Emergency readmission criterion: a technique for determining emergency readmission time window.

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***Abstract*—A frequently chosen time window in defining readmission is 28 days after discharge. Yet in the literature, shorter and longer periods such as 14 days or 90–180 days have also been suggested. In this paper, we develop a modeling approach that systematically tackles the issue surrounding the appropriate choice of a time window as a definition of readmission. The approach is based on the intuitive idea that patients who are discharged from hospital can be broadly divided in to two groups—a group that is at high risk of readmission and a group that is at low risk. Using the national data (England), we demonstrate the usefulness of the approach in the case of chronic obstructive pulmonary disease (COPD), stroke, and congestive heart failure (CHF) patients, which are known to be the leading causes of early readmission. Our findings suggest that there are marked differences in the optimal width of the time window for COPD, stroke, and CHF patients. Furthermore, time windows and the probabilities of being in the high-risk group for COPD, stroke, and CHF patients for each of the 29 acute and specialist trusts in the London area indicate wide variability between hospitals. The novelty of this modeling approach lies in its ability to define an appropriate time window based on evidence objectively derived from operational data. Therefore, it can separately provide a unique approach in examining variability between hospitals, and potentially contribute to a better definition of readmission as a performance indicator.**

***Index Terms*—Emergency readmission, mixture distribution, time window.**

I. Introduction

SINCE the 1980s, the U.K. health service has undergone major changes in its organization and delivery. The rising cost of care, changes in technology, pressures associated with demographic change (e.g., aging population) and different patterns of health-seeking behavior have forced the U.K. government to adapt new strategies that encompass whole health provisions, of which hospitals seek optimal output under strict economical constraints. Reducing average length of stay (LOS) is central to these plans. Rapid patient discharge is one primary way that health care administrators seek to free beds for incoming patients. However, if patients are discharged too soon, they may have to be readmitted, which raises the issue that patients are being discharged "sicker and quicker" [1]. Generally, readmission is often seen as an inevitable consequence of early discharges [2]. Thus, the increase in early discharges may generate high levels of readmissions, which could possibly be seen as patients being discharged inappropriately. These factors are likely to have motivated the use of readmission rate as a key indicator in the performance rating framework for the National Health Service (NHS) in England [3].

In this paper, we study readmission in the context of emergency or unplanned readmission, since planned readmission is simply a part of the care plan for a patient. Currently, the NHS performance rating framework defines readmission for adults as an emergency or unplanned admission to the hospital within 28 days following discharge [3]. In other contexts, shorter and longer periods such as 14 days or 90–180 days have also been quoted in the literature [4]. Sibbritt [5] attempted the validation of the use of 28 days by constructing histograms of time between successive hospital admissions for the categories of general medicine, surgery, paediatrics, obstetrics, and gynaecology. For each specialty, the distribution of time between successive admissions exhibited a lognormal or exponential shape with approximately 32% of admissions occurring within 28 days after discharge. A similar pattern was found by Chambers and Clarke [6], where the number of readmissions shows an early peak (0–6 days), then level off by 28 days after discharge from the hospital. However, in both cases, the justification for the choice of 28 days relied solely on visual inspection of the graphical output, which could result in an inaccurate definition of readmission.

Literature concerning readmission is mostly focused on the clinical and social factors that influence readmission [7], [8]. These studies are often inconclusive and contradict each other. The lack of a unified definition of readmission motivated the development of this modeling approach, which systematically tackles the issue surrounding the appropriate choice of a time window. In this paper, we extend a modeling approach reported in [9], to study differences in what constitutes a readmission among various clinical conditions such as stroke, congestive heart failure (CHF), and chronic obstructive pulmonary disease (COPD). We further investigate the variability in readmission time windows among acute and specialist trusts in London.

This paper is organized into the following sections: a brief description of the data is in Section II; the methods for modeling the time to readmission and for determining the optimal time window are presented in Section III; Section IV demonstrates the usefulness of our proposed methodology in estimating the appropriate width of a time window, in the case of COPD,

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TABLE I
LEVELS OF READMISSION FOR COPD, STROKE, AND CHF (AS DEFINED USING 28 DAYS) IN ENGLAND FOR CALENDER YEARS 1998 TO 2003

	COPD	Stroke	Congestive Heart Failure
1998	96,841 (28.0%)	90,826 (39.3%)	81,954 (31.8%)
1999	101,819 (24.2%)	92,653 (35.3%)	81,907 (27.6%)
2000	98,470 (23.1%)	89,774 (29.3%)	77,790 (23.4%)
2001	99,795 (22.3%)	90,579 (28.3%)	74,823 (21.4%)
2002	101,970 (22.2%)	94,815 (29.0%)	72,469 (21.0%)
2003	112,918 (22.0%)	92,120 (26.2%)	70,280 (21.2%)

The numbers in parentheses are the corresponding percentage of readmission within 28 day interval. Data are extracted from the HES dataset.

stroke, and CHF; discussion and comments on future work are in Section V.

II. DATA

The Department of Health in England releases annually hospital episode statistics (HES) data. The HES dataset captures all the consultant episodes of patients during their stay in hospital in England. During a hospital stay (called spell), a patient might encounter several successive episodes. We focus our study on COPD, stroke, and CHF. These are known to be the leading causes of early readmission in the U.K. [10], [11]. Spells ending with discharge by death are excluded as no further admission is possible. Furthermore, since death in the community is not recorded by the HES data, we have no information on the up-to-date status of a patient who was discharged alive. As a result, we limit our data selection to patients who had a subsequent admission following a discharge. Since our aim is to study patients who are admitted to hospital soon after their discharge, this data selection procedure is justified. For each patient, time to readmission is the time from discharge to admission.

Using the HES dataset from 1997 to 2004, we extracted 962 656, 951 869, and 728 906 episodes from patients who had the primary diagnosis code corresponding to COPD (ICD-10 codes J40–J44), stroke (I60.0–I67.0), and CHF (I150.0), respectively. A set of 696 911, 546 406, and 533 439 spells were derived for COPD, stroke, and CHF, respectively. Since HES data are released based on financial years, which vary widely within and across sectors and countries (in the NHS in England, a financial year is from April 1 to March 31 the following year), necessary steps were taken to restore the data to be based on calendar years. Using the time window of 28 days as currently defined by the Department of Health, we observed that in the case of COPD, the number of admissions has increased between 1998 and 2003; the percentage of readmission has actually remained relatively stable from 2001 to 2003 (see Table I). The number of admissions for stroke has been relatively stable; however, a dramatic decrease is noticeable in the percentage of readmission, from 39.3% for the year 1998 to 26.2% in 2003. This decrease could possibly be due to the inclusion of emergency readmission to hospital following treatment for stroke, as one of the indicators in the performance rating framework, and the NHS Trusts effort to achieve to reduce rate of readmission. We observe a similar reduction in the percentage of readmission for CHF patients.

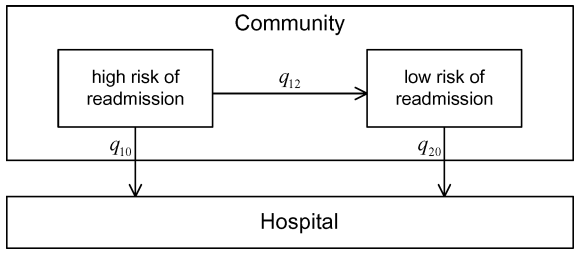

Fig. 1. Coxian phase-type model for the phases patients experience in the community before readmission to hospital.

There are five major types of trusts carrying out direct services: NHS Primary Care Trusts; NHS Hospital Trusts (often referred as Acute Trusts); NHS Ambulance Services Trusts; NHS Care Trusts; and NHS Mental Health Services Trusts. In this paper, we focus on Acute Trusts, where NHS Trusts are hospitals that are part of the NHS in England.

The NHS hospitals in London are divided into five strategic health authorities (SHAs) that map onto five regions: north east London (NEL), north central London (NCL), north west London (NWL), south east London (SEL), and south west London (SWL). Within each SHA, there are five categories of hospitals: small, medium, large, specialist, and teaching hospitals. These hospitals are managed by Acute Trusts, which make sure that hospitals provide quality healthcare. Some acute trusts are regional or national centers for more specialized care. To investigate variability in the definition of readmission among various clinical conditions and regions, we further partition our COPD, stroke, and CHF data according to each acute and specialist trusts, and estimate the appropriate time window for each in London.

III. METHODS

The approach can be divided in two stages. First, we capture the readmission process by fitting to the time to readmission a two-phase Coxian phase-type distribution, which is equivalent to a mixture of exponential and generalized Erlang distributions. This may, therefore, be thought as a type of model-based clustering. Second, we apply a Bayesian classification approach to determine the optimal time window in defining readmission.

A. Modeling the Time to Readmission

Using a simple graphical inspection of patterns of readmission for the COPD, Demir *et al.* [9] observed that there was a change in the risk of readmission, which was also recognized implicitly by Sibbritt [5]. That is, the risk of readmission is high soon after a hospital discharge, and is substantially reduced after a period of time in the community. The conceptual movements of patients in the community can be represented as a two-phase model, as illustrated in Fig. 1. Following discharge, patients first go through a phase of high risk of readmission, when they are more likely to be readmitted, possibly because of premature discharge from their previous hospital stay; if not readmitted during this phase, they enter another phase of low risk of readmission and stay longer in the community.

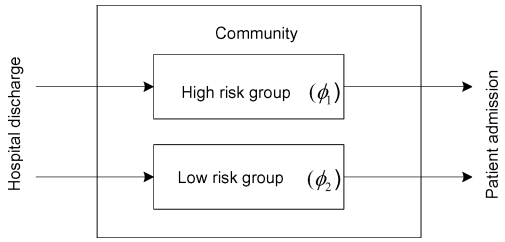

Fig. 2. Two groups of patients in the community following hospital discharge.

In Fig. 1, the rate q_{12} represents the transfer rate from phase 1 to phase 2; and q_{10} and q_{20} are the readmission rates from phase 1 and phase 2, respectively, where subscript 0 represents the state being in hospital. If we assume that all rates (i.e., q_{12}, q_{10}, and q_{20}) are constant, then the time to readmission follows a Coxian phase-type distribution [12], which describes the distribution of time to absorption of an absorbing continuous-time Markov chain where the transient states are structured in a sequential manner.

Given a set of data on time to readmission, the rates are estimated by fitting Coxian phase-type distributions to the data via the method of maximum likelihood. All model fitting is done by using general numerical optimizers such as those available in the R statistics computing language [13]. In order to ascertain the hypotheses of two readmission risk phases, we tested our model based on a sequential procedure, starting with one phase (corresponding to the exponential distribution), two phases, and three phases. The selections are based on the best compromise between model complexity and goodness of fit according to both the Akaike's information criterion (AIC) [14] and the Bayesian information criterion (BIC) [15].

B. Determining an Optimal Time Window

The population of discharged patients from hospital to the community is divided in two groups, namely, a group at "high risk" of readmission (denoted as ϕ_1) and the other at "low risk" of readmission (ϕ_2). This is illustrated in Fig. 2. For each patient, we observe the time to readmission. However, we do not know which group a patient belongs to. Therefore, using the estimated rates in Fig. 1, the time to readmission (random variable denoted by X) can be considered to follow a mixture distribution [16] with probability density function (pdf)

$$f(x) = pf_1(x) + (1-p)f_2(x) \tag{1}$$

where p, the probability of a patient being in the high-risk group (ϕ_1), can be expressed in terms of the rates derived in the previous section as

$$p = \frac{q_{10}}{q_{10} + q_{12}} \tag{2}$$

$f_1(x)$, the pdf of the time to readmission for the high-risk group (ϕ_1), is exponential with parameter $\lambda_1 = q_{10} + q_{12}$, i.e.,

$$f_1(x) = \lambda_1 \, e^{-\lambda_1 x} \tag{3}$$

and $f_2(x)$, the pdf of the time to readmission for the low-risk group (ϕ_2), is the convolution of an exponential with parameter (λ_1) and an exponential with parameter $\lambda_2 = q_{20}$, i.e.,

$$f_2(x) = \frac{\lambda_1}{\lambda_1 - \lambda_2}\lambda_2 \, e^{-\lambda_2 x} + \frac{\lambda_2}{\lambda_2 - \lambda_1}\lambda_1 \, e^{-\lambda_1 x}. \tag{4}$$

Given the observed time to readmission for a patient, the probability of belonging to ϕ_1 (and respectively ϕ_2) can be determined from the posterior probability expressed via Bayes' theorem as $p(\phi_1|x) = pf_1(x)/f(x)$ [and respectively $p(\phi_2|x) = (1-p)f_2(x)/f(x)$]. Using a Bayesian classification argument [17], one can show that the optimal way to assign the group membership of a patient with observed time to readmission x is: assign to ϕ_1 if $p(\phi_1|x) > p(\phi_2|x)$; and to ϕ_2 otherwise. In other words, the optimal cutoff in time to readmission that "best" separates the high-risk group and the low-risk group is determined by solving $p(\phi_1|x) = p(\phi_2|x)$ for x, or equivalently given by the time value x where $pf_1(x) = (1-p)f_2(x)$, that is, where the two corresponding curves intersect. Hence, the optimal cutoff time is

$$\psi = \frac{\ln\left[\lambda_2(1-p)/(-2p\lambda_2 + p\lambda_1 + \lambda_2)\right]}{(\lambda_2 - \lambda_1)}. \tag{5}$$

TABLE II
MODEL SELECTION FOR DETERMINING PATIENT EXPERIENCE IN COMMUNITY BEFORE READMISSION

Number of phases	COPD		Stroke		CHF	
	AIC	BIC	AIC	BIC	AIC	BIC
1	2814736	2814752	249448	249292	939746	939798
2	2791670	2791722	226243	226282	927472	927518
3	2791962	2791994	226270	226294	927528	927556

IV. RESULTS

When applying the previous approach to the COPD, stroke, and CHF data, we found that models with two phases were consistently superior to those with one or three phases (lower AIC and BIC in Table II). This supports the case for the existence of two groups of discharged patients. Table III shows the estimated rates for the model depicted in Fig. 1, and their standard errors approximated from the Hessian matrix. These can be used to calculate the probability of belonging to the high-risk group and the corresponding pdf of time to readmission. Fig. 3 shows the fitted and the observed distribution of time to readmission for the selected clinical conditions. The close agreement between the observed and fitted distribution confirms that the model with two phases is able to capture the overall pattern of time to readmission.

Given the rates in Table III, the estimated time window using (5) is 45, 16, and 39 days for COPD, stroke, and CHF, respectively. The time windows for COPD and CHF patients are greater than the 28 days defined by the Department of Health. However, the time window for stroke is almost half of the government published figure. Using the complete stroke dataset, 29% of all readmissions occur within the first 16 days. Hence, a large proportion of readmissions occurs soon after discharge. This raises the issue that stroke patients may have been discharged "sicker and quicker," and early readmissions may become

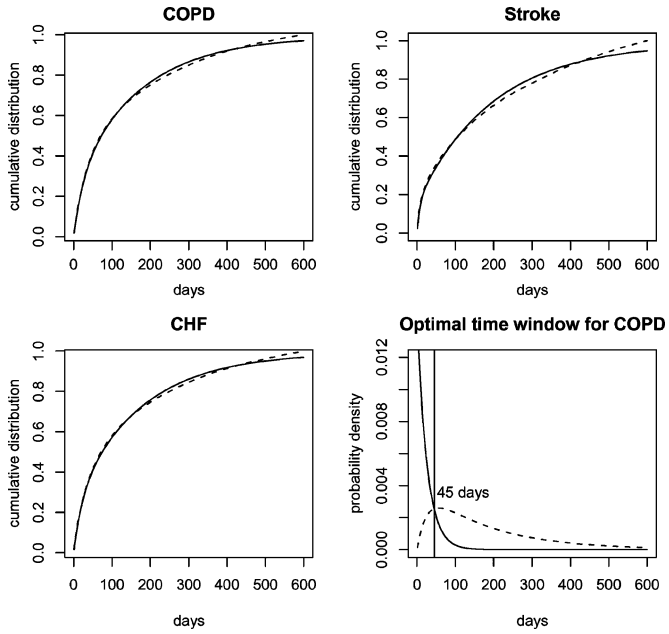

Fig. 3. Fitted (solid) and empirical (dotted line) distribution of time to readmission for the COPD, stroke, and CHF clinical conditions; and illustrating the identification of the optimal time window for the case of COPD (bottom right). The curves represent $f_1(x)$ and $f_2(x)$ as in (1) corresponding to high and low risk pdf, respectively. The vertical line indicates the point of intersection.

TABLE III
ESTIMATED PARAMETERS FOR THE TWO-PHASED COXIAN MODEL FOR COPD, STROKE, AND CONGESTIVE HEART FAILURE DATA

Parameter	COPD	Stroke	CHF
q_{12}	0.024589	0.105921	0.029005
	(0.000318)	(0.004242)	(0.000675)
q_{10}	0.014847	0.026385	0.015623
	(0.000075)	(0.000702)	(0.000146)
q_{20}	0.005821	0.005063	0.005769
	(0.000018)	(0.000042)	(0.000030)

The numbers in parentheses are the corresponding standard errros.

TABLE IV
ESTIMATED TIME WINDOW FOR THE 29 ACUTE AND SPECIALIST TRUSTS IN THE LONDON AREA FOR COPD, STROKE, AND CHF PATIENTS

Acute and specialist Trust name	COPD	Stroke	CHF
Barnet and Chase Farm	42 (0.39)	29 (0.34)	52 (0.46)
North Middlesex Hosp.	41 (0.31)	24 (0.28)	51 (0.37)
Royal Free Hampstead	45 (0.36)	30 (0.31)	53 (0.43)
University College Hosp.	43 (0.37)	32 (0.55)	41 (0.31)
Whittington	50 (0.42)	22 (0.28)	55 (0.40)
Barking Havering & Redbridge	34 (0.29)	N/A	34 (0.28)
Barts and The London	56 (0.44)	40 (0.41)	57 (0.42)
Homerton	63 (0.53)	36 (0.38)	61 (0.41)
Newham Healthcare	52 (0.45)	30 (0.33)	66 (0.45)
Whipps Cross Univ. Hosp.	43 (0.41)	18 (0.26)	46 (0.38)
Chelsea and Westminster	58 (0.49)	69 (0.63)	54 (0.47)
Ealing	48 (0.42)	20 (0.37)	37 (0.34)
Hammersmith	35 (0.31)	17 (0.33)	38 (0.31)
Hillingdon	42 (0.40)	27 (0.26)	50 (0.40)
North West London NHS Trust	46 (0.40)	49 (0.45)	46 (0.37)
Royal Brompton and Harefield	40 (0.36)	N/A	28 (0.34)
St Mary's	38 (0.35)	22 (0.29)	37 (0.36)
West Middlesex Univ. Hosp.	56 (0.41)	23 (0.27)	21 (0.24)
Bromley	40 (0.32)	21 (0.25)	32 (0.33)
Guys St Thomas's	43 (0.36)	25 (0.26)	49 (0.41)
King's Healthcare	50 (0.38)	29 (0.34)	N/A
Lewisham	54 (0.43)	30 (0.29)	46 (0.38)
Queen Mary's Sidcup	43 (0.40)	19 (0.28)	14 (0.21)
Queen Elizabeth NHS Trust	47 (0.40)	17 (0.17)	40 (0.33)
Epsom and St Helier	29 (0.24)	31 (0.23)	41 (0.35)
Kingston	39 (0.34)	26 (0.27)	56 (0.41)
Mayday Healthcare	34 (0.29)	41 (0.31)	63 (0.43)
St Georges Healthcare	32 (0.28)	38 (0.47)	38 (0.30)
The Royal Marsden	N/A	N/A	N/A

Trusts are grouped by the SHA (NCL, NEL, NWL, SEL, and SWL). The number in parentheses is the corresponding probability of being in the high risk group. N/A referes to data not available.

inevitable consequences of such action. Using (2), the probability of belonging to the high risk (of readmission) group is estimated to be about 0.38, 0.20, and 0.35 for a COPD, stroke, and CHF patient, respectively. The probability of readmission within x days can be estimated by $\int_0^x f(u)\,du$, where $f(u)$ is the pdf as in (1). Therefore, the estimated probabilities of readmission within the time windows of 45 (COPD), 16 (stroke), and 39 (CHF) days are 0.39, 0.21, and 0.36, respectively. We also fitted the model to data for each of the 29 acute and specialist trusts in London area. Table IV summarizes the estimated time windows and corresponding probabilities of being in the high-risk group for these trusts. There is a marked difference in the estimated optimal time window among trusts. However, the estimated time windows for COPD and CHF patients for each trust display similarities.

With the exception of COPD patients in Queen Mary's Sidcup and Queen Elizabeth NHS Trust, CHF and stroke patients in Mayday Healthcare, and CHF patients in Kingston, trusts within the SWL SHA have the lowest time windows and the lowest probability of being in the high-risk group following a discharge. On the other hand, Homerton, Newham Healthcare, Chelsea and Westminster, and Barts and The London acute and specialist trusts have some of the largest estimated time windows, and more than a third of discharged patients for the selected clinical conditions are at high risk of being readmitted quickly.

Our findings provide little support for the use of 28 days as the time window in defining readmission. They also show that estimated time windows and probabilities vary widely between trusts. We can only speculate the causes of such marked regional variation in readmission rate for these clinical conditions. Possible causes could be the differences in the quality of healthcare provided between hospitals. A further bias might be the increased morbidity of patients seen in hospitals in some trusts that are national referral centers for the CHF and COPD, such as Brompton and University College Hospital (UCH). Deprivation differences among the regions should also be considered. The SWL, which has a low estimated probability of being in the high-risk group, is known to be one of the least deprived [18] locations in London, whereas trusts in the NEL and NCL are

among the most deprived. A recent study in the Greater Manchester area (U.K.) [19] showed that deprivation indeed exerted a significant effect on the risk of emergency readmission. A report published by the Commission for Healthcare Audit and Inspection [20] confirms that many people with COPD come from communities with high level of deprivation and often experience difficulty in gaining access to appropriate services.

V. Conclusion

Using the concept of change in risk of readmission, where the risk of readmission is high soon after hospital discharge, and substantially reduced after a period of time in the community, we illustrated that a patient LOS in the community before readmission is well described by a two-phase Coxian phase-type distribution. Using the national HES dataset, we showed that, in the case of COPD, stroke, and CHF patients, there are potential problems in how readmission is currently defined.

The analysis for CHF patients provided some support for a 28 days time window; however, in the case of COPD and stroke, 28 days may not be an appropriate choice of a time window. Determining the time windows for each acute and specialist trust in London revealed that there are marked differences between hospitals and regions. Given that the NHS performance rating framework regards readmission rate as one of its key indicators, our research suggests that some hospitals may be disadvantaged by the use of one single number to define a time window. The estimated probabilities of being in the high-risk group could also be used to monitor quality of care of hospitals. Some trusts possess a high risk of readmission after discharge, e.g., COPD patients discharged from Homerton hospital have a 53% chance of being in the high-risk group, whereas Epsom and St Helier has a low probability (0.24). In the case of stroke patients, the UCH has a significantly higher probability (0.55) of being in the high-risk group. The UCH is one of the main healthcare provider in London with a diverse range of services and patients. This high-probability of being in the high-risk group does not necessarily indicate poor quality of care at UCH. However, more research is needed to understand emergency readmission, particularly, the variability between individuals and hospitals.

The model we presented in Section III assumes there are only two phases that patients will experience during their stay in the community. We recognize that this can be restrictive in practice. Furthermore, differences in case mix, i.e., deprivation, mix of local populations, age, and sex may contribute to the variation of the estimated time windows for different diagnosis and regions. Future work will be directed at extending this modeling approach to a more general situation. The novelty of this approach lies in its ability to estimate an appropriate time window based on evidence objectively derived from operational data. Furthermore, this method could easily be implemented as a software toolkit to estimate optimal time windows for different diagnosis groups for each hospital, thus providing the means of monitoring time windows and probabilities of being in the high-risk group. Therefore, this can be a valuable tool in helping to tailor hospital care to local needs and ultimately contribute to improved measures for hospital performance management.

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He is engaged in research on modeling time to readmission, emphasizing admission rates after discharge. The objective is to illustrate patterns of unplanned readmission rates to hospital and develop a method of determining time windows of readmission. His research involves the use of hospital episodes statistic (HES) dataset.

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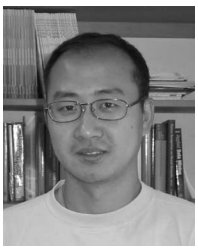
Prof. Chaussalet is the Chair of the Health and Social Services Study Group and a member of the Council of the Operational Research Society, and the Chair of the Steering Group of MASHnet, a health care modeling and simulation network, funded by the Engineering and Physical Sciences Research Council (U.K.).



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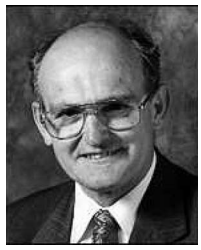
He was engaged in research on modeling of placement, survival, and costs of elderly people in long-term care. He is currently a Research Fellow with the Health and Social Care Modelling Group, University of Westminster. His current research interests include the modeling of healthcare systems using stochastic processes and statistical data mining on healthcare datasets.



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He is currently a Visiting Professor in the University of Westminster, London, U.K. In 1968, he was the first consultant in geriatric medicine appointed to St. George's Hospital, London. During 1993–2002, he was a Visiting Professor in the Department of Mathematics, University of Ulster. He is the coauthor of many articles published. In 1999, he was an expert Advisor to the Council of Europe. He is an Editor of the *Nosokinetics News*.

Prof. Millard is the President of the British Geriatrics Society and the President of the Geriatrics and Gerontology Section of the Royal Society of Medicine.