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# Modeling the benefits of cross-training to address the nursing shortage

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ABSTRACT

This paper seeks to offer insight into cross training strategies that could be effective in aiding in alleviating the nurse shortage issue and its potential to negatively impact on patient safety and mortality. We develop optimization models to evaluate the benefits of cross-training, in particular chaining practices, on nurse workforce planning under stochastic demand, and determine the optimal allocation of both regular and cross-trained staff at a minimum cost. We demonstrate the benefits of cross-training in terms of a reduction in the total number of nurses required to satisfy demand across multiple departments as well as from an economic (i.e. overall cost savings) perspective, while simultaneously meeting the hospitals service and quality of care requirements. In particular, the results indicate that cross-training strategies could help with optimal utilization of constrained nursing resources and thereby limit the negative implications of the growing nurse shortage crisis.

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## 1. Introduction

The United States is facing a severe shortage of nurses due to supply side issues. It is projected that by 2020, this number will be approximately 808,000 in terms of registered nurses (Buerhaus et al. 2009). This issue has resulted in patient safety concerns and affected the hospital staff's ability to detect complications in patients, potentially leading to increased patient death rates (Aiken et al., 2002; Stanton, 2004). Research has shown that hospitals with higher nurse to patient ratios have better outcomes in terms of quality of care, patient safety, mortality, etc. (Aiken et al., 2010; Needleman et al., 2006; Stone et al., 2007). Some states have even mandated ratios, which vary based on the hospital department (IHSP, 2001). While there is some evidence to support enforcing specific nurse to patient ratios (Aiken et al., 2010), this is an extreme measure in terms of controlling the planning and deployment of nursing resources and may exacerbate the nursing shortage (Paul and MacDonald, 2013). As well, such a strategy assumes that demand for services and the supply of nurse resources in a hospital behaves in a linear manner, when in fact it is very complex and dynamic in nature (Clancy, 2007).

The effective use of available resources is possible through an accurate estimation of demand at each of these complex units. However, given the nursing shortages observed across hospitals in the US (Domagala and Rowles, 2002; Sarudi, 2000; Hacket et al., 1989), it might not be possible to always have enough supply to meet this demand. One way to mitigate this issue is via cross-training of nurses (Grandinetti, 2000; Tzirides et al., 1991; Wheaton, 1996; Snyder and Nethersole-Chong, 1999). In this paper, we focus on developing optimization models to evaluate the benefits of cross-training, in particular chaining practices (Jordan and Graves, 1995), on nurse workforce planning within a multi-department setup.

Through the optimization models we evaluate total staffing across departments, and determine the optimal allocation of both regular and cross-trained staff at a minimum cost. Further, we consider practical limitations including constraints on total available resources as well as minimum quality as a function of experience levels (worker heterogeneity), demand variability and patient service levels. Finally, given the limitations of exact analytical methods in evaluating the benefits of cross-training policies, we develop an evolutionary optimization based heuristic that yields time efficient high quality solutions regardless of the problem size. Realistic examples featuring Emergency and Surgery Departments demonstrate that when there were no constraints on the maximum number of nurses, cross-training resulted in a lower total number of nurses required for achieving departmental service goals. When such a constraint was imposed, we found that both departments achieved both higher s ervice levels and overall cost savings when cross-training was implemented. Our analysis confirmed that these results hold regardless of the distribution that described the nursing demand. Further, we were able to confirm the directional nature of the above policy implications within a multi-department setup.

## 2. Literature review

The primary focus of this paper is on evaluating the benefits of cross-training as it applies to hospital settings, which forms the motivation for the extant literature discussed below. First, we

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discuss the generic cross-training literature and then present research specifically related to various hospital departments.

Cross-training is basically a process of determining the skill patterns of a workforce. The skill pattern can range from an extreme, wherein all workers are capable of performing all the tasks involved, to one where each worker is specialized to do only one task. The first scenario is generally referred to as full cross-training whereas the second one is a case of no cross-training. There are also intermediate policies such as chaining (Jordan and Graves, 1995), wherein each worker could have one or more other skills, in addition to their normal skill set that he or she would use for their home department. In this study, we evaluate the benefits of chaining policies in both a two and multi-department setting.

The popularity of cross-training policies stems from its ability to provide flexibility to an organization's workforce. However, it has been shown that this flexibility may be expensive and difficult to maintain (Hopp and Van Oyen, 2004; Inman et al., 2004). Further, cross-trained personnel might not be as efficient as a dedicated workforce. For instance, Karuppan (2006) showed that there is a decrease in the productivity and quality of output when using cross-training. This decrease is attributed to cross-trained workers not being able to exercise or practice their skills as often, and thus causing them to forget basic skills related to their additional tasks. Similar findings have been reported by Chakravarthy and Agnihothri (2005), who show that a slide in the relative efficiency of cross-trained workers when compared to dedicated staff may negate the benefits of a flexible cross-trained workforce. However, in a recent study, Easton (2011), using a two stage stochastic model, presented some new and different results from a cross-training perspective when compared to the prior literature. For example, they demonstrate that cross-training often leads to improved performance when compared to dedicated specialists. In scenarios wherein the cross-trained workforce was less efficient than dedicated specialists, they found that increased cross-training resulted in trade-offs between capacity (i.e. workers with the required skills to meet a specific type of demand) shortages and workforce size, where work force size represents the total number of workers irrespective of their skills.

It should be noted that some of the above experiences presented in the literature that preceded Easton (2011) may not apply in a hospital setting, as the underlying uncertainty is considerably higher than what is experienced in manufacturing or other non-hospital environments. This comparatively smaller uncertainty in non-hospital environments could also explain reduced opportunities for workers to practice their additional skills. Further, the experiences in hospitals who have implemented cross-training policies are similar to the findings presented in Easton (2011). This is evident from the extant literature on cross-training policies applied in hospital environments. For instance, it has been reported that cross-training can improve the quality of care, often by mitigating the impacts of uncertain patient arrivals and absenteeism, by reducing the need for temporary staffing while still maintaining service levels (Inman et al., 2005). In one of the earliest papers, Tzirides et al. (1991) recommend implementing flex teams involving related hospital departments in order to handle random patient census. Wheaton (1996) reports on a successful cross-training program for nurses in the Neuro-critical care unit of the ICU of a particular hospital. Similarly, Snyder and Nethersole-Chong (1999) report on cross-training surgical nurses for the ICU, which not only reduced overtime in the ICU but also boosted morale across the units. Grandinetti (2000) studied care teams, which included implementations of cross-training to, in part, improve staff flexibility. A recent paper that aimed to address the nursing shortage is that of Wright and Bretthauer (2010). The authors focus on scheduling flexibility and efficient use of available nursing resources, which included creating a pool of cross-trained nurses. Their research showed that coordination across departments in implementing flexible scheduling could reduce labor costs as well as overtime and undesirable staff schedules.

However, though there exists literature on the application of cross-training across different hospital departments as detailed above, most do not evaluate the impacts or attempt to model or determine the levels of cross-training. One exception is the paper by Inman et al. (2005), in which the authors used simulations to model different cross-training strategies, such as reciprocal pairs and chaining, to determine the impact on costs resulting from absenteeism and random patient census. In addition, Gnanlet and Gilland (2009) developed a two-stage stochastic programming model to find the optimal level of cross-training and allocation of beds for a pair of hospital units that face random patient census and the resulting demand.

In this paper, given uncertain demand, we determine the optimal allocation of both regular and cross-trained staff to minimize cost considering practical limitations, including constraints on total available resources, while maintaining minimum quality (worker heterogeneity) and patient service levels. Our models extend the literature (for example, Campbell, 1999, Inman et al., 2005) on the effect of demand variability on expected shortage levels and optimal staff allocation decisions by being capable of handling various probability distributions in addition to the normal distribution, as well as incorporating the impacts of the costs of cross-training and temporary staffing. The motivation for inclusion of worker heterogeneity in our models, in addition to its impact on staff costs, is the significant influence it has on productivity rates when considering cross-training policies, as these policies have been shown to have a greater benefit when applied to the best subset of workers (Jordan et al., 2004; Kim and Nembhard, 2010). Similarly, our models consider service levels in our analysis as it not only impacts the number of nurses from a cost and service goals perspective, but also because it has been shown that return on cross-training declines rapidly as customer service levels increase (Robbins et al., 2007). Our models, by considering worker heterogeneity in addition to demand variability, service levels and resource costs, contributes to the general worker productivity related cross-training literature (for example, Brusco and Johns, 1998). Further, the models developed are capable of studying the impact of cross-training on nurse workforce planning in both simple two and multi-department environments. Finally, we develop an evolutionary optimization based heuristic that yields time efficient high quality solutions regardless of the problem size.

## 3. Methodology

The goal of the proposed model is to evaluate staffing policies for nurses across departments with cross-training. Specifically, we study the chaining problem for two and multi-department setups. The simple two department case is equivalent to full cross-training; however the multi-department setup would be one wherein the first department has cross-trained nurses for the second, the second has cross-trained staff for the third and so on, with the last department in the chain having nurses that are cross-trained for the department at the start of the chain. The rationale behind considering this particular chaining arrangement is that given the complexity of nursing duties within a given department, cross-training across more than two departments is unlikely. This is a valid assumption based on our discussions with hospital staff and evidence available in the extant literature on the disadvantages resulting from excessive cross-training (Inman et al., 2005). Further, this type of chaining has been demonstrated to be cost efficient (Inman et al., 2005). Several key aspects of the staffing problem such as costs, service levels, quality, and constraints on available staff are considered. Before elaborating on the model, we present the following notation in Table 1.

**Table 1**
Model notation.

| | |
|---|---|
| ***Indices*** | |
| $i$ | Department |
| $k$ | Experience level of the nurse (being the lowest or entry level) |
| $r$ | Regular nurse |
| $c$ | Cross-trained nurse |
| $t$ | Temporary nurse |
| ***Domains*** | |
| $I$ | Total number of departments |
| $K$ | Total number of experience levels |
| ***Parameters*** | |
| $c_i{}^r$ | Cost for a regular nurse in department $i$ |
| $c_i{}^c$ | Cost for a cross-trained nurses in department $i$ |
| $c_t$ | Cost for a 'temporary' nurse ( all departments) |
| $D_i$ | Random variable for demand for nursing staff in department $i$ |
| $\lambda_i$ | Mean demand for nursing staff in department $i$ |
| $S_{min}$ | Minimum service level required |
| $Q_{min}$ | Minimum quality level required |
| $\varepsilon_k$ | Relative quality level of nurse with experience level $k$ |
| $\varepsilon^c$ | Relative quality for cross-trained nurses |
| $n_i{}^{max}$ | Maximum number of nurses available in department $i$ |
| ***Decision variables*** | |
| $n_i{}^r$ | Number of regular nurses in department $i$ |
| $S_i$ | Service level in department $i$ |
| $Q_i$ | Quality level in department $i$ |
| $n_{ik}{}^c$ | Number of cross-trained nurses in department $i$ of experience level $k$ |
| $n_{ik}{}^r$ | Number of regular nurses in department $i$ of experience level $k$ |
| $n_{ik}$ | Total number of nurses in department $i$ of experience level $k$ |
| $n_i$ | Total number of nurses in department $i$ |
| ***Utility*** | |
| E(shortage) | Total expected shortage of nurses |

### 3.1. Model development

In our model, we consider $K$ levels of experience for regular (i.e. non-cross-trained) nurses, each with differing salaries/costs as well as differential impacts on service quality. Staff costs are based upon the experience level of the nurses in each department, which is denoted as $c^r_{ik}$, with a premium $c^c > 0$ associated with salaries of cross-trained nurses $c^c_{ik}$, i.e. $c^r_{ik} < c^c_{ik} = c^r_{ik} + c^c$. This salary premium can in part be attributed to the costs of cross-training, as well as an increase in value to the organization that is reflected in increased salary, increase risk of loss of cross-trained staff and other associated costs. Further, when shortages occur in a department, a cost $c_t > c^c_{ik} (\forall k)$ is attributed per unit shortage, either as a penalty function for reduced patient service or the costs associated with the temporary nurse staffing to cover the shortage.

The demand for nurse staffing in each department is uncertain and based upon random patient arrivals. Random demand for staffing in each department is assumed to be independent. We denote the random variable for staffing requirements to meet patient needs in department $i$ as $D_i$, with mean $\lambda_i$. Given this random demand, we determine the number of entry, mid-level and senior regular ($n^r_{ik}$) and cross-trained ($n^c_{ik}$) nurses for each department, while meeting specified service and quality levels, to minimize the total expected cost, which includes the staffing costs related to the number of regular and cross-trained staff as well as the expected total shortage across departments and the associated cost of temporary staffing. This is expressed as

$$\text{Total cost} = \left\{ \sum_{k=1}^{K} \sum_{i=1}^{I} n^r_{ik} c^r_{ik} + n^c_{ik} c^c_{ik} \right\} + E[\text{shortage}] c_t \tag{1}$$

The first components are linear in the number of nurses for both regular and cross-trained staff and are straightforward given available salary data. However, the expected shortage is non-linear in the staffing levels, the details for which are presented in detail later in this section.

Within the optimization, we also consider a number of constraints for both realistic and/or logical reasons. First, we assume only nurses with experience beyond entry level ($k > 1$) are available for cross-training, as the entry level nurses are still gaining expertise in their home department. In addition, service levels, i.e. the ability to meet patient demand with current available resources, and quality are also significant, if not of utmost importance in a health care setting. We consider service levels, in our analysis not only because it impacts the number of nurses from a cost and hospital goals perspective, but also because it has been shown that the return on cross-training declines rapidly as customer service levels increase (Robbins et al., 2007). For a given department $i$, we define the expected service level, $E[S_i]$, as the probability that there are sufficient staff, both departmental nurses as well as available cross-trained nurses from the second department, to meet the demand; or equivalently, the probability of a shortage of zero in a given department. To demonstrate this, we develop the equations for expected service level for two and multi-department chains respectively. Consider two departments, denoted as $i$ and $i-1$ in which department $i-1$ has nurses cross-trained to serve in $i$ and vice-versa, then the expected service of department $i$ is given as

$$E[S_i] = P(D_i \le n_i) + \sum_{x_{i-1}=1}^{n^c_{i-1}} P(D_i = n_i + x_{i-1}) P(D_{i-1} \le n_{i-1} - x_{i-1}) \tag{2}$$

where $x_i$ and $x_{i-1}$ are counters that implement the various cross-training combinations possible, based upon the number of cross-trained staff, that result in full coverage for department $i$, which occurs when the sum of shortages and surplus staff in the chain equal zero. The expected service for department $i-1$ can be similarly determined by reversing $i-1$ and $i$ in Eq. (2).

For the multi-department case, we begin by developing the equation where three departments are involved, which we denote as $i$, $i-1$ and $i+1$. In a three department chained cross-training scenario, $i$ would provide cross-trained staff to department $i+1$, $i+1$ for $i-1$ and $i-1$ for $i$. For three departments, the expected service level in department $i$ is:

$$\begin{aligned} E[S_i] = {} & P(D_i \le n_i) + \sum_{x_{i-1}=1}^{n^c_{i-1}} P(D_i = n_i + x_{i-1}) \\ & \times P(D_{i-1} \le n_{i-1} - x_{i-1}) + \sum_{x_{i+1}=1}^{n^c_{i+1}} P(D_{i+1} \le n_{i+1} - x_{i+1}) \\ & \times \left[ \sum_{x_{i-1}=1}^{n^c_{i-1}} P(D_{i-1} = n_{i-1} - n^c_{i-1} + x_{i-1} + x_{i+1} - 1) \right. \\ & \left. \times P(D_i = n_i + n^c_{i-1} - x_{i-1} + 1) \right] \end{aligned} \tag{3}$$

As with (2) above, the various combinations of cross-trained staff resulting in full service for department $i$ are considered, with the resulting sum of shortage and surplus staff across the chained departments being zero.

Thus each additional department in the chain adds a term to the expectation describing how cross-trained staff in that department contributes to covering shortages in the target department via the chain. As with the two and three department cases, the sum of the shortages and surpluses within the chain equal zero. This establishes the structure of the algorithm for a departmental chain of an arbitrary length. Given a department $i$, we can first determine the range of shortage or surplus for the $i+1$ department as 1 to $n^c_{i+1}$, while the range for the $i^{th}$ department's shortage is restricted by the preceding department's available cross-trained staff, i.e. 1 to $n^c_{i-1}$. Similarly, the remaining departments within the chain will vary based upon the number of

cross-trained staff in the departments immediately preceding and following within the chain. Thus the $i^{th}+1$ department's contribution (i.e. the next department following department $i$) to department $i$ is given as

$$\sum_{x_{i+1}=1}^{n^c_{i+1}} P(D_{i+1} \le n_{i+1} - x_{i+1}) \left[ \begin{array}{c} \sum_{x_{i+2}=1}^{n^c_{i+2}} P(D_{i+1} = n_{i+2} - n^c_{n+2} + x_{i+1} + x_{i+2}) \cdots \\ \sum_{x_{i-1}=1}^{n^c_{i-1}} P(D_{i-1} = n_{i-1} - n^c_{i-1} + x_{i-1} + x_{i-2} - 1) P(D_i = n_i + n^c_{i-1} - x_{i-1} + 1) \end{array} \right] \tag{4}$$

which is applied for each step in the chain from department $i-1$ back to $i+1$ to give the expected service level for the $i^{th}$ department:

$$E[S_i] = P(D_i \le n_i) + \sum_{x_{i-1}=1}^{n^c_{i-1}} P(D_i = n_i + x_{i-1}) P(D_{i-1} \le n_{i-1} - x_{i-1}) + \cdots + \sum_{x_{i+1}=1}^{n^c_{i+1}} P(D_{i+1} \le n_{i+1} - x_{i+1}) \left[ \begin{array}{c} \sum_{x_{i+2}=1}^{n^c_{i+2}} P(D_{i+1} = n_{i+2} - n^c_{n+2} + x_{i+1} + x_{i+2}) \cdots \\ \sum_{x_{i-1}=1}^{n^c_{i-1}} P(D_{i-1} = n_{i-1} - n^c_{i-1} + x_{i-1} + x_{i-2} - 1) P(D_i = n_i + n^c_{i-1} - x_{i-1} + 1) \end{array} \right] \tag{5}$$

Thus Eq. (5) allows us to set a minimum expected service level, denoted as $S_{min}$ for each department.

We estimate the overall quality level ($Q_i$) in turn, based upon the number of nurses of differing experience levels in a department, as well as whether they are dedicated to a single department or have undergone cross-training. The quality of care provided by a given nurse in a department, based upon experience level and the type (i.e. regular or cross-trained) is denoted by $\varepsilon_k \varepsilon^c$, where $\varepsilon_k$ represents the quality measure related to experience level and $\varepsilon^c$ differentiates between dedicated and cross-trained nurses. For experience, we designate a quality of care rating of 1 for nurses with a $K^{th}$ level of experience, that is $\varepsilon_K = 1$, with $\varepsilon_1 \le \varepsilon_2 \le \cdots \le \varepsilon_K = 1$. For regular nurses, i.e. those dedicated to a single department, by definition $\varepsilon^c = 1$ within the quality of care rating, with $\varepsilon^c \le 1$ assigned to nurses that have undergone cross-training. The overall quality in a department is a proxy for the staff mix within a given department, and is given by $Q_i = \sum_{k=1}^{K} (n^r_{ik} + n^c_{ik} \varepsilon^c) \varepsilon_k$. Within the optimization, we then set the minimum quality of care $Q_{min} \le 1$. Finally, we may also designate the maximum number of nurses available to each department, denoted by $n_{i,max}$, to model issues associated with nursing shortages common across the U.S.

The resulting optimization model is given as

$$\text{Minimize } Z = \sum_{k=1}^{K} \sum_{i=1}^{N} n^r_{ik} c^r_{ik} + n^c_{ik} c^c_{ik} + E[\text{total shortage}] c_t \tag{6}$$

Subject to

$$E[S_i] \ge S_{min}, \quad \text{for } i = 1, 2, \ldots I \tag{7}$$

$$Q_i \ge Q_{\min}, \quad \text{for } i = 1, 2, \ldots I \tag{8}$$

$$Qi = \sum_{k=1}^{K} (n^r_{ik} + n^c_{ik} \cdot \varepsilon^c) \varepsilon_k \quad \text{for } i = 1, 2, \ldots I \tag{9}$$

$$Q_{min} \le 1, \quad \text{for } i = 1, 2, \ldots I \tag{10}$$

$$n^c_{ik} \le n_{ik}, \quad \text{for } i = 1, 2, \ldots I; \quad k = 1, 2, \ldots K \tag{11}$$

$$n_i \le n_{i,\max}, \quad \text{for } i = 1, 2, \ldots I \tag{12}$$

$$n_i = \sum_{k=1}^{K} n_{ik}, \quad \text{for } i = 1, 2, \ldots I \tag{13}$$

$$n_{ik} = n^r_{ik} + n^c_{ik}, \quad \text{for } i = 1, 2, \ldots I \quad k = 1, 2, \ldots K \tag{14}$$

$$n_i,\ n^c_{ik},\ n^r_{ik},\ n_{ik} = \text{integer} \tag{15}$$

$$\varepsilon_1 \le \varepsilon_2 \le \cdots \le \varepsilon_K = 1 \tag{16}$$

The objective function minimizes the total expected cost, which includes the costs related to the number of regular and cross-trained staff as well as the expected total shortage across both departments and the associated cost of temporary staffing. Constraints (7) and (8) ensure that the expected service and quality in department $i$ are at least equal to the minimum limits set by the hospital. Constraints (9) and (10), which are related to quality, have been discussed earlier. Constraint (11) ensures that the number of cross-trained nurses in department $i$ is less than or equal to the total number of nurses. Constraint (12) makes sure that the total number of nurses in department $i$ is less than or equal to the maximum available to the department. Constraints (13) and (14) describe the relationships between the makeup of nurses for each department in terms of experience and cross-training skills. Constraint (15) ensures that all nurse staffing decision variables assume integer values. Constraint (16) related with quality differentials that exist among nurses of different experience levels has been discussed above. We next focus on the derivation of the expected shortage across departments.

### 3.2. Calculation of expected shortages

We first consider cross-training across two departments, or a pairing system, in which nurses in each department can be cross-trained for the other. This may be considered a realistic restriction as given the complexity of nursing duties within a given department, cross-training across more than two departments is considered unlikely.

In general, the probability of a total shortage '$s$' across departments is the product of the shortages in each individual department that sums to the total '$s$'. For example, a total shortage of one requires a shortage of one in department $i$ and a shortage of zero in department $i-1$. However, given the availability of cross-trained nurses for each department, the various probabilities that yield a shortage of zero and one are not independent. To determine the expected shortage, we first calculate the probability of a shortage in either of the departments given the demand, as well as the number of regular and cross-trained nurses. For a two department chain, again denoting the two departments as $i$ and $i-1$, the probability that a shortage of $s$ occurs in department $i$ can be divided into a base effect (i.e. without any cross-training) and direct cross-training effects. For department $i$, with staff in department $i-1$ cross-trained for department $i$, by combining and simplifying conditions resulting in a shortage of $s$ we can calculate the probability of a shortage as (See Appendix A for proof)

$$P(\text{shortage department } i = s) = P(D_i = n_i + s) + \sum_{T_{i-1}=1}^{n^c_{i-1}} P(D_{i-1} \le n_{i-1} - T_{i-1}) [P(D_i = n_i + s + T_{i-1}) - P(D_i = n_i + s + T_{i-1} - 1)] \tag{17}$$

where the first term is based upon home department nursing resources, while the second term is the result of available cross-trained nurses in $i-1$.

We now extend our analysis to multiple departments where again, as in the previous section, nurses are cross-trained to work only in a total of two departments including their home department. Thus the system being described is a cross-training chain

as previously discussed. To extend the approach for two departments given above, we need to consider both the direct and indirect cross-training effects on a given department. The direct effects are those in which a department immediately preceding has cross-trained staff for the department of interest. For example, department $i-1$ has staff that are cross-trained for department $i$. Direct effects are as determined above for the two department case.

To complete the analysis, we need to now incorporate indirect cross-training effects. For example, consider a three department case, where a third department (denoted as $i+1$) has no staff cross-trained for department $i$ but does have cross-trained staff for department $i-1$. Thus, these staff can be used to free up cross-trained staff in department $i-1$ that would not be otherwise available to reduce a shortage in department $i$. This indirect impact is given by

$$P(\text{shortage department } i=s)=\sum_{T_{i+1}=1}^{n_{i+1}^c} P(D_{i+1}\le n_{i+1}-T_{i+1}) \left[\begin{array}{c}\sum_{T_{i-1}=1}^{n_{i-1}^c} P(D_{i-1}=n_{i-1}+T_{i-1}-n_{i-1}^c+T_{i+1}-1)\\ (P(D_i=n_i+s+n_{i-1}^c-T_{i-1}+1)-P(D_i=n_i+s+n_{i-1}^c-T_{i-1}))\end{array}\right] \tag{18}$$

Combining these results, the probability of a shortage $s$ in department $i$ with three departments in a cross-training chain is given as:

$$\begin{aligned}&P(\text{shortage departmenti}=s)=P(D_i=n_i+s)\\&+\sum_{T_{i-1}=1}^{n_{i-1}^c} P(D_{i-1}\le n_{i-1}-T_{i-1})[P(D_i=n_i+s+T_{i-1})-P(D_i=n_i+s+T_{i-1}-1)]\\&\quad+\sum_{T_{i+1}=1}^{n_{i+1}^c} P(D_{i+1}\le n_{i+1}-T_{i+1})\\&\left[\begin{array}{c}\sum_{T_{i-1}=1}^{n_{i-1}^c} P(D_{i-1}=n_{i-1}+T_{i-1}-n_{i-1}^c+T_{i+1}-1)\\ (P(D_i=n_i+s+n_{i-1}^c-T_{i-1}+1)-P(D_i=n_i+s+n_{i-1}^c-T_{i-1}))\end{array}\right]\end{aligned} \tag{19}$$

where the first term is the shortage based upon own department staffing, the second term addresses the direct effect of cross-trained staff in department $i-1$ and the last term the indirect effects of cross-trained staff in department $i+1$ that can substitute in department $i-1$, thus freeing up staff from $i-1$ to $i$.

Using the above shortage probabilities, we can in turn calculate the expected shortage in an individual department based upon the number of regular and cross-trained nurses given the mean demand as

$$E[\text{total shortage department } i]=\sum_{s=1}^{\infty} P(\text{shortage department } i=s)s \tag{20}$$

which can be readily estimated numerically. The total shortage across all departments can then be taken as the sum of the individual shortages based upon the total and cross-trained staff in each department:

$$E[\text{total shortage}]=\sum_{for\ all\ i}\left\langle \sum_{s=1}^{\infty} P(\text{shortage in dept. } i=s)s\right\rangle \tag{21}$$

The proof of this result is presented in Appendix B for the two department case, with a similar derivation applicable to the multi-department case, and verified via Monte Carlo simulations.[1] Substituting (21) into the above total cost expression allows the optimization of the staffing/cross-training problem with the objective of minimizing total costs.

Note that, although these equations apply to a cross-training chain, they can be easily extended to include a more general cross-training, where any and all departments may have staff cross-trained for an individual department. Under this scenario, direct effects are given as above for each department that has cross-trained staff for the department of interest. Then, the indirect effects are modified to account for staff that is directly cross-trained to assist in the selected department. Eqs. (17)–(21) can be extended to account for shortages with more than three departments similarly to that given for expected services in Eq. (5).

The above model as presented in Sections 3.1 and 3.2 via Eqs. (1)–(21) can be utilized to perform various sensitivity analyses including studying the effect of quality, cross-training, service levels, number of nurses, etc. on optimal use of budgetary resources with one exception, that being incorporating minimum service and maximum nursing levels constraints in a single setup, as such a scenario could lead to potential conflict. As can be noted, the comprehensive cross-training model discussed above is difficult to solve analytically and heuristics may be warranted. This forms the focus of the next section.

### 3.3. Evolutionary algorithm (EV)

Even for small problems, an exact solution methodology for the model described in Sections 3.1 and 3.2 above may not be a practical option for determining the optimal workforce mix from a time to solution perspective. This would be particularly true for large problems wherein the department size could be in the range of hundreds. Therefore, we propose the following heuristic optimization approach to handle such problem scenarios. As the optimization involves a nonlinear, non-smooth problem, we chose an evolutionary algorithm (EV), as this method has been shown to produce efficient solutions for nonlinear programming problems (Costa and Oliveira, 2001; Danish et al., 2006; Srinivas and Rangaiah, 2007). We specifically utilized and built on the evolutionary algorithm Evolver 5.7 developed by Palisade (2011), which proceeds as follows:

1. *Initialization*: The initial population, consisting of points in the search space, is randomly created.
2. *Evaluation*: Each organism in the population is evaluated through the objective (fitness) function discussed earlier as part of the optimization model and ranked from best to worst.
3. *Genetic operators*: Selects good organisms and swap their variables using genetic operators such as 'crossover' and 'mutation' to produce 'offspring'. If offspring do not produce a good result, two more parents are selected.
4. *Stopping criterion*: These steps (2) and (3) are repeated till the specified number of generations is reached or population converges.

The parameter settings for our EV runs are presented in Table 2.

Tables 3–5 compare the results of the EV with solutions from a complete enumeration algorithm (SA) that yields global optimal solutions (see Appendix C for details on SA). Specifically, Table 3 presents the problem settings tested. Table 4 shows the SA and EV

**Table 2**
Evolutionary algorithm parameters.

| | |
|---|---|
| Population size | 50 |
| Trials | 20000 |
| Crossover probability | 0.5 |
| Mutation probability | 0.1 |

[1] Results pertaining to the validation of Eq. (21) using Monte Carlo simulation are available upon request from the authors.

**Table 3**
Scenarios run for comparison purposes.

| Scenario run settings | | | |
|---|---|---|---|
| **Mean demand ER** | **Mean demand OR** | **Required service (%)** | **Required quality** |
| 5 | 10 | 50 | 0.9 |
| 5 | 10 | 75 | 0.9 |
| 10 | 5 | 50 | 0.9 |
| 10 | 5 | 75 | 0.9 |
| 5 | 5 | 50 | 0.9 |
| 5 | 5 | 75 | 0.9 |
| 10 | 10 | 50 | 0.9 |
| 10 | 10 | 75 | 0.9 |

**Table 4**
Comparison of evolutionary algorithm and complete enumeration (results output – Part 1).

| **Department 1** | | | | | | **Department 2** | | | | | | **CT Dept. 1** | | **CT Dept. 2** | | **E[temps]** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EV | | | **SA** | | | **EV** | | | **SA** | | | **EV** | **SA** | **EV** | **SA** | **EV** | **SA** |
| Entry | Mid | Senior | Entry | Mid | Senior | Entry | Mid | Senior | Entry | Mid | Senior | | | | | | |
| 0 | 3 | 0 | 0 | 3 | 0 | 6 | 0 | 6 | 6 | 0 | 6 | 0 | 0 | 4 | 4 | 1.609 | 1.609 |
| 1 | 3 | 1 | 0 | 5 | 0 | 5 | 1 | 5 | 5 | 1 | 5 | 2 | 2 | 3 | 3 | 1.145 | 1.145 |
| 1 | 4 | 1 | 0 | 8 | 0 | 4 | 1 | 4 | 3 | 1 | 3 | 0 | 0 | 5 | 4 | 1.652 | 1.609 |
| 2 | 7 | 2 | 0 | 11 | 0 | 2 | 1 | 2 | 2 | 1 | 2 | 3 | 3 | 2 | 2 | 1.145 | 1.145 |
| 0 | 6 | 0 | 0 | 3 | 0 | 2 | 0 | 2 | 3 | 1 | 3 | 3 | 0 | 1 | 4 | 1.290 | 1.290 |
| 2 | 1 | 2 | 0 | 5 | 0 | 3 | 0 | 3 | 3 | 0 | 3 | 1 | 1 | 2 | 2 | 0.925 | 0.925 |
| 3 | 2 | 3 | 0 | 8 | 0 | 5 | 2 | 5 | 6 | 0 | 6 | 0 | 0 | 4 | 4 | 1.918 | 1.918 |
| 1 | 8 | 1 | 0 | 10 | 0 | 5 | 2 | 5 | 6 | 0 | 6 | 1 | 1 | 3 | 3 | 1.124 | 1.124 |

**Table 5**
Comparison of evolutionary algorithm and complete enumeration (results output – Part 2).

| **Service level Dept. 1** | | **Service level Dept. 2** | | **Quality level Dept. 1** | | **Quality level Dept. 2** | | **Total cost** | | | **Run time (min)** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **EV** | **SA** | **EV** | **SA** | **EV** | **SA** | **EV** | **SA** | **EV** | **SA** | **% Difference** | **EV** | **SA** |
| 0.591 | 0.591 | 0.792 | 0.792 | 0.90 | 0.90 | 0.90 | 0.90 | 4150 | 4150 | 0.00 | 15 | > 180 |
| 0.771 | 0.771 | 0.758 | 0.758 | 0.90 | 0.90 | 0.90 | 0.90 | 4217 | 4198 | 0.45 | 15 | > 180 |
| 0.534 | 0.580 | 0.968 | 0.867 | 0.90 | 0.90 | 0.90 | 0.90 | 4236 | 4186 | 1.19 | 15 | > 180 |
| 0.758 | 0.758 | 0.771 | 0.771 | 0.90 | 0.90 | 0.90 | 0.90 | 4272 | 4234 | 0.90 | 15 | > 180 |
| 0.790 | 0.599 | 0.641 | 0.867 | 0.90 | 0.90 | 0.90 | 0.90 | 2922 | 2910 | 0.40 | 15 | > 180 |
| 0.752 | 0.752 | 0.808 | 0.808 | 0.90 | 0.90 | 0.90 | 0.90 | 2982 | 2944 | 1.29 | 15 | > 180 |
| 0.577 | 0.577 | 0.792 | 0.792 | 0.90 | 0.90 | 0.90 | 0.90 | 5492 | 5423 | 1.27 | 15 | > 180 |
| 0.751 | 0.751 | 0.825 | 0.825 | 0.90 | 0.90 | 0.90 | 0.90 | 5540 | 5509 | 0.56 | 15 | > 180 |

outputs from a staff mix perspective i.e. regular and cross-trained and also shows the expected shortage for each of the scenarios. Table 5 presents results on total cost and the percentage difference between the solutions generated by the EV and the global optimal solutions generated by the SA. Finally, Table 5 also indicates the approximate gains from a run time perspective when using the EV.

As can be noted from comparison of the SA and EV outputs in Tables 4 and 5, the evolutionary algorithm is able to generate accurate solutions within reasonable processing times when compared to the search algorithm. This is evident from the percentage difference in total cost results (Table 5), with the difference being less than 2% for all of the runs. Further, the department staff mix (regular and cross-trained) and expected temporary staffing (shortage) results are almost identical when comparing results from the EV and SA. The similarity is also noted with the service and quality levels achieved for each of the departments. These results thus both validate and provide confidence in the efficiency and quality of solution generated by the evolutionary algorithm.

## 4. Numeric results

In this section, we first focus on an empirical application of our algorithms via an illustrative example involving two hospital departments: the Emergency Department (ED) and the Surgical Department (OR). Secondly, we perform sensitivity analysis on the effect of cost parameters on chaining when considering a multi-department setup.

### *4.1. Two department hospital example*

In Section 3 we developed models to study and utilize the positive effects of cross-training for both two and multi-department setups. These models were motivated by the goal of contributing to the theoretical literature on cross-training, while still focusing on the primary objective of studying how cross-training via chaining could help to alleviate the nursing shortage. As discussed previously in Section 3, as chaining across more than two departments is unlikely and may actually be counterproductive,

in this section we focus our analysis on a two department chain. We do however note that there are reported exceptions wherein nurses have been trained to operate in multiple units in a hospital environment (see for example, http://www.stlouischildrens.org/health-care-professionals/nurses/pediatric-nursing-specialties/float-pool). However, we would make an important distinction, in that these often involve subunits within the same department. For example, at the children's hospital referenced above, the cross-trained units all provided pediatric intensive care, which involves operational challenges much different than that of a multi-department setup in which ER, OR, ICU, etc. are involved.

A number of optimizations were performed with a mix of variables, including quality and service levels, mean demands as well as maximum available staffing. For nursing salaries, reported ranges of salaries by experience level for the two departments, the ED and OR were used. The reported data included five levels based upon years of experience: $<1$ yr; 1–4 yrs; 5–9 yrs; 10–19 yrs and 20 yrs+ (AllNursingSchools, 2011; StudentDoc, 2011). For regular (non-cross-trained nurses), we considered three levels of experience, entry, mid-level and senior, each with differing salaries/costs as well as impacts on service quality. For salaries, we used the average of the $<1$ yr for our entry level category. For both mid and senior nurses, the middle and final two categories based upon years of experience were averaged. For cross-trained nurses, a 10% premium ($c^c$) of the overall average was used for all optimizations, while temporary costs ($c_t$) were taken as approximately double the average nursing salaries. The random variable demand for nurses in each department ($D_i$) was assumed to follow a Poisson distribution, with means of either 5 or 10, denoted as low (L) and high (H) demand respectively, and applied to each department. The quality weighting and minimum quality levels were set such that $Q_{min}$ was initially taken as the average weighting of the three nursing categories, and then varied by $\pm$half the difference between weights. Specifically, $\varepsilon_3=1$ as stated earlier, with $\varepsilon_2=0.9$ and $\varepsilon_1=0.8$, then the optimizations were run at $Q_{min}$ of 0.85, 0.9 and 0.95. For a fixed available pool of staff, the maximum available number of nurses was taken at levels of 7, 9, and 11, while the number of cross-trained nurses was allowed to vary up to the available mid and senior level staff. The minimum service level, $S_{min}$, was set at 50% or 75%.

The variables service level and maximum number of nurses were not used in the same optimization due to their potential conflict. Specifically, we studied two scenarios: one where there were no constraints on the maximum number of nurses available to a department and a second where such a constraint was imposed denoted as scenarios A and B respectively. For both these scenarios, we first assumed that there was no difference in quality of service offered by a cross-trained nurse when compared to that by a dedicated/regular nurse, i.e. $\varepsilon^c=1$ for both regular and cross-trained nurses. If the maximum number of nurses was not constrained (scenario A), a minimum service level ($S_{min}$) was specified. For all of the above, a second set of optimizations was then performed, with an identical mix of variables but no cross-training, to evaluate the impact of cross-train across a range of situations.

#### 4.1.1. Impact of cross-training on staffing

We first evaluated the staffing benefits of cross-training at various demand scenarios when subject to different quality and service requirements and constraints on available nursing staff. For scenario A as defined above, we evaluated the benefits of cross-training by analyzing the number of total nurses required in both departments to achieve the minimum service level constraint. For scenario B, as the maximum number of nurses allowable was constrained, we determined that the service level achieved in each of the departments was the appropriate metric.

**Table 6**
Comparative staffing levels.

| | L,H (5,10) | H,L (10,5) | L,L (5,5) | H,H (10,10) |
|---|---|---|---|---|
| Cross-training | 16 | 16 | 11 | 22 |
| No Cross-training | 18 | 18 | 12 | 24 |

**Table 7**
Comparison of service levels (ED).

| | L,H (5,10) | H,L (10,5) | L,L (5,5) | H,H (10,10) |
|---|---|---|---|---|
| Cross-training | 0.797 | 0.580 | 0.641 | 0.525 |
| No Cross-training | 0.616 | 0.458 | 0.616 | 0.458 |

*4.1.1.1. Scenario A.* Under scenario A, we found that when using cross-training in the scenarios tested, the total number of nurses required was less than or equal that without cross-training. Table 6 shows the results for a service level of 75% and the minimum quality level set at 0.90. As would be expected, higher reductions in required staffing were observed in at least one of the departments with higher demand levels. These results in general validate the strategy of cross-training in optimally using the scarce nurse resources and thereby partially alleviating the nurse shortage crisis while maintaining prescribed service levels.

*4.1.1.2. Scenario B.* Under scenario B, we observed that with cross-training, the service level achieved in both departments was generally higher than that in scenarios without cross-training. This was true for most scenarios with few exceptions. Within the exceptional cases, the total overall cost savings and total service level across both departments was higher than that without cross-training explaining the apparent discrepancy. As above, we present results for selected scenarios, specifically those that had quality level set at 0.90 and maximum number of nurses as 9. Tables 7 and 8 present results for service levels achieved in the ED and OR respectively at various demand scenarios with $n_{i,max}=9$ and $Q_{min}=0.90$. In general, service level impacts are highest under a H,L type demand pattern, as the cross-trained nurses in the low demand unit are more likely to be available to the other department. Similarly it was observed that the impact of cross-training on service levels was higher when the constraints imposed on available nurses was lower, i.e. $n_{i,max}=7$. Thus given a fixed resource such as the number of nurses within a department, cross-training can be employed to optimally utilize such a scarce resource to provide for improved service levels. These results further validate the use of cross-training to mitigate the impacts of nursing shortages.

Given the above benefits from a staffing level or service level perspective, it is unlikely that either would be sufficient without considering costs. It would be particularly useful to a decision maker or a health care manager if the above benefits were also achieved at a reduced cost, with the cost savings providing further justification for implementing cross-training. The next subsection therefore focuses on the impact of cross-training on costs and is able to demonstrate that this strategy is beneficial from a cost perspective as well.

#### 4.1.2. Impact of cross-training on costs

Overall, costs savings with cross-training ranged for scenario A ranged from 3.2% to 6.0%, while for scenario B ranged from a low

**Table 8**
Comparison of service levels (OR).

| | L,H (5,10) | H,L (10,5) | L,L (5,5) | H,H (10,10) |
|---|---|---|---|---|
| Cross-training | 0.867 | 0.610 | 0.790 | 0.525 |
| No Cross-training | 0.616 | 0.458 | 0.616 | 0.458 |

**Table 9**
Percentage cost savings with cross-training.

| | L,H (5,10) | H,L (10,5) | L,L (5,5) | H,H (10,10) |
|---|---|---|---|---|
| Scenario A | 5.3 | 5.2 | 5.4 | 5.5 |
| Scenario B | 3.9 | 5.3 | 4.4 | 2.9 |

of 0.7% to 9.2%. The average was similar for both scenarios, being 4.7% and 4.4%. Thus we see more consistent cost savings under scenario A, given the flexibility to determine the staffing level unconstrained by an upper bound. In general, cross-training savings were higher when demand in one department was low, with the minimum savings realized when both demands were high. The added value of cross-training in which at least one of the two department experience low demand is due to the higher probability of cross-trained nurses being available under low demand to assist in the other department. The cost savings as a percentage over no cross-training for both scenarios are presented in Table 9. Consistent with the results given in Section 4.1, the results are presented for a quality level of 0.9, with $S_{min}=75\%$ for scenario A and $n_{i,max}=9$ for scenario B.

Under scenario A, the results are largely unaffected by $Q_{min}$ and see a modest increase when $S_{min}$ is raised from 50% to 75%. This could be attributed to the increased overall staffing levels and associated costs with the higher service levels, thus enabling increased cost savings through cross-training. As noted above, a much larger range is observed under a hard constraint on the maximum number of nurses (scenario B). In general, savings increase as the number of available nurses or the quality levels are reduced. However, it should be noted that both the minimum and maximum savings occur when $n_{i,max}=7$. Specifically the minimum savings occurs with $n_{i,max}=7$ and a H,H demand scenario and $Q=0.95$, while the highest savings occurred with a H,L demand scenario and $Q=0.85$. This discrepancy occurs as with demand in both departments being highly relative to available staffing, the impact of cross-training is reduced as cross-trained nurses are unlikely to be available to their cross-trained department given the high probability of being required in their home department.

Thus, over all scenarios tested cost savings are realized, in addition to the staffing benefits described in Section 4.1.1. Further, these savings tend to increase when tighter constraints on available nursing staff exist. Finally, it should also be noted that these results are actually somewhat conservative as the impact of absenteeism is not considered. As determined by Inman et al. (2005) and others, the benefits of cross-training increase with higher rates of absenteeism.

### 4.1.3. Impact of quality of cross-trained staff

In Sections 4.1.1 and 4.1.2, we assumed that cross-trained staff and regular nurses provide the same quality of service for a given level of experience. However, given findings in the extant literature for non-health care problem settings that indicate that quality may be adversely affected by cross-training, this assumption may not always be true in a hospital setting either. Retaining all the settings as those applied in prior sections, we evaluated scenario A with $\varepsilon^c$ set at 0.7, 0.8 and 0.9 to differentiate quality of care between regular and cross-trained nurses.

**Table 10**
Impact of cross-training quality on staffing levels.

| | L,H (5,10) | H,L (10,5) | L,L (5,5) | H,H (10,10) |
|---|---|---|---|---|
| Cross-training[a] | 16, 17, 17, 18 | 16, 17, 17, 18 | 11, 11 11 12 | 22, 22 22, 23 |
| No cross-training | 18 | 18 | 12 | 24 |

[a] Quality weightings ($\varepsilon^c$) of 1, 0.9, 0.8, and 0.7.

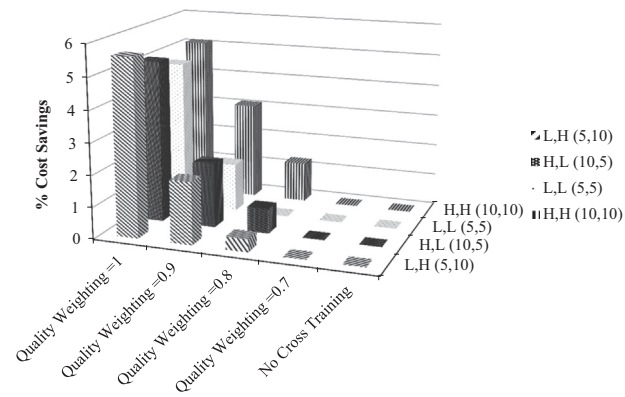


**Fig. 1.** Impact of quality of cross-trained staff on cost savings.

**Table 11**
Service levels with and without cross-training.

| | L,H (5,10) | H,L (10,5) | L,L (5,5) | H,H (10,10) |
|---|---|---|---|---|
| Cross-training | 0.868 | 0.371 | 0.868 | 0.502 |
| No Cross-training | 0.642 | 0.478 | 0.642 | 0.478 |

**Table 12**
Percent cost savings under a maximum staffing constraint.

| | L,H (5,10) | H,L (10,5) | L,L (5,5) | H,H (10,10) |
|---|---|---|---|---|
| Scenario B | 3.7 | 3.7 | 4.4 | 3.4 |

We found that cross-training was beneficial only when the quality weighting of cross-trained nurses, when compared to dedicated nurses, was above 0.7. We present the results on both the total number of nurses required (Table 10) and costs of providing service for all four demand scenarios and quality weighting scenarios (Fig. 1) to demonstrate this finding. This indicates that steps need to be taken to ensure that cross-trained staff meets certain quality requirements, or are evaluated at regular intervals, to ensure that the desired performance levels expected by institutions that employ a cross-training strategy are met.

### 4.1.4. Other demand distributions

In this subsection, our aim is to demonstrate the ability of the model to handle other demand distributions. We present results for a few select scenarios using a gamma distribution with an equivalent mean and variance to the Poisson distribution for demand in the previous sections, with the quality level set to 0.9 and a maximum number of nurses of 9. Table 11 and 12 present the effect of cross-training in terms of service level achieved and cost savings when the maximum number of nurses is fixed (scenario B). As can be seen, the findings are consistent with those

presented in Sections 4.1.1 and 4.1.2, Tables 6 and 7, when using the Poisson distribution, both from a service level and a cost perspective. This demonstrates that regardless of the distribution required to describe the nursing demand, we can generate equivalent results with respect to the impact in the allocation of nursing resources and addressing nursing shortage crisis.

### 4.2. Multi-department setup

In the final set of results, we apply the expected total shortage models within a multi-department environment to study the sensitivity of the optimal (minimum cost) staffing strategy to the cost of hiring regular ($c_r$), cross-trained ($c_c$) and temporary staff ($c_t$). Specifically, we present a qualitative analysis of the impact of chaining on expected shortage and service levels. We define the propensity to chain as the overall average of the proportion of staff that is cross-trained across departments. For example, if one department has 2 out of 5 staff that are cross-trained, with no cross-training occurring in the other two departments, then the propensity to cross-train (denoted as $p$) would be $(2/5+0/5+0/5)/3=0.13$. By using various representative values of the costs given above we define a series of cost ratios, those being $c_t/c_c$, $c_t/c_c$ and $c_t/c_c$, and obtain a number of fundamental relationships, which are presented in Fig. 2.

The key relationships depicted in Fig. 2 are as follows: (a) as the cost of a temporary nurse increases when compared to that of a cross-trained nurse, the propensity to chain in an organization increases as well, as the benefits from cross-training in terms of overall costs makes the use of temporary nursing staff less attractive, even on a temporary basis, and vice versa; (b) as the cost of a temporary nurse increases when compared to that of a regular nurse, the propensity to chain increases as shown in the figure, as long as cross-training costs are fixed relative to the cost of a regular nurse, and vice-versa. This is related to the first result, as the use of temporary staff are less economically viable compared to cross-training; and finally (c) as the cost of a cross-trained nurse increases when compared to that of a regular nurse, the propensity to chain reduces and vice versa. Here, cross-training is not beneficial economically, and a hospital would rather obtain services from a temporary staffing service to cover shortages in a given department. These results, in combination, point to a possibility of mixed responses or trends if market pressures on salaries were to result in simultaneous changes in both temporary and cross-training costs relative to the cost of a regular nurse. For example, if an increase in temporary staffing costs were to also put upward pressure on the salaries of cross-trained staff, depending upon the relative increase in both salaries compared to that of regular nursing staff, the increasing temporary costs could decrease the propensity to cross-train, a reversal of the trend noted in Fig. 2b.

Fig. 3 depicts the impact of the chaining on the expected total shortage and average service levels in a multi-department setup. With everything else remaining constant, as the propensity to chain increases, it has, as expected, a positive impact on the expected total shortage and expected service levels, with expected shortages decreasing and overall service levels increasing.

The results presented in Figs. 2 and 3 hold regardless of the number of departments involved given the chaining method incorporated in this study. Further, the findings highlight the need to consider chaining when making resource allocation decisions especially when faced with tight budgetary constraints. However, decision makers do need to exercise caution with regard to impact of chaining or any cross-training on the operational efficiency, particularly the potential to affect quality of care and service levels as reported in the extant literature.

Another consideration when implementing a cross-training chain involving multiple departments is the order of the departments in the chain. That is, which department should precede another so that

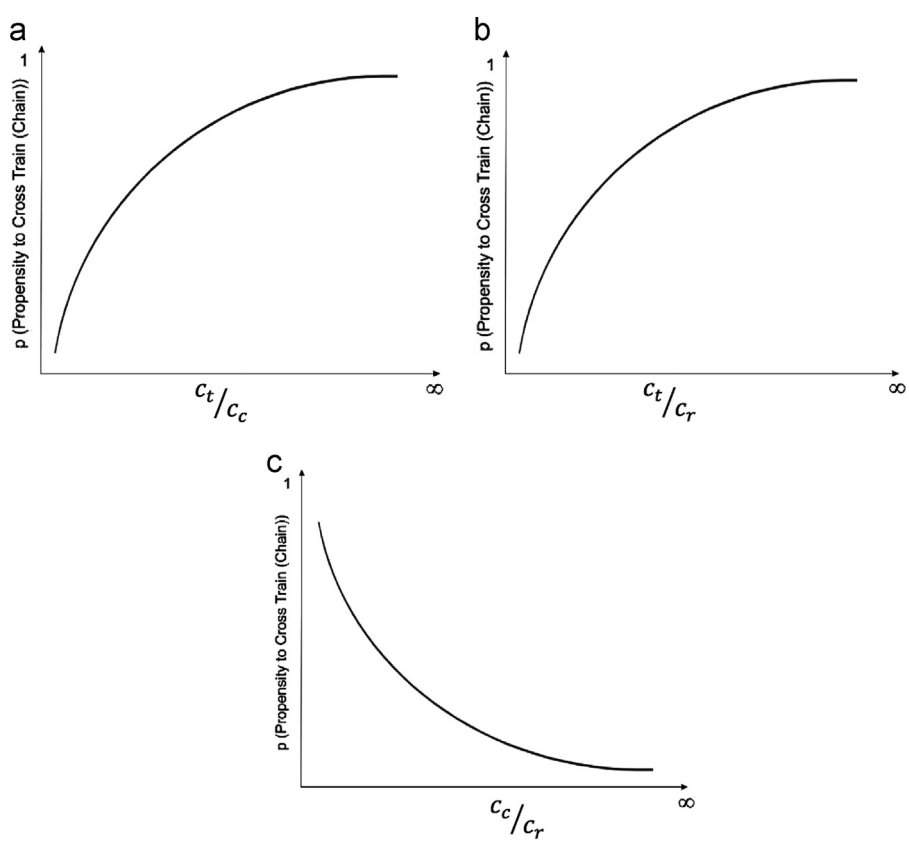


**Fig. 2.** Sensitivity analysis – multi-department scenario.

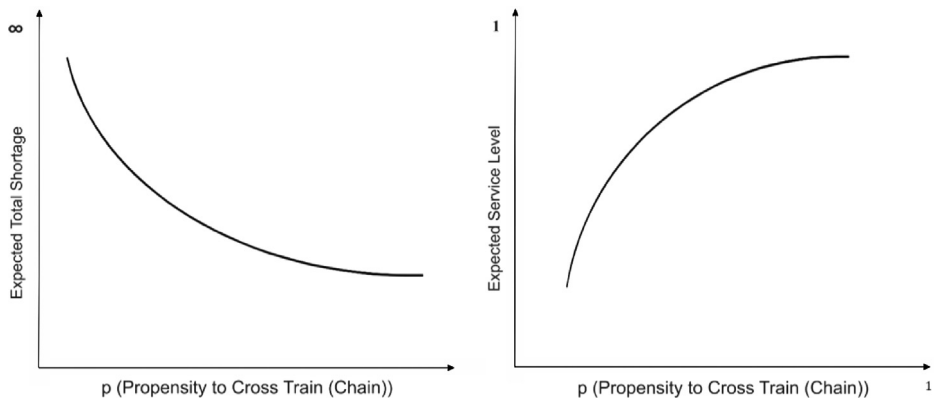


**Fig. 3.** Impact of chaining on shortage and service level – multi-department scenario.

particular department provides cross-trained nurses to the next department in the chain. There are two specific issues related to the order of chaining. The first is strategic, in terms of skill sets available/required in both the home and cross-trained departments, as closely matching skill sets could decrease the likelihood of reduced quality resulting from cross-training. The second is related to the demand levels in various departments as well as the number of nurses assigned to that department. As noted above in Section 4.1.2, cost savings resulting from cross-training are affected by both demand and available staff, with increased savings in paired departments of high/low demand patterns. Thus strategically ordering the chain correctly results in higher overall cost effectiveness. Thus an important application of the multi-departmental model above is to allow administrators to test various scenarios, given demand and staffing levels, to determine the most effective chaining strategies including the optimal ordering across a group of departments.

## 5. Conclusions and future research

As part of this research endeavor, we developed optimization models to maximize the benefits of cross-training policies for both two department and a multi-department setups, considering the costs of hiring temporary nurses and constraints such as minimum quality and service levels that organizations aim to achieve. Though implementation of any cross-training strategy must consider available and required skill sets, as well as broader policy issues in terms of the integration of nursing resources across multiple departments, the above models allow administrators to evaluate the economic, quality and service impacts as part of any overall cross-training strategy. We developed a heuristic solution method to generate reliable solutions in reasonable run times and validated its effectiveness by comparing the heuristic results with those generated by a complete enumeration search algorithm. Further, we are able to demonstrate the benefits of cross-training in term of costs and required nursing resources to meet the patient demand by taking advantage of cross-training strategies, in particular chaining, via a case study focusing on the emergency department and surgical department using real world data.

One limitation in the current models is we do not account for the effect of absenteeism on the benefits resulting from cross-training policies. We plan to investigate this issue in the future extensions of our research effort. We also did not consider the benefits from other possible variations of cross-training policies such as full cross-training on the nurse shortage problem. However, several other problem settings such as within manufacturing, the military, and various service industries, where customer demand under consideration is not as sensitive as patient care, etc., might extract higher benefits from full cross-training policies. We plan to consider this aspect in our future research. We also have not considered the impacts of constraints such as staff retirement age when optimally determining the number of cross-trained nurses. For example, cross-training may not pay off for individual staff member that do not have sufficient remaining years of service to justify the investment.

## Appendix A. Expected shortage for department *i* – two department case

Given the number of cross-trained nurses in department $i-1$ as $n^c_{i-1}$, then to obtain the probability of a shortage $s$ in department $i$ we consider all possible scenarios for a specific shortage to occur:

(1) With a demand in department $i$ of $n_i+s$, with no cross-trained nurses available from $i-1$, resulting in

$$P(D_i=n_i+s)P(D_{i-1}\geq n_{i-1}) \tag{A1}$$

(2) With a demand in department $i$ of $n_i+s+T_{i-1}$, where $1\leq T_{i-1}\leq n_{i-1}-1$ and exactly $T_{i-1}$ cross-trained nurses available from $i-1$, resulting in

$$\sum_{T_{i-1}=1}^{n^c_{i-1}-1} P(D_{i-1}=n_{i-1}-T_{i-1})P(D_i=n_i+s+T_{i-1}) \tag{A2}$$

(3) For a demand of $s+n^c_{i-1}$ in $i$ and all cross-trained nurses available from $i-1$, resulting in

$$P(D_{i-1}\leq n_{i-1}-n^c_{i-1})P(D_i=n_i+s+n^c_{i-1}) \tag{A3}$$

Referring to Eq. (17), wherein the probability of a shortage 's' is department $i$ is given as follows:

$$P(\text{shortage department } i=s)=P(D_i=n_i+s)$$
$$+\sum_{T_{i-1}=1}^{n^c_{i-1}} P(D_{i-1}\leq n_{i-1}-T_{i-1})[P(D_i=n_i+s+T_{i-1})-P(D_i=n_i+s+T_{i-1}-1)],$$

we demonstrate its equivalence to the three shortage components as presented in (A1)–(A3).

Starting at $T_{i-1}=1$, we first expand the above summation term as

$$P(D_{i-1}\leq n_{i-1}-1)P(D_i=n_i+s+1)-P(D_{i-1}\leq n_{i-1}-1)P(D_i=n_i+s) \tag{A4}$$

And replacing $P(D_{i-1}\leq n_{i-1}-1)$in the second term with $1-P(D_{i-1}\geq n_{i-1})$ results in

$$P(D_{i-1}\leq n_{i-1}-1)P(D_i=n_i+s+1)-P(D_i=n_i+s)$$
$$+\boldsymbol{P(D_i=n_i+s)P(D_{i-1}\geq n_{i-1})} \tag{A5}$$

The last term in Eq. (A5) in bold above is first shortage component as shown in Eq. (A1) above.

Further, the second term, $-P(D_i=n_i+s)$ cancels the first term given in Eq. (17), i.e. $P(D_i=n_i+s)$, leaving $P(D_{i-1}\le n_{i-1}-1)P(D_i=n_i+s+1)$.

This term can further be rewritten as

$$P(D_{i-1}\le n_{i-1}-2)P(D_i=n_i+s+1)+P(D_{i-1}=n_{i-1}-1)P(D_i=n_i+s+1) \tag{A6}$$

Next, taking $T_{i-1}=2$, we again expand the summation term as follows:

$$P(D_{i-1}\le n_{i-1}-2)P(D_i=n_i+s+2)-P(D_{i-1}\le n_{i-1}-2)P(D_i=n_i+s+1) \tag{A7}$$

where the second (negative) term cancels the first term in (A2), leaving

$$P(D_{i-1}\le n_{i-1}-2)P(D_i=n_i+s+2)+P(D_{i-1}=n_{i-1}-1)P(D_i=n_i+s+1) \tag{A8}$$

which again can be rewritten as

$$P(D_{i-1}\le n_{i-1}-3)P(D_i=n_i+s+2)+P(D_{i-1}=n_{i-1}-2)P(D_i=n_i+s+2)$$
$$+P(D_{i-1}=n_{i-1}-1)P(D_i=n_i+s+1) \tag{A9}$$

Continuing in the identical fashion from $T_{i-1}=3, 4, \ldots n^c_{i-1}$, and canceling successive positive and negative terms results in

$$\begin{aligned}&\mathbf{P(D_{i-1}\le n_{i-1}-n^c_{i-1})P(D_i=n_i+s+n^c_{i-1})}\\&+P(D_{i-1}=n_{i-1}-n^c_{i-1}+1)P(D_i=n_i+s+n^c_{i-1}-1)\\&+\cdots+P(D_{i-1}=n_{i-1}-2)P(D_i=n_i+s+2)\\&+P(D_{i-1}=n_{i-1}-1)P(D_i=n_i+s+1)\end{aligned} \tag{A10}$$

Now, the first term in bold above is the third shortage component as demonstrated in Eq. (A3) above.

Finally, we collect the remaining individual product terms from (A10), which can be written as

$$\sum_{T_{i-1}=1}^{n^c_{i-1}-1} P(D_{i-1}=n_{i-1}-T_{i-1})P(D_i=n_i+s+T_{i-1}) \tag{A11}$$

which is the final (second) shortage component as shown in Eq. (A2) above.

## Appendix B. Expected total shortage – two department case

Given the number of cross-trained nurses in department $i$ as $n^c_i$ and department $j$ as $n^c_j$, then to obtain the expected total shortage of $s$ across both departments requires

$$E[\text{total shortage}]=\sum_{s=1}^{\infty} P(\text{total shortage}=s)s$$

To determine the probability of a shortage of s across departments, we simply consider all probabilities across departments that result in a net shortage of 's' given $n^c_i$ and $n^c_j$.

Thus, starting with an overall shortage of $s=1$, we get

$$\begin{aligned}&\boldsymbol{P(D_i=n_i+(n^c_j-1)+1)P(D_j=n_j-(n^c_j-1))}\\&+P(D_i=n_i+(n^c_j-2)+1)P(D_j=n_j-(n^c_j-2))\\&+\cdots+P(D_i=n_i+1)P(D_j=n_j)+P(D_i=n_i)P(D_j=n_j+1)+\cdots\\&+P(D_i=n_i-(n^c_i-2))P(D_j=n_j+(n^c_i-2)+1)\\&+P(D_i=n_i-(n^c_i-1))P(D_j=n_j+(n^c_i-1)+1)\\&+P(D_i=n_i+n^c_j+1)P(D_j\le n_j-n^c_j)+P(D_i\le n_i-n^c_i)P(D_j=n_j+n^c_i+1)\end{aligned}$$

Similarly for $s=2$,

$$\begin{aligned}&P(D_i=n_i+(n^c_j-1)+2)P(D_j=n_j-(n^c_j-1))+P(D_i=n_i+(n^c_j-2)+2)\cdot P(D_j=n_j-(n^c_j-2))\\&+\ldots+P(D_i=n_i+2)P(D_j=n_j)+P(D_i=n_i+1)P(D_j=n_j+1)+P(D_i=n_i)P(D_j=n_j+2)\\&+\ldots+P(D_i=n_i-(n^c_i-2))P(D_j=n_j+(n^c_i-2)+2)\\&+P(D_i=n_i-(n^c_i-1))P(D_j=n_j+(n^c_i-1)+2)\\&+P(D_i=n_i+n^c_j+2)P(D_j\le n_j-n^c_j)+P(D_i\le n_i-n^c_i)P(D_j=n_j+n^c_i+2)\end{aligned}$$

with the primary difference being the inclusion of the term: $P(D_i=n_i+1)P(D_j=n_j+1)$

In general, for $s=1$ to $\infty$, this can be expressed as

$$\sum_{z=1}^{n^c_i+n^c_j+s-1} P(D_i=n_i-n^c_i+z)P(D_j=n_j+n^c_i-z+s) \tag{B1}$$

$$+P(D_i=n_i+n^c_j+s)P(D_j\le n_j-n^c_j)+P(D_i\le n_i-n^c_i)P(D_j=n_j+n^c_i+s)$$

where the first group of terms are replaced with the above summation, and the expected shortage given as

$$\begin{aligned}&E[\text{total shortage}]=\textstyle\sum_{s=1}^{\infty}s[\sum_{z=1}^{n^c_i+n^c_j+s-1}P(D_i=n_i-n^c_i+z)P(D_j=n_j+n^c_i-z+s)\\&P(D_i=n_i+n^c_j+s)P(D_j\le n_j-n^c_j)+P(D_i\le n_i-n^c_i)P(D_j=n_j+n^c_i+s)]\end{aligned} \tag{B2}$$

which can be separated into the individual components to give

$$\sum_{s=1}^{\infty} s\left[\sum_{z=1}^{n^c_i+n^c_j+s-1} P(D_i=n_i-n^c_i+z)P(D_j=n_j+n^c_i-z+s)\right]+ \tag{B3}$$

$$\sum_{s=1}^{\infty} s[P(D_i=n_i+n^c_j+s)P(D_j\le n_j-n^c_j)]+ \tag{B4}$$

$$\sum_{s=1}^{\infty} s[P(D_i\le n_i-n^c_i)P(D_j=n_j+n^c_i+s)] \tag{B5}$$

Taking (B3) and starting with department $i$ we collect terms starting with $P(D_i=n_i)$, $P(D_i=n_i+1)$, $P(D_i=n_i+2),\ldots$, we can take each successive term out of the summation resulting in

$$\begin{aligned}&P(D_i=n_i)\sum_{s=1}^{\infty}s[P(D_j=n_j+s)]+P(D_i=n_i+1)\sum_{s=1}^{\infty}s[P(D_j=n_j+s)]\\&\quad+P(D_i=n_i+2)\sum_{s=1}^{\infty}s[P(D_j=n_j+s)]+\cdots\end{aligned}$$

or equivalently as

$$\begin{aligned}&[P(D_i=n_i)+P(D_i=n_i+1)+P(D_i=n_i+2)+\cdots]\sum_{s=1}^{\infty}s[P(D_j=n_j+s)]\\&=\sum_{x=0}^{\infty}P(D_i=n_i+x)\sum_{s=1}^{\infty}s[P(D_j=n_j+s)]\\&=P(D_i\ge n_i)\sum_{s=1}^{\infty}s[P(D_j=n_j+s)]\end{aligned} \tag{B6}$$

An equivalent expression for department $j$ results in

$$\begin{aligned}&[P(D_j=n_j)+P(D_j=n_j+1)+P(D_j=n_j+2)+\cdots]\sum_{s=1}^{\infty}s[P(D_i=n_i+s)]\\&=\sum_{x=0}^{\infty}P(D_j=n_j+x)\sum_{s=1}^{\infty}s[P(D_i=n_i+s)]\\&=P(D_j\ge n_j)\sum_{s=1}^{\infty}s[P(D_i=n_i+s)]\end{aligned} \tag{B7}$$

Finally, collecting the remaining terms from (B3), which are composed of intermediate terms that result in a total shortage of $s$, i.e. from $P(D_i=n_i-(n^c_i+1))P(D_j=n_j+(n^c_i+1)+s)$ to $P(D_i=n_i+(n^c_j+1)+s)P(D_j=n_j-(n^c_j+1))$, which may be rewritten as

$$\sum_{s=1}^{\infty} s\left[\sum_{x=1}^{n^c_i-1} P(D_i=n_i-x)P(D_j=n_j+x+s)\right] \tag{B8}$$

and

$$\sum_{s=1}^{\infty} s\left[\sum_{y=1}^{n_j^c-1} P(D_i=n_i+y+s)P(D_j=n_j-y)\right] \tag{B9}$$

Last, we regroup the various equations, specifically combining (B4), (B7) and (B9), and (B5), (B6) and (B8), to get

$$\sum_{s=1}^{\infty} s\left[\begin{array}{c} P(D_i=n_i+n_j^c+s)P(D_j\le n_j-n_j^c)+ \\ P(D_j\ge n_j)[P(D_i=n_i+s)]+ \\ \sum_{y=1}^{n_j^c-1} P(D_i=n_i+y+s)P(D_j=n_j-y) \end{array}\right] = \sum_{s=1}^{\infty} s[P(\text{shortage}=s \text{ in dept. } i)] \tag{B10}$$

and

$$\sum_{s=1}^{\infty} s\left[\begin{array}{c} P(D_i\le n_i-n_i^c)P(D_j=n_j+n_i^c+s)+ \\ P(D_j\ge n_j)[P(D_i=n_i+s)]+ \\ \sum_{x=1}^{n_i^c-1} P(D_i=n_i-x)P(D_j=n_j+x+s) \end{array}\right] = \sum_{s=1}^{\infty} s[P(\text{shortage}=s \text{ in dept. } j)] \tag{B11}$$

Thus the total expected shortage across both departments can be expressed as

$$E[\text{total shortage}] = \sum_{i=1}^{2}\sum_{s=1}^{\infty} P(\text{shortage in dept } i=s)s$$

as given by Eq. (21).

**Complete Enumeration Search Algorithm**

**Input:**

$D_i$ - {demand in department i}
$c_{temp}$ - {cost of temp nurse}
$c_{ik}$ - {cost in department i for a nurse at experience level k}
$c_i^c$ - {cost of cross-training a nurse in department i}
$s_i^s$= {set service level in department i}
$q_i^s$= {set quality level in department i}
$qw_k$= { quality weight for nurse of experience k}
$n_i^{min}$= {lower bound on number of nurses in department i}
$n_i^{max}$= {upper bound on number of nurses in department i}
$c_c$= {current cost}
$n_i$= {current total number of nurses in department i}
$n_{ic}$= {current number of cross-trained nurses in department i}
$n_{ik}$= {current number of nurses in department i of experience k}
i={1,2}
k ={1,2,3}
M=Huge Number

**Subroutines:**

***Determine service()*** – calculates service level for a particular nurse mix in each department
***Determine quality()*** - calculates quality level for a particular nurse mix in each department
***Determine cost()*** – calculates total cost for a particular nurse mix across departments

**Output:**

$n_i^{opt}$ = {optimal number of total nurses in department i}
$n_{ik}^{opt}$ = {optimal number of nurses in department i at experience level k}
$n_{ic}^{opt}$ ={ optimal number of cross-trained nurses in department i}
$s_i$= {service level in department i}
$q_i$= {quality level in department i}
$C_T$ = Total cost

**Process:**

```
Initialize {n_i1=n_i^min; n_i2=0; n_i3=0; n_ic=0; c_c = M }
for i=1 to 2 do
    for n_i=n_i^min to n_i^max
        for n_ic=0 to n_i2+n_i3
            Determine service()
            if s_i≥ s_i^s then
            Determine quality()
                if q_i>=q_i^s and s_i>=s_i^s then
                Determine cost()
                    if C_T < c_c then
                    n_ik^opt=n_ik; n_ic^opt=n_ic ; c_c = C_T
                    end if
                end if
            end if
        end for
    end for
end for
return {n_i^opt, n_ik^opt, n_ic^opt, C_T}
```

**Fig. C1.** Pseudo code for complete enumeration search algorithm.

## Appendix C. Search algorithm (SA)

In this section, we discuss a complete enumeration algorithm (Fig. C.1) designed to serve as a metric to evaluate the quality of the proposed heuristic, by comparing the global optimal solution it generates with those generated by the evolutionary algorithm. The algorithm enumerates all staffing levels combinations of regular, including all experience levels, and cross-trained nurses to determine the minimum cost while satisfying the service and quality goals set by the two interacting departments. To bound the search space, an upper bound was established as approximately two standard deviations above the mean demand, rounded to the next integer value, resulting in service levels in each department in excess of 90% without cross-training. The lower bound was then set to the minimum number of total nurses required to meet the required service level for each department, given that the other department had its maximum number of nurses all of which were cross-trained.

The following is an explanation of the subroutines in our enumeration algorithm. ***Determine service***() calculates the expected service level in each department, given the specific demand and number of regular and cross-trained nurses in both departments. The respective expected service levels are then compared to the minimum required service level. Similarly, the ***Determine quality***() subroutine calculates the total quality using a weighted quality approach for a specific number of regular nurses of different experience levels. Only enumeration values that met both the minimum service and quality requirements were considered a feasible solution set. To determine the final optimal solution, the costs associated with each feasible solution were calculated. This calculation within the ***Determine cost***() subroutine based upon Eq. (6) and the expected shortage Eqs. (13) and (17). As each cost is estimated, it is compared with the last best solution, with that having the minimum cost retained as the current optimal solution. This procedure is repeated for the entire solution space resulting in a global optimal solution. The entire algorithm was run on an Intel Processor, 2.8 GHz with 3.83 GB Ram (see Fig. C1).

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