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Single versus hybrid time horizons for open access scheduling

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ABSTRACT

Difficulty in scheduling short-notice appointments due to schedules booked with routine check-ups are prevalent in outpatient clinics, especially in primary care clinics, which lead to more patient no-shows, lower patient satisfaction, and higher healthcare costs. Open access scheduling was introduced to overcome these problems by reserving enough appointment slots for short-notice scheduling. The appointments scheduled in the slots reserved for short-notice are called open appointments. Typically, the current open access scheduling policy has a single time horizon for open appointments. In this paper, we propose a hybrid open access policy adopting two time horizons for open appointments, and we investigate when more than one time horizon for open appointments is justified. Our analytical results show that the optimized hybrid open access policy is never worse than the optimized current single time horizon open access policy in terms of the expectation and the variance of the number of patients consulted. In nearly 75% of the representative scenarios motivated by primary care clinics, the hybrid open access policy slightly improves the performance of open access scheduling. Moreover, for a clinic with strong positive correlation between demands for fixed and open appointments, the proposed hybrid open access policy can considerably reduce the variance of the number of patients consulted.

1. Introduction

Open access scheduling, introduced in the early 1990s, is a just-in-time concept that seeks to schedule both short-notice and routine appointments. While open access scheduling can be applied to services such as accounting, financial planning, real estate, law, and healthcare, this paper was motivated by primary care clinics seeking to schedule their provider capacity more effectively. Over the past 10 years, open access scheduling has been implemented in various types of healthcare practices, with many reports appearing from primary care practices (Herriott, 1999; Murray & Tantau, 2000; Forjuoh et al., 2001; Kennedy & Hsu, 2003; Meyers, 2003; O'Hare & Corlett, 2004; Solberg, Hroscikoski, Sperl-Hillen, O'Connor, & Crabtree, 2004; Armstrong, Levesque, Perlin, Rick, & Shectman, 2005; Bundy, Randolph, Murray, Anderson, & Margolis, 2005). It is reported that open access scheduling reduces healthcare costs by decreasing patient no-shows, while improving clinic resource utilization and physician productivity (Kodjababian, 2003; Mallard, Leakeas, Duncan, Fleenor, & Sinsky, 2004; O'Hare & Corlett, 2004; Pierdon, Charles, McKinley, & Myers, 2004; Bundy et al., 2005). Meanwhile, it has also been shown to facilitate timely and patient-centered care, and to improve patient satisfaction (Herriott, 1999; Murray & Tantau, 2000; Kennedy & Hsu, 2003; Mallard et al., 2004; O'Hare & Corlett, 2004; Pickin, O'Cathain, Sampson, & Dixon, 2004; Bundy et al., 2005; Parente, Pinto, & Barber, 2005). In contrast, traditional appointment scheduling systems schedule routine check-ups months in advance but lead to more patient no-shows (Bean & Talaga, 1995; Lacy, Paulman, Reuter, & Lovejoy, 2004; Lee, Earnest, Chen, & Krishnan, 2005) and undermine the timely delivery of healthcare (Pinto, Parente, & Barber, 2002; Murray & Berwick, 2003). Yet, the open access scheduling concept, still under development, is far from mature. Reports of implementation failures demonstrate the challenges in implementing open access scheduling (Murray, Bodenheimer, Rittenhouse, & Grumbach, 2003; Mehrotra, Keehl-Markowitz, & Ayanian, 2008). In an open access clinic, the short-notice appointments are called *open appointments*. However, some appointments are still scheduled weeks in advance, which are commonly called *fixed appointments*. The just-in-time principle of open access scheduling is to deliver healthcare to patients on the day they request it (Murray & Tantau, 2000; Murray & Berwick, 2003). An interesting research question is whether to define only one short-notice time frame or two short-notice time frames in an open access scheduling system.

While over 50 years of appointment scheduling research has proposed many quantitative models to optimize the parameters for traditional outpatient appointment scheduling (Kaandorp & Koole, 2007; Muthuraman & Lawley, 2008) (see the review by Cayirli & Veral, 2003) or for surgery scheduling (Fei, Meskens, &

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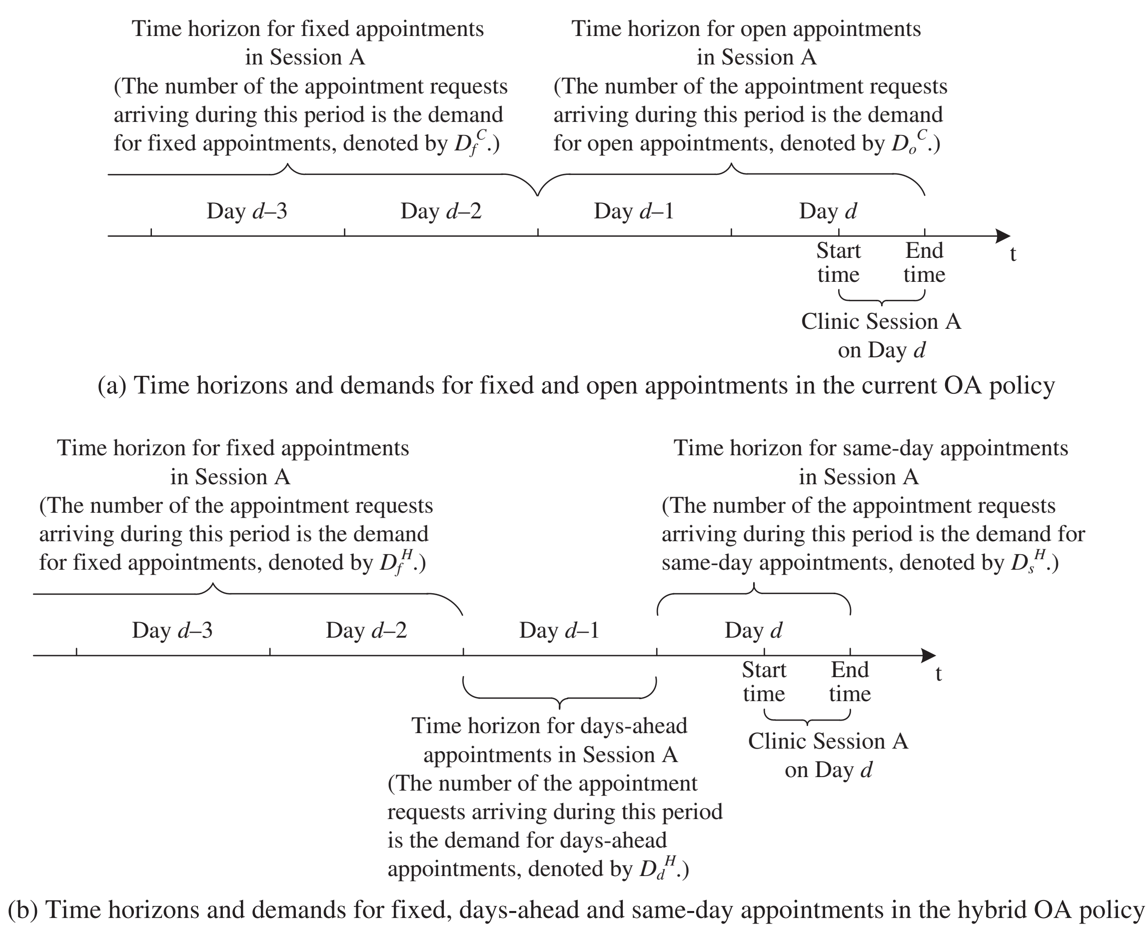
Chu, 2009; Roland, Martinelly, Riane, & Pochet, 2009) (see the review by Gupta & Denton, 2008), only a few studies have proposed quantitative approaches to determine the critical parameters for open access scheduling (Green, Savin, & Murray, 2007; Kopach et al., 2007; Qu, Rardin, Williams, & Willis, 2007). Green et al. (2007) provide a quantitative approach to determine an appropriate panel size that ensures the desired overflow frequency level, defined as the fraction of days when demand exceeds the average number of appointment slots available. For an open access scheduling policy with only one short-notice time frame, Qu et al. (2007) propose a probability model and a recursive procedure to determine the lowest percentage of open appointments that maximizes the expected number of patients consulted. Kopach et al. (2007) develop a simulation model to investigate the effects of open access scheduling parameters, such as the lowest percentage of open appointments and time horizon for fixed appointments, on clinic performance. Our paper aims at making contributions to determine whether one or two short-notice time frames should be included in an open access scheduling system while considering two performance metrics: both the expected number of patients consulted and the variance in the number of patients consulted.

In the literature, the time horizon for open appointments used in open access clinics has been reported as short as same day and as long as one week depending on the clinical practices, physicians' schedules, and patient population (Kennedy & Hsu, 2003; Newman, Harrington, Olenginski, Perruquet, & McKinley, 2004; O'Hare & Corlett, 2004). Therefore, an important question for clinic administrators and experts in healthcare is whether more than one time horizon for open appointments provides adequate flexibility and benefits to justify its complexity in an open access clinic. To answer this question, we compare two scheduling policies in open access scheduling: one having a single time horizon for open appointments, and the other adopting two time horizons for open appointments.

This paper is organized as follows. In Section 2, we describe a typical open access scheduling policy reported in the literature, and then propose a hybrid open access policy. In Section 3, we discuss two performance measures to compare open access scheduling policies. In Sections 4 and 5, we present the analytical and numerical results of the comparison between the two policies. Finally, conclusions and insights for clinic administrators are discussed in Section 6.

2. Hybrid open access scheduling policy

In open access clinics, some appointment slots are held for short-notice scheduling. Usually, clinic administrators specify the limit for the number of fixed appointments or the lowest percentage of open appointments in a clinic session (typically 4 h). When the number of fixed appointments scheduled in a session reaches the limit before the time horizon for open appointments in the session, patients who request fixed appointments in the session have to choose fixed appointments in other sessions or call again later for an open appointment. In most open access clinics, the time horizon for open appointments is same day or two days, which is illustrated in Fig. 1a. Therefore, the open access scheduling policy currently used in outpatient clinics specifies a single time horizon for open appointments and the lowest percentage of appointments held for short-notice scheduling. We call this the *current open access policy* (*current OA policy*).



(a) Time horizons and demands for fixed and open appointments in the current OA policy

(b) Time horizons and demands for fixed, days-ahead and same-day appointments in the hybrid OA policy

Fig. 1. Time horizons and demands for different types of appointments in the current and hybrid OA policies.

Since the time horizon for open appointments can be as long as several days or even one week in some clinics, we propose a *hybrid open access policy* (*hybrid OA policy*), which adopts two time horizons for open appointments and two lowest percentages of open appointments. One time horizon for open appointments is same day, which means that some open appointments can only be scheduled on the same day. We call these open appointments *same-day appointments* in this paper. The other time horizon for open appointments is two days or several days (not exceeding a week). Those open appointments scheduled one day or several days ahead are called *days-ahead appointments* in this paper. Fig. 1b illustrates the time horizons for fixed, days-ahead and same-day appointments in the hybrid OA policy. The hybrid OA policy needs to specify the lowest percentage of days-ahead appointments and the lowest percentage of same-day appointments.

Recent research suggests that continuity of care with a primary care provider has multiple benefits to patient and healthcare systems (De Maeseneer, De Prins, Gosset, & Heyerick, 2003; Nutting, Goodwin, Flocke, Zyzanski, & Stange, 2003; Wilson, Rogers, Chang, & Safran, 2005; Rodriguez, Rogers, Marshall, & Safran, 2007). Some clinics group a few physicians as a provider group in an effort to balance continuity of care with scheduling flexibility. To compare the performances of the current and hybrid OA policies, we assume that the clinic seeks continuity of care with patient scheduling so that each physician (or provider group) sees only his/her own patients or new patients. Thus, the schedule and patient demand of one physician (or provider group) is independent of the schedules and patient demands of other physicians (or provider groups). Meanwhile, it is assumed that the two policies do not influence patient demand. We assume that the patients independently request appointments and independently choose appointments in other sessions when the desired session is full. Many discrete models for customer choice behavior make a similar assumption about independent customer choice (Puig-Junoy, Saez, & Martínez-Garcıa, 1998; McFadden, 2001). The patient no-shows defined as the missed scheduled appointments are independent of each other. The no-show rates are assumed to increase with the increase in appointment lead time (Bean & Talaga, 1995; Kodjababian, 2003; Lee et al., 2005), which is the interval from the date an appointment is scheduled to the appointment date. In addition, we assume the number of appointments that can be scheduled in a session, the demand distribution, and the no-show rate of each appointment type are given for a physician or provider group.

3. Performance measures for open access scheduling

Since the average number of patients consulted by each physician in each clinic session affects the revenue and cost of a clinic, it is one of the performance measures that concerns clinic administrators. In many clinics, the salary of a physician partly depends on the average number of patients consulted per clinic session by the physician. Another performance measure concerning both clinic administrators and physicians is the variability of the number of patients consulted by each physician in each clinic session. A high variance in the number of patients consulted may result in long overtimes or idle times for each physician and clinic staff. Therefore, two performance measures are used to compare the current and hybrid OA policies: the expected number of patients consulted, and the variance of the number of patients consulted in a session.

3.1. Expected number of patients consulted

Let M^C and M^H denote the numbers of patients consulted by a physician in a clinic session using the current and hybrid OA policies, respectively. We use N to denote the number of appointments that can be scheduled with a physician in a session. In this paper, any symbols with superscripts C denote variables or parameters for the current OA policy, while any symbols with superscripts H are for the hybrid OA policy.

For the current OA policy, q^C denotes the lowest percentage of open appointments to be scheduled with a physician in a clinic session. Thus, the limit of fixed appointments to be scheduled with a physician in a session, denoted by n_1^C, is $\lfloor N - q^C N \rfloor$, where $\lfloor \bullet \rfloor$ means to round down to the closest integer. According to the results in Qu et al. (2007), we know that the expectation of M^C, denoted by $E(M^C, n_1^C)$, is a function of N, n_1^C, the no-show rates of fixed and open appointments, and the demand distribution of fixed and open appointments. For a given N, $E(M^C, n_1^C)$ for all $n_1^C \in \{0, 1, \ldots, N\}$ can be calculated by using the recurrence relation

$$E(M^C, n_1^C) = E(M^C, n_1^C - 1) - (\gamma_f^C - \gamma_o^C)[1 - F_f^C(n_1^C - 1)] + (1 - \gamma_o^C)[F_o^C(N - n_1^C) - F^C(n_1^C - 1, N - n_1^C)], \quad (1)$$

with

$$E(M^C, 0) = (1 - \gamma_o^C)\left[N - \sum_{j=0}^{N}(N - j)p_o^C(j)\right], \quad (2)$$

where γ_f^C and γ_o^C denote the no-show rates of fixed and open appointments, respectively, $F^C(\bullet)$ is the joint cumulative probability distribution function of demands for fixed and open appointments, denoted by D_f^C and D_o^C, respectively, $F_f^C(\bullet)$ and $F_o^C(\bullet)$ are the cumulative probability distribution functions of demands D_f^C and D_o^C, respectively, and $p_o^C(\bullet)$ is the probability mass function of demand D_o^C. According to the recurrence relation in Eqs. (1) and (2), we can calculate $E(M^C, n_1^C)$ for $n_1^C \in \{0, 1, \ldots, N\}$, and then find the maximum expectation of M^C, denoted by $E_{MAX}(M^C)$, and the corresponding n_1^C, denoted by n_{1MAX}^C. Thus, for the current OA policy, n_{1MAX}^C represents the limit of fixed appointments to be scheduled that maximizes the expected number of patients consulted by a physician in a session, and $E(M^C, n_{1MAX}^C) = E_{MAX}(M^C)$.

For the hybrid OA policy, q_d^H and q_s^H denote the lowest percentages of days-ahead and same-day appointments, respectively, to be scheduled with a physician in a clinic session. Thus, the limit of fixed appointments to be scheduled with a physician in a session, denoted by n_1^H, is $\lfloor N - (q_d^H + q_s^H)N \rfloor$, and the limit of fixed and days-ahead appointments to be scheduled with a physician in a session, denoted by n_2^H, is $\lfloor N - q_s^H N \rfloor$. Since $\lfloor N - (q_d^H + q_s^H)N \rfloor \leqslant \lfloor N - q_s^H N \rfloor$, we know $n_1^H \leqslant n_2^H$.

In the appendix, we derive the recurrence relations for calculating the expectation and the variance of the number of patients consulted for the hybrid OA policy (M^H). According to the results in the appendix, we know that the expectation of M^H, denoted by $E(M^H, n_1^H, n_2^H)$, is a function of N, n_1^H, n_2^H, the no-show rates of fixed, days-ahead and same-day appointments, and the demand distribution of fixed, days-ahead and same-day appointments. According to Eqs. (A1), (A3), (A8), (A9), (A13), (A21), (A22), (A23) in the appendix, we know that for a given N and all pairs of (n_1^H, n_2^H) satisfying $0 \leqslant n_1^H \leqslant n_2^H \leqslant N, E(M^H, n_1^H, n_2^H)$ can be calculated by using the recurrence relations

$$E(M^H, n_1^H, n_2^H) = E(M^H, n_1^H - 1, n_2^H) + (1 - \gamma_f^H)[1 - F_f^H(n_1^H - 1)] - (1 - \gamma_d^H)G_{fd}^H(n_1^H - 1, n_2^H - n_1^H) - (1 - \gamma_s^H)G^H(n_1^H - 1, n_2^H), \quad (3)$$

and

$$E(M^H, 0, n_2^H) = E(M^H, 0, n_2^H - 1) + (1 - \gamma_d^H)[1 - F_d^H(n_2^H - 1)] - (1 - \gamma_s^H)G_{ds}^H(n_2^H - 1, N - n_2^H), \quad (4)$$

with

$$E(M^H,0,0) = \left(1-\gamma_s^H\right)\left[N - \sum_{k=0}^{N}(N-k)p_s^H(k)\right], \quad (5)$$

where $p_s^H(\bullet)$ is the probability mass function of demand for same-day appointments, denoted by D_s^H, and γ_f^H, γ_d^H and γ_s^H denote the no-show rates of fixed, days-ahead and same-day appointments, respectively. In Eqs. (3)–(5),

$$G_{fd}^H(n_1^H-1, n_2^H-n_1^H) = 1 - F_f^H(n_1^H-1) - F_d^H(n_2^H-n_1^H) + F_{fd}^H(n_1^H-1, n_2^H-n_1^H),$$

$$G_{ds}^H(n_2^H-1, N-n_2^H) = 1 - F_d^H(n_2^H-1) - F_s^H(N-n_2^H) + F_{ds}^H(n_2^H-1, N-n_2^H),$$

and

$$G^H(n_1^H-1, n_2^H) = \sum_{i=n_1^H}^{\infty}\sum_{j=0}^{n_2^H-n_1^H}\sum_{k=N-n_1^H-j+1}^{\infty} p^H(i,j,k) = F_d^H(n_2^H-n_1^H) - F_{fd}^H(n_1^H-1, n_2^H-n_1^H) - \sum_{j=0}^{n_2^H-n_1^H}\sum_{k=0}^{N-n_1^H-j}\left[p_{ds}^H(j,k) - \sum_{i=0}^{n_1^H-1}p^H(i,j,k)\right].$$

Here $F_{fd}^H(\bullet)$ is the joint cumulative probability distribution function of demands for fixed and days-ahead appointments, denoted by D_f^H and D_d^H, respectively; $F_{ds}^H(\bullet)$ is the joint cumulative probability distribution function of demands D_d^H and D_s^H; $F_f^H(\bullet), F_d^H(\bullet)$ and $F_s^H(\bullet)$ are the cumulative probability distribution functions of demands D_f^H, D_d^H and D_s^H, respectively; $p_{ds}^H(\bullet)$ is the joint probability mass function of demands D_d^H and D_s^H; $p^H(\bullet)$ is the joint probability mass function of demands D_f^H, D_d^H and D_s^H.

According to the recurrence relations in Eqs. (3)–(5), we can calculate $E(M^H, n_1^H, n_2^H)$ for $0 \leqslant n_1^H \leqslant n_2^H \leqslant N$, and then find the maximum expectation of M^H, denoted by $E_{MAX}(M^H)$, and the corresponding pair (n_1^H, n_2^H), denoted by (n_{1MAX}^H, n_{2MAX}^H). Thus, for the hybrid OA policy, n_{1MAX}^H represents the limit of fixed appointments to be scheduled that maximizes the expected number of patients consulted, and n_{2MAX}^H represents the limit of fixed and days-ahead appointments to be scheduled that maximizes the expected number of patients consulted. Thus $E(M^H, n_{1MAX}^H, n_{2MAX}^H) = E_{MAX}(M^H)$.

3.2. Variance of the number of patients consulted

For the current OA policy, according to the results in (Qu, 2006), we know that the variance of M^C, denoted by $V(M^C, n_1^C)$, is a function of $N, n_1^C, \gamma_f^C, \gamma_o^C$, and the demand distribution of fixed and open appointments. For a given N and all $n_1^C \in \{0,1,\ldots,N\}, V(M^C, n_1^C)$ can be calculated by using the recurrence relation

$$V(M^C, n_1^C) = V(M^C, n_1^C-1) + Q_1^C(n_1^C-1) + Q_2^C(n_1^C-1, N-n_1^C) + Q_{12}^C(n_1^C-1), \quad (6)$$

with

$$V(M^C,0) = (1-\gamma_o^C)^2\left[\sum_{j=0}^{N}(N-j)^2p_o^C(j) - (Q_0^C)^2\right] + \gamma_o^C(1-\gamma_o^C)(N-Q_0^C). \quad (7)$$

Here,

$$Q_1^C(n_1^C-1) = (1-\gamma_f^C)^2[1-F_f^C(n_1^C-1)][F_f^C(n_1^C-1) + 2A_1^C(n_1^C-1)] + \gamma_f^C(1-\gamma_f^C)[1-F_f^C(n_1^C-1)],$$

$$Q_2^C(n_1^C-1, N-n_1^C) = (1-\gamma_o^C)^2G^C(n_1^C-1, N-n_1^C)[A_3^C(n_1^C-1) + A_3^C(n_1^C)] - \gamma_o^C(1-\gamma_o^C)G^C(n_1^C-1, N-n_1^C),$$

$$Q_{12}^C(n_1^C-1) = 2(1-\gamma_f^C)(1-\gamma_o^C)[A_2^C(n_1^C-1) - A_1^C(n_1^C-1) - G^C(n_1^C-1, N-n_1^C)A_1^C(n_1^C) + F_f^C(n_1^C-1)A_3^C(n_1^C-1)],$$

and

$$Q_0^C = \sum_{j=0}^{N}(N-j)p_o^C(j),$$

where $G^C(n_1^C-1, N-n_1^C) = 1 - F_f^C(n_1^C-1) - F_d^C(N-n_1^C) + F^C(n_1^C-1, N-n_1^C)$, $A_1^C(n_1^C) = \sum_{i=0}^{n_1^C}(n_1^C-i)p_f^C(i), A_2^C(n_1^C) = \sum_{i=0}^{n_1^C}\sum_{j=0}^{N-i}(N-i-j)p^C(i,j)$, $A_3^C(n_1^C) = A_1^C(n_1^C) - A_2^C(n_1^C) - \sum_{i=n_1^C+1}^{\infty}\sum_{j=0}^{N-n_1^C}(N-n_1^C-j)p^C(i,j)$, and $p_f^C(\bullet)$ is the probability mass function of demand D_f^C. According to the recurrence relation in Eqs. (6) and (7), we can calculate $V(M^C, n_1^C)$ for $n_1^C \in \{0,1,\ldots,N\}$, and then find the minimum variance of M^C, denoted by $V_{MIN}(M^C)$, and the corresponding n_1^C, denoted by n_{1MIN}^C. Thus, for the current OA policy, n_{1MIN}^C represents the limit of fixed appointments to be scheduled that minimizes the variance of the number of patients consulted by a physician in a session, and $V(M^C, n_{1MIN}^C) = V_{MIN}(M^C)$.

For the hybrid OA policy, according to the results in the appendix, we know that the variance of M^H, denoted by $V(M^H, n_1^H, n_2^H)$, is a function of $N,\ n_1^H,\ n_2^H,\ \gamma_f^H,\ \gamma_d^H,\ \gamma_s^H$, and the demand distribution of fixed, days-ahead and same-day appointments. Using Eqs. (A2), (A4), (A14) in the appendix, we know that for a given N and all pairs of (n_1^H, n_2^H) satisfying $0 \leqslant n_1^H \leqslant n_2^H \leqslant N, V(M^H, n_1^H, n_2^H)$ can be calculated by using the recurrence relations

$$V(M^H, n_1^H, n_2^H) = V(M^H, n_1^H-1, n_2^H) + Q_1^H(n_1^H-1) + Q_2^H(n_1^H-1, n_2^H) + Q_3^H(n_1^H-1, n_2^H) + Q_{12}^H(n_1^H-1, n_2^H) + Q_{13}^H(n_1^H-1, n_2^H) + Q_{23}^H(n_1^H-1, n_2^H), \quad (8)$$

and

$$V(M^H, 0, n_2^H) = V(M^H, 0, n_2^H-1) + Q_{02}^H(n_2^H-1) + Q_{03}^H(n_2^H-1) + Q_{023}^H(n_2^H-1), \quad (9)$$

with

$$V(M^H,0,0) = (1-\gamma_s^H)^2\left[\sum_{k=0}^{N}(N-k)^2p_s^H(k) - (Q_0^H)^2\right] + \gamma_s^H(1-\gamma_s^H)(N-Q_0^H), \quad (10)$$

where $Q_0^H = \sum_{k=0}^{N}(N-k)p_s^H(k)$, $Q_1^H(n_1^H-1)$, $Q_2^H(n_1^H-1, n_2^H)$, $Q_3^H(n_1^H-1, n_2^H)$, $Q_{12}^H(n_1^H-1, n_2^H)$, $Q_{13}^H(n_1^H-1, n_2^H)$ and $Q_{23}^H(n_1^H-1, n_2^H)$ are respectively defined by Eqs. (A15)–(A20) in the appendix, and $Q_{02}^H(n_2^H-1)$, $Q_{03}^H(n_2^H-1)$ and $Q_{023}^H(n_1^H-1)$ are respectively defined by Eqs. (A5)–(A7).

According to the recurrence relations in Eqs. (8)–(10), we can calculate $V(M^H, n_1^H, n_2^H)$ for $0 \leqslant n_1^H \leqslant n_2^H \leqslant N$, and then find the minimum variance of M^H, denoted by $V_{MIN}(M^H)$, and the corresponding pair (n_1^H, n_2^H), denoted by (n_{1MIN}^H, n_{2MIN}^H). Thus, for the hybrid OA policy, n_{1MIN}^H represents the limit of fixed appointments to be scheduled that minimizes the variance of the number of patients consulted, and n_{2MIN}^H represents the limit of fixed and days-ahead appointments to be scheduled that minimizes the variance of the number of patients consulted. Thus $V(M^H, n_{1MIN}^H, n_{2MIN}^H) = V_{MIN}(M^H)$.

4. Analysis of hybrid open access scheduling policy

In Section 3, we discussed two performance measures of open access scheduling, the expected number of patients consulted and the variance of the number of patients consulted. Next, we compare the current and hybrid OA policies in terms of the two performance measures. The time horizon for open appointments in the current OA policy could be same day or several days (not exceeding a week). To compare the hybrid OA policy and the current OA policy, we assume that the time horizon for open appointments in the current OA policy is two days. Under the assumption that the two policies do not change the patient demand of a physician, we know $D_f^C = D_f^H$, $D_o^C = D_d^H + D_s^H$ (see Fig. 1), $\gamma_f^C = \gamma_f^H$, and $\gamma_o^C = [\gamma_d^H E(X_d) + \gamma_s^H E(X_s)]/[E(X_d) + E(X_s)]$, where X_d and X_s are the numbers of days-ahead and same-day appointments scheduled, respectively, in the hybrid OA policy, and $E(X_d)$ and $E(X_s)$ are the expectations of X_d and X_s.

Proposition 1. *For the current and hybrid OA policies, when* $D_f^C = D_f^H$, $D_o^C = D_d^H + D_s^H$, $\gamma_f^C = \gamma_f^H$, *and* $\gamma_o^C = [\gamma_d^H E(X_d) + \gamma_s^H E(X_s)]/[E(X_d) + E(X_s)]$, *then* $E_{MAX}(M^H) \geqslant E_{MAX}(M^C)$.

Proof. Assuming that n_{1MAX}^C is the limit of fixed appointments to schedule in the current OA policy that maximizes the expected number of patients consulted, $E(M^C, n_{1MAX}^C) = E_{MAX}(M^C)$. Since $D_f^C = D_f^H, D_o^C = D_d^H + D_s^H, \gamma_f^C = \gamma_f^H$, and $\gamma_o^C = [\gamma_d^H E(X_d) + \gamma_s^H E(X_s)]/ [E(X_d) + E(X_s)]$, we know $E(M^C, n_{1MAX}^C) = E(M^H, n_1^H, n_2^H)$ for $n_1^H = n_{1MAX}^C$ and $n_2^H = N$. Since $E_{MAX}(M^H) \geqslant E(M^H, n_1^H, n_2^H)$ for any pair (n_1^H, n_2^H), then $E_{MAX}(M^H) \geqslant E_{MAX}(M^C)$. □

Proposition 2. *For the current and hybrid OA policies, when* $D_f^C = D_f^H$, $D_o^C = D_d^H + D_s^H$, $\gamma_f^C = \gamma_f^H$, *and* $\gamma_o^C = [\gamma_d^H E(X_d) + \gamma_s^H E(X_s)]/[E(X_d) + E(X_s)]$, *then* $V_{MIN}(M^H) \leqslant V_{MIN}(M^C)$.

The proof of Proposition 2 is similar to that of Proposition 1. According to Propositions 1 and 2, the hybrid OA policy is never worse than the current OA policy in terms of the maximum expectation and the minimum variance of the number of patients consulted.

5. Numerical scenarios

In Section 4, we analytically compare the current and hybrid OA policies. Since there are no closed-forms for $E_{MAX}(M^C)$, $E_{MAX}(M^H)$, $V_{MIN}(M^C)$, and $V_{MIN}(M^H)$, we investigate the performance improvement by using the hybrid OA policy over a population of 288 scenarios representative of the possibilities, which consider different total numbers of appointments available (N), different no-show rate combinations $(\gamma_f^H, \gamma_d^H, \gamma_s^H)$, and different demand distributions.

5.1. Characteristics of numerical scenarios

The clinics visited by the authors usually have 4-h clinic sessions with 15-min appointment slots, i.e. 16 appointment slots that can be booked. Since some appointments are scheduled in two successive appointment slots, the number of appointments available may be less than 16. Therefore, in the numerical scenarios at most 12 or 16 appointments can be scheduled. The total number of appointments available is also called physician capacity in this paper.

Since fixed appointments can be scheduled weeks in advance, the associated no-show rates can reach as high as 50–55% (George & Rubin, 2003; Lee et al., 2005). It is also reported that the average no-show rate increases from 15% to over 35% when the length of interval from the date an appointment is scheduled to the appointment date increases from 4 weeks to over 10 weeks (Kodjababian, 2003). Meanwhile, the no-show rate of open appointments is generally much lower than that of fixed appointments as reported in the literature. For example, the no-show rate resulting from an open access pilot project for primary care decreased from 16% to 11% (Bundy et al., 2005). The average no-show rate decreased from 31% to 16% after the implementation of open access scheduling in another primary care clinic (Kodjababian, 2003). The no-show rates of 20% and 10% are used for days-ahead and same-day appointments, respectively, in one combination of no-show rates $(\gamma_f^H, \gamma_d^H, \gamma_s^H)$ to examine the influence of the no-show rates γ_d^H and γ_s^H in an undesirable scenario, while the no-show rates of 5% and 2% are used for days-ahead and same-day appointments in a significantly improved scenario. Therefore, the four combinations of $(\gamma_f^H, \gamma_d^H, \gamma_s^H)$ tested in the numerical scenarios are (0.4, 0.2, 0.1), (0.4, 0.1, 0.05), (0.25, 0.1, 0.05) and (0.25, 0.05, 0.02).

Since the demand for fixed or open appointments is the number of requests for appointments occurring in a given time period, a Poisson distribution is a routine choice for the demand. Unlike the traditional outpatient scheduling systems which postpone a large portion of today's work into the future, open access clinics schedule appointments for patients on the day that they request to be seen. As a result, demand in a session is typically independent of demands in previous days' sessions. However, during a demand surge period such as influenza season or when the clinic reopens following a holiday, demands between the sessions may be highly correlated. Therefore, in the numerical scenarios, independent Poisson distributions and a trivariate Poisson distribution are used to capture the distribution of demands for fixed, days-ahead and same-day appointments in these scenarios, respectively. The trivariate Poisson distribution has positive correlation coefficients of $\rho_{fd} = \rho(D_f^H, D_d^H) = 0.2$, $\rho_{fs} = \rho(D_f^H, D_s^H) = 0.2$ and $\rho_{ds} = \rho(D_d^H, D_s^H) = 0.5$. Meanwhile, eighteen combinations of average demands for fixed, days-ahead and same-day appointments, which match with N, are considered in the numerical scenarios. Table 1 summarizes the levels of N, $(\gamma_f^H, \gamma_d^H, \gamma_s^H)$, and the demand distributions for 288 numerical scenarios.

5.2. Performance comparison between the current and hybrid OA policies

According to Propositions 1 and 2, we know that the optimized hybrid OA policy is never worse than the current OA policy in terms of the maximum expectation and the minimum variance of the number of patients consulted. Table 2 summarizes the ranges of the performance change by comparing the hybrid OA policy with the current OA policy for different levels of physician capacity, different demand correlations, and different combinations of the no-show rates $(\gamma_f^H, \gamma_d^H, \gamma_s^H)$ for fixed, days-ahead and same-day appointments. It can be noted in Table 2 that by using the hybrid OA policy, the maximum expected number of patients consulted increases by at most 1.0%, and the minimum variance of the number of patients consulted decreases by at most 21.26% in all 288 numerical scenarios. Table 2 reveals that the performance improvement by using the hybrid OA policy, in terms of the maximum expectation and the minimum variance of the number of patients consulted, increases with the increase in the demand correlation between fixed and open appointments, or the increase in the no-show rates of days-ahead and same-day appointments. This implies that the flexibility of the hybrid OA policy makes it easier to control the variability of the number of patients consulted caused by strong demand correlations and higher patient no-show rates.

Fig. 2 illustrates the distributions of the changes in the two performance measures by comparing the hybrid OA policy to the current OA policy. Fig. 2a shows that the increase in the maximum expected number of patients consulted by using the hybrid OA policy ranges from 0 to 1%. While Fig. 2b demonstrates that the decrease in the variance of the number of patients consulted is less than 1% in more than half of the numerical scenarios, it also shows that the hybrid OA policy improves the minimum variance of the

Table 1
Levels of clinic characteristics in numerical scenarios.

Clinic characteristics	Levels
Number of appointments available (N), i.e. physician capacity	12 and 16
No-show rates of fixed, days-ahead and same-day appointments $(\gamma_f^H, \gamma_d^H, \gamma_s^H)$	(0.4,0.2,0.1), (0.4,0.1,0.05), (0.25,0.1,0.05) and (0.25,0.05,0.02)
Demand distribution	
Distribution of D_f^H, D_d^H and D_s^H	Independent Poisson distributions and trivariate Poisson distributions with ρ_{fd} = 0.2, ρ_{fs} = 0.2 and ρ_{ds} = 0.5
Average demands for fixed, days-ahead and same-day appointments $(E(D_f^H), E(D_d^H), E(D_s^H))$	(0.25N,0.625N,0.375N), (0.25N,0.5N,0.5N), (0.25N,0.375N,0.625N), (0.5N,0.5N,0.25N), (0.5N,0.375N,0.375N), (0.5N,0.25N,0.5N), (0.625N,0.375N,0.25N), (0.625N,0.3125N,0.3125N), (0.625N,0.25N,0.375N), (0.3N,0.75N,0.45N), (0.3N,0.6N,0.6N), (0.3N,0.45N,0.75N), (0.6N,0.6N,0.3N), (0.6N,0.45N,0.45N), (0.6N,0.3N,0.6N), (0.75N,0.45N,0.3N), (0.75N,0.375N,0.375N), (0.75N,0.3N,0.45N)

Table 2
Performance change by using the hybrid OA policy.

Physician capacity (N)	Correlation coefficient			No-show rate			Change in the number of patients consulted[a]					
							$\frac{E_{MAX}(M^H)-E_{MAX}(M^C)}{E_{MAX}(M^C)}$			$\frac{V_{MIN}(M^C)-V_{MIN}(M^H)}{V_{MIN}(M^C)}$		
	ρ_{fd}	ρ_{fs}	ρ_{ds}	γ_f^H	γ_d^H	γ_s^H	Min (%)	Avg (%)	Max (%)	Min (%)	Avg (%)	Max (%)
12	0	0	0	0.4	0.2	0.1	0.11	0.26	0.50	0.50	1.96	7.98
				0.4	0.1	0.05	0.01	0.05	0.15	0.01	0.41	1.00
				0.25	0.1	0.05	0.01	0.10	0.22	0.02	0.61	1.75
				0.25	0.05	0.02	0.00	0.03	0.07	0.00	0.31	1.11
	0.2	0.2	0.5	0.4	0.2	0.1	0.45	0.65	0.91	0.13	3.49	*21.26*
				0.4	0.1	0.05	0.12	0.18	0.33	0.01	2.06	14.68
				0.25	0.1	0.05	0.15	0.27	0.43	0.00	1.75	10.72
				0.25	0.05	0.02	0.07	0.12	0.21	0.00	0.92	5.68
16	0	0	0	0.4	0.2	0.1	0.08	0.27	0.60	0.62	1.94	4.91
				0.4	0.1	0.05	0.01	0.06	0.18	0.20	0.66	2.01
				0.25	0.1	0.05	0.06	0.11	0.25	0.23	0.87	2.46
				0.25	0.05	0.02	0.01	0.04	0.08	0.08	0.47	1.35
	0.2	0.2	0.5	0.4	0.2	0.1	0.46	0.62	*1.00*	0.35	3.56	17.93
				0.4	0.1	0.05	0.10	0.19	0.34	0.08	1.79	10.23
				0.25	0.1	0.05	0.19	0.28	0.44	0.01	1.25	4.33
				0.25	0.05	0.02	0.07	0.13	0.21	0.02	0.53	1.47

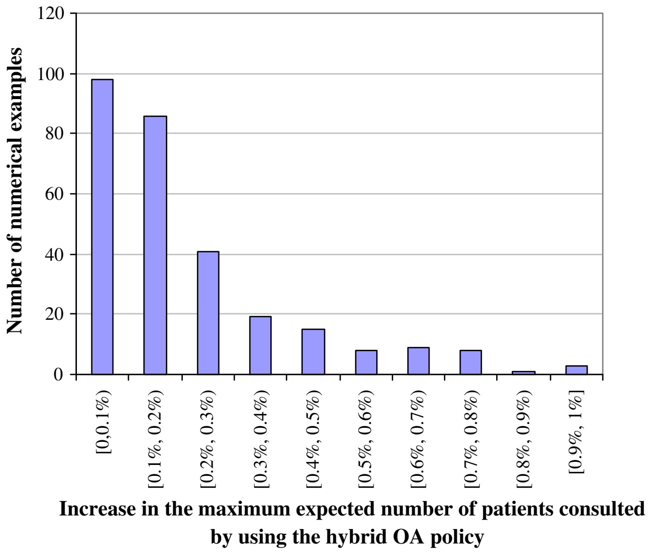
[a] $[E_{MAX}(M^H) - E_{MAX}(M^C)]/E_{MAX}(M^C)$ represents the relative increase in the maximum expected number of patients consulted by using the hybrid OA policy. $[V_{MIN}(M^C) - V_{MIN}(M^H)]/V_{MIN}(M^C)$ represents the relative decrease in the minimum variance of the number of patients consulted by using the hybrid OA policy. The italicized numbers are the maximum values of $[E_{MAX}(M^H) - E_{MAX}(M^C)]/E_{MAX}(M^C)$ and $[V_{MIN}(M^C) - V_{MIN}(M^H)]/V_{MIN}(M^C)$ in all numerical scenarios.

Table 3
Nine numerical scenarios with significant decreases in the minimum variance by the hybrid OA policy.

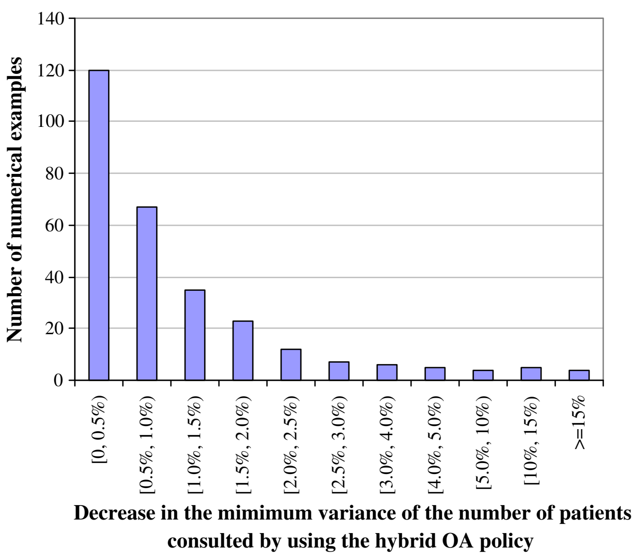
Physician capacity (N)	$(\gamma_f^H, \gamma_d^H, \gamma_s^H)$	$(E(D_f^H), E(D_d^H), E(D_s^H))$	$(\rho_{fd}, \rho_{fs}, \rho_{ds})$	$V_{MIN}(M^C)$	$V_{MIN}(M^H)$	$\frac{V_{MIN}(M^C)-V_{MIN}(M^H)}{V_{MIN}(M^C)}$ (%)
12	(0.4,0.2,0.1)	(7.5,4.5,3)	(0.2,0.2,0.5)	2.70	3.43	21.26
12	(0.4,0.2,0.1)	(6,6,3)	(0.2,0.2,0.5)	2.70	3.42	21.12
16	(0.4,0.2,0.1)	(10,6,4)	(0.2,0.2,0.5)	3.60	4.39	17.93
16	(0.4,0.2,0.1)	(8,8,4)	(0.2,0.2,0.5)	3.60	4.36	17.43
12	(0.4,0.1,0.05)	(7.5,4.5,3)	(0.2,0.2,0.5)	2.85	3.34	14.68
12	(0.4,0.1,0.05)	(6,6,3)	(0.2,0.2,0.5)	2.85	3.29	13.39
12	(0.25,0.1,0.05)	(7.5,4.5,3)	(0.2,0.2,0.5)	2.85	3.19	10.72
16	(0.4,0.1,0.05)	(10,6,4)	(0.2,0.2,0.5)	3.80	4.23	10.23
12	(0.25,0.1,0.05)	(6,6,3)	(0.2,0.2,0.5)	2.85	3.17	10.21

number of patients consulted by more than 1% in 35% of the scenarios. While the hybrid OA policy only slightly improves the performance of open access scheduling in terms of the maximum expectation and the minimum variance of the number of patients consulted in most scenarios, there are scenarios in which the improvement is noticeable.

Nine scenarios demonstrated variance may decrease more than 10%. Table 3 shows that all nine scenarios have correlated demands for fixed, days-ahead and same-day appointments, and the lowest average demand for same-day appointments. The results imply that the minimum variance of the number of patients consulted decreases more by using the hybrid OA policy as the positive correlations between demands for fixed, days-ahead and same-day appointments increase. This conclusion is also supported by the data summarized in Table 2. Therefore, for a clinic with strong positive correlation between demands for fixed and open appointments, the hybrid OA policy can reduce the minimum variance of the number of patients consulted considerably.



(a)



(b)

Fig. 2. Changes in the two performance measures by using the hybrid OA policy.

6. Conclusions

In various open access clinics, the time horizon for open appointments is defined differently. While some open access clinics define the time horizon for open appointments as one day, others define it as several days or even one week. In this paper, we investigate whether more than one time horizon for open appointments should be used in an open access clinic. We compare two open access policies: the current OA policy and the hybrid OA policy. The current OA policy uses a single time horizon for open appointments, while the hybrid OA policy adopts two time horizons for open appointments. The two policies are compared in terms of the maximum expectation and the minimum variance of the number of patients consulted. To compare the performance of the two policies, we derive the recurrence relations to determine the maximum expectation and the minimum variance of the number of patients consulted when using the hybrid OA policy.

Our analytical results show that the hybrid OA policy is never worse than the current OA policy in terms of the maximum expectation and the minimum variance of the number of patients consulted. Since there are no closed-forms for the maximum expectation and the minimum variance of the number of patients consulted for the current and hybrid OA policies, we investigate the performance improvement by using the hybrid OA policy through representative numerical scenarios. Our numerical results show that in most situations, the hybrid OA policy only slightly changes the performance of open access scheduling in terms of the two performance measures. Therefore, a single time horizon for open appointments should be adopted in most open access clinics. For clinics that plan to implement open access scheduling, starting with a single time horizon may be advised. However, for clinics with strong positive correlation between demands for fixed and open appointments, the proposed hybrid OA policy may be considered because it could reduce the minimum variance of the number of patients consulted significantly in such clinics.

Our analysis and numerical results provide insights for clinical administrators to determine whether two time horizons for open appointments are needed in their clinics. For open access clinics, administrators could calculate the correlation coefficient of historical requests for fixed and open appointments in each session. If the correlation coefficient is high and positive, the proposed hybrid OA policy could be considered; otherwise, a single time horizon for open appointments is advised.

In conclusion, this paper determines when to use a single time horizon or two time horizons for open appointments. Interesting extensions are to determine the best lengths of time horizons for open appointments.

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Appendix A. Recurrence relations for the expectation and variance of the number of patients consulted by using the hybrid open access policy

In this paper, we propose a hybrid open access policy (hybrid OA policy), which adopts two time horizons for open appointments, a lowest percentage of same-day appointments, and a lowest percentage of days-ahead appointments. To compare the hybrid OA policy, we derive the recurrence relations for calculating the expectation and the variance of the number of patients consulted when adopting the hybrid OA policy.

For the hybrid OA policy, let N denote the number of appointments that can be scheduled, n_1^H the limit of fixed appointments to be scheduled, and n_2^H the limit of fixed and days-ahead appointments to be scheduled, with a physician in a clinic session. Use D_f^H, D_d^H and D_s^H to denote the demands for fixed, days-ahead, and same-day appointments, respectively, and γ_f^H, γ_d^H and γ_s^H to denote the no-show rates of fixed, days-ahead and same-day appointments, respectively.

Let M_f, M_d and M_s denote the numbers of fixed, days-ahead and same-day appointments kept, respectively, and X_f, X_d and X_s denote the numbers of fixed, days-ahead and same-day appointments scheduled, respectively. $X_f = \min(D_f^H, n_1^H)$ because if there are more than n_1^H requests for fixed appointments, only n_1^H of them are granted. Similarly, $X_d = \min(D_d^H, n_2^H - X_f)$ and $X_s = \min(D_s^H, N - X_d)$. Thus, X_f is a function of n_1^H, while X_d and X_s are functions of n_1^H and n_2^H. We can explicitly denote them as $X_f = X_f(n_1^H)$, $X_d = X_d(n_1^H, n_2^H)$, and $X_s = X_s(n_1^H, n_2^H)$. Since M_f, M_d and M_s are functions of X_f, X_d and X_s, respectively, M_f is also a function of n_1^H, while M_d and M_s are functions of n_1^H and n_2^H. We can explicitly denote them as $M_f = M_f(n_1^H), M_d = M_d(n_1^H, n_2^H)$, and $M_s = M_s(n_1^H, n_2^H)$.

Since the number of patients consulted $M^H = M_f + M_d + M_s$, it is also a function of n_1^H and n_2^H. Therefore, we denote its expectation as $E(M^H, n_1^H, n_2^H)$ and its variance as $V(M^H, n_1^H, n_2^H)$. Assuming independent patient no-shows, we have

$$E[M_f(n_1^H)] = (1-\gamma_f^H)E[X_f(n_1^H)],$$

$$E[M_d(n_1^H, n_2^H)] = (1-\gamma_d^H)E[X_d(n_1^H, n_2^H)],$$

$$E[M_s(n_1^H, n_2^H)] = (1-\gamma_s^H)E[X_s(n_1^H, n_2^H)],$$

$$Var[M_f(n_1^H)] = (1-\gamma_f^H)^2 Var[X_f(n_1^H)] + \gamma_f^H(1-\gamma_f^H)E[X_f(n_1^H)],$$

$$Var[M_d(n_1^H, n_2^H)] = (1-\gamma_d^H)^2 Var[X_d(n_1^H, n_2^H)] + \gamma_d^H(1-\gamma_d^H)E[X_d(n_1^H, n_2^H)],$$

$$Var[M_s(n_1^H, n_2^H)] = (1-\gamma_s^H)^2 Var[X_s(n_1^H, n_2^H)] + \gamma_s^H(1-\gamma_s^H)E[X_s(n_1^H, n_2^H)],$$

$$Cov[M_f(n_1^H), M_d(n_1^H, n_2^H)] = (1-\gamma_f^H)(1-\gamma_d^H)Cov[X_f(n_1^H), X_d(n_1^H, n_2^H)],$$

$$Cov[M_f(n_1^H), M_s(n_1^H, n_2^H)] = (1-\gamma_f^H)(1-\gamma_s^H)Cov[X_f(n_1^H), X_s(n_1^H, n_2^H)],$$

and

$$Cov[M_d(n_1^H, n_2^H), M_s(n_1^H, n_2^H)] = (1-\gamma_d^H)(1-\gamma_s^H)Cov[X_d(n_1^H, n_2^H), X_s(n_1^H, n_2^H)].$$

Thus,

$$\begin{aligned}E(M^H, n_1^H, n_2^H) &= E[M_f(n_1^H)] + E[M_d(n_1^H, n_2^H)] + E[M_s(n_1^H, n_2^H)] \\ &= (1-\gamma_f^H)E[X_f(n_1^H)] + (1-\gamma_d^H)E[X_d(n_1^H, n_2^H)] \\ &\quad + (1-\gamma_s^H)E[X_s(n_1^H, n_2^H)],\end{aligned}$$

and

$$\begin{aligned}V(M^H, n_1^H, n_2^H) &= Var[M_f(n_1^H)] + Var[M_d(n_1^H, n_2^H)] + Var[M_s(n_1^H, n_2^H)] \\ &\quad + 2Cov[M_f(n_1^H), M_d(n_1^H, n_2^H)] \\ &\quad + 2Cov[M_f(n_1^H), M_s(n_1^H, n_2^H)] \\ &\quad + 2Cov[M_d(n_1^H, n_2^H), M_s(n_1^H, n_2^H)] \\ &= (1-\gamma_f^H)^2 Var[X_f(n_1^H)] + \gamma_f^H(1-\gamma_f^H)E[X_f(n_1^H)] + (1 \\ &\quad -\gamma_d^H)^2 Var[X_d(n_1^H, n_2^H)] + \gamma_d^H(1-\gamma_d^H)E[X_d(n_1^H, n_2^H)] \\ &\quad + (1-\gamma_s^H)^2 Var[X_s(n_1^H, n_2^H)] + \gamma_s^H(1 \\ &\quad -\gamma_s^H)E[X_s(n_1^H, n_2^H)] + 2(1-\gamma_f^H)(1 \\ &\quad -\gamma_d^H)Cov[X_f(n_1^H), X_d(n_1^H, n_2^H)] + 2(1-\gamma_f^H)(1 \\ &\quad -\gamma_s^H)Cov[X_f(n_1^H), X_s(n_1^H, n_2^H)] + 2(1-\gamma_d^H)(1 \\ &\quad -\gamma_s^H)Cov[X_d(n_1^H, n_2^H), X_s(n_1^H, n_2^H)].\end{aligned}$$

If only same-day appointments are allowed to be scheduled, i.e. $n_1^H = n_2^H = 0$, then $X_f = X_d = 0$ and $X_s = \min(D_s^H, N)$. As a result, $E[M_f(n_1^H)] = 0$, $E[M_d(n_1^H, n_2^H)] = 0$, $Var[M_f(n_1^H)] = 0$, $Var[M_d(n_1^H, n_2^H)] = 0$, $Cov[M_f(n_1^H), M_d(n_1^H, n_2^H)] = 0$, $Cov[M_f(n_1^H), M_s(n_1^H, n_2^H)] = 0$, and $Cov[M_d(n_1^H, n_2^H), M_s(n_1^H, n_2^H)] = 0$. Thus, we obtain

$$E(M^H, 0, 0) = (1-\gamma_s^H)E[X_s(0,0)] = (1-\gamma_s^H)\left[N - \sum_{k=0}^{N}(N-k)p_s^H(k)\right]. \tag{A1}$$

and

$$\begin{aligned}V(M^H, 0, 0) &= (1-\gamma_s^H)^2 Var[X_s(0,0)] + \gamma_s^H(1-\gamma_s^H)E[X_s(0,0)] \\ &= (1-\gamma_s^H)^2\left\{\sum_{k=0}^{N}(N-k)^2 p_s^H(k) - \left[\sum_{k=0}^{N}(N-k)p_s^H(k)\right]^2\right\} \\ &\quad + \gamma_s^H(1-\gamma_s^H)\left[N - \sum_{k=0}^{N}(N-k)p_s^H(k)\right],\end{aligned} \tag{A2}$$

where $p_s^H(\bullet)$ is the probability mass function of demand D_s^H.

If no fixed appointments are allowed to be scheduled, i.e. $n_1^H = 0$, then $X_f = 0$, $X_d = \min(D_d^H, n_2^H)$, and $X_s = \min(D_s^H, N - X_d)$. Thus, $E[M_f(n_1^H)] = 0$, $Var[M_f(n_1^H)] = 0$, $Cov[M_f(n_1^H), M_d(n_1^H, n_2^H)] = 0$, and $Cov[M_f(n_1^H), M_s(n_1^H, n_2^H)] = 0$. Therefore, when the limit of fixed and days-ahead appointments to be scheduled changes by 1, the change in the expected number of patients consulted is

$$\begin{aligned}&E(M^H, 0, n_2^H) - E(M^H, 0, n_2^H - 1) \\ &\quad = (1-\gamma_d^H)\{E[X_d(0, n_2^H)] - E[X_d(0, n_2^H - 1)]\} \\ &\qquad + (1-\gamma_s^H)\{E[X_s(0, n_2^H)] - E[X_s(0, n_2^H - 1)]\},\end{aligned} \tag{A3}$$

and the change in the variance of the number of patients consulted

$$\begin{aligned}&V(M^H, 0, n_2^H) - V(M^H, 0, n_2^H - 1) \\ &\quad = (1-\gamma_d^H)^2\{Var[X_d(0, n_2^H)] - Var[X_d(0, n_2^H - 1)]\} \\ &\qquad + \gamma_d^H(1-\gamma_d^H)\{E[X_d(0, n_2^H)] - E[X_d(0, n_2^H - 1)]\} \\ &\qquad + (1-\gamma_s^H)^2\{Var[X_s(0, n_2^H)] - Var[X_s(0, n_2^H - 1)]\} \\ &\qquad + \gamma_s^H(1-\gamma_s^H)\{E[X_s(0, n_2^H)] - E[X_s(0, n_2^H - 1)]\} \\ &\qquad + 2(1-\gamma_d^H)(1-\gamma_s^H)\{Cov[X_d(0, n_2^H), X_s(0, n_2^H)] \\ &\qquad - Cov[X_d(0, n_2^H - 1), X_s(0, n_2^H - 1)]\} \\ &\quad = Q_{02}^H(n_2^H - 1) + Q_{03}^H(n_2^H - 1) + Q_{023}^H(n_2^H - 1),\end{aligned} \tag{A4}$$

where

$$\begin{aligned}Q_{02}^H(n_2^H - 1) &= (1-\gamma_d^H)^2\{Var[X_d(0, n_2^H)] - Var[X_d(0, n_2^H - 1)]\} \\ &\quad + \gamma_d^H(1-\gamma_d^H)\{E[X_d(0, n_2^H)] - E[X_d(0, n_2^H - 1)]\},\end{aligned} \tag{A5}$$

$$\begin{aligned}Q_{03}^H(n_2^H - 1) &= (1-\gamma_s^H)^2\{Var[X_s(0, n_2^H)] - Var[X_s(0, n_2^H - 1)]\} \\ &\quad + \gamma_s^H(1-\gamma_s^H)\{E[X_s(0, n_2^H)] - E[X_s(0, n_2^H - 1)]\},\end{aligned} \tag{A6}$$

and

$$\begin{aligned}Q_{023}^H(n_1^H - 1) &= 2(1-\gamma_d^H)(1-\gamma_s^H)\{Cov[X_d(0, n_2^H), X_s(0, n_2^H)] \\ &\quad - Cov[X_d(0, n_2^H - 1), X_s(0, n_2^H - 1)]\}.\end{aligned} \tag{A7}$$

Here

$$E[X_d(0, n_2^H)] - E[X_d(0, n_2^H - 1)] = 1 - F_d^H(n_2^H - 1), \tag{A8}$$

$$\begin{aligned}E[X_s(0, n_2^H)] - E[X_s(0, n_2^H - 1)] &= -1 + F_d^H(n_2^H - 1) + F_s^H(N \\ &\quad - n_2^H) - F_{ds}^H(n_2^H - 1, N - n_2^H),\end{aligned} \tag{A9}$$

$$\begin{aligned}&Var[X_d(0, n_2^H)] - Var[X_d(0, n_2^H - 1)] \\ &\quad = [1 - F_d^H(n_2^H - 1)]\left[F_d^H(n_2^H - 1) + 2\sum_{j=0}^{n_2^H - 1}(n_2^H - 1 - j)p_d^H(j)\right],\end{aligned} \tag{A10}$$

$$\begin{aligned}&Var[X_s(0, n_2^H)] - Var[X_s(0, n_2^H - 1)] \\ &\quad = [1 - F_d^H(n_2^H - 1) - F_s^H(N - n_2^H) + F_{ds}^H(n_2^H - 1, N - n_2^H)] \\ &\qquad \times \{E[X_s(0, n_2^H - 1)] + E[X_s(0, n_2^H)] - 2N + 2n_2^H - 1\},\end{aligned} \tag{A11}$$

and

$$\begin{aligned}&Cov[X_d(0,n_2^H),X_s(0,n_2^H)]-Cov[X_d(0,n_2^H-1),X_s(0,n_2^H-1)]\\&=\sum_{j=0}^{n_2^H-1}\sum_{k=0}^{N-j}(N-j-k)p_{ds}^H(j,k)-\sum_{j=0}^{n_2^H-1}(n_2^H-1-j)p_d^H(j)\\&\quad+F_d^H(n_2^H-1)\{E[X_s(0,n_2^H-1)]-N+n_2^H-1\}\\&\quad-[1-F_d^H(n_2^H-1)-F_s^H(N-n_2^H)\\&\quad+F_{ds}^H(n_2^H-1,N-n_2^H)]\sum_{j=0}^{n_2^H}(n_2^H-j)p_d^H(j),\end{aligned}\tag{A12}$$

where $p_d^H(\bullet)$ is the probability mass function of demand D_d^H, $p_{ds}^H(\bullet)$ is the joint probability mass function of demands D_d^H and D_s^H, $F_d^H(\bullet)$ and $F_s^H(\bullet)$ are the cumulative probability distribution functions of demands D_d^H and D_s^H, respectively, and $F_{ds}^H(\bullet)$ is the joint cumulative probability distribution function of demands D_d^H and D_s^H.

For a given n_2^H, when the limit of fixed appointments to be scheduled changes by 1, the change in the expected number of patients consulted is

$$\begin{aligned}&E(M^H,n_1^H,n_2^H)-E(M^H,n_1^H-1,n_2^H)\\&=(1-\gamma_f^H)\{E[X_f(n_1^H)]-E[X_f(n_1^H-1)]\}\\&\quad+(1-\gamma_d^H)\{E[X_d(n_1^H,n_2^H)]-E[X_d(n_1^H-1,n_2^H)]\}\\&\quad+(1-\gamma_s^H)\{E[X_s(n_1^H,n_2^H)]-E[X_s(n_1^H-1,n_2^H)]\},\end{aligned}\tag{A13}$$

and the change in the variance of the number of patients consulted is

$$\begin{aligned}&V(M^H,n_1^H,n_2^H)-V(M^H,n_1^H-1,n_2^H)\\&=(1-\gamma_f^H)^2\{Var[X_f(n_1^H)]-Var[X_f(n_1^H-1)]\}\\&\quad+\gamma_f^H(1-\gamma_f^H)\{E[X_f(n_1^H)]-E[X_f(n_1^H-1)]\}\\&\quad+(1-\gamma_d^H)^2\{Var[X_d(n_1^H,n_2^H)]-Var[X_d(n_1^H-1,n_2^H)]\}\\&\quad+\gamma_d^H(1-\gamma_d^H)\{E[X_d(n_1^d,n_2^d)]-E[X_d(n_1^d-1,n_2^d)]\}\\&\quad+(1-\gamma_s^H)^2\{Var[X_s(n_1^H,n_2^H)]-Var[X_s(n_1^H-1,n_2^H)]\}\\&\quad+\gamma_s^H(1-\gamma_s^H)\{E[X_s(n_1^H,n_2^H)]-E[X_s(n_1^H-1,n_2^H)]\}\\&\quad+2(1-\gamma_f^H)(1-\gamma_d^H)\{Cov[X_f(n_1^H),X_d(n_1^H,n_2^H)]\\&\quad-Cov[X_f(n_1^H-1),X_d(n_1^H-1,n_2^H)]\}\\&\quad+2(1-\gamma_f^H)(1-\gamma_s^H)\{Cov[X_f(n_1^H),X_s(n_1^H,n_2^H)]\\&\quad-Cov[X_f(n_1^H-1),X_s(n_1^H-1,n_2^H)]\}\\&\quad+2(1-\gamma_d^H)(1-\gamma_s^H)\{Cov[X_d(n_1^H,n_2^H),X_s(n_1^H,n_2^H)]\\&\quad-Cov[X_d(n_1^H-1,n_2^H),X_s(n_1^H-1,n_2^H)]\}\\&=Q_1^H(n_1^H-1)+Q_2^H(n_1^H-1,n_2^H)+Q_3^H(n_1^H-1,n_2^H)\\&\quad+Q_{12}^H(n_1^H-1,n_2^H)+Q_{13}^H(n_1^H-1,n_2^H)+Q_{23}^H(n_1^H-1,n_2^H),\end{aligned}\tag{A14}$$

where

$$\begin{aligned}Q_1^H(n_1^H-1)&=(1-\gamma_f^H)^2\{Var[X_f(n_1^H)]-Var[X_f(n_1^H-1)]\}\\&\quad+\gamma_f^H(1-\gamma_f^H)\{E[X_f(n_1^H)]-E[X_f(n_1^H-1)]\},\end{aligned}\tag{A15}$$

$$\begin{aligned}Q_2^H(n_1^H-1,n_2^H)&=(1-\gamma_d^H)^2\{Var[X_d(n_1^H,n_2^H)]-Var[X_d(n_1^H-1,n_2^H)]\}\\&\quad+\gamma_d^H(1-\gamma_d^H)\{E[X_d(n_1^d,n_2^d)]-E[X_d(n_1^d-1,n_2^d)]\},\end{aligned}\tag{A16}$$

$$\begin{aligned}Q_3^H(n_1^H-1,n_2^H)&=(1-\gamma_s^H)^2\{Var[X_s(n_1^H,n_2^H)]-Var[X_s(n_1^H-1,n_2^H)]\}\\&\quad+\gamma_s^H(1-\gamma_s^H)\{E[X_s(n_1^H,n_2^H)]-E[X_s(n_1^H-1,n_2^H)]\},\end{aligned}\tag{A17}$$

$$\begin{aligned}Q_{12}^H(n_1^H-1,n_2^H)&=2(1-\gamma_f^H)(1-\gamma_d^H)\{Cov[X_f(n_1^H),X_d(n_1^H,n_2^H)]\\&\quad-Cov[X_f(n_1^H-1),X_d(n_1^H-1,n_2^H)]\},\end{aligned}\tag{A18}$$

$$\begin{aligned}Q_{13}^H(n_1^H-1,n_2^H)&=2(1-\gamma_f^H)(1-\gamma_s^H)\{Cov[X_f(n_1^H),X_s(n_1^H,n_2^H)]\\&\quad-Cov[X_f(n_1^H-1),X_s(n_1^H-1,n_2^H)]\},\end{aligned}\tag{A19}$$

and

$$\begin{aligned}Q_{23}^H(n_1^H-1,n_2^H)&=2(1-\gamma_d^H)(1-\gamma_s^H)\{Cov[X_d(n_1^H,n_2^H),X_s(n_1^H,n_2^H)]\\&\quad-Cov[X_d(n_1^H-1,n_2^H),X_s(n_1^H-1,n_2^H)]\}.\end{aligned}\tag{A20}$$

Here

$$E[X_f(n_1^H)]-E[X_f(n_1^H-1)]=1-F_f^H(n_1^H-1),\tag{A21}$$

$$\begin{aligned}&E[X_d(n_1^H,n_2^H)]-E[X_d(n_1^H-1,n_2^H)]\\&=-1+F_f^H(n_1^H-1)+F_d^H(n_2^H-n_1^H)-F_{fd}^H(n_1^H-1,n_2^H-n_1^H),\end{aligned}\tag{A22}$$

$$\begin{aligned}&E[X_s(n_1^H,n_2^H)]-E[X_s(n_1^H-1,n_2^H)]\\&=-\sum_{i=n_1^H}^{\infty}\sum_{j=0}^{n_2^H-n_1^H}\sum_{k=N-n_1^H-j+1}^{\infty}p^H(i,j,k),\end{aligned}\tag{A23}$$

$$\begin{aligned}&Var[X_f(n_1^H)]-Var[X_f(n_1^H-1)]\\&=[1-F_f^H(n_1^H-1)]\left[F_f^H(n_1^H-1)+2\sum_{i=0}^{n_1^H-1}(n_1^H-1-i)p_f^H(i)\right],\end{aligned}\tag{A24}$$

$$\begin{aligned}&Var[X_d(n_1^H,n_2^H)]-Var[X_d(n_1^H-1,n_2^H)]\\&=[1-F_f^H(n_1^H-1)-F_d^H(n_2^H-n_1^H)+F_{fd}^H(n_1^H-1,n_2^H-n_1^H)]\\&\quad\times\{E[X_d(n_1^H-1,n_2^H)]+E[X_d(n_1^H,n_2^H)]-2n_2^H+2n_1^H-1\},\end{aligned}\tag{A25}$$

$$\begin{aligned}&Var[X_s(n_1^H,n_2^H)]-Var[X_s(n_1^H-1,n_2^H)]\\&=\{E[X_s(n_1^H-1,n_2^H)]+E[X_s(n_1^H,n_2^H)]\}\\&\quad\times\sum_{i=n_1^H}^{\infty}\sum_{j=0}^{n_2^H-n_1^H}\sum_{k=N-n_1^H-j+1}^{\infty}p^H(i,j,k)\\&\quad-\sum_{i=n_1^H}^{\infty}\sum_{j=0}^{n_2^H-n_1^H}\sum_{k=N-n_1^H-j+1}^{\infty}(2N-2n_1^H-2j+1)p^H(i,j,k),\end{aligned}\tag{A26}$$

$$\begin{aligned}&Cov[X_f(n_1^H),X_d(n_1^H,n_2^H)]-Cov[X_f(n_1^H-1),X_d(n_1^H-1,n_2^H)]\\&=\sum_{i=0}^{n_1^H-1}\sum_{j=0}^{n_2^H-i}(n_2^H-i-j)p_{fd}^H(i,j)\\&\quad-\sum_{i=0}^{n_1^H-1}(n_1^H-1-i)p_f^H(i)+F_f^H(n_1^H-1)\{E[X_d(n_1^H-1,n_2^H)]\\&\quad-n_2^H+n_1^H-1\}-[1-F_f^H(n_1^H-1)-F_d^H(n_2^H-n_1^H)\\&\quad+F_{fd}^H(n_1^H-1,n_2^H-n_1^H)]\sum_{i=0}^{n_1^H}(n_1^H-i)p_f^H(i),\end{aligned}\tag{A27}$$

$$
\begin{aligned}
&Cov[X_f(n_1^H),X_s(n_1^H,n_2^H)] - Cov[X_f(n_1^H-1),X_s(n_1^H-1,n_2^H)]\\
&\quad = (N-n_2^H)[1-F_f^H(n_1^H-1)-F_d^H(n_2^H-n_1^H)+F_{fd}^H(n_1^H-1,n_2^H-n_1^H)]\\
&\qquad - \sum_{i=n_1^H}^{\infty}\sum_{j=n_2^H-n_1^H+1}^{\infty}\sum_{k=0}^{N-n_2^H}(N-n_2^H-k)p^H(i,j,k)\\
&\qquad + \sum_{i=n_1^H}^{\infty}\sum_{j=0}^{n_2^H-n_1^H}\sum_{k=0}^{N-n_1^H-j}kp^H(i,j,k) - \sum_{i=n_1^H}^{\infty}\sum_{j=0}^{n_2^H-n_1^H}\sum_{k=N-n_1^H-j+1}^{\infty}jp^H(i,j,k)\\
&\qquad - E[X_s(n_1^H-1,n_2^H)][1-F_f^H(n_1^H-1)]\\
&\qquad + \sum_{i=n_1^H}^{\infty}\sum_{j=0}^{n_2^H-n_1^H}\sum_{k=N-n_1^H-j+1}^{\infty}p^H(i,j,k)\left[N-n_1^H+1-\sum_{l=0}^{n_1^H}(n_1^H-l)p_f^H(l)\right],
\end{aligned}
\tag{A28}
$$

and

$$
\begin{aligned}
&Cov[X_d(n_1^H,n_2^H),X_s(n_1^H,n_2^H)] - Cov[X_d(n_1^H-1,n_2^H),X_s(n_1^H-1,n_2^H)]\\
&\quad = -(N-n_2^H)[1-F_f^H(n_1^H-1)-F_d^H(n_2^H-n_1^H)+F_{fd}^H(n_1^H-1,n_2^H-n_1^H)]\\
&\qquad + \sum_{i=n_1^H}^{\infty}\sum_{j=n_2^H-n_1^H+1}^{\infty}\sum_{k=0}^{N-n_2^H}(N-n_2^H-k)p^H(i,j,k)\\
&\qquad - \sum_{i=n_1^H}^{\infty}\sum_{j=0}^{n_2^H-n_1^H}\sum_{k=N-n_1^H-j+1}^{\infty}jp^H(i,j,k) + E[X_d(n_1^H,n_2^H)]\\
&\qquad \times \sum_{i=n_1^H}^{\infty}\sum_{j=0}^{n_2^H-n_1^H}\sum_{k=N-n_1^H-j+1}^{\infty}p^H(i,j,k)\\
&\qquad + E[X_s(n_1^H-1,n_2^H)][1-F_f^H(n_1^H-1)\\
&\qquad - F_d^H(n_2^H-n_1^H)+F_{fd}^H(n_1^H-1,n_2^H-n_1^H)],
\end{aligned}
\tag{A29}
$$

where $p_f^H(\bullet)$ is the probability mass function of demand D_f^H, $p_{fd}^H(\bullet)$ is the joint probability mass function of demands D_f^H and D_d^H, $p^H(\bullet)$ is the joint probability mass function of demands D_f^H, D_d^H and D_s^H, $F_1^H(\bullet)$ is the cumulative probability distribution function of demand D_f^H, and $F_{fd}^H(\bullet)$ is the joint cumulative probability distribution function of demands D_f^H and D_d^H.

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