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A HYBRID MODELLING APPROACH USING FORECASTING AND REAL-TIME SIMULATION TO PREVENT EMERGENCY DEPARTMENT OVERCROWDING

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ABSTRACT

Emergency Department (ED) overcrowding is a pervasive problem worldwide, which impacts on both performance and safety. Staff are required to react and adapt to changes in demand in real-time, while continuing to treat patients. These decisions and actions may be supported by enhanced system knowledge. This is an application of a hybrid modelling approach for short-term decision support in urgent and emergency healthcare. It uses seasonal ARIMA time-series forecasting to predict ED overcrowding in a near-future moving-window (1-4 hours) using data downloaded from a digital platform (*NHSquicker*). NHSquicker delivers real-time wait-times from multiple centers of urgent care in the South-West of England. Alongside historical distributions, this data loads the operational state of a real-time discrete-event simulation model at initialization. The ARIMA forecasts trigger simulation experimentation of ED scenarios including proactive diversion of low-acuity patients to alternative facilities in the urgent-care network, supporting short-term decision-making toward reducing overcrowding in near real-time.

1 INTRODUCTION

Emergency Department (ED) overcrowding is broadly defined as a situation where the identified need for emergency services outstrips available resources (Asplin et al. 2003). Worldwide, the problem of overcrowding is pervasive and often at crisis levels (DiSomma et al. 2015). The effects of overcrowding are seen in both patient outcomes and staff morale (Morley et al. 2018), as well as in operational performance, which declines beyond 70% occupancy against the 4-hour ED target (Higginson et al. 2017). A widely used conceptual framework of crowding is the input-throughput-output model (Asplin et al. 2003). Input relates to the demand for ED services and any condition that contributes to this; throughput relates to internal ED processes; and output factors are related to disposition of patients to discharge, admission, or transfer to either another service or leaving without being seen. The multifactorial nature of the problem does not suggest a single solution. Studies by Morley et al. (2018) and Higginson and Boyle (2018) found contributing factors included increases in elderly presentations, complex presentations, low-acuity presentations, lack of staff, reduced access to alternative services, and declining bed base. These factors point toward a local solution, which includes demand prediction, demand management and capacity management (Harper et al. 2017).

Demand management can take two forms. Firstly, patients can be provided with additional information that can support decisions about the most appropriate place to attend, based on their beliefs regarding the acuity of their condition, and knowledge of current wait times. The *NHSquicker* platform - https://nhsquicker.co.uk/ (Health & Care IMPACT Network 2018), in the form of a mobile app, has demonstrated the applicability of this approach, and provides the data used in this study (Mustafee et al. 2017). In this application, patients may choose to visit a Minor Injury Unit (MIU) with lower wait times, even if it is not the nearest facility to them, rather than an Emergency Department, where waits may be longer, but more serious conditions can be treated. Secondly, as per the aim of this paper, demand management can take the form of redirecting appropriate patients to alternative services as queues become unmanageable. Xu and Chan (2016) investigated this analytically through proactive patient diversion using demand predictions. They found that this approach could outperform diversion based on real-time information; however, a significant limitation of their study is that it is unable to account for congestion in alternative centers. As NHSquicker receives data from multiple centers of urgent care, congestion levels across the urgent care network are able to inform decision-making.

This paper employs a case study to propose a hybrid application of discrete-event simulation (DES) and time-series forecasting across multiple centers in an urgent care network. Applications of hybrid simulation approaches are becoming an important research area within the field of modeling and simulation (Brailsford et al. 2018). Mustafee and Powell (2018) define *hybrid modeling (HM)*, as the use of inter-disciplinary approaches and techniques combined with computer simulation at various stages of an M&S study. The objective is to capture a better representation of the system and the problem situation. Using one UK urgent care network as a case study, this paper demonstrates the applicability of a HM approach in a real-life setting to support short-term decision-making in emergency care based on forecasts of future demand. The remainder of the paper is structured in the following way. Section 2 provides an introduction to time-series forecasting and DES in ED. In section 3 we present our conceptual framework for the HM approach. Section 4 describes the case study and implementation of the framework and Section 5 concludes with challenges and future work.

2 LITERATURE REVIEW

The process of forecasting involves the prediction of future events by acquiring foreknowledge using quantitative approaches or estimation (Soyiri and Reidpath 2013). While forecasting has wide application, it remains relatively undeveloped in health compared with other fields (Soyiri and Reidpath 2012; Soyiri and Reidpath 2013), yet healthcare services are under significant pressure due to variable and increasing demand. For health services, predicting patient demand is a first stage toward managing demand (Harper et al. 2017).

There is an extensive body of work predicting demand for emergency services, using quantitative methods including linear regression (Jones et al. 2008; Ekstrom et al. 2015); machine learning (Khatri 2018; Rahimian et al. 2018); and time-series forecasting (Jalapour et al. 2015; Calegari et al. 2016). The field of machine learning is advancing rapidly, with an increase in publications applying these methods for healthcare forecasting. However, complex machine learning methods may not be a good approach where interpretability and clinician buy-in are priorities (Graham et al. 2018). For predicting emergency admissions, Wong et al. (2018) addressed the complexity of the approach as an implementation barrier in clinical practice. Additionally, these methods can require very large quantities of data, and data quality, collection and management requires substantial resources and commitment by healthcare stakeholders (Janke et al. 2016).

Time-series approaches have shown considerable success in predicting emergency demand, in particular variations of auto-regressive moving averages (ARMA) as developed by Box and Jenkins (1976). ARMA models combine elements of autoregressive and moving averages models, but require fewer parameters than either used alone. For example, Aboagye-Sarfo et al. (2015) showed that ARMA and VARMA (vector autoregressive moving average) methods outperformed Winter's forecasting method, a widely used univariate method used for predicting seasonal data. Similarly, Calegari et al. (2016) found that SARIMA (seasonal autoregressive integrated moving average) provided better predictions of ED arrivals compared with more traditional seasonal approaches. There has been significant interest in the use of climate factors for predicting ED demand, such as temperature and air quality, however these have shown mixed results, with Calegari et al. (2016) and Marcilio et al. (2013) demonstrating little to no additional predictive value. Time-series analysis can provide accurate forecasts of future ED attendance for allocation of resources, such as optimum staff scheduling by day and time (Morzuch and Allen 2006). Short-term forecasts are more accurate for short-term operational planning compared with longer-range forecasts, but few papers indicate how demand forecasts can be used for planning. Boyle et al. (2012) acknowledged the need to capture real-world benefit from forecasting ED demand, such as identifying appropriate triggers for escalation responses. A logical extension of demand forecasting in ED is the use of DES to plan for recovery based on forecasts of overcrowding.

A number of ED simulation studies and reviews have been published (eg Paul et al. 2010; Salmon et al. 2018; Salleh et al. 2017), summarizing objectives and approaches. While the majority of studies use DES, most focus on medium-term operational decision-making and are parameterized using historical data. This means that they can be inaccurate in the short-term, yet ED is characterized by short-term variability in demand, and staff activities are adaptive hour-to-hour. Real-time simulation has been proposed as a potential solution to the problem of systems which are highly stochastic in the short-term (Bahrani et al. 2013; Tavakoli et al. 2008; Mousavi et al. 2011), but has had limited application in healthcare. It involves linking a simulation model with an automated data acquisition system, such that the simulation system benefits from the real-time data stream provided by the real system, which in turn benefits from the near real-time decisions provided by the simulation. The RH-RT framework presented by Mustafee et al. (2018) illustrates this. Similarly, Onggo et al. (2018) proposed an architecture which combines real-time data with forecasting, optimization, machine learning and computer simulation, highlighting the theoretical and practical challenges of such an implementation. This is made possible by increasing availability and quality of data through improved data collection technologies, enabling interaction between the physical system and the simulation model which represents it. This allows the model to adapt to changes in the physical system, such that at initialization it is in a steady state representing the physical system (Onggo et al, 2018). in our case, the physical system is the ED and the data generated in early runtime is the primary focus, as increasing run-lengths reduces the dependence of simulation outputs from its initialized state, reducing the significance of the real-time data to the model. For this reason, real-time simulation has particular value in determining how a system might evolve over short time-periods, which is the focus of this study.

The purpose of real-time simulation is to find a solution to recover as quickly as possible, meaning the model and its multiple runs must be completed in a short time-frame to be used in subsequent decision-making processes. However, it is also possible to forecast a future critical situation, where the purpose of the real-time simulation is to prevent the critical condition from occurring, or at least to minimize its effects (Augusto et al. 2018; Marmor et al. 2009; Aydt et al. 2008).

Hybrid modelling (HM) is the combined application of simulation with methods and techniques from disciplines such as Applied Computing, Computer Science, Systems Engineering and OR, with the aim of best representing the system of interest (Mustafee and Powell 2018). The combined application may be in the implementation / model development stages, or at the conceptual modelling, model verification and validation, or experimentation stages (Powell and Mustafee 2017). Mustafee and Powell (2018) proposed a unifying conceptual representation of HM approaches classified according to paradigm, methodology and techniques into Types A-D1. Within this classification, Types A-C are hybrid simulation, Type D is HM within the same paradigm, and Type D1 is a multi-paradigm HM, combining simulation with a qualitative technique. This study combines forecasting with real-time simulation, hence proposes a Type D model at two levels, where simulation is combined with one or more quantitative methods at specific stage/s of the simulation study. Thus (a) Near real-time data (together with historical data) inputs into the model, that is, "Input/Output Data and Analysis" (Powell and Mustafee 2017), where real-time data is an example of Business Intelligence, and (b) Hybridity is also operating at a second level at the experimentation stage, where the forecasting models trigger the simulation.

We propose that the combined use of time-series forecasting with real-time simulation can support short-term decision-making in ED toward reducing overcrowding situations, and its subsequent impacts on performance and safety. Forecasting is used to detect the onset of ED overcrowding, with real-time simulation to support recovery, where near real-time data keeps the model updated, and hence is a better representation of the system. As the near real-time data is made available across the urgent care network via NHSquicker, it is possible to test demand management via redirecting appropriate patients to alternative centers within the urgent care network, given sufficient capacity.

3 CONCEPTUAL FRAMEWORK FOR THE HYBRID MODEL

The conceptualization encompasses an urgent care network with at least one ED and one MIU to support knowledge about capacity in alternative facilities, and access to real-time data feeds and historical data comparable to those provided by *NHSquicker* and ED operational data, for creating forecasts and populating the simulation model. An urgent care network describes the facilities provided by one healthcare region to support urgent and emergency care needs, in this case an ED for emergency and life-threatening conditions, and community-based MIUs, which provide care for urgent but non-life-threatening situations. Previous studies, including some in the healthcare domain, have implemented aspects of the HM conceptualization, as indicated below, but we conceptualize an interoperable implementation of the multi-disciplinary components. The architecture of the conceptual framework (Figure 1) consists of:

1. The implemented near real-time data component (*NHSquicker*), with historical streams for developing forecasting models. This approach has been applied in healthcare for forecasting ED crowding in real-time up to 8 hours ahead (Hoot et al. 2009), although the authors questioned how interventions triggered by the forecasts could directly impact patient care. Barnes et al. (2015) showed how real-time predictions of inpatient length of stay might be used for discharge prioritization.
2. Historical operational data from the urgent care network. This is used to populate stable aspects of the simulation model, and data inputs that are not available in real-time. Model constraints can be imposed using the known data (Adra, 2016). Espinoza et al. (2014) compared the ability of real-time simulation models to predict ED performance with limited real-time input compared with models with additional knowledge of patient care pathways. They found that both generated similar performance measures.
3. Data preprocessing for moving window analyses as new data is received. Boriboonsomsin et al. (2012) integrated historical and real-time traffic information from multiple sources to reduce the environmental impact of road travel using eco-routing. Other examples for traffic information exist (e.g., Gong et al. 2013).
4. Time-series forecasts creating predictions up to four hours into the near-future. This short window allows the forecasts to retain maximal accuracy, while providing adequate time to trigger the execution of intervention scenarios through the real-time DES model. No predictive model is perfect, however Xu and Chan (2016) found using an analytical approach that even noisy predictions of ED arrival counts can successfully be used to improve ED performance. Lin and Chia (2017) used ARIMA forecasts of patient arrivals as inputs into a DES model to optimize staff rosters, which improved patient waiting times in the simulation results.
5. Trigger points, given a specific decision rule based on: the total number of patients in the department; the number waiting to be assessed; and the maximum wait-time until assessment, for each facility in the network. These are all measures of overcrowding. Most applications of real-time simulation use a reactive approach to triggering scenario what-if analysis, however Aydt et al. (2008) investigated triggering based on forecasts, as well as the risks of inappropriate triggering and failing to trigger (Types 1 and 2 errors). Bae et al. (2004) showed how the automatic execution of processes using Event-Condition-Action rules can be automatically triggered by an active database without user intervention.
6. A set of predefined scenarios, including diverting low-acuity patients to alternative facilities. This approach was found to be successful in theory using analytical methods (Xu and Chan 2016). However other scenarios, for example derived from ED escalation policies, can also be explored. With the aim of reducing ED overcrowding, Nahhas et al. (2017) used simulation to explore a range

of scenarios, for example flexible treatment rooms, flexible staff activities and flexible shifts, and found the first of these two to be useful.

7. The DES model to test scenarios.
8. Information provided to decision-makers to support short-term planning to reduce overcrowding. A range of input, throughput and output KPIs were investigated by Khalifa and Zabani (2016) for monitoring ED performance with a focus on improvement. For operational performance, length of stay, patients leaving without being seen, and staff/room utilization are of most interest to staff.

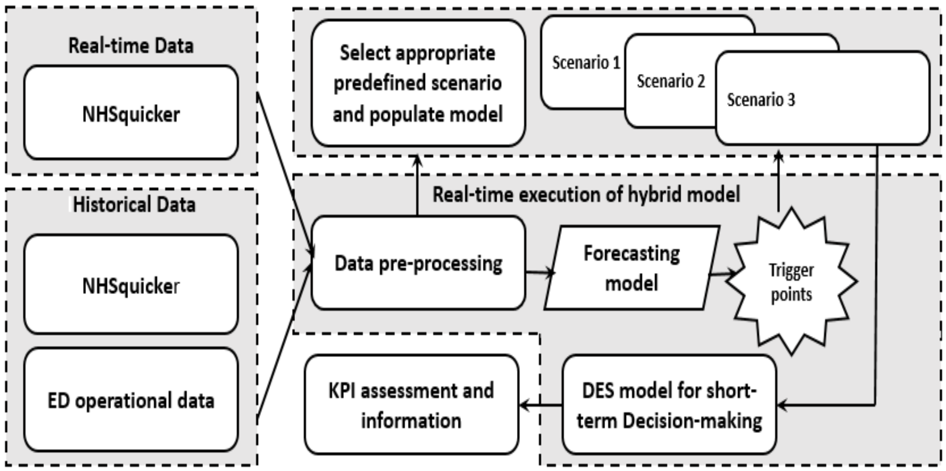

Figure 1: Conceptual framework of HM.

4 CASE STUDY

The case study is conducted in Torbay and South Devon NHS FT (TSDFT) in the South-West of England. Its catchment area is approximately 280,000 people, with around 75,000 visits per year to the ED and approximately 25,000 emergency admissions per year, excluding pediatric and maternity cases. Within the urgent care network is one acute ED and 3 MIUs. TSDFT is one of six urgent care networks (30 facilities) currently feeding data to the *NHSquicker* platform. We download this data every 30 minutes, thereby providing us with time-series data to develop the forecasting models. The simulation model will be populated by the NHSquicker data for *current number waiting to be assessed; total number of patients in the department* and *maximum wait time to be assessed*. Other elements, such as hourly arrivals, treatment times, triage category, mode of arrival/departure and admissions, are parameterized using historical data. ED patient flow systems are widely deployed in healthcare facilities to collect, store and retrieve patient-specific information. The data captured by such systems also include non-clinical data as described, and is standardized for performance reporting against a national schema.

Additional observational data includes staff schedules as key human resources within the model. Most patients will interact with nurses, nurse practitioners and doctors (at different grades) within the same visit, who will be engaged with multiple patients in parallel.

4.1 Time-series forecasting using Seasonal ARIMA

It is difficult to know exactly how many patients will be in an ED per hour of any day, however, patterns of historical data can be analyzed to make statistical inferences. Time series forecasting assumes that future demand will continue to behave similarly to past demand within a short time period. ARIMA captures the behavior of the time-series autocorrelation and uses this behavior to predict future values. For time-series with seasonality, such as daily, weekly, or yearly, Seasonal Autoregressive Moving Averages (SARIMA) models can be usefully applied, by incorporating a regular repeating pattern. Using the SciPy and

Statsmodels libraries in Python, Seasonal ARIMA (SARIMA) modelling was used to forecast the *total number of patients in the department*. One year of data is available in 30-minute time intervals for analysis.

SARIMA is represented as (p,d,q)(P,D,Q)[s], representing the order of auto-regression (p), order of differencing (d), and order of moving averages (q). (P, D, Q) are the seasonal counterparts and [s] is the seasonal period. The selection of an appropriate model depends upon the autocorrelation and partial auto correlation statistics (AC and PAC). Lin and Chia (2017) illustrated the process of ARIMA forecasting methodology in a flowchart. The general multiplicative form is:

$$\emptyset_P(B^s)\varphi_p(B)(1-B)^d(1-B^s)^D Z_t = \theta_q(B)\,\vartheta_Q(B^s)e_t$$

where B is the backshift operator (i.e. Z(t)B=Z(t-1)).

The best SARIMA model for the NHSquicker data was identified by choosing the lowest RMSE using a grid search of parameter configurations. SARIMA (1,1,2)(1,1,1)[48] provides a good fit using one-step validation for *the total number of patients in the department*. The main seasonal effect is 24 hourly (48 data points). Its mathematical structure can be expressed as:

$$\varphi_1(B)\emptyset_1(B^{48})(1-B)(1-B^{48})Z_t = (1-\theta_1 B-\theta_2 B^2)(1-\vartheta_1 B^{48})e_t$$

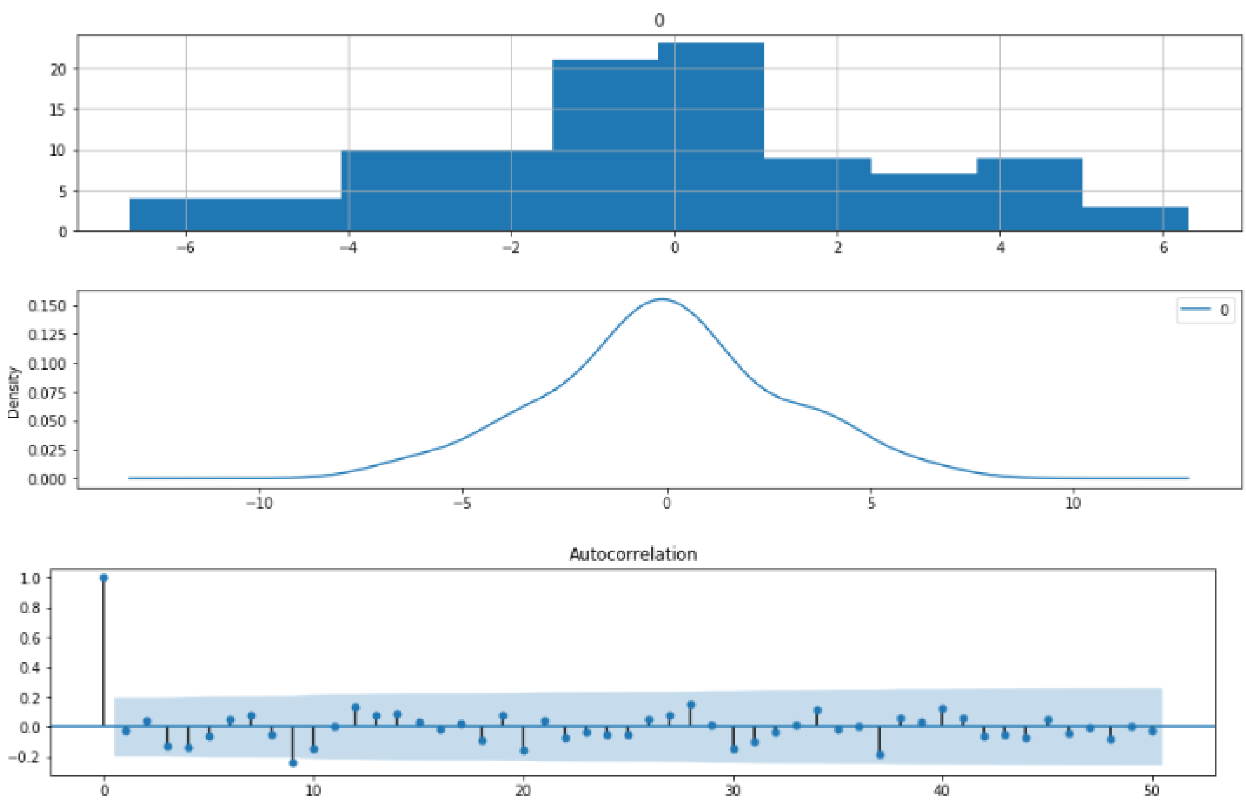

Figure 2: Residuals of SARIMA (1,1,2)(1,1,1)[48] for 'Total Number in Department' TSDFT ED (Series 1): (a) Histogram of the residuals; (b) density distribution of the residuals; (c) ACF of the residuals.

The model was analyzed on its residuals to examine the goodness-of-fit (Figure 2). A histogram and density distribution verify the assumption that residuals are normally distributed with a mean close to zero (mean = -0.070284). The ideal ACF for residuals is that all autocorrelations are zero. No autocorrelation remains including at the seasonal values; a significant lag at 9 is likely due to chance. The Ljung-Box statistic (Q) is a diagnostic tool used to test the lack of fit of a time-series model, applied to the residuals. Residuals are assumed to be "white noise," meaning that they are identically, independently distributed. The ideal Q is zero for any given lag, which means that the p-value for the Ljung-Box statistic should be non-significant. Python returns an array for the Q-statistic and the p-value. Hyndman and Athanasopoulos (2018) recommend using 2*m, where m is the period of seasonality. All p-values to lag=96 were non-significant.

One-step forecasts based on the fitted model for two days (96 observations) are plotted with the first two days of the test set (Figure 3) with a RMSE of 2.804. This is an average forecast error of 2.8 patients. The forecasts will be used in a window of 2 hours and 4 hours.

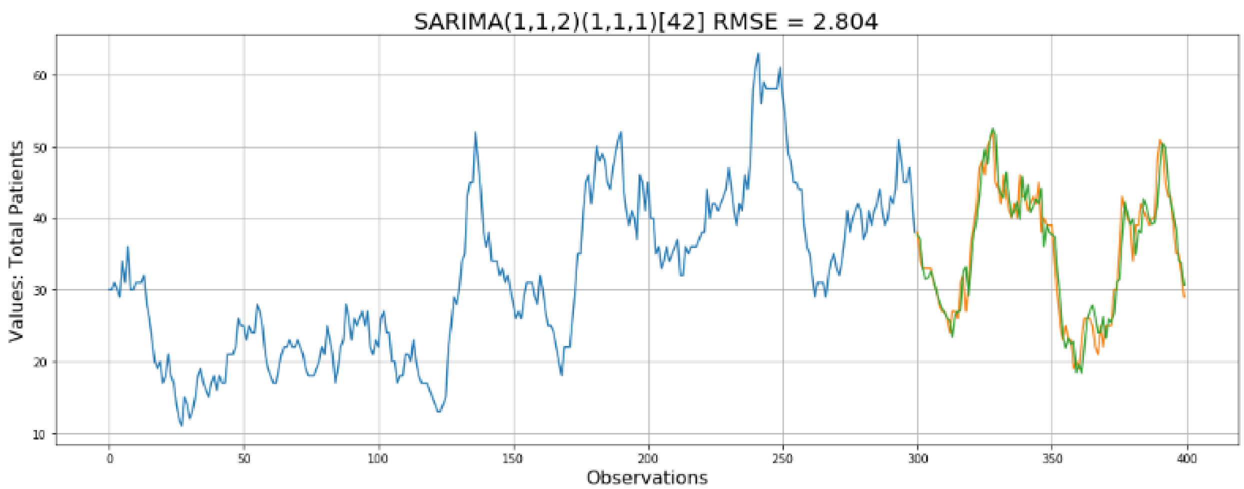

Figure 3: Out-of-sample forecasts (green) for 2 days with first two days of test set (orange) for 'Total Number in Department' TSDFT ED.

4.2 Discrete-event Simulation

To support an integrated hybrid model, the DES model, which runs in minutes, has been built in AnyLogic™, as the download and parser programs are written in Java. Due to the availability of time-series forecasting libraries in Python, the forecasting models use a Java/Python interface. The development of the integration framework, which brings together the near real-time data, forecasting models and real-time simulation, is a work in progress.

The ED component is a DES model which is initialized using both near real-time data downloaded from the *NHSquicker* platform alongside historical distributions, which uses short runtimes when triggered by forecasted thresholds. Staffing/resource deviations are updated manually at runtime.

Patients can enter the model via the walk-in route or ambulance. A one-week hourly schedule of arrival rates (from 2018 data) defines entry into the model, and patients are allocated a severity level (triage category) on arrival, according to historical probability. Data for 2016/17/18 is stable for this distribution, and each triage category conforms with the overall daily arrival pattern. Patients are allocated a probability of X-Ray according to their triage category. Patients can be discharged home via any component part and the performance monitoring 'clock' stops for discharge home, or admission to the EAU, CDU or inpatient wards. We are working on the mechanisms to automate the ED model execution process such that as soon as new data is downloaded, it is parsed, the model variables are assigned relevant data items, and model execution starts.

A flowchart of the ED processes is shown in Figure 4, with mapping against the real-time data components. Patients who walk in enter the reception area to be registered, where they may immediately be directed to the treatment area, or enter the waiting room for triage. At triage patients may immediately enter the treatment area, or return to the waiting room to be called for treatment. Patients who arrive by ambulance will immediately enter the treatment area. Patients who require X-ray may return to the waiting area or return to the treatment area. Following this, they are either discharged (or other form of 'disposition', such as transfers) or admitted. Real time data is available for (a) (b) and (c) as illustrated in Figure 4.

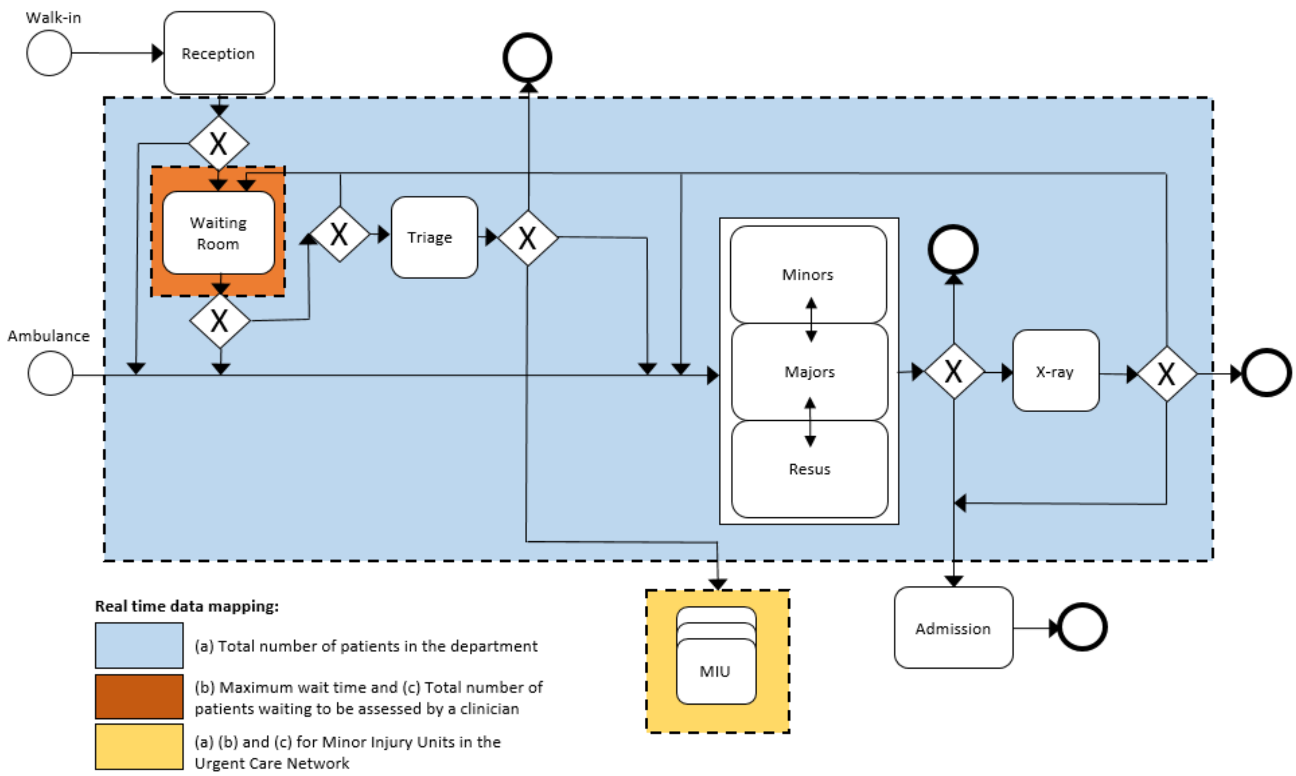

Figure 4: Flow chart of ED with real-time data mapping.

Scenarios include diverting patients from the ED at the triage stage, given a set of conditional decision rules regarding the status of each facility in the urgent care network. This allows simulation of forecasted surges in arrivals of patients with low-acuity conditions, and provides decision makers the information required to assess whether patients are to be diverted to MIUs after triage, before queues actually build up. This proactive diversion (if implemented in practice) allows faster recovery and it is predicted will reduce overall wait-time in the department, a scenario that will be explored through the simulation model. The model is sufficiently granular to allow other scenarios, such as changing the numbers of admission beds in the Emergency Assessment Unit (EAU) and increasing or decreasing waits for admission to inpatient wards. It includes modular component parts: ED (minors, majors and resus); EAU; Clinical Decision Unit (CDU); Acute Medical Unit (AMU) and inpatient admission, as well as a component for minor patient diversion, with information about wait times and patient numbers in the MIUs in the network.

The DES will be designed to communicate with the data-acquisition component at runtime, re-initializing the system states using the most recent data captured by the ED patient flow systems made available by NHSquicker, as illustrated in Figure 4. However our data is incomplete as we currently have access to only the data received by NHSquicker, and Espinoza et al (2014) and Marmor et al (2009) have observed that data completeness is an key issue when using real-time DES over time-scales of less than a day. This is one important challenge, nonetheless the data streams available have been validated by several NHS Trusts and our aim is to maximize the value that can be gained from these data streams which execute every 30 minutes. This is achieved through preprocessing, executing the forecasts, and providing a trigger for the DES to initialize using a combination of historical distributions and real-time data, and to run for 4-6 hour of simulated time based on historical distributions. In the future we plan to have other variables that are made available to us in real-time.

5 CONCLUSION AND FUTURE WORK

Validation and verification of the HM remains a challenge. The near real-time data has been validated by multiple NHS Trusts, but as it is pushed from multiple sources, the opportunity for data outages/errors increases; these must be managed at the data pre-processing stage. Understanding the effects of forecast errors is a further challenge, for example the costs of Types 1 and 2 errors (i.e. triggering unnecessarily, or not triggering when it is subsequently found to be necessary). Weather studies have found that non-compliance with forecasts occurs with experience of false alarms, with very low and very high false alarms resulting in inferior decision making, although probabilistic uncertainty improves compliance (LeClerc and Joslyn 2015). The DES is currently undergoing consultation with domain experts to ensure that the structures and processes are a sufficient representation of the ED department. A further conceptual challenge is integrating the real-time and historical data for the model to initialize, when triggered, with sufficient accuracy. The model must be validated using historical data to ensure it behaves as expected over long runs prior to using it for short run-times with real-time inputs. Validation of the real-time simulation is a challenge, as the simulation outputs are time-dependent (Hoot et al. 2009).

ED overcrowding is a multifactorial problem, with a range of unsatisfactory outcomes for staff, patients and the organization. Staff must react and adapt their behavior in response to a buildup of queues to maintain safe performance and meet operational targets, while continuing to treat patients. Foreseeing the onset of surges in demand means that proactive policies can be explored and implemented which aim to reduce overcrowding before it occurs, maintaining system agility, performance and safety. Decision support tools, which react as the system changes, are needed to support short-term decision making with the aim of maintaining system resilience in the face of demand variability. While both the forecasting models and the DES are works-in-progress, their combined application in a HM approach aims to more fully capture the problem situation of variable demand within a single interoperable implementation.

This paper contributes to debates around the value of HM approaches, by demonstrating the potential usefulness of such an approach which we claim can deliver additional value beyond the individual methods used in isolation. Additionally, due to the availability of standardized national datasets, the implementation is potentially generalizable to other urgent care networks. The approach may be useful for policy makers, clinicians and managers at the regional level who are responsible for managing ED operational performance.

Alongside the challenges discussed above, the use of the limited near real-time feeds available, which aims to maximize the value that can be gained from the data, presents a further challenge compared with having access to ED Patient Flow Systems directly. Nonetheless we expect to have results available in the near future.

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