Modeling Hospital Resources with Process Oriented Simulation

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Abstract

A hospital environment is a complex system that requires appropriate allocation of human and material resources in order to optimize its effectiveness and efficiency. This paper utilizes an AWESIM simulation model to investigate patients' flow in a hospital, and how the resources are utilized to respond to the health care system. Results of the study provide insight to the management as to how the patient, doctors, paramedics and other non-clinical resources compete to respond to the health care needs. As an example of how to reduce patients' queue time, the administrator may use the response surface results showing how to combine resources to improve resource deployment and enhance operational efficiency. Additionally, to be truly competitive in the healthcare market, hospital administrators must use a mix of strategies to respond to structural changes in the healthcare industry.

Keywords: Simulation, Medical, Hospital Resources, Design of experiment

1. Introduction

There has been continued interest in ensuring that health care organizations meet the needs and demands of patients while ensuring effective and efficient use of resources (Harper et al., 2005). The provision and use of health services is of great significance in meeting the healthcare needs of a population (Vasilakis and Marshall, 2005). The internal dynamics of a hospital represent complex non-linear structures that require a high degree of coordination and interaction between human and material elements. To plan and manage these resources require a good understanding of the hospital system. The perception of the quality of care for patients is based on the attitudes displayed by the hospital staff, the willingness of the facility to provide information, the attention shown by individuals within the hospital, and the amount of time they are required to wait for service (Blake et al., 1996; Yeh and Lin, 2007). The existence of long waiting time is generally indicative of high customer flow or server capacity problems, or lack of quality improvement measures. Indeed, Wang et al. (2006) state that many healthcare organizations pay a lot of attention to quality improvement, because not only can higher quality of care increase patient satisfaction, overall cost may be decreased as well. In other words, high quality of care increases the overall competitiveness of healthcare organizations. A clear indicator of quality of service in a hospital is patient waiting time. Derlet et al. (2001) and Carter and Lapierre (1999) point out that the causes of hospital overcrowding include low staff (physicians and nurses) availability, high patient acuity, hospital bed shortage, high patient volume, radiology and lab delays, and insufficient hospital space.

Since healthcare systems involve the coordination of interacting resources and human activities, it is natural that they generate a range of organizational problems that can be adequately addressed by scientific approaches of operations research, such as simulation modeling. Such a model can be used in conjunction with performance indicators, like time in the system, and time spent waiting in queues, to test the effects of different levels of capacity in a hospital system. The inherent flexibility of simulation modeling allows decision makers to implement different strategies in order to achieve desired objectives. Consequently, the stochastic nature of health systems and variability in the input and output parameters can be easily accommodated (Blake et al., 1996; Harper and Shahani, 2002). Furthermore, the simulation approach captures the variability of the input parameters, and introduces capacity constraints in the various stages of care (Wang et al., 2006).

The effectiveness of a hospital system depends not only on the amount of resources assigned to it, but also the efficiency with which they are used. Simulation model is potentially useful for tactical decisions in the day-to-day scheduling of the waiting list and the allocation of patients to hospitals. One advantage of the flexible nature of the model is that the user is able to investigate the likely consequences of changes in capacities and hospital practices. This may be through changing current configurations of existing wards or through the creation of new clinical groupings or units (Harper and Shahani, 2002). Applying the model to waiting list data aids the periodic review of system performance (Yeh and Lin, 2007). The model can be used in strategic or planning role to investigate alternative configurations and redeployment of resources, and the likely response to changes in case load or resource availability (Everett, 2002). The purpose of this paper is to investigate the waiting time and total time patients spend in a hospital. A patient's waiting time here refers to the waiting time in various queues when going through the health care facility. This includes the waiting time for the doctor's diagnosis, waiting for various related examinations, and the time during which the nursing staff fails to provide immediate care. Results of the simulation model would help hospital managers address the substantive areas in the hospital system in order to improve patient throughput. Additionally, suggestions are given on how hospital managers can to respond to changes in the external environment in order to increase competitive advantage.

2. Literature Review

Long waiting time in a hospital facility is one of the indicators of poor quality assurance. Long queue is symptomatic of hospital inefficiency and indicative of the system's inability to satisfy patients' demand within a reasonable period of time (Gonzalez-Busto and Garcia, 1999). The health of patients could be jeopardized by long queues due to hospital overcrowding. Infact, Bloom and Fenderick (1987) claim that longer waits downgrade care. In their study, survey feedback from patients indicated that shorter waits and more convenience for patients tend to lead to better patient response to care. Additionally, Bindman et al. (1991) suggest that patients are likely to leave without receiving care because of long waiting lines. They also claim that without the necessary care, patients are twice as likely to suffer more from their sicknesses.

Several studies have shown that simulation is an effective tool for investigating complex problems such as the hospital environment, and that the result can be used to enhance quality of care (Lopez-Valcarcel and Perez, 1994; Jones et al., 1997). For example, Jones et al. (1997) demonstrate how the quality of service in an emergency room can be improved by utilizing total quality management (TQM) concepts and simulation-animation tool in the generation of feasible alternatives. Yeh and Lin (2007) investigated how to improve the quality of service at a hospital emergency department by using simulation and genetic algorithm to appropriately adjust nurses' schedules without hiring additional staff. The simulation model was developed to cover the complete flow of patients through the emergency department. Genetic algorithm was then applied to find a near-optimal nurse schedule based on minimizing the patients' queue time. Results of the study indicate that by making appropriate adjustments to the nurses' schedules, the patients queue time could be shortened by 43 percent without increasing the number of nurses in the system.

Similarly, Jun et al (1999) conducted a simulation of nurse workload in an emergency room and its effect on the average number of patients, and average time in the system. By comparing the current schedule with alternative schedules, it was found that both the average waiting time, and the average time in the system could be reduced without increasing cost. It was also found that patient's length of stay could also be reduced by finding the optimal number of nurses and technicians that should be on duty during four shift periods in an emergency room. Wang et al. (2006) also used queuing theory and simulation to investigate the waiting time in a healthcare facility in Taiwan by incorporating sources and methods of prevention of human errors into the model. By categorizing and prioritizing the levels of care as critical, serious, and stable, the model reduced expected waiting time by 50 percent, without employing additional staff.

Ahmed and Amagoh (2007) used a design of experiment model to conduct a time study of the accident and emergency department (AED) of a hospital. The time study analysis was used to derive the necessary parameters in the AED system, and identifies system characteristics needed to reduce waiting time and improve the overall patient care management system. The study identified the time slot with the highest patient arrival rate, and suggested measures to enhance the AED's operational efficiency and improve patients' throughput.

In order to determine expected waiting time for patients, Cromwell (2004) proposed a clearance time function as a more informed predictor of patient waiting time. The clearance time is defined as the number of patients on a waiting list divided by the expected rate of admission from the list. The technique is a crude approximation of the expected waiting time of the next person to join the waiting list. However, the study cautions that the clearance time estimate can be made more realistic by basing it on urgency category and accounting for the prioritization of admissions.

Harper and Shahani (2002) designed a simulation model to study the planning and management of bed capacities in a UK hospital. The study considered various types of patient flow and the resulting bed needs over time. Results of the study indicate a possible reduction of 10 to 30 percent bed-days between the various units of the hospital. Finally, Everett (2002) designed a simulation model to support the scheduling of patients waiting for surgery in the Australia public hospital system. Patients were categorized by urgency and type of operation. Results of the study indicate that urgent and semi-urgent cases were being coped with adequately, while routine cases needed some improvement. Such evidence aided hospital administrators in investigating alternative configurations and deployment of resources.

These findings suggest that simulation modeling is an effective decision making tool that can help hospital managers enhance quality of care by reducing patient waiting time.

3. Background of the Study

The ministry of health in a country in the Asian region commissioned tertiary and secondary healthcare establishments to provide professional and quality healthcare services to the citizens, through a balanced program of healthcare, research and education. Consistent with the mission of one of the hospitals, the medical staff provides quality services and is responsive to the medical care needs and expectations of its patients. The hospital management aims to advance and upgrade the medical practices and technology with periodic reviews of programs, services and equipments in order to improve the quality of care delivered to patients.

The hospital occupies an area of 160,000 square feet, has a 500-bed capacity and an occupancy rate of 75 percent. It employs approximately 730 health care workers, which include doctors and other employees that give care to patients. The hospital also serves as a referral center for different clinical specialties. It serves about 1000 outpatients a day, while the surgical department performs approximately 500 operations a month. The medical records department is computerized to keep fast and accurate records of the large turnover of patients. There are also well-trained medical secretaries that serve all departments. The following section provides a summary of the medical facilities within the hospital.

3.1 Clinical Departments

The medical department includes specialties in Neurology, Endocrinology, Gastroenterology and Infectious Diseases. It also has other departments, such as the orthopedic department, which performs joint replacement surgery routinely and has a large number of trauma cases. The ophthalmology department is equipped with the most modern equipments, including Argon and Nd-Yag laser, and performs complicated Vitreo-Retinal surgery routinely. It performs a total of about 700 major eye operations yearly. The physical medicine department has all the facilities for physiotherapy and rehabilitation. The Urology department has a Lithotripter for non-invasive dissolution of renal stones. The general clinic serves as a prescreening facility that recommends treatment plans for patients.

3.2 Non Clinical Departments

The radiology department is equipped with the latest technological equipments, including computerized topography and digital subtraction angiography. The laboratories are equipped with the most modern facilities to provide fast and efficient services in the hospital. The nuclear medicine department is equipped with facilities and isotopes to scan most organs with the latest version of gamma cameras.

3.3 Tertiary Facilities

Cardiology, Cardiac Surgery, Renal Transplantation, Oncology Services, Burns Unit, Plastic Surgery and Neonatology are the specialties for which the hospital is a national referral center. The Cardiology Department performs all diagnostic and therapeutic invasive procedures including Percutaneous Transluminal Coronary Angioplasty, and Intra-Coronary Stent Implantation. The Cardiac Surgery Department performs 450 open heart and closed heart operations a year. The Oncology Department provides a multidisciplinary approach in diagnosing and treating tumors, while the Radiology Department is equipped with the most advanced equipments. The Renal Transplant Department regularly performs live related transplants.

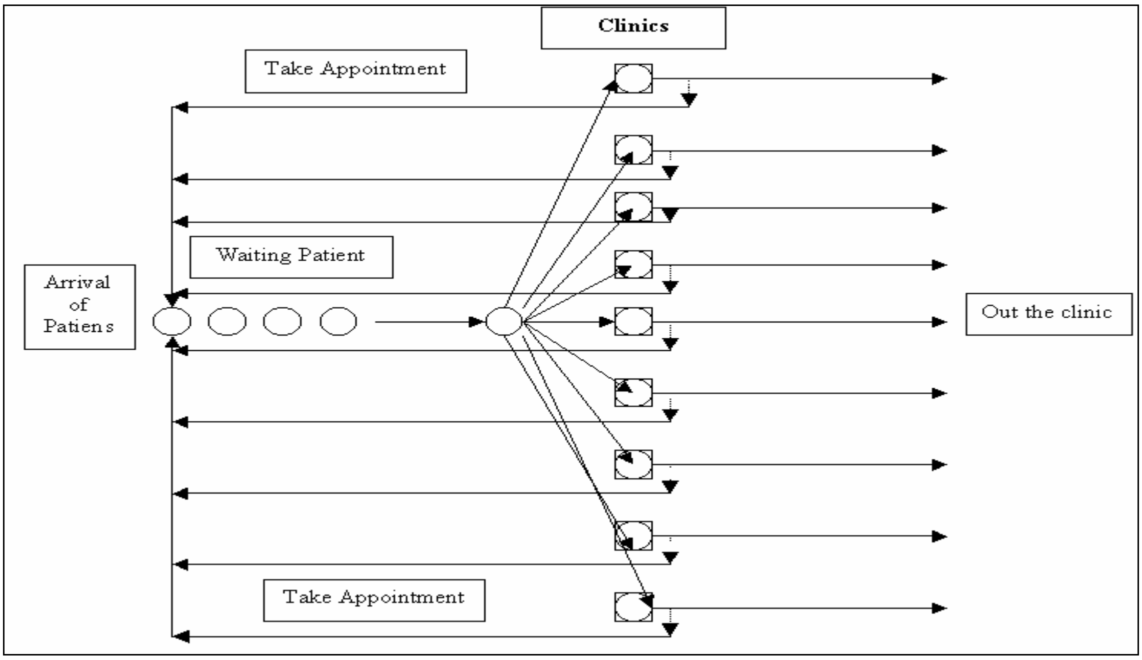

Figure 1: Patient Processing Logic

4. Simulating the Hospital Patient Flow

A process oriented simulation model using AWESIM is developed with the patient flow pattern through the hospital system. Iconic representations of the AWESIM simulation blocks model the hospital clinics system. It is usually difficult to construct analytic models to represent such complex environments (Fishwick, 1995). AWESIM is a discrete event simulation model that changes its state each time a new event occurs (Delaney and Vaccari, 1989). The simulation approach is based on the description of the series of events that occur in sequence, in order to replicate the system behavior. To understand the system and determine the control variables that would improve the hospital preferences and determine policies, it is necessary to setup a number of defined and appropriately designed experiments. It is also necessary to understand the kinds of control variables, which represent the critical resources, and performance measures that would have significant influence on the overall system performances.

In this paper, we consider the patient arrival in the hospital as discrete elements. The events that trigger the clinic to respond to patient's needs are modeled as sequence of discrete events connected logically in order to construct the overall simulation model. The patients flow through the system at different locations and interact with the resources that are necessary to facilitate their care. The resources are the clinic premises, waiting room, administrative staff, nurses, doctors, emergency equipments, and other necessary inventories. In addition, the system is governed by other important system parameters. Some of these parameters can be listed as: total time a patient is spending in the clinics to go through the healthcare phases, the waiting time, the idle time of the resources, and busy time of the paramedics and doctors, including nurses. Essentially, the simulation should run for a long period of time to avert the unbiased estimate of the system performances. AWESIM is powerful enough to keep track of the system behavior and generates statistics and other data that can be used later for detailed analysis. Furthermore, AWESIM allows a modeler to incorporate priority processing, and allocate different resources when necessary at any stage of the treatment process.

In Figure 1, the patient arrival pattern is uniformly distributed between 5 and 25 minutes. Upon arrival, patients wait in queue for registration. Once it is time to attend to the patient, the patient is assigned the clinics to visit. The simulation study focuses on the nine clinical sections. This is used to analyze the patient flow through the clinic, the time to finish consultations and treatment, resources utilization, waiting time due to scheduling of doctors, nurses and equipment facilities, and queue length at any time inside the clinical departments. The purpose is to develop a knowledge based system that identifies the causes and effects of the resource utilization, and the effects of resource deployment on the overall service system in the clinics. Additionally, the results obtained from the simulation study would be used to construct decision support model to aid hospital management identify possible strategies to manage the hospital resources efficiently. The simulation study would identify the related service parameters that are needed to improve the quality of services in the hospital.

For example, in the dental clinic, the patient's waiting time is normally distributed with a mean of 15 minutes and standard deviation of 10 minutes. The clinic consultation time is normally distributed with a mean of 30 minutes and standard deviation of 12 minutes. Service time is uniformly distributed between 5 and 25 minutes. Upon consultation, the patient leaves the clinic or is recommended for further visits to one of the other clinics.

According to Figure 1, arriving patients wait for registration. Accordingly, the patients are routed to one of the clinics. We consider two scenarios to route the patients; in Scenario 1 the patients are routed to the clinics according to the preferences, while in Scenario 2 patients are routed based on prior probabilistic assignments. We develop a simulation model to understand the behavior of the clinical system in terms of all internal resources utilization. Since we have the prior knowledge of how patient are routed to the different clinics, this could be used as a base scenario. Therefore, Scenario 2 can be compared with Scenario 1.

4.1 Properties of Discrete Event Simulation

AWESIM, being a process-oriented language is used to construct simulation model and is a convenient devise to describe a system. In AWESIM, there are blocks, which serve as graphical description of events or actions in a system in order to illustrate the occurrence of events in the environment. The software can model the time requirements for a patient to arrive at the waiting room of a clinic in order to extract information about the true situation of the clinic's management. The blocks can record statistics, such as length of a waiting queue. Modeling capability includes preserving the state of a system at a particular time and simulating from a state previously stored. It is also possible with advance features, to communication with other applications. The simulation model developed using AWESIM depicts real-life events, and possesses generalization features with well-designed experiments.

This language with block features is suited for discrete and continuous event simulation. Each block has the capability to carry out multiple activities and events. Patients inside the system are referred to as entities. Procedures, such as demand and employment of resources, synchronization, waiting, bulking operations, priority setting, queue selection rule, priority rule assignment, branching decisions, assigning multiple servers and many other features are also available. Appropriate blocks describe patient arrival, patient characteristics, types of services required and time to finish consultations, and adds other features to model the hospital simulation conveniently. The average time a patient spends in a queue as well the system time describing the total time a patient spend in the clinic or hospital to finish a treatment, is used by hospital management to interpret how efficiently the hospital system is working. In addition, the utilization statistics of resources and employees are management decision parameters utilized to develop efficient hospital management from administrators' and customers' viewpoint.

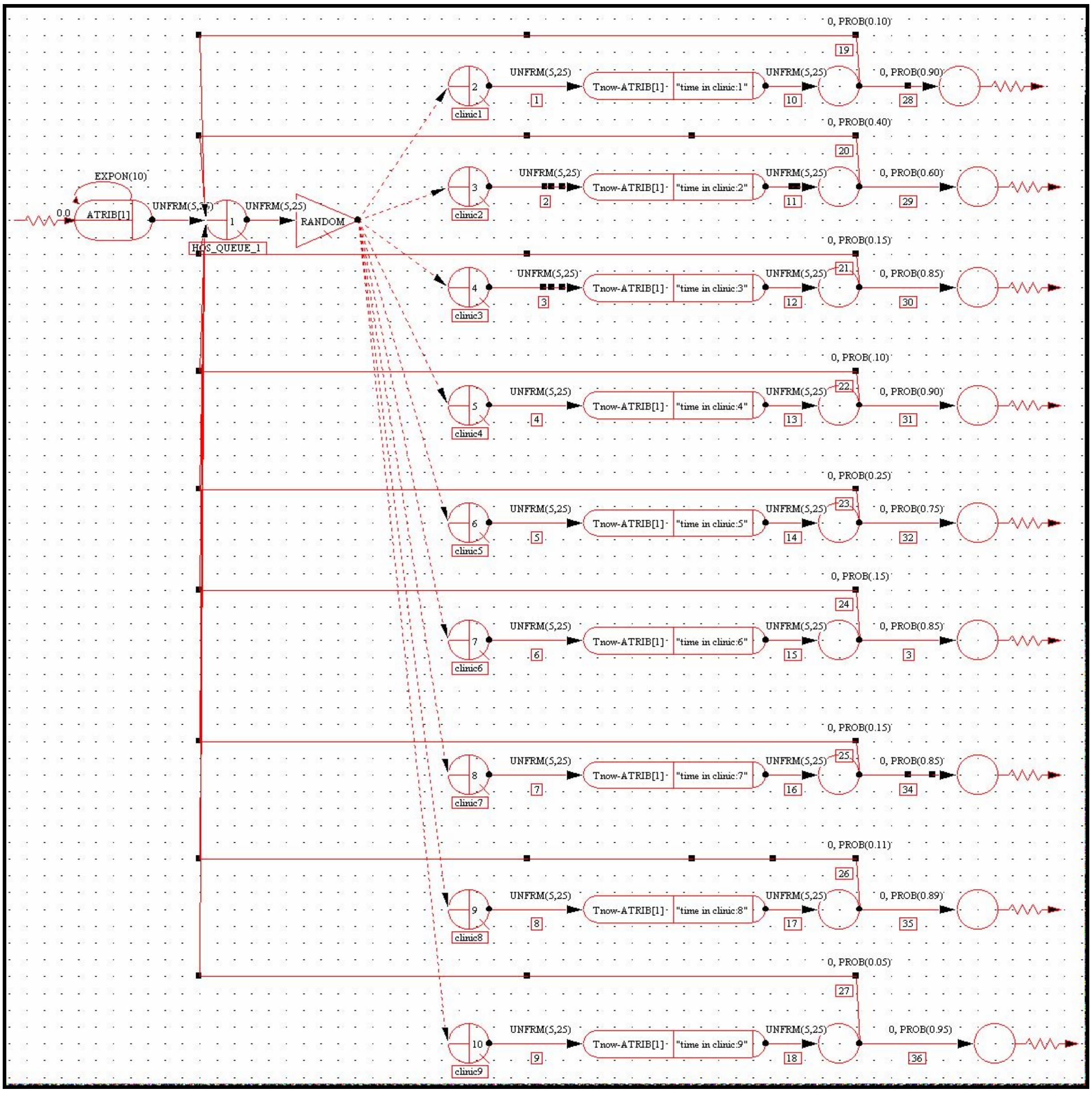

Figure 2: Scenario 1 Clinic Model

4.2 The Simulation Model

In this study, two scenarios (Scenario 1 and Scenario 2) are modeled using a simulation of the hospital environment. Figure 3 depicts the simulation model to describe the patient arrival, wait and consultation process in addition to registration and further referral within the clinic for Scenario 1. The model is explained with the simulation blocks called CREATE node. The block records patient arrival into the hospital according to the time between previous arrivals with exponential distributions with a mean of 10, defined as EXPON (10). The current time of arrival is stored in attribute one, denoted as ATRIB (1). This block helps to identify the patient's time within the hospital. To facilitate the patient waiting in case resources are busy or inadequate for the service facility, the patients are held in queue in a waiting room. The queue statistics are recorded in file number 1, as shown in Figure 4.

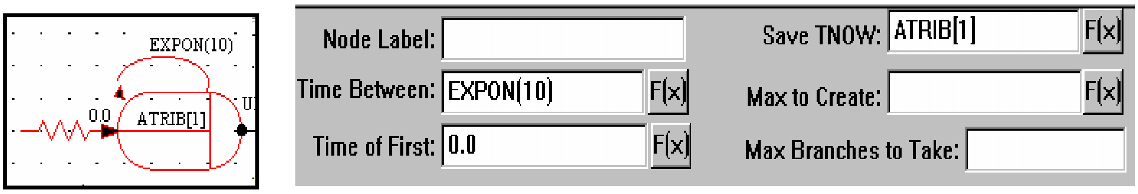

Figure 3: CRAETE Node

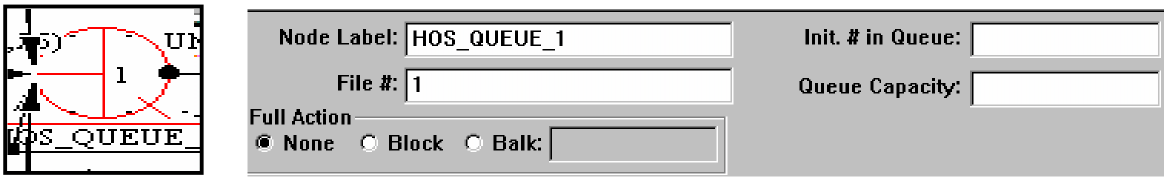

Figure 4: QUEUE Node

Selecting one of the clinics upon arrival is based on a random rule in this model, prior to registration. The queue selection rule may have different options and depending on the general observations a rule may be adopted. The SELECT node with random rule accomplishes this as shown in Figure 5.

Figure 5: SELECT Node

The queue at the clinic is used to assign the patient in a designated area adjacent to the clinic. The block QUEUE in Figure 6 is used for this purpose, with file number 2 to keep the statistical records.

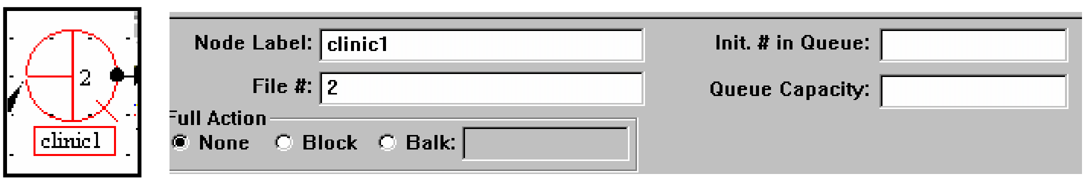

Figure 6: QUEUE Node

To understand how much time a patient is spending in a clinic, it is necessary to record the patient system time as a measure of the difference between the times a patient enters the clinic and when the patient finally leaves the clinic after treatment. In Figure 7, a COLCT node is used to achieve this objective.

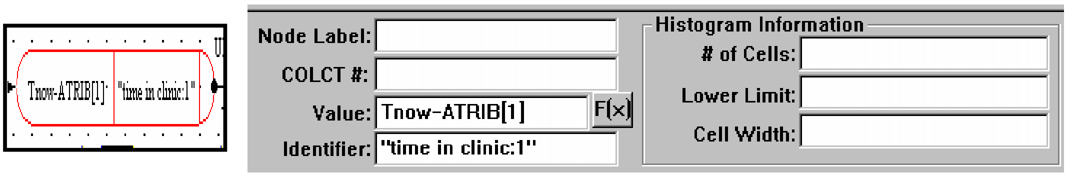

Figure 7: COLCT Node

A GOON node is shown in Figure 8, to facilitate the model clarity and model building logic. Its function is to connect two blocks in series or sequence.

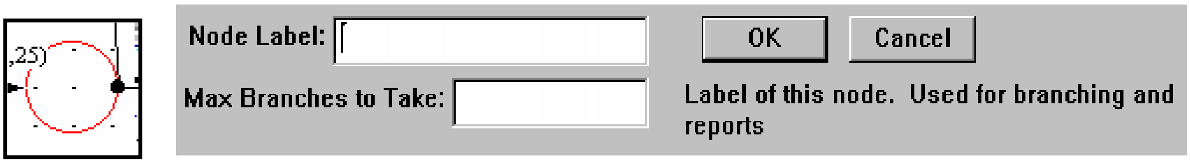

Figure 8: GOON Node

A TERMINATE node is shown in Figure 9 to remove a patient from the clinic when the consultations are over. This node can model predetermined number of patients to be processed in the clinics, if need arises. This helps to enforce management quota in order to process desired number of patients, based on resource requirements.

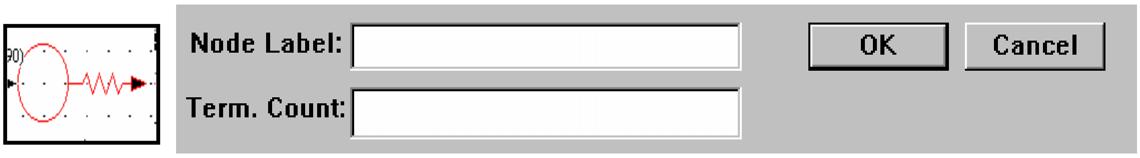

Figure 9: TERNINATE Node

The model is simulated 9 times with time steps of 100 minutes each, while average system time, waiting time, queue length as well as idle time of the server, are noted. Figure 10 shows the measurements that illustrate system performance for Scenario 1, while figure 11 shows the queue behavior, its standard deviation, maximum length of the queue, current queue length, and average waiting time.

In Scenario 2 simulation model, the arrival of patients is routed to the clinics with probabilistic branches. All nine clinics are assigned patients according to past records of percentage of visits to the clinics.

5. Results and Analysis

It is important for healthcare facilities to have reliable measures for predicting and modeling patient flow within the system (Vasilakis and Marshall, 2005). In this study, two scenarios (Scenario 1, and Scenario 2) are utilized in the simulation model of a hospital environment. Figure 1 depicts the control system time with respect to idle time and waiting time. This is an illustration of how the hospital management may design or reconfigure hospital resources with regards to idle time and waiting time. This may imply deployment or adjustment of resources, such that the waiting time and idle time are varied in ways that would influence the system time. The ability to configure system time with such combinations would improve the overall performance of the clinics from the patients' viewpoint.

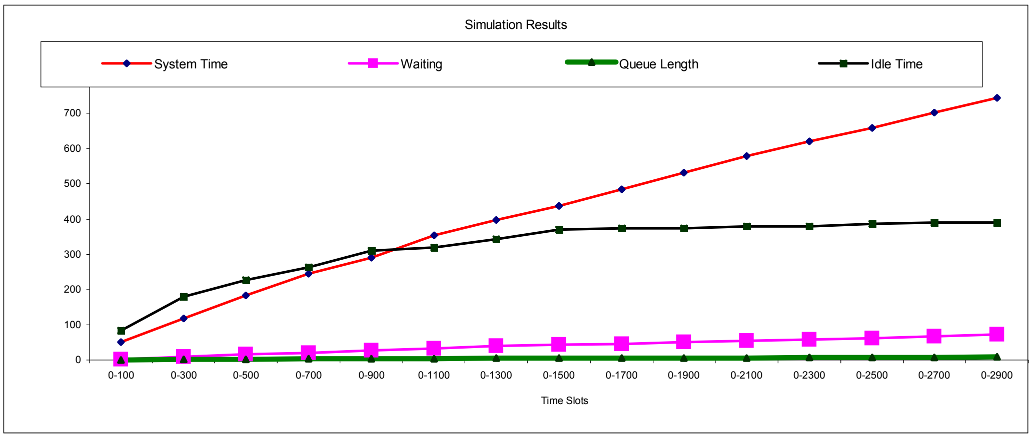

Figure 10: Clinic System Performance (Scenario 1)

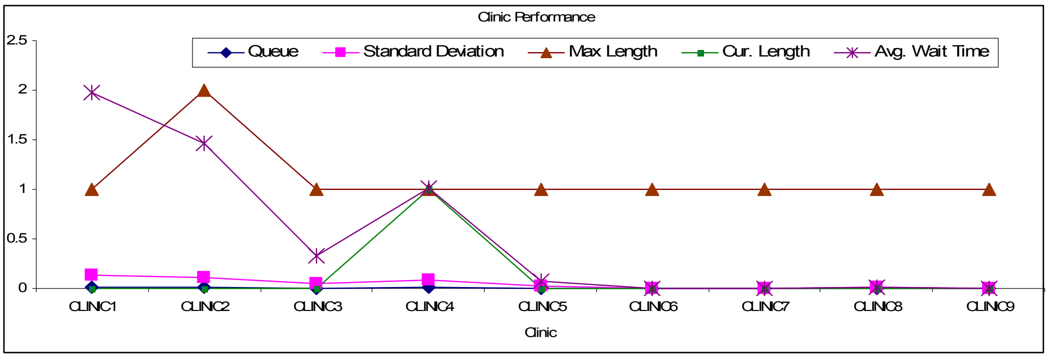

Figure 11: Clinic System Performance (Scenario 1)

Figure 12 shows the system time for Scenario 1 through the surface response diagram and equation. In Scenario 1, the patient enters either of the clinics based on systematic queue selection rule. Using response surface analysis, we developed the system time as a function of waiting time and idle time. Waiting time refers to average queue length in the clinic, while idle time refers to either doctors or nurses' utilization. The system time is modeled as $65.062-0.4258x+85.2978y+0.0003x^2+0.05xy-0.8788y^2$, whereby x and y refer to idle time and waiting time, respectively.

The study illustrates the complex relationship between idle time and waiting time, as well as the interactions between these two parameters. From the hospital management viewpoint, the response surface equation suggests that in Scenario 1, a patient at least has to be in the system for 65 minutes in order to complete the treatment even if we reduce idle time and waiting time to zero. A calibration graph of this kind provides significant insights to hospital management on how resources should be deployed in order to achieve a set target. Similar explanations hold for Scenario 2.

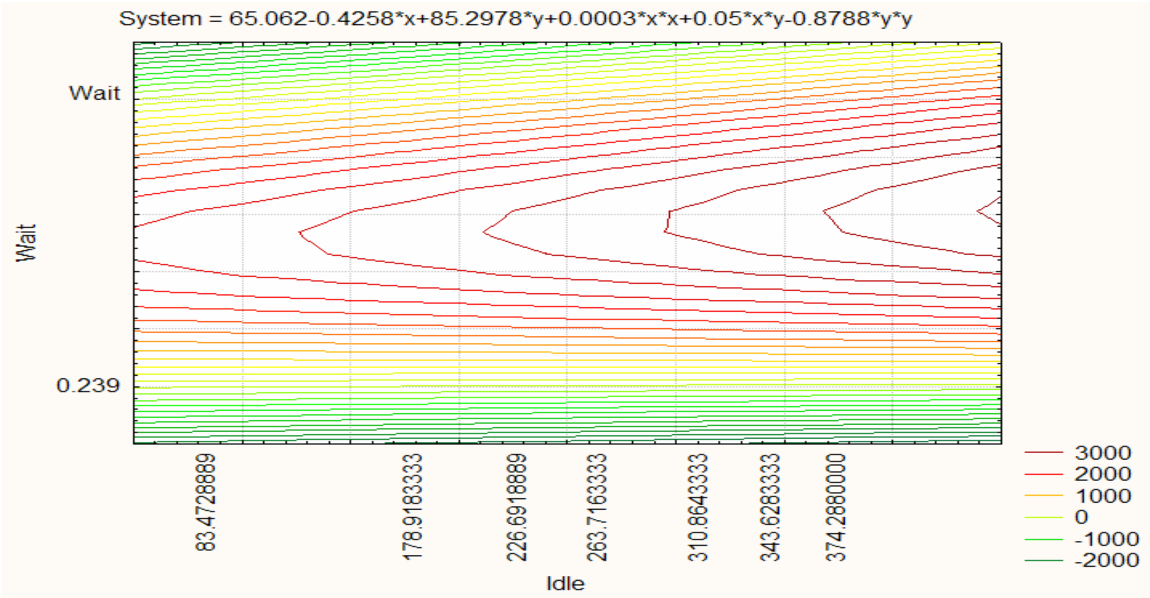

Figure 12: System Time with Scenario 1

Figure 10 shows the system waiting time, queue length and idle time behavior for Scenario 1. As we varied the simulation time due to complex behavior, there is a tendency of the system time to have a positive correlation with idle time and waiting time. In other words, it seems that waiting time and idle time are influencing the system. Figure 11 depicts the clinic system performance with respect to queues, its standard deviation, maximum length, current length, and average waiting time. To an extent, clinics 5, 6, 7, 8, and 9 show consistent performance, while there are variations in clinics 1, 2, 3, and 4 with respect to these parameters. It may imply that clinics 1, 2, 3, and 4 require additional resources.

6. Measures to Improve Performance

This paper uses AWESIM simulation model to identify system parameters that affect patient queue time in order to enhance hospital service quality. An important aspect of understanding the competitive advantage in the hospital industry is an evaluation of its internal and external environments (Cueille, 2006). The system parameters identified in this study demand attention from management in order to improve service quality. Consequently, efforts to reduce patient waiting time would require the optimization of hospital operational/internal factors. For example, Jun et al. (1999) suggest that one of the causes of long patient waiting time is hospital-specific inefficiency. This may be addressed by appropriate patient scheduling and admission rules, patient routing and flow schemes, and judicious scheduling of human and material resources (Jun et al., 1999; Ahmed and Amagoh, 2007). Other measures that have been suggested to reduce waiting time include quasi-parallel processing where patients are directed to the shortest queue to maintain flow, vis-à-vis serial processing, whereby patients wait in a single queue (Edwards, 1994). Blake et al. (1996) also suggest implementation of a fast-track lane for non-urgent patients as a way of reducing waiting time at minimal costs.

Three important strategies that hospital management should consider are patient mix, positioning, and cost leadership. Patient mix strategy relate to the types of patients that uses the hospital, such as type and seriousness of illness, patient demographics, and specialty versus general care (Langerbeer, 1998). Positioning strategy reflects the market share and how the hospital has competitively positioned itself in the market, while cost leadership strategy focuses mostly on internal processes as means of reducing costs (Kumar and Subramanian, 2000; Langerbeer, 1998; Ozgulbas and Koyuncugil, 2006).

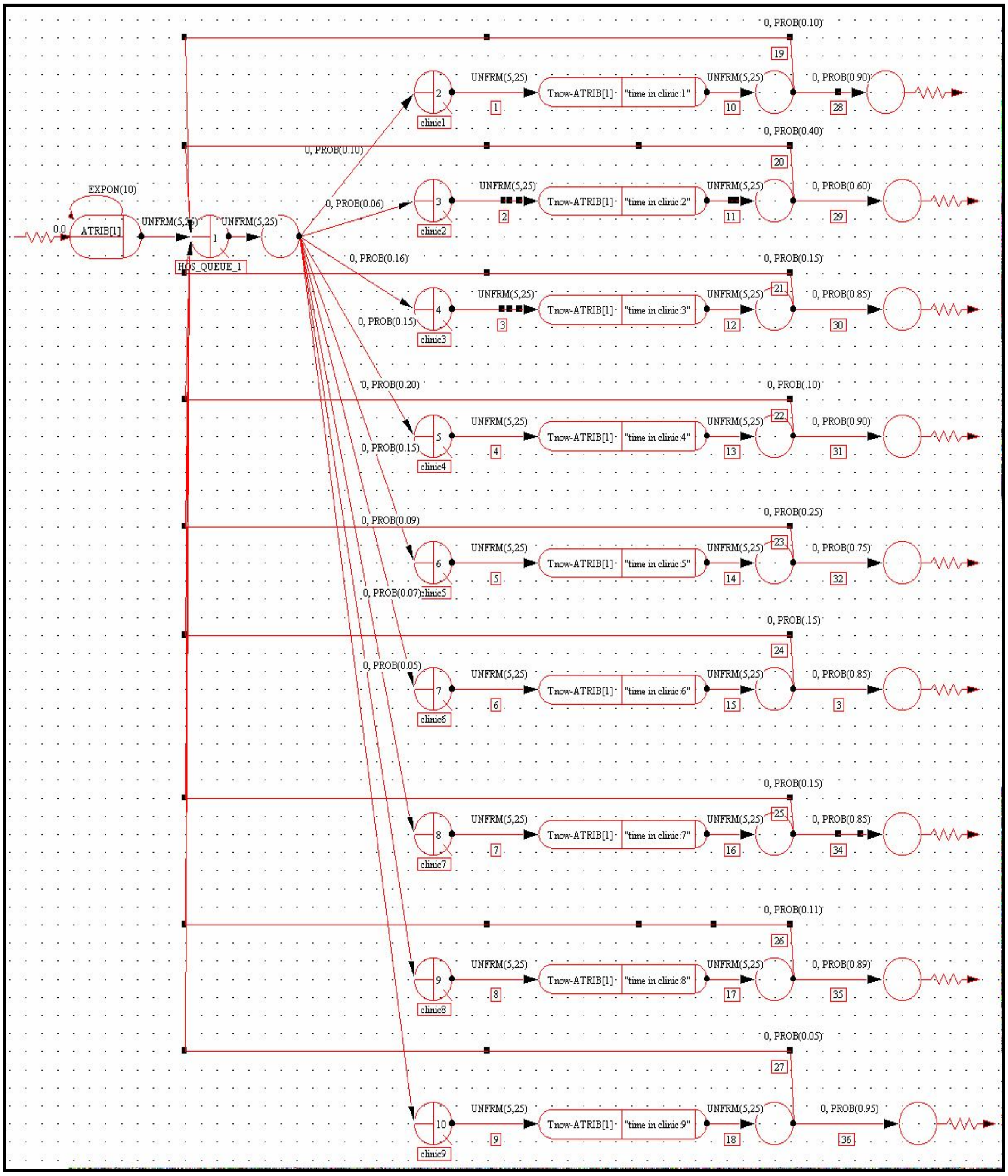

Figure13: Scenario 2 Clinic model

Since our analysis indicates that the minimum waiting time for a patient in Scenario 1 is 65 minutes, management should consider whether the hospital should concentrate on certain specialties rather than being involved on too many specializations. In fact, the minimum wait time in Scenario 2 (Figure 16), whereby patients are routed to clinics based on past records of percentage of visits to the nine clinics is 240 minutes. Further, the fact that the system time continues to rise as shown in Figure 10 implies that the hospital is not capable to cope with the demands of patients. Unless major operational changes occur, the situation will worsen and overall service quality will continue to deteriorate.

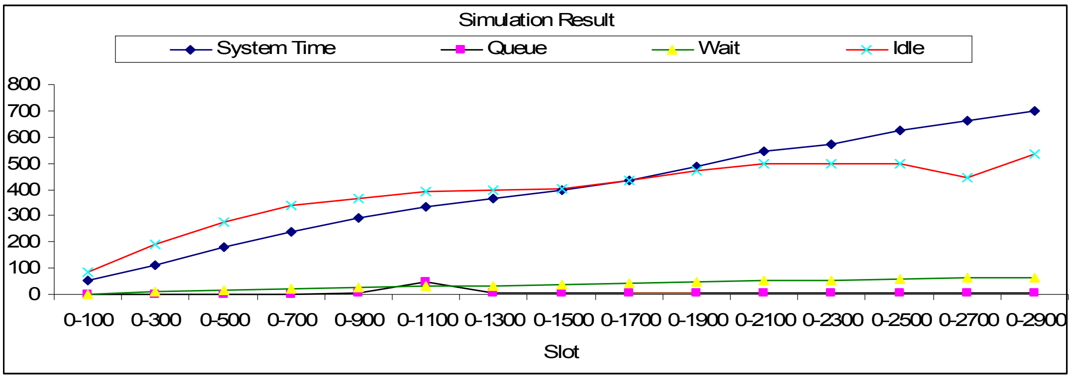

Figure 14: Clinic System Performance (Scenario 2)

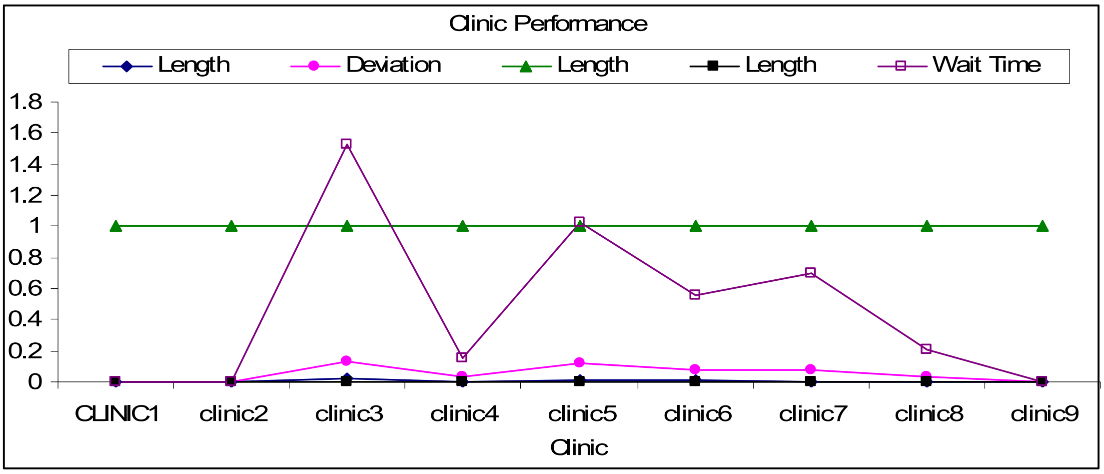

Figure 15: Clinic Performance (Scenario 2)

While these measures account for improving operational factors to reduce patient wait time, to be truly competitive a hospital must also focus on its external environment. Porter (1991) identifies the two key areas that enhance an organization's success as an understanding of industry structure and firm core competencies. Hospital management should be aware of structural changes in the healthcare industry and how to respond to such changes. For example, competition from other hospitals and specialty clinics, schemes by health insurance industry to reduce healthcare payments for treating patients, attitudes of doctors and nurses unions, and the trend in government subsidies. These factors and how they are addressed affect the competitive position of a hospital.

7. Conclusion

This study reports on a simulation model to investigate patients waiting time in a hospital system using AWESIM modeling technique. We have two simulation models where the queue selection is based on probabilistic and selection rules. Using patient flow analysis, we develop a discrete simulation model for two scenarios in a hospital system. The main feature of this modeling is to translate chronological occurrence of events in real time by means of discrete event simulation method. This discrete simulation characterizes a real life scenario based on dynamic modeling characteristics. AWESIM simulation blocks possess statistical properties and hence complex modeling is not impossible. We simulate the system behavior for long enough time in order to eliminate bias in the system. The system performance, however, has not been benchmarked, but we repeated the simulation several times to construct a design of experiment model. The statistics that we accumulate are queue length, standard deviation of queue length, median queue length, average patient waiting time in the clinics, and current queue length at the time of simulation.

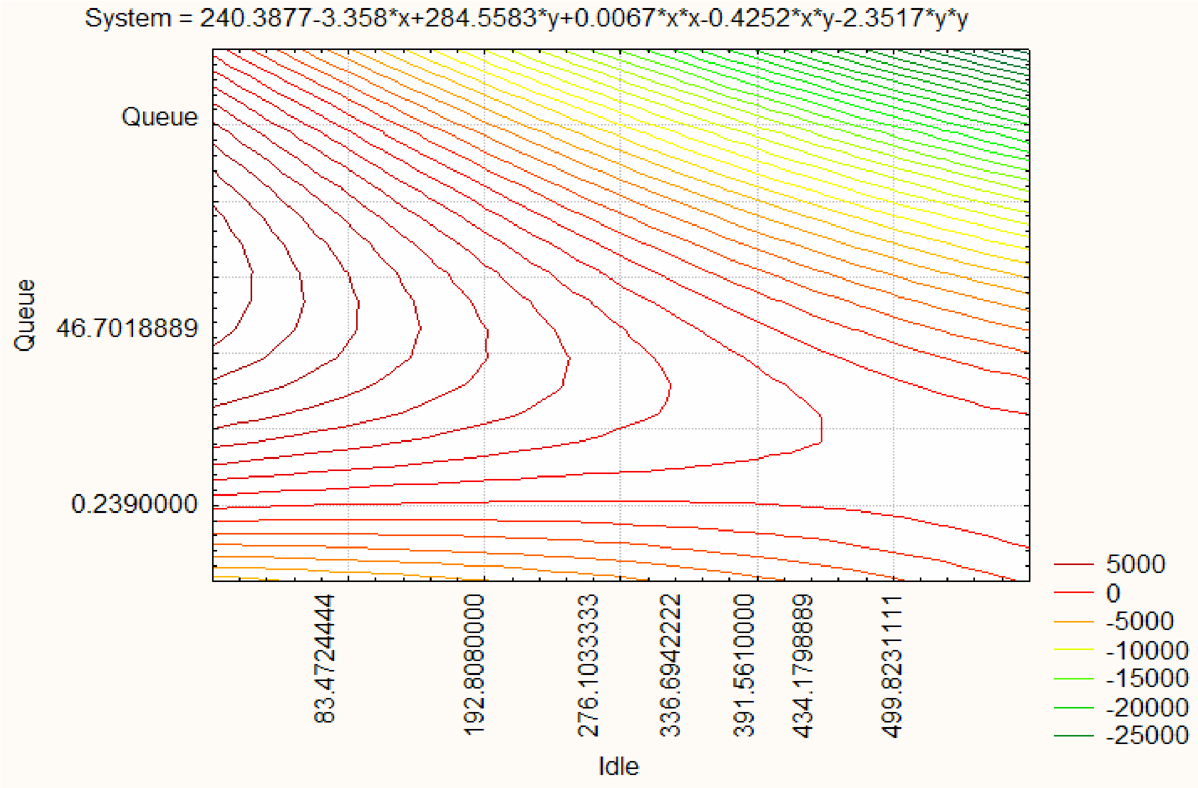

Figure 16: System Time with Scenario 2

In addition, we record patient waiting time, server idle time, and system time, which refers to the total length of time a patient spends inside the clinic. Using design of experiment, we develop system time as a function of patient waiting time and server idle time. The server idle time can alternately be interpreted as server utilization as a complement of idle time. Since idle time is an index of wastage of resources, we incorporate this parameter as a penalty to the system time. Waiting time on the other hand, implies that resources are busy hence the patient in the clinic needs to wait. As a consequence of these resources competing for service to be provided to the patient, the hospital system is affected. A hospital must optimize its material and human resources in order to reduce patient wait time. However, to be truly competitive, it must respond to the external environment by evaluating and understanding the structural changes in the hospital industry.

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