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## MODELLING STROKE PATIENT PATHWAYS USING SURVIVAL ANALYSIS AND SIMULATION MODELLING

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**Abstract:** Stroke disease is the third leading cause of death in the UK, placing a heavy burden on society at a cost of 7 billion pounds per year. Prolonged length of stay in hospital is considered to be an inefficient use of hospital resources. In this paper we present results of survival analysis that utilise length of stay and destination as outcome measures, based on data from the Belfast City Hospital. Survival probabilities were determined using Kaplan-Meier survival curves and log rank tests. Multivariate Cox proportional hazards models were also fitted to identify independent predictors of length of stay including age, gender and diagnosis. Elderly patients showed a decreased hazard ratio of discharge. However, gender was not a significant hazard risk for length of stay in hospital. Those patients with a diagnosis of cerebral haemorrhage showed an increased hazard ratio and hence were most likely to have a shorter length of stay and to die in hospital. Those who were eventually discharged to a Private Nursing Home had the lowest probability of early discharge.

On the basis of these results we have created several groups, stratified by age, gender diagnosis and destination. These groups are then used to form the basis of a simulation model where each group is a patient pathway within the simulation. Various scenarios are explored with a particular focus on the potential efficiency gains if length of stay in hospital, prior to discharge to a Private Nursing Home, can be reduced.

**Keywords:** survival analysis; simulation, healthcare; stroke patients; length of stay; efficiency gains

### 1. Introduction

Stroke disease is the third leading cause of death in the UK, placing a heavy burden on society at a cost of 7 billion pounds per year (National Audit Office, 2005). Due to the debilitating nature of stroke such costs are partly incurred by a prolonged length of stay in hospital (LOS), considered to be an inefficient use of resources. In addition, on-going care such as long-term nursing care, community based care and rehabilitation service place substantial costs on the health service (Sundberg et al, 2003). Between 10% and 30% of stroke survivors enter institutional care (Leibson, 1998) and many of those who return home require a long full-time carer. Initiatives such as early discharge schemes have been shown to be as effective as conventional care in terms of clinical benefit and have produced significant reductions in bed usage. The National Clinical Guidelines for Stroke (2004) state that specialist stroke services should be available in the community as part of an integrated system of care to facilitate early discharge.

In this paper we present results of survival analysis that utilise length of stay and destination as outcome measures, based on 5 year retrospective data of patients admitted to Belfast City Hospital with a diagnosis of stroke (haemorrhagic stroke, cerebral infarction, transient ischaemic attack (TIA) and stroke unspecified). Survival probabilities are determined using Kaplan-Meier survival curves and log rank tests (Cox and Oates, 1984). Survival times are measured from date of admission to date of discharge or death. Multivariate Cox proportional hazards models (Cox and Oates, 1984) are fitted to identify independent predictors of length of stay including age, gender and diagnosis.

We then create several groups, stratified by age, gender, diagnosis and destination. These groups are used to form the basis of a simulation model where each group is a patient pathway within the system. We develop various scenarios that evaluate the potential efficiency gains should LOS in hospital of patients eventually discharged to a Private Nursing Home (PNH) be reduced.

## 2. Survival Analysis

Kaplan-Meier curves were performed to examine the relationship between gender and diagnosis and LOS. The log rank test for equality between survival distributions showed a significant difference ( $\chi^2$  statistic 5.80,  $p < .05$ ) between gender groups on having a shorter LOS. Male patients had a higher probability of being discharged within the first 120 days. The log rank test for equality between survival distributions also showed a significant difference ( $\chi^2$  statistic 363.26,  $p = 0.00$ ) between diagnosis groups with regard to LOS.

Multivariate analysis using the Cox proportional hazards models were fitted to identify independent predictors of LOS including age, gender and diagnosis. As can be seen from Table 1 increasing age placed patients at risk of a longer LOS in hospital. Although a log rank test demonstrated a significant difference in regard to gender ( $p < 0.05$ ), gender was not a significant hazard risk for length of stay in hospital. Those patients with a diagnosis of cerebral infarction had a decreased hazard ratio, thus were least likely to have a shorter LOS, while patients with a diagnosis of TIA had an increased hazard ratio, thus were most likely to have a shorter length of stay in comparison to the reference category. Those patients with a diagnosis of cerebral haemorrhage did not significantly differ ( $p > 0.05$ ) from the reference category (see Table 1).

**Table 1.** Cox Regression of risk factors for LOS

Characteristic	Hazard Ratio (95%)	p value
Age	.984 (CI .980 to .987)	.000
Sex		
Male	.974 (CI .890 to 1.065)	>0.05
Female	1.0(reference category)	>0.05
Diagnosis		
Stroke (unspecified)	1.0(reference category)	
Haemorrhage	.984 (CI .827 to 1.171)	>0.05
Cerebral Infarction	.883 (CI .795 to .980)	.000
TIA	2.540(CI 2.246to 2.873)	.000

Due to the debilitating nature of cerebral haemorrhage we would have expected this category have a significantly less hazard risk of discharge (more days to discharge) compared to the reference category. It was therefore decided to carry out an adjusted Kaplan-Meier restricting the sample to those patients that died in hospital. The log-rank test for the equality between survival distributions shows a significant difference ( $\chi^2$  statistic 15.83,  $p < 0.01$ ) between diagnosis groups on having a shorter LOS. Patients hospitalised with a cerebral haemorrhage had the highest probability of death within approximately the first 100 days. After this period all groups had a similar probability of death.

A second multivariate analysis using Cox proportional hazard model was applied to re-examine diagnosis as an independent predictor of LOS as measured by failure to survive in hospital. Within this equation those patients with a diagnosis of cerebral haemorrhage had an increased hazard ratio (hence fewer days to the event - in this case death) (HR 1.449; 95% CI 1.113 to 2.018) in comparison to the reference category. This finding suggests that whilst patients with cerebral infarction are most likely to have a longer LOS in hospital prior to discharge, those patients with a diagnosis of cerebral haemorrhage are most likely to have a shorter LOS and to die within that time period.

Kaplan-Meier curves were performed to examine the relationship between LOS in hospital and destination on discharge. The log rank test for the equality between survival distributions shows a significant difference ( $\chi^2$  statistic 115.36,  $p = 0.00$ ) between LOS and destination to which discharged, with the survival plot given in Fig. 1. As can be seen from Fig. 1 those who are eventually discharged to a Private Nursing home have the lowest probability of being discharged within approximately the first 120 days. This finding may reflect the patient requiring further care in hospital due to disability or the existence of a bottleneck in the system delaying early discharge to residential care.

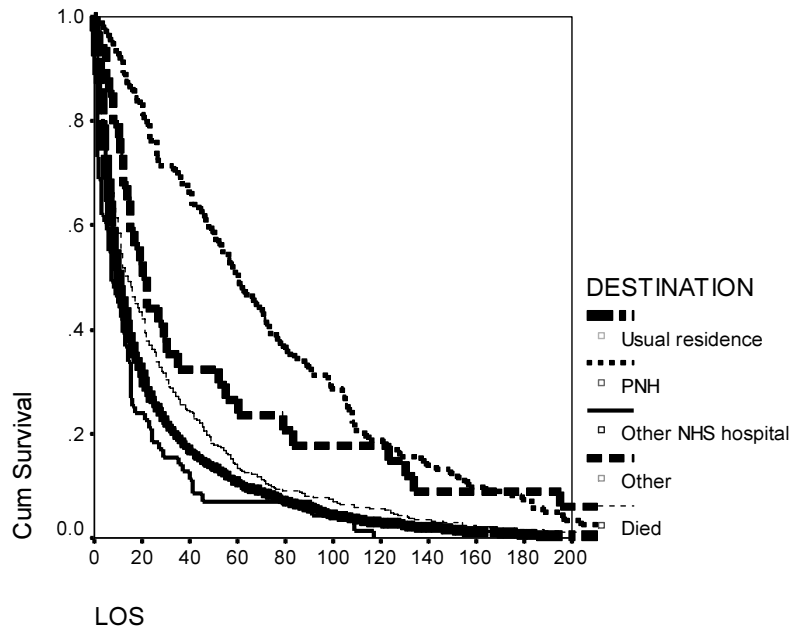


Fig. 1. Kaplan-Meier destination distributions on survival times.

### 3. Simulation Model

On the basis of the survival analysis we have created 12 groups, stratified by age, gender, diagnosis and destination. These groups are constructed to be homogeneous with respect to the survival distribution of length of stay in hospital (LOS). The groups were then used to develop a simulation model, using the software package SIMUL8, where each group represents a patient pathway within the simulation. In each case the Coxian phase type distribution was then used to model the length of stay for each group. Such models have been previously shown to give a good fit to such data. (Marshall and McClean, 2004, Faddy and McClean, 2005). They are intuitively appealing as we can think of the patient as progressing through various phases of care, such as acute, assessment, treatment, and rehabilitation.

In general, Coxian phase type models describe duration as an  $n$  state continuous time Markov model where the absorbing state ( $n+1$ ) represents the event death or discharge of the patient. A patient can be admitted to the system only in the first state. Transitions are possible from any state  $i$  ( $i = 1, 2, \dots, n-1$ ) to the next state  $i+1$  with transition rate  $\lambda_i$ . Also transition is possible from any state  $i$  to the absorbing state  $n+1$  with transition rate  $\mu_i$  (Fig. 2). The time spent in the hospital before death or discharge has the probability density function:

$$f(t) = \mathbf{p} \exp(\mathbf{Q}t) \mathbf{q} \tag{1}$$

where the row vector  $\mathbf{p}$  is the initial probability distribution and is defined as:

$$\mathbf{p} = (1 \ 0 \ 0 \ \dots \ 0 \ 0)$$

The transition matrix  $\mathbf{Q}$  is defined as

$$\mathbf{Q} = \begin{pmatrix} -(\lambda_1 + \mu_1) & \lambda_1 & 0 & \dots & 0 & 0 \\ 0 & -(\lambda_2 + \mu_2) & \lambda_2 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \dots & 0 & 0 \\ 0 & 0 & 0 & 0 & -(\lambda_{n-1} + \mu_{n-1}) & \lambda_{n-1} \\ 0 & 0 & 0 & \dots & 0 & -\mu_n \end{pmatrix}$$

and  $\mathbf{q} = (\mu_1 \ \mu_2 \ \dots \ \mu_{n-2} \ \mu_n)^T$ .

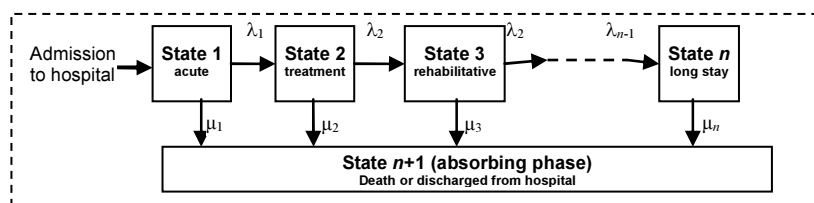


Fig. 2. A patient care system modelled as an  $n$  state Coxian phase type distribution

Phase-type models were then fitted to each group starting with one phase (exponential) and progressively increasing the number of phases until, using a penalised likelihood approach, an optimal number of phases was determined. Since our groups have already been homogenised, using survival analysis, here one or two phases was sufficient in each case.

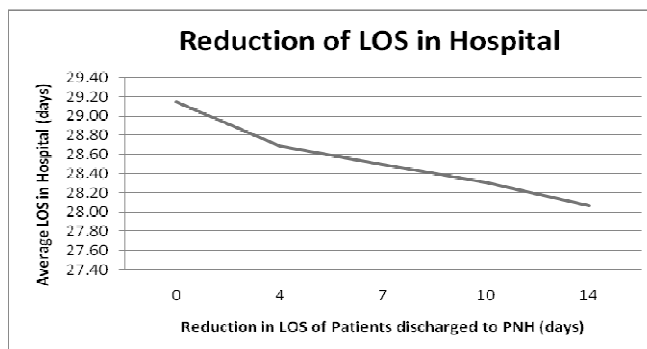


Fig. 3. Reduction of LOS in Hospital

Mean duration of length of stay in hospital was then estimated from the simulation, separately for each of the three absorbing destinations, Private Nursing Home, Death and Other. The transition rates in each case were estimated using maximum likelihood estimation. Inter-arrival rates (admissions to hospital) were estimated using statistical analysis of the PAS data, based on a Poisson assumption. Different scenarios were then tested by adjusting the expected duration of stay, for each group of patients who were later discharged to a PNH. The simulation was carried out for a total of 5 runs with a time period of 30000 days (100 days warm up period) to obtain average values for LOS prior to discharge. A reduction in the LOS of stay of patients discharged to PNH resulted in an overall reduction of LOS in hospital (Fig. 3).

#### 4. Further Work

In this paper we have carried out a survival analysis on data for length of stay of stroke patients in hospital. On the basis of these results we have developed a preliminary simulation model. In future work we plan to look at more complex simulation scenarios, involving, for example, limited capacity within the hospital, queues for discharge to Private Nursing Homes, differential costs, various treatment regimes and different discharge strategies.

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