

Maternity Service Capacity – Model, Simulation & Analysis

CONTENTS

Objective 1 - Model current Maternity Service activity using process mapping and queuing network analysis 1.1 Raw Data Manipulation & Variability Analysis\ 1.2 Establish Input Profiles for Mathematical Model

Objective 2 - Determine current capacity requirements using simulation and mathematical modeling 2.1 Current Capacity Requirements – Historical Data\ 2.2 Current Capacity Requirements – Simulated Model\ 2.3 Results Analysis – Simulated Model Accuracy

Objective 3 - Determine future capacity requirements at 5 and 10 years based on population demographics projections data. 3.1 Capacity Requirements – 5 year forecast\ 3.2 Capacity Requirements – 10 year forecast

Objective 1 – Model current Maternity Service activity using process mapping and queuing network analysis

1.1. RAW DATA MANIPULATION & VARIABILITY ANALYSIS

Aim: Convert the raw data from the extracted hospital data into a form that can be analysed.\ Analysis how different events vary the three critical inputs for the mathematical model;

- Inter-arrival Time,
- Length of Stay, and
- Patient Flow Probability

IMPORT PROJECT LIBRARIES

```
In [2]: import pandas as pd
import datetime
import time
import os
#import dash # USE THIS IF RUNNING ON SERVER
import dash_core_components as dcc
import dash_html_components as html
from dash.dependencies import Input, Output
import plotly.express as px
#import plotly.io as pio
import plotly.graph_objects as go
from plotly.subplots import make_subplots
from jupyter_dash import JupyterDash # USE THIS IF RUNNING ON JUPYTER
import numpy as np
import math
```

CONVERSION OF EVENTS INTO LIKE GROUPINGS

Based on results of variability analysis events that have the same profile for the three mathematical models are grouped together.\ Grouping like factors together improves the accuracy of the model by providing more historical data points

```
In [3]: ##### CONVERSION FACTORS BASED ON FINDINGS FROM VARIABILITY ANALYSIS
timeconv = {'Admission_Period': ['Planned', 'Unplanned', 'Unplanned', 'Unplanned',
                                'Planned', 'Planned', 'Planned', 'Unplanned',
                                'Unplanned', 'Unplanned', 'Unplanned', 'Unplanned',
                                'Planned', 'Planned', 'Planned', 'Planned', 'Planned'],
            'Hour_of_Day': [0, 1, 2, 3, 4, 5,
                           6, 7, 8, 9, 10, 11,
                           12, 13, 14, 15, 16, 17,
                           18, 19, 20, 21, 22, 23]}

dayconv = {'Day_Type': ['Weekday', 'Weekday', 'Weekday', 'Weekday', 'Weekday', 'Weekend', 'Weekend'],
           'Day': [0, 1, 2, 3, 4, 5, 6]}

event_activity = {'Event_Activity': ['High', 'High', 'High', 'Low', 'Normal', 'Normal', 'Normal'],
                  'Event': ['AFTERXMAS', 'B4EASTER', 'BEFOREXMAS', 'EASTER', 'NOEASTER', 'NOEASTER', 'NOEASTER'],
                  'Event_Significance': [3, 3, 3, 1, 3, 3, 1, 2]}
}
```

```
In [4]: timeconv_df = pd.DataFrame.from_dict(timeconv)
timeconv_df
```

Out[4]:

	Admission_Period	Hour_of_Day
0	Planned	0
1	Unplanned	1
2	Unplanned	2
3	Unplanned	3
4	Unplanned	4
5	Planned	5
6	Planned	6
7	Planned	7
8	Planned	8
9	Unplanned	9
10	Unplanned	10
11	Unplanned	11
12	Unplanned	12
13	Unplanned	13
14	Unplanned	14
15	Unplanned	15
16	Unplanned	16
17	Planned	17
18	Planned	18
19	Planned	19
20	Planned	20
21	Planned	21
22	Planned	22
23	Planned	23

In [5]:

```
dayconv_df = pd.DataFrame.from_dict(dayconv)
dayconv_df
```

Out[5]:

	Day_Type	Day
0	Weekday	0
1	Weekday	1
2	Weekday	2
3	Weekday	3
4	Weekday	4
5	Weekend	5
6	Weekend	6

	Day_Type	Day
0	Weekday	0
1	Weekday	1
2	Weekday	2
3	Weekday	3
4	Weekday	4
5	Weekend	5
6	Weekend	6

In [6]:

```
event_activity_df = pd.DataFrame.from_dict(event_activity)
event_activity_df
```

Out[6]:

	Event_Activity	Event	Event_Significance
0	High	AFTERXMAS	3
1	High	B4EASTER	3
2	High	BEFOREXMAS	3
3	Low	EASTER	1
4	Normal	NONE	3
5	Normal	SCHOOL	3
6	Low	XMAS	1
7	Low	PUBLIC	2

FUNCTIONS FOR DATA MANIPULATION

In [7]:

```
def clean_transfers_data():
    ##### CLEAN TRANSFERS DATA
    df = pd.read_csv('transfers.csv')
    df = df.rename(columns = {'Start_Bed_Dttm': 'Start', 'End_Bed_Dttm': 'End'})
    df = df.drop(columns=['Transfers', 'Bed_Code', 'Full Flow Code', 'Current Flow Code'])
    date_cols = ['Start', 'End']
    df[date_cols] = df[date_cols].apply(pd.to_datetime, format='%d/%m/%y %H:%M:%S')
    return df

def clean_events_data():
    ##### CLEAN EVENTS AND PUBLIC HOLIDAY DATA
    df = pd.read_csv('exception_dates.csv')
    df = df.rename(columns = {'DATE': 'Date', 'EVENT': 'Event'})
    df['Date'] = df['Date'].apply(pd.to_datetime, format='%d/%m/%Y', errors='coerce')
    df['Date'] = df['Date'].dt.date
    df = pd.merge(df, event_activity_df, how='left', on='Event')
    df = df.sort_values(['Date', 'Event_Significance'], ascending = True)
    df = df.groupby(['Date']).first().reset_index()
    df = df.drop(columns=['Event_Significance'])
```

```

return df

def drop_records(df):
    ##### DROPS WARD CODES DPS AND ON FROM THE ANALYSIS
    index_names = df.loc[(df.Ward_Code == 'DPS') | (df.Ward_Code == 'ON')]
    df = df.drop(index_names)
    return df

def add_next_ward(df):
    ##### ADDS A COLUMN TO THE DATA TABLE THAT SHOWS WHICH WARD THE PATIENT
    df = df.sort_values(['Link', 'Start'])
    df['Next_Ward'] = np.where(df.Link == df.Link.shift(-1), df.Ward_Code.s
                                np.where(df.Ward_Code != 'OUT', 'OUT', 'NONE')

    return df

def add_out_transfer(df):
    ##### ADDS RECORD IN ROW IN RECORD TO SHOW WHEN THE PATIENT LEAVES TH
    df = df.loc[df.Next_Ward == 'OUT',:].copy()
    df['Start'] = df['End']
    df['Ward_Code'] = 'OUT'
    df['Next_Ward'] = 'NONE'
    return df

def add_hierarical_data(df):
    ##### ADD HIERARICAL DATA TO THE DATASET
    #DAY OF THE WEEK
    df = df.dropna(subset=['Start'])
    df = df.copy()
    df['Day'] = df.Start.dt.weekday
    df = pd.merge(df, dayconv_df, how='left', on='Day')
    #MONTH NAME
    df['Month'] = df.Start.dt.month_name()
    #YEAR
    df['Year'] = df.Start.dt.year
    #HOUR OF DAY
    df['Hour_of_Day'] = df.Start.dt.hour
    df = pd.merge(df, timeconv_df, how='left', on='Hour_of_Day')
    df.drop(columns='Hour_of_Day')
    #DATE WITHOUT TIME
    df['Date'] = df.Start.dt.date
    return df

def add_events_data(df):
    ### ADD EVENTS TO DATASET
    df = pd.merge(df, events_df, how='left', on='Date')
    df['Event'] = df['Event'].fillna('NONE')
    df['Event_Activity'] = df['Event_Activity'].fillna('Normal')
    return df

def prev_flow(df, n):
    ##### ADD A CALCULATES WHERE THE PATIENT HAS BEEN PRIOR TO THE CURRENT
    for i in range(n, 0, -1):
        df.Prev_Flow = np.where(df.Link == df.Link.shift(i),
                                df.Prev_Flow + '-' + df.Ward_Code.shift(i))

    return df.Prev_Flow

def ideal_flow_conversion(df):
    ##### RENAME WARD_CODES THAT ARE NOT PART OF THE IDEAL PATH AND DELE
    #CA, CL & HE Codes are converted to MT
    df.loc[(df['Ward_Code'] == 'CA') | (df['Ward_Code'] == 'CL') | (df['Ward
    df.loc[(df['Next_Ward'] == 'CA') | (df['Next_Ward'] == 'CL') | (df['Nex

```

```

# PATIENT PREVIOUS FLOW PATH
df = df.sort_values(['Link', 'Start'])
df['Prev_Flow'] = 'IN'
df['Prev_Flow'] = prev_flow(df, 7)
# REMOVE DUPLICATE ENTRIES CAUSED BY REPLACING WARD CODES WITH IDEAL W
duplicate_df = df.loc[(df.Ward_Code == df.Next_Ward) | (df.Ward_Code == c
duplicate_grp_df = duplicate_df.groupby(['Link', 'Ward_Code'])
#get the min start date and max end date from the grouped results
df['min_start'] = duplicate_grp_df['Start'].transform('min')
df['max_end'] = duplicate_grp_df['End'].transform('max')
#Drop the Original start & end dates & rename the new calculated start
df['Start'] = np.where(df.min_start.notnull(), df.min_start, df.Start)
df['End'] = np.where(df.max_end.notnull(), df.max_end, df.End)
df = df.sort_values(['Link', 'Start'], ascending = True)
df = df.drop_duplicates(keep='first', subset=['Link', 'Ward_Code', 'Start'])
df = df.drop(columns=['min_start', 'max_end'])
df = df.dropna(subset=['Start'])
return df

def add_analysis_info(df):
##### CALCULATE THE CRITICAL VARIABLES FOR COMPARISON ON THE SIMULA
duration = df['End'] - df['Start']
df['LOS'] = (duration.dt.days * 24) + (duration.dt.seconds / (60*60))
df['LOS'] = df['LOS'].round(2)
# DETERMINE PREVIOUS PATIENT FLOW PATH
#if ('Prev_Flow' in df.columns) == False:
df = df.sort_values(['Sim_Name', 'Sim_No', 'Link', 'Start'])
df['Prev_Flow'] = 'IN'
df['Prev_Flow'] = prev_flow(df, 7)
# SHOW ALL OF THE FLOW CODES FOR PATIENT
df['Full_Flow_Code'] = 1
df['Full_Flow_Code'] = df.groupby(['Sim_Name', 'Sim_No', 'Link'])['Ward_C
df['Full_Flow_Code'] = 'IN' + '-' + df.Full_Flow_Code
#INTERARRIVAL TIME
df = df.sort_values(['Sim_Name', 'Sim_No', 'Start'])
temp_df = df.loc[df.Prev_Flow == 'IN', 'Start'] - df.loc[df.Prev_Flow ==
df['Int_Arrival'] = pd.to_numeric(temp_df.dt.days*24 + temp_df.dt.secon
df['Int_Arrival'] = df.Int_Arrival.round(2)
return df

```

UPDATE HISTORICAL DATA TABLE

Calculate the input variables; Inter-Arrival Time, Patient Flow Path and Length of Stay(LOS).\ Add event information that affect input variables, include; Year, Month, Holidays, Day of Week, Time of Day

```

In [8]: base_df = clean_transfers_data()
events_df = clean_events_data()

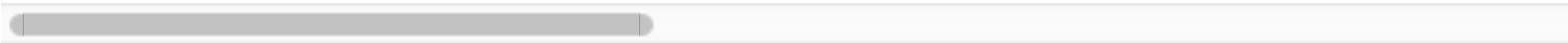
orig_df = base_df.copy(deep=True)
orig_df = drop_records(orig_df)
orig_df = add_next_ward(orig_df)
orig_df = pd.concat([orig_df, add_out_transfer(orig_df)])
orig_df = add_hierarchical_data(orig_df)
orig_df = add_events_data(orig_df)
orig_df['Sim_Name'] = 'orig_hist'
orig_df['Sim_No'] = 1
orig_df = add_analysis_info(orig_df)
orig_df

```

Out[8]:

	Link	Ward_Code	Start	End	Next_Ward	Day	Day_Type	Month	Year
1	ADE-271206	DS	2013-06-27 12:40:00	2013-06-28 10:20:00	MT	3	Weekday	June	2013
280	ADE-282775	MT	2013-06-27 16:00:00	2013-07-01 11:05:00	OUT	3	Weekday	June	2013
3	ADE-271551	MT	2013-06-27 23:54:00	2013-07-01 09:25:00	OUT	3	Weekday	June	2013
286	ADE-282886	MT	2013-06-28 06:30:00	2013-07-02 10:09:00	OUT	4	Weekday	June	2013
2	ADE-271206	MT	2013-06-28 10:20:00	2013-07-03 09:59:00	OUT	4	Weekday	June	2013
...
14657	ADE-501861	OUT	2020-07-29 10:57:00	2020-07-29 10:57:00	NONE	2	Weekday	July	2020
14756	ADE-506202	OUT	2020-07-29 15:58:00	2020-07-29 15:58:00	NONE	2	Weekday	July	2020
14738	ADE-505713	OUT	2020-07-30 09:52:00	2020-07-30 09:52:00	NONE	3	Weekday	July	2020
14633	ADE-501132	OUT	2020-07-31 10:04:00	2020-07-31 10:04:00	NONE	4	Weekday	July	2020
14631	ADE-501113	OUT	2020-08-01 10:01:00	2020-08-01 10:01:00	NONE	5	Weekend	August	2020

14802 rows × 20 columns



MODIFY HISTORICAL DATA TO THE IDEAL FLOW PATH

Convert non-ideal patient flow paths seen in the historical data to a path that the hospital is aiming to achieve to improve patient care and hosipital resourcing.

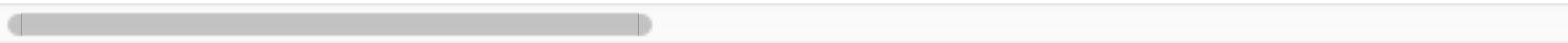
In [9]:

```
ideal_df = ideal_flow_conversion(orig_df.copy())
ideal_df = add_next_ward(ideal_df)
ideal_df['Sim_Name'] = 'ideal_hist'
ideal_df = add_analysis_info(ideal_df)
ideal_df
```

Out[9]:

	Link	Ward_Code	Start	End	Next_Ward	Day	Day_Type	Month	Year
1	ADE-271206	DS	2013-06-27 12:40:00	2013-06-28 10:20:00	MT	3	Weekday	June	2013
280	ADE-282775	MT	2013-06-27 16:00:00	2013-07-01 11:05:00	OUT	3	Weekday	June	2013
3	ADE-271551	MT	2013-06-27 23:54:00	2013-07-01 09:25:00	OUT	3	Weekday	June	2013
286	ADE-282886	MT	2013-06-28 06:30:00	2013-07-02 10:09:00	OUT	4	Weekday	June	2013
2	ADE-271206	MT	2013-06-28 10:20:00	2013-07-03 09:59:00	OUT	4	Weekday	June	2013
...
14657	ADE-501861	OUT	2020-07-29 10:57:00	2020-07-29 10:57:00	NONE	2	Weekday	July	2020
14756	ADE-506202	OUT	2020-07-29 15:58:00	2020-07-29 15:58:00	NONE	2	Weekday	July	2020
14738	ADE-505713	OUT	2020-07-30 09:52:00	2020-07-30 09:52:00	NONE	3	Weekday	July	2020
14633	ADE-501132	OUT	2020-07-31 10:04:00	2020-07-31 10:04:00	NONE	4	Weekday	July	2020
14631	ADE-501113	OUT	2020-08-01 10:01:00	2020-08-01 10:01:00	NONE	5	Weekend	August	2020

14315 rows × 20 columns



1.2 ESTABLISH INPUT PROFILES FOR MATHEMATICAL MODEL

CALCULATE SUMMARY TABLES

Convert input probability distributions into a mathematical model that can be used by the Monte Carlo Simulation

In [10]:

```
def interarrival_summary(df):  
    ##### CREATE SUMMARY TABLE FOR INTERARRIVAL TIME  
    df = df.loc[df.Int_Arrival.notnull(),:]  
    df = df.drop(columns=['Link', 'Ward_Code', 'Day', 'Month', 'Year', 'Hour_of_Day'])  
    #create bins for all of counts  
    df['Int_Arrival_Bins'] = pd.cut(x=df['Int_Arrival'], bins=[0,9,19,29,49], labels=[0,1,2,3,4])  
    #temp_df.Int_Arrival.max() #used to find the biggest number  
    df = df.groupby(['Event_Activity', 'Day_Type', 'Admission_Period', 'Int_Arrival_Bins']).count().reset_index()
```



```

df = df.reset_index()
df['Total_Counts'] = df.groupby(['Event_Activity', 'Day_Type', 'Admission_Period']).Int_Arrival.agg('sum')
df['Arrival_Probability'] = df.Int_Arrival / df.Total_Counts
df['Arrival_Probability'] = df.groupby(['Event_Activity', 'Day_Type', 'Admission_Period']).Arrival_Probability.agg('sum')
df = df.dropna()
df = df.drop(columns = ['Int_Arrival', 'Total_Counts'])
df = df.set_index(['Event_Activity', 'Day_Type', 'Admission_Period', 'Int_Arrival'])
return df

```

```

def year_modification(df):
    ##### CREATE MODIFIER FOR ARRIVAL INTERVAL YEAR TO YEAR & MONTH TO MONTH
    overall_mean = df.groupby(['Prev_Flow']).Int_Arrival.mean().loc['IN']
    df = df.groupby(['Prev_Flow', 'Year']).Int_Arrival.mean().loc['IN'].reset_index()
    df['Int_Arrival'] = df.Int_Arrival / overall_mean
    annual_plot_df = df.copy(deep=True)
    min_date = df.Year[0]
    max_date = df.Year[7]
    min_date_modifier = df.Int_Arrival[0]
    max_date_modifier = df.Int_Arrival[7]
    # Determine Linear equation for year modifier based on 2013 to 2020
    x_yr = np.array([2021, 2022, 2023, 2024, 2025, 2026, 2027, 2028, 2029, 2030])
    A = np.array([[min_date, 1], [max_date, 1]])
    B = np.array([min_date_modifier, max_date_modifier])
    m, b = np.linalg.solve(A, B)
    y_mod = m * x_yr + b
    x_yr = np.append(df['Year'], x_yr)
    y_mod = np.append(df['Int_Arrival'], y_mod)
    # Look up table for year modifier
    year_modifier={'year': x_yr,
                  'modifier': y_mod}
    return pd.DataFrame.from_dict(year_modifier)

```

```

def month_modification(df):
    # Determine Month by Month modifier
    overall_mean = df.groupby(['Prev_Flow']).Int_Arrival.mean().loc['IN']
    df = df.groupby(['Prev_Flow', 'Month']).Int_Arrival.mean().loc['IN'].reset_index()
    df['Int_Arrival'] = df.Int_Arrival / overall_mean
    month_modifier = {'month': df['Month'].values.tolist(),
                     'modifier': df['Int_Arrival'].values.tolist()}
    return pd.DataFrame.from_dict(month_modifier)

```

```

def patient_flow_summary(df):
    ##### CREATE SUMMARY TABLE FOR PATIENT FLOW CODE
    df = df.loc[:, ['Prev_Flow', 'Ward_Code', 'Link']]
    df = df.groupby(['Prev_Flow', 'Ward_Code']).count()['Link']
    df = df.reset_index()
    df = df.rename(columns = {'Link': 'Next_Ward_Count'})
    df['Total_Counts'] = df.groupby(['Prev_Flow']).transform('sum')['Next_Ward_Count']
    df['Cummulative_Count'] = df.groupby(['Prev_Flow']).cumsum()['Next_Ward_Count']
    df['Next_Ward_Cum_Prob'] = df.Cummulative_Count / df.Total_Counts
    df = df.drop(columns=['Next_Ward_Count', 'Total_Counts', 'Cummulative_Count'])
    df = df.set_index(['Prev_Flow', 'Ward_Code'])
    return df

```

```

def LOS_summary(df):
    ##### CREATE SUMMARY TABLE FOR LENGTH OF STAY
    df = df.loc[:, ['Ward_Code', 'Prev_Flow', 'LOS']]
    #df = df.drop(columns=['Link', 'Start', 'End', 'Day', 'Month', 'Year', 'Int_Arrival'])
    #print(df.LOS.describe()) #used to find the biggest number
    df['LOS_Bins'] = pd.cut(x=df['LOS'], bins=[0,19,39,59,79,99,119,139,159,179,199,219,239,259,279,299,319,339,359,379,399,419,439,459,479,499])

```

```

df = df.groupby(['Prev_Flow', 'Ward_Code', 'LOS_Bins']).count()
df = df.reset_index()
df['Total_Counts'] = df.groupby(['Prev_Flow', 'Ward_Code']).transform('sum')
df['LOS_Probability'] = df.LOS / df.Total_Counts
df['LOS_Cum_Probability'] = df.groupby(['Prev_Flow', 'Ward_Code']).cumsum()
df = df.dropna()
df = df.drop(columns = ['Total_Counts', 'LOS', 'LOS_Probability'])
df = df.set_index(['Prev_Flow', 'Ward_Code', 'LOS_Bins'])
return df

```

SUMMARY TABLES

```

In [11]: arrivalsum_df = interarrival_summary(ideal_df.copy(deep=True))
arrivalsum_df

```

Out[11]:

				Arrival_Probability
Event_Activity	Day_Type	Admission_Period	Int_Arrival_Bins	
High	Weekday	Planned	(0, 9]	0.727599
			(9, 19]	0.903226
			(19, 29]	0.978495
			(29, 49]	0.985663
			(49, 59]	0.992832
...
Normal	Weekend	Unplanned	(9, 19]	0.641975
			(19, 29]	0.836420
			(29, 49]	0.984568
			(49, 59]	0.990741
			(59, 69]	1.000000

74 rows × 5 columns

```

In [12]: year_mod_df = year_modification(ideal_df.copy(deep=True))
year_mod_df

```

Out[12]:

	year	modifier
0	2013	1.051309
1	2014	0.956950
2	2015	1.025211
3	2016	1.008904
4	2017	1.115643
5	2018	1.008395
6	2019	0.945023
7	2020	0.894929
8	2021	0.872590
9	2022	0.850250
10	2023	0.827910
11	2024	0.805570
12	2025	0.783230
13	2026	0.760890
14	2027	0.738550
15	2028	0.716210
16	2029	0.693870
17	2030	0.671530
18	2031	0.649190

In [13]:

```
month_mod_df = month_modification(ideal_df.copy(deep=True))  
month_mod_df
```

Out[13]:

	month	modifier
0	April	1.028202
1	August	1.063501
2	December	1.000796
3	February	1.012897
4	January	0.907832
5	July	1.154971
6	June	0.963055
7	March	0.981020
8	May	0.974898
9	November	1.054925
10	October	0.926893
11	September	0.962463

In [14]:

```
patientflowsum_df = patient_flow_summary(ideal_df.copy())
patientflowsum_df
```

Out[14]:

		Next_Ward_Cum_Prob
Prev_Flow	Ward_Code	
IN	DS	0.383094
	ICU	0.391663
	MT	1
IN-DS	ICU	0.00602151
	MT	0.877849
	OUT	1
IN-DS-ICU	MT	1
IN-DS-ICU-MT	OUT	1
IN-DS-MT	DS	0.00296004
	ICU	0.00641342
	OUT	1
IN-DS-MT-DS	MT	1
IN-DS-MT-DS-MT	OUT	1
IN-DS-MT-ICU	MT	1
IN-DS-MT-ICU-MT	OUT	1
IN-ICU	MT	0.961538
	OUT	1
IN-ICU-MT	OUT	1
IN-MT	DS	0.00379198
	ICU	0.00568797
	OUT	1
IN-MT-DS	ICU	0.0714286
	MT	1
IN-MT-DS-ICU	DS	1
IN-MT-DS-ICU-DS	MT	1
IN-MT-DS-ICU-DS-MT	OUT	1
IN-MT-DS-MT	OUT	1
IN-MT-ICU	MT	1
IN-MT-ICU-MT	ICU	0.142857
	OUT	1
IN-MT-ICU-MT-ICU	MT	1
IN-MT-ICU-MT-ICU-MT	OUT	1

```
In [15]: LOSsum_df = LOS_summary(ideal_df.copy())
        LOSsum_df
```

Out[15]:

		LOS_Cum_Probability	
Prev_Flow	Ward_Code	LOS_Bins	
IN	DS	(0, 19]	0.396129
		(19, 39]	0.934194
		(39, 59]	0.991398
		(59, 79]	0.998710
		(79, 99]	0.999570
...
IN-MT-ICU	MT	(59, 79]	0.714286
		(79, 99]	0.857143
		(239, 259]	1.000000
IN-MT-ICU-MT	ICU	(0, 19]	1.000000
IN-MT-ICU-MT-ICU	MT	(139, 159]	1.000000

106 rows × 1 columns

Objective 2 - Determine current capacity requirements using simulation and mathematical modeling

2.1 - CURRENT CAPACITY REQUIREMENTS - HISTORICAL DATA

CALCULATE CURRENT OCCUPANCY

```
In [16]: def add_patient_occupancy(df):
        ### ADDS PATIENT OCCUPANCY TO THE DATA
        #### add for loop that runs through all sims and all sim numbers
        sim_names = df.Sim_Name.unique()
        for sim_name in sim_names:
            sim_nos = df.Sim_No.unique()
            for sim_no in sim_nos:
                df = df.loc[(df.Sim_Name == sim_name) & (df.Sim_No == sim_no),:]
                df = df.sort_values(['Start'])
                df['MT_Occupancy'] = 0
                df['DS_Occupancy'] = 0
                df['MT_Occupancy'] = np.where((df.Prev_Flow.str[-2:] == 'MT') &
                                                np.where((df.Ward_Code == 'MT') &
                                                         (df.Start > 0)), 1, 0)
                df['DS_Occupancy'] = np.where((df.Prev_Flow.str[-2:] == 'DS') &
                                                np.where((df.Ward_Code == 'DS') &
                                                         (df.Start > 0)), 1, 0)
            return df
```

HISTOGRAM FUNCTION FOR DATA VISUALISATION

```
In [17]: def plot_histogram(df, x_axis, plot_type, folder_loc, name, sim_name):
    filename = folder_loc + '/' + sim_name + '_' + x_axis + '_' + plot_type
    if plot_type == 'Histogram':
        fig = px.histogram(df, x=x_axis, nbins=20)
        #fig.show()
        fig.write_image(filename)
    if plot_type == 'Cumulative Histogram':
        x_axis_values = df.loc[:,x_axis]
        fig = go.Figure(data=[go.Histogram(x=x_axis_values, cumulative_enabled=True)])
    fig.update_layout(
        title = sim_name + " - " + name,
        xaxis_title = x_axis,
        yaxis_title = "Count"
    )
    fig.write_image(filename)
    fig.show()

def new_dir(folder_name):
    today = datetime.date.today()
    todaystr = today.isoformat()
    full_path = folder_name + todaystr
    if not(os.path.isdir(full_path)):
        os.mkdir(full_path)
    return full_path
```

OCCUPANCY PROFILE VISUALISATION - ORIGINAL HISTORICAL

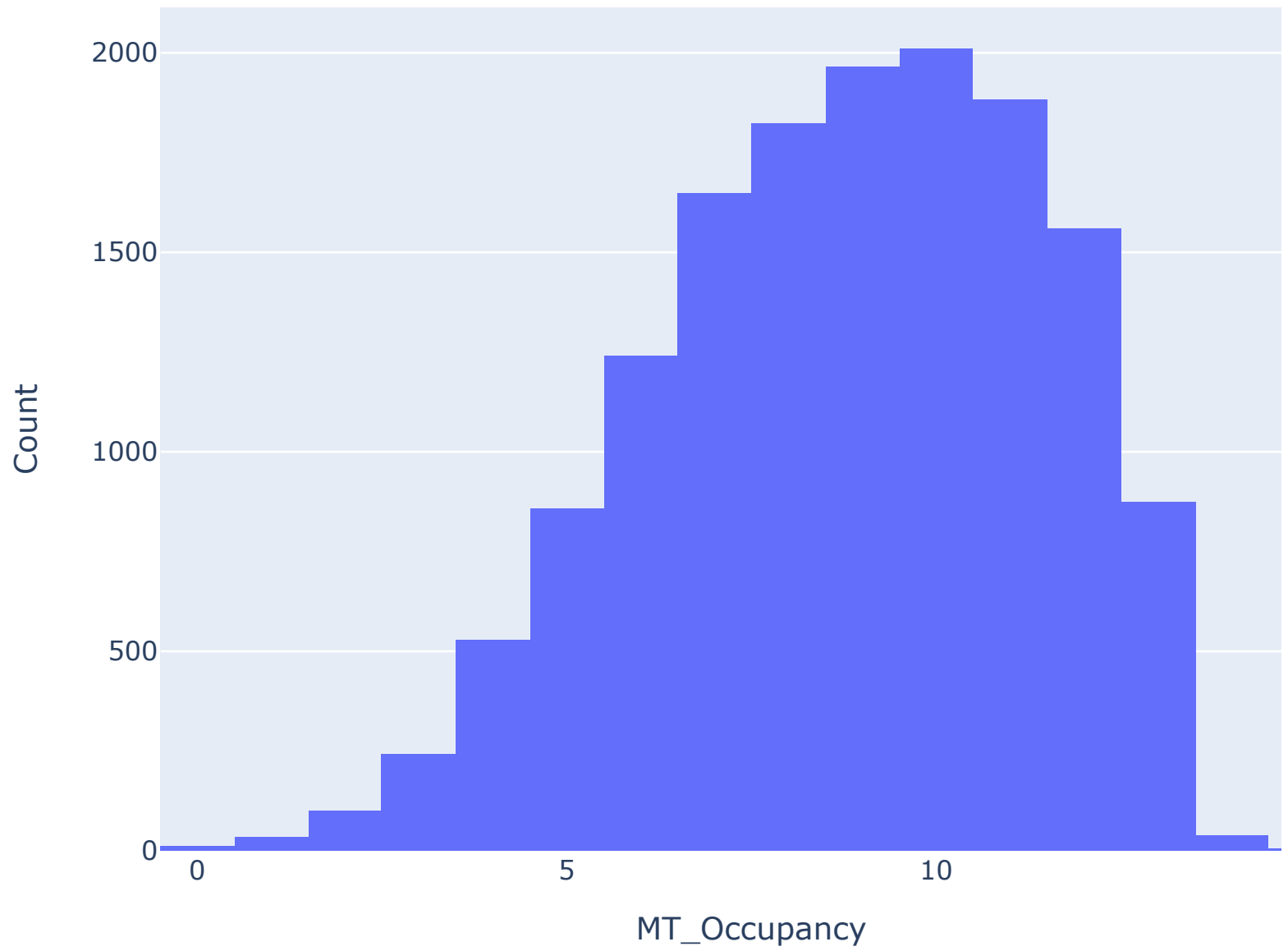
```
In [18]: orig_df = add_patient_occupancy(orig_df)
orig_df.loc[:,['MT_Occupancy', 'DS_Occupancy']].describe()
```

```
Out[18]:
```

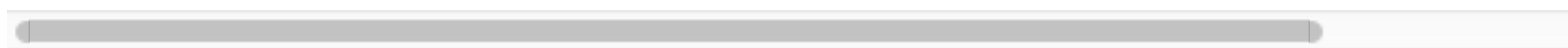
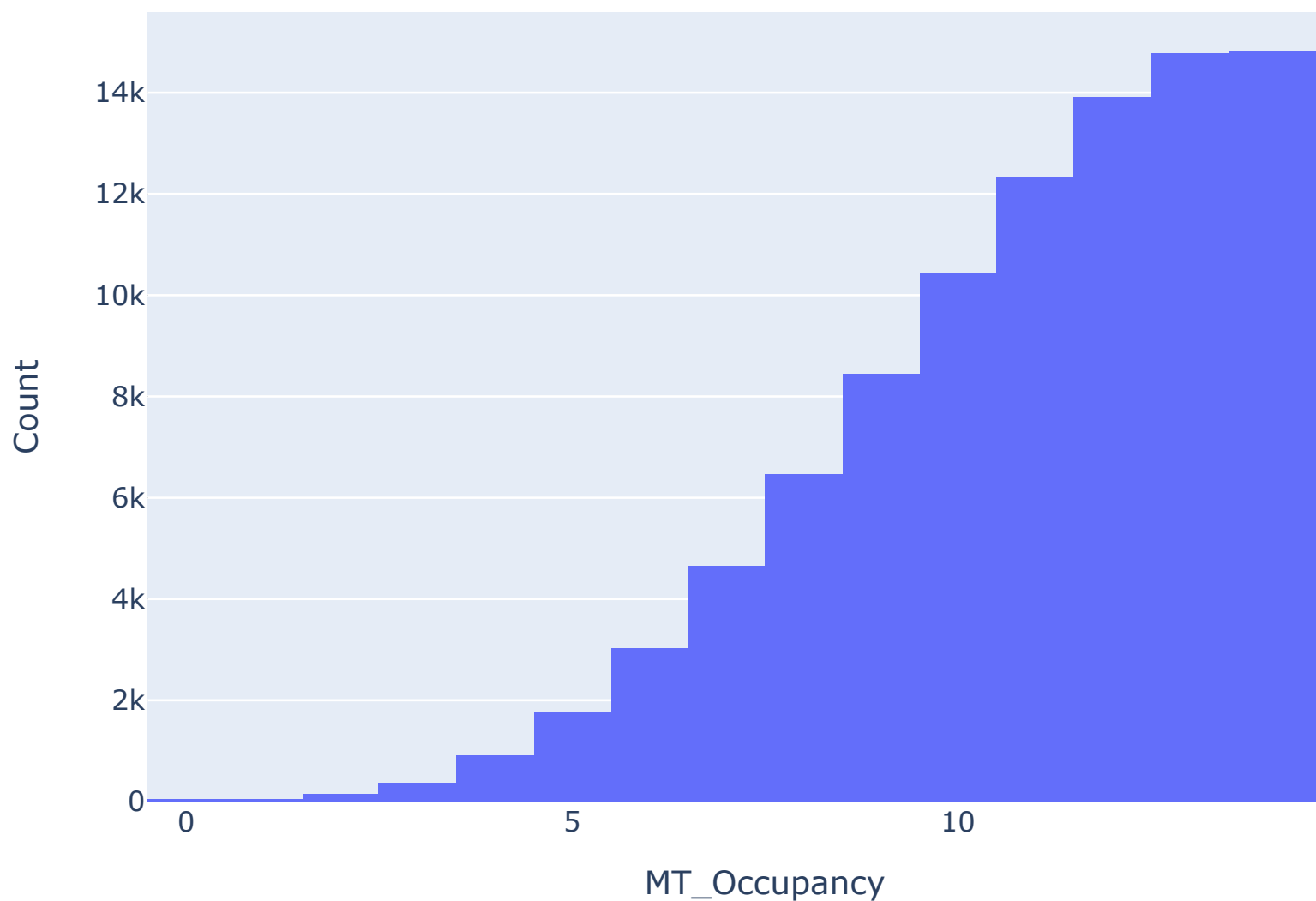
	MT_Occupancy	DS_Occupancy
count	14802.000000	14802.000000
mean	8.781921	1.054655
std	2.607231	1.024357
min	0.000000	0.000000
25%	7.000000	0.000000
50%	9.000000	1.000000
75%	11.000000	2.000000
max	15.000000	5.000000

```
In [19]: plot_histogram(orig_df, 'MT_Occupancy', 'Histogram', new_dir('plots/'), 'Ma
plot_histogram(orig_df, 'MT_Occupancy', 'Cumulative Histogram', new_dir('p
plot_histogram(orig_df, 'DS_Occupancy', 'Histogram', new_dir('plots/'), 'De
plot_histogram(orig_df, 'DS_Occupancy', 'Cumulative Histogram', new_dir('p
```

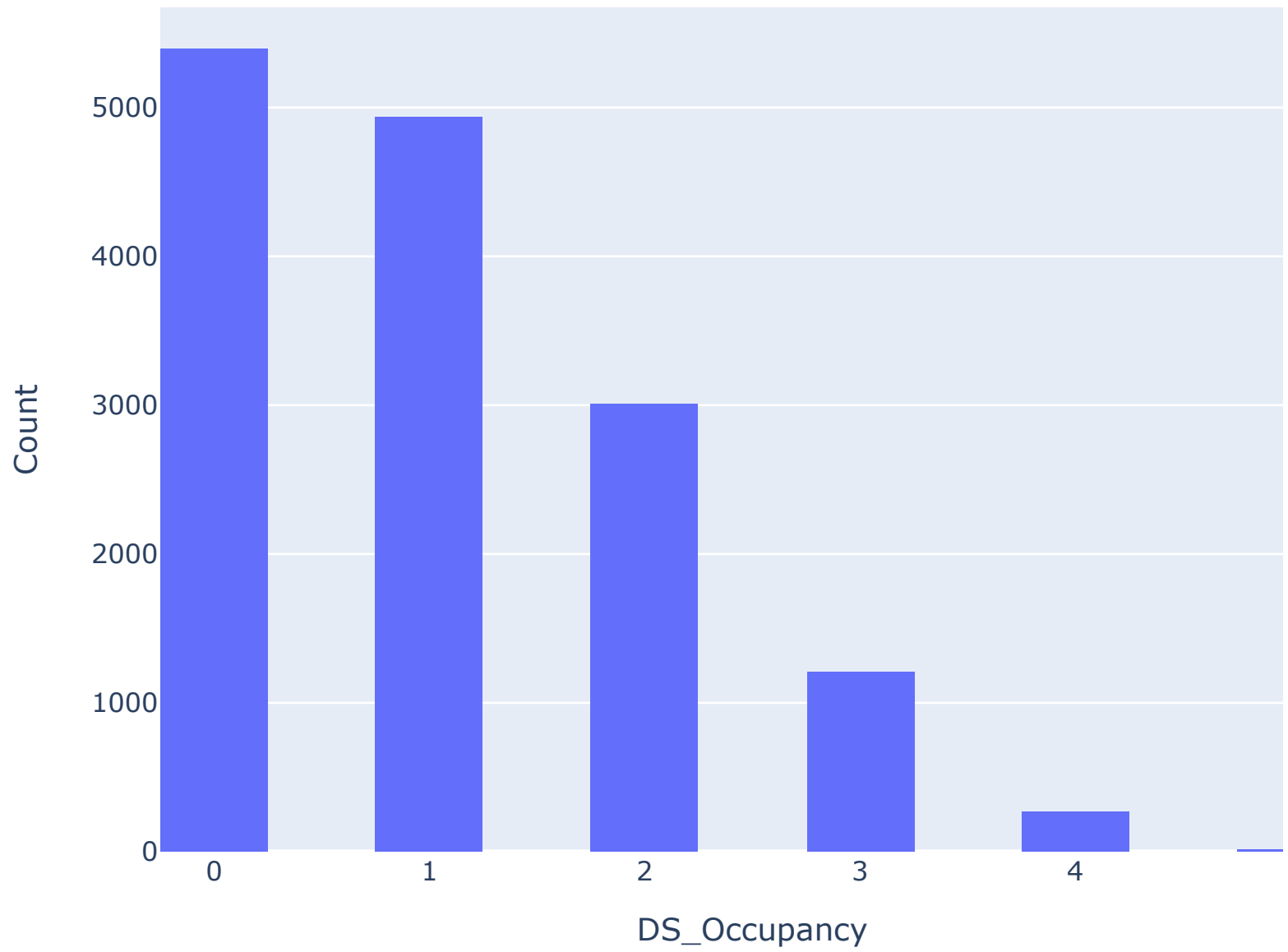
Original Historical - Maternity Occupancy Probability Distribution



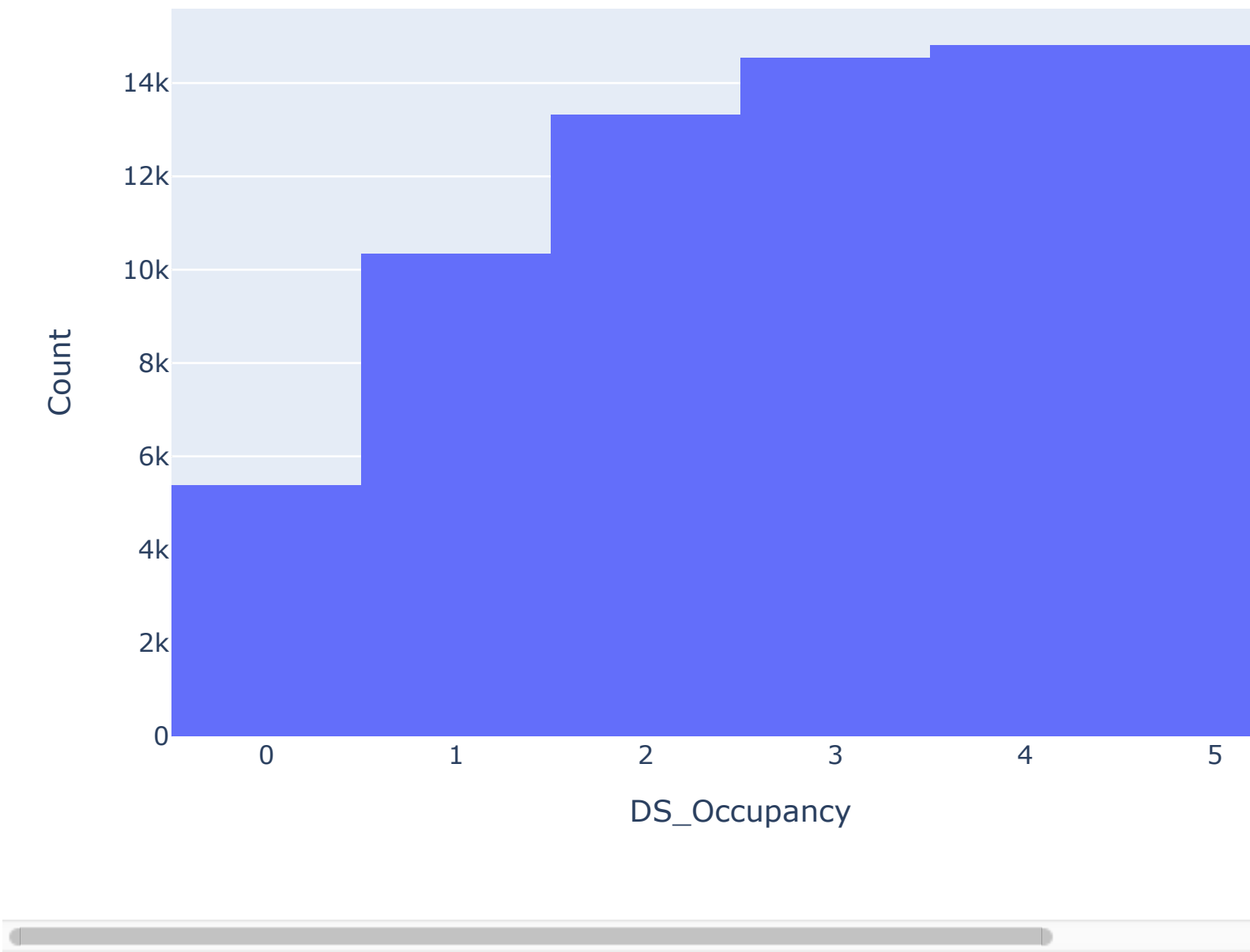
Original Historical - Maternity Occupancy Cumulative Probability I



Original Historical - Delivery Suite Occupancy Probability Distribu



Original Historical - Delivery Suite Occupancy Cumulative Probab



OCCUPANCY PROFILE VISUALISATION - IDEAL FLOW HISTORICAL

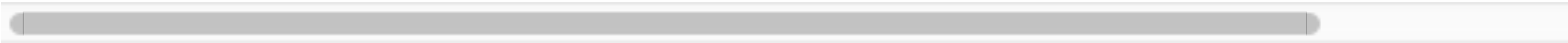
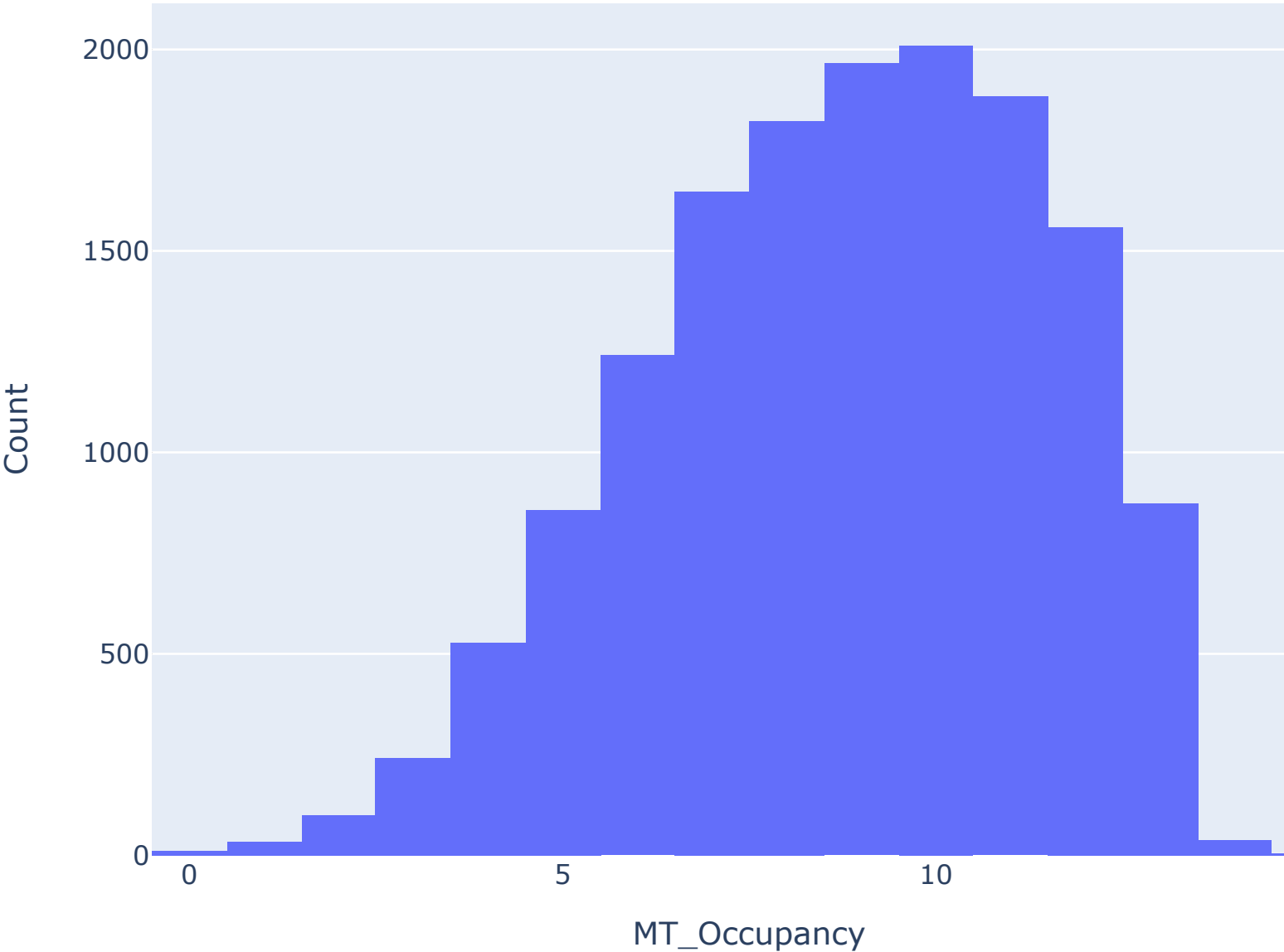
```
In [20]: ideal_df = add_patient_occupancy(ideal_df)
         ideal_df.loc[:,['MT_Occupancy', 'DS_Occupancy']].describe()
```

Out[20]:

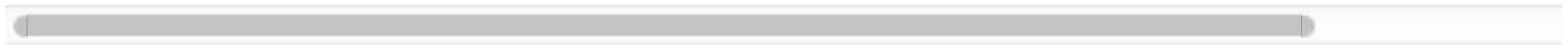
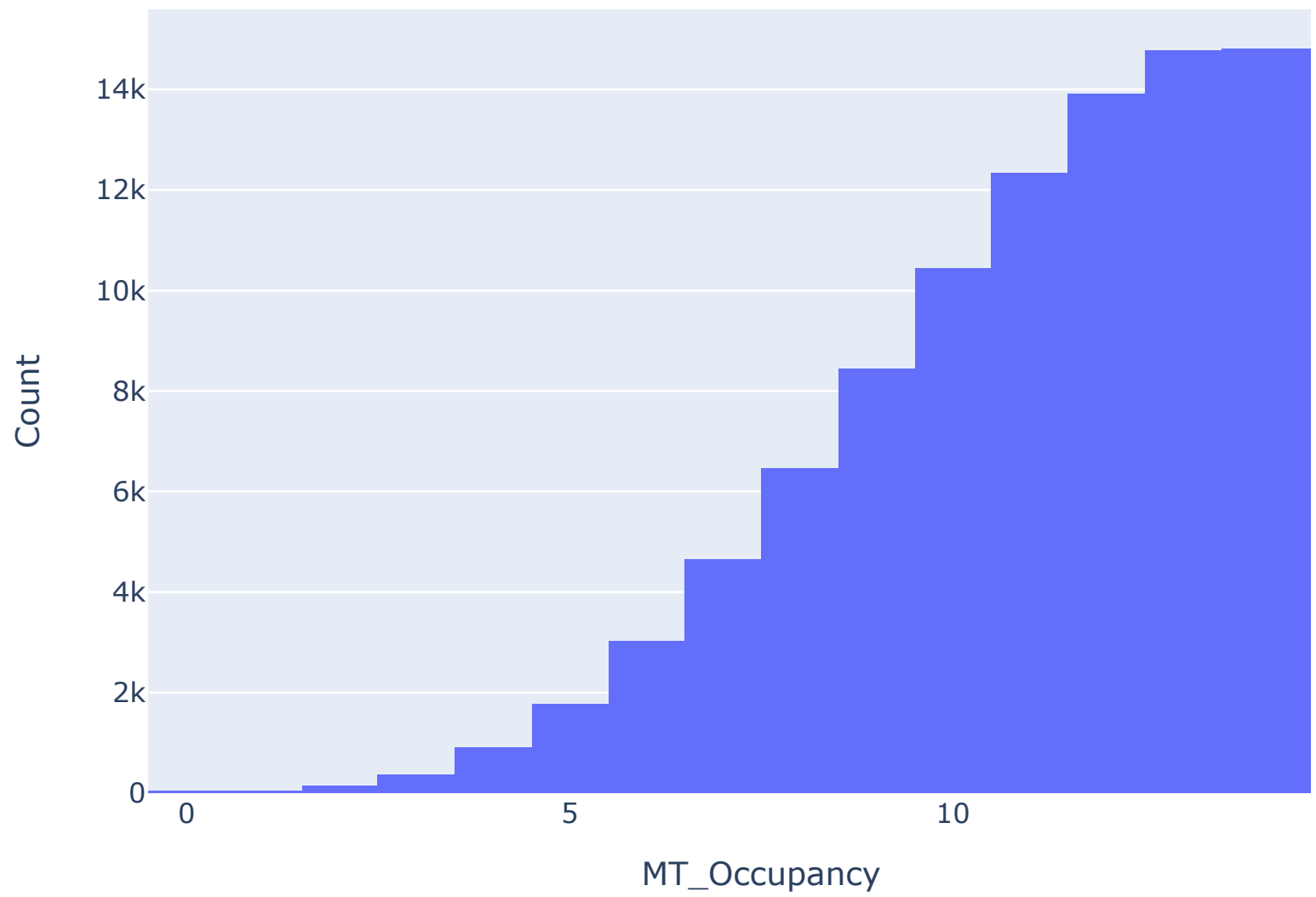
	MT_Occupancy	DS_Occupancy
count	14315.000000	14315.000000
mean	9.064198	1.059029
std	2.964369	1.023857
min	0.000000	0.000000
25%	7.000000	0.000000
50%	9.000000	1.000000
75%	11.000000	2.000000
max	20.000000	5.000000

```
In [21]: plot_histogram(orig_df, 'MT_Occupancy', 'Histogram', new_dir('plots/'), 'Maternity Occupancy')
plot_histogram(orig_df, 'MT_Occupancy', 'Cummulative Histogram', new_dir('plots/'), 'Maternity Occupancy')
plot_histogram(orig_df, 'DS_Occupancy', 'Histogram', new_dir('plots/'), 'Delivery Suite Occupancy')
plot_histogram(orig_df, 'DS_Occupancy', 'Cummulative Histogram', new_dir('plots/'), 'Delivery Suite Occupancy')
```

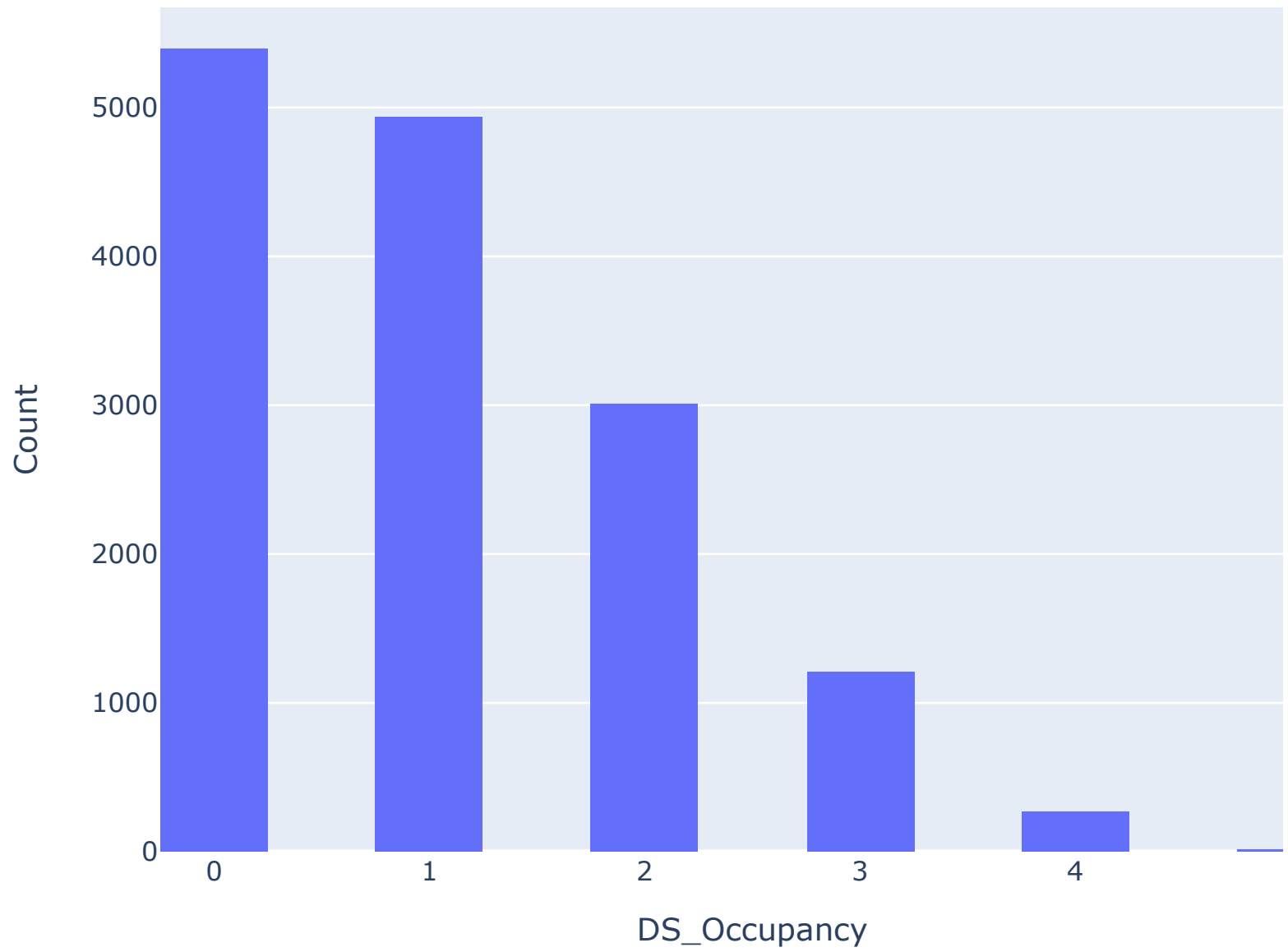
Ideal Patient Flow Historical - Maternity Occupancy Probability Distribution



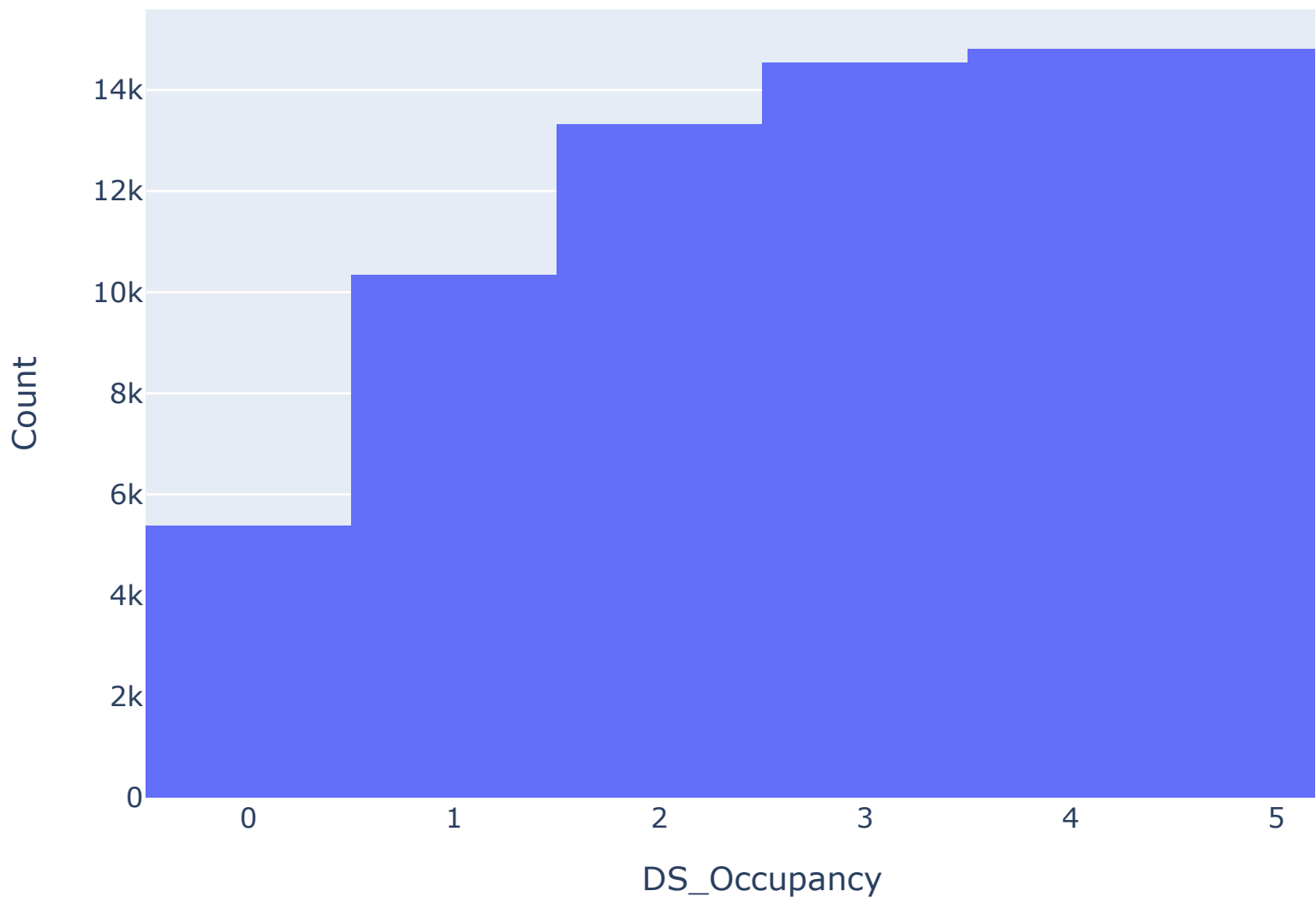
Ideal Patient Flow Historical - Maternity Occupancy Cumulative Pi



Ideal Patient Flow Historical - Delivery Suite Occupancy Probability



Ideal Patient Flow Historical - Delivery Suite Occupancy Cumulative



SIMULATION CODE

```
In [22]: def next_arrival(df, event_activity, day_type, admission_period, from_year,
xp = pd.Series([0]).append(df.loc[event_activity, day_type, admission_p
fp = pd.Index([0]).append(df.loc[event_activity, day_type, admission_p
random_no = np.random.rand()
result = np.interp(random_no, xp, fp) # Straight result based on Mean
year_mod = year_mod_df.loc[year_mod_df.year == from_year, 'modifier'].i
month_mod = month_mod_df.loc[month_mod_df.month == from_month, 'modifier
result_modified = result * year_mod * month_mod
return result_modified
#print(next_arrival(arrivalsum_df, 'High', 'Weekday', 'Planned', 2020, 'Jan

def date_to_hierarchy(date_stamp):
    date_stamp = pd.Timestamp(date_stamp, unit='%d/%m/%Y %H:%M:%S')
    #Extract time period
    hour_of_day = date_stamp.hour
    admission_period = timeconv['Admission_Period'][hour_of_day]
    #Extract type of day (i.e Weekday or Weekend)
    day_of_week = date_stamp.dayofweek
    day_type = dayconv['Day_Type'][day_of_week]
    #Extract Event based activity
    date_only = date_stamp.date()
```

```

    try: event = events_df.groupby('Date').Event.first().loc[date_only]
    except: event = 'NONE'
    event_index_no = event_activity['Event'].index(event)
    event_activity_level = event_activity['Event_Activity'][event_index_no]
    #Extract Month
    month = date_stamp.month_name()
    #Extract Year
    year = date_stamp.year
    return {'Admission_Period':admission_period, 'Day_Type':day_type, 'Event':event}
#print(date_to_hierarchy('01/01/2020 05:00:00'))

def simulate_arrivals(df, n_sims, start, finish):
    results = {'Sim_No':[], 'Arrival_Time':[]}
    current_timestamp = pd.Timestamp(start, unit='%d/%m/%Y')
    finish_timestamp = pd.Timestamp(finish, unit='%d/%m/%Y')
    for i in range(0, n_sims):
        while current_timestamp < finish_timestamp:
            hierarchy = date_to_hierarchy(current_timestamp)
            arrival_interval = round(next_arrival(df, hierarchy['Event_Activity']))
            try: current_timestamp += datetime.timedelta(seconds=arrival_interval)
            except: print(arrival_interval)
            results['Sim_No'].append(i)
            results['Arrival_Time'].append(current_timestamp)
            current_timestamp = pd.Timestamp(start, unit='%d/%m/%Y')
            i += 1
        return results
#print(simulate_arrivals(arrivalsum_df, 2, start, finish))

def simulate_patient_flow(df, group_cat, prev_flow):
    ward_prob = df.loc[(prev_flow)] #group_cat['Event_Activity'], group_cat
    n = ward_prob.count().iloc[0]
    random_no = np.random.rand()
    for i in range(0, n):
        if random_no <= ward_prob.iloc[i,0]:
            ward_code = ward_prob.index[i]
            if (prev_flow == 'IN-MT') & (ward_code == 'MT'):
                print(random_no)
            break
    return ward_code
#print(simulate_patient_flow(patientflow_df, date_to_hierarchy(start), 'IN-MT'))

def simulate_patient_end(df, start, group_cat, prev_flow, ward_code):
    xp = pd.Series([0]).append(df.loc[prev_flow, ward_code].iloc[:,0]) #group_cat
    fp = pd.Index([0]).append(df.loc[prev_flow, ward_code].index.remove_unused_index())
    #print (xp, fp)
    random_no = np.random.rand()
    dec_result = np.interp(random_no, xp, fp)
    end = start + datetime.timedelta(seconds = int(dec_result*60*60))
    return end
#print(simulate_patient_end(LOS_df, start, date_to_hierarchy(start), 'IN-MT', 'MT'))

def run_simulation(n_sims, arrival_df, LOS_df, patientflow_df, start, finish):
    arrivals_data = simulate_arrivals(arrival_df, n_sims, start, finish)
    no_of_admissions = len(arrivals_data['Sim_No'])
    transfer_info = {'Sim_No':[], 'Link':[], 'Ward_Code':[], 'Start':[], 'End':[]}
    sim_no = 1
    print(sim_no)
    for i in range(0, no_of_admissions):
        prev_flow, prev_ward = 'IN', 'IN'
        if sim_no != arrivals_data['Sim_No'][i]:
            sim_no = arrivals_data['Sim_No'][i]

```



```

        print(sim_no)
start = arrivals_data['Arrival_Time'][i]
link = i
patient_discharged = False
group_categories = date_to_hierarchy(start)
while patient_discharged == False:
    ward = simulate_patient_flow(patientflowsun_df, group_categories)
    try: end = simulate_patient_end(LOSsum_df, start, group_categories)
    except:
        end = start
    if ward == 'OUT':
        patient_discharged = True

    transfer_info['Sim_No'].append(sim_no)
    transfer_info['Start'].append(start)
    transfer_info['Link'].append(link)
    transfer_info['Prev_Flow'].append(prev_flow)
    transfer_info['Ward_Code'].append(ward)
    transfer_info['End'].append(end)

    #create new starting information
    start = end
    prev_flow = '-'.join((prev_flow, ward))
    prev_ward = ward
    #patient_discharged = True

results_df = pd.DataFrame.from_dict(transfer_info)
return results_df

```

```

%%time run_simulation(n_sims, arrival_df, LOS_df, patientflow_df, start, f.

```

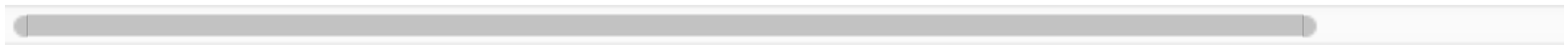
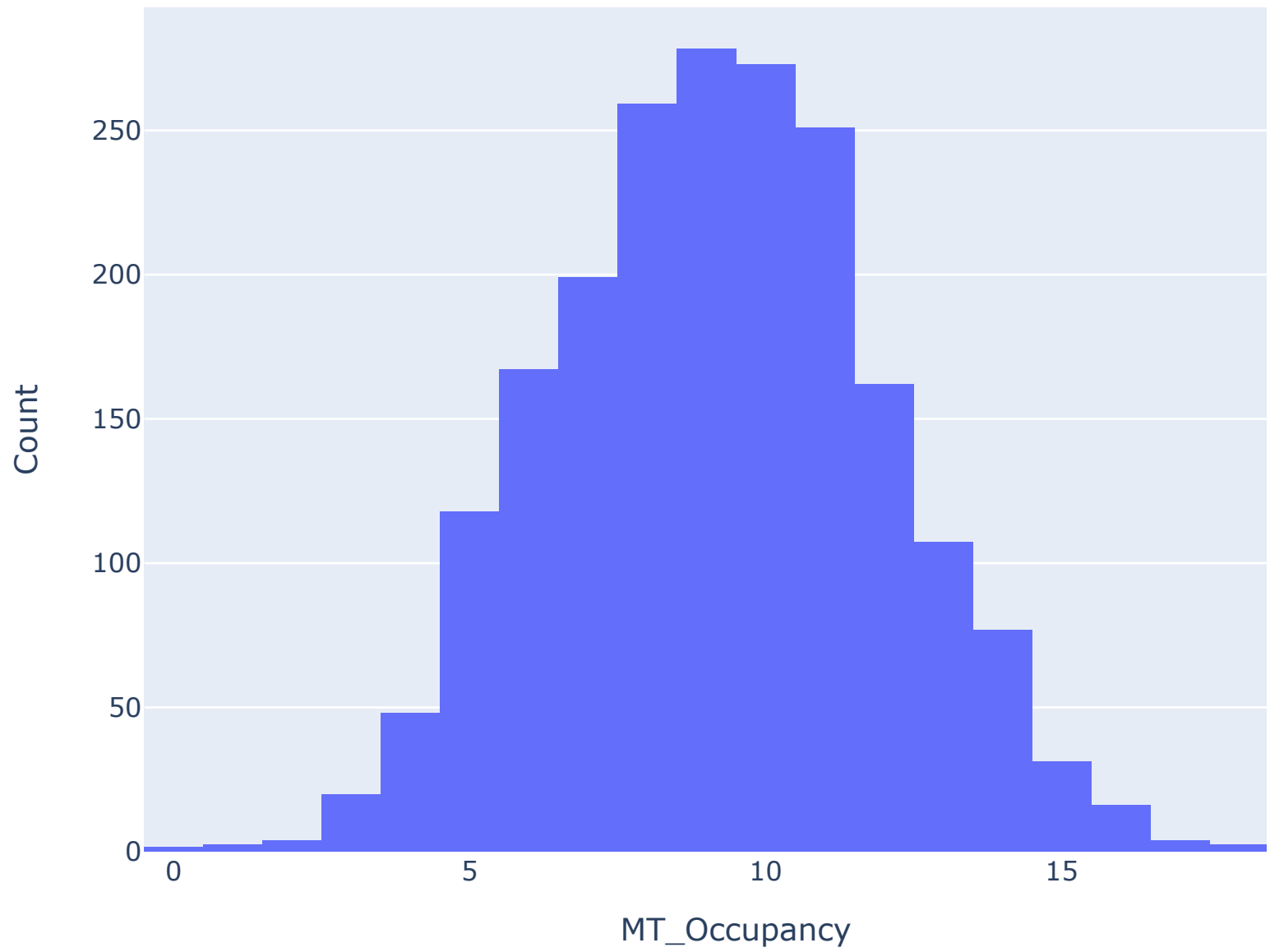
```
In [23]: sim_source = {'no_sims':1,
                        'arrival_df':arrivalsum_df,
                        'LOS_df':LOSsum_df,
                        'patientflow_df':patientflowsun_df,
                        'sims': {'title':['sim2020','sim2025','sim2030'],
                                'start':['01/01/2020','01/01/2025','01/01/2030'],
                                'finish':['01/01/2021','02/01/2026','02/01/2031'],
                                'plot_info': {'name':['Maternity Occupancy Probabilit
                                                'Maternity Occupancy Cumul
                                                'x_axis':['MT_Occupancy','DS_Occupanc
                                                'MT_Occupancy','DS_Occupanc
                                'plot_type':['Histogram','Histogram',
                                                'Cummulative Histogram'],'(
                                }
                        }
                    }
```

```
def all_sims_and_plots(sim_source):
    folder_loc = new_dir('plots/')
    filename = folder_loc + '/Simulation_Data_' + datetime.date.today().iso
    sims = sim_source['sims']
    prev_df = pd.DataFrame()
    no_scenarios = len(sims['title'])
    no_plots = len(sims['plot_info']['name'])
    for i in range(no_scenarios):
        sim_name = sims['title'][i]
        start = pd.Timestamp(sims['start'][i], unit='%d/%m/%Y %H:%M:%S')
        finish = pd.Timestamp(sims['finish'][i], unit='%d/%m/%Y %H:%M:%S')
        print(sim_name)
        df = run_simulation(sim_source['no_sims'], sim_source['arrival_df']
        df['Sim_Name'] = sim_name
        df = add_patient_occupancy(df)
        for n in range(no_plots):
            plot_histogram(df, sims['plot_info']['x_axis'][n], sims['plot_
        if prev_df.empty == False:
            df = pd.concat([df, prev_df])
        prev_df = df.copy()
        ##### ADD ALL DESCRIPTIVE COLUMNS TO SIMULATED DATA
        df = add_next_ward(df)
        df = add_hierarical_data(df)
        #df = add_events_data(df)
        df = add_analysis_info(df)
        df.to_csv(filename, index=False)
    return df
```

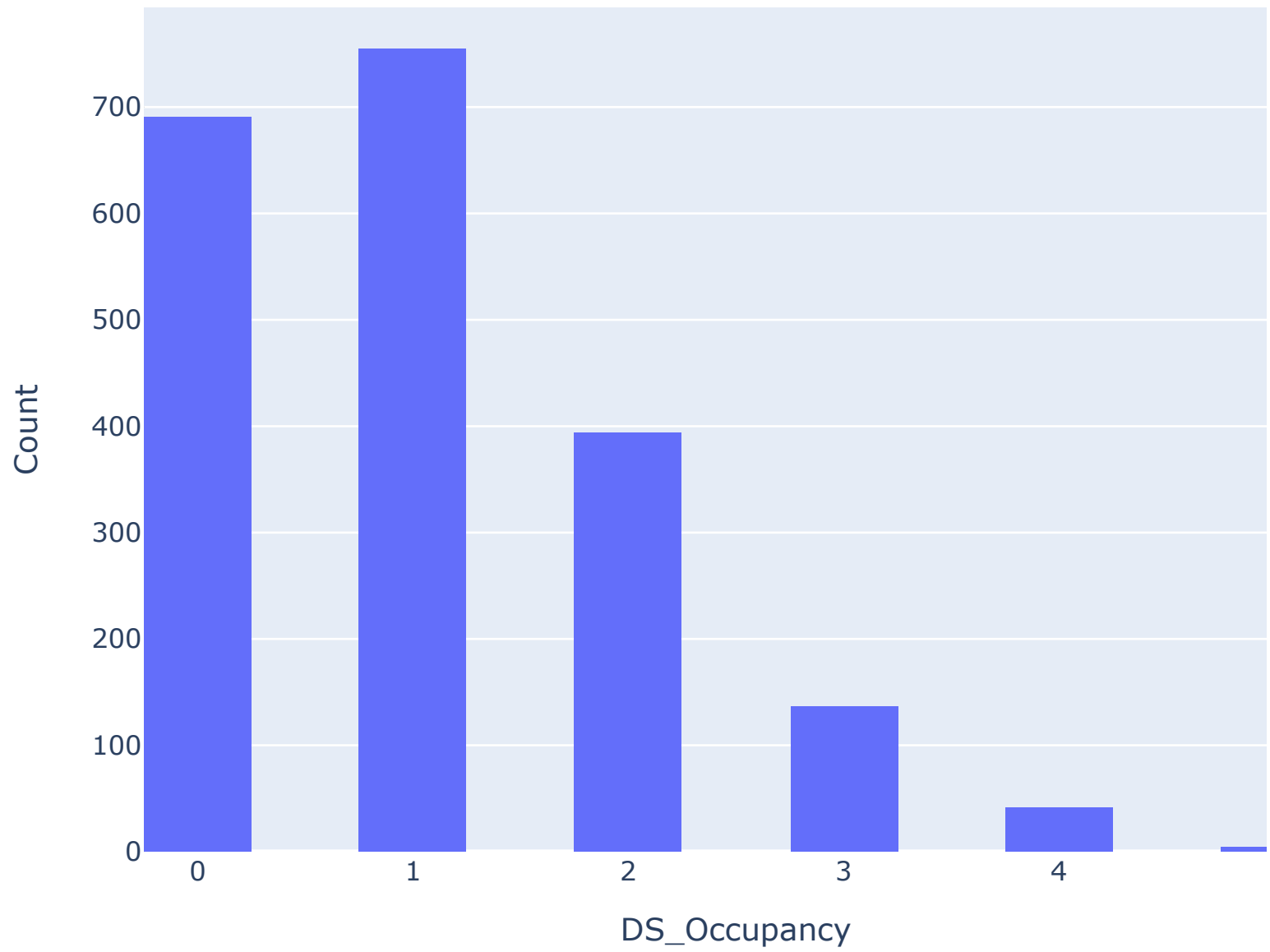
```
%time simrun_df = all_sims_and_plots(sim_source)
```

```
sim2020
1
0
```

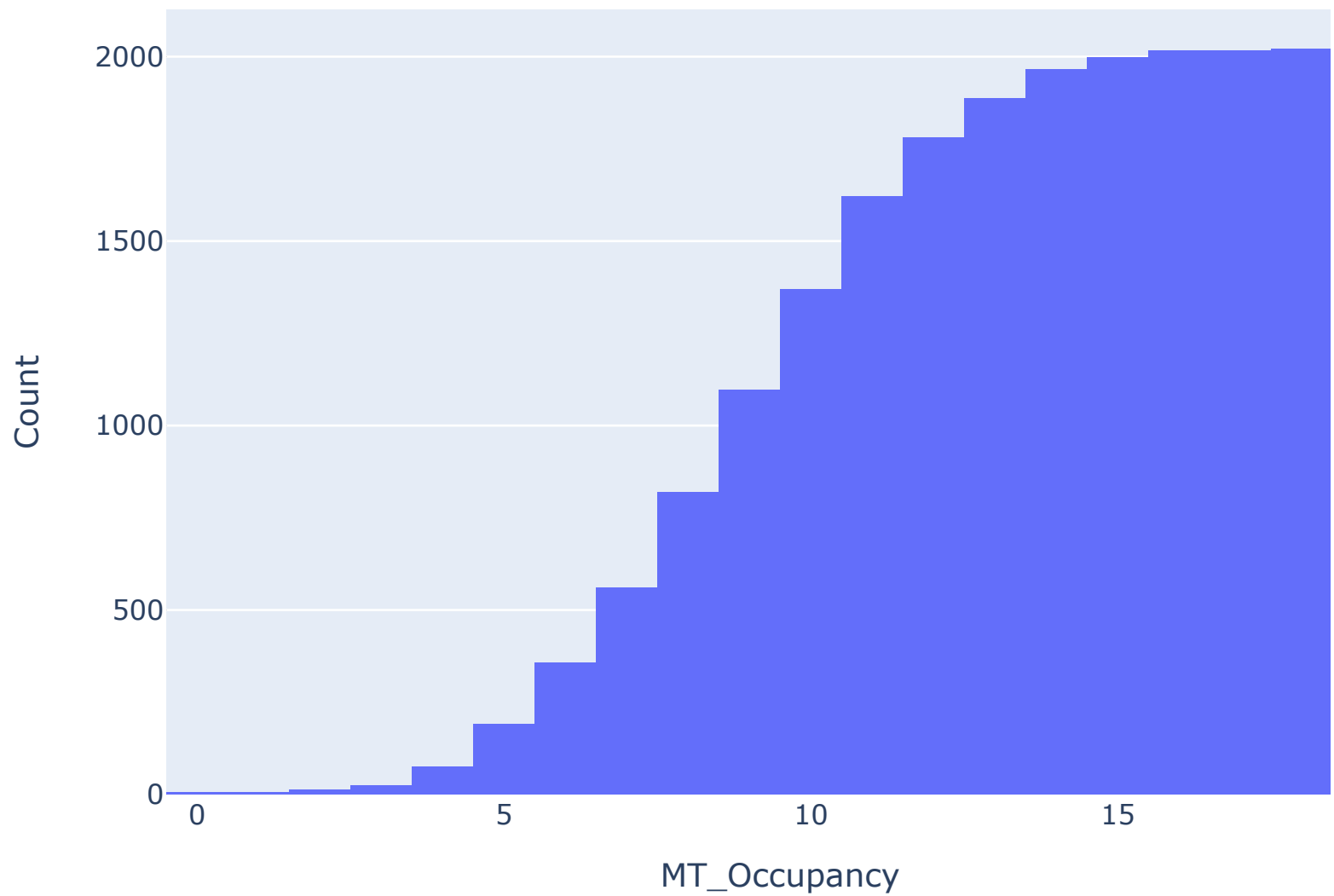
sim2020 - Maternity Occupancy Probability Distribution



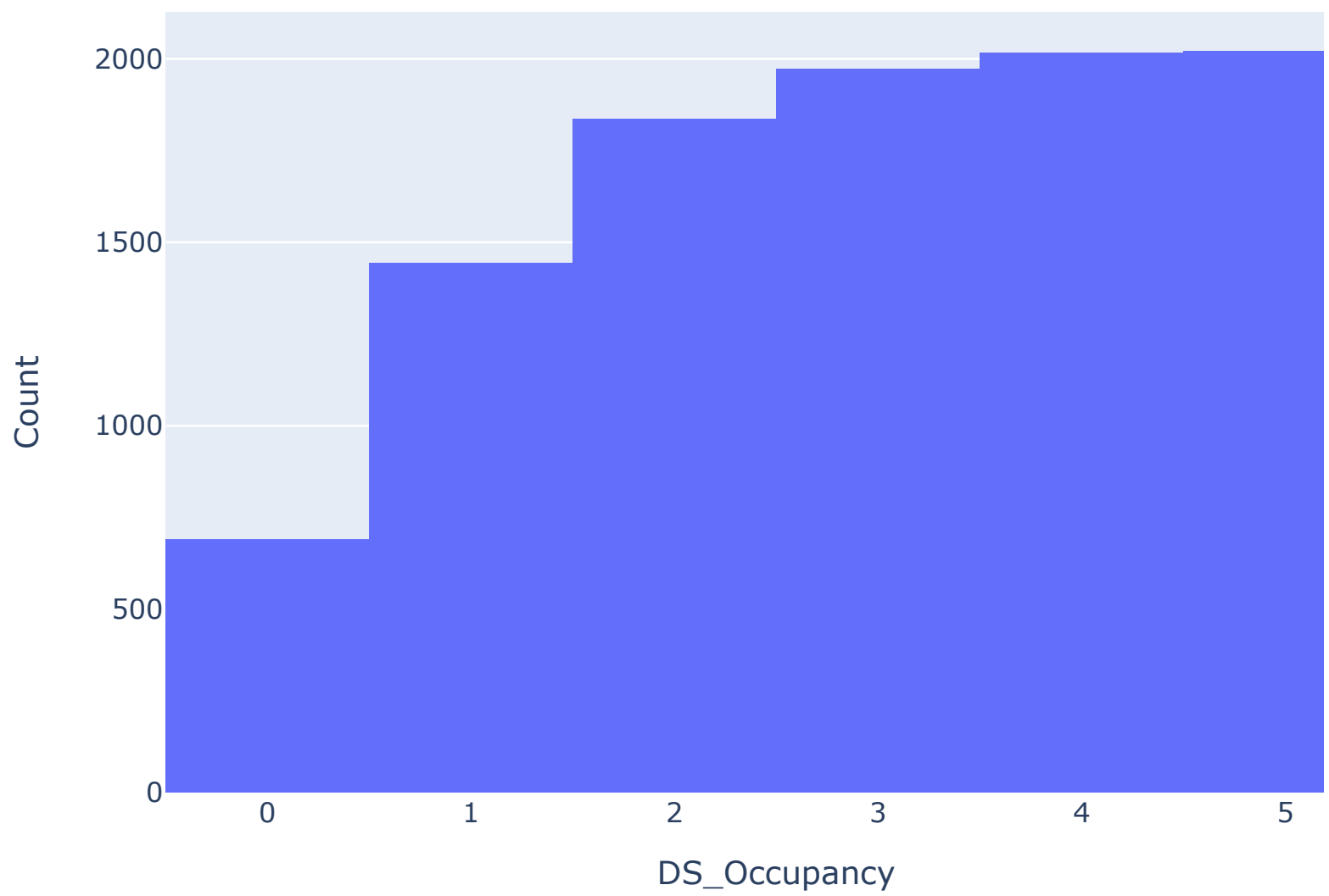
sim2020 - Delivery Suite Occupancy Probability Distribution



sim2020 - Maternity Occupancy Cumulative Probability



sim2020 - Delivery Suite Occupancy Cumulative Probability

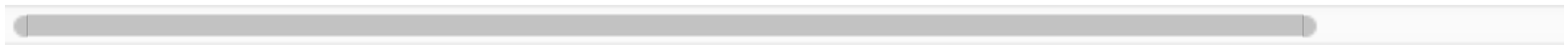
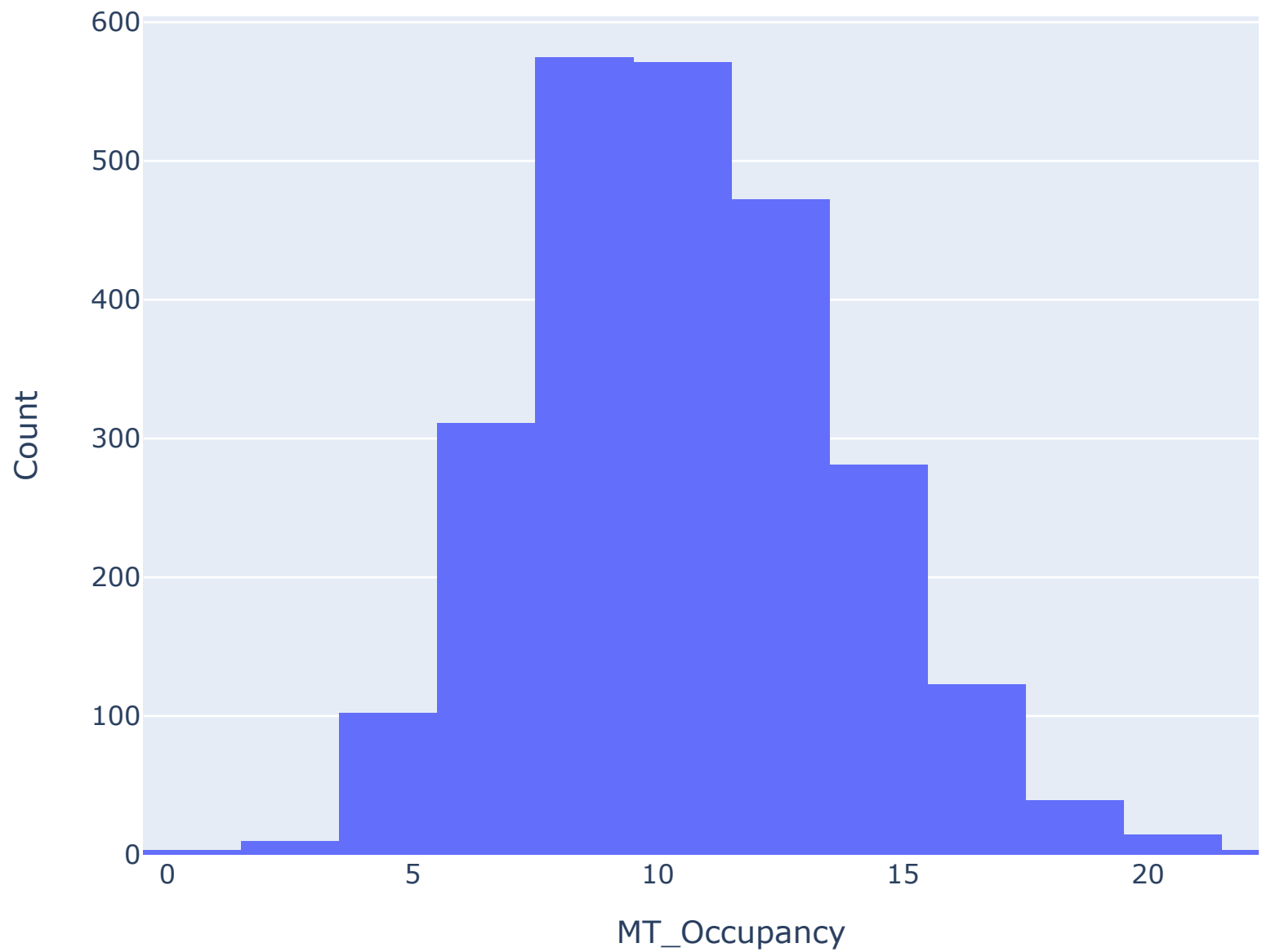


sim2025

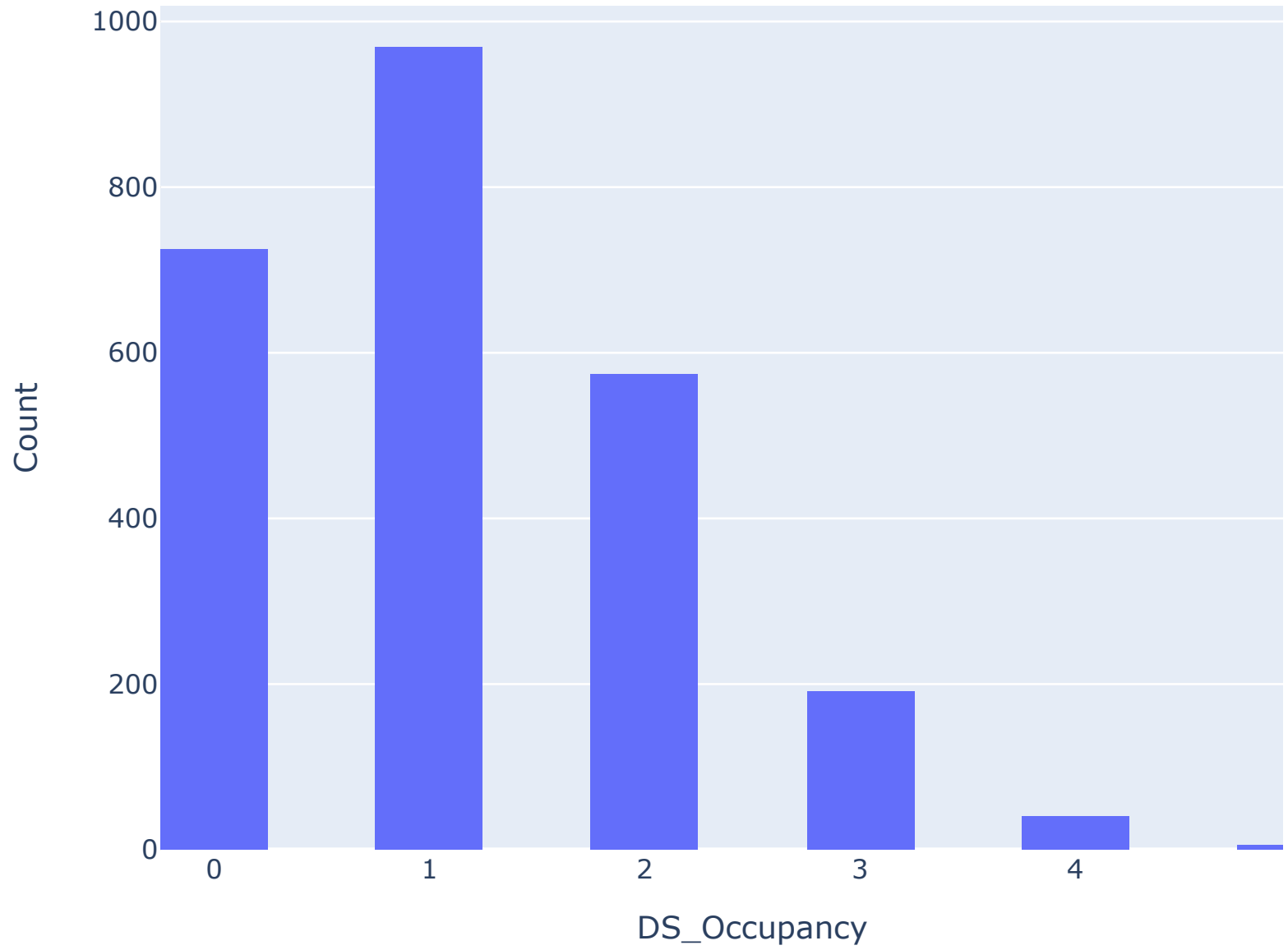
1

0

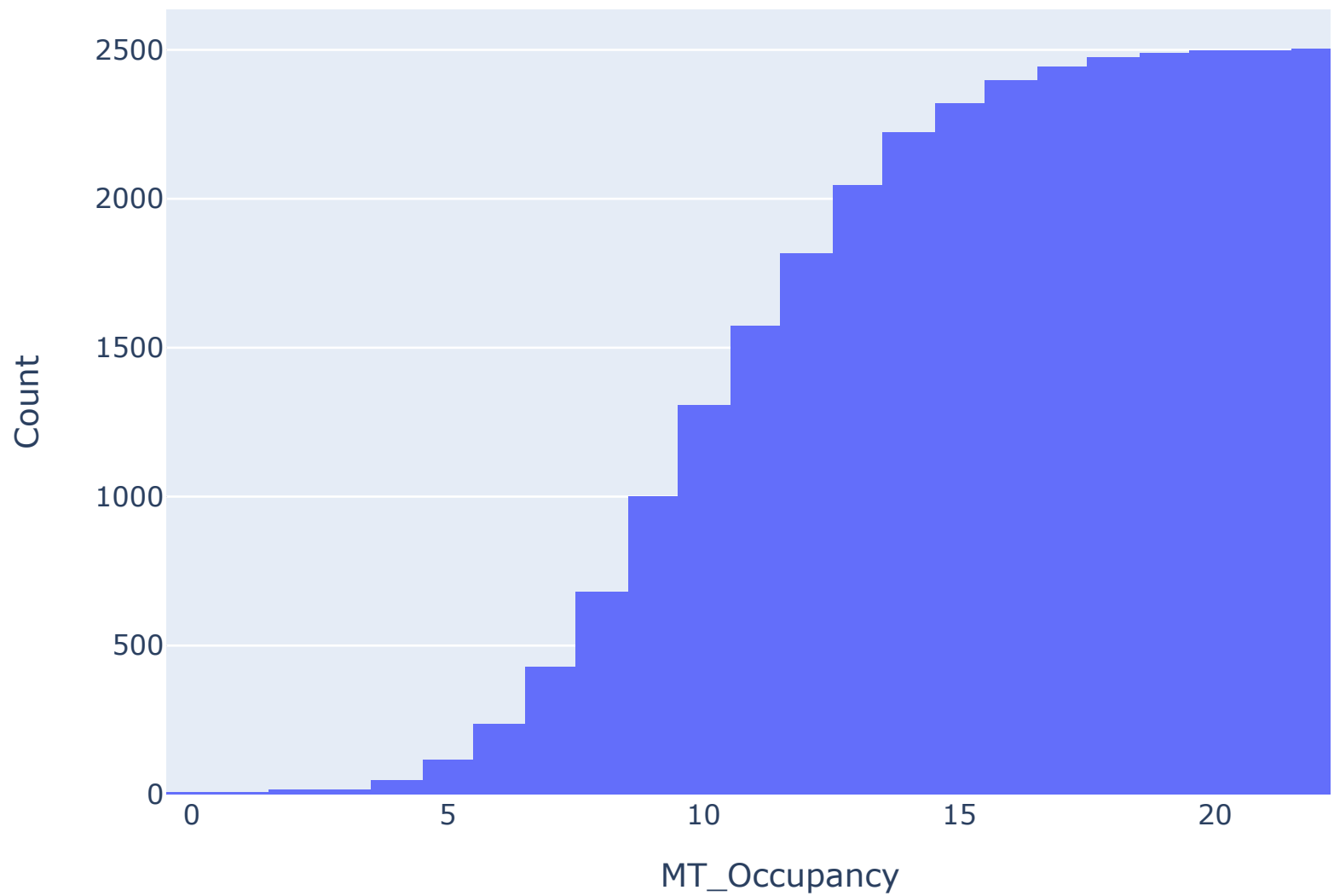
sim2025 - Maternity Occupancy Probability Distribution



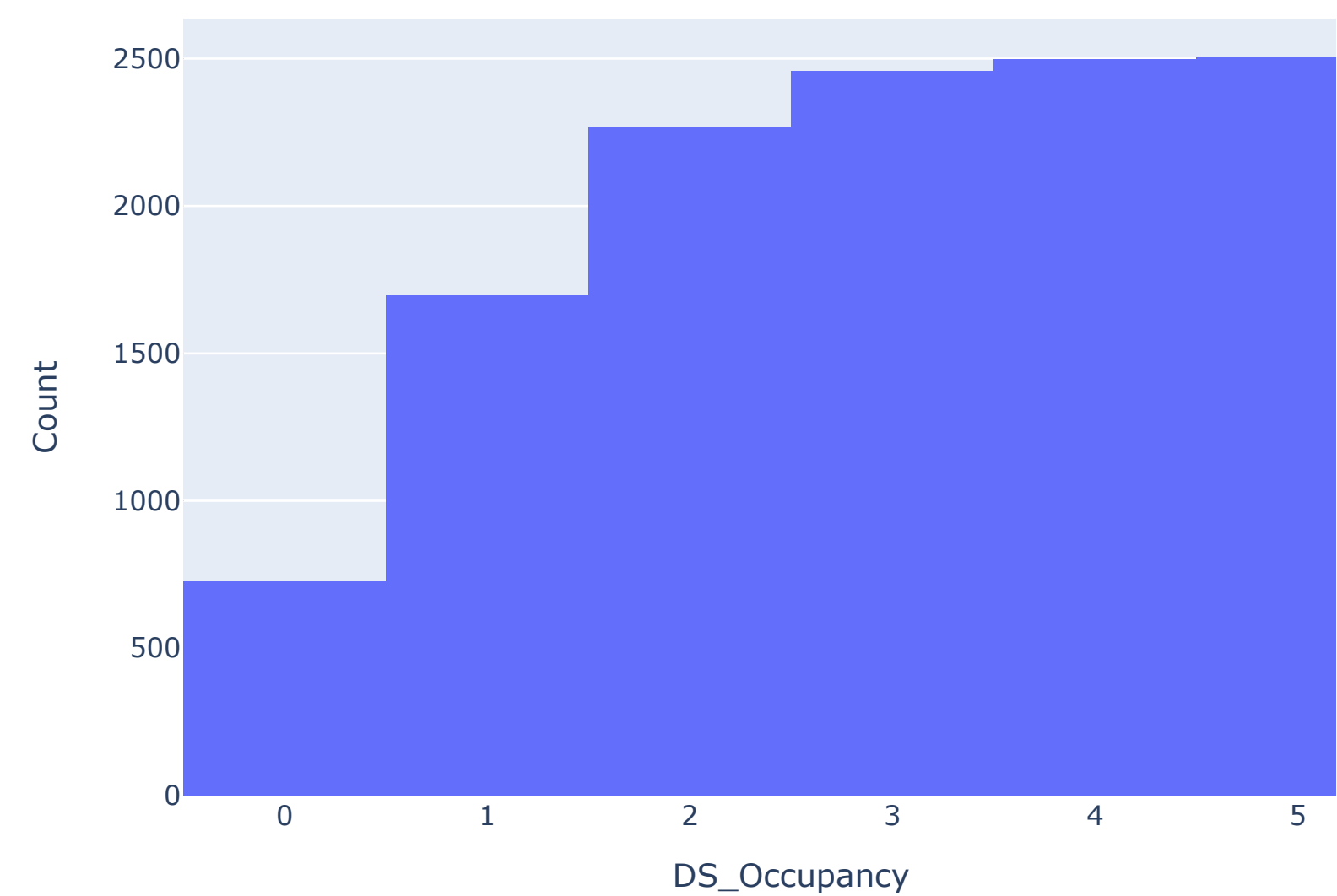
sim2025 - Delivery Suite Occupancy Probability Distribution



sim2025 - Maternity Occupancy Cumulative Probability



sim2025 - Delivery Suite Occupancy Cumulative Probability

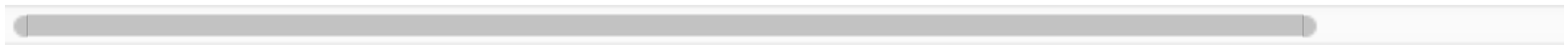
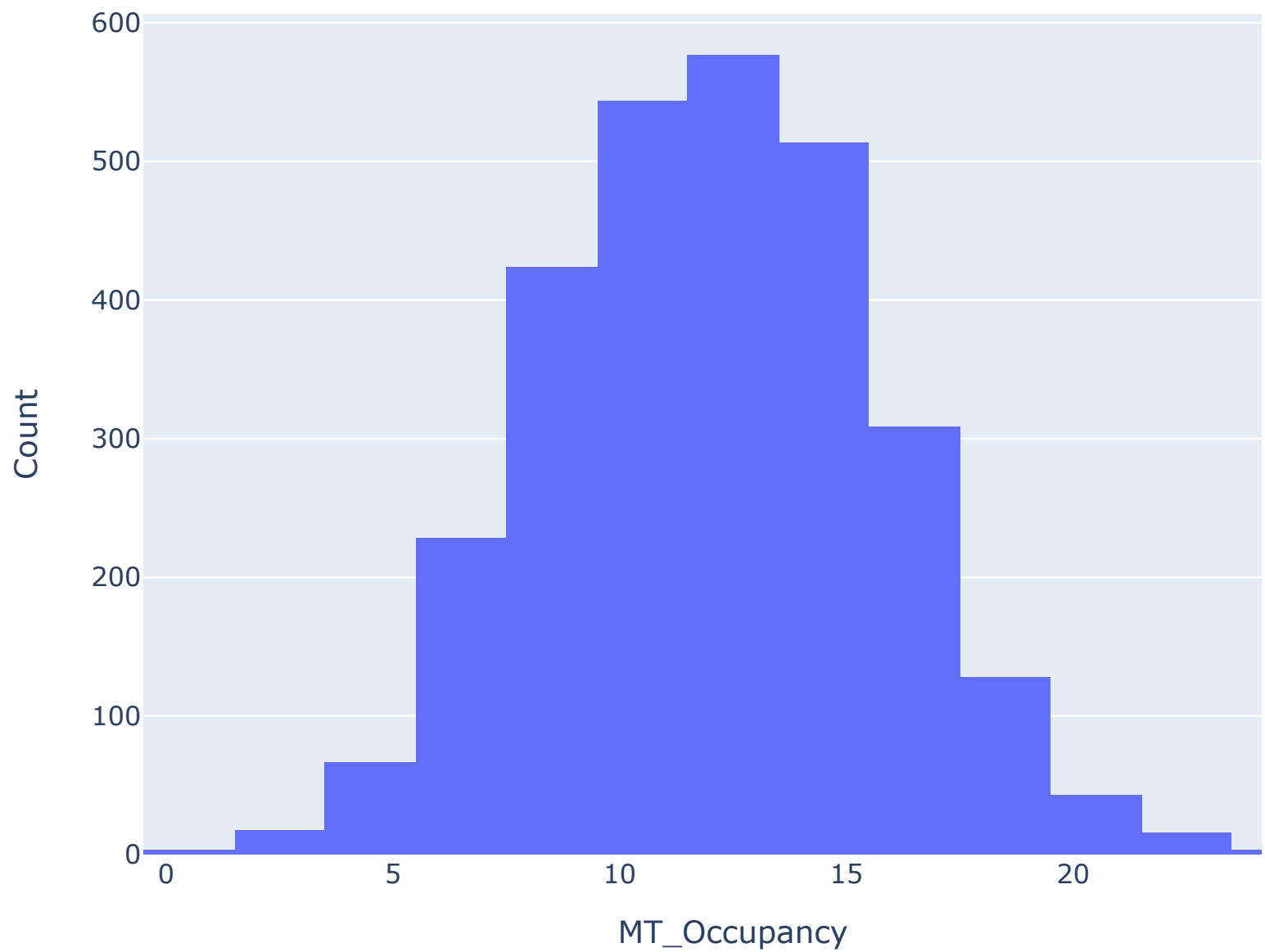


sim2030

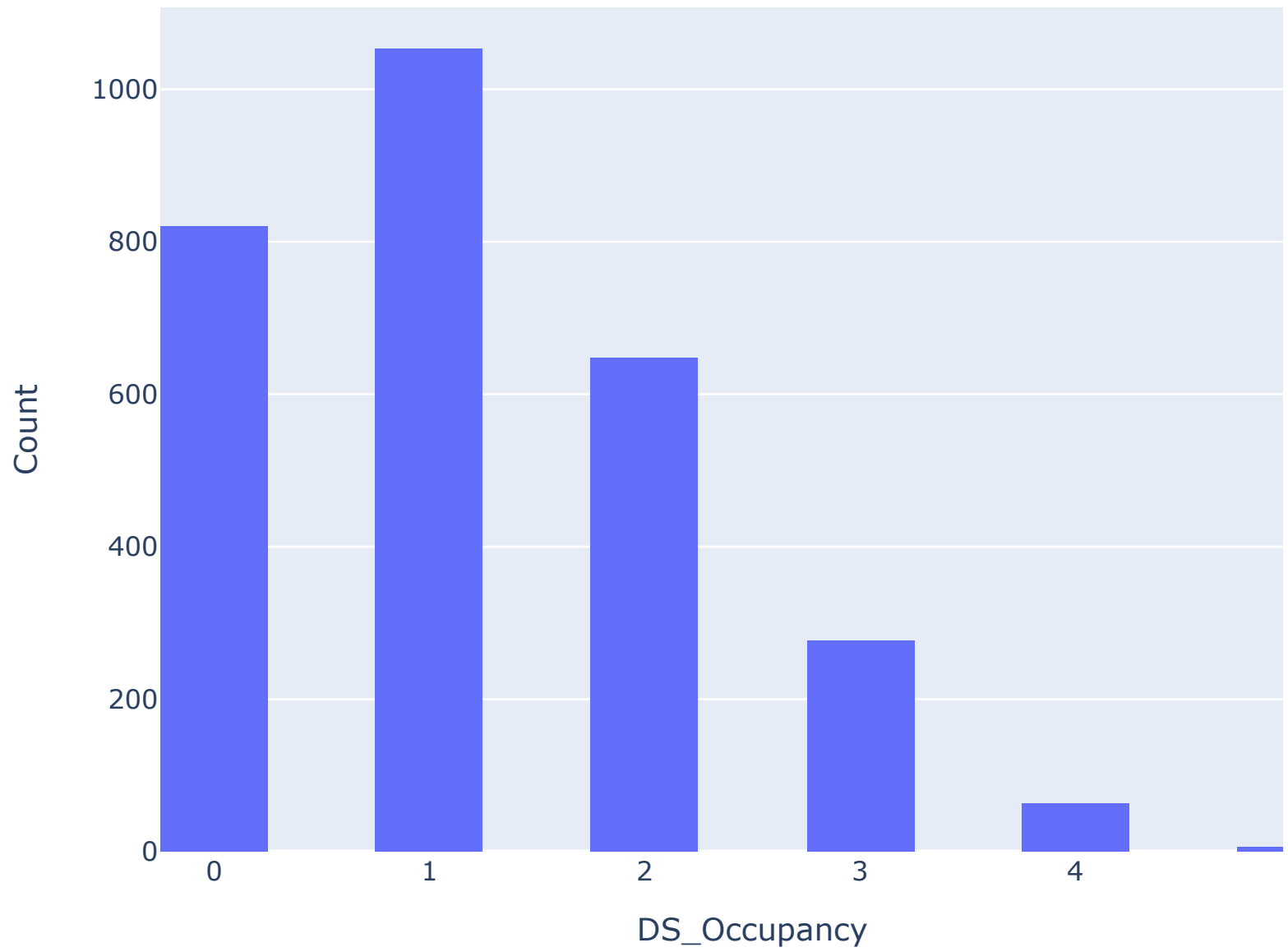
1

0

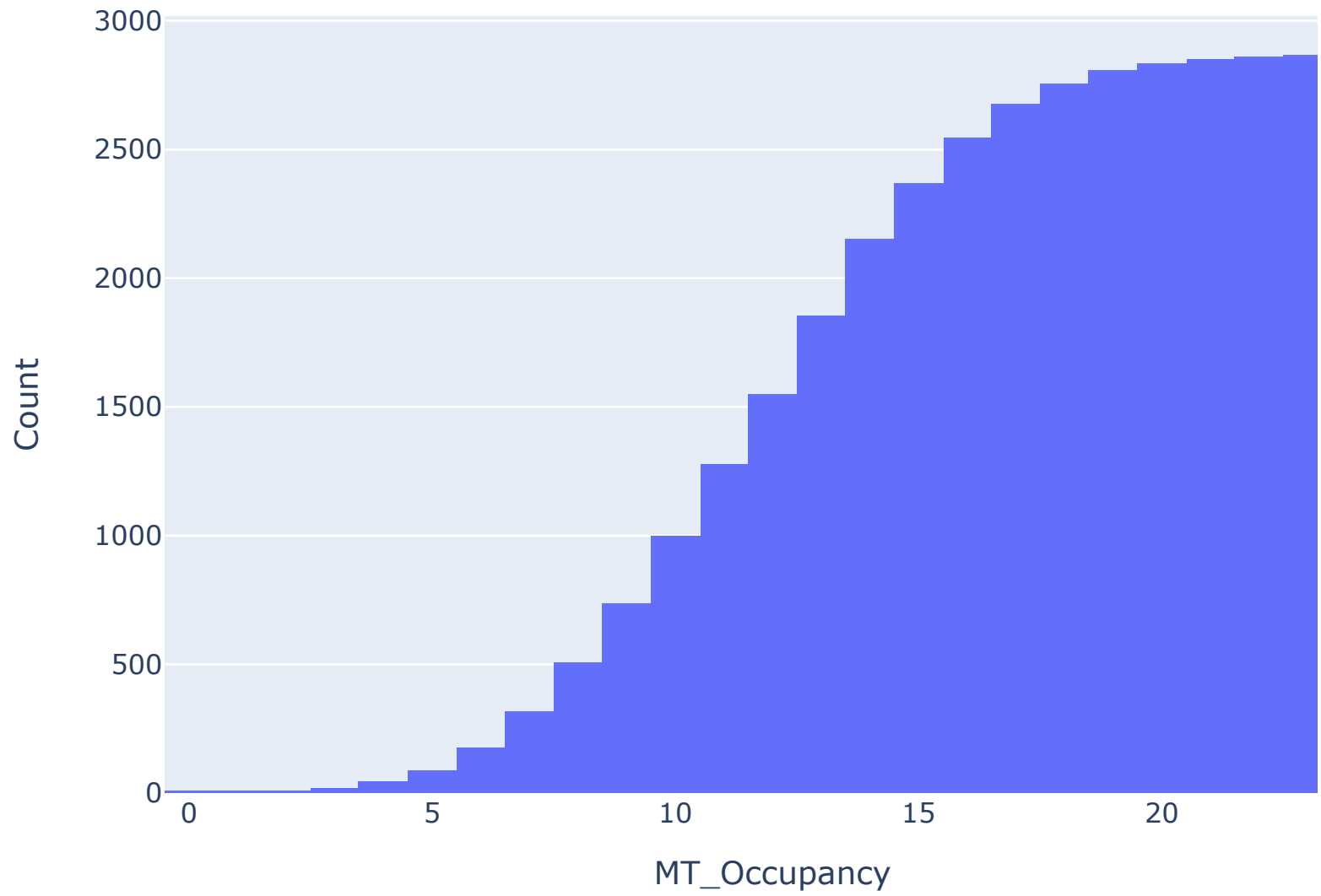
sim2030 - Maternity Occupancy Probability Distribution



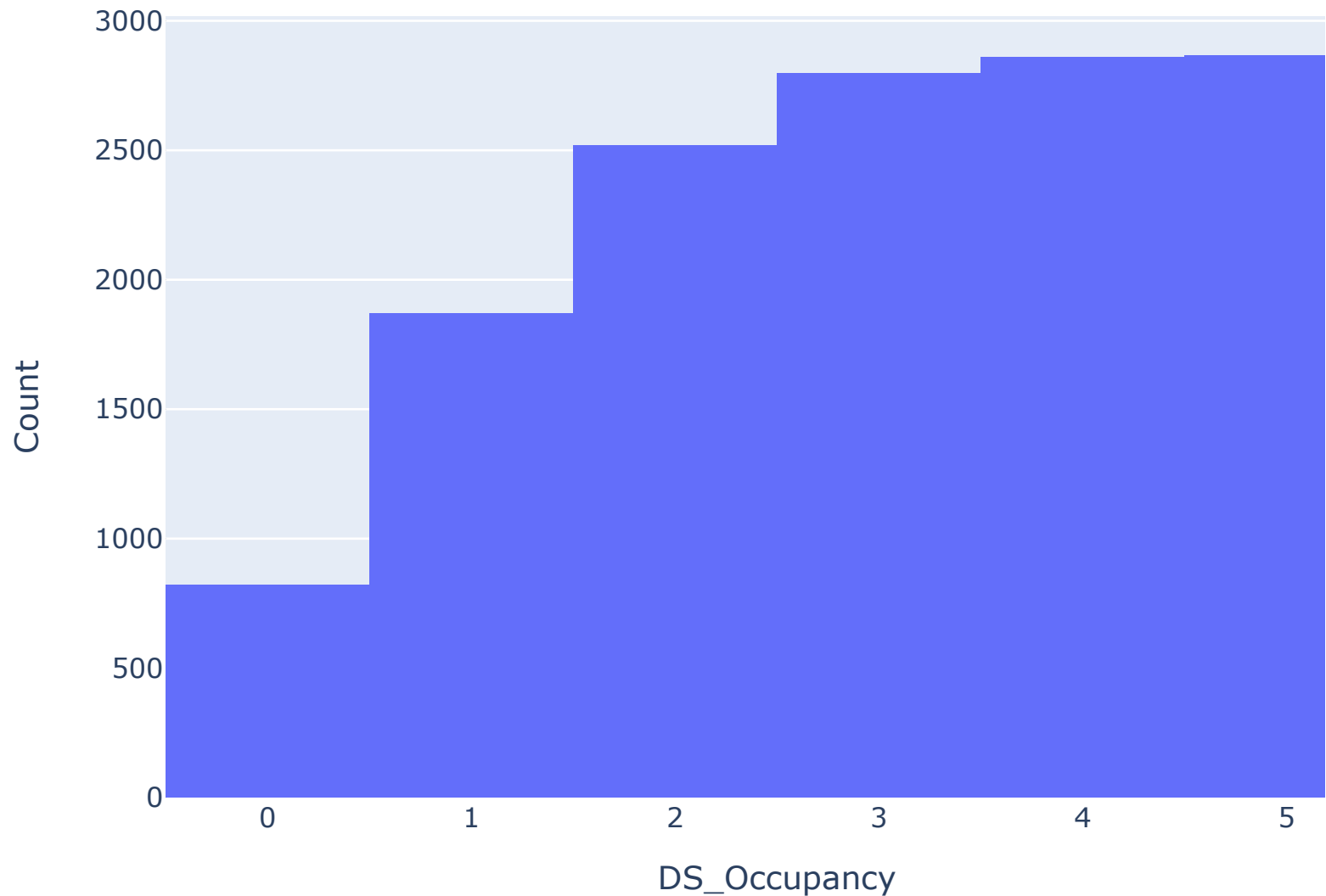
sim2030 - Delivery Suite Occupancy Probability Distribution



sim2030 - Maternity Occupancy Cumulative Probability



sim2030 - Delivery Suite Occupancy Cumulative Probability



CPU times: user 51.7 s, sys: 693 ms, total: 52.4 s
Wall time: 1min 1s

COMBINE ALL DATASETS

```
In [24]: df = pd.concat([simrun_df, ideal_df, orig_df])
#df.loc[(df.Sim_Name == 'ideal_hist'),'Full_Flow_Code'].unique()
#df.loc[(df.Sim_Name == 'sim2020') & (df.Full_Flow_Code == 'IN-MT-MT-OUT'),:]
df.loc[df.Sim_Name == 'ideal_hist',:].describe()
```

Out[24]:	Sim_No	MT_Occupancy	DS_Occupancy	Day	Year	Hour_of_Day
count	14315.0	14315.000000	14315.000000	14315.000000	14315.000000	14315.000000
mean	1.0	9.064198	1.059029	2.782885	2016.613273	12.368984
std	0.0	2.964369	1.023857	1.967410	2.119510	5.163953
min	1.0	0.000000	0.000000	0.000000	2013.000000	0.000000
25%	1.0	7.000000	0.000000	1.000000	2015.000000	10.000000
50%	1.0	9.000000	1.000000	3.000000	2017.000000	11.000000
75%	1.0	11.000000	2.000000	4.000000	2018.000000	16.000000
max	1.0	20.000000	5.000000	6.000000	2020.000000	23.000000

```

In [25]: ##### REVIEW DATA FROM OBSTETRICS CASES
##### CLEAN TRANSFERS DATA
df = pd.read_csv('Obs_ObstetricCases.csv')
df = df.loc[:,('Link', 'Ward', 'Admit', 'SeparationDRGGroupCode')]
obs_df = df
#df = df.loc[df.Ward == 'Maternity',]

df = pd.merge(ideal_df, obs_df, how='left', on='Link')
df.loc[(df.Ward.notnull())].groupby(['Ward_Code', 'Ward']).count()['Link']

```

Out[25]:	Ward_Code	Ward	
	DS	Delivery Suite	271
		Maternity	2049
		St Catherine	7
		St Clares	19
	ICU	Intensive Care Unit	2
		Maternity	79
		St Clares	1
	MT	Intensive Care Unit	1
		Maternity	5714
		St Catherine	39
		St Clares	59
		St Helens	5
	OUT	Delivery Suite	271
		Intensive Care Unit	3
		Maternity	5690
		St Catherine	39
		St Clares	61
		St Helens	5
	Name: Link, dtype: int64		

```

In [26]: obs_df.groupby('SeparationDRGGroupCode').count()['Link']

```

```
Out[26]: SeparationDRGGroupCode
001      2151
002       98
004       62
060     3295
061       76
064       86
065       60
066     435
Name: Link, dtype: int64
```

```
In [27]: import plotly.express as px
fig = px.bar(annual_plot_df, x='Year', y='Int_Arrival', title='Interarrival Time by Overall Interarrival mean')
fig.show()
```

```
-----
NameError                                Traceback (most recent call last)
<ipython-input-27-301e3fc20e9f> in <module>
      1 import plotly.express as px
----> 2 fig = px.bar(annual_plot_df, x='Year', y='Int_Arrival', title='Interarrival Time by Overall Interarrival mean')
      3 fig.show()

NameError: name 'annual_plot_df' is not defined
```

ARRIVALS PER YEAR

```
In [ ]: # PREPARE DATA FOR ARRIVALS PLOT
df = ideal_df
df = df.loc[df.Year == 2013, 'Start'].min()
daysin2013 = df.dayofyear
percentdaysin2013 = (365 - daysin2013) / 365
df = ideal_df
df = df.loc[df.Year == 2020, 'End'].max()
daysin2020 = df.dayofyear
percentdaysin2020 = daysin2020 / 365
df = ideal_df
df = df.loc[df.Int_Arrival.notnull(), ('Year', 'Int_Arrival')]
df = df.groupby('Year').count()
df = df.reset_index()
df = df.rename(columns={'Int_Arrival': 'No_of_Patients'})
nopatients2013 = df.loc[df.Year == 2013, 'No_of_Patients']
df.loc[df.Year == 2013, 'No_of_Patients'] = int(nopatients2013 / percentdaysin2013)
nopatients2020 = df.loc[df.Year == 2020, 'No_of_Patients']
df.loc[df.Year == 2020, 'No_of_Patients'] = int(nopatients2020 / percentdaysin2020)
#Export Plot to external sheet
df.to_csv("Arrivals_per_Year.csv", index=False)
plot_arrivals_year = df
#Show plot of data
fig = px.line(plot_arrivals_year, x='Year', y='No_of_Patients', title='Number of Arrivals per Year')
fig.show()
```

IDEAL FLOW PROBABILITY


```
In [ ]: df = ideal_df
total_patients = df.count().iloc[0]
df = df.loc[df.Prev_Flow == 'IN'].groupby(['Full_Flow_Code']).count()['Link']
df = df.reset_index()
df = df.rename(columns={'Link': 'No_of_Patients'})
df['Total_Patients'] = total_patients
df['Full_Flow_Code'] = df['Full_Flow_Code'].str[3:-4]
df = df.sort_values('No_of_Patients', ascending = False)
df['Percentage_Patients'] = df.No_of_Patients / df.Total_Patients
df['Cumulative_Probability'] = df.Percentage_Patients.cumsum()
df = df.drop(columns=['No_of_Patients', 'Total_Patients'])
ideal_patient_flow_prob_plot_df = df
df.to_csv("Ideal_Flow_Probability.csv", index=False)
#Show plot of data
fig = px.bar(ideal_patient_flow_prob_plot_df, x=df['Full_Flow_Code'], y=df['Percentage_Patients'])
fig.add_scatter(x=df['Full_Flow_Code'], y=df['Cumulative_Probability'], name='Cumulative Probability')
fig.show()
```

```
In [ ]: ideal_patient_flow_prob_plot_df
```

BRANCHING PROBABILITIES

```
In [ ]: ##### Data Table for Pie Charts
# Split Full flow code data up
df = ideal_df.copy(deep=True)
df = df.loc[df.Prev_Flow == 'IN'].groupby('Full_Flow_Code').count()['Link']
df1 = df.Full_Flow_Code.str.split(pat="-", expand=True)
df = pd.merge(df, df1, left_index=True, right_index=True)
df = df.rename(columns={'Link': 'Values'})
# format each level correctly for plats
lv11_df = df.iloc[:, 0]
lv11_df['Prev_Flow'] = df[0]
lv11_df['Ward_Code'] = df[1]
lv12_df = df.iloc[:, 1]
lv12_df['Prev_Flow'] = df[0] + '-' + df[1]
lv12_df['Ward_Code'] = df[2]
lv13_df = df.iloc[:, 2]
lv13_df['Prev_Flow'] = df[0] + '-' + df[1] + '-' + df[2]
lv13_df['Ward_Code'] = df[3]
lv14_df = df.iloc[:, 3]
lv14_df['Prev_Flow'] = df[0] + '-' + df[1] + '-' + df[2] + '-' + df[3]
lv14_df['Ward_Code'] = df[4]
lv15_df = df.iloc[:, 4]
lv15_df['Prev_Flow'] = df[0] + '-' + df[1] + '-' + df[2] + '-' + df[3] + '-' + df[4]
lv15_df['Ward_Code'] = df[5]
lv16_df = df.iloc[:, 5]
lv16_df['Prev_Flow'] = df[0] + '-' + df[1] + '-' + df[2] + '-' + df[3] + '-' + df[4] + '-' + df[5]
lv16_df['Ward_Code'] = df[6]
#bring information back into single dataframe
df = pd.concat([lv11_df, lv12_df, lv13_df, lv14_df, lv15_df, lv16_df])
df = df.dropna(subset=['Ward_Code'])
df = df.drop(columns=['Full_Flow_Code', 0, 1, 2, 3, 4, 5, 6])
pie_df = df.copy(deep = True)
pie_df.head()
```

```
In [ ]: def flow_code_pie_chart(df, prev_flow_code):
    title = prev_flow_code
    filename = 'plots/Patient_Flow/' + title + '.png'
    df = df.loc[df.Prev_Flow == title].groupby('Ward_Code').sum()['Values']
    fig = px.pie(
        data_frame=df,
        values='Values',
        names='Ward_Code',
        color='Ward_Code',
        color_discrete_map = {'MT':'royalblue',
                               'DS':'green',
                               'ICU':'goldenrod',
                               'OUT':'salmon'},
        labels={'Ward_Code':'Next Ward'},
        title=title,
        template='presentation',
        width=800,
        height=600,
        hole=0
    )
    fig.update_traces(textinfo='percent+label')
    #fig.show()
    fig.write_image(filename)
    #flow_code_pie_chart(pie_df, 'IN-DS')

def all_flow_code_pie_charts(df):
    temp_df = df.groupby('Prev_Flow').count()['Values'].reset_index()
    for entry in temp_df['Prev_Flow']:
        flow_code_pie_chart(df, entry)

%time all_flow_code_pie_charts(pie_df)
```

VERIFICATION OF DATA

```
In [ ]: df = orig_df
        #df = ideal_df
```

```
In [ ]: df.loc[df.Prev_Flow=='IN'].groupby('Ward_Code').count()['Link']
        #df.groupby('Full_Flow_Code').count()['Link']
        #df.count()['Link']
        #df.loc[df.Prev_Flow=='IN'].groupby('Full_Flow_Code').count()['Link']
        #df.groupby('Full_Flow_Code').count()['Link']
```

```
In [ ]: #IN-DS-MT-OUT
        #df.loc[(df.Full_Flow_Code=='IN-DS-MT-OUT') & (df.Prev_Flow=='IN'), ('Link', "I
        #IN-MT-OUT
        df.loc[(df.Full_Flow_Code=='IN-MT-OUT') & (df.Prev_Flow=='IN'), ('Link', "Ward
```

```
In [ ]: arrivalsum_df.head(30)
```

```
In [ ]: patientflowsum_df.head(50)
```

```
In [ ]: LOSsum_df.head(50)
```

INTERPRETING RESULTS

```
In [ ]: ideal_df.groupby('Year').describe()['Int_Arrival']
```

```
In [ ]: #####PRINTING  
#jupyter nbconvert Patient_Cap_Sim.ipynb --to webpdf --allow-chromium-down.
```