular cost of an additional nurse ($c_r \times$ total regular

Table 4 Numerical example data for primary nurse model

Patient number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Appointment duration	9	5	6	7	4	4	3	4	5	3	4	6	1	5	7	9	8	6	7	5
Acuity level	3	2	2	1	3	1	1	2	3	2	2	3	2	1	2	2	3	2	3	1
Primary nurse	1	3	2	3	2	2	2	1	2	3	1	1	3	1	3	2	1	3	2	3

Table 5 Nondominated solutions for patient scheduling for primary care delivery model

Nondominated solution	Upper bound on excess workload (E_s)	Objective function values		Total excess workload per slot (min, average, max)	Total overtime per nurse (slots) (min, average, max)
		Total excess workload	Total overtime (slots)		
1	0, 6	0	2	0, 0, 0	0, 0.7, 2
2	6	3	1	0, 0.2, 1	0, 0.3, 1
3	6	7	0	0, 0.4, 2	0, 0, 0

working time of an additional nurse), then it will be beneficial to have one more nurse. In our numerical example, if we take c_w=1, c_r=1, and c_o=1.5 to compare nondominated solutions 1 and 4, the decrease in total waiting time and overtime costs will be $(1 \times (14-4) + 1.5 \times (3-0) = 14.5)$ and the increase in regular cost of an additional nurse will be $(1 \times 16 = 16)$. That means, having three nurses is better than having four nurses in terms of total cost.

Patient scheduling model:

For patient scheduling, we solve the same numerical example with 20 patients. We consider 3 nurses with skill levels of 3, 3, and 2, and maximum acuity levels of 6, 5, and 5, respectively. Table 4 shows the appointment durations, acuity levels, and primary nurses assigned to each patient for the primary nurse model. We solve the proposed multiobjective optimization model to find the optimal appointment times with the objectives of minimizing total overtime and total excess workload.

Table 5 shows the objective function values of the nondominated solutions for primary care delivery model. When there is no excess workload allowed ($E_s = 0$), the patient scheduling model gives 1 nondominated solution. When the upper bound on total excess workload per slot is increased to 6 ($E_s = 6$), the patient scheduling model gives 3 nondominated solutions including the one found by $E_s = 0$.

Figure 5 shows the appointment schedule for two nondominated solutions: nondominated solution 1 and nondominated solution 3. Based on the provided nondominated solutions, decision maker can decide whether a part time nurse is required or not. Similar to nurse assignment model, the overtime cost and cost of part-time nurse can be compared. If overtime cost per unit time is c_o, and cost of part-time nurse per unit time is c_p, then it will be more beneficial to use a part-time nurse when total overtime cost ($c_o \times TOT$) exceeds the total part-time nurse cost ($c_p\times$ total duration

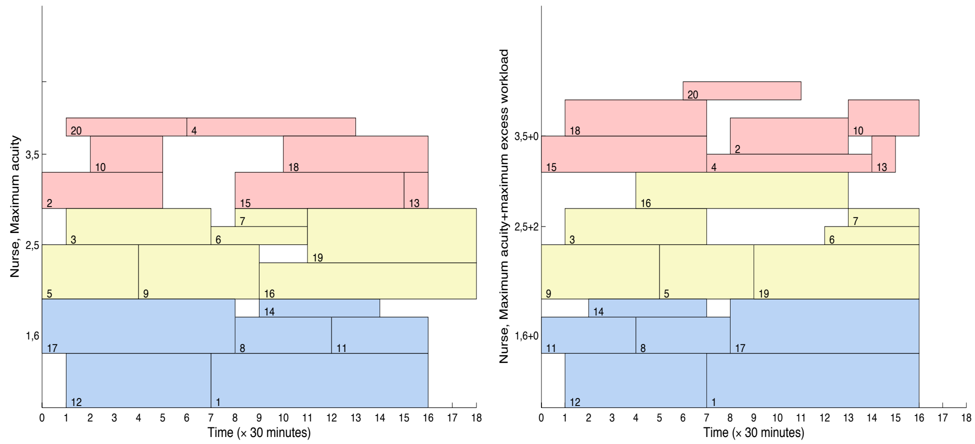


Figure 5 **(a) Nondominated solution 1 (Maximum total excess workload allowance E_s is 0 (and 6), total excess workload is 0, total overtime is 2), (b) Nondominated solution 3 (Maximum total excess workload allowance E_s is 6, total excess workload is 7, total overtime is 0)**

part time nurse is required). In our example, if patients 6 and 7 are assigned to a part-time nurse and patient 16 is scheduled to arrive at time slot 7 instead of 4, then a part-time nurse is enough for 4 slots. If patient schedule cannot be changed at this point, then the part time nurse is required at time slots 4, 5, 6, and 12 to share the workload of primary nurse 2.

For this small example, it is easy to find an alternative schedule when one part-time nurse is added to the team. However, as the number of nurses with excess workload increases, it will become more difficult to find a solution manually. In that case, the first constraint of the primary care delivery model (constraint 1.b) can be updated as follows:

$$\sum_{s=H^s_{r_i}+1}^{S} y_{i,r_i,s} + \sum_{g\in G_i}\sum_{s=H^s_g+1}^{S} y_{i,g,s} = 1 \qquad \forall i = 1\cdots P \tag{1.c}$$

where G_i is the set of part-time nurses that can be assigned to patient i. This constraint makes sure either the primary nurse or a part-time nurse from set G_i is assigned to patient i. The revised model assigns nurses to patients, and finds an optimal appointment schedule. In this study, since our aim is to provide alternative solutions that minimize total excess workload and total overtime simultaneously, this last model that assigns patients to primary or part-time nurses will not be solved in the computational study section.

4.4. Spreadsheet-based optimization tools

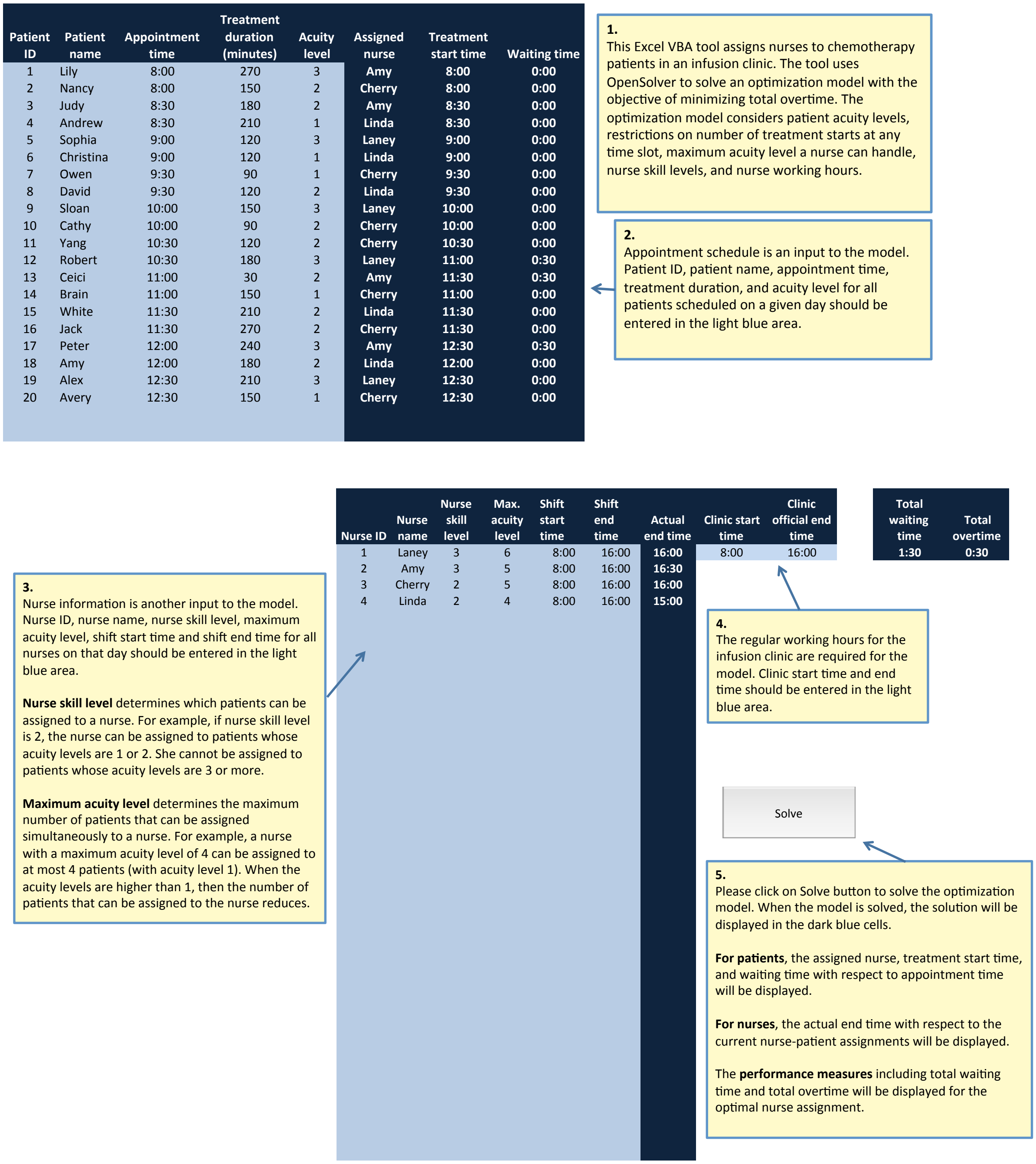
Our aim is to provide optimization tools that can easily be used by nurse managers and schedulers. We developed spreadsheet-based optimization tools to solve nurse assignment and patient scheduling problems. The optimization tool uses Opensolver to solve the proposed models. Opensolver is an Excel VBA add-in that extends Excel's built-in Solver capabilities with a more powerful linear programming solver. It is developed and maintained by Andrew Mason and students at the Engineering Science Department, University of Auckland, New Zealand [14, 11].

Figure 6 shows the screenshots of the tool for nurse assignment model. The patient information (patient ID, name, appointment time, treatment duration, and acuity level), nurse information (nurse ID, name, skill level, maximum acuity level, shift start time, and shift end time) and clinic hours (start time and end time) are the inputs to the model. After the user enters all the required information in light blue area, and presses the "Solve" button, the optimization model is solved and the solution is displayed in the dark blue area. The solution gives nurse names assigned to each patient, actual treatment start times, waiting times, completion time of last treatment for each nurse, total patient waiting time and total overtime.

Figure 7 shows the screenshot of the spreadsheet based tool that solves the patient scheduling problem for primary nurse model. Similar to functional nurse assignment model, the user needs to enter patient information (patient ID, name, assigned nurse ID and treatment duration), nurse information (nurse ID, name, maximum acuity level, shift start and end time) and clinic start and end times in the light blue area. A maximum overtime allowance is required to determine the maximum number of slots required in the proposed model. The upper bound on total excess workload should also be provided by the user. After the model is solved, treatment start times, total overtime, total excess workload, excess workload in each slot for each nurse are provided in the dark blue areas.

5. Computational study

We performed a computational study to evaluate the performance of proposed nurse assignment and patient scheduling models. We solve 30 problems with different number of patients, patient acuities, and treatment durations. Each problem represents a single day with a set of patients who have to be treated on the same day. There are 40 to 68 patients per day, each patient has an acuity level from 1 to 3, and their treatments last from 1 to 9 slots (30 minutes to 4.5 hours). Table 6 shows the average duration and acuity level per patient, and total workload for each problem. Total workload, which is calculated by multiplying the acuity level and the treatment duration for each patient, shows the total nursing time requirement on a given day. Since the number of nurses affects patient waiting times and nurse overtime, we use different number of nurses changing between 5 and 7. Table 7 shows the skill levels and maximum acuity levels of nurses used in the computational studies. All problems are solved using IBM ILOG Cplex 12.0. The computational results are presented for functional care delivery model and primary nurse model separately in the following sections.



Patient ID	Patient name	Appointment time	Treatment duration (minutes)	Acuity level	Assigned nurse	Treatment start time	Waiting time
1	Lily	8:00	270	3	Amy	8:00	0:00
2	Nancy	8:00	150	2	Cherry	8:00	0:00
3	Judy	8:30	180	2	Amy	8:30	0:00
4	Andrew	8:30	210	1	Linda	8:30	0:00
5	Sophia	9:00	120	3	Laney	9:00	0:00
6	Christina	9:00	120	1	Linda	9:00	0:00
7	Owen	9:30	90	1	Cherry	9:30	0:00
8	David	9:30	120	2	Linda	9:30	0:00
9	Sloan	10:00	150	3	Laney	10:00	0:00
10	Cathy	10:00	90	2	Cherry	10:00	0:00
11	Yang	10:30	120	2	Cherry	10:30	0:00
12	Robert	10:30	180	3	Laney	11:00	0:30
13	Ceici	11:00	30	2	Amy	11:30	0:30
14	Brain	11:00	150	1	Cherry	11:00	0:00
15	White	11:30	210	2	Linda	11:30	0:00
16	Jack	11:30	270	2	Cherry	11:30	0:00
17	Peter	12:00	240	3	Amy	12:30	0:30
18	Amy	12:00	180	2	Linda	12:00	0:00
19	Alex	12:30	210	3	Laney	12:30	0:00
20	Avery	12:30	150	1	Cherry	12:30	0:00

Nurse ID	Nurse name	Nurse skill level	Max. acuity level	Shift start time	Shift end time	Actual end time
1	Laney	3	6	8:00	16:00	16:00
2	Amy	3	5	8:00	16:00	16:30
3	Cherry	2	5	8:00	16:00	16:00
4	Linda	2	4	8:00	16:00	15:00

Clinic start time	Clinic official end time
8:00	16:00

Total waiting time	Total overtime
1:30	0:30

Figure 6 **Screenshot of the spreadsheet-based optimization tool for nurse assignment model**

5.1. Computational results for the functional care delivery model

The multiobjective optimization models are solved using ϵ-constraint approach. The total regular working hours per day is assumed to be 8 hours (16 slots). Since overtime is allowed, a maximum overtime of 8 slots (4 hours) is considered. If the current patient mix cannot be scheduled within 24 slots (16 regular + 8 overtime) with available number of nurses, then the IP model gives infeasible

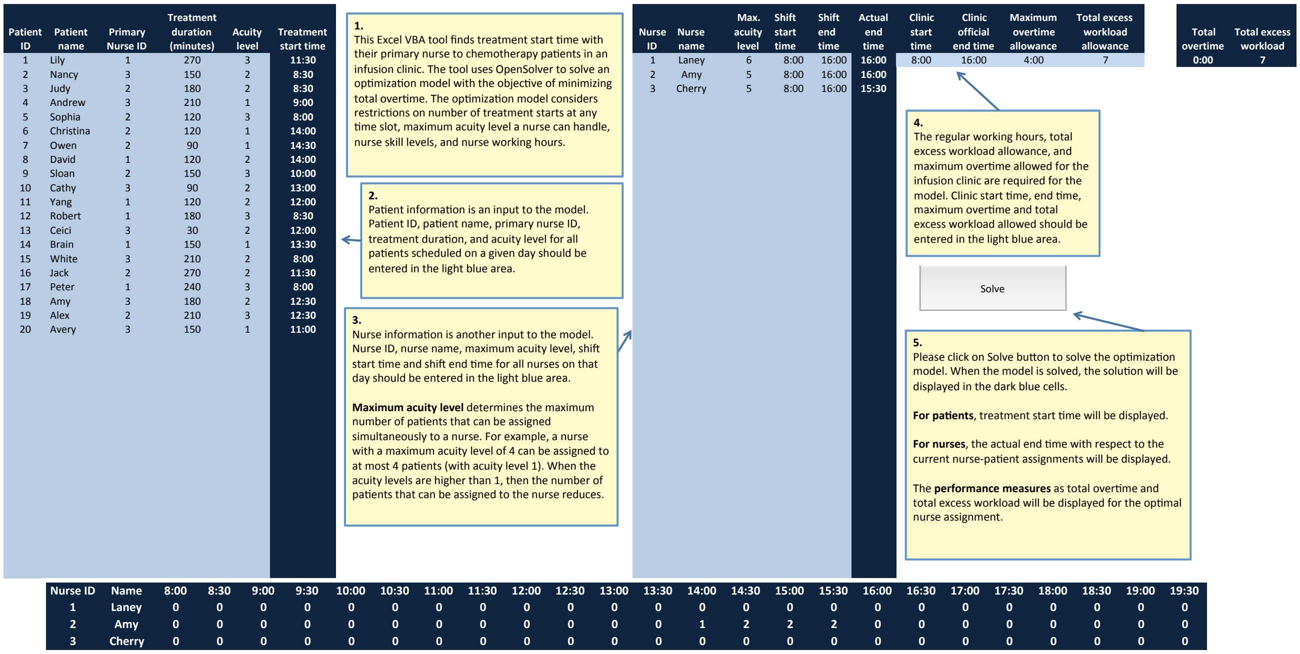


Figure 7 **Screenshot of the spreadsheet-based optimization tool for patient scheduling model**

Table 6 **Summary of characteristics of patient mix for 30 problems**

Problem no.	1	2	3	4	5	6	7	8	9	10
Number of patients	43	47	45	43	57	48	48	42	40	55
Average duration, $\sum_i D_i/n$	3.09	3.04	3.16	3.37	2.91	3.23	3.21	3.57	3.78	3.11
Average of acuity level, $\sum_i A_i/n$	1.60	1.53	1.71	1.63	1.54	1.67	1.67	1.76	1.80	1.60
Total workload, $\sum_i (A_i \times D_i)$	245	255	291	294	295	297	298	311	321	328
Problem no.	11	12	13	14	15	16	17	18	19	20
Number of patients	57	49	59	53	53	58	57	64	53	59
Average duration, $\sum_i D_i/n$	3.11	3.49	3.24	3.45	3.47	3.38	3.56	3.34	3.66	3.39
Average of acuity level, $\sum_i A_i/n$	1.65	1.69	1.66	1.74	1.72	1.69	1.61	1.67	1.81	1.66
Total workload, $\sum_i (A_i * D_i)$	333	348	354	357	359	396	397	404	410	411
Problem no.	21	22	23	24	25	26	27	28	29	30
Number of patients	53	62	55	61	59	56	68	55	56	54
Average duration, $\sum_i D_i/n$	3.75	3.29	3.73	3.31	3.53	3.66	3.34	3.87	3.96	4.07
Average of acuity level, $\sum_i A_i/n$	1.75	1.69	1.87	1.74	1.81	1.84	1.68	2.02	2.07	2.13
Total workload, $\sum_i (A_i * D_i)$	412	414	416	418	445	453	471	510	522	539

Table 7 **Nurse skill levels and maximum acuity levels for each nurse**

Number of nurses	Skill levels	Maximum acuity levels
5	(3, 3, 2, 2, 2)	(6, 5, 5, 4, 6)
6	(3, 3, 2, 2, 2, 3)	(6, 5, 5, 4, 6, 5)
7	(3, 3, 2, 2, 2, 3, 3)	(6, 5, 5, 4, 6, 5, 4)

solution. A computation time limit of 600 seconds is used because of the difficulty of solving large size models in short computation times. Figures 8 and 9 show the total overtime and total waiting

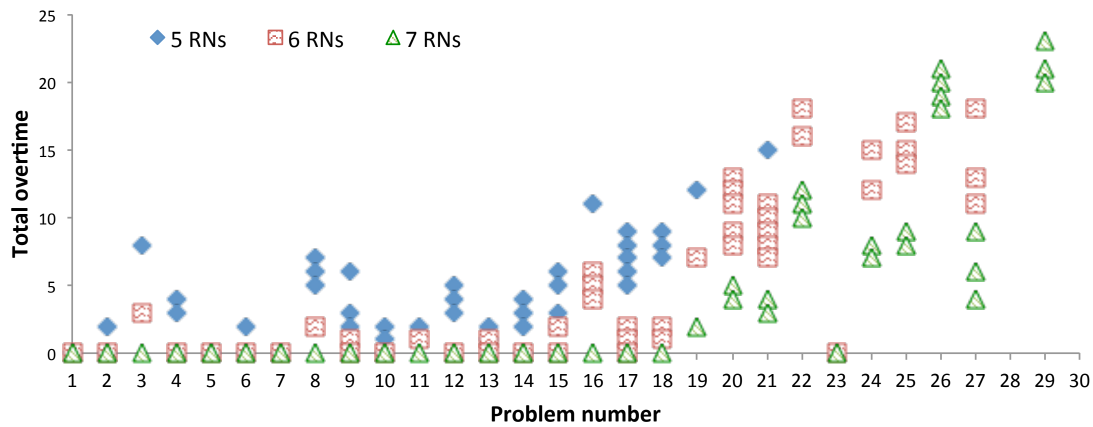


Figure 8 **Total overtime for all nondominated solutions for 30 problems in 5, 6 and 7 nurse settings in functional care delivery model**

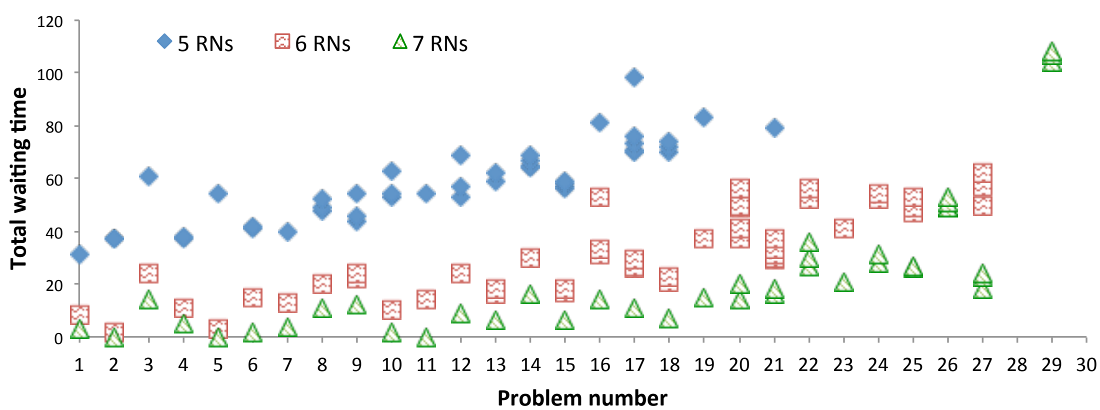


Figure 9 **Total waiting time for all nondominated solutions for 30 problems in 5, 6 and 7 nurse settings in functional care delivery model**

time, respectively, for all nondominated solutions found by solving the 30 problems in 5, 6 and 7 nurse settings. The problems are ranked according to their workload. So problem 1 has the lowest workload and problem 30 has the highest workload. When the workload is low, 5 nurses can find a solution with zero overtime, and less than 40 slots of total waiting time. The total waiting time reduces to less than 10 slots when more nurses are used. As the workload increases, both total overtime and total waiting time increase. The average total overtime over 30 problems is 4, 6, and 6 slots for 5, 6, and 7 nurse settings, respectively. The average total waiting time over 30 problems is 59, 32, and 25 slots for 5, 6, and 7 nurse settings, respectively. Figure 10 shows the trade-off between the two objectives for a single problem. The decision maker can choose one of the solutions based on the importance of each objective and the available number of nurses.

Table 8 shows the minimum, average and maximum computation times, number of nondomi-

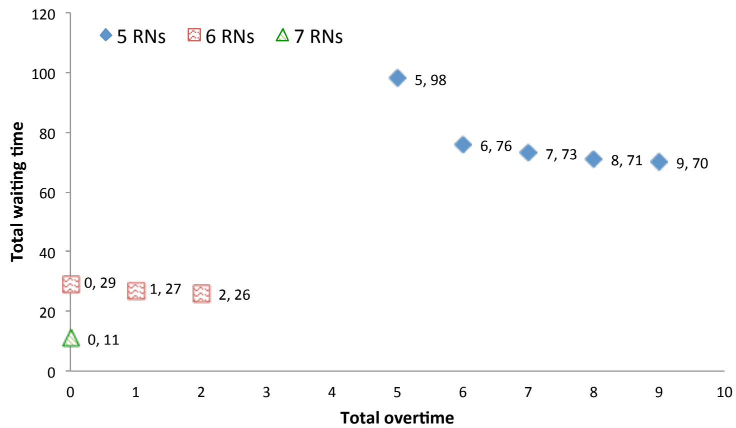


Figure 10 **Pareto optimal solutions for problem number 17 with workload 397**

Table 8 **Functional care delivery model: CPU time, number of nondominated solutions, number of infeasible problems, total waiting time and total overtime**

	Computation times in seconds (min, avg, max)	Number of nondominated solutions (min, avg, max)	Number of infeasible problems	Range of total waiting time (slots) (min, max)	Range of total overtime (slots) (min, max)
5 nurses	0.4, 25.8, 291.6	1, 2.2, 5	10	31, 98	0, 15
6 nurses	0.2, 27.2, 315.2	1, 1.8, 5	4	2, 62	0, 18
7 nurses	0.4, 27.3, 469.8	1, 1.4, 4	2	0, 108	0, 23

nated solutions, number of infeasible problems, and range of total waiting time and total overtime for 5, 6, and 7 nurse settings. The computation time is the total computation time to find all nondominated solutions. For example, the total computation time to find 3 nondominated solutions is 5.9 seconds for problem 17 with 6 nurses. The average computation time per problem is less than 30 seconds. That means, the proposed integer programming model takes almost no time to solve nurse assignment problem compared to manual assignment, which might take 45-60 minutes depending on patient volume. When we look at the maximum computation times, we see that it takes longer time to find all nondominated solutions when more nurses are available. That is because of the increase in number of decision variables and constraints.

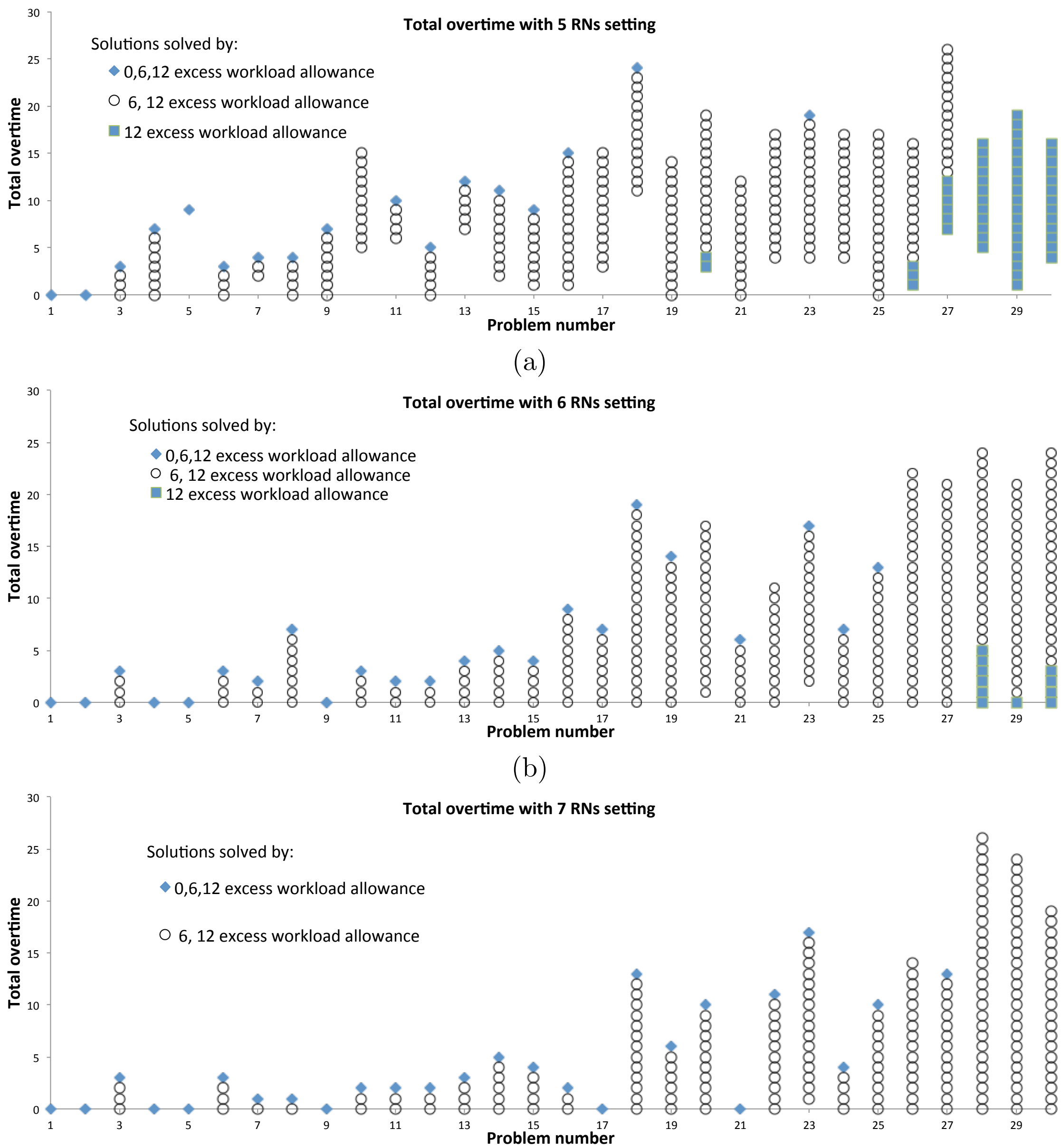
The proposed algorithm finds more nondominated solutions when the number of nurses is small. As the number of nurses increases, the number of nondominated solutions decreases due to the overall decrease in overtime and waiting time. The proposed models may become infeasible when the workload is high and the nurse capacity is not enough. In those cases, the models cannot find any nondominated solution for any of the ϵ values. For example, when number of nurses is 5, 10 out of 30 problems cannot be solved optimally for any ϵ value. As the number of nurses increases to 7, the number of infeasible problems with no nondominated solution reduces to 2. This shows that more nurses are required for these infeasible problems.

5.2. Computational results for the primary care delivery model

For the primary care delivery model, we solve the same 30 problems. That means, the number of patients, acuity levels, and treatment durations are the same as in Table 6. However, since primary nurses should be known in advance, a primary nurse is assigned to each patient randomly while making sure that the nurse's skill level is enough to treat the patient. The proposed integer programming model is solved with different number of nurses and excess workload allowances per slot (E_s). The number of nurses range from 5 to 7 and excess workload allowance in each slot are 0, 6, and 12. When excess workload allowance is 0, the clinic does not have any part-time nurse. When excess workload allowance is 6, then one part-time nurse who has a maximum acuity level of 6 can be used to share the workload of primary nurses. When it is 12, 2 or 3 part-times nurses can be used with maximum acuity levels of 4-6. Similar to functional care delivery model, the number of slots S is taken as 24 (16 slots for regular working hours, 8 slots for overtime). If the current patient mix cannot be scheduled within 24 slots with available number of primary nurses and excess workload allowance, then the IP model gives infeasible solution. A computation time limit of 600 seconds is used to solve each model with different ϵ values.

Figures 11 and 12 show the total overtime and total excess workload, respectively, for all nondominated solutions found by solving the 30 problems in 5, 6 and 7 nurse settings with 0, 6, 12 excess workload allowance. The nondominated solutions are divided into three groups. The first group includes the solutions found by all three excess workload allowances (0, 6, 12), the second group includes the solutions found with excess workload allowances of 6 and 12, and the third group includes the solutions that can only be found with excess workload allowance of 12. The number of nondominated solutions and the range of objective function values increase as the total workload increases. When total workload is small, lower total excess workload allowances (E_s is 0 or 6) are enough to find all nondominated solutions. As the workload increases, higher excess workload allowances (E_s is 6 or 12) are necessary to find more solutions. As the number of primary nurses increases from 5 to 7, the total workload allowance of 12 cannot find any additional nondominated solutions over the allowance of 6. That means, the workload can be handled with only one part-time nurse.

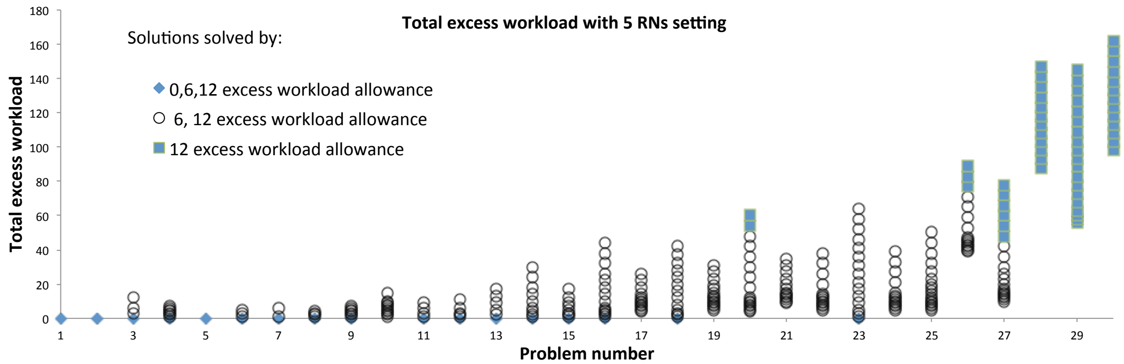
Figure 13 shows the trade-off between the two objectives for a single problem. When there are 5 primary nurses, same solutions can be found with 6 and 12 excess workload allowance. That means, scheduling one part time nurse gives same results as scheduling two part time nurses, so the optimal



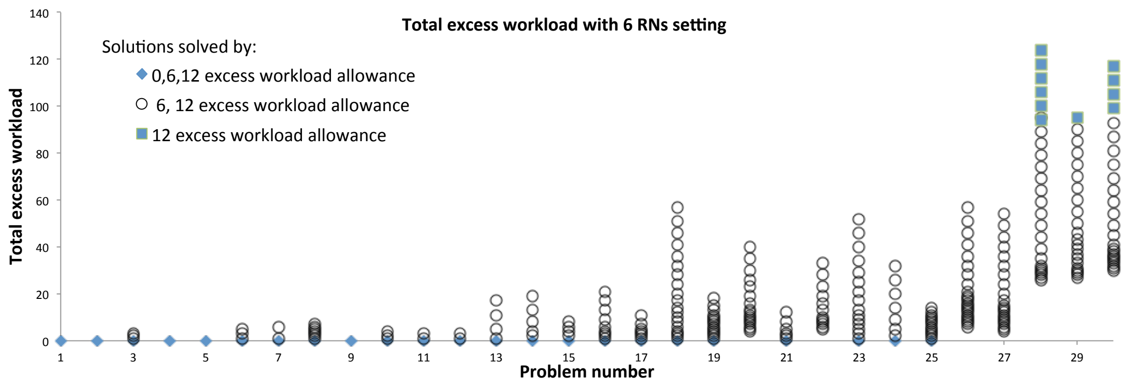
(c)

Figure 11 **Total overtime for all nondominated solutions for 30 problems in (a) 5, (b) 6 and (c) 7 nurse settings in primary care delivery model; solutions are grouped as: solutions found by when 0, 6, and 12 excess workload allowed, 6 and 12 excess workload allowed, and only when 12 excess workload allowed**

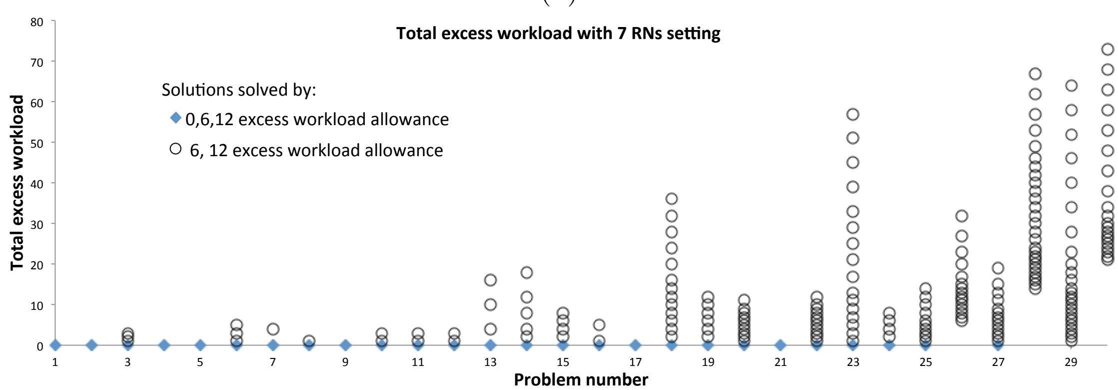
number of part time nurses is one. When the excess workload allowance is 0, no nondominated solution can be found with 5 primary nurses. When there are 6 primary nurses, one solution with total overtime of 7 and total excess workload of 0 can be found with zero workload allowance. The same nondominated solution can be found when workload allowance is increased to 6 or 12. Increasing the workload allowance to 6 or 12 adds more nondominated solutions to the set. That means, when there are 6 nurses, and if total overtime of 7 is acceptable, then there is no need to



(a)



(b)



(c)

Figure 12 **Total excess workload for all nondominated solutions for 30 problems in (a) 5, (b) 6 and (c) 7 nurse settings in primary care delivery model; solutions are grouped as: solutions found by when 0, 6, and 12 excess workload allowed, 6 and 12 excess workload allowed, and only when 12 excess workload allowed**

schedule part time nurses. Otherwise, one part time nurse is needed. Figure 13 also shows that when there are 7 nurses, there is no need to schedule part time nurses since total overtime and excess workload are 0.

Table 9 shows the minimum, average, and maximum computation times, number of nondominated solutions, number of infeasible problems, and range of total waiting time and total overtime

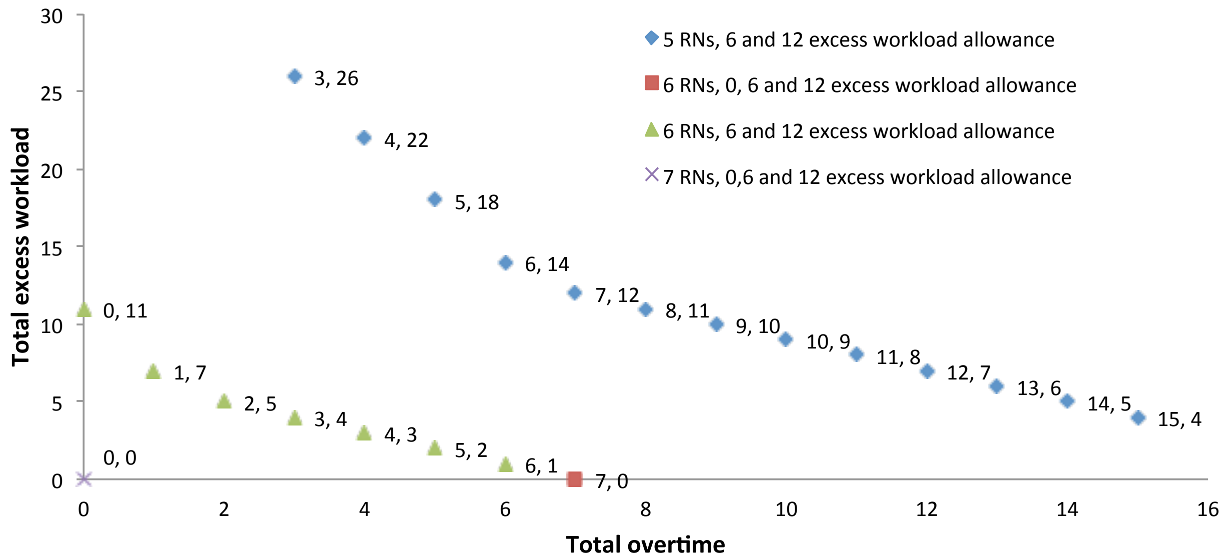


Figure 13 **Pareto optimal solutions for problem number 17 with workload 397; solutions are grouped as: solutions found with 0, 6, and 12 excess workload allowed, 6 and 12 excess workload allowed**

for 5, 6, and 7 nurse settings and 0, 6, and 12 excess workload allowances in primary care delivery model. When excess workload allowance (E_s) is 0, only one solution is found with total excess workload of zero. The average computation times over 30 problems is 1.3 seconds for 5 nurses, less than 1 second for 6 and 7 nurse settings. When excess workload allowance is increased, more nondominated solutions can be found. The average computation times over 30 problems is less than 3 minutes for all problems. The computation time can be as high as 2555 seconds (43 minutes) for a problem. The number of nondominated solutions can reach to 27 solutions for a problem when excess workload allowance is 12. As the number of nurses increases, the number of infeasible problems decreases as expected. The excess workload allowance also reduces the number of infeasible problems.

5.3. Managerial insights

The nurse managers, nurses, and schedulers spend significant amount of time for nurse assignment and patient scheduling every day. Besides these two problems that are solved every day, determining the optimal number of nurses is an important problem for clinic managers. The oncology clinics choose a care delivery model considering several factors including the availability of skilled nurses in that area, staffing costs, patient satisfaction, and patient safety. Some of these factors such as nurse shortage cannot be controlled. Staffing cost is second largest cost after the chemotherapy drug costs in the oncology clinics. The proposed models not only provide optimization methods to reduce the time spent for nurse assignment and patient scheduling tasks, but also provide decision making

Table 9 Primary care delivery model: CPU time, number of nondominated solutions, number of infeasible solutions, total waiting time and total overtime

Number of nurses / excess workload allowance	Computation times (in seconds) (min, avg, max)	Number of nondominated solutions (min, avg, max)	Number of infeasible problems	Range of total excess workload (min, max)	Range of total overtime (slots) (min, max)
5 / 0	0.5, 1.3, 2.1	1, 1, 1	13	0, 0	0, 24
5 / 6	0.6, 140, 2555	1, 9.1, 18	2	0, 89	0, 26
5 / 12	0.5, 138, 2446	1, 10.4, 20	0	0, 162	0, 26
6 / 0	0.3, 0.8, 4.4	1, 1, 1	7	0, 0	0, 19
6 / 6	0.4, 171, 2256	1, 9.5, 23	0	0, 95	0, 24
6 / 12	0.3, 164, 2356	1, 9.8, 25	0	0, 124	0, 24
7 / 0	0.5, 0.8, 1.7	1, 1, 1	4	0, 0	0, 17
7 / 6	0.4, 93, 1196	1, 7.5, 27	0	0, 73	0, 26
7 / 12	0.4, 88, 1205	1, 7.5, 27	0	0, 73	0, 26

tools to determine the optimal staffing levels. To help healthcare practitioners better manage their resources, we provide some managerial insights related to use of the proposed methods.

1. The proposed nurse assignment model allows clinic managers to evaluate the trade-off between total patient waiting time, total staff overtime, and cost of additional nurses. The clinic managers using functional care delivery model can determine the optimal staffing levels on a given day by first checking the total workload required to treat all patients. For example, in our computational results, the problems with 5 nurses started becoming infeasible when the total workload started exceeding 410. This threshold can be used to determine the minimum number of nurses required. However, the clinic managers should also look at patient waiting times and clinic overtime to adjust this threshold. For example, for problem 17, the total waiting time ranges between 70 and 98 slots, which corresponds to an average waiting time of 1.2 and 1.7 slots (36 and 51 minutes) per patient. If this waiting time is not acceptable, then the clinic managers can reduce the threshold of 410 to a lower value, where the total waiting time and overtime are at acceptable levels.

2. The proposed patient scheduling model provides several nondominated solutions that minimize total overtime and total excess workload for a given set of primary nurses. The trade-off between these objectives allows the clinic managers to determine the optimal schedule for the primary nurses and the number of part-time nurses needed when the workload is high for the primary nurses on a given day. The total excess workload and maximum excess workload at each slot can be used to determine the optimal number of part-time nurses. For example, if the total excess workload is low, then other nurses that have available capacity can help the primary nurses to cover the extra workload. If the total excess workload is high, then the clinic managers might use part-time nurses.

3. The functional care delivery model finds less nondominated solutions compared to the primary care delivery model. It also finds solutions with less total overtime due to the flexibility of assigning patients to any of the nurses. Even though the functional care delivery model requires low computation times for nurse assignment, the clinic still needs a scheduling method that considers the cumulative number of nurses to find a good initial schedule. If the initial schedule does not consider the total nurse capacity, the nurse assignment might cause high patient waiting times and overtime.

4. The primary care delivery model can find more nondominated solutions compared to functional care delivery model. This is due to multiple alternative appointment schedules that can be found by the proposed model. The nurses can manage their own schedules and the schedulers might find it easier to schedule the patients with a single nurse. However, the primary care delivery model requires a method to determine the primary nurse for each patient before the treatment starts. Otherwise, the workload of nurses might have high variability on different days.

6. Conclusion

In this study, we considered two different nursing care delivery models used in the oncology clinics. We proposed two optimization models that consider patient acuities, nurse skills, maximum acuity levels, and nurse working hours. For the functional care delivery model, we proposed a multiobjective optimization model to solve nurse assignment problem with the objectives of minimizing total patient waiting time and total nurse overtime. For the primary care model, we proposed another multiobjective optimization model to find the optimal appointment times with the objective of minimizing total overtime and total excess workload. By allowing excess workload, one can determine the number of part-time nurses needed in the clinic. The proposed models are solved using ϵ-constraint approach to find all nondominated solutions. The decision maker can choose a solution based on the availability of nurses and importance of each objective function. We developed two spreadsheet-based optimization tools that can easily be implemented in the clinics. The tools use VBA to read the patient and nurse information, and Opensolver to solve the proposed optimization models. The tools can easily be used by nurse managers and schedulers for daily scheduling without prior knowledge of VBA and Opensolver.

In this study, our aim is not to compare these two delivery models, but rather provide optimization tools to reduce the time spent for nurse assignment and scheduling tasks, and provide decision making tools for clinic managers to determine optimal staffing levels in clinics that use these two care delivery models. In order to make a fair comparison between these two models, a more comprehensive study that measures several measures including staffing costs, patient satisfaction, and

Table 10 Advantages and disadvantages of functional and primary care delivery models

	Functional care delivery model	Primary care delivery model
Advantages	1. Patient scheduling is less restricted due to availability of more nurses for assignment; 2. Nurses can have a more balanced workload due to daily nurse-patient assignment according to patient mix; 3. Less nurses are required; 4. The functional care delivery model can easily be implemented without changing the scheduling system.	1. Nurses can build stronger relationships with patients, which improves patient satisfaction; 2. Nurses can become more knowledgeable about patient's medical history and treatment plan, and can detect small changes in patient's condition to react on time.
Disadvantages	1. Continuity of care is reduced due to random assignment of nurses to patients.	1. Patient scheduling is more restricted due to daily workload and schedule of primary nurse; 2. Nurse workload might vary significantly from day-to-day; 3. More nurses are required; 4. The panel size for each nurse should be determined carefully before the implementation of primary care delivery model.

patient safety is required. Table 10 shows the advantages and disadvantages of both care delivery models.

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