Designing for Economies of Scale vs. Economies of Focus in Hospital Departments

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ABSTRACT

Subject/Research problem

Hospitals traditionally segregate resources into centralized functional departments such as diagnostic departments, ambulatory care centres, and nursing wards. In recent years this organizational model has been challenged by the idea that higher quality of care and efficiency in service delivery can be achieved when services are organized around patient groups. Examples are specialized clinics for breast cancer patients and clinical pathways for diabetes patients. Hospitals are struggling with the question whether to become more centralized to achieve economies of scale or more decentralized to achieve economies of focus. In this paper service and patient group characteristics are examined to determine conditions where a centralized model is more efficient and conversely where a decentralized model is more efficient.

Research Question

When organizing hospital capacity what service and patient group characteristics indicate efficiency can be gained through economies of scale vs. economies of focus?

Approach

Using quantitative Queueing Theory and Simulation models the performance of centralized and decentralized hospital clinics is compared. This is done for a variety of services and patient groups.

Result

The study results in a model measuring the tradeoffs between economies of scale and economies of focus. From this model management guidelines are derived.

Application

The general results support strategic planning for a new facility at the Netherlands Cancer Institute - Antoni van Leeuwenhoek Hospital. A model developed during this research is also applied in the Chemotherapy Department of the same hospital.

1. INTRODUCTION

Health care facilities are under mounting pressure to both improve the quality of care and decrease costs by becoming more efficient. Efficiently organizing the delivery of care is one way to decrease cost and improve performance. At a national level this is achieved by aggregating services into large general hospitals in major urban centres, thereby gaining efficiencies through economies of scale (EOS). At the same time, some hospitals are becoming more specialized by offering a more limited range of services aiming to breed competence and improve service rates (Leung, 2000). Similar strategies are also being considered within the organizational level of hospitals, where management struggles with the decision to become more centralized to achieve EOS or more decentralized to achieve economies of focus (EOF). In this paper service and patient group characteristics are examined to determine which model is more efficient in which setting. The majority of the algebraic computations is excluded from the text but is available in an extended version of this paper (Vanberkel *et al.*, 2009b).

2. PRINCIPLES OF POOLING AND FOCUS

The pooling principle, as described in Cattani and Schmidt (2005), states that the "pooling of customer demands, along with pooling of the resources used to fill those demands, may yield operational improvements." The intuition for this principle is as follows. Consider the situation in the unpooled setting, when a customer is waiting in one queue while a server for a different queue is free. Had the system been pooled in this situation, the waiting patients could have been served by the idle server, and thus experience a shorter waiting time. Statistically, the advantage of pooling is credited to the reduction in variability due to the portfolio effect (Hopp and Spearman, 2001). This is easily demonstrated for cases where the characteristics of the unpooled services are identical (see Joustra *et al.*, 2009, Ata and van Mieghem, 2009).

This gain in efficiency due to pooling is a form of EOS and is the reason many hospitals organized resources into centralized functional departments. It implies that a centralized (pooled) clinic that serves all patient types will achieve shorter waiting times than a number of decentralized (unpooled) clinics. However, pooling is not always of benefit. There can be situations where the pooling of customers actually adds variability to the system thus offsetting any efficiency gains (van Dijk and van der Sluis, 2009). Further when the target performances of the customer types differ, then it may be more efficient to use dedicated capacity i.e. unpooled capacity (Joustra *et al.*, 2009). And finally, in the pooled case all servers must be flexible and able to accommodate all demand. This flexibility may actually cause inefficiencies as servers cannot focus on a single customer type. Hence pooling achieves EOS at the expense of EOF.

The principle of focus advocates for departments to limit the range of services they offer in order to reduce complexity and allow the department to concentrate on doing fewer things more efficiently. This philosophy has been the basis for operating modern manufacturing plants which are often referred to as focused factories. Skinner (1985) argues that focus, simplicity and repetition in manufacturing breeds competence. The gain in efficiency due to focus is referred to in this paper as EOF.

To exploit the principle of focus in health care, it is suggested that hospitals aggregate patients with similar diagnoses together into dedicated departments (Hyer et al., 2009). For example the principle of focus recommends that hospitals eliminate a centralized phlebotomy department and instead have phlebotomy services located in or near diagnosis based care department. Locating all the patient services in one department or in one area reduces the complexity of the process and allows care givers to oversee the complete care process from start to finish.

Pooling resources is offered as a potential method to improve a systems performance without adding additional resources. Interestingly, the principle of focus in hospitals implies the same. In this paper we aim to enhance understanding of these seemingly contradictory view points.

3. MODELLING

To evaluate the tradeoff between EOS and EOF we use operational research models to compare two ambulatory clinic setups. The first setup pools all resources together into a single department which treats all patients. This setup is analogous to the centralized functional department traditionally used in hospitals. The second setup exploits EOF and consists of two departments each treating a different patient population. We represent all of the department resources by consultation rooms and assume staffing and equipment are divided proportionally with the rooms. Patient access time to the clinic is used as the measure of system performance. An example of the two setups is displayed in Figure 1.

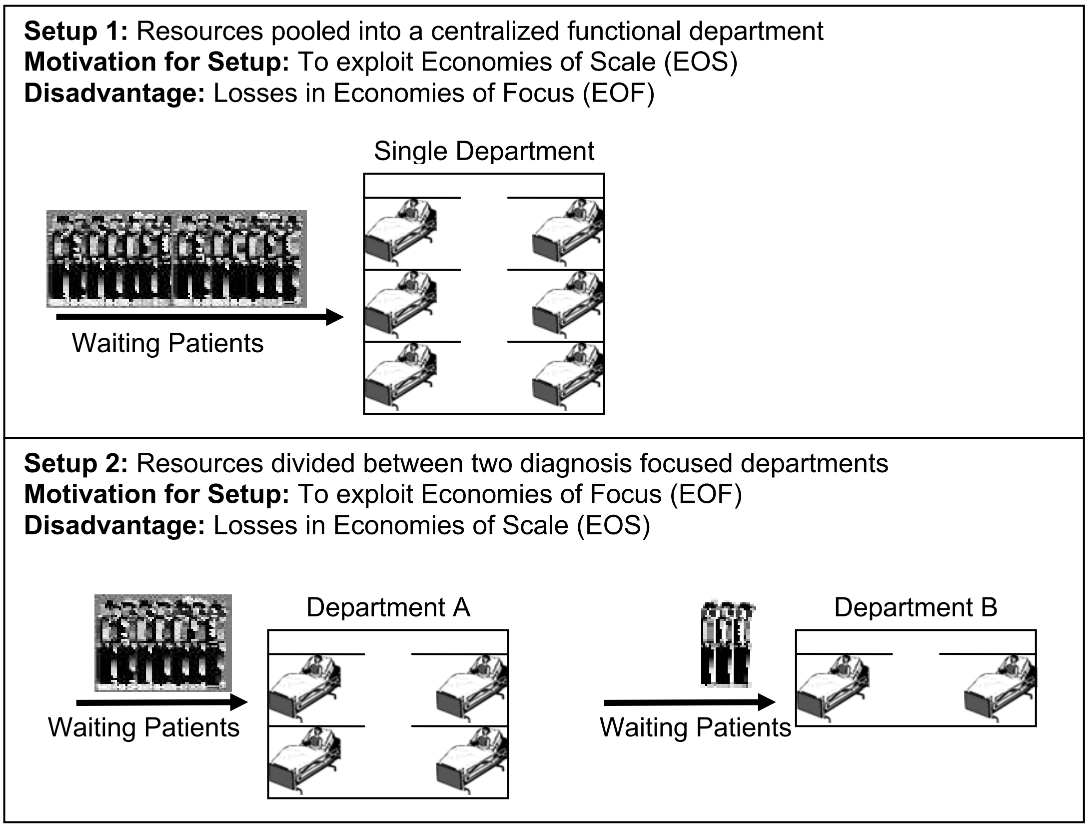

Figure 1: Two Clinic Setups Considered in the paper

To evaluate the performance of both setups the average access time for each clinic is computed, while keeping all other parameters equal. Generally speaking the pooled setup, Setup 1, will result in shorter access time due to EOS. However, Setup 2 will result in more focused clinics, which according to the principle of focus, should result in decreased service times. The objective of the model is to compute the amount of decrease in service time required in the two departments of Setup 2 to make them perform equivalently with the department in Setup 1. As such we can illustrate the amount of service time improvement needed in Setup 2 to offset the losses in EOS associated with the decentralized and more focused clinics. Finally with this model we consider a range of clinic and patient population characteristics to determine which benefit from the use of Setup 1 and likewise from Setup 2.

It should be noted that the advantages associated with Setup 2 may be greater and more diverse than simply a decrease in service time. However many of these improvements are qualitative, such as patient satisfaction, and are difficult to measure. Our approach offers management a quantitative measure of the efficiency losses and the service time improvement required to compensate for the loss. It is our intention that managers use the results to initially screen out which clinics have potential to realize benefits from Setup 2 and which do not. Although we model the tradeoff with an ambulatory clinic analogy, the model is applicable for any hospital department where the service time is less than 1 day and where the system empties between days (e.g. operating room or diagnostic clinics).

Since Setup 1 is traditionally used in hospitals this paper is written from the perspective of a manager who is contemplating switching from Setup 1 to Setup 2. Conclusions and guidelines state how different factors affect this decision. However in the alternative case, a manager considering switching from Setup 2 to Setup 1, the same results are valid but from the opposite perspective.

3.1 Slotted Queueing Model

The two setups described in the previous section are modelled by a slotted queueing model. Slotted queueing models mimic a full day's clinical activity in a single computation, making it particularly convenient for modelling access time for outpatient clinics. The two input parameters of the model are the arrival rate and service rate distributions. The arrival rate (λ) is the daily demand for appointments and is assumed to follow a Poisson distribution. The service rate is the number of patients completed per day and is computed from the appointment length (D), the number of consultation rooms (M) and the working minutes per day (t). The service rate distribution depends on the average appointment length variance (V).

Using arrival rate and service rate distributions the slotted queueing model subtracts the number of patients serviced each day from the number of patients requesting service (the number of patients requesting service is the sum of patients waiting from previous days and the number of newly arrived patients). The difference, when positive is the number of patients that need to wait for service and when negative, is reset to zero. This provides the output from the model, namely the average queue length (L). The average queue length is computed numerically with simulation in Section 3.2 and estimated analytically in Section 3.3. Using the average queue length and Little's Law ($L=\lambda W$) it is possible to compute the average access time (W) for a given clinic.

The notation used in this paper is summarized below:

λ = average demand for appointments per day
D = average service time (appointment length in minutes)
V = Variance of the appointment length
C = Coefficient of Variance for the appointment length ($C= (V/D^2)^{1/2}$)
M = number of rooms
ρ = the utilization of rooms
t = working minutes per day
W = average Access Time in days

A subscript "AB" corresponds to the Setup 1 (pooled case) and a subscript "A" or "B" corresponds to each of the departments in Setup 2. Typically each department in Setup 2 will correspond to a particular patient category. The model schemes for Setup 1 and Setup 2 are show in Figure 2.

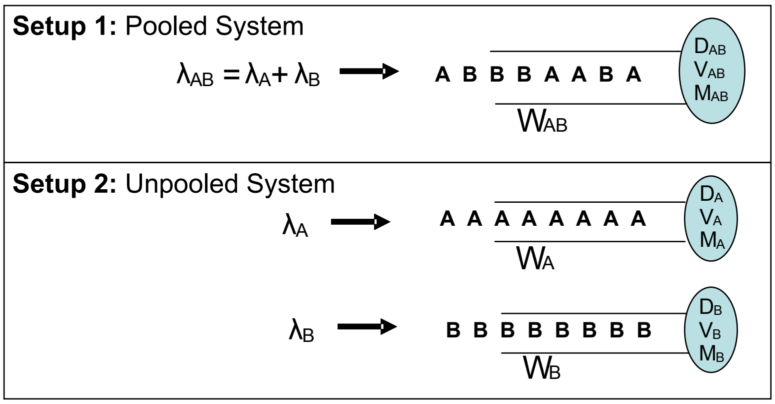

Figure 2: Model Scheme for Setup 1 and Setup 2

When combined, the parameters of the unpooled system must equal the parameters of the pooled system. As such below we describe how the various parameters in the unpooled system relate to the parameters in the pooled system. Practically these division "rules" imply that in Setup 2 no additional resources are available and that patients are strictly divided into one or the other departments.

$M_{AB} = M_A+M_B$ (1)
$\lambda_{AB} = \lambda_A+\lambda_B$ (2)
$D_{AB} = qD_A+(1-q)D_B$ (3)
where $q = \lambda_A / \lambda_{AB}$
$V_{AB} = q(V_A+D_A^2)+(1-q)(V_B+D_B^2)-D_{AB}^2$ (4)

Finally a common metric used to measure the performance of a queueing system is the clinic's load (ρ). A clinic's load is computed by (5) and represents how busy the clinic is, or alternatively, the utilization of a department's resources.

$$\rho = \frac{\lambda D}{Mt} \quad (5)$$

3.2 Simulation Case Study

Initially the slotted queueing model is used for a case study at the Netherlands Cancer Institute - Antoni van Leeuwenhoek Hospital (NKI-AVL) as described in Vanberkel et al. (2009a). At the hospital, the use of focused factories (Setup 2) to treat patients with similar diagnoses is being considered. From a patient satisfaction perspective this setup is preferred, however hospital managers want to know if additional resources are required to compensate for any losses in EOS. To gain initial perspective, a case study evaluated the impact of having two chemotherapy departments, one dedicated to breast cancer patients and a one dedicated to non breast cancer patients.

Results from the study found that EOS losses would result if the hospital abandoned the current clinic arrangement (Setup 1) in favor of the focused factory arrangement (Setup 2). Furthermore since the service time in the chemotherapy clinic is dictated solely by the speed at which a body can absorb the drug, staff does not expect a reduction in service time due to EOF in Setup 2. Thus the study recommendations outlined the additional resources, not the decrease in service time, needed to make Setup 2 as productive as Setup 1.

From this study it became apparent that numerous factors influence the size of EOS losses, such as appointment length, clinic load, number of rooms, patient demand, etc. Furthermore many of these factors are interrelated (see (1-5)) meaning that identifying one factor's influence in isolation from the others was an extremely difficult task using simulation. The simulation model is robust and can be replicated in other departments, however the complexity of the problem made finding general guidelines with this approach difficult.

3.3 Analytic Approach

In contrast to the simulation approach it is possible to estimate L for a slotted queueing model analytically. L in our slotted queueing model is analogous to the average waiting time of a GI/GI/1 queue because both are described by Lindley's recursion (see e.g. Cohen, 1982). The waiting time of a GI/GI/1 queue can be approximated with Allen-Cunneen approximation (Allen, 1990) thus leading to an approximation for *L* in our slotted model. Details of this approximation are in Vanberkel et al. (2009b). This approximation of *L* and Little's Law are used to estimate *W* (6) for the three queueing systems depicted in Figure 2.

$$W = \frac{L}{\lambda} \approx \frac{\rho}{2(1-\rho)\lambda}\left(1+\frac{C^2}{\rho}\right) \qquad (6)$$

In Setup 2 a new shorter service time D_A' (D_B') is required in order to make W_A=W_{AB} (W_B=W_{AB}). We define Z_A to be a standard measure of the proportional difference between D_A and D_A' (likewise for Z_B). Ignoring the subscripts "A" and "B" we offer the following description of *Z*. *Z* essentially measures the EOF needed to make the access time in Setup 2 equal to Setup 1. When *Z* is negative it represents the amount the appointment length must decrease in order to overcome EOS losses resulting from unpooling. When *Z* is positive it indicates that the appointment length can increase and still maintain the same service level as in the pooled system. This happens when the number of rooms assigned to one of the patient populations is disproportionately large. Although practically less relevant, the positive *Z* value does help illustrate how the tradeoff between EOS and EOF is influenced by the distribution of rooms. Formally Z is defined as follows

$$Z = {D'}/{D} - 1$$

As shown in Vanberkel et al. (2009b), one can find an analytical approximation of D_A'/D_A under the following assumptions:

- Servers are divided between the pooled and unpooled clinics in such a way that the clinic load (ρ) remains the same.
- appointment lengths are independent and identically distributed
- appointment lengths are much shorter than the opening hours for the clinic ($D \ll t$)
- Second order and higher terms of ($1-\rho_0$) can be ignored

The approximation equation for Z_A obtained under the conditions above is shown in (7), similarly it can be rewritten to obtain D_B'/D_B. From (4) it can be shown that either D_A'/D_A or D_B'/D_B in (7) is smaller than 1.

$$Z_A \approx (1-\rho_0)\left(\frac{1+C_A^2}{1+C_{AB}^2}\frac{\lambda_{AB}}{\lambda_A}-1\right) \quad (7)$$

Although several assumptions were made deriving (7), it does provide insight into the three main factors effecting Z_A. The least influential of these factors is the ratio of the coefficient of variance of the pooled group and the coefficient of variance of the unpooled group. The coefficient of variance measures the relationship between the mean and variance as defined in (8). As the discrepancy between the C_A and C_{AB} grows, the losses in EOS increase. The second factor indicates that the smaller λ_A is, relative to λ_{AB}, the greater the loss in EOS. The most influential of these factors is the clinic's load. The busier the clinic is, the smaller the loss in EOS. This is consistent with (van Dijk and van der Sluis, 2009), who states "pooling is not so much about *pooling capacity* but about *pooling idleness*" implying that unpooled systems with less idleness can expect less EOS gains when pooled. The practical implication of these factors is illustrated in Section 4. The factors are summarized in Table 1.

$$C = \sqrt{V / D^2} \quad (8)$$

Table 1: Main Factors influencing Z_A

	Factor Description	Effect on Z_A	Summary
1	**Clinic Load: (ρ)**	As ρ_0 increases Z_A increases	Unpooling clinics with high load results in less EOS losses than clinics under lesser load. (Influence: High)
2	**Proportional size of the unpooled patient groups: (λ_A / λ_{AB})**	As λ_A / λ_{AB} increases Z_A decreases	Smaller patient groups generally experiences a greater loss in EOS as a result of unpooling. (Influence: Moderate to High)
3	**Coefficient of Variance Ratio: $(1+C^2_A) / (1+C^2_{AB})$**	As $(1+C^2_A) / (1+C^2_{AB})$ increases Z_A decreases	Unpooling patient groups with highly variable appointment lengths results in larger EOS losses. (Influence: Low)

Besides identifying the most influential factors, (7) also indicates which factors can be ignored. The absences of M_{AB} and D_{AB} implies that there influence is minimal relative to the three factors listed in Table 1. Practically this conclusion implies that the number of rooms in a clinic and the average appointment length are not factors that need considering when contemplating a switch to Setup 2. They are however, considered indirectly when computing the clinic's load, see (5). Another factor of influence is how the rooms are divided between the two departments in Setup 2. In the derivation of (7) we assume they are divided such that the difference in workload for staff in the two unpooled clinics is minimized, i.e. $\rho_A \approx \rho_B$. In the analysis in Section 4 we maintain this assumption and indicate where it becomes problematic. In Vanberkel et al. (2009a) we discuss situation when an alternative room distribution may be more appropriate and in Vanberkel et al. (2009b) we further illustrate its influence.

4. SCENARIO ANALYSIS AND MANAGEMENT GUIDELINES

From the analytical approach the major factors of influences have been narrowed down to the three listed in Table 1. The influences of these factors, plus the service time variability, are illustrated with simulation in this section. The addition of the service time variability as a factor stems from intuition and experiments conducted in Vanberkel *et al.* (2009b). As stated above, M_{AB} and D_{AB} have minimal influence and thus are kept constant at 20 rooms and 30 minutes respectively. The model described in Vanberkel *et al.* (2009b) is used for these simulation experiments.

Results from the simulations are displayed in Tables 2 to 4. Table 2 and Table 3 illustrate the influence of factors 1 (clinic load) and 3 (coefficient of variance ratio) respectively. The influence of service time variability is displayed in Table 4. Finally, the influence of factor 2 (proportional size of the unpooled patient groups) is apparent in all three tables.

The values in each table cell are in the following format "Z_A (M_A), Z_B (M_B)". The Z values, as defined above, measures the percent by which the service time must change in order to let Setup 1 and 2 perform equally. The performances of the departments are measure by patient access time. The M values in parentheses indicate the number of rooms needed in each department in Setup 2. As an example, consider the Base Clinic in Table 2. The cell corresponding to λ_A/λ_{AB}=0.4 contains the result "-9% (8), -5% (12)." This means that given the specific clinic parameters, switching to Setup 2 is favorable if the service time can be decreased by 9% for population A and 5% for population B. Furthermore the 20 rooms should be divided such that the department serving population A receives 8 rooms and population B, 12 rooms.

Table 2: Influence of Clinic Load on EOS losses

λ_A/λ_{AB}	**Less Busy Clinic** (ρ=0.77, C_A=C_B=0.5)	**Base Clinic** (ρ=0.88, C_A=C_B=0.5)	**Busier Clinic** (ρ=0.97, C_A=C_B=0.5)
0.3	-16% (6), -6% (14)	-12% (6), -4% (14)	-3% (6), -2% (14)
0.4	-11% (8), -6% (12)	-9% (8), -5% (12)	-3% (8), -2% (12)
0.5	-10% (10), -10% (10)	-6% (10), -6% (10)	-2% (10), -2% (10)
0.6	-7% (12), -12% (8)	-5% (12), -8% (8)	-2% (12), -3% (8)
0.7	-3% (14), -14% (6)	-4% (14), -11% (6)	-2% (14), -3% (6)

Interpretation of Table 2, Influence of Factor 1 (Clinic Load): As apparent from the table, busier clinics can be switched from Setup 1 to Setup 2 with less negative effects due to EOS losses. Although perhaps counter intuitive, this follows from the reasoning that EOS are gained from better use of idle time and busier clinics have less idle time, thus there is less EOS to begin with. Practically this is important because busier clinics tend to be those targeted first for improvement initiatives and, as is shown here, are prime candidates for Setup 2.

Table 3: Influence of Coefficient of Variance Ratio on EOS losses

λ_A/λ_{AB}	**Different Variability** (ρ=0.88, C_A= 2, C_B=0.5)	**Base Clinic** (ρ=0.88, C_A=C_B=0.5)	**Different Variability** (ρ=0.88, C_A= 0.5, C_B=2)
0.3	-11% (6), 5% (14)	-12% (6), -4% (14)	-4% (6), -3% (14)
0.4	-8% (8), 3% (12)	-9% (8), -5% (12)	-2% (8), -4% (12)
0.5	-6% (10), 2% (10)	-6% (10), -6% (10)	2% (10), -6% (10)
0.6	-4% (12), -2% (8)	-5% (12), -8% (8)	3% (12), -8% (8)
0.7	-3% (14), -4% (6)	-4% (14), -11% (6)	5% (14), -12% (6)

Interpretation of Table 3, Influence of Factor 3 (Coefficient of Variance Ratio): The coefficient of variance is defined in (8) and is a measure of service time variance related to the service time mean. Table 3 illustrates that a patient population with less service time variability experiences smaller losses in EOS. It is also important to note that these results include positive values for Z (see column 4, row 4). In these situations the results imply that the service time can actually increase in one department of Setup 2. As stated earlier this happens when one patient group receives a disproportional amount of the resources. The results in this table remain valid however a different room allocation may result in smaller EOS losses. Practically this means the patient population with the lower service time variance requires proportionally fewer rooms.

Table 4: Influence of Appointment Length Variability on EOS losses (Test 1)

		Less Variability (ρ=0.88, C_A=C_B=0.25)	**Base Clinic** (ρ=0.88, C_A=C_B=0.5)	**More Variability** (ρ=0.88, C_A=C_B=2)
λ_A/λ_{AB}	0.3	-11% (6), -4% (14)	-12% (6), -4% (14)	-19% (6), -6% (14)
	0.4	-8% (8), -5% (12)	-9% (8), -5% (12)	-14% (8), -8% (12)
	0.5	-6% (10), -6% (10)	-6% (10), -6% (10)	-10% (10), -10% (10)
	0.6	-5% (12), -8% (8)	-5% (12), -8% (8)	-8% (12), -14% (8)
	0.7	-4% (14), -11% (6)	-4% (14), -11% (6)	-5% (14), -18% (6)

Interpretation of Table 4, Influence of Service Time Variance: It is immediately noticeable that as the variability increases, the required improvement increases. This result is consistent with the portfolio effect, which indicates that pooling variance decreases the total variance. Practically this result implies that groups with little or no service time variability are also prime candidates for Setup 2.

Influence of Factor 2 (proportional size of the unpooled patient groups): As apparent in all three tables, both the room distribution and the *Z* values change with factor 2. When population A is smaller than population B (i.e. $\lambda_A/\lambda_{AB}<0.5$), population A requires less rooms but a greater decrease in service time. The counter situation (i.e. $\lambda_A/\lambda_{AB}>0.5$) holds for population B. It follows that larger patient groups retain EOS and require less EOF to compensate. Furthermore the smallest total loss in EOS (i.e. Z_A+Z_B) occurs when the two departments in Setup 2 are the same size. Practically this implies that making a small department to serve a small patient population is not a good idea. This influence of λ_A/λ_{AB} is observable in all three results tables.

Finally, Tables 3, 4 and 5 replicate 105 different clinic make ups and, within the range of the parameters, represent many more. Managers can look up their own clinic parameters in these tables and use the results to support their decision to use either Setup 1 or Setup 2. If a clinic's parameters are outside of the range tested then the following guidelines can be used for perspective:

1. Try to ensure the two departments in Setup 2 are the same or nearly the same size
2. Busier clinics are prime candidates for Setup 2
3. Groups with little or no service time variability are prime candidates for Setup 2

5. FURTHER RESEARCH

From the analytic approximation and the simulation experiments we found the most influential factors effecting efficiency loss due to unpooling. Numeric experiments provide a range of results for managers allowing them to make more informed decisions. However, further research is required to hone in on exactly how these factors influence EOS losses. With better descriptions of these relationships we can more concisely narrow down the clinic environments that benefit from each setup. Furthermore with comprehensive descriptions of these relationships, operational researchers can further improve or even optimize the mix of centralized and decentralized hospital departments.

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