

Reallocating Resources to Focused Factories: A Case Study in Chemotherapy

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Abstract - This study investigates the expected service performance associated with a proposal to reallocate resources from a centralized chemotherapy department to a breast cancer focused factory. Using a slotted queueing model we show that a decrease in performance is expected and calculate the amount of additional resources required to offset these losses. The model relies solely on typical outpatient scheduling system data, making the methodology easy to replicate in other outpatient clinic settings. Finally, the paper highlights important factors to consider when assigning capacity to focused factories. These considerations are generally relevant to other resource allocation decisions.

Keywords: Slotted Queueing Model, Focused Factory, Chemotherapy, Resource Allocation, Capacity Planning

1 Introduction

Driven by an aging population, public opinion, increased health expenditures, and long waiting lists, a flood of changes in the health care system have been set into

motion. Ensuring these changes create the intended outcomes is of the greatest importance to the economy and to society, as health care is “one of the largest industries in the developed world” (Carter, 2002). Furthermore, health care is a social good but also a scarce resource (Blake, 2005; Calabresi and Bobbitt, 1978), causing decisions to change to be plagued with ethical, emotional and political considerations and making quantitative analysis an important element for decision support.

One change being considered is to use focused factories to deliver care to large and homogeneous patient groups. Like many operational methodologies, focused factories have evolved from the manufacturing industry, see e.g. (Bozarth, 1993), (Ketokivi and Jokinen, 2005), (Harmon and Peterson, 1990) and (Skinner, 1996). In particular, ? argued that focus, simplicity and repetition in manufacturing breeds competence. Relating these ideas to health care, Bredenhoff et al. (2004) explain that a focused factory within a hospital “means that a part of the hospital is focused and designed for the treatment of a specific group of patients. This should improve the efficiency, safety, patient-centeredness and timeliness of the treatment process.” Successful applications and examples of focused factory are discussed by (Herzlinger, 1997), (Meyer, 1998) and (van Lent et al., 2006). What is missing from the existing literature is whether the efficiency gains due to the focus on a particular patient type are greater than the economies of scale gained from a centralized care department.

Using a discrete-time queueing model this paper provides decision support to hospital policy makers who are contemplating the use of a focused factory to deliver care to cancer patients. Queueing theory is a mature tool applied to health care environments. For detailed surveys of applications see Fomundam and Herrmann (2007) and Worthington (1987).

The case study is completed at the Netherlands Cancer Institute - Antoni van Leeuwenhoek Hospital (NKI-AVL) where, in view of growing demand, a focused factory has been proposed to treat breast cancer patients. The main performance characteristics under consideration are resource utilization and waiting time. Since the majority of patient appointments are planned in fixed treatment intervals, waiting time of greater than zero can be interpreted as meaning that appointments happen at least one day later than requested by the oncologist. Effective chemotherapy requires treatments to happen as designated by the oncologist, and as such the chance of a non-zero waiting time should be kept as low as possible. This paper quantifies the changes in the performance associated with creating a focused factory, and evaluates additional capacity needed to maintain the performance at the

current level. We also discuss extensions and other factors to consider when deciding to decentralize a service. Although this case study is applied for a focused factory scenario, the general methodology and results are applicable in other resource allocation decisions, e.g. assigning capacity to clinical pathways, dividing operating room time and distributing consultation rooms between outpatient services.

The paper is organized as follows. Section 2 describes the existing ambulatory chemotherapy department and outlines the description of the problem. Section 3 described the available data and the chosen modelling technique in view of the model objectives. Section 4 highlights results contrasting the performance of the existing centralized department with the proposed two department scheme. Section 5 discusses extensions and other factors to consider when deciding to decentralize a care service. The concluding section, Section 6 discusses further applications of the model underway at NKI-AVL.

2 Problem Description

NKI-AVL is a comprehensive cancer center providing hospital care and performance research, located in Amsterdam, The Netherlands. The hospital has 150 inpatient beds and sees about 24,000 new patients every year, making it approximately the size of a mid-sized general hospital. As with many Dutch hospitals, NKI-AVL is eager to improve access to their services through efficiency gains and higher quality of patient care. One option under consideration is to use focused factories to treat patients with the most prevalent forms of cancer. This paper focuses on the potential impacts a breast cancer focused factory will have on the chemotherapy department.

NKI-AVL's ambulatory chemotherapy department (ACD) has 30 beds and operates like a typical outpatient clinic with a high rate of recurring appointments. In recent years the department participated in various improvement projects and have made significant gains in efficiency see van Lent et al. (2006). New patients are referred to the department by an oncologist who stipulates the treatment plan, including the type, dosage and frequency of infusions. Patients arrive for their first appointment, have a short orientation meeting with a nurse and then proceed with their first treatment. Treatment involves patients sitting or lying in a bed while receiving chemotherapy drugs intravenously. This treatment could take between 30 minutes and eight hours. While receiving the drug, patients are supervised by

a nurse who can generally oversee three patients at one time. After treatment patients visit the receptionist and plan their next appointments. The time between treatments is set by the oncologist and can range from a single day to six weeks. These recurring visits continue until the end of the treatment plan, which can be as long as one year and may change frequently as related to the condition of the patient. In an average week the clinic sees 15 new patients and 300 return patients. Generally speaking, when you add restrictions to a planning system (such as assigning beds to a particular patient group) the performance of the system will not increase unless efficiency gains result from the focused treatment. In chemotherapy treatment there are no such efficiency gains expected as the time to give treatment is dictated by the speed at which a body can absorb the drug and not by operational considerations such as setup time. As such, the objective of this study is to investigate and quantify losses in efficiencies that can be expected as a result of separating breast cancer chemotherapy treatment (and the associated resources) from the existing centralized department. The project also investigates how best to split the existing department and where possible, how to minimize or mitigate resulting efficiency losses. This information is essential for management to decide if the inclusion benefits of having chemotherapy service in the breast cancer focused factory outweigh the expected decrease in performance.

3 Model Description

In this section, a queueing theory model is developed to compute the performance of the existing department and to compare it to the performance of the proposed two decentralized departments. The measures of performance include waiting time and bed utilization.

3.1 Data

Input parameters of a queueing model are typically derived from historical data recorded in the hospital's information systems (VanBerkel and Blake, 2007). For the present research seven months of data was extracted from the ACD's outpatient scheduling system. The data is typical for such a system and includes patient demographics, appointment dates, times, durations, and diagnosis codes. In our study, all diagnosis codes containing keywords "Breast" and "Mamma" were considered to be breast cancer patients; the remaining diagnosis codes were scanned

Table 1: General Characteristics of the Chemotherapy Department

Cancer Type	Average Appointments			Appointment Duration (mins)	
	per month	daily	% of total	Average	Variance
Total	1316	60.2	100%	157.5	6162
Breast	761	35.5	59%	160.2	4992
Non Breast	555	24.7	41%	153.7	7804

Beds	Nurses	Setup Time (mins)
30	10	30

manually to ensure none were overlooked. From the data statistics are computed which provide perspective on the general characteristics of the clinic. The results summarized in Table 1, indicate, among other things, the average and variance of appointment durations and the proportion of appointments used by the breast cancer and the non breast cancer populations. The period of measure incidentally represents a segment of time with a lower occupancy rate due to a temporary combination of physician change and reduced demand. The principle scheduling mechanisms are however not influenced by these somewhat lower figures.

3.2 Arrival Rate

Using data on completed appointments and the department's access time, the arrival rate distribution is derived from the seven month data set. The number of appointments completed per day is Poisson distributed with a mean of 60.2. Currently patients wait a few days for their initial appointment but have their return appointments without any delay, meaning that the patient access time is negligible. The department has excess capacity and appears to operate analogous to a queueing system with an infinite number of servers, where a server is readily available for each arriving customer. In such a system, Poisson process of departures implies that the arrival process is also Poisson with the same parameter. Thus, we assume that the number of appointment requests per day is $Poisson(60.2)$. In later sections we assume that the arrival rate distribution remains Poisson as the mean is increased.

3.3 Service Rate

Using the chemotherapy appointment length data, we can model the appointment length distribution. When the variance is less than the mean squared, which is the case in our study, “nonexponential distributions can often be well approximated by an Erlang distribution” (Winston, 1994) with shape parameter k and rate parameter μ . If the appointment length is $Erlang(k, \mu)$ then

$$[\text{Appointment Length Average}] = k/\mu, \quad (1)$$

$$[\text{Appointment Length Variance}] = [\text{Appointment Length Average}]^2/k. \quad (2)$$

The appointment length average and variance are available from the data (see Table 1). Based on this we can find the best integer k satisfying (2) and, then μ from (1). For details, see Winston (1994). For the existing case mix, the breast cancer group, and the non breast cancer group, we find that $k = 4, 5, 3$ and $\mu = 0.025, 0.031$ and 0.020 , respectively.

Let the random variable S denote the number of patients that a department with c beds can complete per day, provided that the system operates in saturation, under endless demand. In such a system, immediately after a patient is completed the next patient occupies the bed. The distribution of S represents the capacity of the clinic to meet the demand of its patients, and is needed as an input for our queueing model. Initially we assume that nurses are available for each bed, so S depends only on the appointment lengths.

If an appointment length is $Erlang(k, \mu)$ -distributed, then it is equal to a sum of k independent exponential random variables (*phases*) with parameter μ , and the number of such phases completed in t time units is Poisson with mean μt . Then the number X of completed services at one bed and the associated value of S are given by

$$X = \lfloor Poisson(\mu t)/k \rfloor, \quad S = \sum_{i=1}^c X_i, \quad (3)$$

where $X_i, i \geq 1$, are independent, and X_i represents the number of appointments completed in saturation at bed $i = 1, \dots, c$. Here rounding down to an integer, in practical terms, represents the clinic not allowing overtime. This is a reasonable assumption as less than 3% of the clinic days in the seven month dataset have lasted past the scheduled end time of the clinic.

The model for X and S is verified by using the historical data to compute the actual number of patients completed per bed when the bed appeared to be operating in a saturation state, meaning that the total idle time for that bed between 09:00 and 17:00 is less than 45 minutes. This 45 minutes accounts for staff breaks, which are not scheduled. For the seven months of data available, a bed operated all day in a saturation state 319 times resulting in a mean of 2.66 patients per day and a variance of 1.25. Assuming a normal distribution of the sample mean, the 95% confidence interval for the mean is found to be (2.54, 2.79). From our model (3) with $t = 480$ minutes, $k = 4$, and $\mu = 0.025$ we find $E(X) = 2.67$. This clearly falls into the 95% confidence interval leading to the conclusions that there is no statistically significant difference between the estimation method and the actual data.

3.4 Slotted Queueing Model

The distribution of the number of arrivals and the number of service completions in saturation are the inputs for a slotted queueing model for evaluating the system performance in terms of waiting times and queue lengths.

A discrete-time slotted model fits well in our setting, as the hospital closes at the end of each day (slot). Consider subsequent days $1, 2, \dots$, and let L_n be the queue length at the beginning of day n . Further, let A_n be the number of arrivals on day n , and S_n the number of services that can be possibly completed on day n . We assume that A_n and S_n , $n \geq 1$, are independent and distributed, respectively, as A and S , where A has a Poisson distribution with parameter 60.2, and S has a distribution as in (3) with $c = 30$. The number of appointment requests on day n is then $L_n + A_n$, and the dynamics of the queue length process is given by

$$L_{n+1} = (L_n + A_n - S_n)_+, \quad n \geq 1, \quad (4)$$

where $x_+ = x$ if $x \geq 0$ and $x_+ = 0$ otherwise.

Equation (4) is the well-known Lindley's recursion (see e.g. Cohen (1982)). Besides the queue length in a slotted system, such recursion also describes the waiting time of the $(n + 1)$ -th customer in the continuous-time $GI/GI/1$ model. In general, equation (4) is hard to solve analytically. A variety of techniques, such as Wiener-Hopf factorization, have been developed but they usually lead to explicit solutions only in special cases.

In our case study, the model is numerically solved by a simulation programmed in Visual Basic. The simulation completes 10 repetitions of 10 000 clinic days (100 of which are used for a warmup period). The output from the model is the utilization, and the stationary distributions of the queue length L and waiting time W . The values of L are obtained from (4). To compute the probability $P(W \geq r)$ we observe that out of A_n arrivals on day n at most $(\sum_{i=n}^{n+r-1} S_i - L_n)_+$ will be served before day $n + r$ because of the first-come-first-served discipline. Thus, out of these A_n patients, exactly $Z_n(r) = \left(A_n - (\sum_{i=n}^{n+r-1} S_i - L_n)_+\right)_+$ patients will have to wait r days or more. Now, after simulating the run of N slots, we can estimate the distribution of the waiting time as

$$P(W \geq r) = \frac{\sum_{n=1}^N Z_n(r)}{\text{Total Patients}}, \quad r \geq 1. \quad (5)$$

The described model has been applied to the existing department and the two proposed departments for breast cancer and non breast cancer patients.

4 Results

This section compares the performance of the existing centralized department with the performance of the proposed two decentralized ACDs, and discusses the methods to allocate beds to the decentralized departments.

4.1 Existing Department

The model of the current ACD at NKI-AVL with 30 beds, is depicted in Figure 1. The number of arrivals per day is $Poisson(60.2)$, and the distribution of the appointment duration is $Erlang(4, 0.025)$. A summary of the model inputs and outputs is given in Table 3 of Section 4.3. The output from the model indicates that the existing centralized ACD has significant capacity to cope with the demand and variation. The performance outcomes are consistent with what is expected from the discussion with staff and from the data.

4.2 Two Department Scenario

In this subsection we consider the segregation of patients between the two decentralized departments, where one department with c_{BC} beds is focused on breast



Figure 1: Flow Diagram of the Existing Centralized Chemotherapy Department

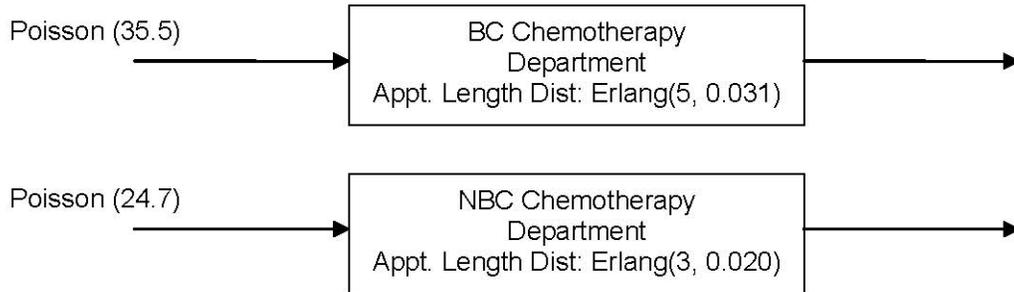


Figure 2: Proposed Flow Diagram of Decentralized Chemotherapy Department

cancer patients, representing 59% of the total demand for appointments. The other department has c_{NBC} beds and is dedicated to the remaining non breast cancer patients, which are responsible for 41% of the total demand. The two department model is depicted in Figure 2. Throughout this section the sub-indexes BC and NBC are used to indicate the parameters related to the breast cancer department and the non breast cancer department, respectively.

The number of new appointment requests per day to the breast cancer and non breast cancer departments are $Poisson(35.5)$ and $Poisson(24.7)$, respectively, which follows from $60.2 \cdot 0.59 = 35.5$ and $60.2 \cdot 0.41 = 24.7$. The appointment length in minutes is fit to $Erlang(k, \mu)$ distributions with parameters $k_{BC} = 5$, $k_{NBC} = 4$, $\mu_{BC} = 0.031$ and $\mu_{NBC} = 0.020$. These model inputs are summarized in Table 3.

The decision on how best to distribute the 30 beds between the two decentralized departments is made by first calculating the lower bound each needs to cope with demand, and then comparing the remaining possible scenarios. To this end, let $x = E(X)$, where X is given by (3) and denotes the number of appointments completed in saturation at one bed. To cope with the average demand of λ patients per day, the number of beds c must satisfy the stability condition $\rho = \lambda/(cx) <$

Table 2: Performance of the Decentralized Departments for various bed Allocations

Beds		Utilization		E[Lq]		E[W] (days)		P(W \geq 1)		P(W \geq 2)	
BC	NBC	BC	NBC	BC	NBC	BC	NBC	BC	NBC	BC	NBC
14	16	97.6%	55.3%	22.6	0.00	0.64	0.00	47.5%	0.0%	12.4%	0.0%
15	15	91.2%	59.0%	3.54	0.01	0.10	0.00	9.9%	0.0%	0.0%	0.0%
16	14	85.5%	63.1%	1.21	0.04	0.03	0.00	3.4%	0.1%	0.0%	0.0%
17	13	80.4%	68.0%	0.49	0.10	0.01	0.00	1.4%	0.4%	0.0%	0.0%
18	12	76.0%	73.8%	0.20	0.28	0.01	0.01	0.6%	1.2%	0.0%	0.0%
19	11	72.2%	80.5%	0.08	0.86	0.00	0.03	0.2%	3.5%	0.0%	0.0%
20	10	68.4%	88.5%	0.03	2.87	0.00	0.12	0.1%	11.4%	0.0%	0.2%
21	9	65.2%	98.8%	0.01	39.66	0.00	1.61	0.0%	68.6%	0.0%	36.7%

1. When $\rho \geq 1$ the demand is greater than the supply and the system becomes unstable. From (3), by using Monte Carlo simulation, we compute $x_{BC} = 2.596$ and $x_{NBC} = 2.791$. Thus, we obtain the constrains

$$\rho_{BC} = \frac{60.2 \cdot 0.59}{2.596 c_{BC}} < 1, \quad \rho_{NBC} = \frac{60.2 \cdot 0.41}{2.791 c_{NBC}} < 1, \quad (6)$$

which results in $c_{BC} \geq 14$, $c_{NBC} \geq 9$. Together with the condition $c_{BC} + c_{NBC} = 30$, this gives the full range of admissible splits. The performance of each configuration is presented in Table 2. In order to chose an optimal configuration, in this study we suggest two methods for the bed allocation.

The first method allocates beds to each department in such a way that the bed utilization in both departments is equal. Setting $\rho_{BC} = \rho_{NBC}$ and $c_{BC} + c_{NBC} = 30$, in our case study we obtain $c_{BC} = 18.22$, $c_{NBC} = 11.77$.

The second method ensures that the average waiting time in the queue is the same in both departments. The mean waiting time can be found from Little's law $E(W) = E(L)/\lambda$, where L is a stationary solution of (4). If $E(L)$ can not be determined analytically, as is the case in our study, an alternative approach is to consider the range of admissible bed allotments and then compute their associated waiting times, as in Table 2. From this, one can simply select the bed allocation that provides the closest waiting time in both departments. In the same respect, if management wished to ensure that a certain proportion of their patients received an appointment in less than one day, this approach can be used.

Table 3: Comparison of the Performance of the Existing Department with the Decentralized Departments

	Existing Department	Breast Cancer Department	Non Breast Cancer Department
Model Inputs			
Arrival Rate Dist. (Pnts/day)	Poisson(60.2)	Poisson(35.5)	Poisson(24.7)
Appointment Length Dist. (mins)	Erlang(4, 0.025)	Erlang(5, 0.031)	Erlang(3, 0.020)
Beds	30	18*	12*
Model Outputs			
Service rate / bed (Pnts/day)	2.672	2.596	2.791
bed Utilization	75.1%	76.0%	73.2%
E[Lq]	0.06	0.20	0.28
E[W] (days)	0.00	0.03	0.01
P(W ≥ 1)	0.1%	0.6%	1.1%
P(W ≥ 2)	0	0	0

*The bed allocate decision is discussed in Section 4.2

In our case, the allotment of 18 and 12 beds to breast cancer and non breast cancer patients respectively, results in the most equal workload distribution as indicated by the bed utilization. Furthermore, with this allotment the sum of the expected waiting time and the probability of a return patient being delayed by one day ($P(W \geq 1)$) is minimized. For the next subsection the 18 and 12 bed allotment is used for comparing the performance of the current centralized department with the proposed two department setup.

4.3 Comparison

Table 3 summarizes the results of the performance of the existing department and the two proposed departments. As expected, the results indicate that the two decentralized departments see decreases in performance. The average queue length and waiting time increases for both. The amount that each performance metric worsens is small and seemingly unsubstantial. The main cause of this result is the excess capacity (as indicated by the low bed utilization) with which the existing department operated during the period of measurement.

NKI-AVL's ACD currently utilizes its bed around 75% of the time. However, a recent management study set the utilization goal at 90%. This target ensures the department is able to cope with daily anomalies such as late arrivals of patients

and staff, urgent add on cases, delays in supporting departments and unexpected patient-drug reactions. To show how the decentralization decision is sensitive to expected increases in demand and bed utilization the situation is reanalyzed. The mean demand for appointments in the model is increased to 72.1 per day implying the desired 90% utilization. The result is shown in Table 4.

Again, all performance metrics worsen in the decentralized department. The greatest decrease in performance is the waiting time. Both decentralized departments expect around 8% of their appointments to be delayed showing that the inefficiencies due to decentralization are more pronounced when separating a department operating at a higher utilization. In order to achieve the same performance in the decentralized departments as in the centralized department additional resources need to be added. Table 4 displays the results of a bed allocation of 19 for the breast cancer department and 13 for the non breast cancer department, which brings the total number of beds up to 32. As a result, all model outputs for performance, except $P(W \geq 1)$, are better than in the existing centralized department. As a final model output for management's consideration, the percentage of days that the extra bed is used in the 19/13 bed scenario (as compared to the 18/12 bed scenario) is calculated and listed in Table 4. In both cases this proportion is close to 30 percent of the time. Hence, it may be possible for management to allocate 19 and 13 beds to the decentralized departments and only schedule and staff them 30% of the time. Since return appointments generally have a two week lead time this provides sufficient time to arrange extra staffing for the additional bed.

5 Further Considerations when Decentralizing Services

5.1 Size of Patient Population

The proposed focused factory for breast cancer patients leaves two relatively large decentralized ACDs, each of which maintains a certain amount of economies of scale. To illustrate how the outcome of this case study would have been different if the breast cancer patients were a smaller proportion of the total chemotherapy population, the case study analysis is repeated with proportional size of the breast cancer population varied from $q = 60\%$ to 10% . The allotment of beds to the breast cancer focused factory is the number required to maintain an average utilization of 90%, the current operating target of NKI-AVL's ACD. Consequently,

Table 4: Comparison of a Highly Utilized Centralized Department with Decentralized Departments

	Existing Department	Breast Cancer Department		Non Breast Cancer Department	
Model Inputs					
Arrival Rate Dist. (Pnts/day)	Poisson(72.1)	Poisson(42.6)		Poisson(29.6)	
Appointment Length Dist. (mins)	Erlang(4, 0.025)	Erlang(5, 0.031)		Erlang(3, 0.020)	
Beds	30	18	19	12	13
Model Outputs					
Service rate / bed (Pnts/day)	2.672	2.596	2.596	2.791	2.791
bed Utilization	90.1%	91.0%	86.4%	88.6%	81.6%
E[Lq]	2.14	3.33	1.28	2.63	0.88
E[W] (days)	0.03	0.08	0.03	0.09	0.03
P(W>1)	3.0%	7.8%	3.0%	8.9%	3.0%
P(W>=2)	0	0	0	0	0
Proportion of days extra bed is used		33.2%		29.7%	

we have $\lambda q / (c_{BC} x_{BC}) \geq 0.9$, and substituting the data we get

$$c_{BC} = \left\lceil \frac{72.1 q}{2.67 \cdot 0.9} \right\rceil. \quad (7)$$

The waiting time results computed by the simulation are summarized in Table 5. The results clearly show that extracting larger patient populations from a centralized department achieves better decentralized performance. Equal consideration must also be made regarding the size of the department that handles the remaining patients.

5.2 Variability in Appointment Length

In our case study one bed allotment proved to be the most equitable in terms of both utilization and waiting time. However, this is not always the case, since waiting time depends on the variation of system parameters while the utilization depends only on the average arrival and service rate. As an example, suppose that the number of arrivals per day and the appointment length is constant. Then the department can schedule their beds to achieve 100% utilization and maintain a 0

Table 5: Department Performance for various Focus Group Sizes

q	c_{BC}	Actual ρ^*	E[W]	P(W \geq 1)	P(W \geq 2)	P(W \geq 3)	P(W \geq 4)	P(W \geq 5)
60%	18	92.8%	0.11	10.8%	0.1%			
50%	15	92.3%	0.14	13.4%	0.2%			
40%	12	92.8%	0.18	17.6%	0.4%			
30%	9	92.5%	0.24	23.0%	1.1%			
20%	6	92.6%	0.42	35.1%	5.8%	0.8%	0.1%	
10%	3	92.8%	0.91	54.5%	21.8%	8.5%	3.5%	1.5%

*Higher than the target of 90% due to rounding (7)

day access time. Practically this means that when segregating a patient population that has low service and/or arrival rate variance it is possible to achieve equitable performance even at higher utilization levels.

5.3 Improvement in Efficiency due to Focus

In this project efficiency improvements were not expected in the decentralized departments and the motivation was to quantify the resulting decreases in performance. However when efficiency improvements are probable, an estimate in the expected decrease in service time is an essential additional factor for consideration. The approach described in this paper can be used determine if the improvements due to focus outweigh the losses in economies of scale. Similarly the model can provide the threshold service time improvement which makes the decentralized option favorable.

6 Future Applications at NKI-AVL

The chemotherapy model and the general methodology will be used for further analysis at NKI-AVL. Other focused factory scenarios are being considered that could see patient populations divided based on lab dependency and infusion type, dosage and frequency. Management and staff from the ACD plan to use the model to measure the impact of alternative treatment options, such as faster infusions and less frequent return appointments. Two patient demand scenarios were considered in this paper, the status quo and the operational maximum given current resources. However, demand is expected to grow and with it the department's resources.

Given patient specific demand projections, the model will be used to determine the timing and scale of capacity expansions, particularly for the breast cancer population. The methodology, which proved to be an efficient way to evaluate the impact of decentralizing services, will also be repeated for decision support for focused factory proposals in other departments.

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