Decreasing Waiting Times with Human and Equipment Resources: Study of the Labor and Delivery Department with the use of Computer Simulation

Completed Research Paper

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Abstract

This paper uses computer simulation to empirically test the sensitivity of a hospital labor and delivery department to the changing factor levels of human and equipment resources. Incremental human and equipment resources are tested to determine if human resources or equipment resources affect total average patient waiting times in the system as well as to whether the effects of each types of resources are equal or similar. Fractional factorial analysis is then used to construct an experiment whereby human and equipment resources are added simultaneously to determine if optimal interactions may be identified. ANOVA is used to identify these interactions and determine if the combination of human and equipment resources has the ability to reduce waiting times. As the climate of the healthcare industry changes with regulations, human and equipment resource management proves to be an important role in hospital design and patient comfort.

Keywords

Hospital Management, Human Resource Management, Computer Simulation, Optimal Resource Allocation

Introduction

As the healthcare environment changes with increased regulations and more patients in need, every resource must be scrutinized. The Affordable Health Care act is expected to make medical insurance available to more than thirty-two million Americans by the year 2019 (Litvak et al. 2011). The "medical arms race" of the past is obsolete as consolidations emerge among hospital groups. However, a revived "new" medical arms race is still prevalent in competing for patients using specialization tactics and retail strategies. (Devers et all, 1999) With ever increasing competition and compliance, hospitals are being forced to undertake efforts towards optimal resource allocation. Hospital resource optimization and efficiency are more important than ever.

The complexity of the hospital service model must not be overlooked. Computer simulation has been helpful in prior healthcare studies (Jahn et al. 2010) as the deterministic allowances the simulation can provide assistance in properly planning for a variety of entity types and outcomes. Expansion of resources requires strict attention to uncertainty, variability and limited resources (Harper 2002). Simulation software can run multiple replications and multifaceted occurrences to provide for these unknown demographical changes.

This article contends computer simulation has the capacity to comply with the diverse nature of the Healthcare industry. We focus on the case study of a hospital's Labor and Delivery (LD) department. For confidentiality reasons, full details of the hospital as well as descriptive information must be omitted. A comparison of how the relationship between the capacity allowances of human resources and equipment resources may lower patient waiting times will be formulated.

A review of pertinent literature in the field of system simulation in the Healthcare industry will commence and then a discussion of the current situation of a hospital's LD department. The appropriate methodology for the study will be delineated as well as a comprehensive explanation of the model development and logic. Finally, results will be discussed and a conclusion will end the article with careful proposals, future research and applications.

Literature Review

Uncertainty is a keystone risk for all health care systems. Over capacity and the ensuing negligence can be extremely detrimental to a hospital (Brennan et al. 1991). In the same respect, under capacity may be costly and effectively lead to the eventual closing of the hospital (Keeler and Ying, 1996). Many studies may attest to the aging population of the baby boomers leading to an increase in expected hospitalization stays and procedures (Shactman et al., 2003). However, this may only affect one department of a hospital, such as cardiology and physical therapy, and not be as relevant to other departments, such as obstetrics and neonatal care. Additionally, estimates are still fuzzy and unreliable. Birth rates specifically have shown correlation with economic and demographic factors (Galbraith and Thomas, 1941). These factors are constantly shifting and difficult to predict.

Computer simulation aids in the aspect of uncertainty by allowing for multiple replications. With this capability, decision makers have the opportunity to review their choices of expansion amongst a multitude of eventualities. Instead of a wait and see approach, computer simulation has the capacity to demonstrate these events in real time and examine how the system will absorb or reject these changes.

Healthcare is a dynamic system, creating a myriad of variability and unpredictability. The environment is so interdependent and complex, the smallest intervention may result in endless possible outcomes. For this reason computer simulation has recently been the tool of choice for hospital administrative decision makers. Within a simulation, the users can easily add a bed station or delete an operating room to observe how this resource's presence or absence will lead to other resource interactions. This "play" is important for planners as it allows them the opportunity to re-allocate resources without undertaking the enormous risks associated with the nature of health care. This has been documented as helpful in the learning of how the systems relate to one another (Forsberg et al. 2001).

The learning outcomes of simulation are also important for the understanding of how resources are utilized. This is especially true in the analysis of waiting times and queue lengths (Aharonson-Daniel et al. 1996). For example, if a simulation identifies a bottleneck in patient transfer, the first thought might be to increase nursing staff to aid in the transfer. However, adding the nursing staff might not reduce this waiting time at all. Through simulation, users may try adding other resources and re-running the model. They may later find it is not the nursing staff that was over utilized but instead the operating room in which the queue was being formed. By adding another operating room, the queue may be reduced and the system no longer balks.

Finally, limited resources prove to be a serious constraint for all hospitals. When faced with budgeting concerns, administrators will do all in their power, such as delay the initiation of a new technology, constrain ranges, or eliminate nonessential services, before care decisions will be affected (Mechanic, 1985). Healthcare payment options in the United States have changed frequently and drastically. As Health Savings Accounts and High-Deductible insurance plans have been introduced, Americans are taking on more responsibility for their health care bills (Robinson, 2005). This will draw close attention to the charges patients incur in the health care management. This will present more cost vigilant patients who may "shop around" for cheaper alternatives. This forces hospitals to focus on efficient resource allocation in order to maintain high care standards whilst keeping costs competitive.

The idea of limited resources and valid constraints bring us to underpin our research with the Goldratt's theory of constraint (1990). This theory postulates the need for managers to locate the constraints in the entire system and not only in the specific process. This is highly relevant to a health care organization where a specific process may flow into another process requiring cooperation. This is empirically supported by Patwardhan et al. (2006) in providing sustainable effects over time. Furthermore the theory discusses the concept of emotional resistance to improvement and change. While the healthcare provider may emotionally view the presence of new bedstations and state-of-the-art recovery room essential to patient care, this may be an overstatement of need and instead further human resources will have a greater effect on the specific goal of the organization.

Realizing the competitive nature of the health care industry and the mission statement of excellent patient care, patient waiting times are a key performance indicator for a hospital. Patient wait times are detrimental to the health of the patient in a number of ways. Patients are left with unnecessary pain and anxiety, negative emotions of both the patient and their escorts may result, and an increased risk of clinical deterioration may take place (Marmor et al. 2009). This will not only threaten the competitiveness of the hospital system but also add to additional costs for the system in real time. Unsatisfied patients lead to disgruntled workforces, which in turn may terminate employment thus creating unnecessary turnover costs for the hospital. There is no question, patient waiting times should be minimized whenever possible.

Contemporary research has realized this dilemma in planning for hospital demand (Gaynor & Anderson, 1995) and has attempted to decrease patient waiting time through strategic scheduling and operating room planning (Dexter et al., 2004). Others have focused on solely expanding human resources in care centers (Spaite et al, 2002) or expanding building resources (Miller et al., 2004; Cauchon & Applyby, 2006). Lovejoy and Li (2002) point out the fact of equipment resources being fixed and permanent whereas human staffing costs are somewhat flexible and can adjust with large demand shifts.

Hypothesis Development

As human resources are added, the need to wait for such resources diminishes. The nurse is required to monitor the patient's status and suppress their pain whenever necessary. Doctors and CRNAs are needed for diagnosis and surgical help throughout the department. As these resources are added, more patients can be seen quickly without having to wait for their attention and diagnosis.

H1: Patient waiting times are negatively related to human resources in the LD Department.

Equipment and technology resources are vital to the function of a hospital. As more rooms become available, more patients can be seen and admitted quickly. This is crucial for a Triage department where lifesaving assessments must be completed immediately.

H2: Patient waiting times are negatively related to equipment resources in the LD Department.

However, not all resources reduce patient waiting times in the same way. Adding more equipment resources may alleviate wait times in certain processes but add additional times in others. As Li and

Benton prove in their empirical study of key determinants of hospital capacity resource management and their effect on performance, cost performance is largely influenced by properly utilized equipment and technology, more so than by workforce development (Li et al. 2003). In this respect, we can see a hospital model is sensitive in different ways to the addition of equipment resources and human resources.

H3: Patient waiting times are affected to different extents by human resource allocation than by equipment resource allocation.

In order to determine optimal resource allocation, both human and equipment resources must be allocated appropriately. Without acknowledging the interactions of one resource on another, inefficient addition of resources will be inevitable. Adding or eliminating resources is a complex task. Interactions between resources must be understood and tested before implementation. When properly employed, the

LD model will be highly sensitive to these changes.

H4: The effect of equipment resources moderates the decrease in patient waiting times and human resources.

Given the above hypotheses the following model is proposed in figure 1:

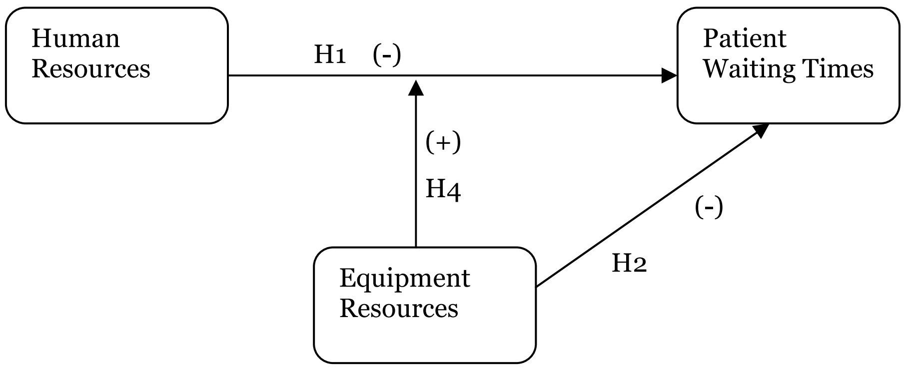


Figure 1: Proposed relationships between human and equipment resources and patient waiting times

The Hospital

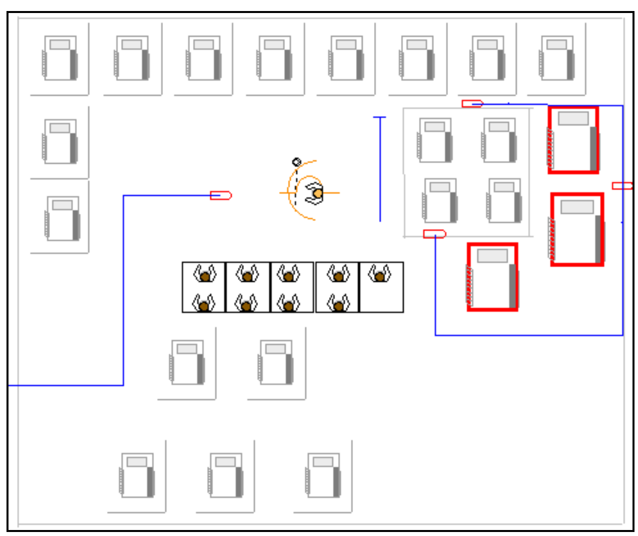


Figure 2: The Labor and Delivery Department

The hospital in this study is an urban general medical and surgical hospital located in the Great Lakes region of the United States. It is classified as a moderately centralized health system with over 450 total beds and 23,000 admissions a year. The LD department is a Level III Obstetric Service facility with over 3,000 births a year. The hospital had originally designed their birthing center to accommodate 175 deliveries a month; their current utilization of the department is between 250-300 births a month (Local Media Source, 2010).

With this new and uncertain demand, the hospital has entertained options to also increase the capacity of their LD departments. Before expansion proposals can be made, the Hospital must locate their current utilization constraints and alleviate any extensive waiting times in their current model. Shortening resource utilization queues decreases the overall throughput time the patient is in the hospital. Waiting times have been shown to be linked with significantly lower patient quality of life through pain and uncertainty (Jahn et al. 2010). The current hospital resources are described in Table 1.

Table 1. Human and Equipment Resources	
Resources Type	*Description*
Equipment	
Bedstations (10)	Used for labor, delivery and recovery for emergency surgery
Recovery Rooms (4)	Used for surgical preparation and post obstetrics surgery care
Operating Rooms (3)	Used for emergency and scheduled surgery
Triage Beds (5)	Used for unscheduled care and emergencies; anything involving a pregnant patient (early spotting, vehicle condition, etc.)
Human	
Doctor (1)	Required for clinical patient delivery, surgery, and emergency care
Nurses (Varies)	Required for each patient the moment they arrive to the moment they are transferred out; responsible for securing other resources and monitoring the patient
Certified Registered Nurse Anesthetists – CRNA (1)	Required for anesthesia administration for delivery and surgical patients

Model Development & Logic

A discrete-event driven simulation model will be used to represent the LD department using Arena computer simulation software (Rockwell Automation, Milwaukee, Wisconsin). Patient types and process submodels have been created showing the processes involved in the Admission area, bed station, operating room, recovery room, and triage. To measure the throughput of common patient types, five entity types were created, described in Table 2.

Table 2. Patient Types	
Resources Type	*Description*
Scheduled	Arrive at their scheduled appointment time
C-Section (SCS)	Arrive at admissions desk and routed to recovery room submodel
Induced (SI)	Arrive at admissions desk and routed to bedstation submodel
Operating Room (SOR)	Arrive at admissions desk and routed to recovery room submodel
Spontaneous	
Normal Delivery (SND)	Arrive at triage, evaluated by a nurse and diagnosed; then routed to appropriate submodel or discharged
Unknown Condition (UC)	Arrive at admissions desk and routed to triage and diagnosed by a doctor; then routed to appropriate submodel or discharged
Emergency C-Section	(Atttribute) May be assigned to a patient (with the exception of SCS and SOR) at any point throughout the model

Labor delay times are highly stochastic and variable. Normal Labor time may vary anywhere from seven minutes to forty-eight hours. While the median length of labor is reported as eight hours and the mean just over ten hours, 41% of women reported laboring for six hours or less and 6% reported labors of over twenty-four hours (DeClercq, 2006). This provides a challenge for most research methodologies, however, the computer simulation allows for a triangular expression to be used.

Validation

All resources and processes must behave in an appropriate way to the assumptions of the real system. (Kelton et al. 2010). Previous research has determined different ways in properly verifying a model. Using the steps from the Arnaout and Rabadi (2005) as well as Rossetti, Trzcinski, and Syverud (1999) the following methods were applied:

- Deterministic data, as opposed to stochastic data, was used to set up the model to ensure processes were linked accordingly. Single entities were simulated and observed through the entire system as the model was developed.
- Animation was created and monitored throughout the simulation. Different entity types were animated with different pictures to be sure all were entering the suitable subprocesses and the simulation is indeed imitating the behavior of the actual system.
- Someone intricately involved in the system should review the flow process and model to ensure real situations have been modeled. In this simulation, the staffing supervisor of the LD Department was contacted to verify the work flow.
- The reasonableness of the model should also be analyzed. In this instance, the hospital has published information confirming over 3,000 births a year, and approximately 250-300 births a month. Additionally, their c-section rate is roughly 30%. The simulation at the current conditions provides output of 298 births a month and a 70% vaginal birth rate and 30% c-section rate. These output statistics confirm the rational nature of the model.

Methodology

To best understand the relationship between resources and patient waiting times a multitude of performance objectives will be analyzed. First, the time waiting at each queue will be determined for each instance, and grouped by sub department in the model. These values will be added together to determine the total time in system. The value will not be per patient, as not every patient will route through each queue. Instead this will be a total value of the average waiting time of the full LD department. This value will aid in the decisions of which resources are best equipped at reducing waiting times as a whole for the department.

Average Waiting Times	
Admitting	
Bedstation	
	Secure a Bed
	Secure a Nurse
	Bedstation Diagnosis
	Secure Staff for a Clinic Delivery
	Secure Staff for a Delivery
	Secure Recovery Nurse from Delivery
	Secure Emergency C-Section Recovery Bed and Nurse
Triage	
	Initial Evaluation
	Secure a Bed
	Secure a Nurse
	Doctor Triage Assessment
	Triage Diagnosis
	Secure Emergency C-Section Recovery Bed and Nurse
Recovery Room	
	Secure a Room
	Secure a Nurse
	Secure Room and Nurse for Post OR Recovery
Operating Room	
	Secure OR for Emergency C-Section from Bedstation
	Secure OR for Emergency C-Section from Triage
	Secure Schedule OR from Recovery Room
Total Average Waiting Time for Department	

Table 1: Average Waiting Times by submodel of the Labor and Delivery Department.

As with other health care simulation studies, auto correlation is a common problem (Dexter et al. 1999). Because the department is inherently steady state, the waiting times cumulate over time and auto correlation is observed. To alleviate this issue, separate replications are performed. Each replication is for two weeks in length with a 168 hour (one week) warm up period. This does well to achieve independent results.

The model must be run in a fashion where values are statistically valid (Kelton et al. 2010). In this regard one replication will most likely not be sufficient to acquire an acceptable confidence interval. Instead multiple replications must be made to ensure a valid sample size. A 95% confidence interval will be sufficient with a terminating condition. The total waiting times and their respective half widths will be tallied. The simulation will continue replicating until an acceptable half width of 0.42 (25 minutes) has been achieved in the Total Wait Time output parameter.

Seven factors will be tested, three human resources and four equipment resources, for the sensitivity analysis of the model. As each resource is added or constrained, a statistically valid simulation is run and the results calculated. To test the final hypothesis, a fractional factorial design was eventually determined as it allows exploration of the interactions between variables instead of observing each variable individually. A random sampling of 180 simulations was generated through the use of the JMP design of experiments software. Fractional factorial design was used to ensure significant information is not lost considering main effects and low-order interactions (Kutner et al. 2005). The performance measures for each factorial combination were recorded to determine if a mix of human and equipment resources would be effective on lowering patient wait times.

Results

Total patient waiting times for incrementally adding resources indicate that the LD Department model is sensitive to additional or fewer human resources. Moreover we see the waiting times for equipment resources are less sensitive to addition or withdraw of resources. To test hypothesis one (H1), a graph has been constructed showing all human resources and their effect on the total average patient waiting times (Figure 3). We can see from the below graphs that the Nurse resource affects patient waiting time significantly until about the 8 or 9 nurse level. From there patient waiting time stabilizes. We also can see the Doctor and CRNA reduce waiting times significantly with the addition of one or two factor levels. This is conclusive in proving H1; patient waiting times decrease with the addition of human resources.

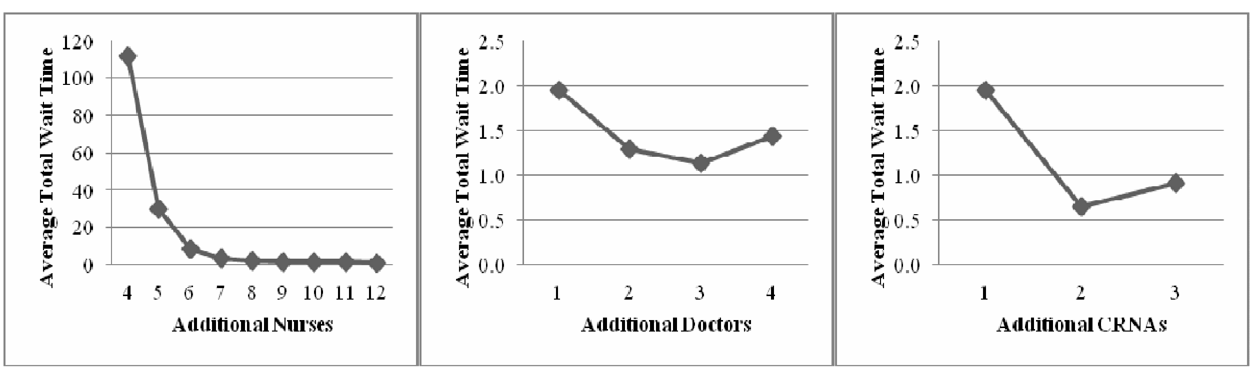


Figure 3: Average total wait time sensitivity with the addition and subtraction of human resources.

To test hypothesis two (H2), Figure 4 shows all equipment resources and their effect on the total average patient waiting times. The data does not conclusively prove or disprove H2. The recovery room resource appears to have an effect on the patient waiting time, however, the addition or subtraction of operating rooms appears to have no bearing. Triage resources affect patient waiting time slightly with the addition of the third room but do not have an effect after adding more. Average total waiting time is reduced with the additions and withdraws of bedstations; however, the effect is smaller than other resources.

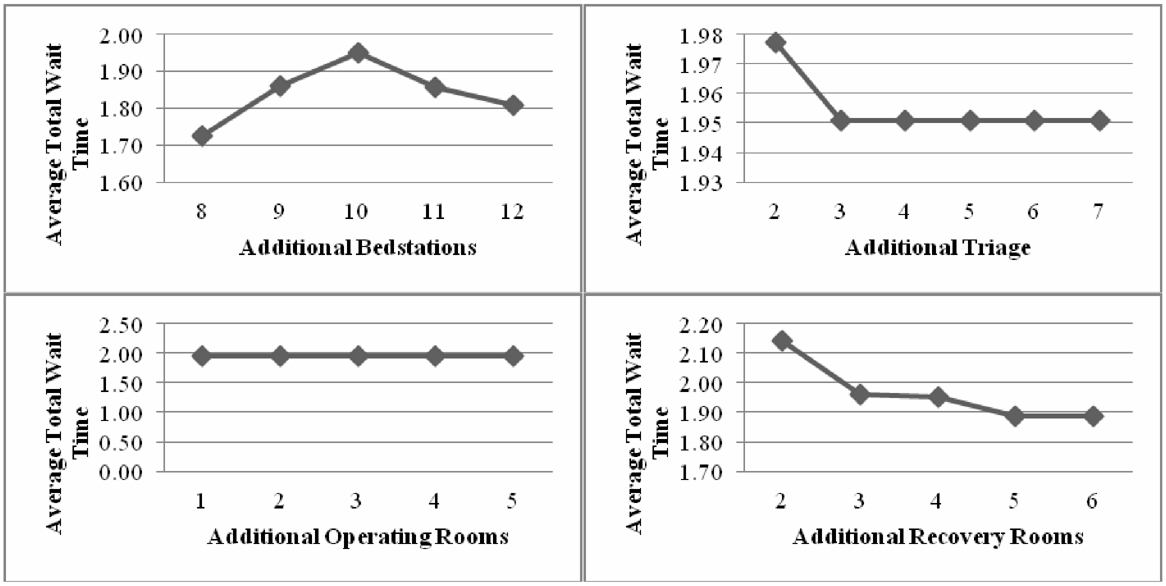


Figure 4: Average total wait time sensitivity with the addition and subtraction of equipment resources.

We observe human and equipment resources do not have the same effects on total average patient waiting times. From this analysis we can tell that human resources play a larger role in reducing patient waiting times than their equipment resource counterparts. This enables us to accept H3; different types of resources affect patient waiting times in different degrees.

A note should be made in regards to the increase in patient waiting times when some resources are added. Intuitively, this effect appears to be erroneous; however, it is the complexity of the simulation that allows observation of these effects. When a doctor or bedstation is added patients may be admitted faster into the system and then must wait for the other resources to "free-up". This is the same with the CRNA, Once three CRNAs are added, they treat and release patients quicker than the other resources can withstand, and the system baulks, increasing waiting times in other processes.

An initial ANOVA was completed using the direct effects of all variables and the effects of all possible interactions through a full factorial cross. We find the initial model to be statistically significant through the F-value and the P-value below a 99% confidence interval. We also observe a significant R-squared showing almost 87% of the variance may be explained by our analysis. When considering factor and cross factor significance we will be using the SAS Type III Sum of Squares. Type I sum of squares is a sequential analysis and will depend on the order, whereas Type III will not take this ordering into effect (Pendleton et al. 1986).

The conclusions from the previous analysis are confirmed. Table 3 shows the F-values and P values of the direct variables on the full model. From this we see the Nurses, CRNAs, and recovery rooms are highly significant as prediction variables; all passing a 90% confidence interval. We also see Bedstations and Triage Beds significant at an 80% confidence level. This indicates that when cross factor interactions are considered, the effect of equipment resources on the sensitivity of average total waiting time is moderated. The other resources are comparatively and statistically less significant as prediction variables.

Source	**Type III SS**	**F Value**	**Pr > F**
CRNA	2297.007	3.68	0.0599
DR	329.1717	0.53	0.4705
BED	1216.444	1.95	0.1679
OR	638.2185	1.02	0.316
RR	1892.343	3.03	0.0869
TR	1379.086	2.21	0.1425
NU	2557.789	4.1	0.0475

Table 3: ANOVA analysis of direct variables

Next, an ANOVA displaying the most significant predictor combinations was constructed. By ordering all sources from the lowest p-value (and statistically most significant), we determined the most effective interactions between variables. All effects passing a 95% confidence interval are listed in Table 4.

Source	Type III SS	F Value	Pr > F
CR*RR*NU	4461.179	7.15	0.0097
CR*TR*NU	3578.250	5.74	0.0199
CR*NU	3487.557	5.59	0.0214
CR*RR	3097.389	4.97	0.0297
RR*NU	3003.876	4.82	0.0322
NU	2557.789	4.1	0.0475
CR*BED*NU	2547.804	4.08	0.0479
RR*TR*NU	2528.784	4.05	0.0487
BED*RR*NU	2504.396	4.01	0.0498

Table 4: Significant resources for the ANOVA of the full model.

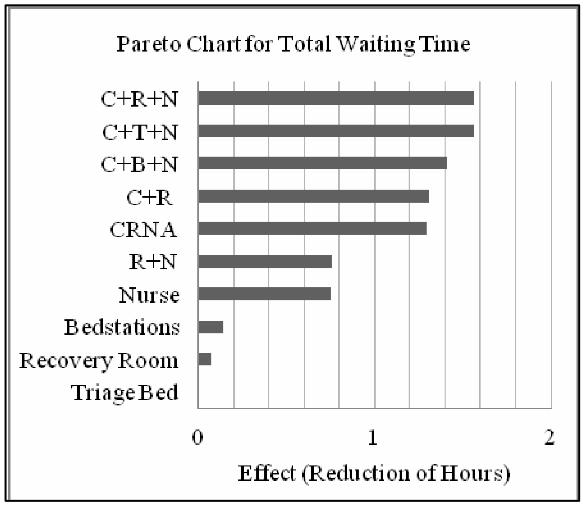
With the exceptions of the highly significant direct effects (Nurses, CRNAs, and Recovery Rooms), most interactions include both human and equipment resources. Only the third interaction of CRNA and Nurses omits a resource from both types of resource. This is expected as CRNAs and Nurses are highly sensitive effects alone.

We must still prove H4, that waiting times can be reduced by these interactions of human and equipment resources. For this we compare the incremental resource additions with the design of experiments simulations data. With incremental additions of resources the lowest average waiting time achievable was 0.6546 hours; when we added an additional CRNA. This is a decrease of 66% from the current state of the department with a wait time of 1.9509 hours. However, by allocating human and equipment resources together, we are able to achieve an average lowest wait time of 0.008, a decrease of over 99%. In fact, 46 of our 180 simulations (25%) improved the lowest average wait time beyond adding one resource type incrementally alone. This goes on to prove H4, waiting times may be reduced by considering both human and equipment resources in the LD department.

Significant Cross Effects

To further prove H4 we next consider how the waiting times can directly be reduced by human and equipment allocation of resources. As the ANOVA displayed, certain crossed effects exist between human and equipment resources with the power to reduce patient waiting times. To further test these interactions another experiment was designed mixing both incremental changes with the crossing of effects.

Each interaction was tested in a separate experiment. We can see from these results the interactions between the human and equipment resources are highly effective in decreasing the total average waiting time in the department. A pareto chart was constructed displaying these variables and the interactions (Figure 5).



B:Bedstation; C:CRNA; N:Nurse; R:Recovery Room; T: Triage Bed

Figure 5: Pareto chart showing the interactions and main effects on total average waiting time.

In terms of reducing the patient wait time the most, the compound effects of mixing human and equipment resources are highly significant. This proves H4 in terms of how integration of different resource types is successful in reducing patient wait times.

Not only are the interactions successful in reducing waiting times, but the reductions are statistically valid. The interaction between the CRNA, Recovery Room, and Nurse resources reduces the total average waiting time in the system by over 80% from 1.9509 to 0.3840. No direct resource alone has this effect. The most successful factor in lowering patient waiting time is the CRNA resource alone. The interaction above still outpaces this reduction by over 41%.

Implications, Future Research, & Applications

We support the idea that combining human and equipment resource optimization is critical to the achievement of reducing patient waiting times. As we saw in the incremental addition of resources, a recovery room expansion may prove to be statistically insignificant when considering patient wait times. However, when added along with the human resources of Nurses and CRNAs, the added equipment resources prove to be worthwhile.

Another important realization is the importance of human resources in the LD Department model. Without proper staffing, expansion and equipment resources cannot be fully realized and utilized. This is also supported in a 2012 empirical study questioning the need for hospital expansion (Bazzoli et al 2012) as the authors found the first constraint to hospital capacity was staff shortages, specifically nursing shortages. The aging population of the nursing personnel as well as the earlier efforts to increase efficiency by adjusting nursing workloads (higher patient loads and more stressful environments later leading to employment termination) may have an additional negative effect on hospital capacity. Waldman et al. (2004) note the expense involved with the turnover of medical practitioners, specifically nurses, is staggering, reaching 3.4%-5.8% of the total operating budget.

The scope of this article is limited to purely the patient waiting times; we have not considered the associated costs and tradeoffs with adding human or equipment resources and at what level. Human resources have historically been the most costly expense for hospitals (Bond et al., 1999). While patient waiting times are negatively related to patient satisfaction (Spaite et al., 2002), further validation of the model, including costs of resources and expected revenues from services, would help determine not only the best combination for reducing waiting times but also for controlling costs and improving service margins.

Hospital expansion is a costly and serious undertaking. Financing is often needed and investors will desire significant return on investment before committing. The inherent financial ratios for hospitals are dynamic and often unique to their own industry (Zeller et al 1996). With verified and validated simulation the hospital has better documentation for the expansion need and added revenue. This data and documentation can aid in securing affordable financing and improving return on investment overall for all investors.

Cost is an opportunity for further analysis. While all patient waiting time is significant and detrimental, some waiting times are more costly than others. Additionally, the waiting time may cause unnecessary stress and uncertainly for the patient, which in turn leads to lower patient comfort and satisfaction (Jahn et al. 2010). However, a patient waiting for a recovery room from a scheduled c-section or other surgery may not require additional drugs nor experience uncertainty (as the procedure has already been completed). In the latter example, the costs may not be as high and therefore are not as critical for the hospital. By further analysis of the costs involved with each queue, the waiting time performance objective takes on a quantitative value in additional to the qualitative value of patient comfort.

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