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# An Agent-Based Modelling Approach for Scheduling and Management of Elective Surgeries

**Neetta Vasudeo Koli[1], Farhaan Mirza[1], Mirza Mansoor Baig[1]* and Ehsan Ullah[2]**

*[1]School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology, New Zealand*

*[2]Clinical Quality and Safety Service, Auckland City Hospital, Auckland District Health Board, New Zealand*

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***Corresponding author**

Mirza Mansoor Baig, School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand, Email: mirzamansoor01@gmail.com



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## Abstract

Efficient elective surgery scheduling is one of the pain points in the current healthcare management and has a serious impact on the overall healthcare delivery. Currently, the health organizations struggle to achieve their elective surgeries/outpatient targets due to clinical and non-clinical reasons. Some of the common factors are day of surgery cancellations, use of medications, and development of unforeseen clinical complexities. Non-clinical factors could be surgeon's schedule and unavailability of the operating rooms or equipment. Overcoming these issues will enable the hospital to increase their efficiency and ultimately serve more patients within the allocated budgets with reduced wait-times for the surgery.

This research presents an in-depth literature review of the elective surgery models, elective health strategies in practice and key enablers for change with regards to the elective procedures. Furthermore, we present a concept of using agent-based model (ABM) to simulate system dynamics of an elective surgery scheduling process. The model is validated by experimentations and altering parameters of the built model. As an outcome, the proposed model is capable of handling hospital resource utilization, time estimation of each case (surgery) from the waiting list and forecasting the scheduling of the surgeons.

## Introduction

Elective Surgery (ES) is any planned surgical procedure that aims to improve an individual's quality of life psychologically and/or physically, reinstate independence and in particular cases prolongs life [1]. ES enables the person to do activities that are important to lead a normal and independent life, but not considered as an hospital emergency which requires immediate treatment [1]. For example, a cataract surgery is not obligatory but the individual who is treated will be able to read and drive like a normal person emphasizing immense lifestyle benefits. Similarly, a grommet procedure can restore the ability to hear with a glue ear. A hip replacement can relieve pain and enhance mobility to carry out day to day tasks [2].

Inaccurate scheduling costs 9% of the annual healthcare budget in the UK [3], hence accurate prediction is a prerequisite to avoid extremes over-utilization and under-utilization of the resources. As per the British study [3], out of 3657 operating schedules, 20.9% of the schedules went over-time and 71.4% were underused. Research findings by Health Funds Association of New Zealand [4] reported that 280,000 people had ES in the year 2014 and since 2008, 41% increase in the demand for ES is recorded [4]. The University of Rochester Medical Centre conducteda research to study the impact of economic downturn on the Elective Lumbar Spine Surgery in the United States. The study illustrated that the economic downturn did not affect elective lumbar fusions as individuals utilize insurance to cover the cost of the procedure [5].

ES scheduling deal with significant wait-lists in almost every public health system across the globe [6], this implies that ES is certainly in demand and require optimum utilization of hospital resources and staff with best possible management strategies and tools [6-7]. For the vast majority of the publicly funded ES, the general population wait-lists with the pain and discomfort experienced for a variable amount of time depending on type of surgery and availability of resources [7].

Health delivery management and planning plays an important role in the allocation of time, budget and resources. The priority criteria to schedule an elective surgery often based on the clinical urgency, wait-list, severity and surgeon's experience (varies case-by-case) [8]. However, worsening of the condition or inappropriate delays in evaluation can lead to increased risk of mortality and morbidity. The challenge for providing equal access with minimal harmful delays are multifactorial and dependent on various policies, protocols, aspects of diseases and capacity of hospitals to accommodate surgeries. This highlights the need of the planning and scheduling tools and computer models required to make better and informed decision about the resource allocations [8-10].

## Modeling Techniques

This research focused on employing simulation modeling technique as a concept to decrease wait-times for surgeries and increase efficient utilization of hospital resources. The following sections describe various modeling approaches investigated for optimized ES scheduling [11].

### Ideal-type models

Ideal-type models use simplification techniques such that some characteristics of the problem simplified. For example, an ideal-traffic model assumes that drivers never get lost, and ideal model of stock-market assumes that flow of information between the traders is instantaneous. These factors are simplified only when they do not affect the working of the models. Idealization removes the complicating factors from the model. It can be wisely used to draw conclusions about the target [11-12].

### Analogical models

Analogical models are based on the analogy between the target and perceived phenomenon. The most commonly used example is Billiard Ball Model of atoms which are based on the perception that atom was the smallest particles of the matter and was perceived to be as the billiard balls. This type of model is known to be useful for the matter of the fact that they have shown proven results that analogy can be applied to the target problem; however, the success depends on the adequacy of the analogy [11-12].

### Mathematical or equation models

Mathematical language and concepts are commonly used for social science experiments. Mathematical models establish relationships based on variables but do not imply analogy or resemblance unlike the other models. Mathematical models are extensively used by physicists, researchers, analysts, and economists. The success of these models often depends on the realistic data fitting in the equation. The origin of the equation should be based upon statistical evidence and not the theories of the behavior of parameters. These models clarify the relationship between variables, however, they fail to explain "why" the variables are inter-related and the mechanism for the relationship.

### Agent-based Modelling Approach

Agent based models (ABMs) simulate simultaneous operations and behaviours of multiple agents. ABMs are useful to illustrate and simulate complex phenomena. The process results in emergence of higher level macro phenomenon from the lower micro level behaviours of agents. In this research we adopted ABM approach, and this is articulated in the following section.

## Methodology

Agent-based modeling is based on simulating the actions and interactions of autonomous agents (both individual and collective entities such as organizations or groups) to asses their effects on the system as a whole.

The main focus of this article is to analyse issues reducing the wait-times, facilitating patients with timely surgery and enhanced the overall surgery management of the hospital. The outcome of the model is the waitlist for the hospital, prediction of the patient's position on the waitlist, cancellations impact, delay time, and impact of absence and efficiency of the resources.

The ABM was adopted to explore micro-level variations in schedule and observe macro-level outcomes in the hospital. The patients and surgeons would be represented as agents. NetLogo provides a simulated parallel environment to produce scientifically reproducible results of reduced wait-times and efficient scheduling techniques. Nevertheless, the impact of other major factors governing the optimum management of ES such as geographic accessibility, funding constraints, and management of personnel are excluded in the proposed model.

The simulation model explores the stability of the dynamics of existing resources, wait-list and current demand. Without actual implementation in the real-world, the model will help analyse the combination of parameters that can cause stability, instability, as well as the perfect balance of the system. We aim to identify, conflicting priorities and preferences of the current healthcare system can be identified with efficient utilization of the resources (surgeons and operating rooms) that leads to the maximum number of surgeries, hence increasing hospital productivity and reducing wait time.

To understand the complex behavior of the patients, clinicians and hospitals, agent-based simulation method is proposed as it will capture the emergent phenomena and provide a natural description of the healthcare system [8]. The model will be designed using patients, surgeons, and operating rooms as the actors and interactions between them will be monitored by modulating the variables like wait-time, the number of operating rooms, and the number of appointments. It is based on allowing overlap of activities between surgical stages such as preoperative and postoperative phases [9].

Key factors/variables to be considered are the surgery time, number of operations performed in a day's time and working hours in a day. Furthermore, number of operating rooms (ORs), cancellations, and surgery time on elective procedures are also found to be critical factors for the model. However, the model doesn't consider disruption of the schedule due to emergency surgical activities which may be needed due to unplanned patient arrivals.

However, the research conducted by the Information Technology in Medicine and Education (ITME) [10], suggested that the surgery, sequence of surgery, surgery rooms, number of days after hospital admissions can profound effects on the operation beds, hence the growing interest to study the operation theatre model in the research [10].

### Netlogo Model Visual Interface

Patients as a visual representation are shaped as a person in the Netlogo user interface. The patients-list is prepared where the patient's id is added in the ascending order of their appointment. Similarly, surgeons are allocated same properties as that of patients, except that surgeons are specifically shown in black color for ease of traceability. The allocated time for surgeons is stored into the surgeons-list.

### Netlogo Procedures

A NetLogo basic model can be defined as,

$$F(x,p,t) = F(x,p,t-1)$$

Where, F = model, X = state variable of the model, P = parameters of the model and T = time during the stimulation hence, at the start of the model, f (x,p,0) is the initialized version of the model [14].

Most of the model is built up on the procedures. Different sub-procedures (g, h,i) may be a call from the main procedure (f). The important aspect to be considered here is the sequence of calling the procedures and sequence in which the variables are set and updated. For example, the procedures patient-arrives surgeon-arrives, enters-operation-room, surgery-executed, surgeon-back-surgeon-room, patient-go-home. On the schedule-time, both the patient-surgeon enters the OR, once the procedures are carried out, the patient goes home and the surgeon is back to the surgeon waiting area [14].

A typical order of events would be in the sequence such as set-appointments -> patient-arrives -> surgeon-arrives -> enters-operation-room -> surgery-executed -> surgeon-back-surgeon-room and patient-go-home. If this sequence is followed in random order for example surgery gets executed before the patient and surgeon arrival, the validity of the model will be challenged. Based on the sequence, and order of updating of the variables, we can tell what impact each agent encounters in the model. Hence, the sequence of procedures defined explains the importance of each.

When a model is initialized the model continues by calculating the updates of the attributes of the agents and the environment. This is archetypally started by clicking on the button "go" in the interface. When you click on "go" you start a sequence of calculations.

### Setting the Procedures

The experiment setup is dynamic. There are other various parameters for example, surgeons list, patients list, the percentage of surgeons and patients absent. These parameters are displayed on the monitors on the Netlogo interface for ease of understanding and visualization. The 'GO' procedure starts off the simulation model.

## Experimentation Setup and Workflow of the Proposed Model

Figure 1 explains the flow of the model in the simulation model. It gives an overall view of the flow of the model, depicting the flow of agents and occurrences of events. Figure 2 is the sub flowcharts depicting the flow of procedures set and the decision flowchart respectively. The sub flowcharts help in understanding the construction of the model step by step.

The visual model as shown in the figure 3 presents the overall aspect of analysis. The black shaped person icons are surgeons and the random colored shaped person icons are patients. The patients and surgeons enter the operation theatres located at the center of the patch and once the procedure is completed the surgeons move to their original surgeons' zone in blue color, whereas, patients go home placed at the bottom of the patch as shown in the figure 3. The issues considered with the ES procedure in the simulation model are:

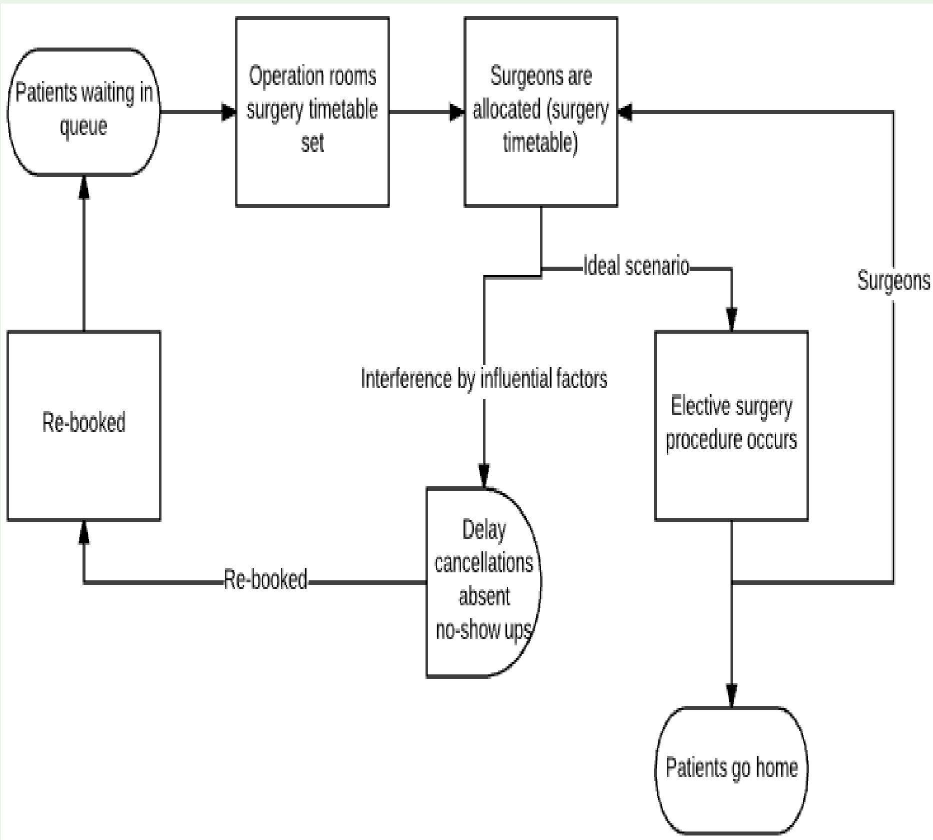


**Figure 1:** Main flowchart- Elective Surgery flow in the model.

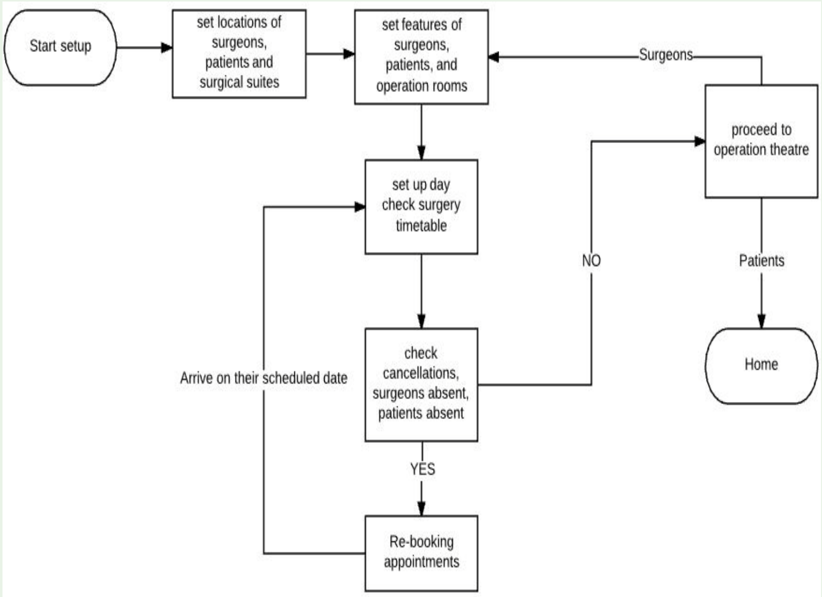


**Figure 2:** Flow of the procedures used in the NetLogo model.

No-show ups by patients

Surgeon absence

Cancellations

OR utilization

Figure 4 shows the main graphical user interface view of the proposed model; each area is described below.

**Area 1: (Red patch):** It represents the surgeon absent area. When the number of surgeons is calculated from the initial population of surgeons, the absent surgeons move to the red patch, displaying the surgeon's absentees'.

**Area 2: (Blue patch):** It displays the initial number of surgeons; it is the start point for surgeons where the surgeons are awaiting their turn for surgery. After the surgeon operates the patient, the surgeon is again moved back to the blue patch.

**Area 3: (ORs):** The three center patches illustrate the hospital operating rooms are depicted as OR1, OR2, and OR3. When the patient-surgeon operation is carried out, the surgeons from the blue patch and patients from the yellow patch move to the ORs OR1, OR2, and OR3 one at a time as per the availability.

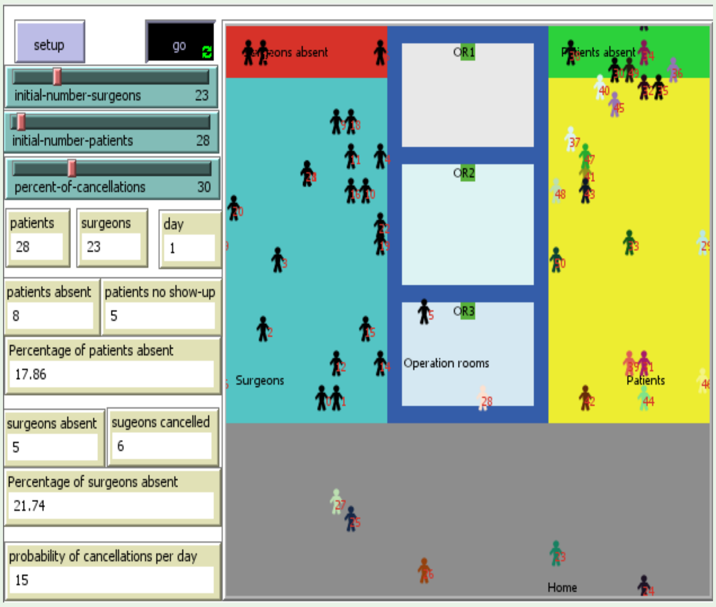


**Figure 3:** NetLogo Interface with configurable dynamics of surgeons, patients and cancellation rate.

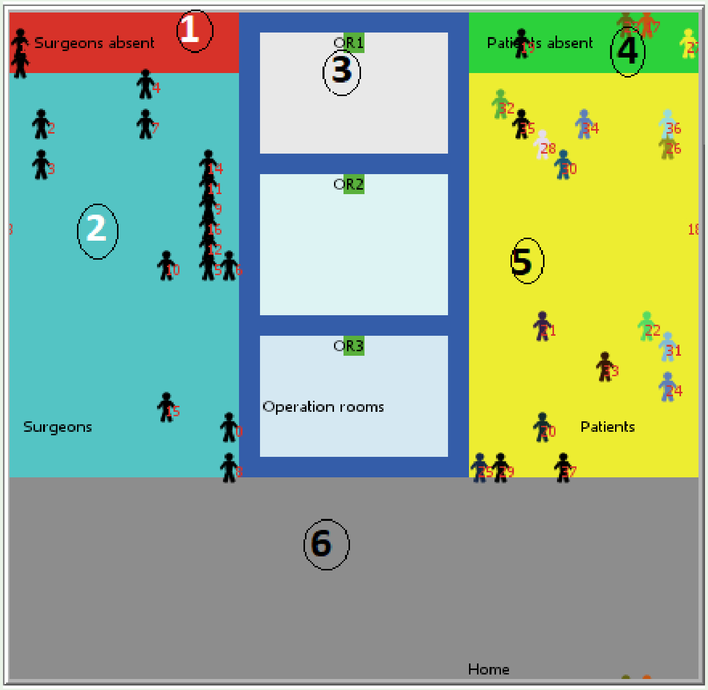


**Figure 4:** Interface of NetLogo (main view of the proposed model).

**Area 4: (Green patch):** represents the patient's absent area. When the number of patients is absent are calculated from the initial population of patients, the absent patients are calculated, and they are moved to green patch displaying patient's absentees'.

**Area 5: (Yellow patch):** Yellow patch is the lineup area for the patients where they await their turn to undergo the procedure. The patients at yellow patch go on decreasing, as the procedures start, and the entire procedure ends when no patients are left on the yellow patch.

**Area 6: (Grey patch):** It is the home area of the patients, after the operation is completed, the patients move to home.

## Results and Evaluation

Figure 5 shows the dynamic distribution used as the weekly utilization of ORs, specialty, surgeon and days of the week used as the simulated input to the proposed model.

**Scenario 1:** A typical work-flow scenario without any cancellations

| Week 1 | | OPR-1 | | OPR-2 | | OPR-3 | |
|---|---|---|---|---|---|---|---|
| | | Specialty | Surgeon | Specialty | Surgeon | Specialty | Surgeon |
| M | AM | Hip | S1, S4 | Knee | S2, S5, S8 | Cataract | S3, SS6, S7 |
| | PM | Hip | S1, S5 | Knee | S2, S5, S9 | Cataract | S3, SS6, S8 |
| T | AM | Hip | S1, S6 | Knee | S2, S5, S10 | Cataract | S3, SS6, S9 |
| | PM | Hip | S1, S7 | Knee | S2, S5, S11 | Cataract | S3, SS6, S10 |
| w | AM | Hip | S1, S8 | Knee | S2, S5, S12 | Cataract | S3, SS6, S11 |
| | PM | Hip | S1, S9 | Knee | S2, S5, S13 | Cataract | S3, SS6, S12 |
| T | AM | Hip | S1, S10 | Knee | S2, S5, S14 | Cataract | S3, SS6, S13 |
| | PM | Hip | S1, S11 | Knee | S2, S5, S15 | Cataract | S3, SS6, S14 |
| F | AM | Hip | S1, S12 | Knee | S2, S5, S16 | Cataract | S3, SS6, S15 |
| | PM | Hip | S1, S13 | Knee | S2, S5, S17 | Cataract | S3, SS6, S16 |
| S | AM | Hip | S1, S14 | Knee | S2, S5, S18 | Cataract | S3, SS6, S17 |
| | PM | Hip | S1, S15 | Knee | S2, S5, S19 | Cataract | S3, SS6, S18 |
| S | AM | Hip | S1, S16 | Knee | S2, S5, S20 | Cataract | S3, SS6, S19 |
| | PM | Hip | S1, S17 | Knee | S2, S5, S21 | Cataract | S3, SS6, S20 |

**Figure 5:** Weekly dynamic distribution.

We set the model's parameters as number of patients 100, number ofsurgeons 20 and three operating theatres (OT). For this scenario, we considered the simplest flow of events. None of the influential factors (cancelations and absenteeism) are considered in this case. The basic scenario depicts the ideal flow for an ES operation. Surgeons are allocated the surgery schedule and patients have fixed appointments and surgical suites are booked as per the surgery time-table. 100 patients were put on a wait-list and get operated in the ascending order as per the scheduled patients list.

**Model's output:** The basic preconditions are fed into the model, executed and output is discussed as follows:

The model shows with 100:20 of patient: surgeon ratio, the entire queue will be successfully completed within 13 working days. However, this scenario is crude and very unlikely to happen. This is possible only when the environmental and situational conditions are optimally conducive, such as there are no cancellations, or surgeons were not on leave, or the entire schedule was executed on time without any delays. The model provides the estimated time of completion for future planning and management of resources.

**Scenario 2:** Workflow with 21% surgery cancelations

Parameters were set as 100 Patients, 20 Surgeons, 3 OT and 21% cancellations.

Surgeons and patients are rostered for their respective schedule. In this scenario, the impact of introducting one influential parameter namely "cancellations" in the model will be analyzed and experimented using the patient-surgeon model.

**Model's output:** For ease of comparison, the same ratio of patient: surgeons are used as in the scenario 1. On introducing cancellations, the model shows that the probability of cancellations per day is 25 with the given experimental set-up. Furthermore, with the 21% cancellations, the number of working days to complete the wait-list is estimated to be 45 days with the same set of 100 patients and 20 surgeons. Hence, with the addition of cancellations, the elective procedures would be delayed by 20 working days, that could have accommodated other surgeries if the cancellations were re-scheduled.

**Scenario 3:** Workflow with 50% surgery cancelations and rescheduling

Parameters were set as 100 Patients, 40 Surgeons, 3 OT, 50% cancellations and 20% rebooked

100:40 patients: surgeons undergo operation with 50% cancellations probability. Also, few surgeons or patients may be absent and they rebooking is handled in the model. The procedure completion duration will be when the cancelled patients undergo surgery.

**Model's output:** When the model is set up for 50% cancellations, there is a probability of 70 cancellations per day. Approximately 37 patients will remain absent and rest of the patients tends to show up on the day of surgery. Whereas, 15 surgeons may cancel the surgery. The entire queue of 100 patients with 40 surgeons will be completed in 65 days given the setting of 50% cancellation.

## Discussion and Conclusions

The primary outcome of the proposed model is forecasting the time required to complete the surgery procedure. The above use cases have developed a step wise univariate, multivariate dependencies on the variables. The dependent parameters involved here in forecasting is the resources namely surgeons, operation suites, and the time required for completing the procedure. With the given number of patients awaiting an ES, number of surgeons, and operation theatres in a facility, the model can determine the total time required to complete the procedure including the dynamics of cancellations and absence.

The statistics collected from the simulation experiments include the current queue length of patients awaiting surgery, length of waitlist before and after the simulation, the position of the patient on the wait-list after cancellations, delay time, wait time, cancellations, and days required to complete wait-list procedures. The model reported the wait-time, delay time, and the position of patients on the wait-list. The model also implies adjustment of resources such that total time is minimized to improve the overall productivity.

The inter-dependency can be applied to the wider environment in a way that statistics obtained with three OTs can be computed to a hospital with twenty OTs. The main outcome of the simulation model is that it illustrates the time lines in terms of number of days required for completion of the elective procedures with the given number of surgeons and surgical suites [13-15].

The system dynamics shows that by simply increasing number of surgeons will have no effect on the reduction of wait-time or speeding the surgeries. Only when accompanied with increased OTs, they can be utilized for speeding the ES and reducing the wait-times. The model gives an estimation in terms of days the patient-surgeon procedures will be completed. It promotes forecasting that helps in decision making process and the surgery schedule can be planned accordingly. The cancellation which is known at the start of the day, that is, early detection can be beneficial in accommodating other appointments.

The three simplistic variables considered absenteeism, cancellations, bed capacity adds to the cost of the government incurred health budget. These factors can be controlled either by detecting early or by being ready if it goes undetected. The simulation can be executed at the start of the day for the given surgeon-patient schedule, cancellations and absenteeism can be estimated based on the results. Due to high levels of variability, improving the overall efficiency of hospitals is a slow process and involves permission of the authorities [14-17].

A value of such models is their capability to construct "what-if" scenarios that can be tested before practically implementing any significant scheduling changes. Instead of the multiple regression analysis, the simulation model helps to make the changes on-the-fly, saving time and interpreting consequences before actually implementing the changes [17-21].

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