ACE

C359 NHS Handover Delay Predictor PoC

IN PARTNERSHIP WITH NIAXO

NIAXO
innovation to insight

Prepared By:

Holly Jones, Parwez Diloo
Bays Consulting Limited
Tel: 07788 643751, Email: sophie@baysconsulting.co.uk
Station View, Austen House, Units A-J, Guildford, Surrey, GU1 4AR
Registered in England & Wales 06995557 VAT No. 978 6752 45
www.baysconsulting.co.uk

2022

TABLE OF CONTENTS

1 EXECUTIVE SUMMARY

1.1 Purpose

This project was an initial investigation to understand if Machine Learning (ML) or Artificial Intelligence (AI) could be used to develop algorithms for proactive management of ambulances to minimise handover times at acute healthcare settings (specifically Emergency Departments (ED) for the scope of this project). The project aims to deliver a Proof of Concept (PoC) model which could be used as a decision support tool.

By minimising the time spent waiting for patient handover, South Central Ambulance Service (SCAS) would be able to maximise the time available to respond to patient calls for help. The focus of the project was to predict the handover delays from ambulances to emergency departments and to understand the potential reason causing the delays, so that effective operational communications can be undertaken between SCAS and colleagues in the receiving facility. The end goal is to assess the capability to make predictions for 3-, 10- and 24-hour intervals for a selected set of hospitals.

Whereas a final operational solution would use live data, this PoC has been created using static data provided by SCAS and other open-source datasets. Conversations with SCAS, National Health Service (NHS) AI Lab Skunkworks & The Accelerated Capability Environment (ACE) have steered the direction of this project and two use cases have been agreed:

1. Understanding reasons that handovers are delayed.
2. Proactive use of predictions to mitigate against delays.

By providing insights to the use cases outlined above, the overall aim is to:

- Reduce stress and improve the overall experience for the patient,
- Reduce the overall clinical risk as handover from the ambulance to the hospital will happen as quickly as possible,
- Reduce operational pressures on the ambulance service provider by reducing the amount of reactive management, thereby also reducing staffing stress levels,
- Increase both the hospital and ambulance efficiency – for every patient waiting to be admitted to the hospital, there is an ambulance crew that is not able to attend another call.

Commission Aim:

SCAS want to be able to predict ambulance delays at hospital, with reasons, to allow them to influence hospital's behaviour to mitigate against queues before they happen.

Having investigated multiple models, we decided to proceed with a Decision Tree model and a Random Forest model as they gave the best trade-off of prediction accuracy versus explainability of results.

Model Choice: From the analyses carried out throughout this project it is recommended to take forward the **Random Forest Model** as it provided the best results in terms of prediction accuracy and interpretability. A model was built for each hospital using their respective data.

Use Case 1: Understanding reasons that handovers are delayed

The top three most influential factors from the model while getting the predictions for handover delays at a hospital are shown in Table 1 below. Results for all hospitals can be seen in Annex H.

Hospital	Feature Number	3hr-Prediction	10hr-Prediction	24hr-Prediction
Southampton General Hospital	1	Month	Month	Month
	2	Missing Crew Skill (TECH)	Number of Priority 7 Cases	Missing Crew Skill (ECA)
	3	Missing Crew Skill (PARA)	Number of 90+ Year Old's Arriving	Number of Priority 2 Cases
Queen Alexandra Hospital	1	Average Handover Delay in Past 6 Hours	Average Handover Delay in Past 6 Hours	Average Handover Delay in Past 6 Hours
	2	Bank Holiday	Number of 55 to 72 Year Old's Arriving	Number of Priority 1 Cases
	3	Number of Priority 2 Cases	Missing Crew Skill (PARA)	Rainfall
Royal Berkshire Hospital	1	Average Handover Delay in Past 6 Hours	Number of 55 to 72 Year Old's Arriving	Average Handover Delay in Past 6 Hours
	2	Arrivals at Hospitals Nearby	Number of Priority 2 Cases	Number of Priority 2 Cases
	3	Number of 55 to 72 Year Old's Arriving	Missing Crew Skill (TECH)	Number of 90+ Year Old's Arriving

Table 1: Top three most influential reasons for delays

Use Case 2: Proactive use of predictions to mitigate against handover delays

We have two scenarios which show the ability to predict the handover delay time and showing the results as the patients' handover times at 3-, 10-, and 24-hours' time. The colour bandings on the charts represent:

- GREEN: Mean handover time is less than 15 minutes (no delay)
- AMBER: Mean handover time is between 15 and 30 minutes
- RED: Mean handover time is more than 30 minutes[1]

By colour coding the cells in the results table, it makes it easier for the person to identify where there will potentially be no delays (green), short delays (amber), and severe delays (red) in the patient handovers. By using the predictions, a person can easily detect where there will be huge delays and therefore can work towards reducing these delays either by the hospitals changing the way they operate or by redirecting the ambulances to hospitals with smaller predicted delays.

Scenario 1: Normal day

The normal day described here is representative of a non-bank holiday Friday morning in the month of April. There are no extreme weather conditions. In terms of the hospital, it is operating under normal operations where there are no large numbers of ambulance arrivals/departures, no big lack of skills in ambulances and no major issues with patients of any age band or priority transportation.

The colour banding for the Table 2 is based on the lower bound, that is, the lowest predicted handover time. While this shows that most handover should complete in under 15 minutes, it can be misleading, as the range of the error bound is not considered. For example, the prediction for Queen Alexandra Hospital at 24 hours is green, but the range of handover time is between 0 and 48 minutes.

[1] These time intervals have been chosen for the purposes of the PoC. The Operational (End) Solution should have these timings configurable to suit the Services.

Hospital	Handover Time Range for 3hr (minutes)	Handover Time Range for 10hr (minutes)	Handover Time Range for 24hr (minutes)
Southampton General Hospital	13 - 21	15 - 23	14 - 22
Queen Alexandra Hospital	2 - 49	0 - 41	0 - 48
Royal Berkshire Hospital	14 - 29	18 - 34	18 - 33
Wexham Park Hospital	12 - 18	11 - 18	11 - 18
John Radcliffe Hospital	9 - 23	8 - 22	9 - 24
Milton Keynes General Hospital	14 - 28	11 - 25	13 - 27
North Hants Hospital	10 - 20	9 - 20	10 - 21
Stoke Mandeville Hospital	5 - 27	6 - 29	4 - 26
Royal Hampshire County Hospital	7 - 22	8 - 23	8 - 23
Frimley Park Hospital	9 - 24	10 - 24	10 - 24
Horton General Hospital	16 - 25	11 - 21	12 - 22

Table 2: Predicted handover delays, lower bound values coloured

In Table 3 we show the same predictions but coloured using the mean values, that is, the actual predicted handover delay time that falls within the range shown on the chart. The colour banding remains the same. Here we see that most handover are predicted to be delayed by 15-30 minutes (amber).

Hospital	Handover Time Range for 3hr (minutes)	Handover Time Range for 10hr (minutes)	Handover Time Range for 24hr (minutes)
Southampton General Hospital	13 - 21	15 - 23	14 - 22
Queen Alexandra Hospital	2 - 49	0 - 41	0 - 48
Royal Berkshire Hospital	14 - 29	18 - 34	18 - 33
Wexham Park Hospital	12 - 18	11 - 18	11 - 18
John Radcliffe Hospital	9 - 23	8 - 22	9 - 24
Milton Keynes General Hospital	14 - 28	11 - 25	13 - 27
North Hants Hospital	10 - 20	9 - 20	10 - 21
Stoke Mandeville Hospital	5 - 27	6 - 29	4 - 26
Royal Hampshire County Hospital	7 - 22	8 - 23	8 - 23
Frimley Park Hospital	9 - 24	10 - 24	10 - 24
Horton General Hospital	16 - 25	11 - 21	12 - 22

Table 3: Predicted handover delays, mean values coloured

<u>Scenario 2: Busy day</u>

The busy day scenario is representative of a bank holiday Friday afternoon in the month of April. The weather is hot. In terms of the hospital, it is operating under pressure as there were lots of ambulance arrivals/departures and significant previous delays in the past 6 hours. There was also a big lack of skills in ambulances and there were more ambulances transporting patients of high age band. There was also more prioritised ambulance transportation over the last few hours.

Please note that it is not representative of an actual date from the data provided. Table 4 shows the predicted range of handover times, where a handover is not considered as delayed until 15 minutes or more have passed. The predictions here have been given a colour banding based on the lower bound values, that is, the minimum predicted handover time.

Hospital	Handover Time Range for 3hr (minutes)	Handover Time Range for 10hr (minutes)	Handover Time Range for 24hr (minutes)
Southampton General Hospital	17 - 25	19 - 27	19 - 27
Queen Alexandra Hospital	55 - 117	70 - 132	41 - 103
Royal Berkshire Hospital	30 - 46	19 - 35	17 - 33
Wexham Park Hospital	21 - 27	15 - 21	16 - 22
John Radcliffe Hospital	21 - 35	27 - 41	20 - 34
Milton Keynes General Hospital	38 - 54	22 - 38	20 - 36
North Hants Hospital	37 - 49	37 - 49	28 - 40
Stoke Mandeville Hospital	27 - 51	13 - 37	19 - 43
Royal Hampshire County Hospital	85 - 101	32 - 48	32 - 48
Frimley Park Hospital	44 - 58	35 - 49	27 - 41
Horton General Hospital	38 - 48	25 - 35	43 - 53

Table 4: Predicted handover delays, lower bound values coloured

In Table 5 we show the same predictions but coloured using the mean values, that is, the actual predicted handover delay time that falls within the range shown on the chart. The colour banding remains the same.

Hospital	Handover Time Range for 3hr (minutes)	Handover Time Range for 10hr (minutes)	Handover Time Range for 24hr (minutes)
Southampton General Hospital	17 - 25	19 - 27	19 - 27
Queen Alexandra Hospital	55 - 117	70 - 132	41 - 103
Royal Berkshire Hospital	30 - 46	19 - 35	17 - 33
Wexham Park Hospital	21 - 27	15 - 21	16 - 22
John Radcliffe Hospital	21 - 35	27 - 41	20 - 34
Milton Keynes General Hospital	38 - 54	22 - 38	20 - 36
North Hants Hospital	37 - 49	37 - 49	28 - 40
Stoke Mandeville Hospital	27 - 51	13 - 37	19 - 43
Royal Hampshire County Hospital	85 - 101	32 - 48	32 - 48
Frimley Park Hospital	44 - 58	35 - 49	27 - 41
Horton General Hospital	38 - 48	25 - 35	43 - 53

Table 5: Predicted handover delays, mean values coloured

1.2 Approach

To deliver this project, five work packages (WP) of work were delivered over a twelve-week period:

WP1: Data Discovery

- Creating a usable representative data set, checking for accuracy, completeness, and consistency. Testing the applicability and utility of the available data for use in AI/ML techniques.

WP2: Algorithm Development

- Investigate the ability of the machine learning models to determine the drivers of queues/handover delays within the available data.

WP3: Analysis of Outputs

- Determining the most appropriate AI/ML model that gives the best trade-off between the accuracy of the predictions and the interpretability of the results.

WP4: Visualisations

- Determining the most appropriate visualisations to meet the needs of the PoC.

WP5: Project Report – Final PoC

- Delivering a final report and presentation of PoC on trained algorithms.
- Codebase Quality Assurance.

1.3 Recommendations – The Headlines

Further Development – What are the immediate next steps?

- **Business Analysis:** Conduct key engagements (for example workshops & interviews) with the SCAS team to understand the problem space and gather detailed requirements (to test against) for how the solution should look and feel to best ensure is solves the business need.
- **Integrating Live Feeds:** By integrating live feed datasets in addition to the static datasets used, we could get a better understanding of the hospital's situation at that specific time of day. One example would be to consider data regarding staff illnesses, this may give us a clearer idea on the situation inside the hospital on that day.
- **Weather Data:** Obtaining more granular weather data, which this PoC identified to influence service demand. Throughout this project we have used weather data from the Oxford weather station, with this being the closest station to the SCAS geographical area.
- **Distance:** Distance between hospitals has been calculated using physical distance between any two points. It is used to compute a weighted sum of patients arriving at other hospitals. This is to see whether a busy hospital nearby has a knock-on effect to the delays at another hospital. It is recommended to consider an alternative distance in case the Euclidean distance does not fully represent the closeness or directness of a hospital.
- **Bank Holidays**: A list of bank holidays that covered the time period of the data was created manually from online sources. A similar list with updated bank holiday dates will need to be created in the future to proceed with model development.
- **Different train/test split**: The available data was split into 80% training and 20% testing at random. Further development could use a different split of the data for training and testing.
- **Aggregation/Cumulative counts**: Investigating the number of ambulances which could form part of a queue will require a different approach to that investigated in this project.
  - Feature engineering: the number of ambulances and length of queue could be inferred from existing data, leading to the potential to predict not just handover delay (mean) but the length of the queue and number of ambulances waiting for each hospital.
  - The number of ambulances in the queue at each timestamp could be inferred using existing columns in the Assignments dataset, such as Time_Destination and Time_Clear. However, these could only be used as proxies, and it would be beneficial to bring in more data sources which outline the exact number of ambulances in the queue at each timestamp.
  - Bringing in additional data sources such as situation reports at the hospital and their process for triaging ambulance arrivals will support this further investigation.

Implementation – Progression towards the implementation of the solution:

- **De-risk the end solution:** Approaches should seek to prove the concept of other wanted capabilities, and progress to de-risking elements of the proof of concept.
- **Obtaining the Necessary Datasets:** For this model to output a prediction for a specific time of day, it would require accessibility to each of the Assignments dataset, Incidents dataset and PTS dataset at the same minute.
- **Weather Data:** As we have used historic weather data in this model, for implementation purposes it would be important to consider forecasted weather rather than historic weather.
- **Ensuring Data Entry is Consistent:** In the data discovery stage of this project, we identified several spelling mistakes in the column detailing the handover type. For example, 'Handed over' was sometimes recorded as 'anded over'. These errors were corrected before moving forward with the analysis and model development. However, to progress to implementation of this solution it is recommended to ensure all data entries are consistent to ensure no important data is being missed. One option to resolve could be to introduce a dropdown list rather than a manual input.

2. MAIN REPORT

2.1 Situation

SCAS provides three core services for 5 million people in Berkshire, Buckinghamshire, Hampshire, and Oxfordshire. Their Business Intelligence team support the planning and delivery of operational services, which experiences a service delivery roughly every 12 seconds.

All ambulances have a 15-minute window in which they should 'handover' their patient (i.e., a patient is transferred from the care of the ambulance paramedics to the care of Hospital staff). The handover timeframe begins when the ambulance arrives at the hospital and ends once the patient has been handed over to the hospital. If there is a queue of ambulances waiting at the hospital, then handovers may be delayed past the 15-minute window ('handover delay').

Each hospital works slightly differently and experiences different volumes of queues. Some could be considered as outliers as they experience much higher volumes of queues. If SCAS are able to see predictions of upcoming queues they will be able to warn the hospitals so that they can make changes to their operations in order to minimise the handover delays.

2.2 Problem

Cause: Many factors can lead to ambulance queues forming outside of hospitals and lead to handover delays. Examples include high volumes of service delivery and number of staff within the hospital.

Effect: A delay to patient care and additional constraints/ pressures on the services personnel.

Current Response: SCAS have implemented workarounds to reduce this queue, such as the HALOing scenario described later in this report. They now wish to understand in more detail the possible reasons for handover delays, and the predicted delays at 3-, 10- and 24-hour intervals to enable improved response.

2.3 What does success look like?

Success of this model is shown across the two use cases:

Use Case 1: Understanding reasons that handovers are delayed.

- Feature importance from the chosen models outlines the factors which are predicted to have contributed to the handover delay.
- Understanding the possible reasons for delays will allow SCAS to mitigate against these through strategic planning.

In future developments, understanding feature importance and reasons for delays will enable a move from a pro-active to re-active management across the ambulance fleet.

Use Case 2: Proactive use of predictions to mitigate against delays:

- Predictions have been generated for 3-, 10-, and 24-hours times.
- This allows SCAS to look ahead at where bottlenecks are forming and divert ambulances before they arrive at a queue.

It is important to note that this PoC has been developed using a single historic static data provided by SCAS. This means that the predictions are based on timestamps within the data and would require further work to run with newer data. The feature importance to understand the reasons for delays will also require further development to bring this into a working model. For the full list of data fields, refer to Annex F.

2.4 Data Discovery

Introduction: This project conducted a data-centric approach to determine the handover delay timings at hospitals under SCAS care.

Purpose: The aim of this piece of work was to investigate different aspects of the data to get a better understanding of it before modelling. It will provide some early insights of the data and help detect anomalies which can then be addressed before the modelling stage.

We outline the areas covered in Data Discovery in Table 6 and give an outline of key insights in Table 7. Further detail can be found in Annex E.

Category	**What has been investigated?**
Accuracy	Does the data contain typos or impossible values, and is the data of the right data types?

Completeness	– What is the number of data points available for each variable?
	– Are there any variables with a lot of/all missing values?
	– What is the ratio of missing data,
	– Is there data missing:
	    o At random (no interdependency)?
	    o Which can be predicted based on other data values?
	    o Not at random (purposefully missing)?
	– Are there any correlations between missing variables?

	– What are the number of distinct counts per variable?
Consistency	– Do the values such as the average vary over time? – Are there any trends in the data, and if so, do they change over time?
Skew	– Is the dataset distorted, or are there any duplicates? – Are there multiple entries for the same ambulance/incident?
Limited features	– Are there any groups in the data that are less represented, and contain far less data points relative to the other groups?

Table 6: Areas investigated in Data Discovery

Category	Key insights	Comments on Insights
Accuracy	Typos and incorrect value (caused by 'general fields')	Presence of some typos and incorrect values in the assignment and incidents data, which is common when General fields are used in data entry. The typos were changed to their corresponding correct names. The incorrect values were those where the handover times were before the time at the destination and where the handover times were days after the time at the destination. After double checking with NHS, they were all excluded from the analysis.
Completeness	No significant missing values	Most columns that were used were complete. Wherever we had columns with missing values (which primarily arose due to the type of incident making the data entry irrelevant/ not required), the fields were altered to have no value to enable analysis.
	No correlation between variables	The correlations between the variables from the assignments dataset and the handover delays were checked, and it was concluded that there was no correlation between them.
Consistency	Trend	There were some patterns in the number of ambulance arrivals at the hospitals from the assignment dataset.
Skew	Multiple ambulance entries for the same incident	In the assignment dataset, there were multiple entries having the same incident number, but different values for the other factors such as time. This represented serious cases where multiple ambulances had to attend to.
Limited features	Number of hospitals	There were initially 73 hospitals in the assignment dataset. Out of those, 46 hospitals had patients being transported to an Emergency Department. In the remaining 46 hospitals, the number of available data points ranged from 1 to 45,757 per hospital.
	Number of patients of different age bands	The number of patients from the incident dataset who were from the different age bands that were transported to an Emergency Department varied a lot. The number of data points per age band ranged from 8,467, which was for those who were less than 1 year old, to 221,955, which was for those who were between 73 and 90 years old.
	Number of different priorities	The number of patients from the incident dataset being transported with the different priority levels to an emergency department varied a lot. The number of data points per priority level ranged from 832, which was for those who were transported with priority 6, to 336,501, which was for those who were transported with priority 1.

Table 7: Key insights from Data Discovery

Project Aims
The aim of the project is to identify the most effective approach to generating 3-, 10- and 24-hourly predictions for the time it takes for an ambulance to handover, and the reasons as to why these delays may be occurring. The model considers the situation at the hospital over the previous 6 hours to make the predictions outlined above. The features used to describe the hospitals situation are as follows:

- Number of ambulances arriving,
- Number of ambulances departing,
- Number of ambulances that are missing specific skills,
- The average time (in minutes) of past delays,
- A weighted sum by distance of the number of ambulances arriving at other hospitals,
- Number of patients arriving in specific age bands,
- Number of patients arriving in each responding priority,
- Number of ambulances arriving that have transported 1, 2 or 3 patients,
- Hour of day,
- Day of week,
- Month,
- Whether it is a bank holiday,
- Maximum temperature,
- Minimum temperature,
- Rainfall,
- Proxy for net flow (using PTS data admissions, discharges, and transfers).

The project only aims to establish handover delays to ED. As such, we have filtered out data points where the ambulance does not arrive at an ED, which included some acute healthcare settings.

Aggregated & number of ambulances (within the queue) predictions were not investigated, as this would require a different approach to that considered for this project. Further detail can be found in Annex B.

2.5 Algorithm Development and Analysis of Outputs

For this project, a range of machine learning techniques were initially considered, namely:

- Linear Regression techniques
- Time Series analysis
- Naïve Bayes
- Decision Trees
- Random Forest

Two models have been taken forward for use: **Decision Trees** and **Random Forest**. Table 8 explains each model and the reason it was taken forward or de-scoped.

Model	**Description**	**Use in this analysis**
Linear Regression techniques	Considers the relationship between the dependent and independent variables.	De-scoped, no significant relationship found between

		the variables. Further detail in Annex J.
Time Series analysis	Shows insights into the trends and seasonality of the data.	De-scoped, useful to predict the handover delays but not to extract the reasons. (Insights into seasonality used in the model). Further detail in Annex J.
Naïve Bayes	Makes use of Bayes' Theorem, which finds the probability of an event occurring given the probability of another event that has already occurred.	De-scoped, the handover delays were not normally distributed. Further detail in Annex J.
Decision Trees	A machine learning algorithm that helps make decisions based on previous experiences. At every step, based on the different features, the model answers questions using which it ultimately comes to a conclusion, which is the prediction.	Taken forward for analysis.
Random Forest	A supervised machine learning algorithm that can be used for classification problems. The approach is similar to the decision trees, but the random forest algorithm contains multiple trees internally. The results can be interpreted as less biased.	Taken forward for analysis.

Table 8: Models investigated in this project

As seen in Figure 1 below, the data has underlying seasonal patterns and trends. When considering which model to take forward, it was important to make sure these patterns and trends were not lost and that they were captured in the model. When proceeding with the models, we could either:

- Remove the seasonal component and add it back in at the end,
- Add in additional features (e.g., hour of day, day of week and month);
    - This is the approach that was taken and allows the Tree models to pick different rules depending on the hour/day/month. Hence, capturing any naturally occurring trends and seasonality in our dataset.

The rest of this section focussed on those Models taken forward for analysis.

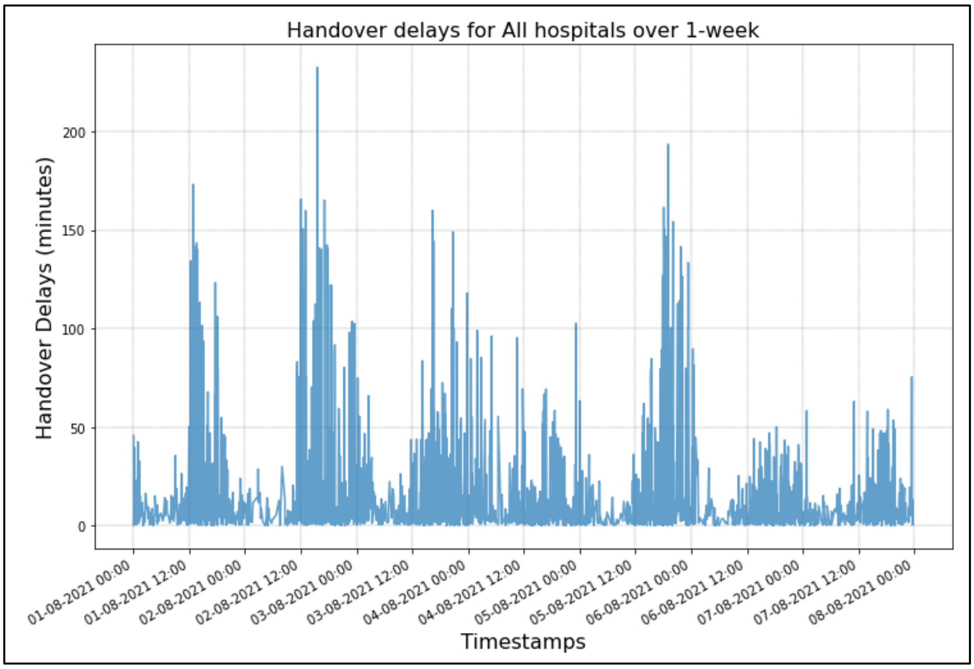


Figure 1: Snapshot from the dataset: Handover delays over one week

<u>Decision Tree Model</u>

A decision tree model can return both numerical and categorical outputs as predictions. The algorithm takes in the values of the features outlined above and makes predictions accordingly. Fundamentally, they ask a series of questions at each step and puts them on different branches depending on the values of the features. The final branch contains the predicted value or group.

Advantages:

- Quick to train and run,
- Easily interpretable – the most important features contributing the prediction can be extracted helping to give an indication as to why we are predicting a specific handover delay for that observation,
- Does not rely on linear relationships and captures interactions between features.

Limitations:

- A Decision Tree is often prone to overfitting. This is when the model works perfectly fine on data it has seen before but fails to provide reliable predictions in production.

<u>Random Forest Model</u>

The random forest uses the same concept as the decision tree model at the core. The only difference is that the random forest is a collection of decision trees instead of just one for the decision tree model described above.

Advantages:

- Quick to run, once the model has been trained,
- Similar to a decision tree, a random forest model can provide the most important features contributing to the prediction,
- Does not rely on linear relationships and captures interactions between features,

- Since it is a collection of decision trees, it is less prone to overfitting and therefore produces more reliable predictions than the decision tree.

Limitations:

- The model is considerably slower to train than a decision tree model. However, once this model has been trained, we can get predictions within 10 minutes (satisfies use case).

For more information on the technical detail and approach, refer to Annex H & J.

2.6 Outcomes

Model Choice: From the analysis carried out throughout this project it is recommended to take forward the **Random Forest Model** as it provided the best results in terms of prediction accuracy and interpretability. We developed a model per hospital rather than one model to predict for all of the hospitals. This is because we had very different handover delays for the different hospitals. By creating a model per hospital, it would be less likely that our results would be skewed.

Use Case 1: Understanding reasons that handovers are delayed

The top three most influential factors from the model while getting the predictions for handover delays at a hospital are shown in the table below.

These have been calculated using the paths taken in the Random Forest model for the observation based on the final timestamp in the static data provided (1 April 2022). The factors can be interpreted as the reasons which will potentially cause the handover delays. They are arranged in descending order in Table 9, starting with the most influential factor/reason.

		3hr-Prediction	10hr-Prediction	24hr-Prediction
Hospital	Feature Number			
Southampton General Hospital	1	Month	Month	Month
	2	Missing Crew Skill (TECH)	Number of Priority 7 Cases	Missing Crew Skill (ECA)
	3	Missing Crew Skill (PARA)	Number of 90+ Year Old's Arriving	Number of Priority 2 Cases
Queen Alexandra Hospital	1	Average Handover Delay in Past 6 Hours	Average Handover Delay in Past 6 Hours	Average Handover Delay in Past 6 Hours
	2	Bank Holiday	Number of 55 to 72 Year Old's Arriving	Number of Priority 1 Cases
	3	Number of Priority 2 Cases	Missing Crew Skill (PARA)	Rainfall
Royal Berkshire Hospital	1	Average Handover Delay in Past 6 Hours	Number of 55 to 72 Year Old's Arriving	Average Handover Delay in Past 6 Hours
	2	Arrivals at Hospitals Nearby	Number of Priority 2 Cases	Number of Priority 2 Cases
	3	Number of 55 to 72 Year Old's Arriving	Missing Crew Skill (TECH)	Number of 90+ Year Old's Arriving

Table 9: Top three most influential reasons for delays

Use Case 2: Proactive use of predictions to mitigate against handover delays

We have two scenarios which show the ability to predict the handover delay time and showing the results as the patients' handover times at 3-, 10-, and 24-hours' time.

The normal day scenario described below is representative of a non-bank holiday Friday morning in the month of April. There are no extreme weather conditions. In terms of the hospital, it is operating under normal operations where there are no large numbers of ambulance arrivals/departures, no big lack of skills in ambulances and no major issues with patients of any age band or priority transportation.

The second scenario, which is the busy day scenario, described further down is representative of a hot-weather bank holiday Friday afternoon in the month of April. In terms of the hospital, it is operating under pressure as there were lots of ambulance arrivals/departures and significant previous delays in the past 6 hours. There was also a big lack of skills in ambulances and there were more ambulances transporting patients of high age band. There were also more prioritised ambulance transportation over the last few hours.

Scenario 1 – Normal day

User Perspective: A SCAS manager comes on shift on 1 April 2022. They want to know the potential delay of handovers in 3-, 10-, and 24-hours' time.
The Visual: The ranges in the table show the estimated time an ambulance will take to handover. The ranges were obtained by first adding the 15-minutes allowed time for patient handovers to hospitals to the predictions, and then adding the uncertainties in the prediction to the values. The table was then colour coded, using the median of the handover time range. The colour coding was made as follows:

- GREEN: Mean handover time is less than 15 minutes (no delay)
- AMBER: Mean handover time is between 15 and 30 minutes
- RED: Mean handover time is more than 30 minutes[2]

By colour coding the cells in the results table, it makes it easier for the person to identify where there will potentially be no delays (green), short delays (amber), and severe delays (red) in the patient handovers, as shown in Table 10.

Hospital	Handover Time Range for 3hr (minutes)	Handover Time Range for 10hr (minutes)	Handover Time Range for 24hr (minutes)
Southampton General Hospital	13 - 21	15 - 23	14 - 22
Queen Alexandra Hospital	2 - 49	0 - 41	0 - 48
Royal Berkshire Hospital	14 - 29	18 - 34	18 - 33
Wexham Park Hospital	12 - 18	11 - 18	11 - 18
John Radcliffe Hospital	9 - 23	8 - 22	9 - 24
Milton Keynes General Hospital	14 - 28	11 - 25	13 - 27
North Hants Hospital	10 - 20	9 - 20	10 - 21
Stoke Mandeville Hospital	5 - 27	6 - 29	4 - 26
Royal Hampshire County Hospital	7 - 22	8 - 23	8 - 23
Frimley Park Hospital	9 - 24	10 - 24	10 - 24
Horton General Hospital	16 - 25	11 - 21	12 - 22

Table 10: Predicted handover delays, mean values coloured

Scenario 2 – Busy day

Scenario 2 follows the same process as Scenario 1. The features that were fed into the model to get the predictions were that of a potentially very hectic day and time of the day as well. The features used to get the predictions were intended to replicate that of a busy afternoon on a bank holiday with lots of things going on such as lots of previous priority patients coming in, and a high mean-handover-delay for the last 6 hours.

[2] These time intervals have been chosen for the purposes of the PoC. The Operational (End) Solution should have these timings configurable to suit the Services.

It can be noted from Table 11 that there are more red in the colours of the handover times than in Table 10 from Scenario 1. With more cells having amber and red as background colours in this table, it is still easy to identify where there will potentially be no delays, short delays, or severe delays in the patient handovers.

Hospital	Handover Time Range for 3hr (minutes)	Handover Time Range for 10hr (minutes)	Handover Time Range for 24hr (minutes)
Southampton General Hospital	17 - 25	19 - 27	19 - 27
Queen Alexandra Hospital	55 - 117	70 - 132	41 - 103
Royal Berkshire Hospital	30 - 46	19 - 35	17 - 33
Wexham Park Hospital	21 - 27	15 - 21	16 - 22
John Radcliffe Hospital	21 - 35	27 - 41	20 - 34
Milton Keynes General Hospital	38 - 54	22 - 38	20 - 36
North Hants Hospital	37 - 49	37 - 49	28 - 40
Stoke Mandeville Hospital	27 - 51	13 - 37	19 - 43
Royal Hampshire County Hospital	85 - 101	32 - 48	32 - 48
Frimley Park Hospital	44 - 58	35 - 49	27 - 41
Horton General Hospital	38 - 48	25 - 35	43 - 53

Table 11: Predicted handover delays, mean values coloured

2.7 Conclusions & Recommendations

Conclusions

Using the available data, predictions can be generated which fit the two Use Cases.

Five models were considered to predict the handover delays at hospitals under SCAS care. The approaches investigated were Time Series Analysis, Naïve Bayes, Linear Regression, Decision Trees, and Random Forests. Naïve Bayes, Linear Regression and Time Series Analysis were discounted after investigation and not taken forward due to the following:

- Naïve Bayes assumes that the target variable (handover delays) is normally distributed. Our data does not follow this assumption and so it was decided that this model would not be taken forward.
- A Time Series Model based on past handover delays would not be able to provide reasons as to why a delay occurred. This was a significant part of the project deliverable and so alternative models were investigated.
- Linear Regression was also disregarded due to the need for linear relationships between features and the target variable (handover delays). There appeared to be no significant correlation between these variables so was not investigated any further.

Both a Decision Tree model and a Random Forest model were investigated to see whether we could achieve accurate predictions in addition to pulling out the reasons as to why these predictions were made. It was important to choose a model that was able to balance accurate predictions with interpretability and explainability.

Since a Random Forest is a collection of Decision Trees, it is recommended that the Random Forest model is the one to be considered when progressing forward into developments which seek to de-risk key aspects of the intended end solution. This is because a Random Forest outperforms a Decision Tree in terms of accuracy, and in this case, without losing interpretability.

By developing a Random Forest model, we have been able to generate predictions for handover delays whilst outputting the key drivers of these delays. These key drivers are to be investigated by SCAS when a prediction is outputted to see what could be causing these delays. For example, if one of the models' key drivers is the day of the week, this could be the reason it is predicting either a high or low handover delay. Pairing this information with the expertise of the SCAS team, an informed decision could be made as to why the model is determining these key drivers.

Further Development – What are the immediate next steps?

- **Business Analysis:** Conduct key engagements (for example workshops & interviews) with the SCAS team to understand the problem space and gather detailed requirements (to test against) for how the solution should look and feel to best ensure it solves the business need.
- **Integrating Live Feeds:** By integrating live feed datasets in addition to the static datasets used, we could get a better understanding of the hospital's situation at that specific time of day. One example would be to consider data regarding staff illnesses, this may give us a clearer idea on the situation inside the hospital on that day.
- **Weather Data:** Obtaining more granular weather data, which this PoC identified to influence service demand. Throughout this project we have used weather data from the Oxford weather station, with this being the closest station to the SCAS geographical area.
- **Distance:** Distance between hospitals has been calculated using physical distance between any two points. It is used to compute a weighted sum of patients arriving at other hospitals. This is to see whether a busy hospital nearby has a knock-on effect to the delays at another hospital. It is recommended to consider an alternative distance in case the Euclidean distance does not fully represent the closeness or directness of a hospital.
- **Bank Holidays**: A list of bank holidays that covered the time period of the data was created manually from online sources. A similar list with updated bank holiday dates will need to be created in the future to proceed with model development.
- **Different train/test split**: The available data was split into 80% training and 20% testing at random. There could be merit to using a different split of the data for training and testing, such as stratified sample.
- **Aggregation/Cumulative counts**: Investigating the number of ambulances which could form part of a queue will require a different approach to that investigated in this project.
    - Feature engineering: the number of ambulances and length of queue could be inferred from existing data, leading to the potential to predict not just handover delay (mean) but the length of the queue and number of ambulances waiting for each hospital.
    - The number of ambulances in the queue at each timestamp could be inferred using existing columns in the Assignments dataset, such as Time_Destination and Time_Clear. However, these could only be used as proxies, and it would be beneficial to bring in more data sources which outline the exact number of ambulances in the queue at each timestamp.
    - Bringing in additional data sources such as situation reports at the hospital and their process for triaging ambulance arrivals will support this further investigation.

Implementation – Progression towards the implementation of the solution:

- **De-risk the end solution:** Approaches should seek to prove the concept of other wanted capabilities, and progress to de-risking elements of the proof of concept.
- **Obtaining the Necessary Datasets:** For this model to output a prediction for a specific time of day, it would require accessibility to each of the Assignments dataset, Incidents dataset and PTS dataset at the same minute.
- **Weather Data:** As we have used historic weather data in this model, for implementation purposes it would be important to consider forecasted weather rather than historic weather.
- **Ensuring Data Entry is Consistent:** In the data discovery stage of this project, we identified several spelling mistakes in the column detailing the handover type. For example, 'Handed over' was sometimes recorded as 'anded over'. These errors were corrected before moving forward with the analysis and model development. However, to progress to implementation of this solution it is recommended to ensure all data entries are consistent to ensure no important data is being missed. One option may be to introduce a dropdown list rather than a manual input.

TECHNICAL ANNEX

Annex A - Abbreviations

Abbreviation	Meaning
A&E	Accident and Emergency
ACE	Accelerated Capability Environment
AI	Artificial Intelligence
ED	Emergency Department
HALO	Hospital Ambulance Liaison Officer
MAE	Mean Absolute Error
ML	Machine Learning
NHS	National Health Service
PII	Personally Identifiable Information
PoC	Proof of Concept
PTS	Patient Transfer System
RMSE	Root Mean Square Error
SCAS	South-Central Ambulance Service
WP	Work Packages

Table 12: Abbreviations list

Annex B - Datasets used

The three main datasets used for the projects were:

Dataset	Description	Use
Assignments data (999 dataset)	Lists the individual ambulances which have been assigned to an incident.	To understand the characteristics of ambulances which completed handovers of one or more patients to an Emergency Department.
Incidents data	Aggregated information on all incidents (some incidents are linked to multiple ambulance instances in the assignments data).	To understand the effect of the age band of the patient and responding priority of the incident.
Patient Transfers System (PTS) data	Lists all transfers made using the PTS.	Used to act as a proxy as the "net flow" which would give us an idea of how many beds might be available using admissions, discharges, and transfers.

Table 13: Main datasets

The data provided was for a 12-month period starting from April 2021 to April 2022, and consisted of various ambulance times such as:

- Destination time and clear times,
- Ambulance vehicle and staff details,

- Details about the incident,
- Details about the flow of patients in and out of the hospitals as well.

A maximum of 73 hospitals were listed in the data, and 46 hospitals had cases going to an Emergency Department. Of the 46 hospitals, only the hospitals numbered 1-11 below were considered for this project. This was mainly due to the disparity in the number of data points available for each of them, and because they were considered to be the most influential hospitals within the SCAS area. The below table shows the number of data points available for each hospital, after all the filters have been applied.

Since a model was made for each hospital, the hospitals with less than 5,000 data points were not taken into consideration because of the disparity between the most common hospital, namely Southampton General Hospital having 45,757 data points. The threshold was set at around 10% of the number of data points for the most common hospital.

	Hospital	**Count of available data points**
1	Southampton General Hospital	45,757
2	Queen Alexandra Hospital	44,756
3	Royal Berkshire Hospital	37,130
4	Wexham Park Hospital	34,951
5	John Radcliffe Hospital	30,824
6	Milton Keynes General Hospital	22,739
7	North Hants Hospital	20,653
8	Stoke Mandeville Hospital	20,425
9	Royal Hampshire County Hospital	15,654
10	Frimley Park Hospital	9,530
11	Horton General Hospital	7,619
12	Bournemouth General Hospital	3,661
13	Royal Surrey County Hospital	2,359
14	Salisbury District Hospital	1,555
15	Great Western Hospital Swindon	1,261
16	Poole General Hospital	313

17	Luton & Dunstable Hospital	218
18	St Richards Hospital	203
19	High Wycombe General Hospital	196
20	Hillingdon Hospital	163
21	Abingdon Community Hospital	109
22	Runnymeade Chertsey Surrey	100
23	Milton Keynes Walkin Centre	34
24	Harefield Hospital	33
25	Watford General Hospital	30
26	Northwick Park Hospital	29
27	Princess Anne Hospital	15
28	Churchill Hospital	12
29	Prospect Park Hospital	12
30	The Heart Hospital London	11
31	Royal Free Hospital	9
32	Lymington Hospital	8
33	Charing Cross Hospital	7
34	Gosport War Memorial Hospital	6
35	Cheltenham General Hospital	3
36	Royal South Hants	2
37	Witney Community Hospital	2
38	St Marks Hospital Maidenhead	2
39	Dellwood Hosp Reading	2
40	Warneford Hospital	1
41	Upton Hospital Slough	1
42	Royal Brompton	1

43	Great Ormond Street Hospital	1
45	Wallingford Comm Hosp	1
46	Sue Ryder Center (Nettlebed)	1
47	Whipps Cross University Hospital	1
48	Ealing Hospital Trust	1
49	Queen Elizabeth Hospital (Birmingham)	1

Table 14: Data points available per Hospital

Annex C - Additional datasets

Additional datasets were brought into feed into model development. These helped us investigate the other factors that potentially affect the handover times at hospitals.

Dataset	Description	Use	License
Historic weather data	Local area reports covering the date range of the main datasets.	Flags to indicate what type of a day it was when the ambulance arrived at the hospital.	Open Government Licence v3
Bank Holidays	List of all Bank Holidays covering the date range of the main datasets.	Flags to indicate what type of a day it was when the ambulance arrived at the hospital.	None, taken from gov.uk

Table 15: Additional datasets used

The below datasets were initially considered to be incorporated into the analyses but were disregarded later for various reasons.

For datasets 1 – 3, since they were aggregated values for NHS Hospital Trusts instead of values at a particular point of time for a hospital, they were disregarded later. This is because we are making predictions for the same day and would not be able to have access to these datasets until after that day had passed.

Dataset 4 contained details of why patients attended Emergency Departments. It could not be used as it did not provide additional insights to support our investigations into handover delays.

For dataset 5, since a model was made for each hospital, the data used in the modelling were subsets of the data for the individual hospitals. And since the indices of deprivation were for the individual hospitals, it resulted in the columns for the indices of deprivation in the subsets to having the same values. This was not very useful for the analysis and therefore the use of the Indices of Deprivation dataset was not taken forward.

Dataset	Title	Description
1	NHS Bed Availability	Number of beds available in NHS Hospital Trusts

2	NHS Ambulance Quality Indicators	Quality indicators of NHS ambulances
3	A&E attendance & emergency admissions	Admissions in the A&E
4	Emergency care	Why patients attended emergency departments
5	Indices of Deprivation (2019)	Used to account for the effect that the indices of deprivation at the hospitals could have on the handover delays at hospitals.

Table 16: Additional datasets investigated but descoped

Annex D - Data Cleansing

Data cleansing was carried out on each dataset to remove rows and columns which were not relevant for the analysis. More detail on which columns were used in the analysis is described in the Data Preparation section of the report in Annex F.

Assignments dataset

Tables 17 & 18 below show the filters that have been applied to the raw data of the assignment dataset, and the number and/or percentages of the data left after having done so:

Assignments	**Rows Available**	**% Of full dataset**
Original dataset	1,150,688	100%
Filtered to remove rows without a Handover Time	358,861	31%
Filtered to remove ambulances which did not arrive at an ED	300,809	26%
Filtered to remove the 62 Hospitals without an ED	290,038	25%

Table 17: Rows used from Assignments

The columns from the assignment dataset were chosen based on their completeness and/or relevance to the project/analysis. The columns that were dropped from the assignment dataset were:

- Insufficiently complete for use in machine learning models.
- Not relevant to the analysis/project. For example, the Time_Enroute would not bring much to the analysis since we already have the Time_Destination column.

Assignments	**Columns Available**	**% Of full dataset**
Original dataset	39	100%
Filtered to remove columns which do not influence the analysis	15	38%

Table 18: Columns used from Assignments

Incidents dataset

Table 19 below shows the filters that have been applied to the raw data of the incident dataset, and the number and/or percentages of the data left after having done so. Please note that no filter was applied on the rows. The incidents data was mapped to the assignment data by using the incident number which is the common key between the two datasets. Certain columns did not contain data that would influence the agreed use cases (such as the time a 999 call was placed) and as such were not used.

Three columns of data were chosen for the following reasons:

1. **Patient Age Band:** Used as a feature to understand if the age of the patient influenced the handover delay. People from different age bands might require different levels of attention and/or care while being transferred from the ambulances to the hospitals.
2. **Responding Priority:** Used as a feature to understand if the level of responding priority of the incident influenced the handover delay. Ambulances of higher priority might be given more priority at the handover stage at the hospital, and therefore further delaying the less prioritised ones.
3. **Incident Number:** This is used to merge onto the assignment's dataset (acting as an identifier).

Incidents	Columns Available	% Of full dataset
Original dataset	19	100%
Filtered to keep the three most useful columns for the analysis	3	16%

Table 19: Data used from Incidents

Incidents Vs Assignments (Aggregated Datasets): Within delivery, the ability to look at the aggregated data (incident level) was considered; however, upon analysis, the recommendation was to proceed with the Assignments data as the main dataset, because this contained more detailed information about individual ambulance arrivals and provided the best chance of achieving the goals in a data-centric approach to this problem space.

For future, investigating the number of ambulances which could form part of a queue will require a different approach to that investigated in this project.

- Feature engineering: the number of ambulances and length of queue could be inferred from existing data, leading to the potential to predict not just handover delay (mean) but the length of the queue and number of ambulances waiting for each hospital.
- The number of ambulances in the queue at each timestamp could be inferred using existing columns in the Assignments dataset, such as Time_Destination and Time_Clear. However, these could only be used as proxies, and it would be beneficial to bring in more data sources which outline the exact number of ambulances in the queue at each timestamp.
- Bringing in additional data sources such as situation reports at the hospital and their process for triaging ambulance arrivals will support this further investigation.

PTS dataset

Table 20 below shows the filters that have been applied to the raw data of the PTS dataset, and the number and/or percentages of the data left after having done so. The rows having "**Outpatient"** as

"**Reason for Transfer**" have been filtered out. This is because the PTS dataset was used to investigate into the net flow of patients in hospitals, more specifically, the capacity at the hospitals. Since outpatient transfers neither take a bed nor free one up at the hospital, they were excluded from the analysis.

PTS	**Rows Available**	**% Of full dataset**
Original dataset	1,035,624	100%
Filtered to remove Outpatient transfers	217,401	21%

Table 20: Data used from PTS

Annex E - Data Discovery

Introduction: Once the cleansing process was complete, the datasets were analysed and a range of potential issues were investigated, as shown in below Tables (21, 22 & 23)

Purpose: The purpose of performing Data Discovery before starting the analysis is to get a better idea of the nature of the data. It is also used to extract basic/initial insights from the raw data. This was achieved by performing several checks on the data, namely:

1. Accuracy
2. Completeness
3. Consistency
4. Skew
5. Limited features

These would help us identify what kind of data we are working with; whether there is anything that needed to be 'fixed' prior to analysis/modelling; the amount of missing data in the dataset; and finally, the data we are left with after the basic data cleaning has been done.

Summary: The available data was sufficient for us to proceed with model development.

Assignments dataset	**Outcome**
1. Accuracy	The dataset contained some inconsistencies. All were resolved without issue.
2. Completeness	Most of the columns used for the analysis were well populated, except for Crew3_Skill. This will not affect the modelling since it is not actually "missing" data, but rather the absence of more skilled staff members in the ambulance.
3. Consistency	There were some patterns in the number of ambulance arrivals at the hospitals. Please refer to the *Time Series* section of Annex J to check the visualisations about the ambulance arrivals over time.
4. Skew	No statistically significant skew was found within the dataset.
5. Limited features	There were initially 73 hospitals in the dataset. Out of those, 46 hospitals had patients being transported to an emergency department. In the

	remaining 46 hospitals, the number of available data points ranged from 1 to 45,757 per hospital.

Table 21: Data Discovery for Assignments dataset

Incidents dataset	**Outcome**
1. Accuracy	The dataset contained some inconsistencies. All were resolved without issue.
2. Completeness	Columns used in the analysis were at least 80% filled.
3. Consistency	No obvious patterns were found within the data.
4. Skew	No statistically significant skew was found within the dataset.
5. Limited features	The number of patients from the different age bands that were transported to an emergency department varied a lot. The number of data points per age band ranged from 8,467, which was for those who were *less than 1 year old*, to 221,955, which was for those who were *between 73 and 90 years old.* The number of patients being transported with the different priority levels to an emergency department varied a lot. The number of data points per priority level ranged from 832, which was for those who were transported with *priority 6*, to 336,501, which was for those who were transported with *priority 1.*

Table 22: Data Discovery for Incidents dataset

PTS dataset	**Outcome**
1. Accuracy	Nothing concerning was found about the accuracy of the PTS data.
2. Completeness	Some of the columns used in the analysis were very minimally filled.
3. Consistency	No obvious patterns were found within the data.
4. Skew	No statistically significant skew was found within the dataset.
5. Limited features	Nothing obvious was found within the data.

Table23: Data Discovery for PTS dataset

Annex F - Data Preparation and Dictionary

Before being able to use the data in the model, the variables had to be manipulated to understand the most useful metrics which would bring greatest value to the overall model.

Below is a breakdown of the different metrics that were derived by using the raw data from the different datasets.

Assignment dataset

Assignments is the dataset on which most of the pre-modelling data preparation was done. The raw columns from the Assignment dataset that were used in some ways in the model are shown in Table 24 below:

<table>
<tr><th>Assignments Column</th><th>Description</th></tr>
<tr><td>num_1</td><td>The case reference number</td></tr>
<tr><td>Hospital_Name</td><td>The name of the hospital</td></tr>
<tr><td>Time_Destination</td><td>The time at which the ambulance reaches the hospital</td></tr>
<tr><td>Time_Handover</td><td>The time at which handover takes place at the hospital</td></tr>
<tr><td>Time_Clear</td><td>The time at which the ambulance is cleaned and ready for the next case</td></tr>
<tr><td>Patients_Transported</td><td>The number of patients transported in the ambulance</td></tr>
<tr><td>Crew1_Skill</td><td rowspan="3">The ambulance crew skill level</td></tr>
<tr><td>Crew2_Skill</td></tr>
<tr><td>Crew3_Skill</td></tr>
<tr><td>Dest_Easting

Dest_Northing</td><td>The coordinates of the destination</td></tr>
</table>

Table 24: Assignments Data Dictionary

<u>Incident dataset</u>

The incident data was used to get the count of patients from the different age bands who were being transported in the ambulance, and the priorities with which the cases were responded to. The raw columns from the Incidents dataset that were used shown in Table 25 below:

Column	**Description**
num_1	The ICAD event number field (the common key to map the rows to their corresponding row in the assignment dataset)
Age Band	The age band which the patient being transported falls into
responding_priority	The responding priority assigned to the case by the ambulance

Table 25: Incidents Data Dictionary

The unique values of the age bands and responding priorities were treated as a column on their own. For each case, a value of +1 is assigned to the age band and responding priority value columns which is relevant to the case. Then the number of ambulances transporting patients of any age band and of any responding priority over any time period was calculated by doing a rolling sum over the time period.

The time period selected for this analysis was 6 hours. This was decided by testing a number of different time periods, for example, from 1 hour up to 6 hours and seeing how the results differed by adjusting these times. There were no significant differences in the results by changing the time period and discussing with the project team it was decided we would continue the analysis looking at a 6-hour period.

It was discussed that often a busy morning could lead to a busy afternoon so looking over a 6-hour period would give us an idea of the hospital's situation earlier on that day and allow us to make predictions for the future. For example, the number of ambulances transporting patients of age band 90-plus years old was calculated by performing a rolling sum (summing as from 6 hours prior to the current timestamp) over the previous 6 hours and this was used as a feature column in our model.

PTS data

The PTS data was used to calculate a proxy for the net flow in and out of the 11 hospitals that were considered. This was calculated detailed below, using data for the admissions, transfers and discharges. This gave us an idea of the capacity at the hospitals. The raw columns from the PTS dataset that were used shown in Table 26 below:

Column	Description
From Hospital	The hospital from which the patient is getting discharged/transferred
To Hospital	The hospital to which the patient is getting admitted/transferred
Direction	Whether the patient is going into or coming out from a hospital
Journey Pick Up Time	The time at which the patient is picked up for the journey
Journey Drop Off Time	The time at which the patient is dropped at their destination
Reason for Transfer	The reason why the patient is being transferred. Also previously used as a filter to exclude 'Outpatients'.

Table 26: PTS Data Dictionary

The cases where the patients were admitted or transferred to a hospital were each given a value of +1 for the "flow" to represent the need for resources for a new patient.

The cases where the patients were discharged or transferred from a hospital were each given a value of −1 for the "flow" to represent the availability of resources for a new patient.

The net flow of patients over a period to a hospital was calculated by doing a rolling sum over that period for that hospital. A positive value for the net flow would indicate the need for resources in the hospital, and conversely, a negative value would indicate the availability of resources in the hospital.

Merging of datasets

The Assignments dataset and the Incidents dataset were merged using the incident number. A proxy is calculated for the number of ambulances arriving and the number of ambulances departing using the time columns in the Assignments dataset. Additionally, still using the Assignments data, the number of each missing skill we have in each ambulance is also calculated along with the number of ambulances carrying either 1, 2 or 3 patients.

Using the information from the Incidents dataset, we count the number of ambulances arriving where the patient (/patients) is (/are) of a certain age band and responding priority.

The PTS dataset was manipulated to include a column which acts as a proxy to the flow of patients (using discharges, admissions, and transfers). Therefore, we are left with a dataset showing the timestamps where a patient is either admitted (+1) or discharged (-1) from a hospital.

These columns were joined together leaving a single interleaved dataset.

Train/test split

Once the data had been prepared, it was split into a training dataset and a test dataset. This split was 80/20 (training/test) and was done completely randomly. The training portion enabled us to train the model using actual SCAS data. We then tested the outputs of the trained model using the test portion to check the accuracy of our predictions. More detail on accuracy measurements can be seen in Annex H.

Annex G – Additional Insights

Data Discovery led us to seven additional insights which enrich our analysis.

1. HALO effect – Insight: it reduces the number of ambulances within the queue but does not speed up the handover process.
2. Handover time – Insight: allows us to calculate the actual time taken to handover.
3. Handover delay – Insight: shows the range and frequency of handover delays.
4. Weighted ambulance arrival – Insight: produced an input variable which investigates the knock-on effect to the delays at surrounding hospitals.
5. Number of patients in ambulance – Insight: shows the number of ambulances which transported 1, 2, or 3 patients over the last 6 hours.
6. Number of missing crew skills in ambulances – Insight: shows the number of ambulances which were missing the different skills over the last 6 hours.
7. Date/Time variables – Insight: Used to account for the seasonality in the data.

1. HALO effect

What is it? A HALO scenario is where an ambulance leaves their patient(s) with a Hospital Ambulance Liaison Officer (HALO) who has an ambulance which is still in the queue, after mutually agreeing to do so. The first ambulance then proceeds to the cleaning and clearing process so that it is made available for the next incident more quickly.

Why is this done? To enable Ambulance preparation for response to another incident, without having to wait to reach the front of the queue.

How does this factor affect the PoC? HALOing reduces the number of ambulances within the queue but does not speed up the handover process.

- **Why?** The patient(s) that was handed over to HALOing might not be handed over to the hospital by the time the ambulance is clear to go on the next case.

How was HALOing considered for the PoC? To check for instances of HALOing, the clear and the handover times are compared. Cases where the clear time is *before* the handover time implies that HALOing has been done, as the ambulance leaves the hospital (clear) before the patient is formally handed over (handover).

Insights: Table 27 below shows the number and percentages of the number of cases where Haloing has been performed for each hospital (arranged in descending order).

- **Number of HALO Occurrences:** These numbers represent the number of ambulances which have HALO-ed within the bounds of the refined datasets (as outlined in Data Discovery).
- **Percentage:** The percentage HALO represents the percentage of the number of ambulances that arrived at that hospital that went through the HALO process**.**

Hospital	Number of HALO Occurrences	Percentage of HALO Ambulances
Frimley Park Hospital	28	0.3
Horton General Hospital	19	0.2
John Radcliffe Hospital	530	1.2
Milton Keynes General Hospital	182	0.7
North Hants Hospital	197	0.9
Queen Alexandra Hospital	728	1.4
Royal Berkshire Hospital	142	0.4
Royal Hampshire County Hospital	112	0.6
Southampton General Hospital	86	0.2
Stoke Mandeville Hospital	462	1.9
Wexham Park Hospital	257	0.7

Table 27: Number and percentage of HALO occurrences

2. Handover time

The next metric that was derived from the raw data is the handover delay (in minutes). This is the variable that needs to be predicted in this project. To get the handover delay, the time taken to handover the patient(s) (in minutes) was first calculated as shown below:

$$\begin{array}{l}\textit{time taken}\\ \textit{to handover}\end{array} = \begin{array}{l}\textit{time at which}\\ \textit{handover was}\\ \textit{completed}\end{array} - \begin{array}{l}\textit{time at which}\\ \textit{ambulance reaches}\\ \textit{hospital}\end{array}$$

Figure 2: Equation to calculate actual handover time

3. Handover delay

Once the Handover Time metric had been calculated, the Handover Delay was calculated for those whose time taken to handover the patients were more than 15 minutes. Delays are counted as from 15 minutes after that the ambulance arrives at the hospital. The equation for the handover delay is as shown below:

Let $p = time\ taken\ to\ handover\ (in\ minutes)$

$$if\ p > 15, then\ handover\ delay = p\ - 15$$
$$else\ if\ p \leq 15, then\ handover\ delay = 0$$

Figure 3: Equation to calculate handover delay

The below Tables 28 & 29 show the mean handover delays and other details about delays (in minutes) in the hospitals:

Hospital	Total number of handovers	Number of handovers that incur a delay	Percentage of handovers that incur a delay
Frimley Park Hospital	10,093	6,023	60
Horton General Hospital	8,772	4,009	46
John Radcliffe Hospital	44,835	23,654	53
Milton Keynes General Hospital	24,320	14,248	59
North Hants Hospital	22,868	5,879	26
Queen Alexandra Hospital	51,947	27,983	54
Royal Berkshire Hospital	39,784	22,934	58
Royal Hampshire County Hospital	17,297	5,614	33
Southampton General Hospital	50,952	26,135	52
Stoke Mandeville Hospital	24,145	13,344	56
Wexham Park Hospital	37,048	13,463	37

Table 28: Handover details for the 11 main hospitals

Hospital	Minimum Delay (HH:MM)	Mean Delay (HH:MM)	Maximum Delay (HH:MM)
Frimley Park Hospital	0:01	0:12	4:13
Horton General Hospital	0:01	0:10	2:43
John Radcliffe Hospital	0:01	0:15	6:41
Milton Keynes General Hospital	0:01	0:14	5:20
North Hants Hospital	0:01	0:21	6:22
Queen Alexandra Hospital	0:01	1:00	10:41
Royal Berkshire Hospital	0:01	0:14	4:52
Royal Hampshire County Hospital	0:01	0:22	5:46
Southampton General Hospital	0:01	0:08	3:12
Stoke Mandeville Hospital	0:01	0:23	9:31
Wexham Park Hospital	0:01	0:09	4:22

Table 29: Min, mean and max handover delays at the 11 main hospitals

Mean Delay (Minutes): The mean handover delay over the last 6-hour window was also calculated for all the hospitals at any given time by doing a rolling mean over the last 6 hours. This accounts for the state of the hospital before the ambulance arrives at the hospital.

Ambulance Flow/ Departures: The ambulance flow was determined by checking the time at which the ambulance leaves the queue and the number of ambulance departures from a hospital. It is based on whether a HALO scenario has occurred or not. Whenever HALOing occurred, time clear is taken as the time that the ambulance left the queue. Otherwise, time handover is taken as the time that the ambulance left the queue.

For the number of ambulance arrivals at any hospital over a time period, a count of the number of cases in that time window was taken.

4. Weighted ambulance arrivals

The “Dest_Easting” and “Dest_Northing” columns were used to calculate the Euclidean distance (which is also the shortest distance) between any two hospitals. Taking Southampton General Hospital as an example, we consider the Euclidean distance between this hospital and all other hospitals in the analysis. We then calculate a weighted sum of the ambulances arriving at the other hospitals over the past six hours (exponentially weighted by their distance). This weighted sum is used as an input variable into the model. This weighted sum was calculated to see whether insights could be made as to whether nearby busy hospitals have a knock-on effect to the delays at surrounding hospitals.

5. Number of patients in ambulance

The unique values of the “Patients_Transported” column were treated separately as new columns, and the relevant column for each case was given a value of 1. Then the count of the ambulances transporting a different number of patients, over any period, was calculated by doing a rolling sum over a 6-hour time period.

6. Number of missing crew skills in ambulances

Likewise, the unique values from the columns “Crew1_Skill”, “Crew2_Skill”, and “Crew3_Skill” were treated separately as new columns. A value of 1 was assigned to any skill that was missing in the ambulance for each case. Then by doing a rolling sum over a 6-hour time period, the count of ambulances that were missing these skills for that time period was calculated.

7. Date/Time variables

The “Time_Destination” was also broken down into “date”, “day of week”, “month”, “year”, and “hour of the day” to account for any patterns that occur over time in the data at the hospitals.

The number of patients in ambulances accounts for the effect that high numbers of ambulances with more than one patient have on the handover delay at hospitals. The missing crew skills accounts for scenarios where a high number of ambulances have been missing any skills. And the date/time variables account for the seasonality/patterns in the data.

Annex H – Results of developed models

Table 30 below shows the results using the **Random Forest** algorithm. The example in Figure 30 is that of the latest timestamp in the given data. The predictions are for if that was run 3-, 10- and 24-hours in advance. In practice, the model will be run, and the predictions will be given from that time 3, 10 and 24 hours ahead. Note that the delays start 15 minutes after that the ambulances reaches the hospitals. Therefore 15 minutes should be added to the values in the below table, which are just the handover delay values, to get the actual handover time that the ambulance will have to wait.

Table 30 below presents the predicted delay in minutes with the associated error bound (also in minutes).

To get the error term, while training and testing the model, the absolute value of the difference (error) between the predicted values and actual values are taken. By taking the mean of the absolute values of the errors, we obtain the Mean Absolute Error (MAE) which is then used as the error metric for the predictions. This can be interpreted as the *average* deviation of the predicted value from the actual value.

Hospital	Predicted Handover Delay in 3hr (minutes)	Predicted Handover Delay in 10hr (minutes)	Predicted Handover Delay in 24hr (minutes)
Southampton General Hospital	2 ± 4	4 ± 4	3 ± 4
Queen Alexandra Hospital	10 ± 23	2 ± 24	8 ± 24
Royal Berkshire Hospital	7 ± 7	11 ± 7	10 ± 7
Wexham Park Hospital	0 ± 3	0 ± 3	0 ± 3
John Radcliffe Hospital	1 ± 7	0 ± 7	1 ± 7
Milton Keynes General Hospital	6 ± 6	3 ± 6	5 ± 6
North Hants Hospital	0 ± 5	0 ± 5	1 ± 5
Stoke Mandeville Hospital	1 ± 11	3 ± 11	0 ± 11
Royal Hampshire County Hospital	0 ± 7	1 ± 7	0 ± 7
Frimley Park Hospital	2 ± 7	2 ± 6	2 ± 7
Horton General Hospital	6 ± 4	1 ± 4	2 ± 4

Table 30: Predicted Handover delays (3,10,24 hours) with the error bound

Table 31 below shows the predicted range of the handover times (including the 15-minute period) instead of only the delay. As such, the delay for Southampton General Hospital in the above table was 2 +/- 4 minutes. This means that the range of the delay was 0 – 6 minutes. When the 15-minute period of the acceptable handover time was added to the handover delay range, the handover time range becomes 13 – 21 minutes. A predicted handover time of zero means that the ambulance is predicted not to wait at all before handover takes place. At the start of this report, we have shown the table below with colour banding on top.

Hospital	Handover Time Range for 3hr (minutes)	Handover Time Range for 10hr (minutes)	Handover Time Range for 24hr (minutes)
Southampton General Hospital	13 - 21	15 - 23	14 - 22
Queen Alexandra Hospital	2 - 49	0 - 41	0 - 48
Royal Berkshire Hospital	14 - 29	18 - 34	18 - 33
Wexham Park Hospital	12 - 18	11 - 18	11 - 18
John Radcliffe Hospital	9 - 23	8 - 22	9 - 24
Milton Keynes General Hospital	14 - 28	11 - 25	13 - 27
North Hants Hospital	10 - 20	9 - 20	10 - 21
Stoke Mandeville Hospital	5 - 27	6 - 29	4 - 26
Royal Hampshire County Hospital	7 - 22	8 - 23	8 - 23
Frimley Park Hospital	9 - 24	10 - 24	10 - 24
Horton General Hospital	16 - 25	11 - 21	12 - 22

Table 31: Predicted Handover times (3,10,24 hours) shown as a range

Analysis of Model Outputs

To analyse the performance of the Random Forest Model, different types of scatter plots were considered. For each hospital, we investigated the following plots for the 3-hour, 10-hour, and 24-hour predictions:

- The actual handover delay values vs our predicted values for the training data
- The actual handover delay values vs our predicted values for the test data
- The average daily handover delay values vs the average daily predicted values for the training data
- The average daily handover delay values vs the average daily predicted values for the test data

The plots in Figures 32 to 33 describe the 3-hour predictions for Southampton General Hospital. At first glance, the predicted vs actual delays on the full test may appear to show that the model is not performing very well. It looks as though the model has been overfitted to the training data and is unable to predict for data it has not seen before. However, these plots are misleading due to the way the model has been built.

The model has been built so that it considers the situation of the hospital over the past six hours and predicts forwards based on this situation. This means that if we take two ambulances as an example that arrive at the same hospital at the same time, these may have very different handover delays but the inputs to the model will be the same (due to the situation at the hospital being the same at that time). Our model would not be able to distinguish between these two ambulances. Our model is predicting for the typical ambulance that were to arrive at a specific time, so we are essentially predicting the average delay and so plotting the predicted vs actual for each observation is not a good representation as to how the model is performing.

The scatterplots in Figures 4 and 5 provide a better view of how the model is performing. These plots are showing the predicted vs actual but averaged over each day. For example, for days with very long delays, these plots give an indication as to whether the model is capturing these long delays.

Considering Figure 4 we see that the averaged predicted vs actual for the test data is still surrounding the diagonal line suggesting that our model is performing reasonably well on the test data. The averaged predicted vs actual for the training data suggests that there may still be some overfitting occurring and this could be considered for further development. There could be merit in tuning the parameters in the Random Forest model to reduce the risk of overfitting even more.

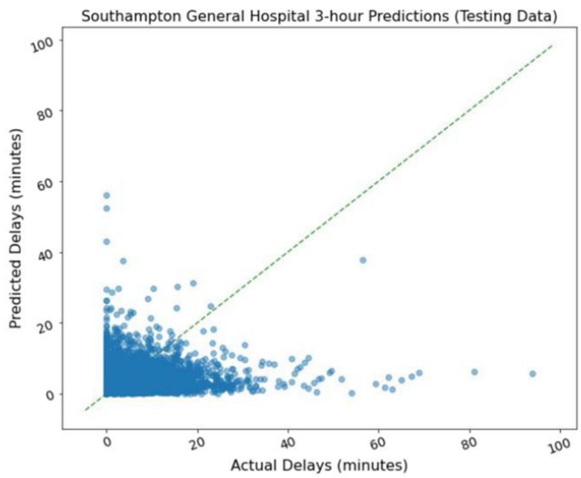


Figure 4: Predicted delays vs actual delays for Southampton General Hospital 3-hour prediction on the test data, Figure 5: Predicted delays vs actual delays for Southampton General Hospital 3-hour prediction on the training data

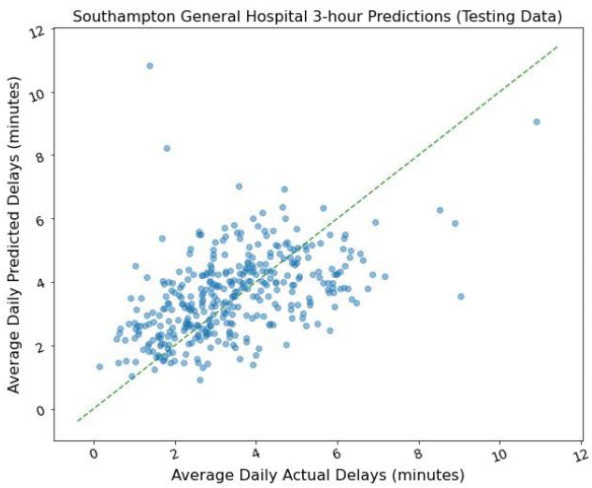
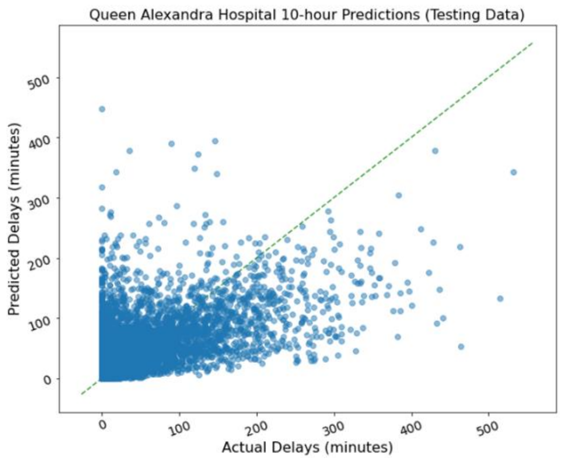


Figure 6: Average daily predicted vs actual delays for Southampton General Hospital 3-hour prediction on the test data, Figure 7: Average daily predicted vs actual delays for Southampton General Hospital 3-hour prediction on the training data

In addition to the figures described above, we have similar plots for Queen Alexandra Hospital for the 10-hour prediction in Figures 8 to 11.



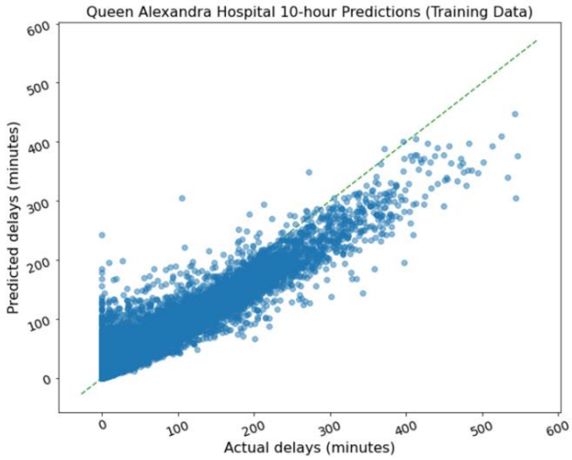
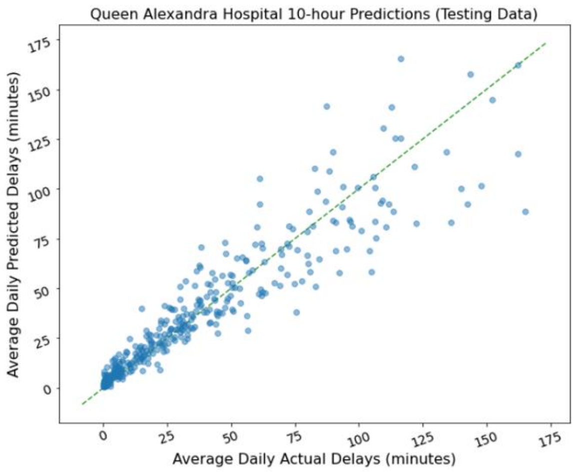


Figure 8: Predicted delays vs actual delays for Queen Alexandra Hospital 10-hour prediction on the test data, Figure 9: Predicted delays vs actual delays for Queen Alexandra Hospital 10-hour prediction on the training data



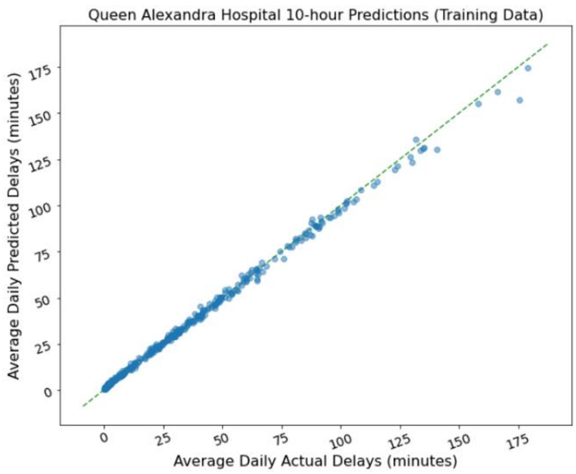


Figure 10: Average daily predicted vs actual delays for Queen Alexandra Hospital 10-hour prediction on the test data, Figure 11: Average daily predicted vs actual delays for Queen Alexandra Hospital 10-hour prediction on the training data

Figures 8 to 11 show a similar result to those in Figures 4 to 7. However, noting this time that the scales of the delay are significantly different. This time we have days where the average delay is considerably high. However, it can be seen in that our model is still capturing those days that have the long delays.

From the above discussion, the plots in Figures 12 to 44 show the plots for each hospital at 3, 10 and 24 hours but only for the average daily predictions.

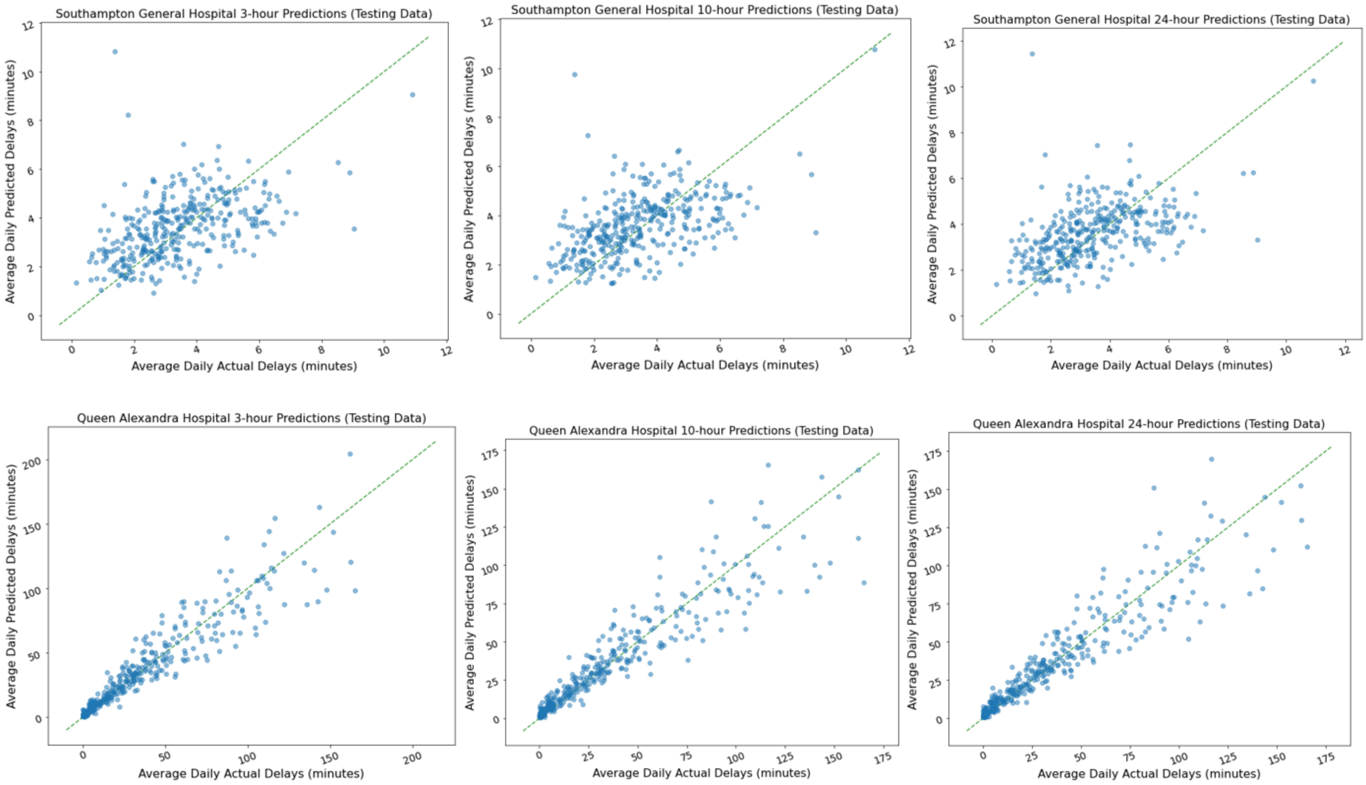


Figure 12 to Figure 17: Average daily predicted vs actual delays for Southampton General Hospital and Queen Alexandra Hospital for the 3-hour, 10-hour and 24-hour model

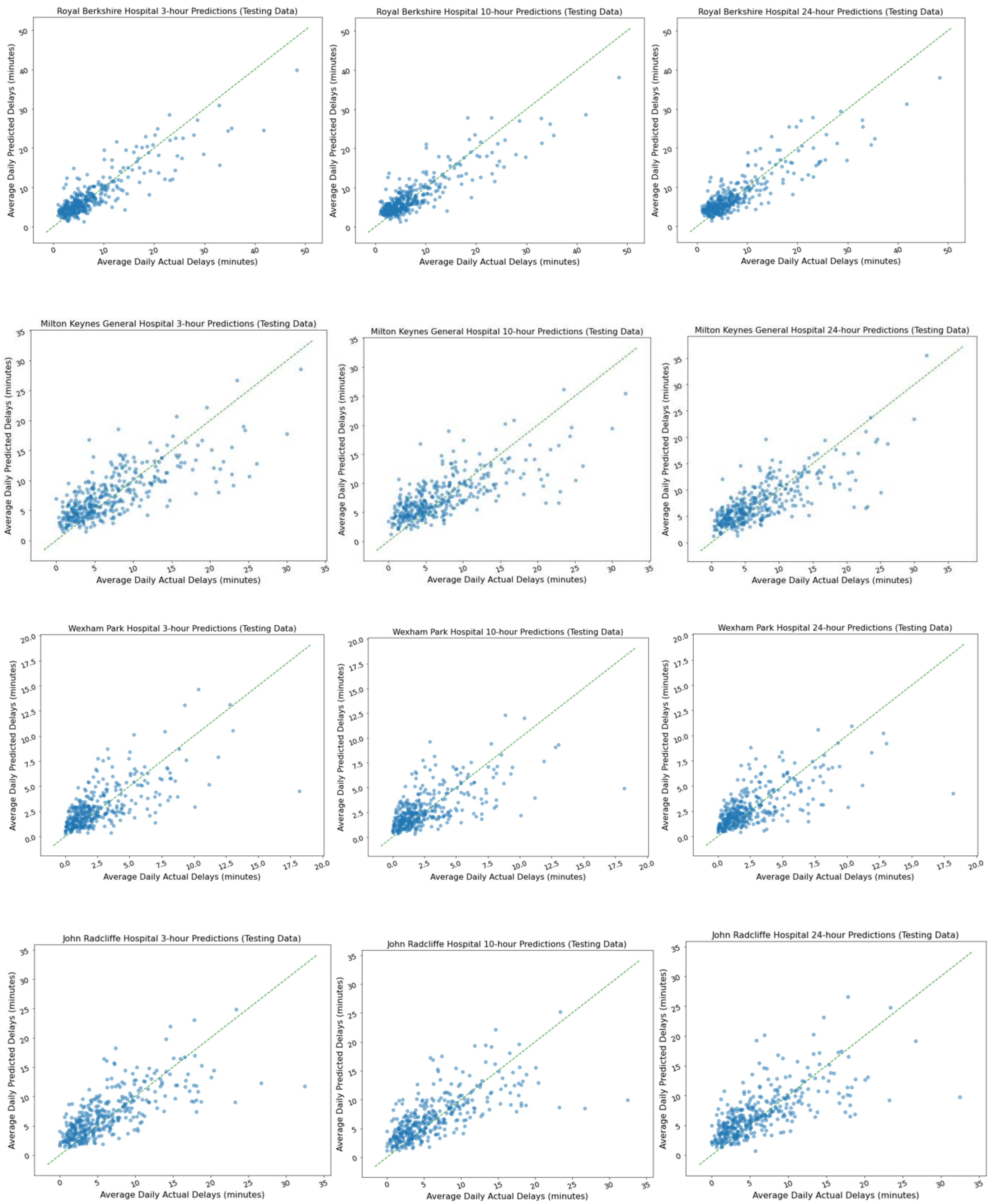


Figure 18 to Figure 29: Average daily predicted vs actual delays for Royal Berkshire, Milton Keynes General, Wexham Park and John Radcliffe hospitals for the 3-hour, 10-hour and 24-hour model

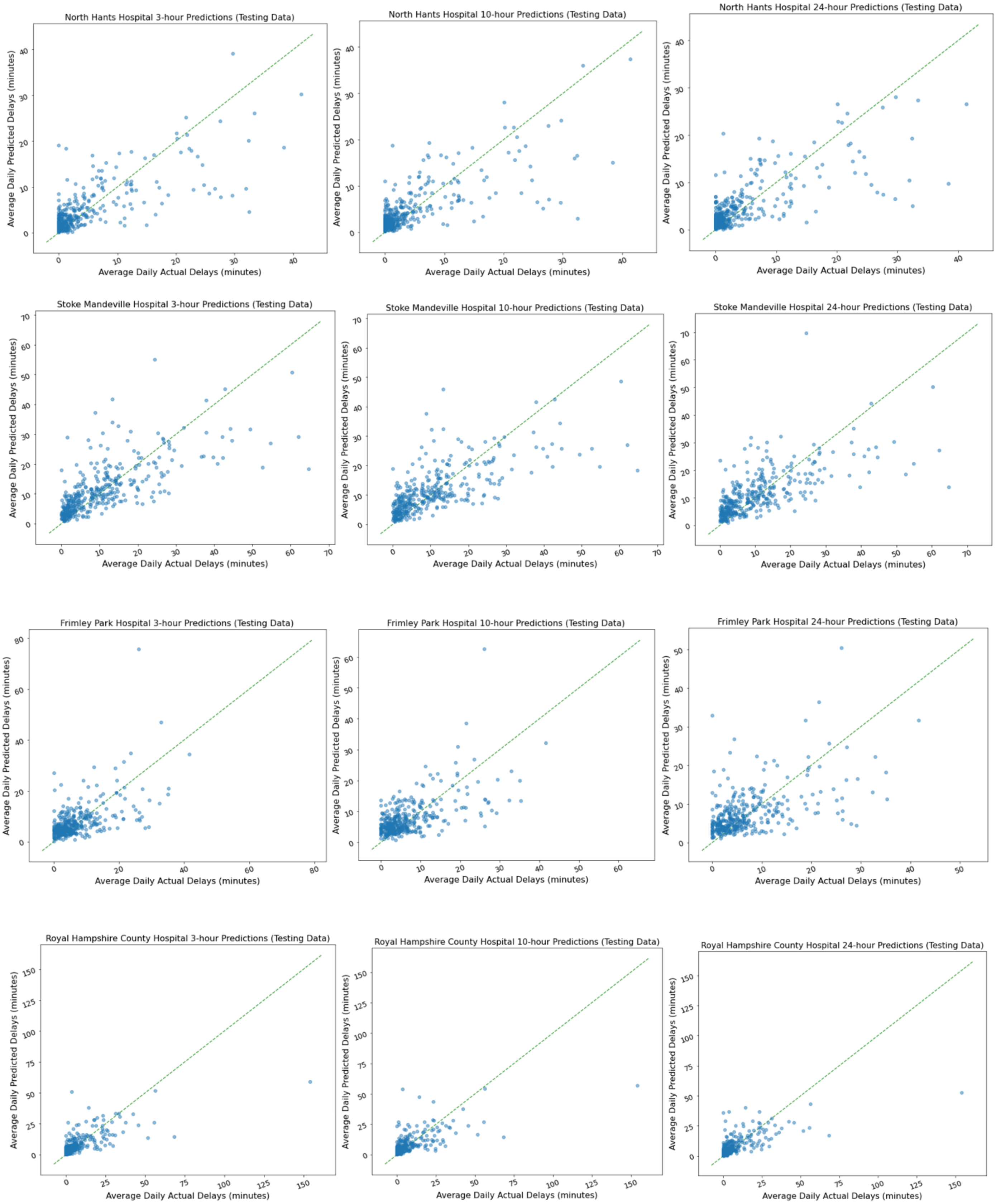


Figure 30 to Figure 41: Average daily predicted vs actual delays for North Hants, Stoke Mandeville, Frimley Park and Royal Hampshire County hospitals for the 3-hour, 10-hour and 24-hour model

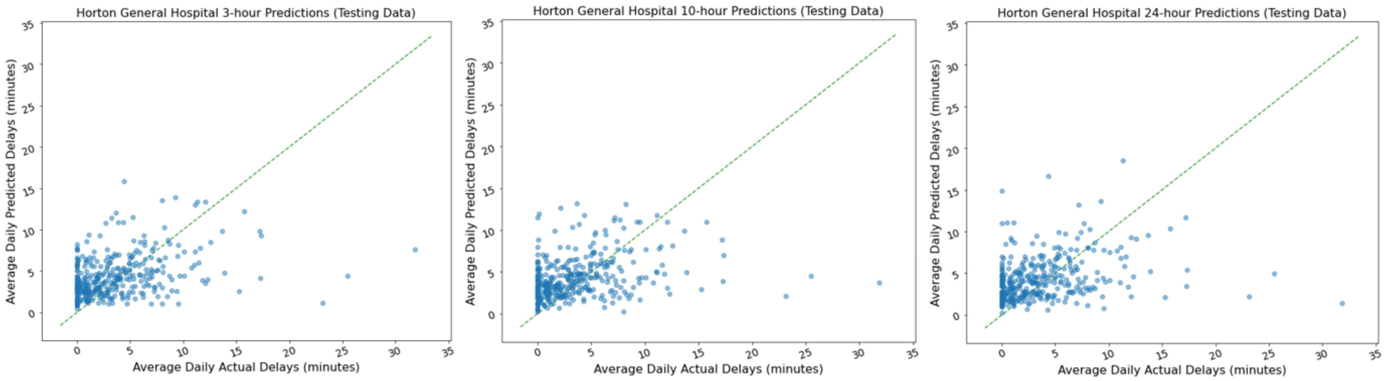


Figure 42 to Figure 44: Average daily predicted vs actual delays for Horton General Hospital for the 3-hour, 10-hour and 24-hour model

Looking at the plots shown in Figures 12 to 44 we can conclude the following:

- There are significant differences in our predictions for each of the 11 hospitals,
- There are considerable differences between the scales of each of the hospitals, noticeably Queen Alexandra Hospital,
- Although Queen Alexandra Hospital appears to have a significant number of days where the delays are long, the model is still able to predict for those days,
- The model appears to be performing reasonably well for all hospitals, however it can predict better for some hospitals,
- The averaged predicted delay vs the averaged actual delay (over a day) does not appear to differ much between the 3-hour, 10-hour and 24-hour prediction for each hospital.

The Root Mean Squared Error (RMSE) has also been calculated for each model and is summarised in the table below.

RMSE values for:	3hr-Predictions	10hr-Predictions	24hr-Predictions
Hospital			
Southampton General Hospital	6.49	6.49	6.44
Queen Alexandra Hospital	46.04	47.16	47.15
Royal Berkshire Hospital	14.27	14.11	14.25
Wexham Park Hospital	7.10	7.08	7.00
John Radcliffe Hospital	13.26	13.34	13.34
Milton Keynes General Hospital	11.27	11.32	11.11
North Hants Hospital	13.13	13.50	13.29
Stoke Mandeville Hospital	21.95	21.92	21.80
Royal Hampshire County Hospital	18.26	18.41	17.69
Frimley Park Hospital	12.04	12.00	11.97
Horton General Hospital	7.43	7.76	7.58

Table 7: The RMSE for each model

Supporting the findings from the scatterplots, there is not much difference between the RMSE for the 3-, 10- and 24-hour predictions for each of the hospitals. For Queen Alexandra Hospital the RMSE is significantly higher than that of the other hospitals. However, as seen from the scatterplots, the range of the handover delays is also considerably higher than that of the others. After discussion with the project team, this hospital has been considered an outlier and these results are to be expected.

Most Important Features

The three most important features used to get the predictions are shown in Table 33 below. These are the features that contributed the most to the model to get the corresponding prediction. The features are arranged in descending order, starting with the most important feature.

These important features have been chosen in a similar way to how the *feature importance* metric is calculated when training a Random Forest. These features are determined by the decrease in impurity (in a Random Forest Regressor the impurity is the error). This helps to identify the features that have had the most impact on the model for each given observation.

		3hr-Prediction	10hr-Prediction	24hr-Prediction
Hospital	**Feature Number**			
Southampton General Hospital	1	Month	Month	Month
	2	Missing Crew Skill (TECH)	Number of Priority 7 Cases	Missing Crew Skill (ECA)
	3	Missing Crew Skill (PARA)	Number of 90+ Year Old's Arriving	Number of Priority 2 Cases
Queen Alexandra Hospital	1	Average Handover Delay in Past 6 Hours	Average Handover Delay in Past 6 Hours	Average Handover Delay in Past 6 Hours
	2	Bank Holiday	Number of 55 to 72 Year Old's Arriving	Number of Priority 1 Cases
	3	Number of Priority 2 Cases	Missing Crew Skill (PARA)	Rainfall
Royal Berkshire Hospital	1	Average Handover Delay in Past 6 Hours	Number of 55 to 72 Year Old's Arriving	Average Handover Delay in Past 6 Hours
	2	Arrivals at Hospitals Nearby	Number of Priority 2 Cases	Number of Priority 2 Cases
	3	Number of 55 to 72 Year Old's Arriving	Missing Crew Skill (TECH)	Number of 90+ Year Old's Arriving
Wexham Park Hospital	1	Average Handover Delay in Past 6 Hours	Hour of the Day	Hour of the Day
	2	Hour of the Day	Maximum Temperature	Maximum Temperature
	3	Month	Arrivals at Hospitals Nearby	Month
John Radcliffe Hospital	1	Average Handover Delay in Past 6 Hours	Month	Month
	2	Month	Average Handover Delay in Past 6 Hours	Average Handover Delay in Past 6 Hours
	3	Maximum Temperature	Rainfall	Rainfall
Milton Keynes General Hospital	1	Average Handover Delay in Past 6 Hours	Arrivals at Hospitals Nearby	Month
	2	Patient Flow	Month	Average Handover Delay in Past 6 Hours
	3	Month	Average Handover Delay in Past 6 Hours	Number of 73 to 90 Year Old's Arriving
North Hants Hospital	1	Hour of the Day	Arrivals at Hospitals Nearby	Hour of the Day
	2	Patient Flow	Hour of the Day	Month
	3	Arrivals at Hospitals Nearby	Average Handover Delay in Past 6 Hours	Number of Priority 1 Cases
Stoke Mandeville Hospital	1	Patient Flow	Hour of the Day	Hour of the Day
	2	Hour of the Day	Maximum Temperature	Arrivals at Hospitals Nearby
	3	Month	Month	Month
Royal Hampshire County Hospital	1	Average Handover Delay in Past 6 Hours	Month	Hour of the Day
	2	Hour of the Day	Hour of the Day	Month
	3	Month	Arrivals at Hospitals Nearby	Average Handover Delay in Past 6 Hours
Frimley Park Hospital	1	Hour of the Day	Hour of the Day	Hour of the Day
	2	Average Handover Delay in Past 6 Hours	Arrivals at Hospitals Nearby	Average Handover Delay in Past 6 Hours
	3	Arrivals at Hospitals Nearby	Average Handover Delay in Past 6 Hours	Maximum Temperature
Horton General Hospital	1	Month	Month	Month
	2	Maximum Temperature	Maximum Temperature	Maximum Temperature
	3	Average Handover Delay in Past 6 Hours	Arrivals at Hospitals Nearby	Average Handover Delay in Past 6 Hours

Table 8: Top three most influential features, for the 11 main hospitals

Annex J – Descoped Modelling Approaches

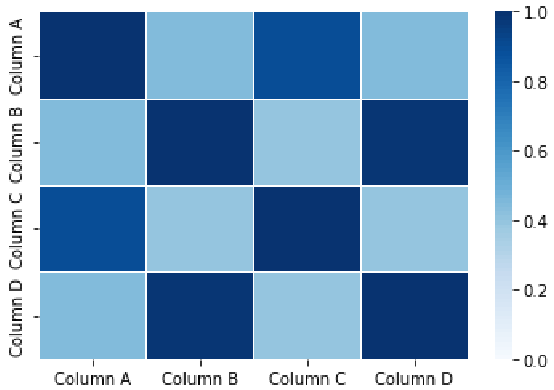
This section talks in more detail about the three modelling approaches which were descoped:

- Linear Regression
- Time Series
- Naïve Bayes

Linear Regression
Linear regression techniques were initially considered as one of the potential approaches that could be used in this project. This technique takes into account the relationship between the dependent variable (the variable to be predicted, which is handover delay in this case) and the independent variables (the other variables used in the model).

The below heatmaps, Figure 45 and Figure 46, show cases where there are correlation and no correlation between the variables. They have been created to show what correlation/no correlation should look like, they do not represent actual data used in this project.

Column D in Figure 45 is correlated to the other columns because judging from the colours of the last row, they are all at least around 0.5. These may be for things that are related such as average speed and time taken of the journey for a road trip. Whereas in Figure 46 it can be noted that Column 4 is not correlated to the other columns because judging from the colours of the last row, they are all less than 0.2. These may be for unrelated cases such as gender of a new-born and day of the week.



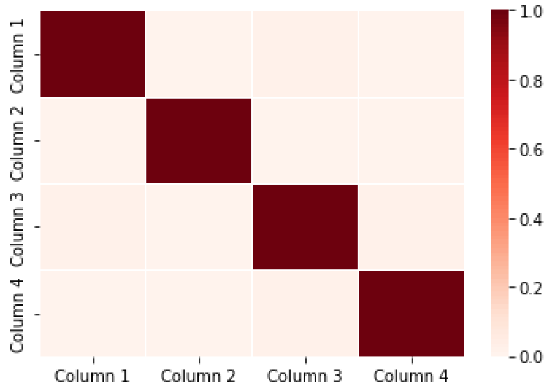


Figure 45: Showing correlation, Figure 46: Showing no correlation

However, while investigating the correlation (relationship) between the dependent and independent variables, it was concluded that there is no significant relationship between the variables, therefore, linear regression cannot be used. The heatmap in Figure 47 shows the correlation between the dependent and independent variables from the final dataset for all hospitals:

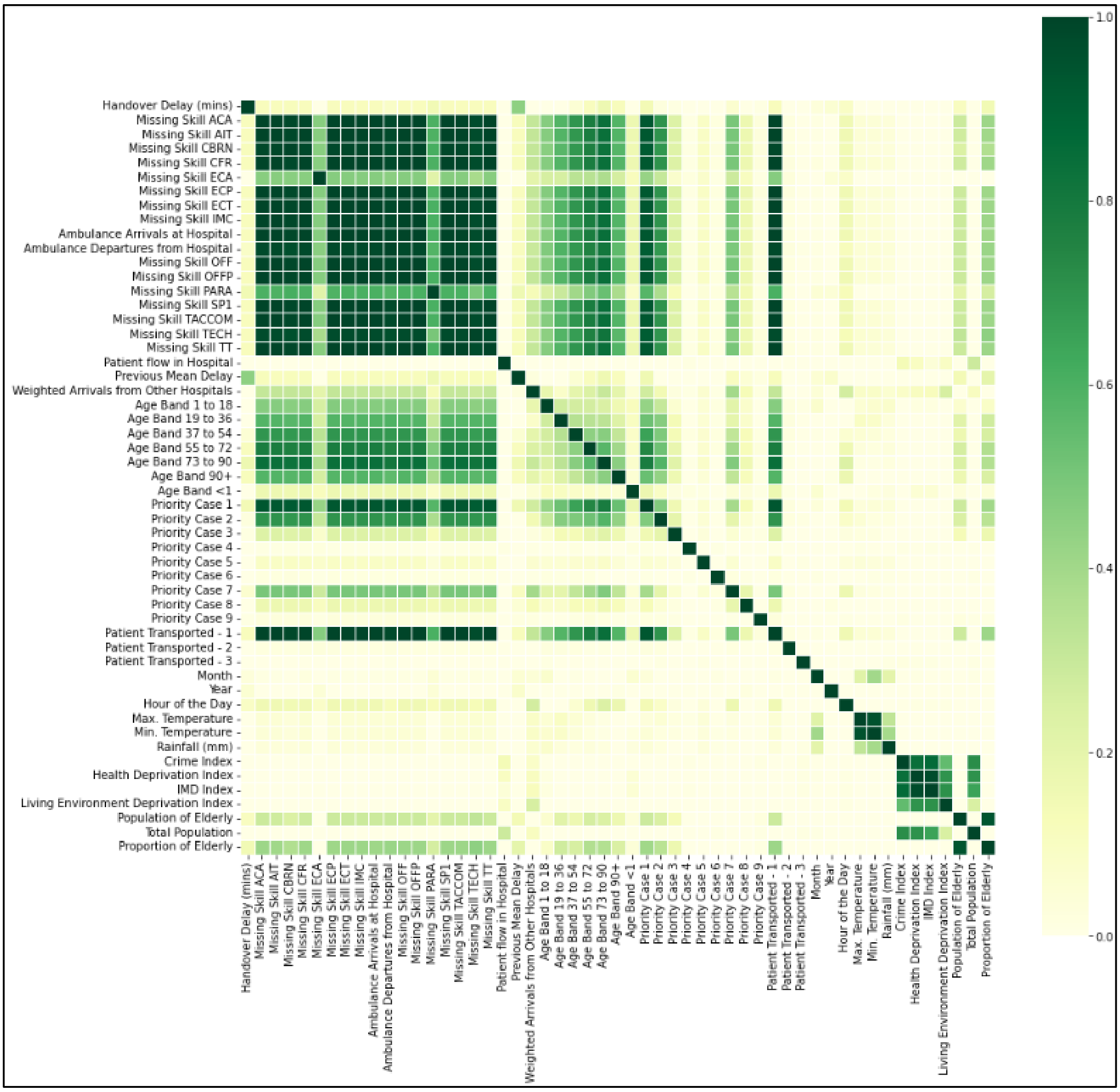


Figure 47: Correlation heatmap for the actual data used in this project

The colours in the heatmap represents the relative correlation between the variables. The lighter the colour (which also means the more the value tends to zero), the less relationship there is between the variables. In Figure 47 above, the heatmap shows that there is very weak correlation (tending to 0), between handover delay (Handover Delay (mins) and the other variables (the first row of the heatmap). From this, it can be concluded that there is minimal correlation in the data, so the linear regression techniques cannot be used. Please note that there seem to be correlation between the "Handover Delay (min)" and "Previous Mean Delay" variables. This is because the "Previous Mean Delay" has been derived using the "Handover Delay (min)".

Time Series

Time Series analysis provided some valuable insights in terms of how the variables change over time. It helped identify the trends and seasonality in the data. However, it could not be taken forward to be used as the main model. A time series model may have given us an accurate prediction for the handover delay based-off previous delays, however, it would not be able to provide the reason(s) or the factor(s) that might be causing this delay. This was a significant deliverable of the project and encouraged us to investigate alternative models that can provide both an accurate prediction and a key driver for that prediction.

To ensure that the valuable insights from the Time Series analysis were not lost and that the seasonality in the data had been captured in the model, extra columns were added to the dataset which included the day of the week, the time of the day and the month at which the ambulance arrives at the hospital.

Figure 48 below shows the *handover delay* for all the hospitals over the 1-year period of the available data. It can be seen that there is a pattern in the data, and also that the magnitudes of the peaks are increasing over time, which means that the maximum handover delays are getting bigger as time passes by.

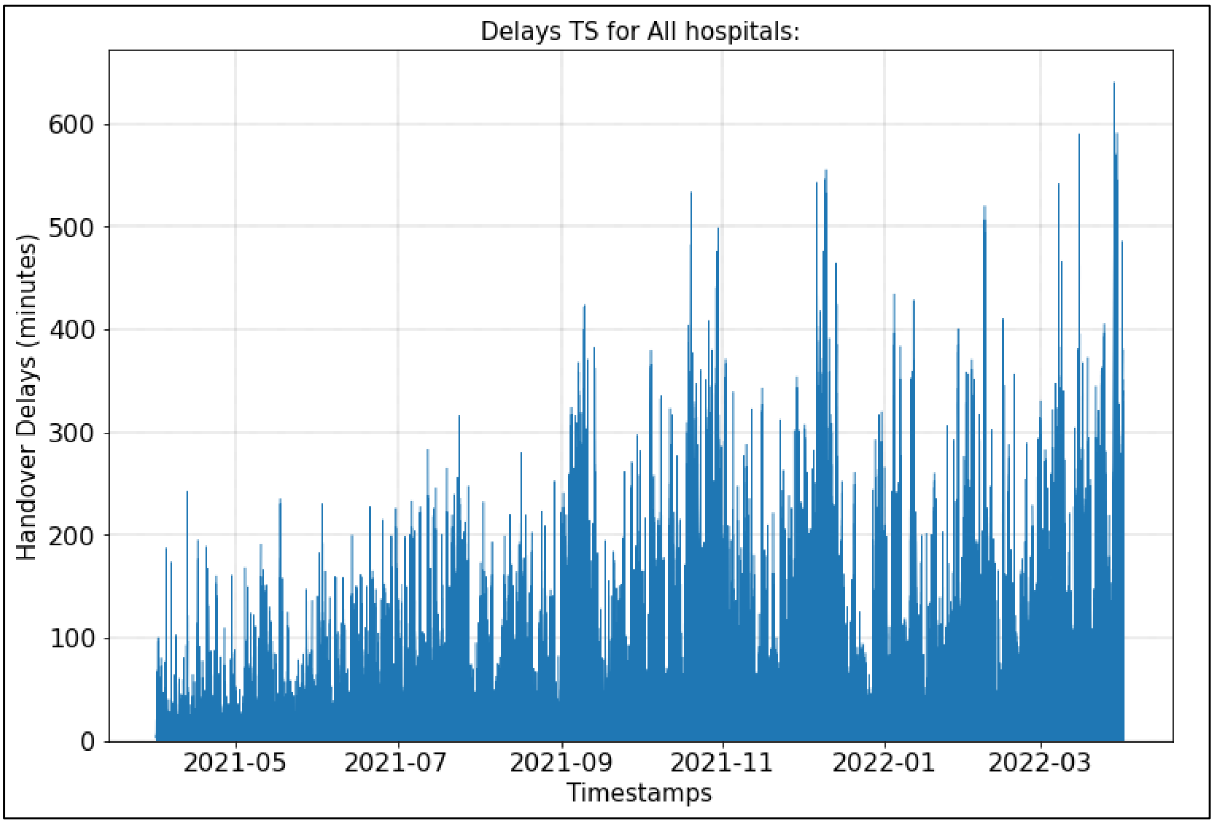


Figure 48: Count of handover delays at all hospitals over 1 year

Figure 49 below shows the *number of ambulance arrivals* at all the hospitals over a 1-week period. It can be seen that here as well there is a pattern in the data, with the number of ambulance arrivals starting to increase as from around mid-day every day, and then decreasing later on during the night.

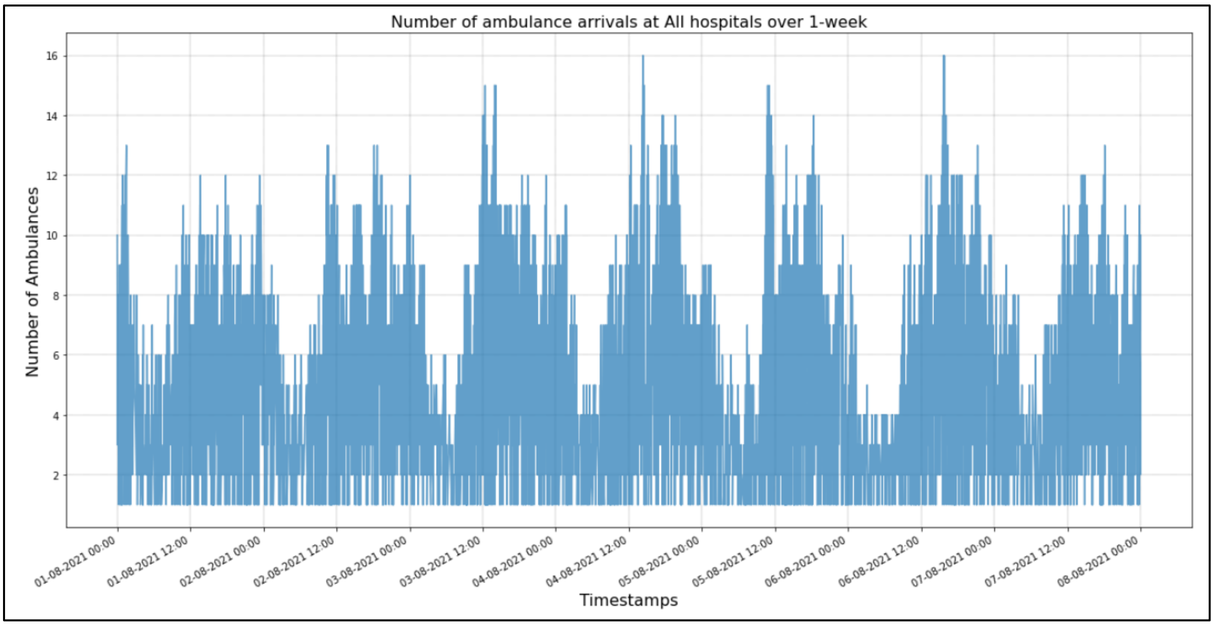


Figure 49: Count of ambulance arrivals to all hospitals over 1 week

Naïve Bayes

The Naïve Bayes makes use of the Bayes' Theorem which finds the probability of an event occurring given the probability of another event that has already occurred.

First, the distribution of the handover delays was checked. It could be noted that the handover delays were not normally distributed, which is one of the major assumptions of the Naïve Bayes model. Therefore, this approach could not be used for the modelling.

The distribution of the handover delay is shown in Figure 50 below. Please note that the cases where there were no delays have been excluded before making the plot.

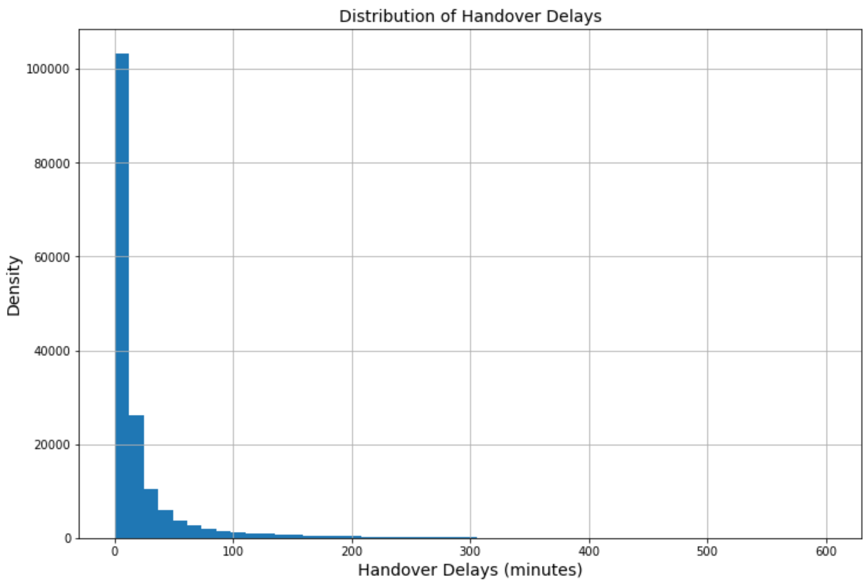


Figure 50: Distribution of handover delays

Annex K – Package Licenses

The licenses for the different work packages used in this project are provided in the Table 34 below:

Package Name	Version	Licences
matplotlib-base	3.5.2	LicenseRef-PSF-based
matplotlib-inline	0.1.3	BSD-3-Clause
numpy	1.22.4	BSD-3-Clause
pandas	1.4.2	BSD-3-Clause
requests	2.27.1	Apache-2.0
scikit-learn	1.1.1	BSD-3-Clause
shapely	1.8.2	BSD-3-Clause
seaborn	0.11.2	BSD-3-Clause
seaborn-base	0.11.2	BSD-3-Clause
typing-extensions	4.2.0	PSF-2.0

Table 9: Licences for packages used