USA Power Outages Analysis

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1 PowerGrid Insights: Illuminating America's Outage Landscape

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Website Link: https://ericsun153.github.io/Illuminating_US_Outage_Landscape/

1.1 Question Identification

How do demographic factors of West Coast states influence the duration and affecting range of power outages, and what mitigation strategies can be employed to reduce the risk of outages in these regions?

1.2 Setup

[1]:
```
import pandas as pd
import numpy as np
import os

import plotly.express as px
import plotly.io as pio
pio.renderers.default = 'png'
pd.options.plotting.backend = 'plotly'


import matplotlib as plt
import seaborn as sns
```

Since the file type of our dataset is xlsx, we first convert it into csv file using the **openpyxl** library and store it into a csv file called 'outage.csv'.

[2]:
```
!pip install openpyxl
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: openpyxl in ./.local/lib/python3.9/site-packages
(3.1.2)
Requirement already satisfied: et-xmlfile in ./.local/lib/python3.9/site-
packages (from openpyxl) (1.1.0)
```

[3]:
```
xlsx_file = 'outage.xlsx'
csv_file = 'outage.csv'

df = pd.read_excel(xlsx_file)

# Write the DataFrame to a CSV file
df.to_csv(csv_file, index=False)
df = pd.read_csv('outage.csv')
df
```

[3]:
```
      Major power outage events in the continental U.S. Unnamed: 1 Unnamed: 2  \
0                   Time period: January 2000 - July 2016        NaN        NaN
1     Regions affected: Outages reported in this dat…        NaN        NaN
2                                                   NaN        NaN        NaN
3                                                   NaN        NaN        NaN
4                                             variables        OBS       YEAR
…                                                   …          …          …
1535                                                NaN       1530       2011
1536                                                NaN       1531       2006
1537                                                NaN       1532       2009
1538                                                NaN       1533       2009
1539                                                NaN       1534       2000

     Unnamed: 3    Unnamed: 4   Unnamed: 5   Unnamed: 6          Unnamed: 7  \
0           NaN           NaN          NaN          NaN                 NaN
1           NaN           NaN          NaN          NaN                 NaN
2           NaN           NaN          NaN          NaN                 NaN
3           NaN           NaN          NaN          NaN                 NaN
4         MONTH    U.S._STATE  POSTAL.CODE  NERC.REGION      CLIMATE.REGION
…           …            …           …           …                   …
1535         12  North Dakota           ND          MRO  West North Central
1536        NaN  North Dakota           ND          MRO  West North Central
1537          8  South Dakota           SD          RFC  West North Central
1538          8  South Dakota           SD          MRO  West North Central
1539        NaN        Alaska           AK         ASCC                 NaN

         Unnamed: 8        Unnamed: 9  …   Unnamed: 47 Unnamed: 48  \
0               NaN               NaN  …           NaN         NaN
1               NaN               NaN  …           NaN         NaN
2               NaN               NaN  …           NaN         NaN
3               NaN               NaN  …           NaN         NaN
4     ANOMALY.LEVEL  CLIMATE.CATEGORY  …  POPPCT_URBAN  POPPCT_UC
…                 …                 …  …            …          …
1535           -0.9              cold  …          59.9        19.9
1536            NaN               NaN  …          59.9        19.9
1537            0.5              warm  …         56.65       26.73
1538            0.5              warm  …         56.65       26.73
```

```
1539            NaN                 NaN  …          66.02        21.56

       Unnamed: 49 Unnamed: 50   Unnamed: 51    Unnamed: 52 Unnamed: 53  \
0              NaN         NaN           NaN            NaN         NaN
1              NaN         NaN           NaN            NaN         NaN
2              NaN         NaN           NaN            NaN         NaN
3              NaN         NaN           NaN            NaN         NaN
4     POPDEN_URBAN  POPDEN_UC  POPDEN_RURAL  AREAPCT_URBAN  AREAPCT_UC
…              …           …             …              …           …
1535        2192.2      1868.2           3.9           0.27         0.1
1536        2192.2      1868.2           3.9           0.27         0.1
1537        2038.3      1905.4           4.7            0.3        0.15
1538        2038.3      1905.4           4.7            0.3        0.15
1539        1802.6        1276           0.4           0.05        0.02

           Unnamed: 54       Unnamed: 55       Unnamed: 56
0                  NaN               NaN               NaN
1                  NaN               NaN               NaN
2                  NaN               NaN               NaN
3                  NaN               NaN               NaN
4             PCT_LAND     PCT_WATER_TOT  PCT_WATER_INLAND
…                    …                 …                 …
1535  97.5996492121418  2.40176525502843  2.40176525502843
1536  97.5996492121418  2.40176525502843  2.40176525502843
1537  98.3077441776026  1.69225582239743  1.69225582239743
1538  98.3077441776026  1.69225582239743  1.69225582239743
1539  85.7611544611833  14.2388455388167  2.90118187392543

[1540 rows x 57 columns]
```

1.3 Data Cleaning

First 5 rows are the header of the dataset, we drop them and filter it into correct format in each column

[4]:
```python
rows_to_skip = list(range(5))
df = pd.read_csv('outage.csv', skiprows=rows_to_skip, index_col='OBS')

# Combine the units line and column names, drop unecessary rows and columns
column = np.array(df.columns).astype('str')
unites = np.array(df.iloc[0].fillna('')).astype('str')
unites = ["(" + i + ")" for i in unites]
for i in range(len(unites)):
    if unites[i] == '()':
        unites[i] = ''
combined_column = np.core.defchararray.add(column, unites)
df.columns = combined_column
```

```
df = df.reset_index().drop(0).drop('variables(Units)', axis=1).
    ↪reset_index(drop=True)
df
```

```
[4]:         OBS    YEAR  MONTH    U.S._STATE POSTAL.CODE NERC.REGION  \
0        1.0  2011.0    7.0     Minnesota          MN         MRO
1        2.0  2014.0    5.0     Minnesota          MN         MRO
2        3.0  2010.0   10.0     Minnesota          MN         MRO
3        4.0  2012.0    6.0     Minnesota          MN         MRO
4        5.0  2015.0    7.0     Minnesota          MN         MRO
…        …      …      …             …           …           …
1529  1530.0  2011.0   12.0  North Dakota          ND         MRO
1530  1531.0  2006.0    NaN  North Dakota          ND         MRO
1531  1532.0  2009.0    8.0  South Dakota          SD         RFC
1532  1533.0  2009.0    8.0  South Dakota          SD         MRO
1533  1534.0  2000.0    NaN        Alaska          AK        ASCC

          CLIMATE.REGION ANOMALY.LEVEL(numeric) CLIMATE.CATEGORY  \
0     East North Central                   -0.3           normal
1     East North Central                   -0.1           normal
2     East North Central                   -1.5             cold
3     East North Central                   -0.1           normal
4     East North Central                    1.2             warm
…                    …                      …                …
1529  West North Central                   -0.9             cold
1530  West North Central                    NaN              NaN
1531  West North Central                    0.5             warm
1532  West North Central                    0.5             warm
1533                 NaN                    NaN              NaN

     OUTAGE.START.DATE(Day of the week, Month Day, Year)  … POPPCT_URBAN(%)  \
0                                   2011-07-01 00:00:00   …           73.27
1                                   2014-05-11 00:00:00   …           73.27
2                                   2010-10-26 00:00:00   …           73.27
3                                   2012-06-19 00:00:00   …           73.27
4                                   2015-07-18 00:00:00   …           73.27
…                                                    …   …             …
1529                                2011-12-06 00:00:00   …            59.9
1530                                                NaN   …            59.9
1531                                2009-08-29 00:00:00   …           56.65
1532                                2009-08-29 00:00:00   …           56.65
1533                                                NaN   …           66.02

     POPPCT_UC(%) POPDEN_URBAN(persons per square mile)  \
0           15.28                                  2279
1           15.28                                  2279
2           15.28                                  2279
```

3	15.28	2279
4	15.28	2279
…	…	…
1529	19.9	2192.2
1530	19.9	2192.2
1531	26.73	2038.3
1532	26.73	2038.3
1533	21.56	1802.6

	POPDEN_UC(persons per square mile)	POPDEN_RURAL(persons per square mile)	\
0	1700.5	18.2	
1	1700.5	18.2	
2	1700.5	18.2	
3	1700.5	18.2	
4	1700.5	18.2	
…	…	…	
1529	1868.2	3.9	
1530	1868.2	3.9	
1531	1905.4	4.7	
1532	1905.4	4.7	
1533	1276	0.4	

	AREAPCT_URBAN(%)	AREAPCT_UC(%)	PCT_LAND(%)	PCT_WATER_TOT(%)	\
0	2.14	0.6	91.5926658691451	8.40733413085488	
1	2.14	0.6	91.5926658691451	8.40733413085488	
2	2.14	0.6	91.5926658691451	8.40733413085488	
3	2.14	0.6	91.5926658691451	8.40733413085488	
4	2.14	0.6	91.5926658691451	8.40733413085488	
…	…	…	…	…	
1529	0.27	0.1	97.5996492121418	2.40176525502843	
1530	0.27	0.1	97.5996492121418	2.40176525502843	
1531	0.3	0.15	98.3077441776026	1.69225582239743	
1532	0.3	0.15	98.3077441776026	1.69225582239743	
1533	0.05	0.02	85.7611544611833	14.2388455388167	

	PCT_WATER_INLAND(%)
0	5.47874298334407
1	5.47874298334407
2	5.47874298334407
3	5.47874298334407
4	5.47874298334407
…	…
1529	2.40176525502843
1530	2.40176525502843
1531	1.69225582239743
1532	1.69225582239743
1533	2.90118187392543

```
[1534 rows x 56 columns]
```

[5]:
```
df['YEAR'] = df['YEAR'].astype('int')
# Combine 'OUTAGE.START.DATE' and 'OUTAGE.START.TIME' into a new pd.Timestamp␣
↪column called 'OUTAGE.START'
start_time = df['OUTAGE.START.TIME(Hour:Minute:Second (AM / PM))']
start_date = df['OUTAGE.START.DATE(Day of the week, Month Day, Year)']
df["OUTAGE.START"] = pd.to_datetime(start_date + " " + start_time)
# combine 'OUTAGE.RESTORATION.DATE' and 'OUTAGE.RESTORATION.TIME' into a new pd.
↪Timestamp column called 'OUTAGE.RESTORATION'.
end_time = df['OUTAGE.RESTORATION.TIME(Hour:Minute:Second (AM / PM))']
end_date = df['OUTAGE.RESTORATION.DATE(Day of the week, Month Day, Year)']
df["OUTAGE.RESTORATION"] = pd.to_datetime(end_date + " " + end_time)
df[['OUTAGE.RESTORATION', 'OUTAGE.START']]
```

[5]:
```
      OUTAGE.RESTORATION        OUTAGE.START
0    2011-07-03 20:00:00 2011-07-01 17:00:00
1    2014-05-11 18:39:00 2014-05-11 18:38:00
2    2010-10-28 22:00:00 2010-10-26 20:00:00
3    2012-06-20 23:00:00 2012-06-19 04:30:00
4    2015-07-19 07:00:00 2015-07-18 02:00:00
…                      …                   …
1529 2011-12-06 20:00:00 2011-12-06 08:00:00
1530                 NaT                 NaT
1531 2009-08-29 23:53:00 2009-08-29 22:54:00
1532 2009-08-29 14:01:00 2009-08-29 11:00:00
1533                 NaT                 NaT

[1534 rows x 2 columns]
```

[6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1534 entries, 0 to 1533
Data columns (total 58 columns):
 #   Column                                                    Non-Null Count
Dtype
---  ------                                                    --------------
-----
 0   OBS                                                       1534 non-null
float64
 1   YEAR                                                      1534 non-null
int64
 2   MONTH                                                     1525 non-null
float64
 3   U.S._STATE                                                1534 non-null
```

```
object
 4   POSTAL.CODE                                                1534 non-null
object
 5   NERC.REGION                                                1534 non-null
object
 6   CLIMATE.REGION                                             1528 non-null
object
 7   ANOMALY.LEVEL(numeric)                                     1525 non-null
object
 8   CLIMATE.CATEGORY                                           1525 non-null
object
 9   OUTAGE.START.DATE(Day of the week, Month Day, Year)        1525 non-null
object
 10  OUTAGE.START.TIME(Hour:Minute:Second (AM / PM))            1525 non-null
object
 11  OUTAGE.RESTORATION.DATE(Day of the week, Month Day, Year)  1476 non-null
object
 12  OUTAGE.RESTORATION.TIME(Hour:Minute:Second (AM / PM))      1476 non-null
object
 13  CAUSE.CATEGORY                                             1534 non-null
object
 14  CAUSE.CATEGORY.DETAIL                                      1063 non-null
object
 15  HURRICANE.NAMES                                            72 non-null
object
 16  OUTAGE.DURATION(mins)                                      1476 non-null
object
 17  DEMAND.LOSS.MW(Megawatt)                                   829 non-null
object
 18  CUSTOMERS.AFFECTED                                         1091 non-null
float64
 19  RES.PRICE(cents / kilowatt-hour)                           1512 non-null
object
 20  COM.PRICE(cents / kilowatt-hour)                           1512 non-null
object
 21  IND.PRICE(cents / kilowatt-hour)                           1512 non-null
object
 22  TOTAL.PRICE(cents / kilowatt-hour)                         1512 non-null
object
 23  RES.SALES(Megawatt-hour)                                   1512 non-null
object
 24  COM.SALES(Megawatt-hour)                                   1512 non-null
object
 25  IND.SALES(Megawatt-hour)                                   1512 non-null
object
 26  TOTAL.SALES(Megawatt-hour)                                 1512 non-null
object
 27  RES.PERCEN(%)                                              1512 non-null
```

```
object
 28  COM.PERCEN(%)                                              1512 non-null
object
 29  IND.PERCEN(%)                                              1512 non-null
object
 30  RES.CUSTOMERS                                              1534 non-null
float64
 31  COM.CUSTOMERS                                              1534 non-null
float64
 32  IND.CUSTOMERS                                              1534 non-null
float64
 33  TOTAL.CUSTOMERS                                            1534 non-null
float64
 34  RES.CUST.PCT(%)                                            1534 non-null
object
 35  COM.CUST.PCT(%)                                            1534 non-null
object
 36  IND.CUST.PCT(%)                                            1534 non-null
object
 37  PC.REALGSP.STATE(USD)                                      1534 non-null
object
 38  PC.REALGSP.USA(USD)                                        1534 non-null
object
 39  PC.REALGSP.REL(fraction)                                   1534 non-null
object
 40  PC.REALGSP.CHANGE(%)                                       1534 non-null
object
 41  UTIL.REALGSP(USD)                                          1534 non-null
object
 42  TOTAL.REALGSP(USD)                                         1534 non-null
object
 43  UTIL.CONTRI(%)                                             1534 non-null
object
 44  PI.UTIL.OFUSA(%)                                           1534 non-null
object
 45  POPULATION                                                 1534 non-null
float64
 46  POPPCT_URBAN(%)                                            1534 non-null
object
 47  POPPCT_UC(%)                                               1534 non-null
object
 48  POPDEN_URBAN(persons per square mile)                      1534 non-null
object
 49  POPDEN_UC(persons per square mile)                         1524 non-null
object
 50  POPDEN_RURAL(persons per square mile)                      1524 non-null
object
 51  AREAPCT_URBAN(%)                                           1534 non-null
```

```
object
 52   AREAPCT_UC(%)                                              1534 non-null
object
 53   PCT_LAND(%)                                                1534 non-null
object
 54   PCT_WATER_TOT(%)                                           1534 non-null
object
 55   PCT_WATER_INLAND(%)                                        1534 non-null
object
 56   OUTAGE.START                                               1525 non-null
datetime64[ns]
 57   OUTAGE.RESTORATION                                         1476 non-null
datetime64[ns]
dtypes: datetime64[ns](2), float64(8), int64(1), object(47)
memory usage: 695.2+ KB
```

We should then convert all the columns into proper data types

[7]:
```
df['ANOMALY.LEVEL'] = df['ANOMALY.LEVEL(numeric)'].astype(float)
df = df.drop(columns=['ANOMALY.LEVEL(numeric)', 'OUTAGE.START.DATE(Day of the␣
 ↪week, Month Day, Year)',
                      'OUTAGE.START.TIME(Hour:Minute:Second (AM / PM))',
                      'OUTAGE.RESTORATION.DATE(Day of the week, Month Day,␣
 ↪Year)',
                      'OUTAGE.RESTORATION.TIME(Hour:Minute:Second (AM / PM))'],␣
 ↪axis=1)
```

[8]:
```
columns_to_convert = {'OUTAGE.DURATION(mins)': float, 'DEMAND.LOSS.
 ↪MW(Megawatt)': float,
                      'RES.PRICE(cents / kilowatt-hour)': float, 'COM.
 ↪PRICE(cents / kilowatt-hour)': float,
                     'COM.PRICE(cents / kilowatt-hour)':float, 'IND.PRICE(cents␣
 ↪/ kilowatt-hour)': float,
                     'TOTAL.PRICE(cents / kilowatt-hour)':float, 'RES.
 ↪SALES(Megawatt-hour)': float,
                     'COM.SALES(Megawatt-hour)':float, 'IND.
 ↪SALES(Megawatt-hour)':float, 'TOTAL.PRICE(cents / kilowatt-hour)':float,
                     'RES.PERCEN(%)':float, 'COM.PERCEN(%)':float, 'IND.
 ↪PERCEN(%)':float, 'RES.CUST.PCT(%)':float,
                     'COM.CUST.PCT(%)':float, 'IND.CUST.PCT(%)':float, 'PC.
 ↪REALGSP.STATE(USD)':float, 'PC.REALGSP.USA(USD)':float,
                     'PC.REALGSP.REL(fraction)':float, 'PC.REALGSP.CHANGE(%)':
 ↪float, 'UTIL.REALGSP(USD)':float, 'TOTAL.REALGSP(USD)':float,
                     'UTIL.CONTRI(%)':float, 'PI.UTIL.OFUSA(%)':float,␣
 ↪'POPPCT_URBAN(%)':float, 'POPPCT_UC(%)':float,
                     'POPDEN_URBAN(persons per square mile)':float,␣
 ↪'POPDEN_UC(persons per square mile)':float,
```

```
                        'POPDEN_RURAL(persons per square mile)':float,␣
↪'AREAPCT_URBAN(%)':float, 'AREAPCT_UC(%)':float,
                        'PCT_LAND(%)':float, 'PCT_WATER_TOT(%)':float,␣
↪'PCT_WATER_INLAND(%)':float,'TOTAL.SALES(Megawatt-hour)':float}
```

[9]:
```
df = df.astype(columns_to_convert)
df
```

[9]:
```
         OBS  YEAR  MONTH    U.S._STATE POSTAL.CODE NERC.REGION  \
0        1.0  2011    7.0     Minnesota          MN         MRO
1        2.0  2014    5.0     Minnesota          MN         MRO
2        3.0  2010   10.0     Minnesota          MN         MRO
3        4.0  2012    6.0     Minnesota          MN         MRO
4        5.0  2015    7.0     Minnesota          MN         MRO
…        …     …     …            …           …          …
1529  1530.0  2011   12.0  North Dakota          ND         MRO
1530  1531.0  2006    NaN  North Dakota          ND         MRO
1531  1532.0  2009    8.0  South Dakota          SD         RFC
1532  1533.0  2009    8.0  South Dakota          SD         MRO
1533  1534.0  2000    NaN        Alaska          AK        ASCC

          CLIMATE.REGION CLIMATE.CATEGORY         CAUSE.CATEGORY  \
0     East North Central           normal         severe weather
1     East North Central           normal    intentional attack
2     East North Central             cold         severe weather
3     East North Central           normal         severe weather
4     East North Central             warm         severe weather
…                    …              …                   …
1529  West North Central             cold          public appeal
1530  West North Central              NaN  fuel supply emergency
1531  West North Central             warm              islanding
1532  West North Central             warm              islanding
1533                 NaN              NaN      equipment failure

     CAUSE.CATEGORY.DETAIL  … POPDEN_UC(persons per square mile)  \
0                      NaN  …                             1700.5
1                vandalism  …                             1700.5
2               heavy wind  …                             1700.5
3             thunderstorm  …                             1700.5
4                      NaN  …                             1700.5
…                      …   …                                …
1529                   NaN  …                             1868.2
1530                  Coal  …                             1868.2
1531                   NaN  …                             1905.4
1532                   NaN  …                             1905.4
1533               failure  …                             1276.0
```

```
      POPDEN_RURAL(persons per square mile)  AREAPCT_URBAN(%)  AREAPCT_UC(%)  \
0                                      18.2              2.14           0.60
1                                      18.2              2.14           0.60
2                                      18.2              2.14           0.60
3                                      18.2              2.14           0.60
4                                      18.2              2.14           0.60
…                                       …                …              …
1529                                    3.9              0.27           0.10
1530                                    3.9              0.27           0.10
1531                                    4.7              0.30           0.15
1532                                    4.7              0.30           0.15
1533                                    0.4              0.05           0.02

      PCT_LAND(%)  PCT_WATER_TOT(%)  PCT_WATER_INLAND(%)        OUTAGE.START  \
0       91.592666          8.407334             5.478743 2011-07-01 17:00:00
1       91.592666          8.407334             5.478743 2014-05-11 18:38:00
2       91.592666          8.407334             5.478743 2010-10-26 20:00:00
3       91.592666          8.407334             5.478743 2012-06-19 04:30:00
4       91.592666          8.407334             5.478743 2015-07-18 02:00:00
…            …                …                    …                    …
1529    97.599649          2.401765             2.401765 2011-12-06 08:00:00
1530    97.599649          2.401765             2.401765                 NaT
1531    98.307744          1.692256             1.692256 2009-08-29 22:54:00
1532    98.307744          1.692256             1.692256 2009-08-29 11:00:00
1533    85.761154         14.238846             2.901182                 NaT

      OUTAGE.RESTORATION  ANOMALY.LEVEL
0    2011-07-03 20:00:00           -0.3
1    2014-05-11 18:39:00           -0.1
2    2010-10-28 22:00:00           -1.5
3    2012-06-20 23:00:00           -0.1
4    2015-07-19 07:00:00            1.2
…                    …             …
1529 2011-12-06 20:00:00           -0.9
1530                 NaT            NaN
1531 2009-08-29 23:53:00            0.5
1532 2009-08-29 14:01:00            0.5
1533                 NaT            NaN

[1534 rows x 54 columns]
```

[10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1534 entries, 0 to 1533
Data columns (total 54 columns):
 #   Column                                 Non-Null Count  Dtype
```

```
---  ------                                   --------------  -----
 0   OBS                                      1534 non-null   float64
 1   YEAR                                     1534 non-null   int64
 2   MONTH                                    1525 non-null   float64
 3   U.S._STATE                               1534 non-null   object
 4   POSTAL.CODE                              1534 non-null   object
 5   NERC.REGION                              1534 non-null   object
 6   CLIMATE.REGION                           1528 non-null   object
 7   CLIMATE.CATEGORY                         1525 non-null   object
 8   CAUSE.CATEGORY                           1534 non-null   object
 9   CAUSE.CATEGORY.DETAIL                    1063 non-null   object
 10  HURRICANE.NAMES                          72 non-null     object
 11  OUTAGE.DURATION(mins)                    1476 non-null   float64
 12  DEMAND.LOSS.MW(Megawatt)                 829 non-null    float64
 13  CUSTOMERS.AFFECTED                       1091 non-null   float64
 14  RES.PRICE(cents / kilowatt-hour)         1512 non-null   float64
 15  COM.PRICE(cents / kilowatt-hour)         1512 non-null   float64
 16  IND.PRICE(cents / kilowatt-hour)         1512 non-null   float64
 17  TOTAL.PRICE(cents / kilowatt-hour)       1512 non-null   float64
 18  RES.SALES(Megawatt-hour)                 1512 non-null   float64
 19  COM.SALES(Megawatt-hour)                 1512 non-null   float64
 20  IND.SALES(Megawatt-hour)                 1512 non-null   float64
 21  TOTAL.SALES(Megawatt-hour)               1512 non-null   float64
 22  RES.PERCEN(%)                            1512 non-null   float64
 23  COM.PERCEN(%)                            1512 non-null   float64
 24  IND.PERCEN(%)                            1512 non-null   float64
 25  RES.CUSTOMERS                            1534 non-null   float64
 26  COM.CUSTOMERS                            1534 non-null   float64
 27  IND.CUSTOMERS                            1534 non-null   float64
 28  TOTAL.CUSTOMERS                          1534 non-null   float64
 29  RES.CUST.PCT(%)                          1534 non-null   float64
 30  COM.CUST.PCT(%)                          1534 non-null   float64
 31  IND.CUST.PCT(%)                          1534 non-null   float64
 32  PC.REALGSP.STATE(USD)                    1534 non-null   float64
 33  PC.REALGSP.USA(USD)                      1534 non-null   float64
 34  PC.REALGSP.REL(fraction)                 1534 non-null   float64
 35  PC.REALGSP.CHANGE(%)                     1534 non-null   float64
 36  UTIL.REALGSP(USD)                        1534 non-null   float64
 37  TOTAL.REALGSP(USD)                       1534 non-null   float64
 38  UTIL.CONTRI(%)                           1534 non-null   float64
 39  PI.UTIL.OFUSA(%)                         1534 non-null   float64
 40  POPULATION                               1534 non-null   float64
 41  POPPCT_URBAN(%)                          1534 non-null   float64
 42  POPPCT_UC(%)                             1534 non-null   float64
 43  POPDEN_URBAN(persons per square mile)    1534 non-null   float64
 44  POPDEN_UC(persons per square mile)       1524 non-null   float64
 45  POPDEN_RURAL(persons per square mile)    1524 non-null   float64
 46  AREAPCT_URBAN(%)                         1534 non-null   float64
```

```
 47   AREAPCT_UC(%)                         1534 non-null   float64
 48   PCT_LAND(%)                           1534 non-null   float64
 49   PCT_WATER_TOT(%)                      1534 non-null   float64
 50   PCT_WATER_INLAND(%)                   1534 non-null   float64
 51   OUTAGE.START                          1525 non-null   datetime64[ns]
 52   OUTAGE.RESTORATION                    1476 non-null   datetime64[ns]
 53   ANOMALY.LEVEL                         1525 non-null   float64
dtypes: datetime64[ns](2), float64(43), int64(1), object(8)
memory usage: 647.3+ KB
```

[11]:
```
all_values = df.value_counts()
```

1.4 EDA

1.4.1 Univariate Analysis

We can first find some relationship or patterns within columns

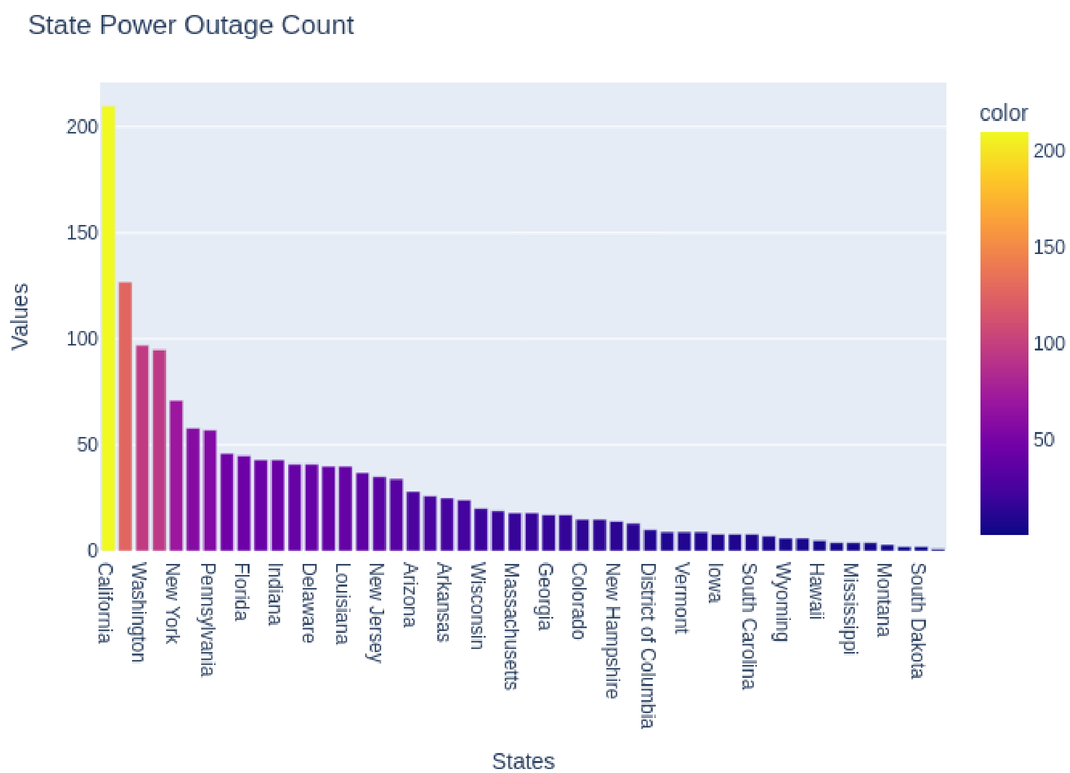
[12]:
```
all_states = df['U.S._STATE'].value_counts()
all_states
```

[12]:
```
California             210
Texas                  127
Washington              97
Michigan                95
New York                71
Maryland                58
Pennsylvania            57
Illinois                46
Florida                 45
Ohio                    43
Indiana                 43
Utah                    41
Delaware                41
North Carolina          40
Louisiana               40
Virginia                37
New Jersey              35
Tennessee               34
Arizona                 28
Oregon                  26
Arkansas                25
Oklahoma                24
Wisconsin               20
Maine                   19
Massachusetts           18
Connecticut             18
Georgia                 17
```

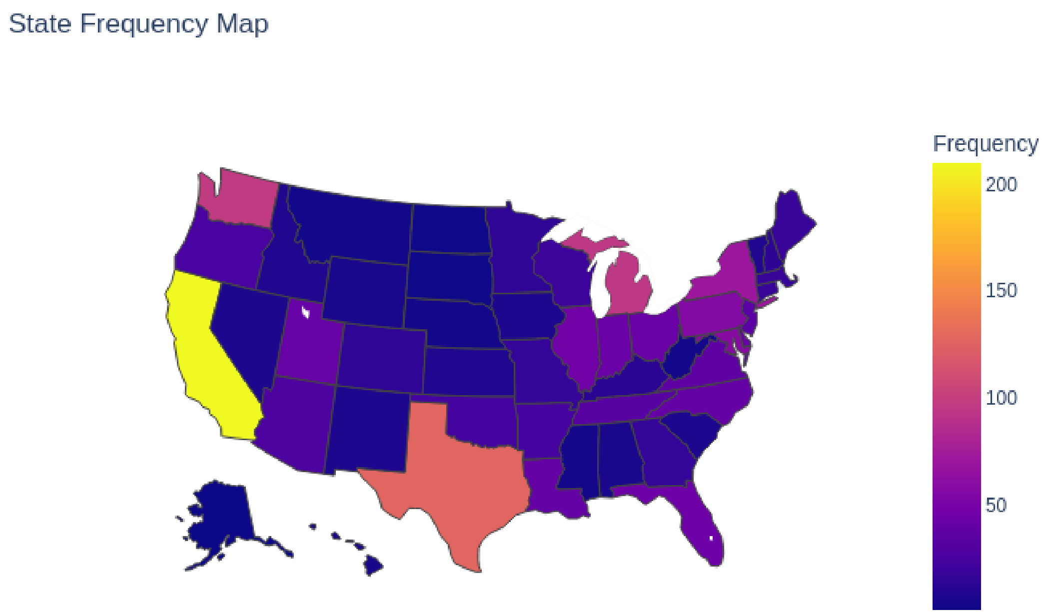
```
Missouri                17
Colorado                15
Minnesota               15
New Hampshire           14
Kentucky                13
District of Columbia    10
Idaho                    9
Vermont                  9
Kansas                   9
Iowa                     8
New Mexico               8
South Carolina           8
Nevada                   7
Wyoming                  6
Alabama                  6
Hawaii                   5
Nebraska                 4
Mississippi              4
West Virginia            4
Montana                  3
North Dakota             2
South Dakota             2
Alaska                   1
Name: U.S._STATE, dtype: int64
```

[13]:

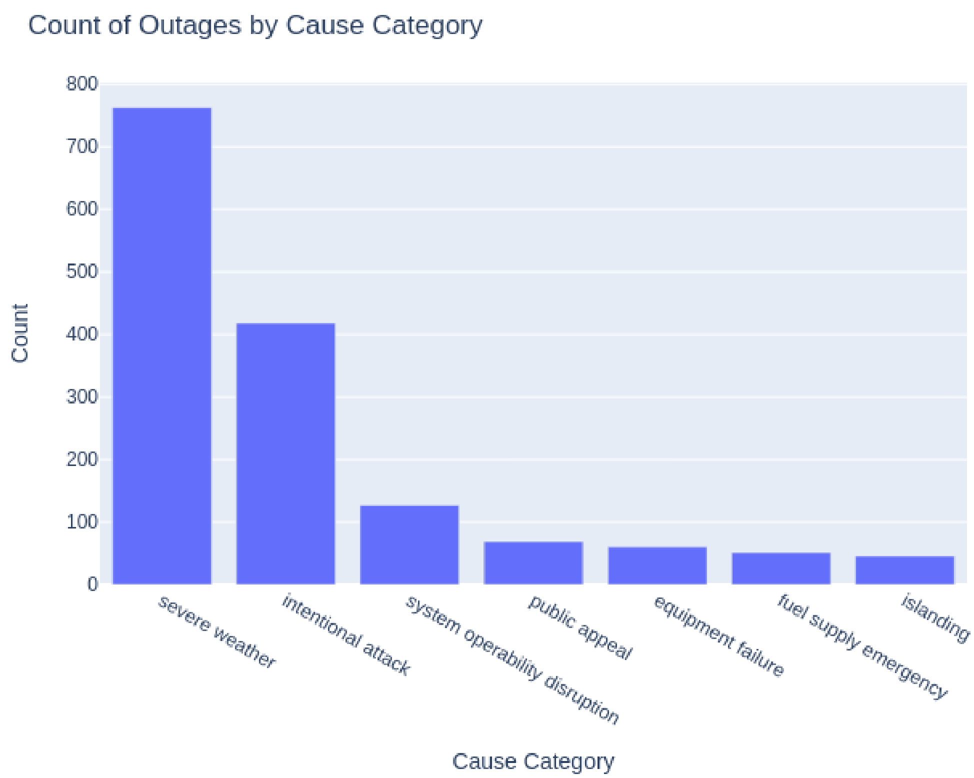
```
fig = px.bar(all_states, color=all_states.values)
fig.update_layout(title='State Power Outage Count', xaxis_title='States',␣
↪yaxis_title='Values')
```



[14]:
```python
state_counts = df['POSTAL.CODE'].value_counts().reset_index()
state_counts.columns = ['POSTAL.CODE', 'Frequency']

# Create the geospatial graph
fig = px.choropleth(state_counts,
                    locations='POSTAL.CODE',
                    locationmode='USA-states',
                    color='Frequency',
                    scope='usa',
                    labels={'Frequency': 'Frequency'},
                    title='State Frequency Map')

fig.show()
```

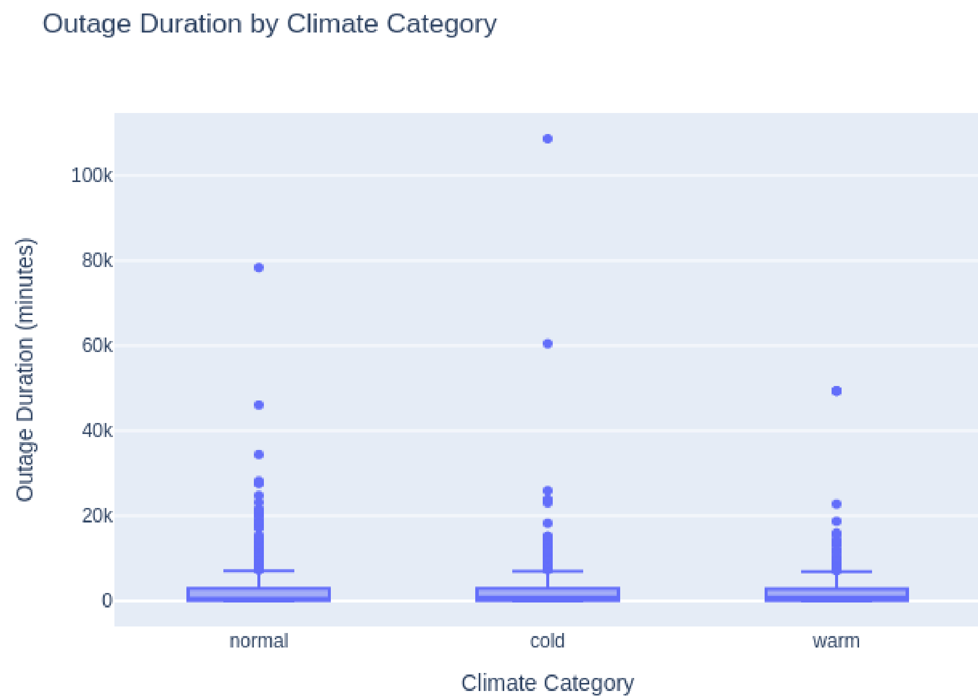


[15]:
```
fig = px.bar(df['CAUSE.CATEGORY'].value_counts(), x=df['CAUSE.CATEGORY'].
    ↪value_counts().index, y=df['CAUSE.CATEGORY'].value_counts().values)
fig.update_layout(title='Count of Outages by Cause Category',␣
    ↪xaxis_title='Cause Category', yaxis_title='Count')
fig.show()
```



1.4.2 Bivariate Analysis

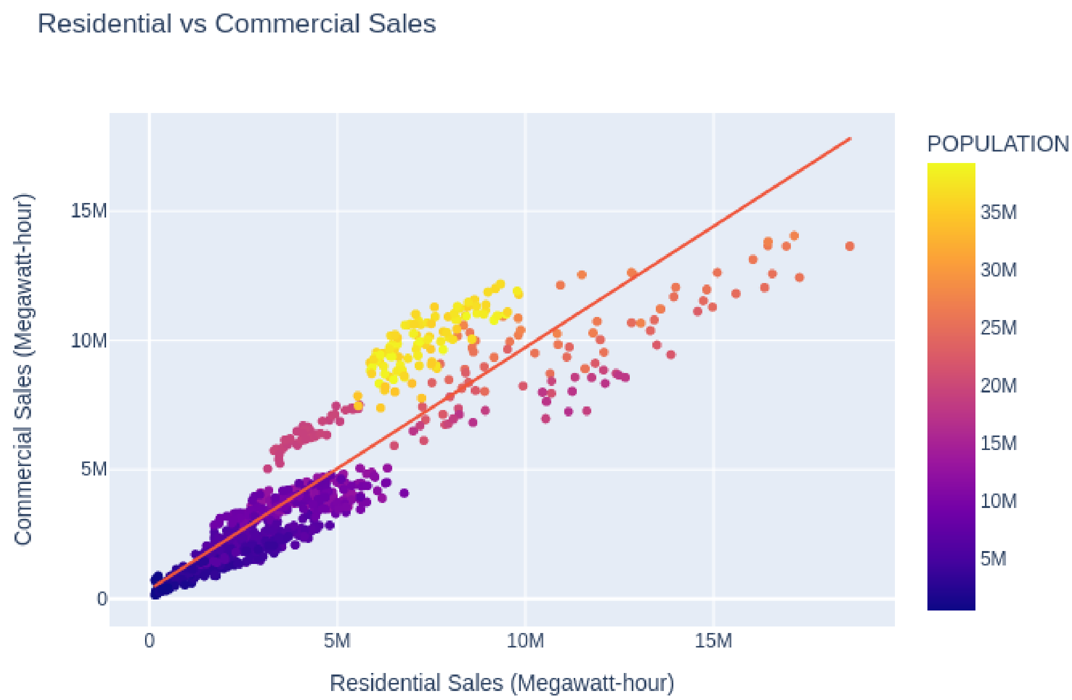
[16]:
```
fig = px.box(df, x='CLIMATE.CATEGORY', y='OUTAGE.DURATION(mins)', title='Outage␣
 ↪Duration by Climate Category')
fig.update_layout(xaxis_title='Climate Category', yaxis_title='Outage Duration␣
 ↪(minutes)')
fig.show()
```



The relationship between residential sales and commericial sales, find some pattern when set the color to population

[17]:
```
fig = px.scatter(df, x='RES.SALES(Megawatt-hour)', y='COM.
↪SALES(Megawatt-hour)', title='Residential vs Commercial Sales',␣
↪trendline='ols',color = 'POPULATION')
fig.update_layout(xaxis_title='Residential Sales (Megawatt-hour)',␣
↪yaxis_title='Commercial Sales (Megawatt-hour)')
fig.show()
```

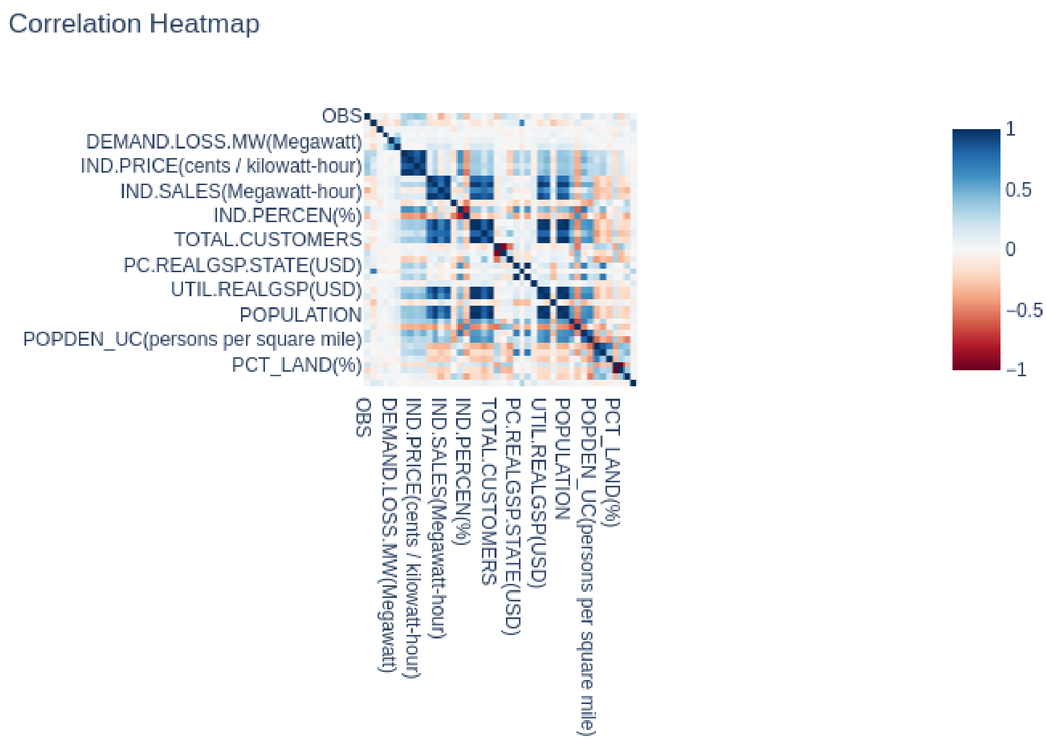
```
/opt/conda/lib/python3.9/site-packages/statsmodels/tsa/base/tsa_model.py:7:
FutureWarning:

pandas.Int64Index is deprecated and will be removed from pandas in a future
version. Use pandas.Index with the appropriate dtype instead.

/opt/conda/lib/python3.9/site-packages/statsmodels/tsa/base/tsa_model.py:7:
FutureWarning:

pandas.Float64Index is deprecated and will be removed from pandas in a future
version. Use pandas.Index with the appropriate dtype instead.
```



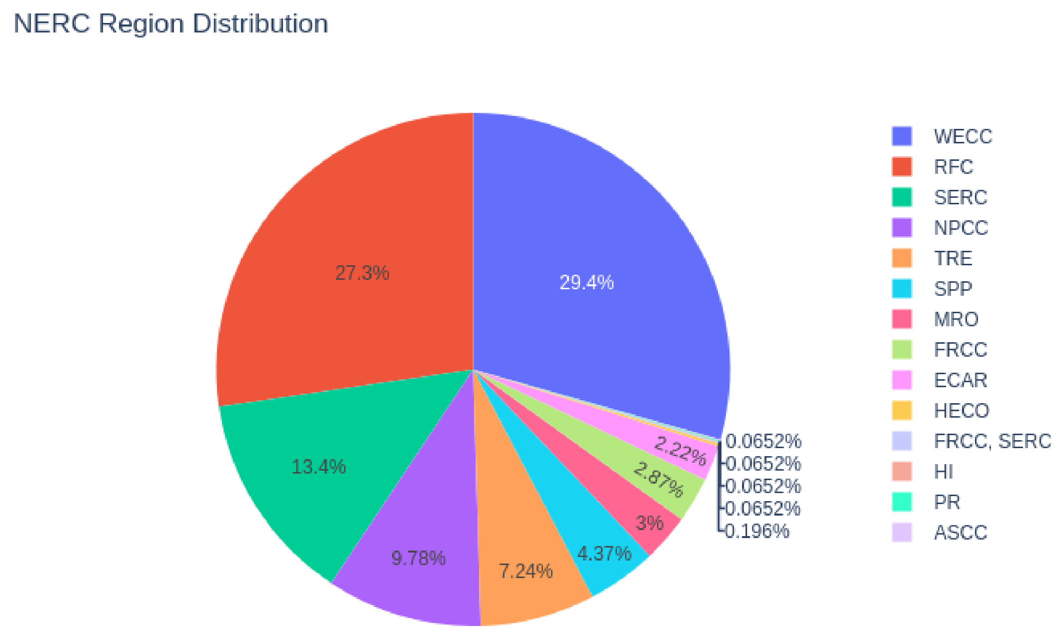
Correlation between each column (Correlation Heatmap)

[18]:
```
corr_matrix = df.corr()  # Assuming you want to calculate correlations between␣
↪all numeric columns
fig = px.imshow(corr_matrix, color_continuous_scale='RdBu', title='Correlation␣
↪Heatmap')
fig.show()
```

```
/tmp/ipykernel_1540/2406824264.py:1: FutureWarning:

The default value of numeric_only in DataFrame.corr is deprecated. In a future
version, it will default to False. Select only valid columns or specify the
value of numeric_only to silence this warning.
```



[19]:
```python
fig = px.pie(df, names='NERC.REGION', title='NERC Region Distribution')
fig.show()
```



1.5 Pivoting and Aggregation – Interesting Aggregates

[20]:
```python
# Calculate the total customers affected per year:
total_customers_affected_per_year = pd.DataFrame(df.groupby('YEAR')['CUSTOMERS.
↪AFFECTED'].sum())
total_customers_affected_per_year
```

[20]:

YEAR	CUSTOMERS.AFFECTED
2000	4270581.0
2001	1431411.0
2002	6382586.0
2003	12463108.0
2004	13592556.0
2005	13552084.0
2006	10152092.0
2007	5973433.0
2008	19964926.0
2009	6813477.0
2010	10108129.0
2011	16438669.0

```
2012         12703973.0
2013          7018398.0
2014          8022197.0
2015          5629211.0
2016          1993908.0
```

[21]:
```
# Determine the average outage duration per U.S. state and cause category:
pivot_table_outage_duration = df.pivot_table(index='U.S._STATE', columns='CAUSE.
 ↪CATEGORY', values='OUTAGE.DURATION(mins)', aggfunc='mean', fill_value=0)
pivot_table_outage_duration
```

[21]:
```
CAUSE.CATEGORY        equipment failure  fuel supply emergency  \
U.S._STATE
Alabama                        0.000000                   0.00
Arizona                      138.500000                   0.00
Arkansas                     105.000000                   0.00
California                   524.809524                6154.60
Colorado                       0.000000                   0.00
Connecticut                    0.000000                   0.00
Delaware                      50.000000                   0.00
District of Columbia         159.000000                   0.00
Florida                      554.500000                   0.00
Georgia                        0.000000                   0.00
Hawaii                         0.000000                   0.00
Idaho                          0.000000                   0.00
Illinois                     149.000000                2761.00
Indiana                        1.000000               12240.00
Iowa                           0.000000                   0.00
Kansas                         0.000000                   0.00
Kentucky                     652.000000               12570.00
Louisiana                    176.333333               28170.00
Maine                          0.000000                1676.00
Maryland                       0.000000                   0.00
Massachusetts                  0.000000                2891.00
Michigan                   26435.333333                   0.00
Minnesota                      0.000000                   0.00
Mississippi                    0.000000                   0.00
Missouri                       0.000000                   0.00
Montana                        0.000000                   0.00
Nebraska                       0.000000                   0.00
Nevada                         0.000000                   0.00
New Hampshire                  0.000000                   0.00
New Jersey                     0.000000                   0.00
New Mexico                     0.000000                  76.00
New York                     247.000000               16687.25
North Carolina                 0.000000                   0.00
North Dakota                   0.000000                   0.00
```

Ohio	0.000000	0.00
Oklahoma	0.000000	0.00
Oregon	200.000000	0.00
Pennsylvania	376.000000	0.00
South Carolina	0.000000	0.00
South Dakota	0.000000	0.00
Tennessee	404.000000	0.00
Texas	405.600000	13920.00
Utah	15.000000	0.00
Vermont	0.000000	0.00
Virginia	0.000000	0.00
Washington	1204.000000	1.00
West Virginia	0.000000	0.00
Wisconsin	0.000000	33971.25
Wyoming	61.000000	0.00

CAUSE.CATEGORY	intentional attack	islanding	public appeal	\
U.S._STATE				
Alabama	77.000000	0.000000	0.000000	
Arizona	639.600000	0.000000	0.000000	
Arkansas	547.833333	3.000000	1063.714286	
California	946.458333	214.857143	2028.111111	
Colorado	117.000000	2.000000	0.000000	
Connecticut	49.125000	0.000000	0.000000	
Delaware	38.918919	0.000000	0.000000	
District of Columbia	0.000000	0.000000	0.000000	
Florida	50.000000	0.000000	4320.000000	
Georgia	108.000000	0.000000	0.000000	
Hawaii	0.000000	0.000000	0.000000	
Idaho	307.500000	0.000000	1548.000000	
Illinois	1450.000000	0.000000	120.000000	
Indiana	421.875000	125.333333	0.000000	
Iowa	5657.800000	0.000000	0.000000	
Kansas	561.000000	0.000000	913.000000	
Kentucky	108.000000	0.000000	0.000000	
Louisiana	0.000000	0.000000	1359.214286	
Maine	82.666667	881.000000	0.000000	
Maryland	225.320000	0.000000	0.000000	
Massachusetts	384.250000	0.000000	0.000000	
Michigan	3635.250000	1.000000	1078.000000	
Minnesota	369.500000	0.000000	0.000000	
Mississippi	12.000000	0.000000	0.000000	
Missouri	408.000000	0.000000	0.000000	
Montana	93.000000	34.500000	0.000000	
Nebraska	0.000000	0.000000	159.000000	
Nevada	553.285714	0.000000	0.000000	
New Hampshire	60.000000	0.000000	0.000000	

New Jersey	91.125000	0.000000	0.000000
New Mexico	174.500000	0.000000	0.000000
New York	309.083333	0.000000	2655.000000
North Carolina	1063.750000	0.000000	0.000000
North Dakota	0.000000	0.000000	720.000000
Ohio	327.285714	0.000000	0.000000
Oklahoma	75.666667	984.000000	704.000000
Oregon	394.105263	0.000000	0.000000
Pennsylvania	1526.833333	0.000000	0.000000
South Carolina	0.000000	0.000000	0.000000
South Dakota	0.000000	120.000000	0.000000
Tennessee	171.000000	0.000000	2700.000000
Texas	298.769231	0.000000	1140.411765
Utah	142.285714	0.000000	2275.000000
Vermont	35.444444	0.000000	0.000000
Virginia	2.000000	0.000000	683.500000
Washington	371.870968	73.333333	248.000000
West Virginia	1.000000	0.000000	0.000000
Wisconsin	459.000000	0.000000	388.000000
Wyoming	0.333333	32.000000	0.000000

CAUSE.CATEGORY	severe weather	system operability disruption
U.S._STATE		
Alabama	1421.750000	0.000000
Arizona	25726.500000	384.500000
Arkansas	2701.800000	0.000000
California	2928.373134	363.666667
Colorado	2727.250000	279.750000
Connecticut	2262.600000	0.000000
Delaware	2153.500000	0.000000
District of Columbia	4764.111111	0.000000
Florida	6420.192308	205.700000
Georgia	1422.750000	0.000000
Hawaii	997.500000	237.000000
Idaho	0.000000	179.666667
Illinois	1650.700000	0.000000
Indiana	4523.291667	4671.600000
Iowa	3353.666667	0.000000
Kansas	9346.000000	0.000000
Kentucky	4480.111111	0.000000
Louisiana	7186.928571	1144.666667
Maine	1669.400000	0.000000
Maryland	4006.937500	304.000000
Massachusetts	1556.571429	67.000000
Michigan	4831.650602	2610.000000
Minnesota	3585.545455	0.000000
Mississippi	0.000000	300.000000

```
Missouri                4483.818182                        65.000000
Montana                    0.000000                         0.000000
Nebraska                3221.333333                         0.000000
Nevada                     0.000000                         0.000000
New Hampshire           1597.500000                         0.000000
New Jersey              6372.863636                       748.500000
New Mexico                 0.000000                         0.000000
New York                6034.575758                      1176.571429
North Carolina          1738.933333                        82.200000
North Dakota               0.000000                         0.000000
Ohio                    4322.269231                      1744.500000
Oklahoma                4206.466667                         0.000000
Oregon                  2295.800000                         0.000000
Pennsylvania            4314.000000                       329.000000
South Carolina          3135.000000                         0.000000
South Dakota               0.000000                         0.000000
Tennessee               1386.350000                        20.000000
Texas                   3854.890625                       810.800000
Utah                     957.000000                       537.500000
Vermont                    0.000000                         0.000000
Virginia                1132.281250                       241.000000
Washington              5473.550000                        25.000000
West Virginia           9305.000000                         0.000000
Wisconsin               1527.428571                         0.000000
Wyoming                  106.000000                         0.000000
```

[22]:
```python
# Determine the outage frequency per U.S. state and cause category:
pivot_table_outage_frequency = df.pivot_table(index='U.S._STATE',␣
    ↪columns='CAUSE.CATEGORY', values='OUTAGE.DURATION(mins)', aggfunc='count',␣
    ↪fill_value=0)
pivot_table_outage_frequency
```

[22]:
```
CAUSE.CATEGORY        equipment failure  fuel supply emergency  \
U.S._STATE
Alabama                               0                      0
Alaska                                0                      0
Arizona                               4                      0
Arkansas                              1                      0
California                           21                     10
Colorado                              0                      0
Connecticut                           0                      0
Delaware                              1                      0
District of Columbia                  1                      0
Florida                               4                      0
Georgia                               0                      0
Hawaii                                0                      0
Idaho                                 0                      0
```

Illinois	1	1
Indiana	1	1
Iowa	0	0
Kansas	0	0
Kentucky	1	2
Louisiana	3	1
Maine	0	1
Maryland	0	0
Massachusetts	0	1
Michigan	3	0
Minnesota	0	0
Mississippi	0	0
Missouri	0	0
Montana	0	0
Nebraska	0	0
Nevada	0	0
New Hampshire	0	0
New Jersey	0	0
New Mexico	0	1
New York	2	12
North Carolina	0	0
North Dakota	0	0
Ohio	0	0
Oklahoma	0	0
Oregon	1	0
Pennsylvania	1	0
South Carolina	0	0
South Dakota	0	0
Tennessee	2	0
Texas	5	3
Utah	1	0
Vermont	0	0
Virginia	0	0
Washington	1	1
West Virginia	0	0
Wisconsin	0	4
Wyoming	1	0

CAUSE.CATEGORY	intentional attack	islanding	public appeal	\
U.S._STATE				
Alabama	1	0	0	
Alaska	0	0	0	
Arizona	15	0	0	
Arkansas	6	1	7	
California	24	28	9	
Colorado	5	1	0	
Connecticut	8	0	0	

Delaware	37	0	0
District of Columbia	0	0	0
Florida	2	0	3
Georgia	1	0	0
Hawaii	0	0	0
Idaho	4	0	1
Illinois	1	0	1
Indiana	8	3	0
Iowa	5	0	0
Kansas	3	0	1
Kentucky	1	0	0
Louisiana	0	0	14
Maine	6	1	0
Maryland	25	0	0
Massachusetts	8	0	0
Michigan	4	1	1
Minnesota	4	0	0
Mississippi	3	0	0
Missouri	3	0	0
Montana	1	2	0
Nebraska	0	0	1
Nevada	7	0	0
New Hampshire	12	0	0
New Jersey	8	0	0
New Mexico	6	0	0
New York	12	0	4
North Carolina	4	0	0
North Dakota	0	0	1
Ohio	14	0	0
Oklahoma	3	1	3
Oregon	19	0	0
Pennsylvania	6	0	0
South Carolina	0	0	0
South Dakota	0	2	0
Tennessee	6	0	1
Texas	13	0	17
Utah	35	0	1
Vermont	9	0	0
Virginia	1	0	2
Washington	62	3	1
West Virginia	1	0	0
Wisconsin	7	0	1
Wyoming	3	1	0

CAUSE.CATEGORY	severe weather	system operability disruption
U.S._STATE		
Alabama	4	0

Alaska	0	0
Arizona	4	2
Arkansas	10	0
California	67	39
Colorado	4	4
Connecticut	10	0
Delaware	2	0
District of Columbia	9	0
Florida	26	10
Georgia	16	0
Hawaii	4	1
Idaho	0	3
Illinois	40	0
Indiana	24	5
Iowa	3	0
Kansas	3	0
Kentucky	9	0
Louisiana	14	6
Maine	10	0
Maryland	32	1
Massachusetts	7	2
Michigan	83	3
Minnesota	11	0
Mississippi	0	1
Missouri	11	1
Montana	0	0
Nebraska	3	0
Nevada	0	0
New Hampshire	2	0
New Jersey	22	2
New Mexico	0	1
New York	33	7
North Carolina	30	5
North Dakota	0	0
Ohio	26	2
Oklahoma	15	0
Oregon	5	0
Pennsylvania	48	2
South Carolina	8	0
South Dakota	0	0
Tennessee	20	2
Texas	64	20
Utah	2	2
Vermont	0	0
Virginia	32	1
Washington	20	1
West Virginia	3	0

```
Wisconsin                       7                              0
Wyoming                         1                              0
```

[23]:
```
# Find the maximum customers affected per climate region and year:
pivot_table_customers_affected = df.pivot_table(index='CLIMATE.REGION',␣
↪columns='YEAR', values='CUSTOMERS.AFFECTED', aggfunc='max', fill_value=0)
pivot_table_customers_affected
```

[23]:
```
YEAR                   2000     2001     2002     2003     2004     2005  \
CLIMATE.REGION
Central              239567        0    95000  1203000   281000   246990
East North Central        0        0   190000  2100000   250000   300000
Northeast                 0   130000   224912  3125350   380000   143000
Northwest                 0        0        0   200000   187000        0
South               2000000   114000  1881134   192000   500000  1100000
Southeast            160000   600000   130000   340000  2775093  3241437
Southwest            500000        0        0    90000    30000        0
West                  32000   430984  1500000   241000   505000  1667316
West North Central        0        0        0        0   120212        0

YEAR                   2006     2007     2008     2009     2010     2011  \
CLIMATE.REGION
Central              471932   629590   653000   383000   400000   500000
East North Central   315000   215000   358000   137000   285000   197166
Northeast            492955   300000   249408   132000   360000   760113
Northwest            700000   160000     8000    93300   123535     9000
South                489478   300000  2504366   800000   500000  1069730
Southeast            126000   107000   584384   217000   145157   285465
Southwest             65000        0    74031   140000    31000   204000
West                1271893   671189  2606931   859554  1700000   165000
West North Central    15000        0   126000    35500        0    34500

YEAR                  2012     2013     2014     2015     2016
CLIMATE.REGION
Central             346000   283451   420000   115000        0
East North Central  140000   400000   164000   250000   160895
Northeast           850000    75000   715000   263000    56645
Northwest           426000   105000        0   500000    56000
South               262000   881000    57200   454000   415103
Southeast           880000   283000   677858   186035   203345
Southwest            30379    35230        0     5763    85179
West                125000   148000  1400000    80000   110000
West North Central       0        0        0        0        0
```

[24]:
```
# Determine the average anomaly level per climate category and cause category␣
↪detail:
```

```
pivot_table_anomaly_level = df.pivot_table(index='CLIMATE.CATEGORY',␣
 ↪columns='CAUSE.CATEGORY.DETAIL',
                                           values='ANOMALY.LEVEL',␣
 ↪aggfunc='mean', fill_value=0)
pivot_table_anomaly_level
```

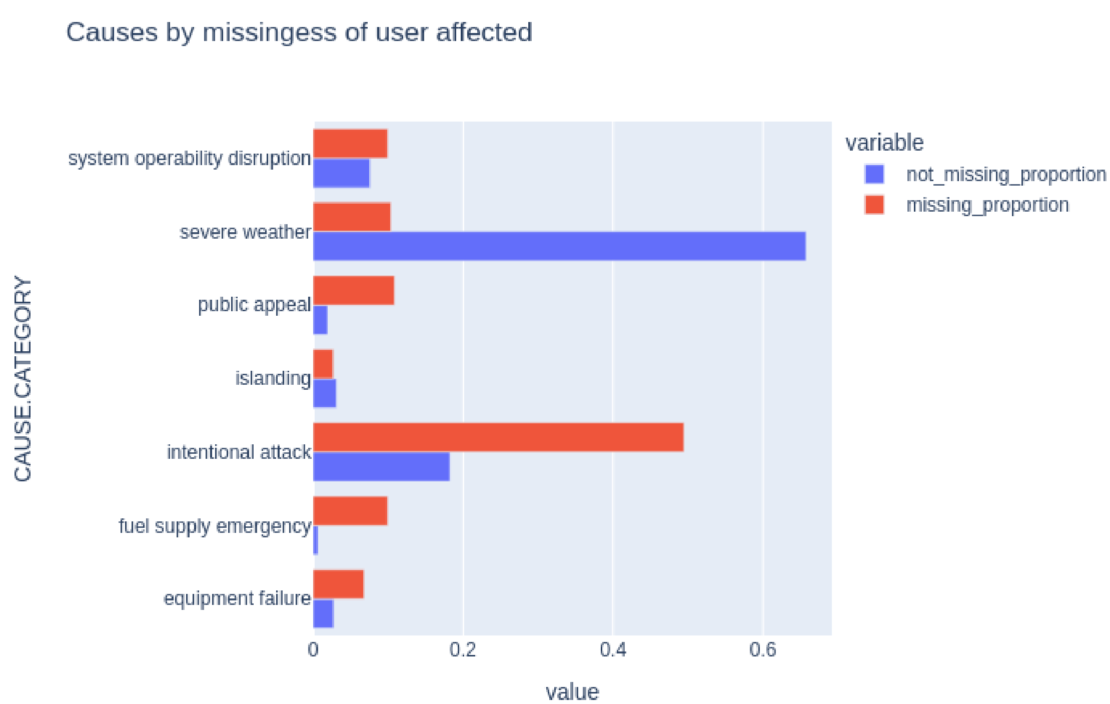
[24]:

```
CAUSE.CATEGORY.DETAIL   Coal  Hydro   Natural Gas  100 MW loadshed  \
CLIMATE.CATEGORY
cold                    -0.5    0.0          -0.6              0.0
normal                  -0.2   -0.4          -0.3             -0.2
warm                     0.0    0.0           0.0              0.0

CAUSE.CATEGORY.DETAIL          Coal  HVSubstation interruption  Hydro  \
CLIMATE.CATEGORY
cold                  -8.250000e-01                        0.0 -1.200
normal                 9.251859e-18                       -0.1  0.025
warm                   0.000000e+00                        0.0  0.000

CAUSE.CATEGORY.DETAIL  Petroleum  breaker trip  cables  …  \
CLIMATE.CATEGORY                                        …
cold                         0.0     -0.500000     0.0  …
normal                      -0.4      0.066667     0.3  …
warm                         0.0      0.000000     0.0  …

CAUSE.CATEGORY.DETAIL  transmission trip  uncontrolled loss  vandalism  \
CLIMATE.CATEGORY
cold                               -0.85          -0.500000  -0.747059
normal                             -0.25          -0.275000  -0.215730
warm                                0.00           1.144444   1.189474

CAUSE.CATEGORY.DETAIL  voltage reduction  wildfire  wind  wind storm  \
CLIMATE.CATEGORY
cold                                 0.0 -0.836364  0.00         0.0
normal                              -0.3 -0.100000 -0.20        -0.3
warm                                 0.0  0.620000  0.55         0.0

CAUSE.CATEGORY.DETAIL  wind/rain    winter  winter storm
CLIMATE.CATEGORY
cold                   -1.500000 -0.527778     -0.963636
normal                  0.066667 -0.400000      0.020000
warm                    0.825000  0.525000      0.958065

[3 rows x 51 columns]
```

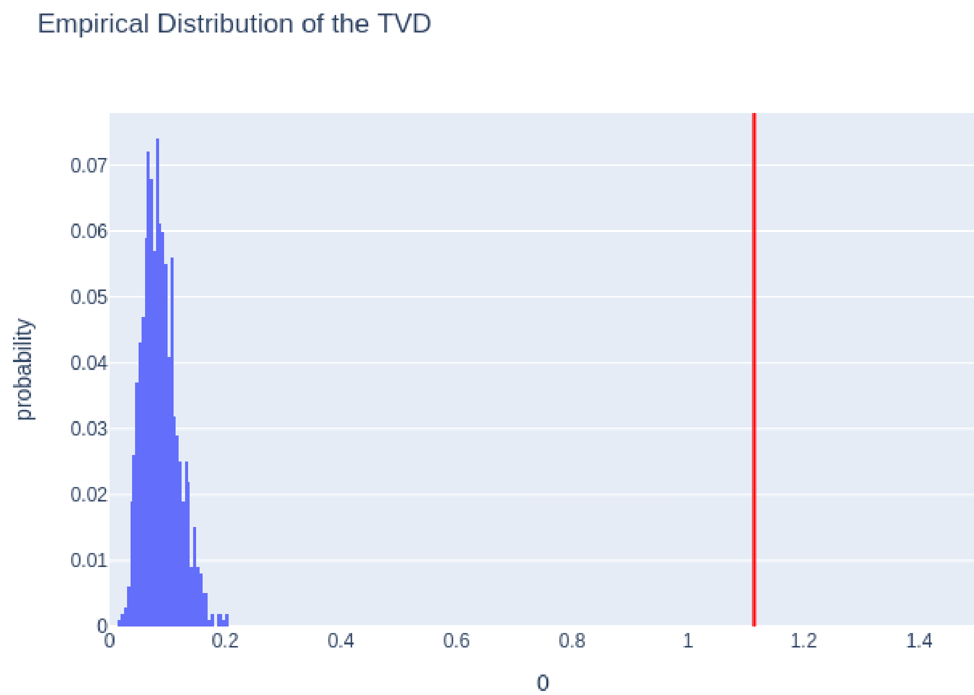
1.6 Assessment of Missingness

1.6.1 NMAR Analysis & Missingness Dependency

[25]:
```
# Does missingness of customers affected depend on the cause category?
df['CAUSE.CATEGORY']
df.groupby('CAUSE.CATEGORY').count()
df_ca_missing = df[df['CUSTOMERS.AFFECTED'].isna()]
df_ca_not_missing = df[~df['CUSTOMERS.AFFECTED'].isna()]
missing_count = df_ca_missing.groupby('CAUSE.CATEGORY').count()['YEAR']
missing_proportion = pd.Series(np.array(missing_count)/((np.
 ↪array(missing_count)).sum()), index=missing_count.index)
not_missing_count = df_ca_not_missing.groupby('CAUSE.CATEGORY').count()['YEAR']
not_missing_proportion = pd.Series(np.array(not_missing_count)/((np.
 ↪array(not_missing_count)).sum()), index=not_missing_count.index)
observed_tvd_statistic = abs(not_missing_proportion - missing_proportion).sum()
observed_dataframe = pd.concat([not_missing_proportion, missing_proportion],␣
 ↪axis=1, keys=['not_missing_proportion', 'missing_proportion'])
observed_dataframe.plot(kind='barh', title='Causes by missingess of user␣
 ↪affected', barmode='group')
```

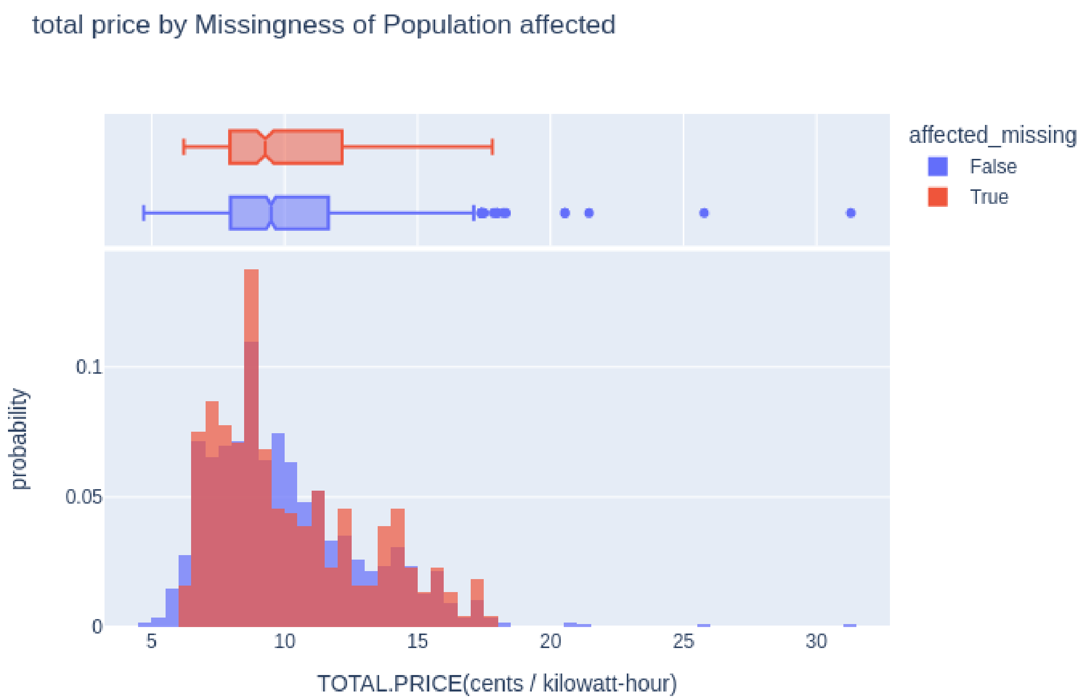


[26]:
```
def cause_one_permutation(df):
    df = df.copy()
    df['CUSTOMERS.AFFECTED'] = np.random.permutation(df['CUSTOMERS.AFFECTED'])
    df['CAUSE.CATEGORY']
    df.groupby('CAUSE.CATEGORY').count()
    df_ca_missing = df[df['CUSTOMERS.AFFECTED'].isna()]
    df_ca_not_missing = df[~df['CUSTOMERS.AFFECTED'].isna()]
    missing_count = df_ca_missing.groupby('CAUSE.CATEGORY').count()['YEAR']
    missing_proportion = pd.Series(np.array(missing_count)/((np.
 ↪array(missing_count)).sum()), index=missing_count.index)
    not_missing_count = df_ca_not_missing.groupby('CAUSE.CATEGORY').
 ↪count()['YEAR']
    not_missing_proportion = pd.Series(np.array(not_missing_count)/((np.
 ↪array(not_missing_count)).sum()), index=not_missing_count.index)
    observed_tvd_statistic = abs(not_missing_proportion - missing_proportion).
 ↪sum()
    return observed_tvd_statistic
# do permutation 1000 times
result = []
for i in range(1000):
    result.append(cause_one_permutation(df))
fig = px.histogram(pd.DataFrame(result), x=0, nbins=50, histnorm='probability',
                   title='Empirical Distribution of the TVD')
fig.add_vline(x=observed_tvd_statistic, line_color='red')
fig.update_layout(xaxis_range=[0, 1.5])
```



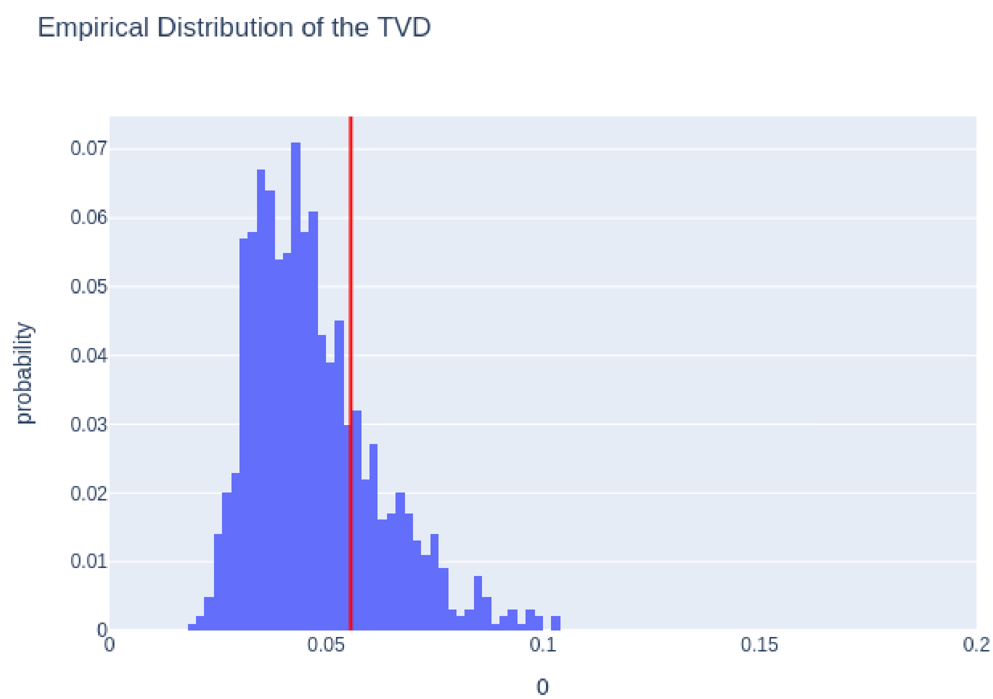
[27]:
```
# Does missingness of customers affected depend on the cause category?
from scipy import stats
df['TOTAL.PRICE(cents / kilowatt-hour)']
df.groupby('TOTAL.PRICE(cents / kilowatt-hour)').count()
df_ca_missing = df[df['CUSTOMERS.AFFECTED'].isna()]
df_ca_not_missing = df[~df['CUSTOMERS.AFFECTED'].isna()]
missing_distribution = df_ca_missing['TOTAL.PRICE(cents / kilowatt-hour)']
not_missing_distribution = df_ca_not_missing['TOTAL.PRICE(cents /␣
↪kilowatt-hour)']
observed_dataframe = pd.concat([not_missing_distribution,␣
↪missing_distribution], axis=1, keys=['not_missing_proportion',␣
↪'missing_proportion'])
specific_df = df[['TOTAL.PRICE(cents / kilowatt-hour)','CUSTOMERS.AFFECTED' ]].
↪copy()
specific_df['affected_missing'] = specific_df['CUSTOMERS.AFFECTED'].isna()
per_na = df_ca_missing['TOTAL.PRICE(cents / kilowatt-hour)']
per_va = df_ca_not_missing['TOTAL.PRICE(cents / kilowatt-hour)']
obsersed_stat2 = stats.ks_2samp(per_na, per_va).statistic
px.histogram(specific_df, x='TOTAL.PRICE(cents / kilowatt-hour)',␣
↪color='affected_missing', histnorm='probability', marginal='box',
```

```
             title="total price by Missingness of Population affected",␣
↪barmode='overlay', opacity=0.7)
```



[28]:
```
def cause_one_permutation2(df):
    df = df.copy()
    df['CUSTOMERS.AFFECTED'] = np.random.permutation(df['CUSTOMERS.AFFECTED'])
    df['TOTAL.PRICE(cents / kilowatt-hour)']
    df.groupby('TOTAL.PRICE(cents / kilowatt-hour)').count()
    df_ca_missing = df[df['CUSTOMERS.AFFECTED'].isna()]
    df_ca_not_missing = df[~df['CUSTOMERS.AFFECTED'].isna()]
    specific_df = df[['TOTAL.PRICE(cents / kilowatt-hour)','CUSTOMERS.AFFECTED'␣
↪]].copy()
    specific_df['affected_missing'] = specific_df['CUSTOMERS.AFFECTED'].isna()
    per_na = df_ca_missing['TOTAL.PRICE(cents / kilowatt-hour)']
    per_va = df_ca_not_missing['TOTAL.PRICE(cents / kilowatt-hour)']
    obsersed_stat = stats.ks_2samp(per_na, per_va).statistic
    return obsersed_stat
result2 = []
for i in range(1000):
    result2.append(cause_one_permutation2(df))
fig2 = px.histogram(pd.DataFrame(result2), x=0, nbins=50,␣
↪histnorm='probability',
```

```
                    title='Empirical Distribution of the TVD')
fig2.add_vline(x=obsersed_stat2, line_color='red')
fig2.update_layout(xaxis_range=[0, 0.2])
```



[29]:
```
p_value1 = (np.array(result) > observed_tvd_statistic).mean()
p_value2 = (np.array(result2) > obsersed_stat2).mean()
observed_tvd_statistic
```

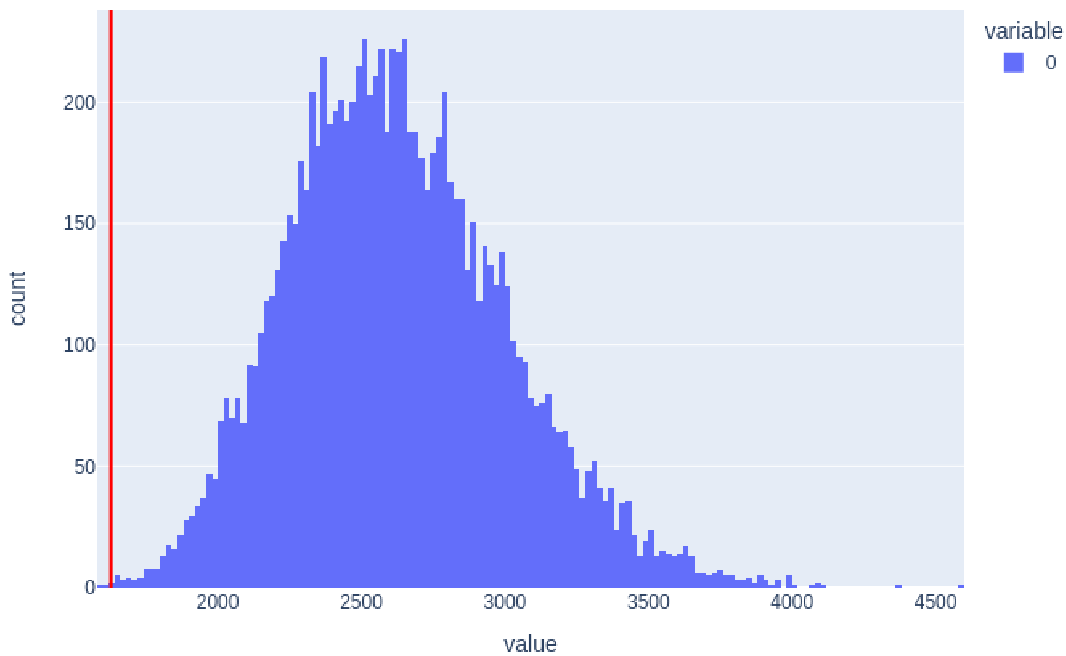
[29]: 1.1148675909814136

1.7 Hypothesis Testing

[30]:
```
west_duration = df[df['CLIMATE.REGION']=='West']['OUTAGE.DURATION(mins)']
overall_duration = df['OUTAGE.DURATION(mins)']
print('observed:', 'overall_duration',overall_duration.mean(),␣
 ↪'west_duration',west_duration.mean())

duration_simulation_result = []
for i in range(10000):
    each_duration_simulation = pd.Series(np.random.choice(overall_duration,␣
 ↪size=len(west_duration), replace=False)).mean()
```

```
    duration_simulation_result.append(each_duration_simulation)
p_val_hypo_1 = (np.array(duration_simulation_result) < west_duration.mean()).
↪mean()
print('p value for the duration hypothesis test = ', p_val_hypo_1)
fig_hyp1 = px.histogram(duration_simulation_result)
fig_hyp1.add_vline(west_duration.mean(), line_color='red')
```

```
observed: overall_duration 2625.39837398374 west_duration 1628.331707317073
p value for the duration hypothesis test =  0.0003
```

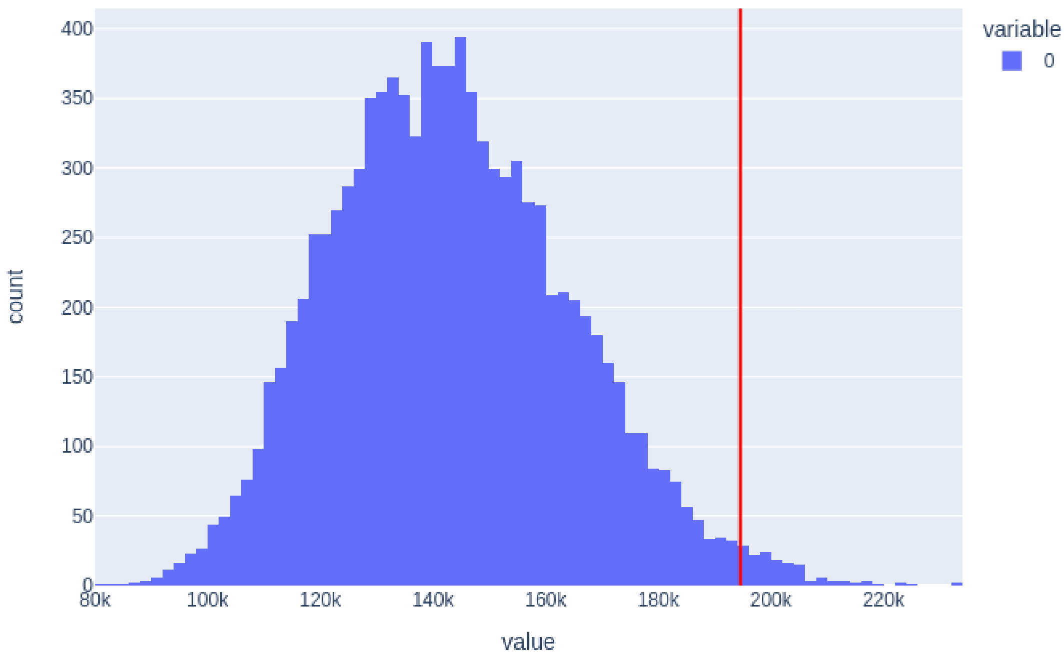


1.8 Hypothesis test: people affected

[31]:
```
west_affected = df[df['CLIMATE.REGION']=='West']['CUSTOMERS.AFFECTED']
overall_affected = df['CUSTOMERS.AFFECTED']
print('observed:', 'overall_affected: ',overall_affected.mean(), 'west_affected:
↪ ',west_affected.mean())

affected_simulation_result = []
for i in range(10000):
    each_affected_simulation = pd.Series(np.random.choice(overall_affected,␣
↪size=len(west_affected), replace=False)).mean()
```

```
    affected_simulation_result.append(each_affected_simulation)
p_val_hypo_2 = (np.array(affected_simulation_result) > west_affected.mean()).
 ↪mean()
print('p value for the duration hypothesis test = ', p_val_hypo_2)
fig_hyp2 = px.histogram(affected_simulation_result)
fig_hyp2.add_vline(west_affected.mean(), line_color='red')
```

```
observed: overall_affected:  143456.22273143905 west_affected:
194579.89393939395
p value for the duration hypothesis test =  0.0144
```



[ ]:

```

```

[ ]:

```

```