

MetSim: A Simulation Decision Support Tool using Meteorological Information for Short-Term Planning of Hospital Services

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Keywords: Forecasting Demand, Hospital Capacity Management, Weather, Simulation.

Abstract: Improved short-term predictions of hospital admissions and bed occupancy offer the potential to plan resource needs more accurately and effectively. The MetSim project explores the relationship between weather and health, building novel Bayesian models that are more sensitive to fluctuations in weather. Short-term forecasts of the numbers of admissions, categorised by age, gender and medical condition, are produced. In turn, coupled with predictions on length of stay and information on current occupancy, MetSim uses hazard ratios embedded within a simulation framework to provide forecasts of short-term bed needs. MetSim is a collaboration between Cardiff University, the University of Southampton, and the Met Office. Cardiff and Vale University Health Board and Southampton University Hospitals NHS Trust have guided the development of MetSim, provided data and piloted the tool.

1 INTRODUCTION

More than 2,000 years ago, Hippocrates first recognised that epidemics were related to seasonal changes in weather. However, it was only during the 1970s that research into connecting weather and health was taken seriously and, for the first time, meteorological variables were investigated to gain insight into the causes of increased mortality in winter and smaller increases in unusually hot weather (Keatinge 2002). Since then, the interest in the effects of weather on health has grown substantially, helped to some extent by raised awareness of global warming and concern about the public health impact of climate change. Knowledge on the influence of weather on health is valuable, and has the ability to contribute greatly to our understanding of epidemiology, the occurrence of accidents and injuries, and of public health issues. Examples of weather-health research from the literature include those relating to: extreme weather events (WMO, 2003); sunshine, such as skin cancer (Cancer Research UK, 2012) and Seasonal Affective Disorder (Garland, 2003); temperature, such as cold weather and mortality (Hajat et al., 2002); Thunderstorms, such as lightning strikes (Elsom, 2001) and leading to increased asthma attacks

(Venables 1997, Dales et al. 2003, New Scientist, February 2006); and snow/ice leading to fractures (Smith and Nelson, 1998).

The ability to predict weather offers the potential to provide valuable information that can be used in planning health services. For example, imagine a short-term hospital planning tool that was able to predict fluctuations in demand and bed occupancy for different specialities by including meteorological predictions alongside other known information such as day of the week. The relationship between weather and health is immediately evident in some specialities, for example respiratory medicine. Figure 1 shows respiratory admissions data from Southampton General Hospital. The top graph shows temperature over a five year period. The remaining graphs show admissions and discharges in black and occupancy in red. We observe that low temperatures lead to an increased number of admissions. Similar plots have been produced with data from other UK hospitals.

The MetSim project is a multidisciplinary collaboration involving academics (from OR and Statistics), meteorologists from the Met Office, and managers and consultants from hospitals.

It is beneficial for managers of hospitals to have short-term forecasts of demand and occupancy. Of

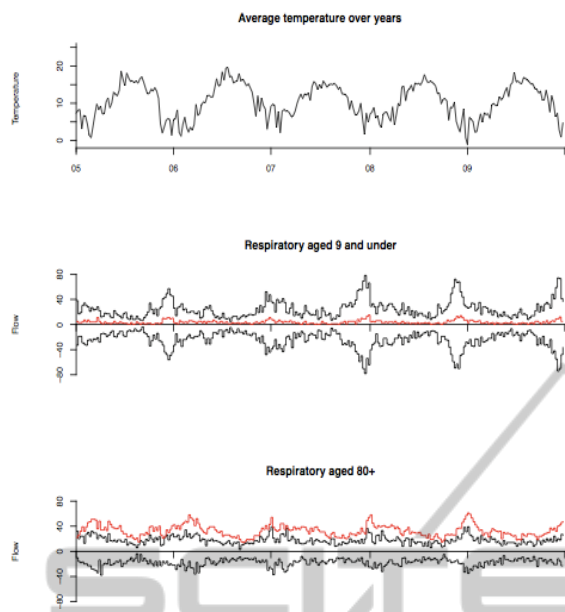


Figure 1: Respiratory patient flows at Southampton General Hospital.

particular interest is the number of non-elective (emergency) patients. Our particular focus is on patients who are admitted into hospital, as opposed to attending Accident and Emergency. The objectives of the MetSim project are:

- To describe hospital occupancy in two parts: rate of admissions and length of stay.
- To explore relationship between weather patterns and hospital admissions.
- To describe different lengths of stay for different classes of patient.
- To build a web-based tool which provides hospitals with short-term (7-day) predictions on demand and corresponding bed occupancy.

Figure 2 presents a high-level schematic of the component parts of the MetSim tool and corresponding responsibilities. These components are discussed in subsequent sections of this paper.

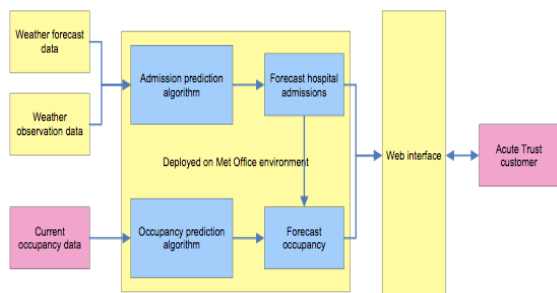


Figure 2: MetSim schematic.

2 DATA

Anonymized patient admission and discharge data from participating hospitals have been linked to meteorological data provided by the Met Office. We summarise the data types below.

2.1 Historic Hospital Data

For every admission/discharge of a patient over the course of a year the hospital records the age at admission, gender, broad class of treatment (medicine, surgery, trauma, paediatric or other), date of admission, and date of discharge. Hour of admission and discharge is optional. Ideally, the year of observation should be from 14 months ago to 2 months ago.

2.2 Current Hospital Data

For some day during the last week, the hospital gives a census of all prevalent patients. The items recorded are as for historic data except that there is, perforce, no date of discharge.

2.3 Meteorological Data

Over the entire time period, historic, current and forecast, the Met Office records the mean temperature on a given day and the minimum one week ago.

2.4 Temporal Data

Other variables needed are school holidays, public holidays, and day of the week. The historic hospital dataset is used to select models and estimate parameters. The current and forecast temperatures are then used to forecast admissions. The current hospital data are used only to simulate occupancy.

2.5 Historiography

We initially analysed datasets much larger than the ones in the final version of the model. The hospitals' historic datasets included the method of admission, full episodic progression of patient-spells and destination on discharge. The meteorological datasets included humidity, pressure, vapour pressure, rainfall and wind speed.

3 FORECASTING ADMISSIONS

As anticipated, age is a significant explanatory variable; we partitioned patients into 0-17 as paediatric, 18-74 as adult and 75+ as elderly (on guidance from the hospitals). We used gender, as much for logistic (planning for single sex wards) as statistical reasons. Temperature is a significant explanatory variable as is current day of the week. Figure 3 illustrates that admissions are higher during weekdays than at weekends.

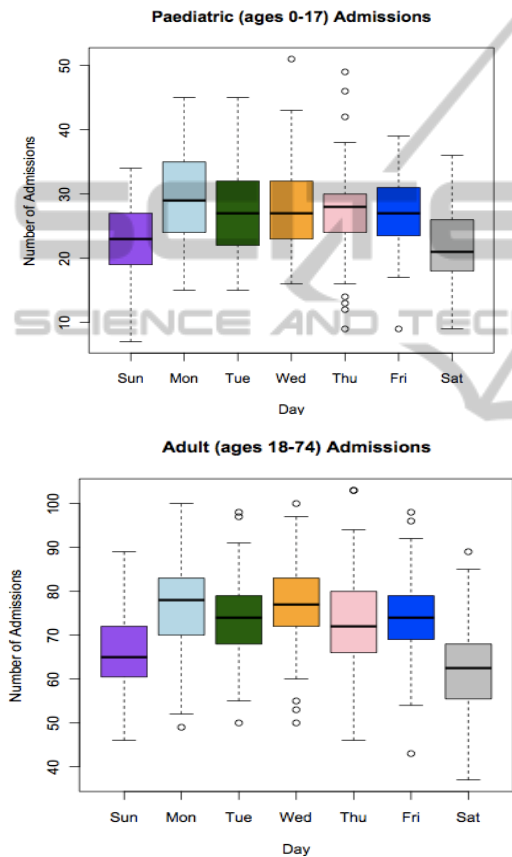


Figure 3: Boxplots of admissions by day.

3.1 Transformation

The data reveal that the number of daily admissions is naturally positively skewed. To overcome this in modelling, it is sufficient to take a square-root transformation. Having fitted a large number of models to the historic hospital dataset we reached the following conclusions:

- A model which includes age, sex, day of the week, whether the day is a school holiday, mean daily temperature and minimum temperature a week ago is the best main effects model

according to both the R^2 and AIC. Such a model is very parsimonious.

- This is improved by adding two-factor interaction terms, namely age-gender and interaction between age and minimum temperature a week ago. In fact, it explains over 80% of the variation in daily admissions. This is the model which will be adopted henceforth.
- Age alone explains a remarkable 74% of the variation in the number of admissions.

3.2 Weather Forecasting: Uncertainty

The model is found from historic data with observed weather temperatures. When predicting future admissions, we rely on weather forecasts. Accordingly, we regard actual future temperature as some linear function of forecast temperature, putting Bayesian uncertainty on the coefficients of the linear relation

4 LENGTH OF STAY

The length of stay is a problem in survival analysis, where “survival” is not leaving the hospital, whether by discharge, transfer or death. We regard the length of stay as a non-negative discrete number of days $n \geq 0$. Let $h(n)$ denote the hazard rate and let Gamma denote the log-odds of the hazard rate.

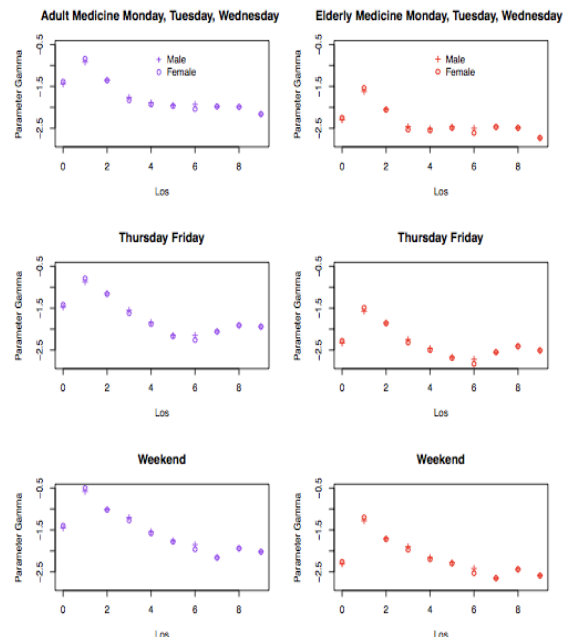


Figure 4: Log-odds of hazard rates for Southampton.

Figure 4 shows how Gamma evolves and depends also on age and current day of the week.

To model the log-odds of the hazard rates, we include the explanatory variables age, gender, day of week together with a broad grouping of the patients' specialities: medicine, surgery, trauma or other. Even in the least favourable cases about 70% of the variation is explained; it is often much higher.

5 SIMULATION STRUCTURE

We are now in a position to describe the flow of patients. It is too difficult to model analytically, so we simulate. We use a discrete timeline in days. We first use the historic weather data together with the historic hospital data to model admissions. From such a model, we use current and forecast weather data to simulate streams of admissions over the next few days (Figure 5). Next we model length of stay. We also simulate the specialities of newly admitted patients (Figure 6). Finally, we use data on current patients together with streams of hypothetical admissions to simulate streams of discharges (Figure 7).

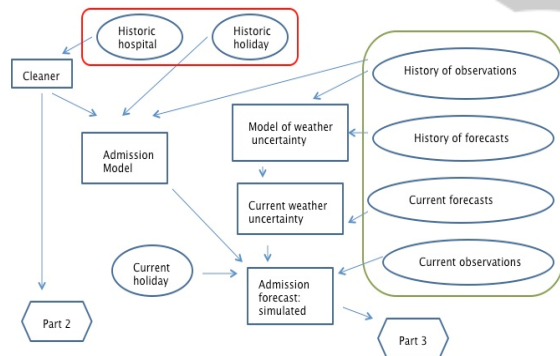


Figure 5: Simulation of admissions.

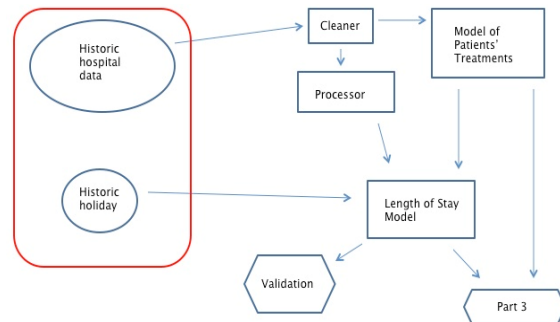


Figure 6: Simulation of length of stay.

We thus obtain forecasts for admissions, discharges, occupancy and change in occupancy.

For example, Figure 8 shows a forecast of admissions for the next week, with 80% and 95% confidence intervals.

The projected is currently being piloted. Cardiff and Southampton hospitals are submitting datasets to the Met Office where our code is implemented. The Met Office returns the forecasts to the hospitals.

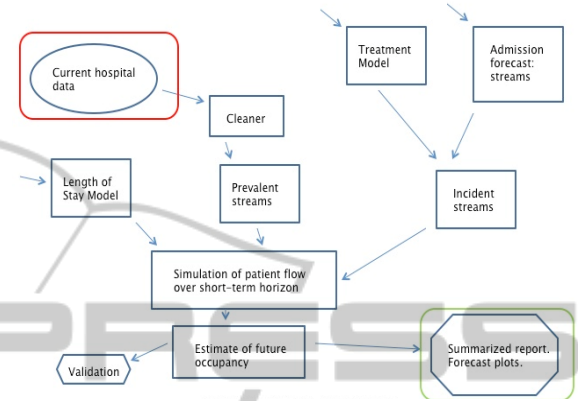


Figure 7: Simulation of patient flow.

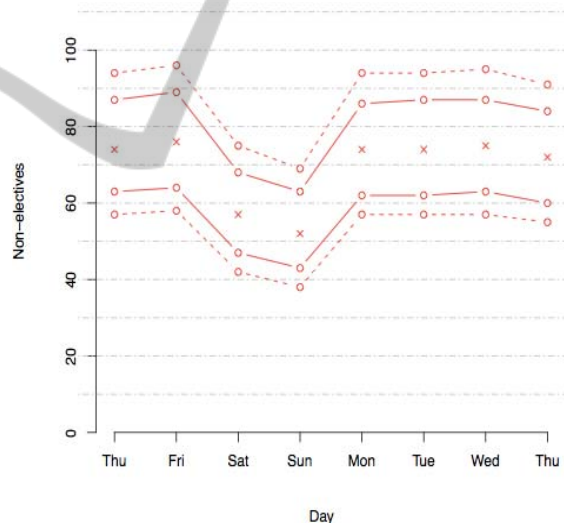


Figure 8: Illustrative MetSim output: Forecasted admissions (non-paediatric).

6 DISCUSSION

This paper outlines the underpinning methodology of the MetSim tool, designed to support hospital managers in predicting short-term demand and bed occupancy. Initially a Bayesian statistical model (full details are not included in this proceedings paper in the interests of space and rather the focus on the simulation components) is used to forecast

demand for different categories/conditions of admissions. This tool is currently being piloted at two hospitals: Cardiff and Southampton, and results at the time of writing this paper are promising. For example, over a period April 25th 2011 to January 31st 2012, the Root Mean Square Error (RMSE) of 7-day ahead forecasts was just 4.8.

Demand forecasts are then fed into a simulation framework to produce corresponding bed occupancy predictions over the planning horizon. To do this, we simulate length of stay for the predicted admissions using hazard rates (such that the time a patient spends in hospital is modelled using 'survival' analysis techniques).

The simulation is coded in C++ and sits on the server at the Met Office, Exeter, UK. A number of routines are run (as shown diagrammatically for simplicity in Figures 5-7) typically for 1000's of iterations (and thanks to the power of the supercomputer at the Met Office, are executed within seconds), thus participating hospitals are provided on a daily basis with forecasts and associated confidence intervals.

Over the next few months we will streamline the system to have a web interface for ease of use. Further piloting is also taking place with more hospitals across the UK.

ACKNOWLEDGEMENTS

This work is supported by the UK Engineering and Physical Sciences Research Council (EPSRC), grant EP/H010637/1.

The authors thank Patrick Sachon from the UK Met Office; Ben Hendy and Alison Gray from Southampton University Hospital Trust; Steve Tarr, Andrew Nelson and John Peters from the Cardiff and Vale University Health Board. These persons provided the data used here and shared their many helpful insights.

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