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SENSITIVITY ANALYSIS FOR A WHOLE HOSPITAL SYSTEM DYNAMICS MODEL

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ABSTRACT

This paper presents a sensitivity analysis of unit capacity and patient flow for a hospital-wide system consisting of interdependent clinical and ancillary departments. The research employs system dynamics to model a hospital-wide system representative of a medium size, semi-urban, acute care community hospital. A sensitivity analysis using regression methods examines emergency department performance in the context of the hospital-wide system using a modified formulation of the Overall Equipment Effectiveness (OEE) hierarchy of metrics as a key performance indicator. The modified OEE metric demonstrates its usefulness first for the purpose of conducting a group screening design, and second for the purpose of performing the sensitivity analysis. The main results of the sensitivity analysis indicate that emergency department performance depends significantly on the unit capacity and patient flow in departments hospital-wide. More importantly, the analysis provides quantitative insight into the factors deemed to be important, their interactive relationships across departments, and their overall relative importance. These findings are useful for recommending hospital-wide performance improvement initiatives.

1 INTRODUCTION

Hospitals throughout the United States have been confronting a challenge to expand access to health care, enhance patient services, improve quality of care delivered, increase patient satisfaction, and achieve financial performance amidst declining reimbursements. At the same time, emergency departments and various units within the hospital frequently experience sustained high-levels of congestion often due to insufficient capacity or inhibitors to patient flow. This problem has been especially prevalent in many urban regions of the country. A common approach to addressing such congestion issues has relied on focused study and improvement plans to the specific area experiencing problems. While this approach may yield some improvement, outcomes have often fallen short of initial expectations. Since hospitals are very complex systems with substantial interdependencies among departments, attempts to optimize a particular subsystem without regard to these interdependencies will likely not result in the desired level of improvement. In certain cases, the outcome may be far worse than the initial conditions.

While research studies and simulation models have sought to examine and improve performance in select areas of the hospital (Gunal and Pidd 2010), few researchers have pursued examination of the whole hospital for insights leading to improved performance or policies (Lane et al. 2000), (Manley et al. 2005), (Hoard et al. 2005), (Manley et al. 2006), and (Gunal and Pidd 2011). This research explores the hospital-wide system interdependencies between clinical and ancillary departments with respect to unit capacity and patient flow. The research employs system dynamics to model a hospital-wide system representative of a medium size, semi-urban, acute care community hospital providing a broad range of health care offerings and services in its catchment area (Smith and Roberts 2014). A whole hospital model presents a challenge to analyze the numerous factors most influential on operational performance and efficiency due to the scale and complexity of the model. A modified formulation of the Overall Equipment Effectiveness (OEE) hierarchy of metrics has been used as the key performance indicator to evaluate emergency department performance. Given the emphasis on capacity rather than equipment, this modified formulation is referenced to as the Overall Capacity Effectiveness (OCE) metric.

Earlier work (Smith and Roberts 2014) presented detail for the whole hospital system dynamics model and identified the important model factors influencing overall hospital-wide patient throughput by using a group screening design known as the sequential bifurcation technique, developed by Bettonvil and Kleijnen (1997). In this paper the sequential bifurcation technique has been applied to screen for important factors influencing the subcomponents of the OCE metric for the emergency department. In order to complete the simulation analysis of the whole hospital model these identified important factors will be used in performing the sensitivity analysis (Dent and Blackie 1979). Van Groenendaal and Kleijnen (1997) have defined sensitivity analysis as the assessment of consequences of changes in the model inputs, not accounting explicitly for the probability of these changes. Sensitivity analysis has been deemed important in the validation of a simulation model particularly when the representative data is not readily available (Kleijnen and Sargent 2000). The whole hospital model presents a case where some representative data have not been readily available and expert judgment has been relied upon. When a model is used for prediction under uncertainty, sensitivity analysis further helps identify those uncertain parameters that are most important and the interactions that may exist between parameters. Insight from the sensitivity analysis results may be used to determine potential leverage points and recommend hospital-wide performance improvement initiatives that would ease congestion by properly aligning unit capacity and improving patient flow.

In the remaining sections the whole hospital system dynamics model is briefly introduced, the system performance measurement is described, the statistical methods and sensitivity analysis results are presented, and the findings are summarized.

2 THE MODEL

The whole hospital model discussed in this paper was modeled using system dynamics where patients, requests, and resources are managed through a series of stocks and flows representative of hospital behavior. A complete description of the hospital model is available elsewhere (Smith and Roberts 2014). This reference contains sections addressing model selection and development, the main explanatory causal loop, the main high-level stock and flow diagram, the model calibration and analysis. The model has been previously validated using hospital reference data and subject matter expert review. This section provides a brief model description and illustrations of model behavior for a 'base case' simulation run.

2.1 Model Description

For organizational purposes the whole hospital model has been conceptualized into two areas: the community, and the hospital. The community serves as a catchment area for a patient population likely to be associated with the hospital. Patient arrivals originating from the community are managed as exogenous inputs and represented using historical time-series data.

The hospital is organized into clinical units and ancillary services within the hospital model. Hospital clinical units are primarily organized into four functions: (1) the emergency department (ED); (2) the surgical unit; (3) the medical wards; and (4) the surgical wards. Hospital ancillary services supporting diagnostics for clinical operations include (1) radiology services and (2) laboratory services.

Figure 1 illustrates the patient flow between the ED, the surgical unit, medical wards, and surgical wards, as well as the supportive relationship that the radiology and laboratory services provide to all the clinical units. All modules for the hospital are briefly described at a high-level detail.

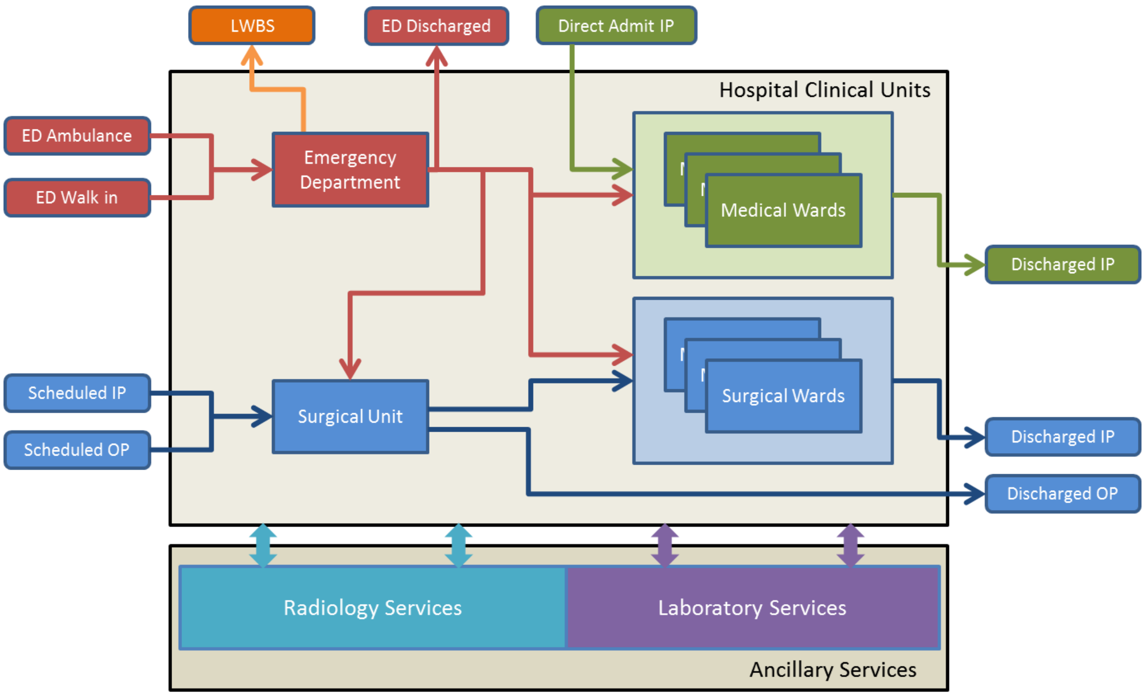

Figure 1: Hospital patient flow, clinical units and ancillary services organization.

2.1.1 The Emergency Department

Many elements make up the time which elapses between a patient arriving in the ED and, if necessary, being admitted to the medical or surgical wards. Patients follow different pathways through the emergency department before they are eventually admitted to the hospital, retained for observation, or discharged home. Patients arriving in the ED are registered, triaged and then wait for an initial evaluation with an ED physician. As part of the evaluation, the ED physician may order laboratory or radiology diagnostics to provide more information. Patients may be treated and discharged, or they may be the subject of further clinical evaluation and testing prior to diagnosis, treatment and discharge. In more severe circumstances, patients may be referred to a consulting specialty physician that maybe called to the ED from elsewhere in the hospital. These severe cases may undergo further test procedures and then be treated and discharged, or admitted and treated.

2.1.2 The Surgical Unit

Patients requiring surgery are generally scheduled as either an inpatient or outpatient surgery patient. Scheduled surgery patients receive pre-operative and post-operative care planning, which includes diagnostic testing, performed prior to the day of surgery. Emergency surgery patients are often considered add-on's to the planned surgery schedule. Emergency patients require timely completion of appropriate diagnostic testing in preparation for surgery. The surgical unit consists of pre-operative care where patients are prepared to undergo surgery, intra-operative care where patients undergo surgery, and post-operative care where patients are overseen in a post anesthesia care unit (PACU). Each area of care has capacity limitations that may restrict the patient flow and influence delay times. Patients remain in the PACU until they are ready to be moved into an available bed in the surgical ward. A scheduled inpatient surgery may be cancelled due to the inadequate availability of staffed beds in the surgical ward.

2.1.3 Inpatient Medical and Surgical Wards

Patients admitted to the hospital will be assigned to either a medical ward or a surgical ward determined by the nature of their admission. Medical admission arrivals are sourced through the ED, or through the direct medical admission (DMA) process by a hospital affiliated physician. Surgical admissions are sourced through the ED or through the scheduled surgery process by a hospital affiliated surgeon. Wards are organized into three types of units: (1) a Critical Care Unit (CCU), also known as an Intensive Care Unit (ICU), provides the highest level of care; (2) a Progressive Care Unit (PCU) provides a "step-down" level of care (intermediate care); and, (3) Acute Care Unit (ACU) provides a standard level of care. Patients may transition from the highest level of care to the lowest level of care prior to being discharged.

2.1.4 Radiology and Laboratory Services

Diagnostic testing in a hospital occurs in two forms: (1) radiology medical imaging services to examine underlying physical human structure; and (2) laboratory services to perform clinical pathology generally on bodily fluids from specimens. Radiology medical imaging generally requires that the patient be transported to a fixed piece of equipment, such as an X-ray machine, Computer Tomography (CT) scanner, Magnetic Resonance Imaging (MRI) scanner, or ultrasound scanner. In a high demand environment, the radiology and medical imaging resources may impose a significant constraint. Laboratory service requests originate with a specimen obtained from the patient which is then submitted to the laboratory for analysis. Specimens are processed and report results returned for clinical evaluation.

2.2 Model Behavior

Behavior of the hospital model with regard to patient flow and delay is described using an illustrative 'base case' simulation run for a patient pathway with arrival to ED, admitted to the medical ward, and discharged. The figures below illustrate for a typical 24 hour period during a weekday the behavior expected within the ED, the expected patient waiting time to complete stages within the ED, and the behavior expected within the medical ward.

Figure 2 illustrates: (1) the time varied rate of emergency patient arrivals to the ED; (2) the rate of leaving-without-being-seen (LWBS) patient departures due to congestion and delay encountered in the waiting room; (3) the rate of patient hospital admission; (4) the rate of patients completing treatment and discharged home; and, (5) the overall utilization of the ED treatment room capacity.

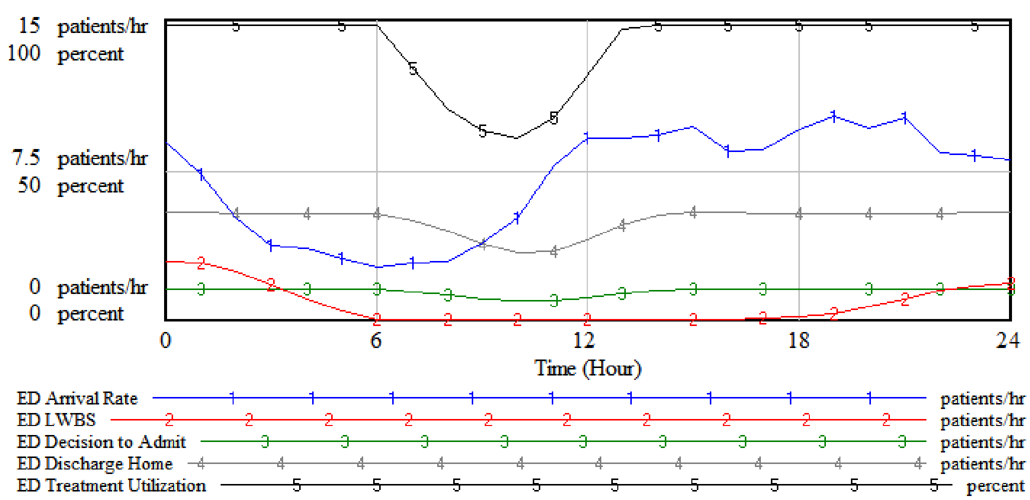

Figure 2: ED patient flow and utilization from the 'base case' run.

Figure 3 illustrates: (1) the rate of ED patients boarding into medical ward beds; (2) the rate of direct admission medical patients boarding into the medical wards; (3) the rate of medical ward patients identified for discharge home (occurs from 10am until 6pm); (4) the rate of medical ward patients transferring beds to step-down from higher levels of care (occurs from 9am until 6pm); and, the medical ward occupancy level for (5) PCU level of care and (6) ACU level of care.

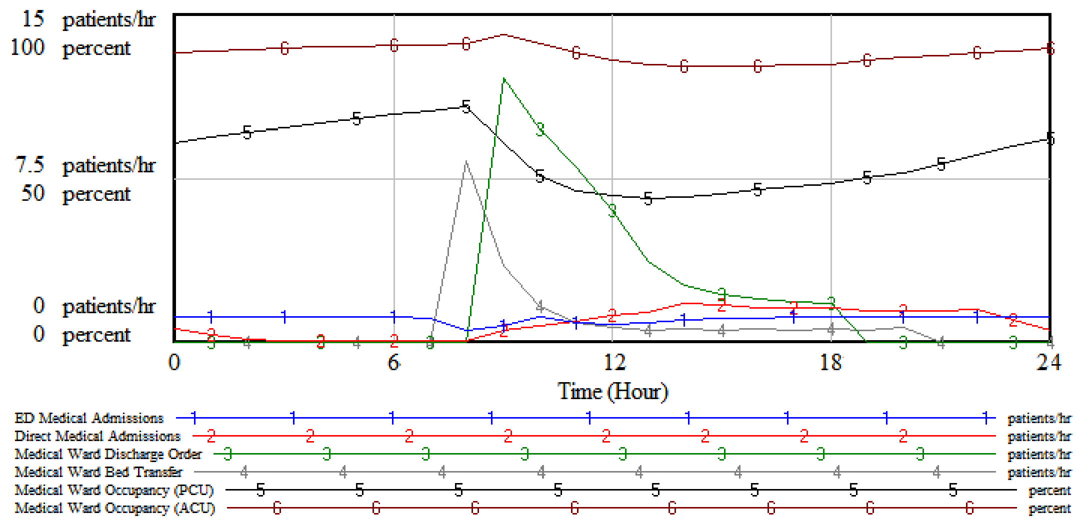

Figure 3: Medical ward patient flow and occupancy from the 'base case' run.

The graph in Figure 4 illustrates the expected time delay for each process within the ED, which reveals a varying pattern typical in hospital behavior. Wait times to initially-be-seen are observed to steadily increase from mid-afternoon until just after midnight. Delays midday occur in the medical ward while beds are in transition due to patient discharges and patient step-down bed transfers, during which many of the vacated beds have not yet been made ready to accept new patient arrivals.

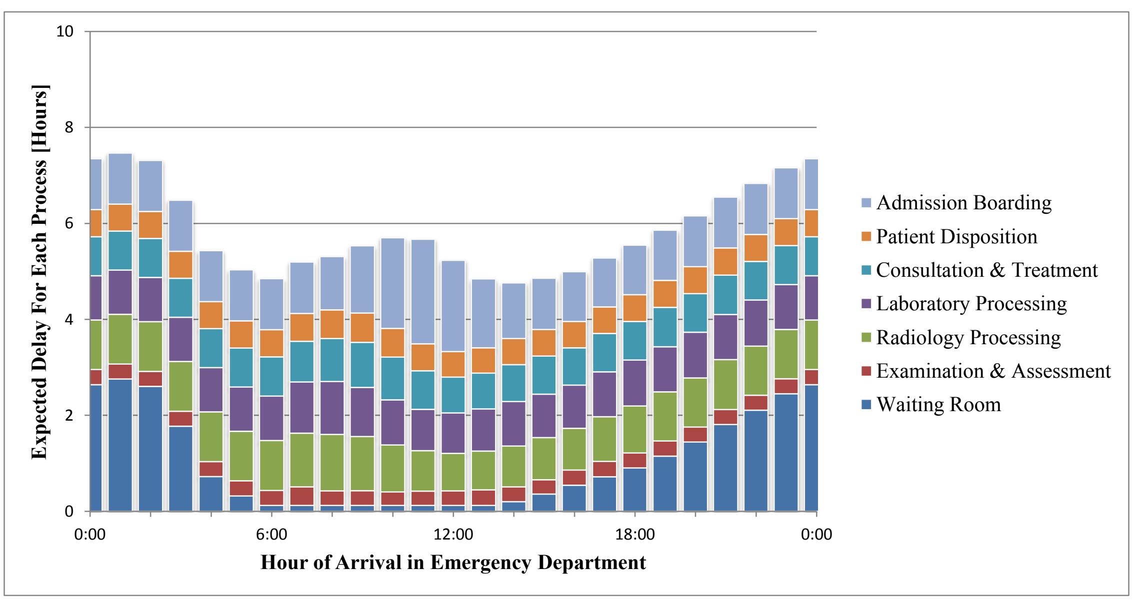

Figure 4: Expected time delay for each major process within the ED.

3 SYSTEM PERFORMANCE MEASURES

This section defines a proposed system performance measurement used to evaluate the ED performance and efficiency in the simulation experiments and provides an illustrative example. Previous work measured the timely, hospital-wide patient throughput performance. In this section an alternate, but more robust, performance measure known as the Overall Capacity Effectiveness (OCE) metric is introduced.

3.1 The Overall Capacity Effectiveness Metric

Traditional single index metrics of productivity, throughput, and utilization often obscure the identification of root causes contributing to reduced productivity. The Overall Equipment Effectiveness (OEE) metric is a time-based, equipment centric, metric often used to assess productivity and efficiency in manufacturing industry (Muchiri 2008). The OEE metric provides an effective performance measure that incorporates equipment availability, the equipment performance, and equipment production quality. The OEE metric can be decomposed into three subcomponents:

$$OEE = Availability \ x \ Performance \ x \ Quality$$

The OEE metric has two practical benefits. First, the OEE metric subcomponents can be individually used to identify bottlenecks and improve productivity. Second, the OEE metric can be used to separate equipment status into regular operating conditions and down states. The availability level quantifies the time made available for production. A lower throughput may be the result of low availability rather than poor performance. The OEE metric decomposition provides a means for equipment diagnosis and productivity improvement. The production oriented OEE metric can be modified for use in a hospital setting by adjusting the focus on resources, such as capacity, rather than equipment.

The modified formulation can described by using the following variables as defined: *TR* is the number of staffed ED treatment rooms; BR_t is the number of blocked ED treatment rooms waiting admissions at time *t*; p_t is the proportion of patients being admitted to the hospital at time *t*; (1-p_t) is the proportion of patients being discharged home at time *t*; *TLOSd* and *TLOSa* are the theoretical length-of-stay times for patients discharged home and admitted, respectively; $ActLOSd_t$ and $ActLOSa_t$ are the actual length-of-stay times for patients discharged home and admitted at time *t*, respectively; LOS_t is the length-of-stay duration while in the ED at time *t*; WT_t represents the waiting time encountered for an available treatment room at time *t*; BT_t represents the waiting time encountered for admissions boarding at time *t*. The modified formulation of the OEE metric, now referenced as the Overall Capacity Efficiency (OCE) metric, is described in equation (1) as follows:

$$OCE(t) = \left[\frac{TR - BR_t}{TR}\right] \times \left[\frac{TLOSa}{Act\ LOSa_t} p_t + \frac{TLOSd}{ActLOSd_t}(1 - p_t)\right] \times \left[\frac{\left(LOS_t - (WT_t + p_t BT_t)\right)}{LOS_t}\right] \quad (1)$$

The average Overall Capacity Efficiency, $OCE_{avg}(t)$, described in equation (2), can be calculated based on the total number patients (*n*) discharged and admitted to the hospital for a specified time period *t*, with rate *R* representing the flow of patients departing the ED at time *t*.

$$OCE_{avg}(t) = \frac{1}{n}\int_0^t OCE(t) \times R(patients\ departing)_t \times dt \quad (2)$$

3.2 Model Behavior for OCE Metric

Figure 5 below illustrates both the OCE and subcomponent performance metrics for the ‘base-case’ simulation run. This illustration corresponds with the time frame shown in previous figures. The graph lines correspond with (1) the overall OCE composite metric; (2) the OCE availability subcomponent; (3) the OCE performance subcomponent; and, (4) the OCE quality subcomponent.

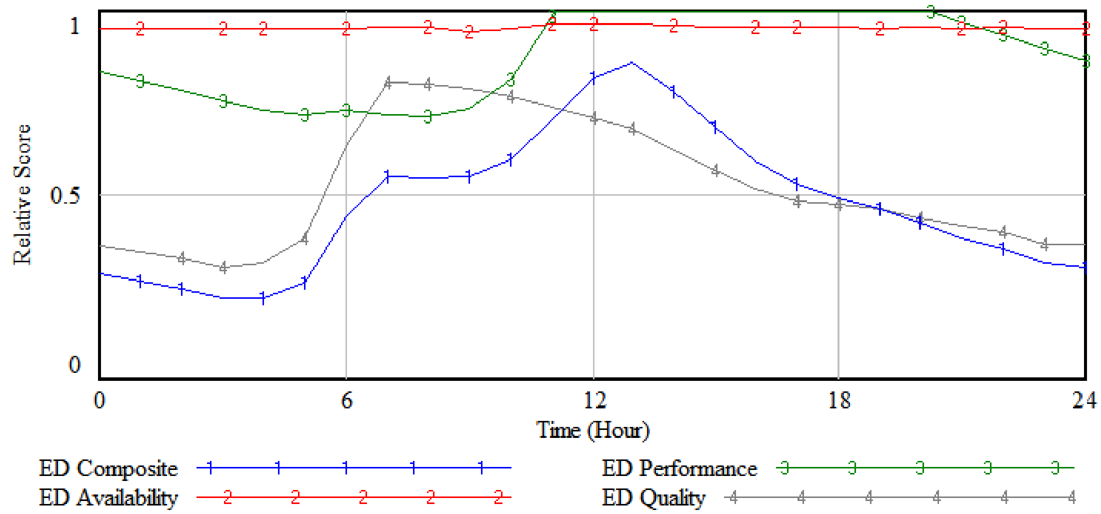

Figure 5: OCE metric results for the 'base case' simulation run.

4 STATISTICAL METHODS

In order to efficiently determine the relatively important factors in a complex simulation model a two stage approach is used. First, a group screening design can be used identify from the large number of factors in a complex simulation model the important factors to be considered. Second, a sensitivity analysis using regression analysis methods can be performed using these identified important factors.

4.1 Group Screening Design

The whole hospital model has more than one hundred conceivably important factors that could be varied. Numerical experiments involving such a large number of factors would require an exorbitant amount of computer time to exhaustively evaluate all factors. Therefore, a group screening design was employed to identify the most important factors through their main effects. The sequential bifurcation (SB) technique (Bettonvil 1995) (Bettonvil and Kleijnen 1997) (Kleijnen 2006) was employed as the group screening design methodology. This technique had previously been applied and reviewed in evaluating overall timely patient throughput for a hospital-wide system (Smith and Roberts 2014).

Herein, the sequential bifurcation technique has been used to evaluate the OCE subcomponent performance metrics. A list of the 15 most important factors has been compiled in Table 1 resulting from the screening. These important factors may serve as candidates for the sensitivity analysis. Seven of these factors were ultimately withheld from the subsequent sensitivity analysis performed for the following reasons: (1) factors *radPROC*, *radSETUP*, *labPROC*, and *labRQRT* due to the necessity of long-term structure changes in the hospital, such as large capital improvements; and (2) factors *labRQPP* and *radRQPP* since this would be a substantial shift inconsistent with present day physician orders and clinical demand.

4.2 Sensitivity Analysis of Simulation Experiments

The main goal of this study is to obtain additional insight into the dynamics of the hospital beyond the identification of the important factors through factor screening. In the case of the hospital model, the simulation model can be treated as a black box with a set of input and output parameters. As a result, statistical experimental methods such using ordinary least squares (OLS) regression may be applied. This section first presents the applicable regression models examined and then presents output and analysis from the experiments.

Table 1: Important factors identified by the Sequential Bifurcation technique.

Factor Reference	Factor Description	Factor Range H	L	Default	OCE Main Effect Availabilty	Performance	Quality
radCAP	Radiology Capacity (patients/hour)	8.00	5.00	6.00		X	
radPROC	Radiology Target Processing Cycle Time (hours/patient)	0.65	0.85	0.75		X	X
radSETUP	Radiology Setup Delay Time (hours)	0.10	0.17	0.13		X	X
labCAP	Laboratory Analyzer Capacity (specimens)	120.00	60.00	90.00		X	X
labPROC	Laboratory Analyzer Cycle Time (hours/specimen)	0.50	0.67	0.58		X	X
labRQRT	Laboratory Stat Request Review Time (hours)	0.10	0.16	0.13		X	X
labRQDT	Laboratory Stat Request Delivery Time (hours)	0.07	0.13	0.08		X	X
labRQPP	Laboratory Test Requests per ED Patient	1.50	2.50	2.00		X	
radRQPP	Radiology Test Requests per ED Patient	0.75	1.25	1.00		X	
edTRMCT	ED Target Treatment Cycle Time (hours/patient)	0.40	0.70	0.55	X	X	
mwACULOS	Medical Ward ACU Length-of-Stay (hours)	90.00	94.00	92.00	X	X	X
edTRMRM	ED Treatment Rooms Staffed (rooms)	28	20	24	X	X	X
mwACUBED	Medical Ward ACU Beds Staffed (beds)	207	177	192	X	X	X
edARRV	ED Patient Arrivals (patients/day)	155.6	181.6	168.12	X	X	X
dmaARRV	Direct Medical Admissions Patient Arrivals (patients/day)	25.00	27.00	26.00	X	X	X

4.2.1 Regression analysis model

Regression analysis is used to determine the factor main effects and factor interaction effects that may be present (Kleijnen 1995). Analysis will first be performed on the unstandardized input values (z_j) to determine significant differences. Subsequent analysis will be performed on the standardized input values (x_j), transformed by equations (5), to determine relative importance. The formulations expressed in equations (3) and (4) present regression models for the first-order and second-order polynomial (Kleijnen 1997). Quadratic effects also may be explored in equation (4).

First-order polynomial

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{i,j} + E_i \qquad (i = 1, \dots, n) \tag{3}$$

Second-order polynomial

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{i,j} + \sum_{j=1}^{k} \sum_{h=j}^{k} \beta_{j,h}\, x_{i,j} x_{i,h} + E_i \qquad (i = 1, \dots, n) \tag{4}$$

where

- y_i : average simulation response of scenario *i*;
- β_0 : the intercept or overall mean response;
- β_j : the main effect of factor *j*;
- $x_{i,j}$: the value of factor *j* in scenario *i*
- $\beta_{j,h}$: the interaction effect of factors *h* and *j*, where *j*<*h*;
- $\beta_{j,j}$: the quadratic effect of factor *j*, where *h* = *j* is explored;
- E_i. : the fitting error of the regression model for scenario *i*;
- k : the number of factor scenarios;
- n : the number of simulated factor scenarios.

Sensitivity analysis intends to quantify the effect of the change of the input over its entire experimental area. Therefore, the relative importance of factor j is measured by the difference between the outputs at the lowest and the highest values by l_j and h_j respectively, where the original variables z_j transform the standardized variables x_j. This transformation is described in the equations (5) below.

$$x_j = (z_j - b_j)/a_j \quad \text{with} \quad a_j = (h_j - l_j)/2 \quad \text{and} \quad b_j = (u_j + l_j)/2 \tag{5}$$

4.2.2 Simulation experiments

Simulation experiments were performed using eight of the identified important factors with their factor ranges. A total of n = 2048 simulation experiment scenarios were performed, where each scenario consisted of 15 weeks of simulated time. The experiment was performed on a single personal computer equipped with an Intel duo-core2 i5-2.83MHz processor with 8 GB RAM running the Microsoft Windows 7 Professional 64 operating system. Total experiment time was about 5.75 hours to complete.

4.2.3 Regression analysis results

Results for the first-order and second-order polynomial regression models are presented in the tables below. The standardized coefficient estimates indicate the relative importance toward the response of the OCE performance metric. The table results shown have been sorted based on relative importance.

Results from the first-order polynomial regression model (3) are presented in Table 2. For this regression model, the R^2 was 0.6775, and the adjusted R^2 was 0.6762. The table includes factors whose estimates significantly different from zero at $p < 0.05$. Seven of the eight factors in the regression were found to be significantly different at this level.

Based on relative importance, factors *dmaARRV*, *edTRMCT*, *mwACUBED* and *edTRMRM* are observed to be the most influential factors with respect to the OCE performance metric. Direct medical admission patients arriving (*dmaARRV*) will compete with ED admission patients for limited resources, such as medical ward ACU bed space. In addition, the ED treatment cycle time (*edTRMCT*), a critical path for emergency patient flow, demonstrates an inverse relationship to the performance metric; thus, as cycle time length increases the performance will decrease. Lastly, availability of medical ward ACU bed space (*mwACUBED*) significantly influences the emergency department performance levels.

Table 2: Significant effects for the first-order regression model (3).

	Unstandardized Coefficients		Standardized Coefficients		
Model	Estimate	Std. Error	Estimate	t-statistic	
dmaARRV	-0.02082	0.00065	0.13643	-32.04	***
edTRMCT	-0.20385	0.01424	-0.09778	-14.32	***
mwACUBED	0.00632	0.00013	0.07977	47.48	***
edTRMRM	0.00592	0.00045	0.04606	13.27	***
mwACULOS	-0.01132	0.00107	-0.04119	-10.58	***
edARRV	-0.00522	0.00027	-0.02625	-19.41	***
labCAP	0.00027	0.00013	-0.01109	2.18	*
intercept	1.62855	0.11441	-	14.23	***

Significance code (p-value): 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Results from the second-order polynomial regression model (4), absent quadratic effects, are presented in Table 3. For this model, the R^2 was 0.9067 and the adjusted R^2 was 0.9049. The table includes factors whose estimates significantly different from zero at $p < 0.05$. Overall, 16 of the 36 factor combinations in the regression were found to be significantly different at this level.

Table 3: Significant effects for the second-order regression model (4).

	Unstandardized Coefficients		Standardized Coefficients		
Model	Estimate	Std. Error	Estimate	t-statistic	
edTRMRM x mwACUBED	0.00149	0.00003	0.08111	49.27	***
mwACUBED	-0.10030	0.00753	0.07734	-13.31	***
edTRMCT x edARRV	0.00673	0.00194	0.05484	3.47	***
mwACULOS x dmaARRV	-0.00144	0.00035	-0.04681	-4.10	***
edTRMRM	0.13350	0.02529	0.04675	5.28	***
labCAP x edTRMRM	0.00008	0.00003	-0.04641	2.77	**
edTRMCT x mwACUBED	-0.01272	0.00094	-0.04617	-13.56	***
edTRMRM x dmaARRV	-0.00402	0.00015	-0.03887	-26.88	***
edTRMRM x edARRV	-0.00069	0.00006	0.03551	-11.55	***
edARRV x dmaARRV	0.00017	0.00009	-0.02253	1.97	*
mwACULOS x edTRMRM	-0.00218	0.00024	0.01782	-9.16	***
mwACULOS x mwACUBED	0.00055	0.00007	-0.01146	7.69	***
edTRMCT x dmaARRV	0.03116	0.00466	-0.00777	6.68	***
mwACUBED x dmaARRV	0.00118	0.00004	0.00360	27.48	***
radCAP x labCAP	-0.00004	0.00002	-0.00164	-1.97	*
radCAP x mwACUBED	0.00014	0.00002	-0.00052	5.79	***
intercept	14.03000	3.05400	-	4.59	***

Significance code (p-value): 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Based on relative importance, the factor interactions for *edTRMRM* x *mwACUBED*, and *edTRMCT* x *edARRV*, along with individual factor *mwACUBED*, are observed to be the most influential on the OCE performance metric. Increasing the number of ED treatment rooms staffed (*edTRMRM*) and staffed medical ward ACU beds (*mwACUBED*) will increase throughput, resulting in improvement to the OCE performance metric. Increasing the number of staffed medical ward ACU beds (*mwACUBED*) will increase throughput across all units, resulting in improvement to the OCE performance metric. Reducing the treatment cycle time (*edTRMCT*) should increase throughput for emergency patients, which some portion will require hospital admission. Reducing the DMA patient arrival rate (*dmaARRV*) will reduce competition for medical ward ACU beds (*mwACUBED*), improving the performance metric.

Quadratic effects were also examined using the second-order polynomial regression model (4); however, due to space restrictions a table is not shown. Incorporating quadratic effects in the model demonstrated a slight improvement where the R^2 was 0.9330 and adjusted R^2 was 0.9316. In total, 28 of the 44 factor combinations in the regression were found to be statistically significant.

The relatively important quadratic effects included the ED patient arrival rate (*edARRV*), the laboratory analyzer maximum workload capacity (*labCAP*), the radiology maximum workload capacity (*radCAP*), direct medical admission patient arrival rate (*dmaARRV*), number of ED treatment rooms staffed (*edTRMRM*), and number of medical ward ACU beds staffed (*mwACUBED*).

5 CONCLUSIONS AND FUTURE WORK

In this research a representative medium sized, semi-urban, acute care community hospital was modeled using system dynamics. The hospital model contained more than one hundred conceivably important factors presenting a sizable challenge to determine which factors are relatively important. The group screening design technique known as sequential bifurcation was successfully applied to identify the most important factors from the individual OCE subcomponent metrics. The identified important factors were used as candidates in performing sensitivity analysis using a regression analysis method. Results of the sensitivity analysis revealed three main findings.

First, the regression analysis for the first-order polynomial model confirmed that the sequential bifurcation technique had identified important factors which possessed strong main effects. All but one of the important factors identified with sequential bifurcation were found to be strongly significant.

Second, the regression analysis for the second-order polynomial model, with and without quadratic effects, revealed the existence of a number significantly different factor interactions and quadratic effects. Overall, for this particular hospital configuration, the most influential factors to achieving a high OCE performance metric score is through provisioning a sufficient number of staffed of ED treatment rooms (*edTRMRM*) and staffed ACU medical ward beds (*mwACUBED*). These factors were relatively important both individually and in combination with other factors. Fluctuations in the ED patient arrivals (*edARRV*) and the direct medical admission patient arrivals (*dmaARRV*) also contributed strongly to overall performance and efficiency levels. Significant variations in patient arrivals to the ED will increase or reduce the congestion level, and thus impact patient throughput. Increasing patient arrivals through direct admissions will intensify competition for medical ward bed space, thus impacting ED throughput particularly for patients requiring hospital admission.

Third, the use of the OCE performance metric proved to be beneficial in the context of studying the ED operational performance and efficiency. Using this metric, and subcomponents metrics, identification of the potential throughput restrictions is improved. Future work should incorporate and study similar performance metrics hospital-wide, such as the surgical unit, and the medical and surgical wards.

Sensitivity analysis has provided valuable insight into hospital-wide performance. While this has revealed detailed information about the identified important factors in this large and complex system, it is important reflect on the fact that this knowledge may serve as a starting point. Using these sensitivity analysis findings, future research may be conducted to evaluate the administration policies and procedures.

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