Capacity Planning for Elderly Care in Ireland Using Simluation Modeling

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Abstract— **Global population aging is creating an immense pressure on healthcare facilities making them unable to cope with the growing demand for elderly healthcare services. Current demand-supply gaps result in prolonged waiting times for patients and substantial cost burdens for healthcare systems due to delayed discharges. This paper describes a project aimed at presenting modeling and simulation to address elderly care pathways within the Irish healthcare sector. The management of frail patients admitted to acute hospitals and the introduction of the new intermediate care beds are alternative interventions that healthcare executives are interested in simulating to examine their impact on the performance of the elderly care system. The developed simulation model, along with the statistical analysis, have enabled the management to assess the current system under the critical financial and performance issues. It also highlights the decision variables that significantly improve the flow of elderly patients.**

Keywords - Population Ageing; Elderly Care; Discrete Event Simulation; Discharge Planning.

I. INTRODUCTION

Advances in pharmaceutical and medical technology during the past century have caused a major shift in global demographics by increasing life expectancy to unprecedented figures. The result is that there are more elderly people today than ever before [1]. Furthermore, the world's elderly population is expected to grow from 650 million to 2 billion people by 2050 [2]. In Europe, there are currently 108 million elderly people who constitute 15% of the European population, and this figure is forecasted to increase to 26% by 2050 [3]. A similar trend is expected in Ireland where the elderly population is projected to grow from 500,000 to 1.3 million over the next 30 years [4]. Although elderly patients represent 11% of the Irish population, they account for up to 50% of hospital bed usage [4]. Consequently, pressures are now on Irish hospitals, not only due to the increase in demand for acute hospital beds, but also because elderly patients use acute hospital resources disproportionately. In response to such demographic changes, hospitals in Ireland are striving to fill the existing supply-demand gap while maintaining their quality of service [4]. Global economic crisis implied a severe cut in healthcare funds and elicited a limited resource policy in hospitals and other healthcare services. This caused Irish hospitals and elderly healthcare facilities to equally face a grave capacity planning issue to respond to the increased demand.

The subsequent shortage of beds has numerous facets that impact adversely on the overall performance of the Irish healthcare system. Firstly, it has a significant impingement to Emergency Department (ED) overcrowding, a problem that has detrimental consequences including higher mortality rates for elderly patients [5]. Secondly, shortage of community care beds leads to delayed discharges from acute hospitals, which not only delays new admissions into hospitals, but also burdens hospitals with high unjustified costs since acute beds are considered among the most expensive resources of the entire healthcare system [6]. Finally, delays due to the lack of short-term and long-term bed supply create substantial waiting times in most stages of the healthcare system. Long waiting times in elderly care services, as well as other services, are the most frequent complaints reported by patients to healthcare executives every year [4].

Simulation models have been proven to be an excellent and flexible tool for modeling processes in such stochastic complex environments [7]. Healthcare managers can apply simulation for assessing current performance, predicting the impact of operational changes, and examining the tradeoffs between system variables [8]. Furthermore, areas of improvement can be identified using simulation models through possible reorganization and allocation of existing resources [9][10]. On a micro-level, simulation is well-suited to tackle problems in hospital departments such as emergency departments [11][12] and operating rooms [13], where resources are scarce and patients arrive at irregular times [14]. Various alternatives and interventions can be evaluated and tested effectively [15]. A more accurate interpretation of the utilization of hospital resources can be envisaged using dynamic capabilities of simulation [16], which in turn supports the hospital management in their decisions on bed usage and patient flow [17]. This can be achieved by modeling the flow of patients through the hospital [18] then using scenarios to illustrate the consequences of possible potential decisions suggested by hospital management [19].

This paper presents a project implemented to support Irish health executives when decisions are to be made regarding elderly care in the Irish system. The developed framework enables the directors to examine the dynamics embedded in the system through the modeling of patients' care pathways. The model also highlights the high level of variability within patients demand and limitations of available resources within healthcare facilities. It aims to provide a comprehensive capacity-planning tool that can be

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used to assess proposed strategies to handle the existing bottlenecks and improve the overall experience of elderly patients. The underlying objective of this project is to introduce a tool that will contribute into significant improvements in elderly patient service by increasing throughput and reducing waiting times and operations costs.

The paper begins by introducing the conceptual model depicting the elderly patient journey within the healthcare system and the different discharge destinations. The development phases of the simulation model are then presented starting by data collection, coding, then validation. Using the model, two scenarios proposed by healthcare policy makers to improve patient flow are then examined followed by a design of experiment and statistical analysis to determine the most significant factors that affect patient flow and the magnitudes of their impact. Finally, the paper's findings are reported along with recommendations for future work.

II. Problem Contextualization

A. Background

Elderly patients are usually defined as those who are aged 65 and older and this convention is used in this study [20]. The most challenging of elderly patients are those referred to as *frail*. Frailty is characterized by suffering from an array of medical conditions that individually may be curable, but collectively create an overwhelming and complex burden of disease [1]. Frail patients constitute 18-20% of the Irish elderly population and usually require treatment for an extended period of time in the healthcare facility followed by rehabilitation and/or community care. Adhering to the length of stay (LOS)-based cut-off point, frail patients were characterized in this study by a treatment period of more than 15 days in the acute system (i.e., hospitals). The remaining 80 - 82% of elderly patients who receive treatment for less than 15 days are referred to as *non-frail.*

The initial scope of this study focused solely on frail patients, however, since all 65+ patients utilize the same resources, it was imperative to widen the project's scope to encompass all 65+ elderly patients, both frail and non-frail. Although elderly patients utilize a wide range of resources, the initial phase of the proposed model gives special attention to bed capacity within healthcare facilities based on a request from healthcare executives. Accordingly, elderly care services that do not necessitate admission, such as outpatient clinics, are excluded from the model because they do not affect hospital bed utilization.

B. Conceptualization

The journey of an elderly patient usually begins with their arrival at the ED by ambulance, walk-in or a referral by a General Practitioner (GP). After admission, elderly patients receive treatment in an acute bed until their care pathway is assigned subject to their diagnosis and frailty level. The duration of this process ranges from few days to two weeks for non-frail patients, but usually exceeds 45 days for frail patients.

Following their stay in acute beds, elderly patients are discharged to one of the following destinations:

Another Hospital: Certain medical procedures may require equipment that is not available in the acute hospital to which an elderly patient has been admitted. In such a case, elderly patients are transferred to another hospital where the required technology is available to undertake the procedure they need. Discharge figures to another hospital (6% of all elderly patients) include patients being moved to undergo a certain procedure, and patients who have received such a procedure and are returning to their original hospital.

Rehabilitation: Patients who are deemed to be in a frail status but have the potential to improve their functional independence are discharged to an on-site or off-site facility where they receive rehabilitation. Rehabilitation is an intermediate destination in which frail patients are no longer categorized as acutely ill, but still need close medical observation with hope that they would recover [21]. After rehabilitation, the majority of patients (80%) are discharged home and the remaining 20% who have not recovered are discharged to long term care.

Convalescence: Around 10% of non-frail patients are usually discharged to a convalescent care facility for a short stay during which they would recover from a medical procedure. Compared to rehabilitation, convalescence offers less intensive care as it prepares patients to go home. In several cases, convalescence may take place within a nursing home facility on dedicated short stay beds.

Long Term Care (LTC): More than a quarter of frail elderly patients would not be able to live alone at their homes because they are unable to care for themselves or sometimes require perpetual medical supervision. They are discharged to a public or private nursing home to receive LTC and usually stay there for years until they die. This prolonged stay in nursing homes hampers the supply of LTC beds into the healthcare system resulting in waiting times that amount to several months. In addition to hospital demand, there is also a community demand in which frail patients apply for LTC and wait in their homes until they are placed in a nursing home.

Home: The vast majority of non-frail elderly patients are eventually discharged to their homes, whether directly or after a short stay in convalescence. On the other hand, 24% of frail patients are directly discharged to their homes followed by another 28% that go home after rehabilitation. More than half of frail patients continue to require medical care within their own homes and thus are provided Home Care Packages (HCP). A HCP comprises a set of services provided by the state that may include home help, nursing, physiotherapy, occupational therapy and other services [4].

Consequently, shortages in rehabilitation, convalescence, LTC and HCP capacity are the main reasons behind delayed discharges from acute hospitals. Elderly patients occupy acute beds for an extended LOS that exceeds their treatment period not because they require acute health services, but because they are waiting to be discharged [22]. The alternative care pathways and their required bed resources are illustrated in Figure 1. The percentages of patients discharged to each destination are then listed in Table 1.

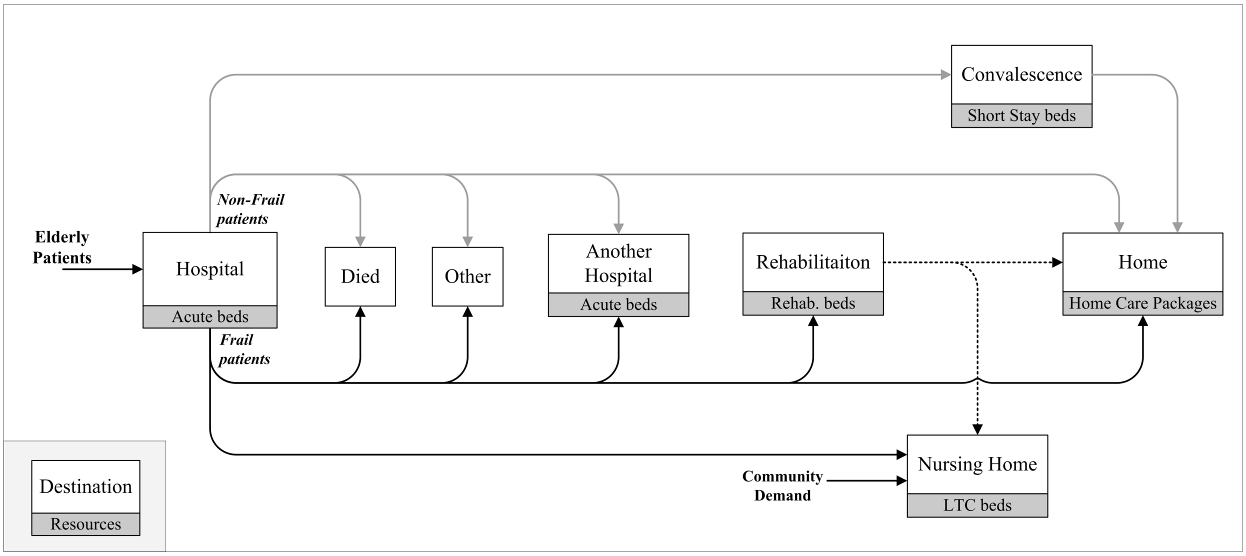

Figure 1. Elderly care pathways

TABLE I. DISCHARGE DESTINATION PERCENTAGES

Discharge Destinations	Percentage of Patients		
	Frail	*Non-frail*	*All 65+ Patients*
Home	24.2 %	78.4 %	68.6 %
Another Hospital	8.2 %	5.7 %	6.1 %
Rehabilitation	36 %	0%	6.5 %
Convalensence	0 %	10.5 %	8.6 %
Long Term Care	19.5 %	0 %	3.5 %
Died	10.8 %	4.3 %	6.1 %
Other	1.3 %	1.1 %	1.1 %

In addition to the previous discharge destinations, 6% of elderly patients may die during their acute stay, with the probability of mortality increasing proportionally with the frailty level. Another minimal number of patients (almost 1%) who have special conditions are discharged to destinations referred to as "*other*" such as a prison or psychiatric facility.

III. SIMULATION MODEL

A. Data Collection

Data quality and precision determines the validity of the simulation model. Hence, the data collection phase represents a critical milestone of any simulation project. Historical admission and discharge data was collected from the central healthcare information system, while bed capacities and LOS data were gathered through surveys. Similar to other healthcare modeling projects, collection of relevant modeling data presented considerable challenges [23]. The first was the dearth of data about certain parameters that were not captured by the central information system. It is worthy to note that a similar project undertaken in the UK to study elderly care diverted its objective from producing quantitative results to only building a simulation model due to the lack of relevant data [21]. The second challenge was data provided in aggregate figures while modeling inputs required them to be broken down into their individual elements. An example was the combination of the numbers of patients discharged to multiple destinations into one numerical figure. The third problem with data was inconsistencies found between different data sources such as variations in figures between hospital data and annual reports. After numerous extensive meetings with hospital officials, the absence of certain data and lack of information on how to decompose aggregated figures were overcome by the use of assumptions based on the opinions of experts in the field [24]. By gaining a deeper understanding of what each figure reflected, in most cases misunderstandings of terminology or scope were the reasons behind what seemed to be inconsistencies in the data.

Patient information was extricated from the raw data by data manipulation and reorganization. Data analysis was then performed to extrapolate important inputs for the model including arrival and discharge patterns, and to segment frail patient data. By clustering this data, frail patients were grouped according to their acute LOS into four categories coded numerically from zero to four, each representing a *degree of complexity* based on the validated assumption that the most complex cases spend more time in hospital. All 65+ patient data was also categorized by age group into five clusters. Based on the data analysis and segmentation, elderly patients' degree of complexity and age group would be used during simulation to define their care pathways within the model. The percentages of patients classified with each degree of complexity are shown in Table 2.

TABLE II. DEGREE OF COMPLEXITY PERCENTAGES

Degree of Complexity	Percentage of Patients		
	Frail	*Non-frail*	*All 65+ Patients*
0	0 %	100 %	82 %
1	42 %	0 %	8 %
2	20 %	0 %	4 %
3	17 %	0 %	3 %
4	21 %	0 %	4 %

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B. Model Development and Validation

Based on the conceptual model and the empirical data analysis, a comprehensive discrete-event simulation model was constructed using a simulation package and an input/output *Excel* spreadsheet was developed as a user-friendly interface. Modules of the simulation model were connected similar to the conceptual flow chart, which eases the model construction phase. Accordingly, the top-level of the simulation model defined the overall model structure, and sub-level blocks comprised additional modules with more details. Object-oriented programming was used to customize pre-defined blocks for constructing the simulation model. The main entities for the simulation were elderly patients, where each patient is assigned a set of attributes that represent their degree of complexity and age group to determine their discharge destination. Statistical assumptions were included by using a Poisson distribution for the arrival rate and exponential distributions for service times [22]. The time unit used was *days* for all modeling inputs and outputs. A database was used to save the measured Key Performance Indicators (KPI) after each simulation run, followed by exporting the KPIs in a tabular form for further analysis and validation.

To reduce the model development cycle time and to increase the confidence in the simulation model results, verification and validation were carried out all the way through the development phase to confirm the model represents the actual patient flow [23]. After each model development phase, the model was verified and validated with respect to other previously completed phases. For the verification process, the model logic was verified to ensure that patients followed the correct care pathway as expected. This was achieved by visual tracking of patients using animation and by checking intermediate output values such as queue lengths and waiting times.

Initially, queues at each stage of patient care were set as empty and idle. A warm-up period of three months was found to mitigate any bias introduced by the initial conditions of the simulation model until the steady state was achieved. In order to be comparable with the provided data, results for one year were generated for each scenario by running the model for 465 days and discarding the results of the first 100 days that represented the warm up period. Different number of runs (i.e., replicates) were tested and it was found that 10 runs per scenario were sufficient to obtain unbiased estimators of the expected average of each KPI.

IV. SCENARIOS

To improve patient flow, a number of strategies were proposed by the project team. Examined scenarios in addition to performance metrics are presented in this section.

A. Key Performance Indicators

Although the model produced a portfolio of results, the following KPIs that focus on acute hospital measures were selected:

- *Acute waiting time*: the average time spent by patients waiting for admission to an acute hospital.
- *Acute access*: the ratio of admitted elderly patients to the demand for admission.
- *Throughput rate*: the total number of elderly patients discharged per year.
- *Average cost per patient*: this cost perspective was added to the model to reflect financial effects of different scenarios. The average cost per patient was calculated by dividing total cost incurred through bed usage by the total number of discharged patients.

Due to data confidentiality of the project, the results reported for each scenario in this paper have been anonymized by normalization by setting the current "*as-is*" values at one and reporting scenario results as percentages relative to the as-is figure.

B. Shorter Acute LOS for Frail Patients

One of the first strategies that the management team proposed to improve patient flow was to set a target of maximum acute LOS for frail elderly patients, whose current LOS exceeds 45 days. In such a case, hospitals would be instructed to make earlier decisions about an elderly patient's medical needs and degree of frailty to accelerate their discharge from hospital. A scenario was tested assuming that frail elderly patients would have a maximum acute LOS of 18 days, slightly longer than non-frail patients.

The results of testing this scenario, presented in the bar chart in Figure 2, show some improvement in patient flow. Throughput rate and acute access have increased by 6% and 8% respectively, while acute waiting time and cost/patient have decreased with similar percentages. Performance improvement in this scenario could be viewed as somewhat limited due to the fact that frail patients whose LOS currently exceeds 18 days constitute 54% of all frail patients and only 10% of the entire elderly population and therefore reducing this duration would not have a major global impact on the efficiency of the entire system.

Despite their interest in testing this scenario, healthcare policy makers foresaw its drawbacks. The dependence of acute LOS on patient diagnosis and required medical procedures could hamper the implementation a maximum LOS policy and may face resistance from medical staff. Hence, other more effective and pertinent solutions should be sought.

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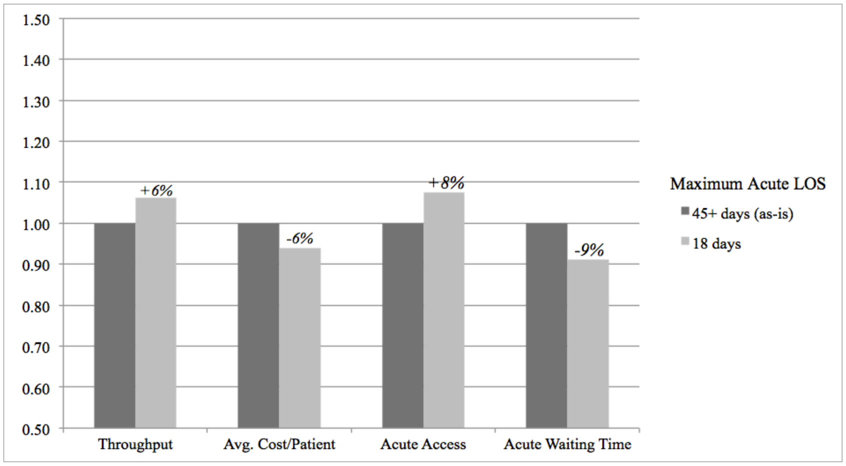

Figure 2. Impact of reducing maximum acute LOS to 18 days

C. *Intermediate Care*

The second proposed strategy was the introduction of a new service similar to *Intermediate Care* in the UK that can serve patients who require an acute or rehabilitation bed for prolonged periods only because they are awaiting discharge to LTC [21]. Intermediate care beds will be mostly located offsite and will provide a transitional venue where frail elderly patients can spend time before they will be placed in a long term facility. The anticipated advantage of intermediate care is reducing the overall time spent by elderly patients in hospitals. This should result in significant cost savings since the operational cost of an intermediate care bed is estimated to be almost half of the cost of an acute bed for the same period of time. To assess the impact of this service on the elderly care system, different scenarios were examined using the developed simulation model where each experiment used a set of different capacities of intermediate care beds. The gradient increase in intermediate care beds is proportional to the static number of acute beds in the system starting with 5% of the acute bed capacity and increasing the intermediate care-to-acute bed ratio up to 20% in subsequent scenarios.

Introducing intermediate care beds appears to have an overall positive effect on patient flow by noticeably increasing throughput rate and acute access to up to 2.5 times while reducing acute waiting time and cost/patient to up to 50% of the current figures as shown in Figure 3. Intermediate care beds reduce waiting times for acute admission and rehabilitation because they accelerate the release of acute and rehabilitation beds back into the system. This results in having more beds available for the incoming demand. Despite the fact that intermediate care would be the last stage that precedes LTC, it is observed that it has almost no effect on LTC waiting time. This was not unexpected, as LTC waiting time is constrained by LTC bed supply, regardless of *where* elderly patients would wait for LTC placement.

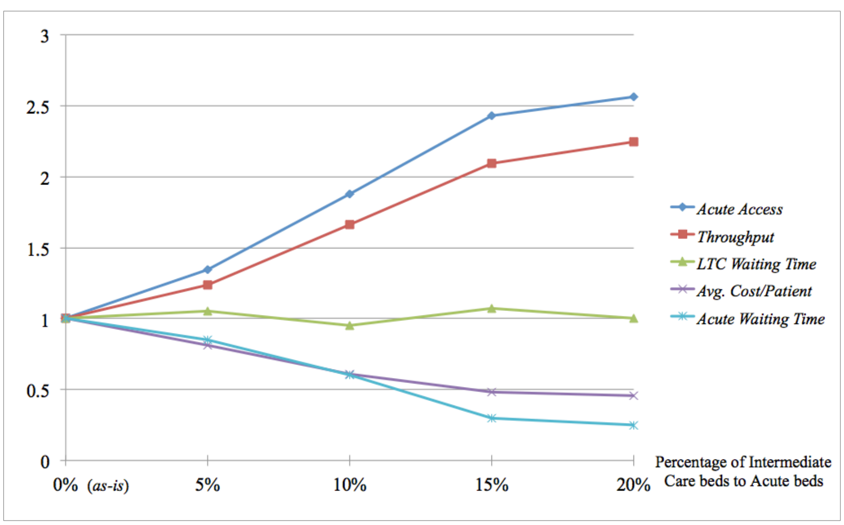

Figure 3. Effect of introducing intermediate care beds on KPIs

D. Design of Experiments and ANOVA

In addition to evaluating the previous strategies, there was an interest from healthcare executives to gain insights of the dynamics of the elderly care system and also to identify the most significant factors that affect its overall performance. Using an orthogonal array (L27) a fractional factorial design of experiment was conducted [25][26]. The L27 design allows for up to 13 factors where each factor is tested at three levels: high, medium and low (*H-M-L*). Six selected factors were tested and the values for H-M-L levels where determined in relation to the current state figures, where one of the three levels was set as the as-is value. Based on the selected orthogonal array, twenty-seven experiments were carried out and the response (i.e., output) measured in each experiment was the system's throughput rate, as recommended by healthcare executives. This was followed by a six-way Analysis Of Variance (ANOVA) test to determine the significance of the six selected factors (Table 3). To mitigate the inflation of error, Bonferroni correction was used to compute the significance level (α) using the following equation:

$$\alpha = \alpha[PT] / n \quad (1)$$

where $\alpha[PT]$ is the significance level per test (i.e., alpha per experiment) and n is the number of comparisons [27]. With $\alpha[PT] = 0.05$ and $n = 18$, the equation produces a significance level of $\alpha = 0.00278$.

TABLE III. ANOVA TEST RESULTS FOR THROUGHPUT RATE

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Squares	F Ratio	P Value
Model	18	0.8678	0.0482	16.369	0.0002
A: Acute bed capacity	1	0.0272	0.0272	9.2441	0.0161
B: Rehab. bed capacity	1	0.0037	0.0037	1.2573	0.2947
C: LTC bed capacity	1	0.0011	0.0011	0.3566	0.5669
D: Acute LOS	1	0.0102	0.0102	3.4698	0.0995
E: Rehab. LOS	1	0.0671	0.0671	22.801	0.0014
F: Percentage of rehab. patients	1	0.0617	0.0617	20.965	0.0018
AB	1	0.0029	0.0029	1.0005	0.3465
AC	1	0.0056	0.0056	1.9165	0.2036
AE	1	0.0038	0.0038	1.2824	0.2903
AF	1	0.002	0.002	0.6796	0.4336
BC	1	0.0054	0.0054	1.8211	0.2141
BE	1	0.0033	0.0033	1.1083	0.3232
BF	1	0.009	0.009	3.065	0.1181
CE	1	0.0057	0.0057	1.9457	0.2006
CF	1	0.0055	0.0055	1.8736	0.2083
DE	1	0.0062	0.0062	2.1218	0.1833
DF	1	0.0055	0.0055	1.8607	0.2097
EF	1	0.0141	0.0141	4.7899	0.0601
Residual	8	0.0236	0.0029		
Lack of Fit	8	0.0236	0.0029		
Total	26	0.8913			
Significance level $\alpha = 0.00278$					

Accordingly, ANOVA results illustrate that the LOS in rehabilitation and percentage of patients that receive rehabilitation are the only significant factors that affect the throughput rate as indicated by P-values that are lower than the computed significance level. Results also clarify that there are no significant interactions between any two factors.

Regression analysis followed the ANOVA test to determine the relative impact of the significant factors on the throughput rate when moving from one level to another. The regression produced negative coefficients for the two significant factors indicating that they are both inversely proportional to the throughput rate. This is explained by the fact that increasing the percentage and LOS of rehabilitation patients decreases throughput rate as less patients are discharged per year. The negative correlations of both factors with the throughput rate are plotted in Figure 4.

V. CONCLUSION AND FUTURE WORK

Healthcare executives in Ireland are confronted by a critical capacity planning challenge due to the mounting demand for elderly healthcare services instigated by population ageing. Developing a simulation model to investigate the service constraints was found to be a well-suited approach to provide decision makers with a tool to evaluate proposed strategies. Conceptual modeling was used to illustrate different elderly patient care pathways and provide a better understanding of resources required during the care journey. This phase was followed by developing a discrete-event simulation model with an objective of investigating the impact of demand uncertainty on available capacity. The model was of great benefit to policy makers in forecasting the outcomes of potential strategies that were under investigation. The reduction of average length of stay of patients using acute beds in hospitals, if possible, can offer a mediocre improvement in patient flow. Results have also shown that the introduction of intermediate care beds can enhance the system's performance significantly by reducing delays and patient cost of stay by almost 50%. Moreover, the proposed model has the potential to fully examine the economic feasibility of implementing this intermediate bed solution based on a cost-benefit analysis in addition to any other scenarios proposed by policy makers.

An ANOVA statistical analysis revealed that the rehabilitation phase is a bottleneck that affects untoward patient flow. It could therefore be concluded that efforts to improve the flow of elderly patients within the healthcare system should be directed more towards rehabilitation rather than other stages of the patient treatment journey. Hence, it is strongly recommended that future research would study the impact of the rehabilitation stage and its capacity on patient throughput. Potential strategies to be considered include setting a maximum rehabilitation LOS and transferring a number of acute beds to rehabilitation.

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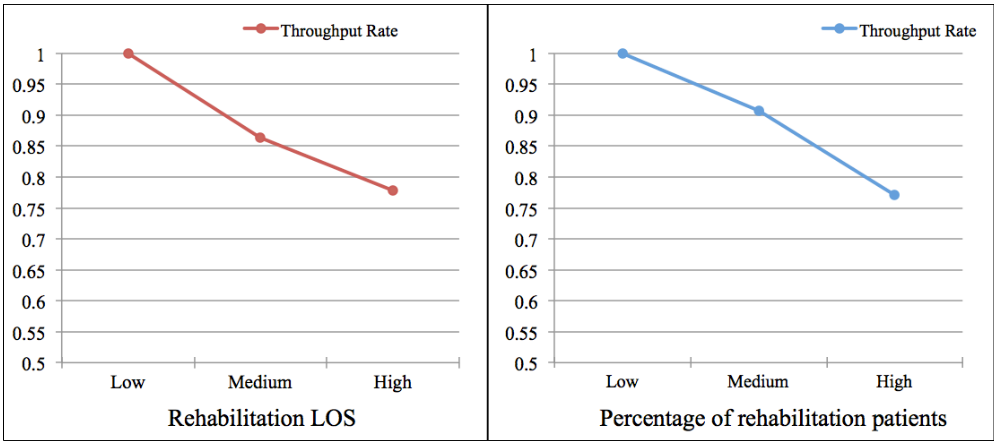

Figure 4. Effect of significant factors on throughput rate

It is worth mentioning that the main challenge in this study was the data collection phase. Problems varied between irrelevant, insufficient, or accuracy issues. In several instances, the lack of data was overcome by relying on assumptions made by healthcare experts. Comprehensive and periodic collection of elderly patient data is strongly recommended to provide decision makers with a solid foundation to use for process improvement strategies. Furthermore, a detailed cost analysis was not possible in this phase of the study due to two main reasons; (1) lack of cost related information and, (2) the high variability in cost models used within Irish public hospitals that creates a high level of complexity. Nevertheless, a recently launched project within the same research group will attempt to create a financial model for public hospitals in Ireland to facilitate cost analysis and optimization.

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