Hierarchical time series forecasting in Emergency Medical Services

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Abstract

Accurate forecasts of ambulance demand are crucial inputs when planning and deploying staff and fleet. Such demand forecasts are required at national, regional and sub-regional levels, and must take account of the nature of incidents and their priorities. These forecasts are often generated independently by different teams within the organization. As a result, forecasts at different levels may be inconsistent, resulting in conflicting decisions and a lack of coherent coordination in the service. To address this issue, we exploit the hierarchical and grouped structure of the demand time series, and apply forecast reconciliation methods to generate both point and probabilistic forecasts that are coherent and use all the available data at all levels of disaggregation. The methods are applied to daily incident data from the Welsh Ambulance Service NHS Trust, from October 2015 to July 2019, disaggregated by nature of incident, priority, managing health board, and control area. We use an ensemble of forecasting models, and show that the resulting forecasts are better than any individual forecasting model. We validate the forecasting approach using time-series cross-validation.

Keywords: forecasting, healthcare, emergency services, forecast reconciliation, hierarchical time series, ambulance demand, attended incidents

1. Introduction

Inability to match the resources with the demand in Emergency Medical Services (EMS) results in an overcrowding care system. This is a serious problem causing challenging situations on patient flow with serious consequences on patients, staff and the entire care system (Ekström et al., 2015; Rostami-Tabar and Ziel, 2022). Demand forecasting in EMS is a vital element that helps to depict various courses of action to avoid the mismatch, which can result in massive savings in terms of patient safety and lives. An accurate daily demand forecasting enables planners and decision makers to manage resources to meet anticipated patients, reconfigure units, redeploy staff and vehicles, where necessary.

Demand forecasts at EMS are typically required at multiple levels of cross-sectional granularities to inform various planning and decision-making processes (Hulshof et al., 2012). There are some planning process at the national level (more strategic or long-term) such as workforce resource planning and budgeting; sub-national, regional or healthcare level (tactical or medium-term) such as temporary capacity expansions, resource sharing and staff-shift scheduling; and hospital or station level (operational or short-term) such as planning rosters for staff and ambulance deployment. Demand forecasts might also be required at different level for a specific group of interest such as nature of demand or priority. Moreover, the time series data in EMS has an inherent hierarchical and grouped structure to support such forecasting requirements. Demand

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for emergency medical services at the country level can be disaggregated in a geographical hierarchy into sub-national, regions, health boards, stations/hospitals or divided into groups such as nature of incidents or demand priority. Therefore, using forecasting methodologies that account for hierarchical and/or grouped structures of time series in EMS seems to be a natural fit.

However, despite a large number of studies dedicated to forecasting for EMS (Shi et al., 2022; Gul and Celik, 2020; Ibrahim et al., 2016; Wargon et al., 2009), this area is neglected and the main focus has been on producing forecasts at a single level, independently. Generating independent forecasts not only ignore the inherent hierarchical and/or grouped structure relationships of the time series demand but also results in a lack of consistency and coordination. Consistent forecasts of the EMS demand across all hierarchical and grouped levels are paramount for an effective planning and decision making. The hierarchical forecasting approaches can not only create consistent forecasts but also achieve more accurate forecasts than the independent (base) forecasts (Hyndman et al., 2011). Obtaining consistent forecasts at different levels is important as it helps to avoid making conflicting decisions. With hierarchical forecasting, plans at any level are based on coherent forecasts and therefore can be aligned. Implementing and sustaining improvements in EMS require alignments and coordination between different stakeholders, without which teams operate in isolation leading to conflicts, duplication work, rework, or work that runs counter to the overall goal to improve the quality of delivery service. Hierarchical forecasting framework can be used as a tool to improve coordination between teams across the care services at the national, sub-national, regional and local levels. To our knowledge, there is not only no research in the EMS forecasting to account for the hierarchical and grouped structure of the system but also in the entire field of forecasting for healthcare management.

In this paper, we address this gap by investigating the application of hierarchical forecasting approaches in the EMS using daily time series of verified incidents from 2015 to 2020 in a major ambulance service in Great Britain. The data has hierarchical and grouped structures with hierarchies at the national, control (i.e. sub-national), health board (i.e. regional) and groups by priority and nature of incidents. We produce not only the point forecast but also the forecast distribution across all levels, which is critical for an effective planning and associated risk management. We compare the point and probabilistic forecast accuracy of the independent forecasts, bottom-up and optimal reconciliation approaches. We first generate independent/based forecasts using Exponential Smoothing State Space (ETS), Generalized Linear Model (GLM), Poisson regression, a simple empirical distribution and an ensemble method followed by applying bottom-up and optimal reconciliation approaches. Forecast performance is assessed by the Root Mean Squared Scaled Error (RMSSE) for point forecasts and the Continuous Ranked Probability Score (CRPS) for the probabilistic forecasts. This paper complies with the principles of the reproducibility (Stodden and Miguez, 2013; Boylan et al., 2015). Therefore, the study could equally be applied to any healthcare service (e.g. emergency department, primary or social care) subject to the time series having a hierarchical and/or grouped structure, which is generally the case in the healthcare sector.

The remainder of this article is structured as follows: In section 2, we provide a brief review of the literature and discuss its limitation to position our work; in section 3, we present the experiment design describing the data set, forecasting methods and forecast evaluation metrics. In Section 4, we discuss the hierarchical time series forecasting approaches to generate both point and probabilistic forecasts. In section 5, we present and discuss our results; in section 7, we summarize our findings and present ideas for future research.

2. Research background

Emergency medical services (EMS) are a critical component in the delivery of urgent medical care to communities. An effective service delivery requires accurate resource planning that are generally replying on demand forecasts at operational, tactical and strategic levels.

There is a substantial number of studies on the application of time series forecasting in the Emergency Medical Services. Various areas have been the focus of the literature. Forecasting call volume arrivals is one of the major research topics. Ibrahim et al. (2016) provide an extensive review of the forecasting models in

this context. Another important area is related to forecasting ambulance demand. Although the definition of demand might not be always clearly stated, however, this is typically referring to a situation where a physical resource has been deployed to respond to an incident. This might be also called *attended incidents*. Another demand related variable is verified incidents. These are all incidents that require an action: either send a physical vehicle, deal with via the Clinical Support Desk (e.g. calls), get an external (private) provider to respond to it, or send it through to other channels such as police, firefighters or general practitioners. Our study is aligned with this stream of the literature. Another similar area that is largely studied in the literature, is Emergency Department forecasting. We refer interested readers to Shi et al. (2022), Gul and Celik (2020) and Wargon et al. (2009) for extensive reviews of the literature on Emergency Department forecasting. Although crucial to EMS performance, Aringhieri et al. (2017) state that demand forecasting has received limited research attention in the EMS context. In this section, we provide a brief review of studies on forecasting ambulance demand in EMS.

There are generally two main streams of research related to forecasting ambulance demand in EMS: i) the first stream focuses on the application of time series methods and regression approaches on forecasting aggregate ambulance demand (Vile et al., 2012; Sasaki et al., 2010); ii) the second stream considers forecasting EMS demand in a more finer temporal and geographical granularities by employing temporal-spatial prediction methods (Zhou and Matteson, 2016; Zhou, 2016). The focus of our study is related to the first stream of research.

Sasaki et al. (2010) develop a multivariable regression model to estimate future EMS demands. In addition to the historical demand, the population census for different age groups and counts of the number of companies employing more than five people are included in the regression. The census variables describe groups who may be more likely to need an ambulance. A stepwise ordinary least squares regression analysis with SPSS is used for estimating the parameter and generating forecast. The only performance measure reported in this study is R^2. The research design of this study is not rigorous and the study is not reproducible. Vile et al. (2012) explore using a Singular Spectrum Analysis (SSA) method to generate forecasts of the EMS demand at the national level for 7-day, 14-day, 21-day and 28-day forecast horizons using data provided by the Welsh Ambulance Service Trust (WAST). The performance of this approach is compared with Auto-Regressive Moving Average (ARIMA) and Holt-winter time series methods using Root Mean Squared Error (RMSE). They concluded that point forecasts generated by SSA are more accurate for longer-term, but ARIMA and Holt-winter performance is superior for shorter-term horizons. Vile et al. (2016) further develop a decision support system to integrate forecasts generated by SSA. However, the study does not compare and contrast the performance of forecasting methods based on utility measures such as cost, resource utilization or response time. The tool contains options that allow generating forecasts at various levels of granularity, however, it ignore the hierarchical and grouped relationships structure, preventing aligned decision making and coordination.

Haugsbø Hermansen and Mengshoel (2021) investigate forecasting EMS demand in a high spatio-temporal resolution of 1×1km spatial regions and 1-hr time intervals using total incidents in Oslo, Norway from January 1st, 2015 up to and including February 11th, 2019. They used multi-layer perceptron (MLP) and long short-term memory (LSTM) models to forecast the EMS demand, and compare them to simple aggregation methods and baselines. The point forecast accuracy is evaluated using Mean Absolute Error (MAE) and Mean Squared Error (MSE) and the forecast distribution is measures by Categorical Cross-Entropy. They shows that while Neural Network models perform better in producing point forecast, a distribution baseline method based on spatial distribution of the incidents across all time steps provide more accurate forecast distribution. Zhou (2016) propose three methods based on Gaussian mixture models, kernel density estimation, and kernel warping to predict 4 weeks into future for a 1-km2 spatial region over an hour. Two years of incidents attended from Toronto, Canada (years 2007 and 2008 with 391,296 events) and Melbourne, Australia (years 2011 and 2012 with 696,975 events) are used to build the model and examine the performance on test data using mean negative log likelihood. They show that forecasts generated by the proposed methods are significantly more accurate than the current industry practice, a simple averaging formula. Grekousis and Liu (2019) investigate the combination of spatial analysis methods with data mining techniques based on

an improved Hungarian algorithm and MLP neural network to identify the most likely locations of future emergency events. The proposed approach is tested using data of 2851 events attended by the EMS in Athens, Greece over 24 weeks. They show that 23.24% of real emergency events lie within 50 meter of the predicted ones and nearly 70% of the real emergency events lie no further away than 150 meter, which is rather accurate given the granularity of the problem at the city level.

We observed a number of limitations in the literature of EMS forecasting, that encourage us to undertake this research. These limitations are summarized as following:

1. Current studies ignore the inherent hierarchical and/or grouped structure of the time series data and the relationship between series at different levels of hierarchy. This may result in incoherent forecasts leading to misaligned planning and decision making. While the hierarchical forecasting methodology has been developed and applied in various domains over the past 10 years (Panagiotelis et al., 2022), it has never been explored in this area.
2. Current research is mainly concerned with generating point forecast at a single level of hierarchy. There is a lack of studies presenting the entire forecast distribution of daily ambulance demand for the entire hierarchy to inform the whole decision-making process and to better represent the uncertainty of future demand, providing a risk management tool for planners.
3. Reproducibility is still a major challenge in EMS forecasting, as it is unlikely to reproduce the results without the help of the authors of those papers.
4. Another limitation is related to the generated forecasts that are not integer counts. Since actual ambulance counts cannot be negative or fractions, ambulance demand forecasts should be the same. While this might not be an issue when producing forecasts at a single level, producing non-negative count forecasts in a hierarchical/grouped structure is challenging and requires further investigation in the future.

This paper concerns the problem of hierarchical forecasting in EMS and generates and evaluates both point and probabilistic forecast across different levels of the hierarchy, hence addressing some important gaps identified in the literature.

3. Experiment setup

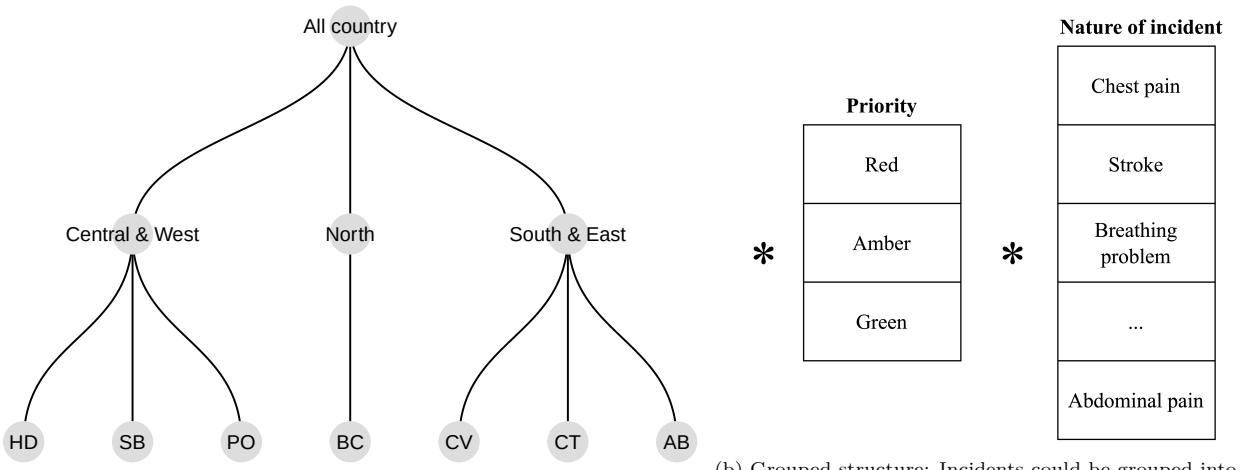
We are interested in generating forecasts to inform the planning horizon of $ph = 42$ days, required by planners in the ambulance services trust. The forecast horizon in this study is $fh = 2 \times ph$ days ahead (2*42 days planning horizon). This is because the planning is generally frozen for ph days and considering a forecast horizon of ph days might not be helpful for planning. While forecasts are generated for $2 \times ph$ days ahead, performance evaluation is only assessed based on the last ph days and not the $2 \times ph$ days. The forecasts are produced for the holdout of 365 days using time series cross-validation (Hyndman and Athanasopoulos, 2021).

In the following section, we discuss the dataset, describe the forecasting methods used to generate base forecasts and present the point and probabilistic accuracy measures.

3.1. Data

The dataset used in this study is from a major ambulance service trust in Great Britain. It contains information relating to the daily number of attended incidents from 10 October 2015 to 31 July 2019 by nature of incidents, priority, the health board managing the service and the control area (or region). Figure Figure 1 depicts both the hierarchical and grouped structure of the data. Figure Figure 1a illustrates the nested hierarchical structure based on control area and health board and Figure Figure 1b shows the grouped structure by priority and the nature of incident.

Table Table 1 also displays the structure of data with the total number of series at each level. At the top level, we have the total attended incidents for the country. We can split these total attended incidents by



(a) Hierarchical structure: Attended incidents in all country is disaggregated into 3 control areas /regions and then into 7 different healthboard at the bottom

(b) Grouped structure: Incidents could be grouped into priority (i.e. Red, Amber & Green) and the nature of attended incident (i.e. there are 35 different nature of incidents including chest pain , breathing problems, heart attack, stroke, and so on). The symbol * refers to the crossed attributes between hierarchical and grouped levels.

Figure 1: The hierarchical and grouped structure of attended incidents (ambulance demand).

control area, by health board, by priority or by nature of incident. There are 3 control areas breakdown by 7 local health boards. Attended incident data are categorized into 3 priority classes of red, amber and green. There are also 35 different nature of incidents such as chest pain, stroke, breathing problem, etc. In total, across all levels of disaggregation, there are 1530 time series.

Given the total number of time series, direct visual analysis is infeasible. Therefore, we first compute features of all 1530 time series and display the strength of trend and weekly seasonality strength in Figure Figure 2. Each point represents one time series with the strength of trend in x-axis and the strength of seasonality in y-axis. It is clear that there are some series showing strong trends and/or seasonality, corresponding to series at the higher levels of the hierarchy. The majority of series show low trend and seasonality. These are time series belonging to the bottom series, series related to the nature of incidents for a given control, health board and priority level. Bottom series are dominated by noise with little or no systematic patterns.

In addition to displaying the trend and seasonality features, we also visualize few time series at various levels of the aggregation. Figure Figure 3 reveals different information such as trend, seasonality and noise. For example, some series depict seasonality and trend, whereas some other series report low volume of attended incidents and entropy, making them more volatile and difficult to forecast. At the level on nature of incidents combined with categories of other levels, there are many series that contain zeros with low counts. As such, the data set represents a diverse set of daily time series patterns.

We consider several forecasting models that account for the diverse patterns of the time series across the entire hierarchy. In developing the forecasting models, the time series of holidays are also used in addition to the attended incidents. We use public holidays, school holidays and Christmas Day and New Year's Day as predictors of incident attended. These type of holidays will affect peoples' activities and may increase or decrease the number of attended incidents.

3.2. Forecasting methods

Given the presence of various significant patterns in the past attended incidents, we consider three different forecasting models to generate the base forecasts. Once the base forecasts are produced, hierarchical and grouped time series methods are used to reconcile them across the all levels. We briefly discussed forecasting models in the following sections, and the hierarchical forecasting methods are discussed in Section 4.

Table 1: Number of time series in each level for the hierarchical & grouped structure of attended incidents

Level	Number of series
All country	1
Control	3
Health board	7
Priority	3
Priority * Control	9
Priority * Health board	21
Nature of incident	35
Nature of incident * Control	105
Nature of incident * Health board	245
Priority * Nature of incident	104
Control * Priority * Nature of incident	306
Control * Health board * Priority * Nature of incident (Bottom level)	691
Total	1530

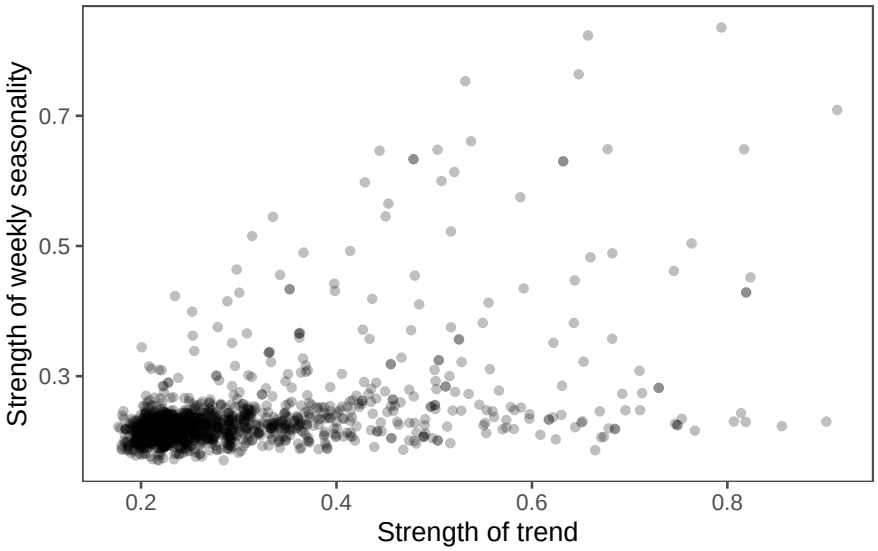


Figure 2: Time series features of attended incidents across all levels (1530 series)

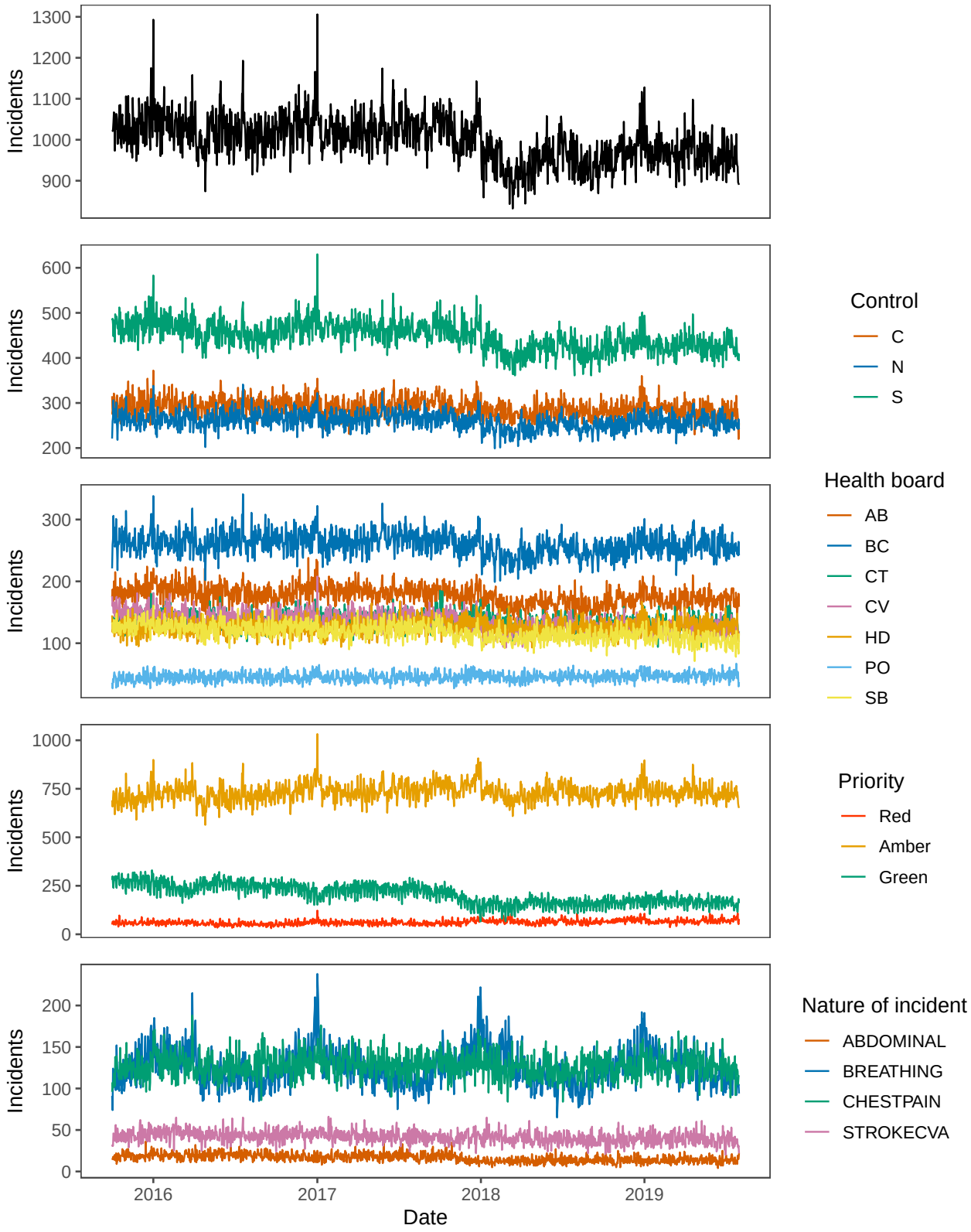


Figure 3: Time series of attended incidents at various levels.

Naive: We start with one of the simplest forecasting approaches used in practice - assuming that in the next few days, everything will be the same as similar days in the past. This is called "Naïve". In our case, given that we need a distribution of values, we will use a modified approach, where the empirical distribution of the daily attended incidents time series is used to forecast the future attended incidents distribution. We consider the empirical distribution of the most recent year of historic data on a rolling basis to capture potential changes in behavior over time.

Exponential Smoothing State Space model (ETS): ETS models (Hyndman and Athanasopoulos, 2021) can combine trend, seasonality and error components in a time series through various forms such as additive, multiplicative or mixed. The trend component can be none ("N"), Additive ("A"), damped ("Ad") or multiplicative ("M"). The seasonality can be none ("N"), Additive ("A"), or multiplicative ("M"). The error term can also be additive ("A") or multiplicative ("M"). To forecast the attended incidents at each level, we use the `ETS()` function in the `fable` package (O'Hara-Wild et al., 2022) in R. To identify the best model for a given time series, the ETS function uses the corrected Akaike's Information Criterion (AICc).

Despite the popularity and the relevance of automatic `ETS` in this study, however it may produce forecasts that are non-integer and negative. However, the number of attended incidents is an integer and non-negative. When using `ETS` , a time series transformation approach could be used to generate strictly positive forecasts, however forecasts are still not integer. An alternative is to use forecasting models that produce integer, non-negative forecasts. in the following section we present Generalized Linear Models (GLMs) and Poisson Regression to produce count base forecasts.

Generalized Linear Model (GLM): GLMs are a family of models developed to extend the concept of linear regression models. They perform a regression by modeling the response variable as coming from a particular member of the exponential family, and then transforming the mean of the response so that the transformed mean is a linear function of the predictors. One of the models that is frequently used in practice to generate count forecasts is the Poisson regression. We will consider forecasting attended incidents using the covariates spline trend, day of the week dummy variables (from Monday to Sunday), Fourier terms to capture yearly seasonality, public holidays (1 when is public holiday, 0 otherwise), school holidays (1 when is school holiday, 0 otherwise) and Christmas Day (1 when is Christmas Day, 0 otherwise) and New Year's Day (1 when is New Year's Day, 0 otherwise). We fit a Poisson regression model using the function `glm()` from the package in R, with the argument `family = poisson` to specify that we wish to fit a Poisson regression model.

Poisson Regression using tscount: We consider another Poisson regression model that takes into account serial dependence in addition to covariates used in the GLM model. To that end, we use `tsglm()` function in *tscount* package in R to model the attended incidents. The logarithmic link function is used to ensure that the parameter of Poisson distribution is always positive. This model can be estimated via maximization of the likelihood function based on Poisson mass function. The regression model captures the short range serial dependence by including the three order autoregressive terms.

Ensemble method: we also use an ensemble method that combines forecasts generated from Naive, ETS, GLM and Poisson regression together to make more accurate forecasts than any individual model.

3.3. Performance evaluation

The data is spitted into training (up until 2018-07-31) and test (from 2018-08-01 to the end) sets, with all model development and hyper-parameter tuning performed using training data only. The time series cross validation is performed with a forecast horizon of $2 * 42$ days and advances in 42-day steps. Forecasting performance is evaluated using both point and probabilistic error measures. Forecast error is calculated by considering only the last 42 days and not the entire $2 * 42$ days. This corresponds on how forecasts are generated for planning in practice. Forecasting performance is evaluated using both point and probabilistic error measures. The point forecast accuracy is measured via Root Mean Squared Scaled Error (RMSSE) and Mean Absolute Scaled Error (MASE) that are describes below:

$$RMSSE = \sqrt{mean(q_j^2)}, \tag{1}$$

where,

$$q_j^2 = \frac{e_j^2}{\frac{1}{T-m}\sum_{t=m+1}^{T}(y_t - y_{t-m})^2},$$

e_j is the point forecast error j and $m = 1$ for non-seasonal series and $m = 7$ for daily seasonal series, y_t is the observation for period t and T is the sample size (observations used for training the forecasting model). Smaller RMSSE values suggest more accurate forecasts. Note that the measure is scale-independent, thus allowing us to average the results across series.

Mean Absolute Scaled Error (MASE) is calculated as:

$$MASE = mean(|q_j|),$$

where,

$$q_j = \frac{e_j}{\frac{1}{T-m}\sum_{t=m+1}^{T}|y_t - y_{t-m}|}.$$

The denominator is the mean absolute error of the naive method in the fitting sample of n observations and is used to scale the error.

To measure the forecast distribution performance, we calculate the Continuous Rank Probability Score (Gneiting and Katzfuss, 2014). It rewards sharpness and penalizes miscalibration, so it measures overall performance.

$$CRPS = \frac{1}{h}\sum_{j=1}^{h}\int_{-\infty}^{\infty}\left(F_j^f(x) - F_j^0(x)\right)^2 dx \tag{2}$$

where $F_j^f(x)$ is the forecasted Cumulative Density Function (CDF) of period j and $F_j^0(x)$ is the true CDF of period j.

4. Hierarchical and grouped time series forecasting techniques

There are many applications in the healthcare and in particular in EMS where a collection of time series is available. These series are generally hierarchically organized based on multiple levels such as area/region, health board and/or are aggregated at different levels in groups based on nature of demand, priority of demand or some other attributes. While series could be strictly hierarchical or only grouped bases on some attributes, in many situation a more complex structures arise when attributes of interest are both nested and crossed, having hierarchical and grouped structure. This is also the case as discussed in Section 3.1

4.1. Independent (base forecast)

A common practice in healthcare (and EMS) to predict hierarchical and grouped series relies on producing independent forecast, also refereed to as base forecast, typically by different teams as the need for such forecasts arise. This is also known as base forecast. We observe n time series at time t, across the entire hierarchical and grouped structure, written as y_t. The base forecasts of y_{T+h} given data $y_1, \ldots, y_T$ are denoted by $\hat{y}_h$ for h steps-ahead for all n series ($n = 1530$ in this study). Forecasts generated in this way are nor coherent.

4.2. Reconciliation methos

Traditionally, alternative approaches to produce coherent forecasts for hierarchical and grouped time series involves using bottom-up and top-down methods by generating forecasts at a single level and then aggregate or disaggregate. Top-down requires having a unique structure to disaggregated forecasts generated at top level by proportions. However, given that we have multiple grouped attributes combined with the hierarchical structure, there is no unique way to disaggregate top forecast. Hence the top-down can not be used in this case, so either we can do some kind of reconciliation or must define our own top-down method for each hierarchy. The recommended approach is to use reconciliation. In the following sections, we first discuss some notations and then present bottom-up and forecast reconciliation approach used in this study to generate coherent forecasts.

4.2.1. Notations

Let b_t be a vector of n_b "bottom-level" time series at time t, and let a_t be a corresponding vector of $n_a = n - n_b$ aggregated time series, where

$$a_t = Ab_t$$

and A is the $n_a \times n_b$ "aggregation" matrix specifying how the bottom-level series b_t are to be aggregated to form a_t. The full vector of time series is given by

$$y_t = \begin{bmatrix} a_t \\ b_t \end{bmatrix}.$$

This leads to the $n \times n_b$ "summing" or "structural" matrix given by

$$S = \begin{bmatrix} A \\ I_{n_b} \end{bmatrix}$$

such that $y_t = Sb_t$.

4.2.2. Bottom-up (BU) and linear reconciliation methods

Bottom-Up is a simple approach to generate coherent forecasts. It first involves creating the base forecasts for the bottom level series. These forecasts are then aggregated to the upper levels which results in generating coherent forecasts. BU approach can capture the dynamics of the series at the bottom level, but they may be noisy and difficult to forecast as well. BU approach is limited on using only forecasts at the bottom level and does not utilize all the information available across the hierarchical and grouped structure. Forecast reconciliation approaches fill this gap and combine and reconcile all the base forecasts in order to produce coherent forecasts.

Given the summing matrix and base forecasts, bottom-up and linear reconciliation methods can be written as $\tilde{y}_h = SG\hat{y}_h$ for different matrices G.

Optimal reconciled forecasts are obtained with $G = (S'W^{-1}S)^{-1}W^{-1}$, or $\tilde{y}_h = M\hat{y}_h$, where the $n \times n$ "mapping" matrix is given by $M = S(S'W^{-1}S)^{-1}W^{-1}$, where $\hat{y}_h$ are the h-step forecasts of y_{T+h} given data to time T, and W is an $n \times n$ positive definite matrix. Different choices for W lead to different solutions such as Ordinary Least Square (OLS) , Weighted Least Square (WLS) and Minimum Trace (MinT) (Wickramasuriya et al., 2019). We use the implementation of these methods in the fable package in R in the experiment.

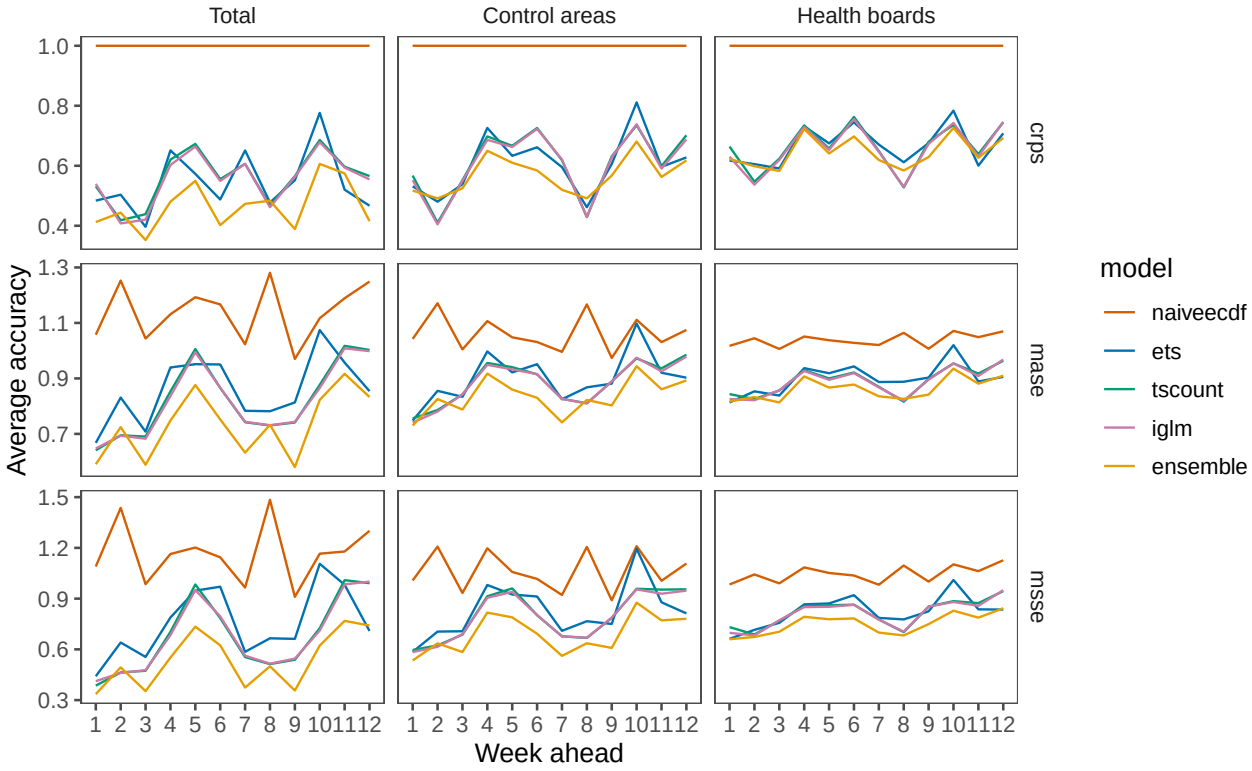


Figure 4: Average accuracy by week for 12 weeks. CRPS is relative to a naive ECDF. MASE and MSSE are relative to the corresponding values for the training set.

5. Results and discussion

5.1. Point forecast

5.2. Probabilistic forecast

6. Conclusion

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