Development and implementation of a real time statistical control method to identify the start and end of the winter surge in demand for paediatric intensive care

Christina Pagel[1] PhD, Padmanabhan Ramnarayan[2] MD, FRCPCH, Samiran Ray[2] MD, Mark J. Peters[2,3] FRCPCH, PhD

1. UCL Clinical Operational Research Unit, University College London, London
2. Children's Acute Transport Service (CATS), Great Ormond Street Hospital NHS Foundation Trust, 26-27, Boswell Street, London, WC1N 3JZ, UK
3. Respiratory, Anaesthesia and Critical Care Group, Institute of Child Health, University College London, London

Corresponding author: Christina Pagel
Email:c.pagel@ucl.ac.uk
Phone number: +44 (0)20 7679 4501

Work performed at the Children's Acute Transport Service (CATS), Great Ormond Street Hospital NHS Foundation Trust, 26-27, Boswell Street, London, WC1N 3JZ, UK.

Financial Support: Christina Pagel's time on this project was part-funded by an infrastructure grant from the Great Ormond Street Hospital Charity.

KEYWORDS
OR in health services; Analytics; Statistical Process Control; Implementation; Emergency Medical Services

ABSTRACT

Winter surge management in intensive care is hampered by the annual variability in the winter surge. We aimed to develop a real-time monitoring system that could promptly identify the start, and accurately predict the end, of the winter surge in a paediatric intensive care (PIC) setting. We adapted a statistical process control method from the stock market called "Bollinger bands" that compares current levels of demand for PIC services to thresholds based on the medium term average demand. Algorithms to identify the start and end of the surge were developed for a specific PIC service: the North Thames Children's Acute Transport Service (CATS) using eight winters of data (2005-12) to tune the algorithms and one winter to test the final method (2013/14). The optimal Bollinger band thresholds were 1.2 and 1 standard deviations above and below a 41-day moving average of demand respectively. A simple linear model was found to predict the end of the surge and overall demand volume as soon as the start had been identified. Applying the method to the validation winter of 2013/14 showed excellent performance, with the surge identified from 18th November 2013 to 4th January 2014.

An Excel tool running the algorithms has been in use within CATS since September 2014. There were three factors which facilitated the successful implementation of this tool: the perceived problem was pressing and identified by the clinical team; there was close clinical engagement throughout and substantial effort was made to develop an easy-to-use Excel tool for sustainable use.

1. INTRODUCTION

Clinicians from Great Ormond Street Hospital (GOSH) in the UK run the Children's Acute Transport Service (CATS) which is responsible for transporting very sick children from non-specialist hospitals to paediatric intensive care units (PICUs) in north London. They are staffed by intensive care doctors and nurses and have two emergency paediatric ambulances for the North Thames area. While the numbers of children transported using such specialist retrieval teams are relatively small, all such retrievals are potentially life-saving and represent an important and expensive NHS resource (Ramnarayan, 2009). If the two teams are out on a call and cannot meet demand, that child must be transferred to another transport service (if possible) or else wait for the next CATS team to be free, with a risk of further clinical deterioration while waiting. If there is no local specialist PICU bed available, teams will need to transport the child further afield to the nearest hospital that has capacity (which can be as far away as the very north of England), which further impacts the service as that team is then unavailable for a considerable amount of time. Thus, when demand stretches capacity there is a risk of a worse clinical outcome for the children waiting longer for transport to a specialist unit and significant experienced stress for the CATS team.

In the UK, every winter brings with it an increase in the number of emergency admissions (particularly patients with respiratory disease). The British Medical Association ("BMA - Winter pressures") and most hospitals (e.g. "Winter preparedness 2013-14") have preparedness plans in place to try to cope with this increase. However, these plans tend to focus on what do when pressures arise and less on whether we can forecast the start of the annual surge (Hanratty and Robinson, 1999). The pressure on children's services is often particularly acute since PICU beds are not an abundant resource and young children, particularly the most vulnerable ones (for instance those with cystic fibrosis), are proportionately more susceptible to respiratory illnesses than adults (O'Donnell et al., 2010). Every winter, the CATS service has been severely stretched by increasing demand with no accompanying increase in capacity. However, there is now the possibility for CATS to temporarily increase its capacity during the winter surge through staffing additional retrieval teams. There is also potential for triggering different procedures for elective admissions to paediatric intensive care units when there is indication that the annual winter peak is beginning (for instance pre-emptively re-scheduling some operations). Currently, the UK Paediatric Intensive Care Society (PICS) identifies the winter surge as starting in mid-November and ending the first week of January and discusses various operational ways services can try to cope with the extra demand, including regular regional and national conference calls sharing information on experienced demand.

Previous approaches to the winter surge in emergency demand in adult intensive care have involved using disease surveillance (Hiller et al., 2013; Moriña et al., 2011; Nguyen et al., 2016), and/or weather and seasonal information (Batal et al., 2001; Boyle et al., 2012; Diehl et al., 1981; Jones et al., 2002; Marcilio et al., 2013; Shiue et al., 2016), and/or previous demand (Abraham et al., 2009; Jones, 2007; Jones et al., 2008; Proudlove et al., 2003), using a range of techniques including regression, stochastic Markov models and time series analysis methods such as Autoregressive Integrated Moving Average (ARIMA) models. In general, while emergency demand was universally found to be strongly seasonal and autoregressive it was also extremely variable, with its stochastic nature making accurate forecasts beyond seasonal or monthly means difficult. Additional problems for paediatric emergency retrievals at CATS is that vulnerable children tend to be the first population cohort to fall ill every winter, so that the peak in paediatric intensive care is often a month or two earlier than in adults meaning that using sentinel disease methods are less useful. At the same time case volume and resources are much lower in this context, so that the stochastic nature of the demand tends to have even greater influence on experienced daily demand.

The primary question we address in this paper is thus: can we find and implement a simple, feasible, method to improve on the PICS identification of the winter surge and thus help the CATS team with their winter planning? Real time identification of the surge could also be of benefit beyond CATS as their data feed into other regional and national services throughout the winter. We describe the novel adaptation of a statistical process control method adopted from the stock market to build a signalling algorithm to identify the start and end of the winter surge. We also discuss the process of developing this solution with the clinical team and how this method was successfully implemented within CATS.

2. DATA

Data on all CATS referrals are checked and entered onto a dedicated database daily so that the database is up to date and of high quality in almost real time. In practice, at 9 am on any given day, data exist up until the day before. We used anonymised reports generated from routinely collected data in our analysis. The study was discussed with the local Independent Review Board Chair who confirmed that ethical approval was not required.

To develop our signalling algorithm, we used data on all calls to CATS from April 2005 to July 2013. We quarantined data from July 2013 to February 2014 to validate the final algorithm. All analysis was carried out using a combination of Stata IC12 (StataCorp) and Microsoft Excel 2010.

3. TIME SCALES AND VARIABLE OF INTEREST

Each call is logged in the database with the exact time of call. We first had to decide what time scale to use (for instance, daily or weekly) and what the main variable of interest should be.

All calls that come into CATS need to be answered and dealt with by a member of the clinical team. However, only a subset of these calls result in the retrieval team leaving to pick up and transport a critically ill child. Discussing this with the clinical team at CATS, it was decided that “busy-ness” was experienced as demand for retrieval rather than just volume of calls; an increase in call volume without a corresponding increase in retrievals (for instance, many more calls for advice) could be absorbed relatively easily by the team. Thus it was decided to consider “demand for retrievals” as the variable of interest. This was defined as the sum of calls that actually ended in a retrieval and calls that would have resulted in a retrieval if capacity had been available (i.e. refusals due to no available team). The latter were identified by calls with an outcome of “refused” where the reason for refusal was either no available retrieval team or no available paediatric intensive care bed.

A surge in demand occurs whenever current demand is significantly higher than the recent average. However, from an operational point of view, surges only matter to a service if demand is high enough to strain capacity. For instance, in a service that has experienced consistently low demand (e.g. during August), a surge to medium demand is unlikely to present any problems in meeting that demand. To be useful for winter planning purposes, the identification of the start of the winter surge should occur only when demand has reached a level that strains available capacity. Reviewing the time series data with the clinical team and discussing “busy-ness”, revealed that 4 or more retrievals (or demand for retrievals) a day was experienced as “busy”. It was agreed to consider the start of the CATS winter surge as when demand first consistently breached “4 a day” or “28 a week” and the end of the surge when “4 a day on average” period was over.

To explore appropriate timescales for the data, we first transformed the raw data into three time series at daily, weekly and monthly timescales. For the weekly data, we worked with consecutive seven day periods rather than “week of year” to avoid disproportionately low numbers in the last week of the year which is less than 7 days. For monthly data, we used calendar month to define each time period. Figure 1 shows the full monthly and weekly time series from 2005-2013 while Figure 2 shows example daily data comparing the summer (Panel A) and winter (Panel B) of 2009. The monthly time series shows the annual winter surge in demand very clearly (Panel A, Figure 1).

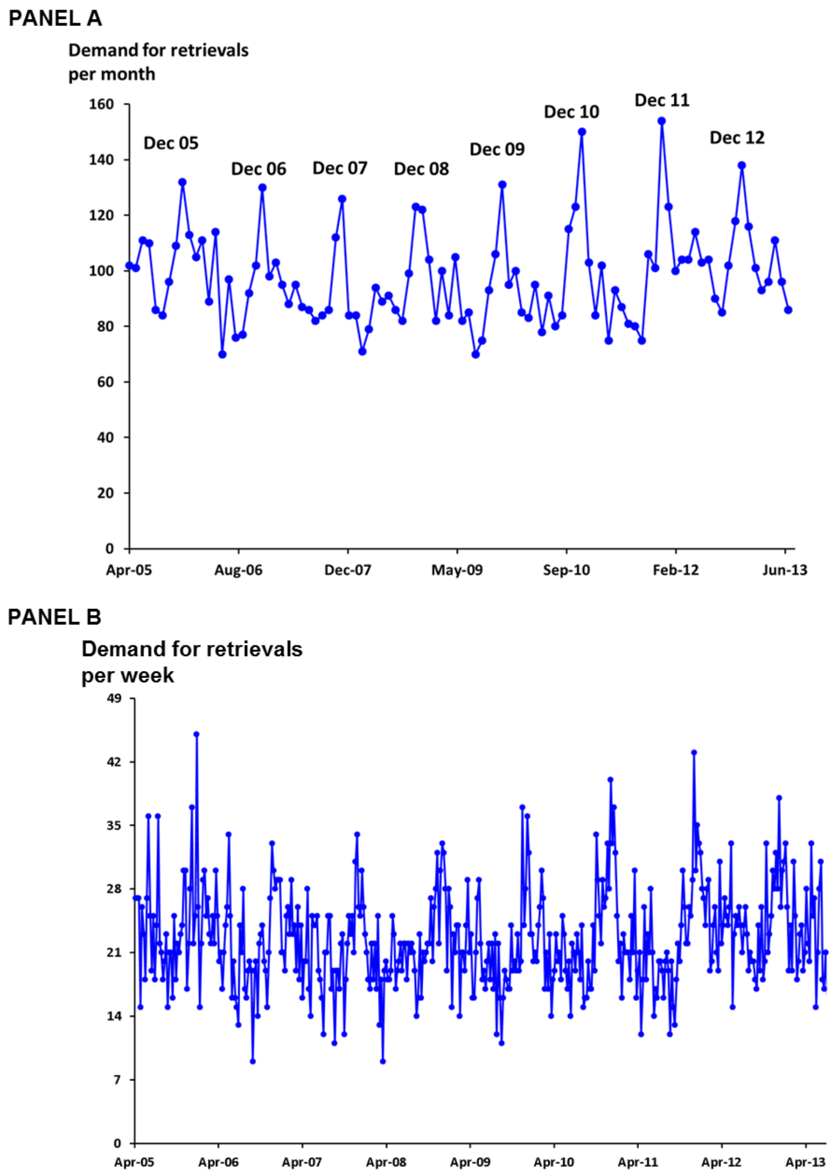
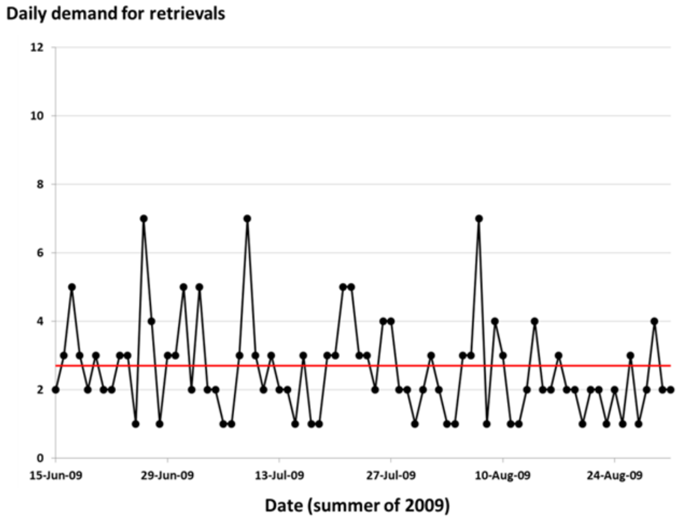


Figure 1 – Demand for emergency CATS retrieval from 2005-2013 at monthly (Panel A) and weekly (Panel B) resolution.

The monthly time series (Figure 1, Panel A) highlights that we can predict roughly when the winter surge will occur – December will be the busiest month of the year. However, the week the winter surge starts is variable – certainly more variable than the current identification of 14 November – 1 January allows for.

PANEL A



PANEL B

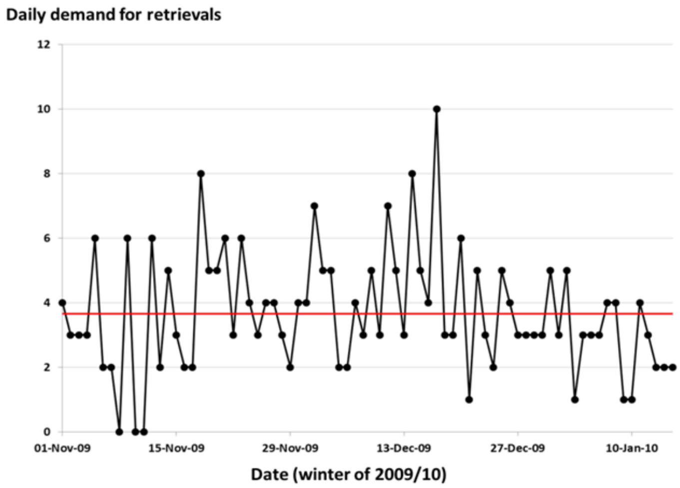


Figure 2 - Example daily time series data from the summer (Panel A) and winter (Panel B) of 2009. The horizontal red lines show the mean demand for retrievals over these periods (2.7 and 3.8 per day respectively)

The time series of demand for emergency retrieval by the CATS team is very variable, particularly at timescales of days and weeks which are most useful for short term service planning (see Figures 1 and 2). Figure 2 illustrates that even in summer, when demand is lowest, demand can still be high on any given day and conversely, in winter when demand is highest, demand can still be very low on any given day. For winter surge identification to be operationally useful, it is important to be able to monitor demand levels every day. However, using raw daily demand data, given we are looking for a move from an average daily demand of about “3 a day” to one of about “4 a day (or more)”, seems futile given the variability of the daily demand. (Figure 2).

Instead, we used the rolling 7-day total demand as a daily time series. That is, if $\{y_t\}$ is the daily demand for retrievals at time *t*, then the rolling 7-day total demand time series is defined by:

$$\{w_t\} = \sum_{j=0}^{6} y_{t-j} \quad (1)$$

In what follows, we use $\{w_t\}$ throughout as the daily time series of interest.

4. DATA OVERVIEW

Between 1 April 2005 and 15 July 2013, CATS received 17,527 calls. Of these, 9,731 represented genuine demand for retrieval, with a daily mean of 3.2 and standard deviation 1.7. The overall referral breakdown by outcome is given in Table 1, along with an indication of which referrals corresponded to genuine demand for retrieval.

Table 1 - Number of calls by type of call received by Children's Acute Transport Service (CATS) and outcome of call between 1 April 2005 and 15 July 2013. The final column indicates which calls were considered to represent "demand for retrieval".

Outcome of call	**Frequency (% of calls)**	**Counts as demand for retrieval?**
CATS team deployed	9337 (53%)	Yes
Transfer request refused due to no CATS team or PICU bed	394 (2%)	Yes
Transfer request refused but not due to capacity constraint	2434 (14%)	No
Call cancelled by referrer	1397 (8%)	No
Child died before team deployed	119 (1%)	No
Courtesy call	488 (3%)	No
Advice given	3343 (19%)	No
Unknown	15 (0%)	No
Total number of calls	**17527 (100%)**	
Total demand for retrieval	**9731 (56%)**	

5. DEFINING HISTORICAL WINTER SURGES

To define the historical winter surges, the lead author (CP) sat down with a senior CATS consultant (PR) and we manually identified the start and end dates for the surge each year from the rolling week time series $\{w_t\}$ and the "28 a week" high demand threshold. An example winter is shown in Figure 3 for 2007/8 and the full list of manually identified start and end dates is given in Table 2. Note that the start of the surge is quite variable (ranging from 8 October to 25th November).

Table 2- Identified start and end of the winter surge for each winter up to 2012/13.

Year	Identified start of surge	Identified end of surge
2005/6	04-Nov-05	10-Jan-06
2006/7	18-Nov-06	05-Jan-07
2007/8	25-Nov-07	03-Jan-08
2008/9	04-Nov-08	24-Dec-08
2009/10	19-Nov-09	23-Dec-09
2010/11	08-Oct-10	11-Jan-11
2011/12	23-Oct-11	10-Jan-12
2012/13	20-Oct-12	26-Jan-13

Although there is a level of subjectivity to choosing exact start and end dates in this way, identifying dates allows us to train identification algorithms on historical data and there is no “gold standard” method for retrospectively defining the winter surge.

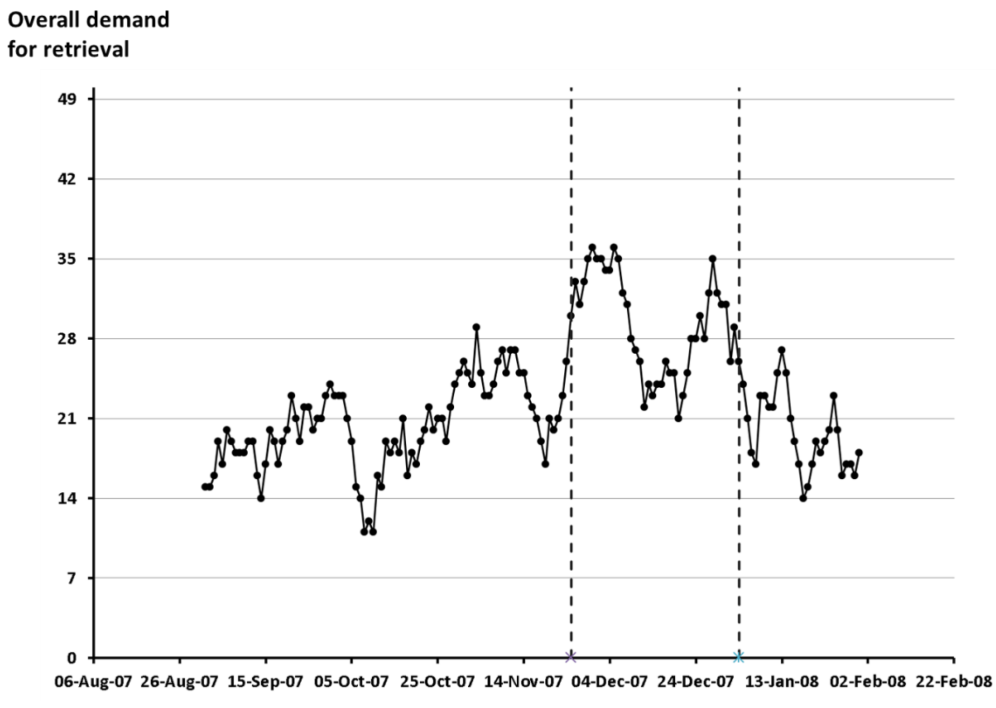


Figure 3 - the identified start and end of the winter surge for the winter of 2007/8 using the rolling week time series. Note that we did not identify the start until demand had risen consistently above the "4 a day/28 a week" threshold.

6. ALTERNATIVE APPROACHES TO THE PROBLEM

We note that before turning to Bollinger Bands and statistical process control methods, we had tried other approaches to identifying the winter surge in demand. This included ARIMA and SARIMA auto-regressive models fitted to all demand and separately to different diagnostic categories (Box and Jenkins, 2011) and using external data as an ‘upstream’ causal signal such as daily weather data (temperature and humidity) ("Weather Online UK"), national flu surveillance ("Weekly national flu reports - GOV.UK") and Google flu trends ("Google Trends"). While auto-regressive models could be successfully fitted and showed highly significant seasonal patterns, their white noise terms swamped the other terms so that, in identifying the start of the winter surge, these models performed no better than simply using the historical mean. Using external weather data was initially promising with strong correlation between temperature and demand for CATS, but at the granular daily scale this correlation was much weaker and not useful for identifying the winter surge. Meanwhile the influenza peak in adults, usually peaking in January or February, was generally later than the peak in CATS demand for retrievals. A possible reason for this is that the children who require CATS services in winter for respiratory conditions are the very sickest children in the population; since they are most vulnerable it is plausible they are at the vanguard of infections in the population rather than at the trailing edge, which makes tracking infections in the general population less useful for predicting the CATS winter surge.

7. BOLLINGER BANDS

Bollinger bands were introduced by stock market investor John Bollinger in 1992 (Bollinger, 1992) as a way to trigger buy and sell signals on shares by comparing current prices to medium term moving averages. Bollinger did not recommend them as absolute indicators to buy or sell stock but rather as reliable indicators of "whether prices are high or low on a relative basis".

For a given time series $\{y_t\}$, we define a moving average with window width *k* as:

$$\overline{y_k} = \frac{1}{k}\sum_{j=1}^{k} y_{t-j} \qquad (2)$$

We similarly define a moving variance as:

$$\sigma_k^2 = \frac{1}{k}\sum_{j=1}^{k}\left(y_{t-j} - \overline{y_k}\right)^2 \qquad (3)$$

Standard Bollinger bands (a time series of lower (l) and upper (u) limits) use a window width of 20 days and 2 standard deviations from the moving average, i.e. they are defined as:

$$b_l = \overline{y_{20}} - 2\sigma_{20} \qquad (4)$$

$$b_u = \overline{y_{20}} + 2\sigma_{20} \qquad (5)$$

However, the window size used to calculate the moving average and variance depends on what you are trying to achieve. For instance a smaller window width would be more sensitive to short-term changes but have lower specificity (i.e. the signal is more likely to be a false positive). Similarly the multiple of standard deviations (band width) used to define the upper and lower bands is also flexible. The basic trading rule applied is that when the price of a stock exceeds the upper limit ($y_t > b_u$), the stock should be sold and when $y_t < b_l$ the stock should be bought.

Although very simple, Bollinger bands have been shown to be profitable rules of thumb and continue to be used today in the stock market (Lento and Gradojevic, 2011; Leung and Chong, 2003). They have also been used in completely different contexts such as identifying fabric defects during manufacturing (Ngan and Pang, 2006), although an academic literature search reveals few documented uses outside of finance and none in health care.

8. USING BOLLINGER BANDS TO IDENTIFY THE START AND END OF A WINTER SURGE

Use of Bollinger bands in the stock market is focused on spotting when a time series has deviated significantly from a recent medium term average. The underlying assumption is that such deviations cannot be predicted. In the stock market, all deviations are important regardless of when in the year they occur. However the situation for paediatric intensive care services is somewhat different: there *is* a surge *every* winter that places significant pressure on PICU services. Thus, if looking at daily demand over the year, demand *will* breach an upper Bollinger band at some point in the autumn as demand increases at the start of the surge and it *will* breach a lower Bollinger band as demand decreases once the surge is over. Those breaches could then act as surge identifiers, signalling the start and end of the winter surge. Our aim was to choose a window size and band width that respond quickly to changes in demand (to provide timely warning that the surge has started or ended) but not so quickly that a transient spike or dip in demand will result in a ‘false positive’ identification. Allowing the band width and window size to be determined by tuning the identification algorithms to historical data (the identified winter surges) is a key and novel difference in our approach from both the use of Bollinger Bands in the stock market and other statistical process control (SPC) methods in health care.

Additionally, the likelihood of a false positive identification can be reduced by requiring that daily demand must consistently breach either the upper Bollinger band (to define the start of the surge) or the lower Bollinger band (to define the end of the surge) (e.g. see Wheeler, 2003).

Finally, daily demand breaches the upper Bollinger Band whenever current demand is significantly higher than the recent average. However, while this does represent a surge in demand, it only matters to a service if demand is high enough to strain capacity. To be useful for winter planning purposes, the identification of the start of the winter surge should occur only when demand has reached a level that strains available capacity.

The most suitable choices for window size, band width, consistency and absolute demand requirements are likely to depend on the particular paediatric intensive care service. The level of demand that is considered to strain available capacity must be defined by the local team (at CATS it has been defined as “4 a day”). Choices for window size, band width and consistency can then be optimised by defining start and end dates for previous winter surges in that service.

Let b_u and b_l represent upper and lower Bollinger band limits for some chosen window width *k* and multiple, *c*, of the standard deviation so that $b_u = \overline{w_k} + c\sigma_k$, where $\overline{w_k} = \frac{1}{k}\sum_{j=1}^{k} w_{t-j}$.

9. OPTIMISING *c* AND *k*

For any given choice of *c* and *k* and a given specification of an identification algorithm defining consistency and absolute “busy-ness” thresholds, we calculated the goodness of fit to the identified dates in Table 2 using the sum of the squared difference:

$$S_{c,k} = \sum_{m=1}^{8} (a_m - f_m)^2 \qquad (6)$$

where *a* is the manually identified date, *f* is the algorithm identified date and *m* is the year. Using the algorithms above we calculated $S_{c,k}$ for values of *c* (the multiple of the standard deviation) from 0.6 to 2.2 in increments of 0.1 and values of *k* (the window width) from 15 to 49. We then chose *c* and *k* to minimise $S_{c,k}$. Note that we ran this optimisation process separately for the start and end of the winter surge, allowing *c* and *k* to be different for signalling the start and end of the surge. Due to the small number of historical winters, we used brute force optimisation implemented in STATA IC 12, with a nested loop incrementing *c* within increments of *k,* choosing those values of *c* and *k* that minimised $S_{c,k}$ across the 595 combinations. The output of the brute force optimisation is given in the supplementary table. The optimisation took about 2 minutes to run on a standard desktop computer.

10. DEVELOPING ALGORITHMS FOR IDENTIFYING THE START AND END OF THE SURGE

We explored several options for algorithms to identify the start and end of the surge to reduce false positives. These included specifying a certain number of days that the Bollinger threshold had to be breached to ensure consistency of elevated demand and experimenting with hard threshold cut-offs for demand to ensure that demand was high enough to constitute a strain upon the service. We allowed different algorithms to be used to identify the start and the end of the surge.

For the consistency criteria, we explored specifying a range of consecutive days that the demand, w_t, had to exceed the upper (or be under the lower) Bollinger Band from 2 to 5 consecutive days. We also explored relaxing the consecutive condition, specifying instead that at least 3 out of the 5 or at least 2 out of the last 4 previous days had breached the upper or lower threshold (following the approach discussed in Wheeler, 2003).

For levels of absolute demand, we explored specifying that the demand had to be greater than 28 or greater or equal to 28 for the start of the surge and below 28 for the end of the surge, and again explored the impact of requiring consecutive days to meet the same threshold criteria.

Finally, we hard coded into the algorithm *a prioiri* knowledge about winter: the requirement that it could feasibly be winter for the start of the surge and the requirement that the surge lasted at least a month for the end of the surge.

The final algorithms that optimised the goodness of fit criteria defined above are given below.

ALGORITHM FOR START:
The start of the surge is signalled if:

EITHER:
$w_t > b_{ut}\ AND\ w_{t-1} > b_{u(t-1)}\ AND\ w_{t-2} > b_{u(t-2)}$ AND $w_t \geq 28$ AND month>=10

OR
$w_t \geq 28\ AND\ w_{t-1} \geq 28\ AND\ w_{t-2} \geq 28\ AND\ w_{t-3} \geq 28$ AND month ≥10

That is, in all cases it had to be at least October and EITHER the rolling week demand had breached the upper Bollinger limit three days in a row and the most recent week demand total had reached 28 (i.e. "4 a day") OR we had seen demand at or above 28 for four consecutive days. The latter was included as a potential signal to allow for the (unlikely) possibility of a slow rising tide of demand.

ALGORITHM FOR END:
The end of the surge is signalled if:

The start of the winter surge has been signalled AND the signalled start was at least 31 days ago AND $w_t < b_{lt}\ AND\ w_{t-1} < b_{l(t-1)}\ AND\ w_{t-2} < b_{l(t-2)}$.

The demand volume just after the winter surge varied greatly year to year and so we did not use an absolute volume threshold to identify the end of the surge, since it reduced goodness of fit.

Note that we are not attempting to fit a statistical model to the running totals (or their moving averages) and nor are we asserting any deep meaning to breaches of upper or lower limits. We have used a deliberately pragmatic approach, using the time series that is readily available, to try to spot in a timely manner when current demand is exceeding recent average demand as a way of determining when the winter surge has started (and similarly for the end of the surge).

11. RESULTS OF THE OPTIMISATION

The optimal Bollinger bands identified are shown in Table 3 while their corresponding signalled start and end dates, along with the sum of square errors, are shown in Table 4. The optimised Bollinger bands, together with the algorithms given above, matched the identified start and end dates very well, particularly for the start of the surge (arguably the most important).

Table 3 - Optimal Bollinger bands for spotting the start and end of the winter surge. For both, the optimal lag is 41 days, but for the start the best multiple for the standard deviation is 1.2 and for the

end it is 1. For interested readers, the full results of the optimisation for the identification of the start are provided as supplementary material.

Start of winter surge	$b = \overline{w_{41}} + 1.2\sigma_{41}$
End of winter surge	$b = \overline{w_{41}} - \sigma_{41}$

Table 4 –The signalled start and end dates using the Bollinger bands defined in Table 3

Year	Manually Identified start	Signalled start	Squared difference for start	Manually Identified end	Signalled end	Squared difference for end
2005/6	04-Nov-05	07-Nov-05	9	10-Jan-06	14-Jan-06	16
2006/7	18-Nov-06	23-Nov-06	25	05-Jan-07	08-Jan-07	9
2007/8	25-Nov-07	26-Nov-07	1	03-Jan-08	06-Jan-08	9
2008/9	04-Nov-08	07-Nov-08	9	24-Dec-08	26-Dec-08	4
2009/10	19-Nov-09	20-Nov-09	1	23-Dec-09	29-Dec-09	36
2010/11	08-Oct-10	08-Oct-10	0	11-Jan-11	12-Jan-11	1
2011/12	23-Oct-11	24-Oct-11	1	10-Jan-12	15-Jan-12	25
2012/13	20-Oct-12	21-Oct-12	1	26-Jan-13	19-Jan-13	49
Total S			47			75

An example of the Bollinger bands and signalled start and end of the surge for the winter of 2007/8 is shown in Figure 4.

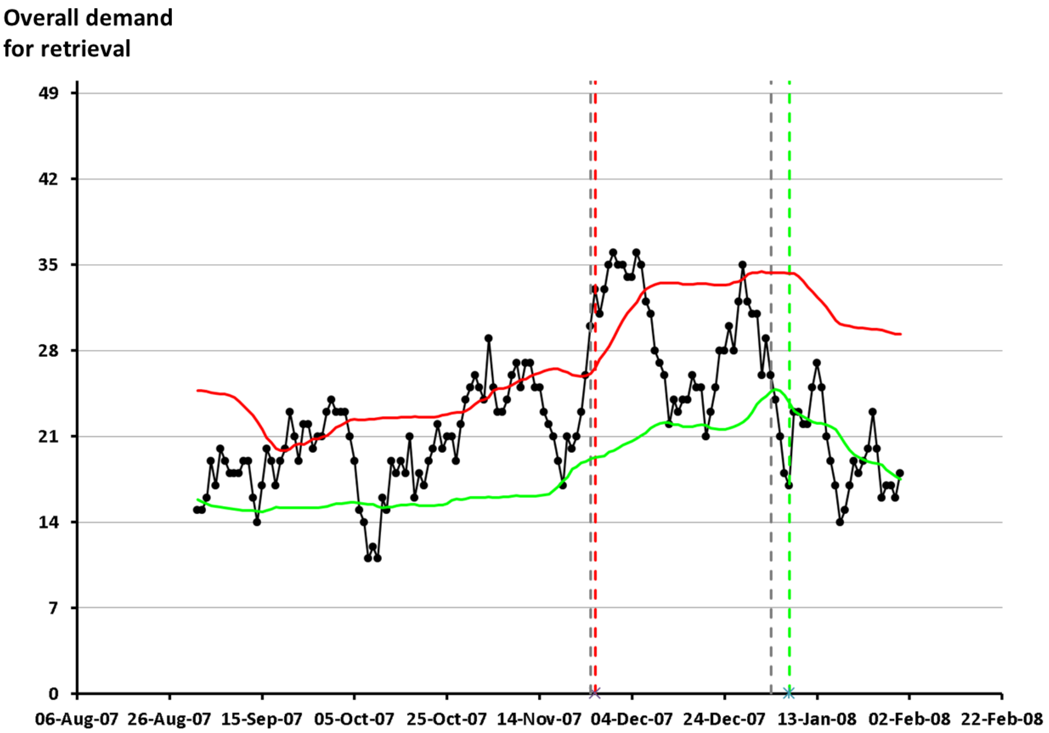


Figure 4 - Example of the signalled start and end of the surge for the winter of 2007/8. The upper and lower Bollinger bands are shown in red and green respectively and the corresponding triggered start and end dates as red and green dashed vertical lines. The grey vertical dashed lines show the manually identified start and end of the surge.

We can see that the daily rolling 7-day totals (w_t) breach the upper Bollinger bands in mid-September and mid-October as well, indicating that demand was higher than the previous 6 week average. However, the September breach is still at low overall volume (just over 3 a day/21 a week) and so well below the agreed threshold for high demand. In October, the start is almost signalled but is not because it either fails the "$w_t \geq 28$" condition or the condition of at least 3 consecutive days OVER the upper Bollinger band.

The relatively large window width for the moving average would help to prevent early signalling of the end of the surge and has the effect of reducing the influence of short term changes in demand while the relatively low multiple of standard deviations (1.2) means that the we are not looking for a large shift in demand (remember that the average daily demand shifts from 3 to 4 per day during the surge). Thus the optimised values for the window width and multiple of standard deviation have the effect of selecting for a moderate but consistent shift in demand, which is intuitively appropriate for this winter surge context. As seen in Figure 2, the daily demand is still very variable during winter and there can be natural peaks and troughs even during the surge (e.g. mid-December in Figure 4). In almost all cases, the signalled date is after the manually identified date for both the start and the end of the surge. This is not surprising since a delay of at least three days is built into the algorithms by requiring a consistent breach. This is not a weakness of the method since when looking at historical data with the benefit of hindsight (as was done to manually identify historical dates), it is relatively easy to select the start and end of the surge. However, if using this method to signal the start and end in real time, it is important to be relatively sure that that the signal is not simply a transient spike (or dip).

12. CHECKING THE STABILITY OF THE CHOSEN BOLLINGER BAND PARAMETERISATION

When using all 8 years of historical data, a window width of 41 days was chosen as optimal for both start and end and multiples of 1.2 and 1 for the standard deviation respectively. We also wanted to check that this parameterisation was reasonably stable (to provide more confidence in using the chosen bands in the future). To do this, we re-ran the Bollinger band optimisation process eight more times, each time excluding one year from analysis. The optimal values for *c* and *k* for the start and end of the surge are shown in Tables 5 and 6 respectively. It is clear from this that the parameterisation is very stable.

Table 5 - Optimal window width and standard deviation multiplier for the *start* of the surge excluding one year at a time

Years	Best window width FOR START	Best SD multiplier	Minimum sum of squared errors

All years	41	1.2	47
Excluding 2005/6	41	1.2	38
Excluding 2006/7	41	1.2	22
Excluding 2007/8	21	1	46
Excluding 2008/9	41	1.2	38
Excluding 2009/10	41	1.2	46
Excluding 2010/11	41	1.2	47
Excluding 2011/12	41	1.2	46
Excluding 2012/13	41	1.2	46

Table 6 - Optimal window width and standard deviation multiplier for the *end* of the surge excluding one year at a time

Years	Best window width FOR END	Best SD multiplier	Minimum sum of squared errors
All years	41	1	149
Excluding 2005/6	41	1	133
Excluding 2006/7	41	1	140
Excluding 2007/8	41	1	140
Excluding 2008/9	41	1	145
Excluding 2009/10	42	1	108
Excluding 2010/11	41	1	148
Excluding 2011/12	41	1	124
Excluding 2012/13	41	1	52

13. PREDICTING THE END OF THE WINTER SURGE AND TOTAL VOLUME OF DEMAND

The developed algorithm based on Bollinger bands allows us to monitor demand in real time for signalling the start and end of the winter surge. However, it would also be very useful to have an idea of the duration of the surge and overall volume of demand at the beginning of the surge, since this could inform any special measures that are put in place once the surge has been signalled.

Define a new variable h_m as the number of days after the 1st October that the winter surge is signalled each year, *m*. Plotting the duration of the surge, d_m, defined as the number of days between the signalled start and signalled end vs h_m, we see an excellent linear relationship (Figure 5). Clearly h_m is not independent of the duration (since both depend on the signalled start date), but we are not using the observed relationship to model the duration. Instead, we simply want a convenient and easy way to estimate the end of the surge once the start has been signalled. We suspect that the relationship in Figure 5 is telling us is that regardless of when the surge starts, it will continue until approximately the first week of January and that there is a slight tendency for surges that start early to continue longer. Using a simple linear regression we obtain a fitted R^2 value of 0.91 and the equation:

$d_m = 108.7 - 1.26h_m$ (7)

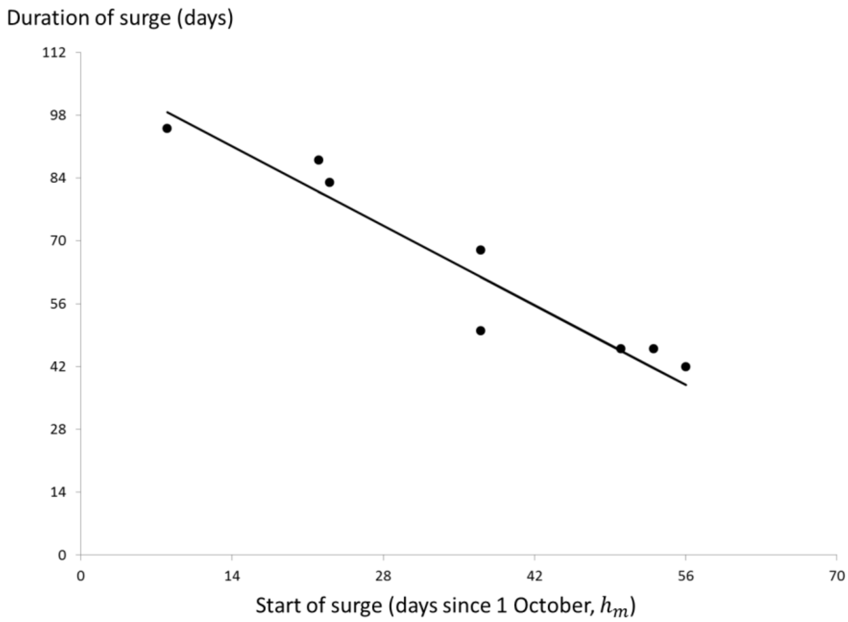


Figure 5 - relationship between $\boldsymbol{h_m}$and the duration of the surge, d_m.

We similarly explored the relationship of total volume of demand, v_m , with h_m (Figure 6). Again we see an excellent linear relationship. This is a result of the fact that during the surge each year, despite the peaks and troughs, the average daily volume of demand was very close to 4. Thus the overall volume during the surge is simply (approximately) 4 times the number of days it lasted. Given the linear relationship seen in Figure 5 we should thus not be surprised to see this reflected in volume. However, this is very useful, since we can now calculate a reasonable estimate for total volume of demand over the surge. Since demand for a CATS retrieval translates directly to a demand for a PICU bed in North London, this enables us to give the hospitals receiving CATS patients an early estimate of the likely number of beds needed for emergency cases that winter. This could simply be communicated as the rule of thumb “from now until early January we are likely to need an extra PICU bed a day in North London”.

The fitted linear relationship for volume, v_m , has an R^2 of 0.91 and equation:

$v_m = 452.7 - 5.12h_m$ (8)

When using equations (7) and (8) to predict duration and volume at the start of the surge, we apply prediction intervals to the point estimates using:

$\hat{y} \pm t^*_{n-2} s_y \sqrt{1 + \frac{1}{n} + \frac{(x^* - \bar{x})^2}{(n-1)s_x^2}}$ (9)

where $\hat{y}$ is the point estimate for duration (or volume), n=8 (the number of data points used to fit the line), x* is the new x observation (the new $h_{\boldsymbol{m}}$), s_y is the root mean squared error from the regression fit, s_x^2 is the observed variance of the eight h_m observations used for the regression and t_{n-2}^* is the two sided T-distribution threshold.

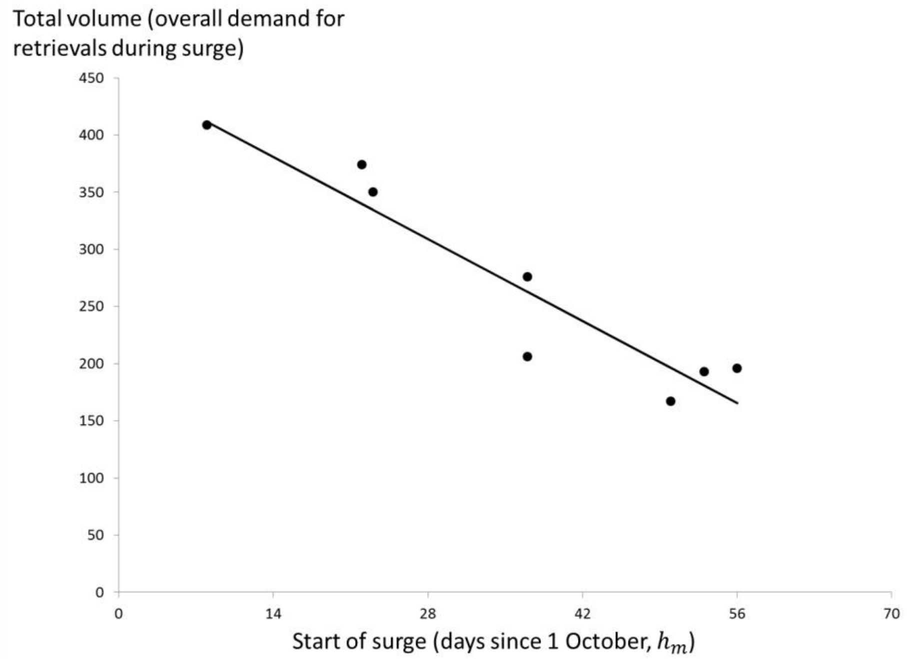


Figure 6 - relationship between $h_{\boldsymbol{m}}$ and the volume v_m

13. TESTING THE ALGORITHMS ON THE WINTER OF 2013/4

We tested the new algorithms and duration and volume prediction on the winter of 2013/14 (which was not used for algorithm development or the optimisation process).

Running the algorithm, the start of the winter surge was signalled on the 18th November 2013 (Figure 7). We can see that the algorithm has signalled the start of surge at a point when a purely visual inspection would not have been able to. Applying equations 7 and 8 to predict the duration and volume and equation 9 to provide 60% prediction intervals, we obtain an expected end of surge to be 5th January 2014 [29 December, 11th January] (shown as the grey dashed line in Figure 7) and an expected overall volume of demand of 207 [181, 241].

Continuing the algorithm through the winter of 2013/14, the end of the surge was signalled on the 4th January 2014 and the overall volume of demand was 235 (see Figure 8). The algorithm has done a good job in identifying the winter surge, although it could be argued that the actual end of the surge was slightly later, around the 21st January 2014. However, either the triggered end (4th January) or a later end of 21st are reasonable and the choice is somewhat subjective. Certainly, as tested on the winter of 2013/4, the method for picking out the start and end of the winter surge is fit for purpose, as was agreed with the clinical team.

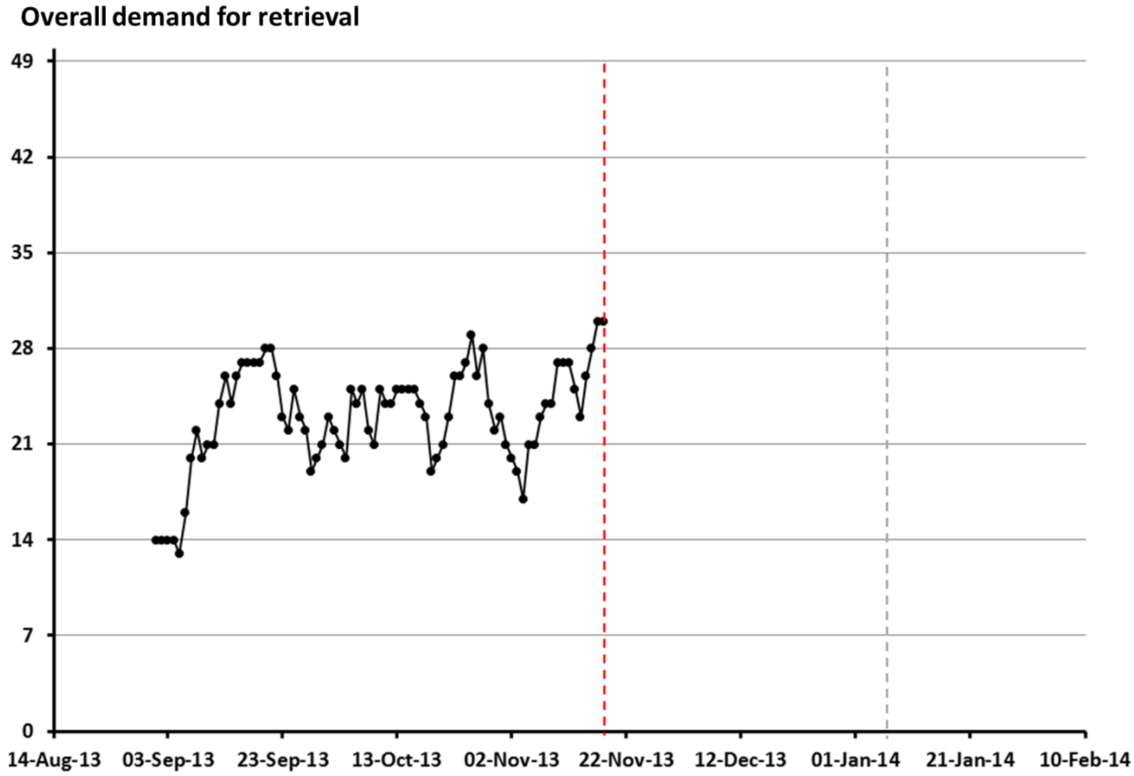


Figure 7- running on the algorithm on the winter of 2013/4 to find the start of the winter surge. These data were not used to develop the algorithm or optimise the Bollinger bands. The red dashed line shows the signalled start of the surge and the grey dashed line the predicted end of the surge.

We note that demand for CATS services is experienced by the team as a daily burden rather than a weekly burden. It is interesting to see how the algorithm has made sense of the much messier daily demand for the winter of 2013/14 (Figure 9). The variability is evident – using just the daily data, it would be harder to pick out a winter surge period, but we can also see that the signalled surge period does indeed have a higher average demand than the non-surge period.

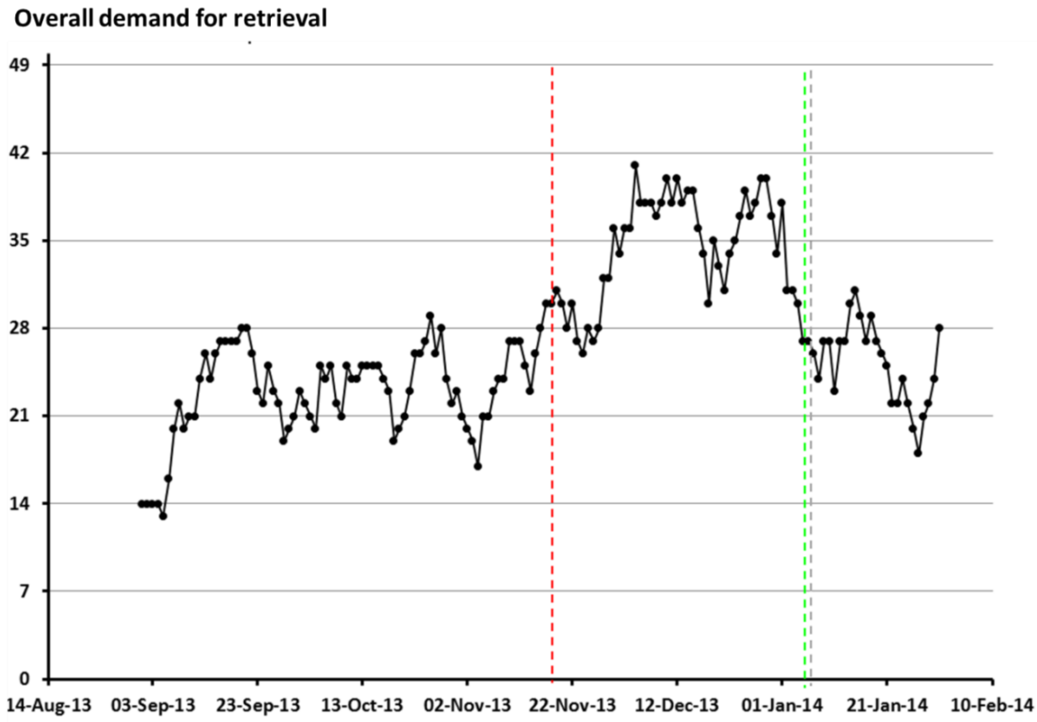


Figure 8 - running on the algorithm on the winter of 2013/4 to find the end of the winter surge. These data were not used to develop the algorithm or optimise the Bollinger bands. The green dashed line shows the signalled end of the surge and the grey dashed line the predicted end of the surge.

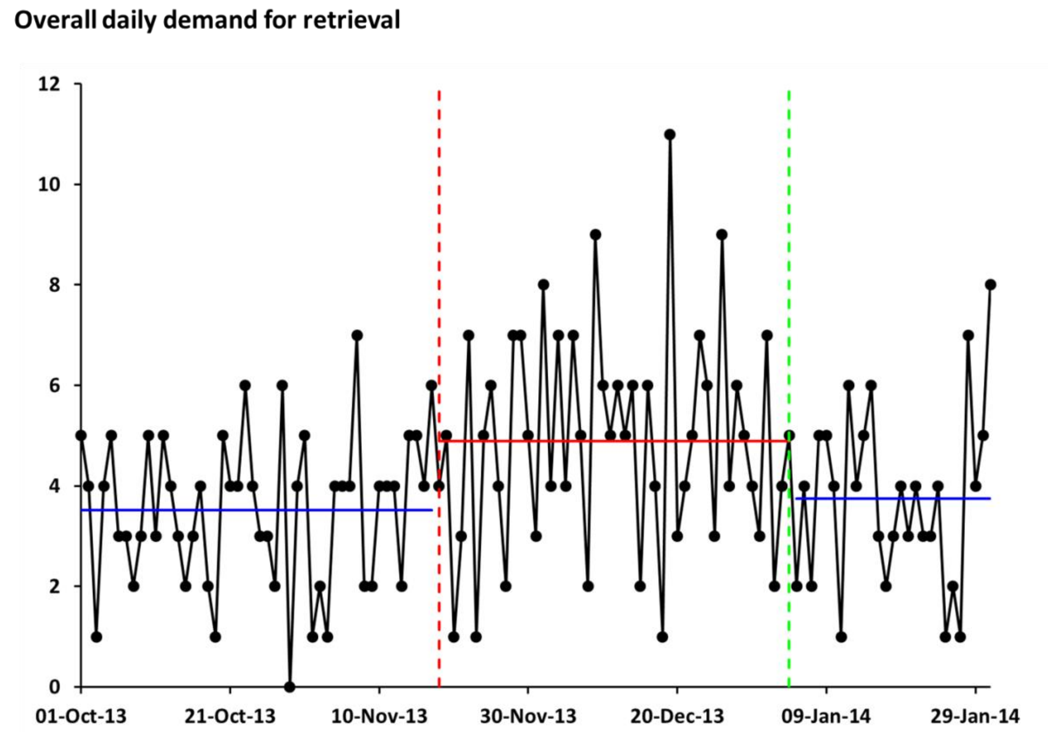


Figure 9 - Daily demand for retrieval for the winter of 2013/4. The blue lines show the average daily demand outside of the identified surge period while the red line shows the average demand within surge period (almost 5 a day). The vertical dashed lines show the signalled start and end of the surge.

14. IMPLEMENTATION

This special issue of EJOR arising from the 27th European Conference on Operational Research has a focus OR in practice and a key component of OR is the “real world” application of analytical methods (“The Science of Better”). Thus we highlight here the elements of this work that enabled rapid and successful implementation of this work, all of which were facilitated by the OR analyst (CP) working in an embedded research role for two days a week within Great Ormond Street Hospital.

Addressing a pressing problem

The winter surge is experienced as a difficult period by those working within CATS, due to the large increase in demand for services. This project was focused on, and motivated by, finding an approach that could be used by the team in real time to mitigate some of the perceived burden. This meant that the method used was secondary and the primary requirement was for feasibility of daily on-going use. The focus on usability and the clear desire for such a tool among the CATS team facilitated the quick implementation of the final algorithms.

Engaging key clinical team members throughout

The problem came from the clinical team and was discussed throughout development with three key clinical champions within CATS (all co-authors on this paper), which included the clinical lead for data within CATS (PR). This ensured that the analytical development used the available data appropriately, in particular in defining: what constituted “demand” for the CATS team, the threshold for “busy-ness” and in establishing what output would be useful for the clinical team. These discussions were also useful for the clinical team in aiding thinking about the winter surge as a whole and its impact on the service. Having developed a methodology for identifying the winter surge, the lead author (CP) then discussed it in detail with the whole CATS team, including clinicians, administrators and nursing staff. They were very enthusiastic and were keen to use the method for the coming winter of 2014/5.

Producing an easy-to-use software tool

Although both Bollinger Bands and the final algorithms are relatively simple, they do require data manipulation to implement and update every day with the most recent available data. Key to the sustainable use of this method was the development of a simple Excel spreadsheet that would take as input the standard data report generated from the CATS database and, on the click of a button, clean and process the data to produce charts as shown in Figure 10. Had there been any substantive additional burden in terms of time taken or difficulty for the CATS administrative or clinical team, the tool would not have been successfully implemented. This final step in enabling the move from potential to actual use of a new method was crucial.

The lead author (CP) implemented the Bollinger bands and the algorithms within Microsoft Excel 2010 using Visual Basic so that the spreadsheet:

– carries out automated data-cleaning and checking
– processes the cleaned data to provide daily totals of genuine demand
– updates the information on the 7-day running totals, the 41 day moving average and upper and lower Bollinger bands
– checks for the winter signalled start and end (depending on time of year)
– updates a chart displaying the recent few months of demand along with upper and lower Bollinger bands (with signals if appropriate).
– If the start of the winter has been signalled, writes out the predicted end and volume on a separate worksheet.

Note that for the implementation, we updated the best linear fits in equations (7) and (8) to include the observations from 2013/14 data. These have continued to be updated every year as more data becomes available. In 2014, we also shifted the potential start of winter back from 1 October to a week later (8th October).

Example output from the Excel file for from the winter of 2014/15 is shown in Figure 10. We can see that the algorithm identifies the surge well and that a predicted end of the surge is also shown on the graphic (the actual end of the winter surge was signalled on 5th January 2015).

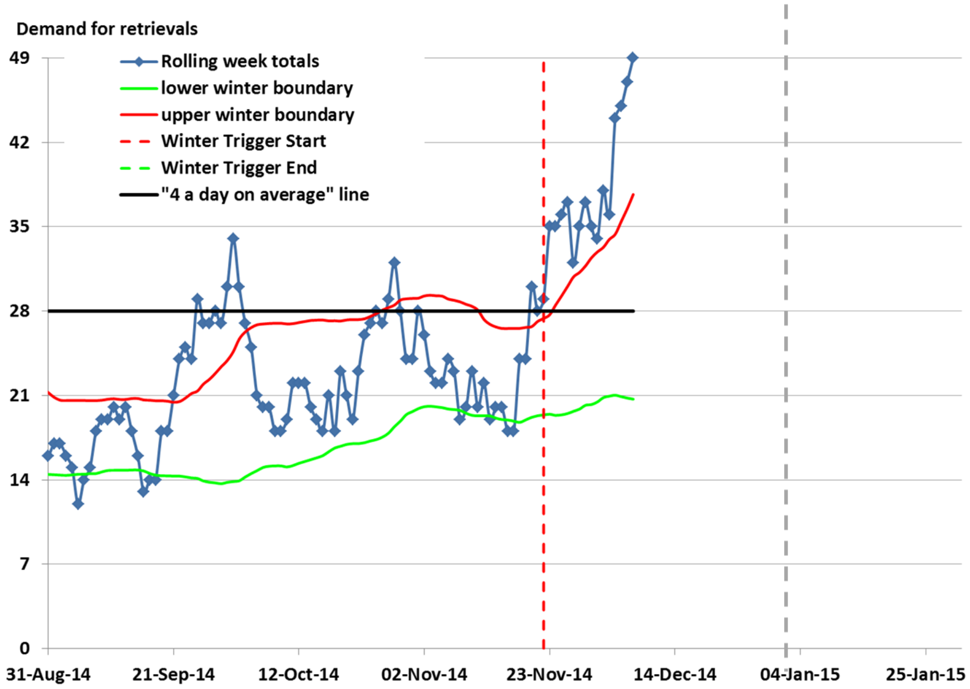


Figure 10 - example output for the CATS service from the implemented Excel file from mid-winter 2014/15.

15. LIMITATIONS

The method is deliberately simple and pragmatic but it does come with limitations. By responding to changes in demand, it is necessarily reactive and does not predict the start of the winter surge ahead of time. While the start and duration will always be stochastic to some extent, there undoubtedly exist to a complex set of causal factors that determine its start and duration. Possible causal contributors include the weather (temperature; humidity), circulation of respiratory viruses that year and the size and characteristics of the local (relatively small) population of vulnerable children. Exploring and modelling these causal factors, let alone then developing a predictive real time forecasting tool based on them, would be a fascinating but large project and outside the scope of this work.

A related limitation is that although the method identifies the start in real time and can be used to predict its likely end, it cannot predict the size, timing or duration of the peak demand for that specific winter. On average, demand over the winter surge is "4 a day" and the peak is usually mid-December, but this can change from year to year. Some winters are worse than others and some have short high peaks; others longer, less high peaks and some can be both long and very busy with little respite. It would be useful for a service to have an indication of the type of the winter likely for that season, but our method is unable to provide this information.

16. DISCUSSION

Using methods adapted from the stock market, we have developed a system for monitoring daily demand that can be used to identify the start and end of the winter surge for emergency paediatric intensive care services in real time. Importantly, the system also provides robust predictions of the duration of the winter surge and the total volume of demand during that time at the beginning of the surge. We suspect that the accuracy of these predictions is due at least partly to the fact that the winter surge almost always ends during the first ten days of January, regardless of when the winter surge started (i.e. starting earlier does not mean it will end sooner). The method performed very well when tested on a validation dataset.

The method identifies the start and end of the winter surge by comparing current demand to a medium-term moving average, where the optimal window size for the moving average was 41 days. Although demand for paediatric ICU is not exclusively from external emergency referrals, it is such external referrals that drive the increase in demand every winter. Retrieval services cover an entire geographical area and, from an emergency demand point of view, sit "upstream" of individual PICUs. Applying this method within a retrieval service thus provides a practical way to alert clinical teams within local PICUs and local commissioners when the winter surge has started. The ability to know when the surge has started provides significant advantages over the current crude fixed dates used by several national bodies. A key advantage is that the method also predicts the end date of the surge once the start has been signalled; this can be simply translated into a more approximate rule of thumb "the surge for PIC services will end during the first two weeks of January regardless of how early or late it starts".

The availability of a system to alert clinical teams to the start of a surge in demand, along with predictions of the end of the surge and the total volume of demand, will have significant implications on how emergency preparedness plans are implemented in PIC in the future. Since emergency demand is inherently unpredictable and cannot be controlled, the main response from the retrieval service could be to increase the number of available teams from the identified date (rather than a fixed date) until the predicted end of the surge, although we acknowledge difficulties with designing rotas that are flexible enough to cope with short term changes. Knowledge of the predicted demand will also help plan for the number of such additional teams required. Other possible responses by retrieval services could include reducing the number of non-essential meetings, restricting annual leave or using non-clinical staff days. Sharing information regarding the surge with the regional PICUs will help them prepare for the excess demand by hiring temporary staff to open more beds or by rescheduling elective surgery cases to after the end of the surge period. While these measures have already been tried in the past, they have either been too late (long after the surge has started) or too early (weeks before any surge), resulting in an ineffective response both clinically and from a cost perspective. The tool was used successfully in real time at CATS for the winters of 2014/15 and 2015/16 and its outputs shared with other regional retrieval services and local service commissioners. We have agreed with the clinical team that as each winter passes, we will review the algorithms and modify them if appropriate. We also note that since the implemented tool runs throughout the year, plotting the current and recent demand with the upper and lower Bollinger Bands provides a daily visual check for sudden increases in demand outside of winter and would highlight unexpected demand due to, for instance, a new epidemic. If considered useful by the clinical team, further development could include exploring signalling of the much shorter surges (typically 5-10 days long) that occur unpredictably throughout the year. This has not been explored in detail to date because it is unclear whether any operational response is possible for such short surges.

The method's robustness and simplicity should also allow for a relatively straightforward application to any PIC service, and indeed, other health care environments where external demand for services is both highly variable and unpredictable. Applying it to another PIC service does require local knowledge of what is a suitable threshold of high demand and requires data to be available on refusals that were in scope of the service. Although the timing of seasonal surges may vary with geographical location (Ong et al. 2009; Wiler et al. 2011), this does not affect the applicability of the method to other contexts. For very different contexts, the methodology for signalling a surge would be the same but the range of possible responses/implications would differ.

We believe there were three factors which facilitated the successful implementation of this tool in practice: the perceived problem was pressing, identified by the clinical team and not driven by methodology; extensive clinical engagement throughout and academic time taken to develop an easy-to-use Excel tool to enable daily use of the method. The embedded research role held by the lead author facilitated this engagement and seems a promising approach for implementing practical OR solutions within clinical settings (Marshall et al., 2014).

16. CONCLUSIONS

We have developed and tested a novel method to identify the start and end of the winter surge in emergency demand for paediatric intensive care depending on absolute levels of demand and how these compare to the 41-day moving averages and standard deviation of demand. Close collaboration with the clinical team and a focus on a practical solution was key to the project's success.

ACKNOWLEDGEMENTS

Christina Pagel's time on this project was part-funded by an infrastructure grant from the Great Ormond Street Hospital Charity.

This study received no direct funding from but was supported by the National Institute for Health Research Biomedical Research Centre at Great Ormond Street Hospital for Children NHS Foundation Trust and University College London.

REFERENCES

Abraham, G., Byrnes, G.B., Bain, C.A., 2009. Short-term forecasting of emergency inpatient flow. IEEE Trans. Inf. Technol. Biomed. Publ. IEEE Eng. Med. Biol. Soc. 13, 380–388. doi:10.1109/TITB.2009.2014565

Batal, H., Tench, J., McMillan, S., Adams, J., Mehler, P.S., 2001. Predicting patient visits to an urgent care clinic using calendar variables. Acad. Emerg. Med. Off. J. Soc. Acad. Emerg. Med. 8, 48–53.

BMA - Winter pressures [WWW Document], URL http://bma.org.uk/winter-pressures (accessed 8.29.14).

Bollinger, J., 1992. Using Bollinger Bands. Tech. Anal. Stocks Commod. V 10, 47–51.

Boyle, J., Jessup, M., Crilly, J., Green, D., Lind, J., Wallis, M., Miller, P., Fitzgerald, G., 2012. Predicting emergency department admissions. Emerg. Med. J. EMJ 29, 358–365. doi:10.1136/emj.2010.103531

Box, G.E.P., Jenkins, G.M., 2011. Time Series Analysis: Forecasting and Control, 4 edition. ed. Wiley.

Diehl, A.K., Morris, M.D., Mannis, S.A., 1981. Use of calendar and weather data to predict walk-in attendance. South. Med. J. 74, 709–712.

Google Trends [WWW Document], n.d. URL http://www.google.com/trends (accessed 8.28.14).

Hanratty, B., Robinson, M., 1999. Coping with winter bed crises. BMJ 319, 1511–1512.

Hiller, K.M., Stoneking, L., Min, A., Rhodes, S.M., 2013. Syndromic surveillance for influenza in the emergency department-A systematic review. PloS One 8, e73832. doi:10.1371/journal.pone.0073832

Jones, S.A., Joy, M.P., Pearson, J., 2002. Forecasting demand of emergency care. Health Care Manag. Sci. 5, 297–305.

Jones, S.S., 2007. Real-time demand forecasting in the emergency department. AMIA Annu. Symp. Proc. AMIA Symp. AMIA Symp. 997–998.

Jones, S.S., Thomas, A., Evans, R.S., Welch, S.J., Haug, P.J., Snow, G.L., 2008. Forecasting Daily Patient Volumes in the Emergency Department. Acad. Emerg. Med. 15, 159–170. doi:10.1111/j.1553-2712.2007.00032.x

Lento, C., Gradojevic, N., 2011. The Profitability Of Technical Trading Rules: A Combined Signal Approach. J. Appl. Bus. Res. JABR 23.

Leung, J.M.-J., Chong, T.T.-L., 2003. An empirical comparison of moving average envelopes and Bollinger Bands. Appl. Econ. Lett. 10, 339–341. doi:10.1080/1350485022000041032

Marcilio, I., Hajat, S., Gouveia, N., 2013. Forecasting daily emergency department visits using calendar variables and ambient temperature readings. Acad. Emerg. Med. Off. J. Soc. Acad. Emerg. Med. 20, 769–777. doi:10.1111/acem.12182

Marshall, M., Pagel, C., French, C., Utley, M., Allwood, D., Fulop, N., Pope, C., Banks, V., Goldmann, A., 2014. Moving improvement research closer to practice: the Researcher-in-Residence model. BMJ Qual. Saf. bmjqs-2013-002779. doi:10.1136/bmjqs-2013-002779

Moriña, D., Puig, P., Ríos, J., Vilella, A., Trilla, A., 2011. A statistical model for hospital admissions caused by seasonal diseases. Stat. Med. 30, 3125–3136. doi:10.1002/sim.4336

Ngan, H.Y.T., Pang, G.K.H., 2006. Novel method for patterned fabric inspection using Bollinger bands. Opt. Eng. 45, 87202-87202–15. doi:10.1117/1.2345189

Nguyen, J.L., Yang, W., Ito, K., Matte, T.D., Shaman, J., Kinney, P.L., 2016. Seasonal Influenza Infections and Cardiovascular Disease Mortality. JAMA Cardiol. 1, 274–281. doi:10.1001/jamacardio.2016.0433

O'Donnell, D.R., Parslow, R.C., Draper, E.S., 2010. Deprivation, ethnicity and prematurity in infant respiratory failure in PICU in the UK. Acta Paediatr. Oslo Nor. 1992 99, 1186–1191. doi:10.1111/j.1651-2227.2010.01803.x

Ong, M.E.H., Ho, K.K., Tan, T.P., Koh, S.K., Almuthar, Z., Overton, J., Lim, S.H., 2009. Using demand analysis and system status management for predicting ED attendances and rostering. Am. J. Emerg. Med. 27, 16–22. doi:10.1016/j.ajem.2008.01.032

Proudlove, N.C., Gordon, K., Boaden, R., 2003. Can good bed management solve the overcrowding in accident and emergency departments? Emerg. Med. J. EMJ 20, 149–155.

Ramnarayan, P., 2009. Measuring the performance of an inter-hospital transport service. Arch. Dis. Child. 94, 414–416. doi:10.1136/adc.2008.147314

The Science of Better [WWW Document], n.d. URL http://www.scienceofbetter.co.uk/ (accessed 4.26.16).

Shiue, I., Perkins, D.R., Bearman, N., 2016. Hospital admissions of hypertension, angina, myocardial infarction and ischemic heart disease peaked at physiologically equivalent temperature 0°C in Germany in 2009-2011. Environ. Sci. Pollut. Res. Int. 23, 298–306. doi:10.1007/s11356-015-5224-x

Weather Online UK - current weather and weather forecast worldwide [WWW Document], URL http://www.weatheronline.co.uk/ (accessed 8.28.14).

Weekly national flu reports - Publications - GOV.UK [WWW Document], URL https://www.gov.uk/government/statistics/weekly-national-flu-reports (accessed 4.26.16).

Wheeler, D.J., 2003. Making Sense of Data. Spc Pr, Knoxville, Tenn.

Wiler, J.L., Griffey, R.T., Olsen, T., 2011. Review of modeling approaches for emergency department patient flow and crowding research. Acad. Emerg. Med. Off. J. Soc. Acad. Emerg. Med. 18, 1371–1379. doi:10.1111/j.1553-2712.2011.01135.x

Winter preparedness 2013-14 [WWW Document], URL https://www.uclh.nhs.uk/aboutus/wwd/Pages/Winterpreparedness.aspx (accessed 8.29.14).