Tarea1_Montero_Medina

May 5, 2025

Se importan las librerías a utilizar

[201]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
import sklearn
import scipy
from scipy.stats import nbinom
import seaborn as sns
from statsmodels.iolib.summary2 import summary_col

import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
```

0.1 1.-

Lectura y limpieza de datos

[ ]:
```
#Lectura del Dataframe
df= pd.read_csv('../../data/machine_failure_data.csv')
```

[203]:
```
#limpieza de datos
variables = df.columns.values.tolist() #visualizamos los nombres de las␣
↪variables
print(variables)
def contador_nulos(columnas):
    return columnas.isnull().sum()          #analizamos cuales datos tienen␣
↪mayor cantidad de errores o nulos
for columnas in variables:
    a = contador_nulos(df[columnas])
    if contador_nulos(df[columnas])/len(df[columnas]) > 0.35:
        print(a/len(df[columnas]), 'porcentaje de nulos')
        print(f"-------la variable {columnas} tiene un alto porcentaje de␣
↪valores nulos-------")
total_data_len=len(df['Date'])
```

```
['Date', 'Location', 'Min_Temp', 'Max_Temp', 'Leakage', 'Evaporation',
'Electricity', 'Parameter1_Dir', 'Parameter1_Speed', 'Parameter2_9am',
'Parameter2_3pm', 'Parameter3_9am', 'Parameter3_3pm', 'Parameter4_9am',
'Parameter4_3pm', 'Parameter5_9am', 'Parameter5_3pm', 'Parameter6_9am',
'Parameter6_3pm', 'Parameter7_9am', 'Parameter7_3pm', 'Failure_today']
0.42789026182723483 porcentaje de nulos
-------la variable Evaporation tiene un alto porcentaje de valores nulos-------
0.47692924405561454 porcentaje de nulos
-------la variable Electricity tiene un alto porcentaje de valores nulos-------
0.3773533155640573 porcentaje de nulos
-------la variable Parameter6_9am tiene un alto porcentaje de valores
nulos-------
0.4015246882757942 porcentaje de nulos
-------la variable Parameter6_3pm tiene un alto porcentaje de valores
nulos-------
```

[204]:
```
df.dropna(inplace=True) #eliminar filas con valores nulos
print('la cantidad de datos usables es:', len(df['Date'])/
 ↪total_data_len*100,'%')
```

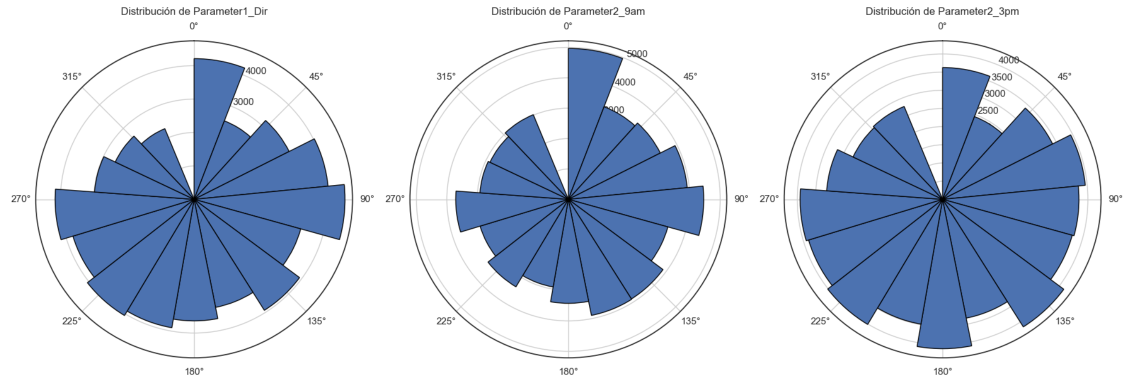
```
la cantidad de datos usables es: 39.67846518464341 %
```

transformación de variables que representan el sentido del viento en un esquema de seno y coseno

[205]:
```
df['Failure_today'] = df['Failure_today'].map({'No': 0, 'Yes': 1}) #mapear␣
 ↪valores de la columna Failure_today
direccion_en_grados = {'N': 0, 'NNE': 22.5, 'NE': 45, 'ENE': 67.5, #transformar␣
 ↪direcciones a grados
               'E': 90, 'ESE': 112.5, 'SE': 135, 'SSE': 157.5,
               'S': 180, 'SSW': 202.5, 'SW': 225, 'WSW': 247.5,
               'W': 270, 'WNW': 292.5, 'NW': 315, 'NNW': 337.5}

df['Parameter1_Dir'] = df['Parameter1_Dir'].map(direccion_en_grados)
df['Parameter2_9am'] = df['Parameter2_9am'].map(direccion_en_grados)
df['Parameter2_3pm'] = df['Parameter2_3pm'].map(direccion_en_grados)

# Lista de columnas de dirección
dir_cols = ['Parameter1_Dir', 'Parameter2_9am', 'Parameter2_3pm']

for col in dir_cols:
    # Convierte a radianes
    df[f'{col}_rad'] = np.deg2rad(df[col])
    # Calcula seno y coseno
    df[f'{col}_sin'] = np.sin(df[f'{col}_rad'])
    df[f'{col}_cos'] = np.cos(df[f'{col}_rad'])
```

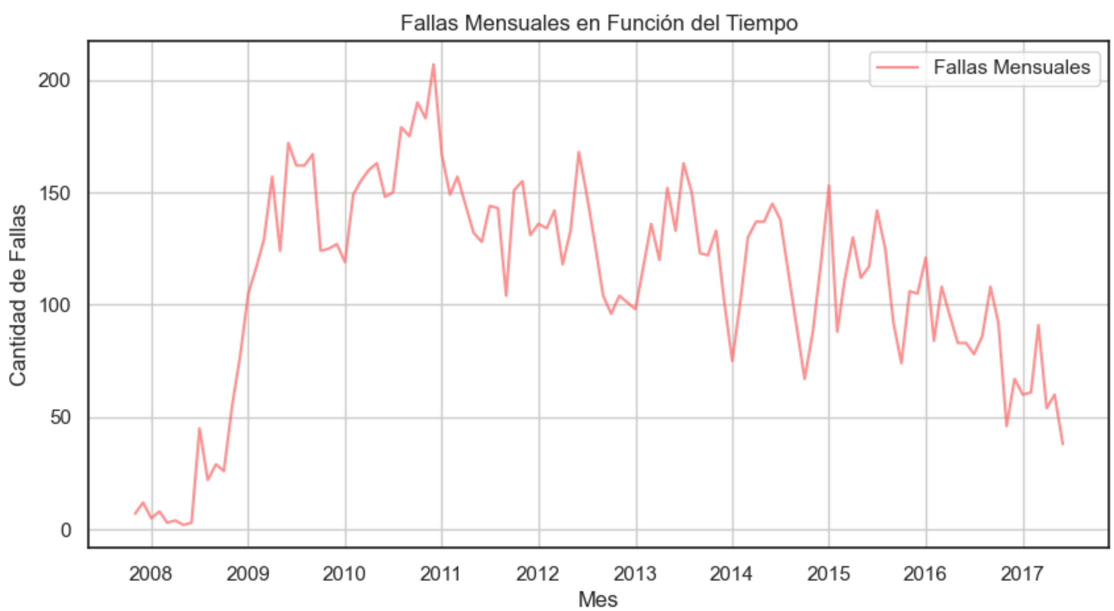
0.2 distribución de los sentidos del vientos para parametros 1 y 2

[206]:
```
param_cols = [
    ('Parameter1_Dir_rad', 'Parameter1_Dir'),
    ('Parameter2_9am_rad', 'Parameter2_9am'),
    ('Parameter2_3pm_rad', 'Parameter2_3pm')
]
titulos = [
    'Distribución de Parameter1_Dir',
    'Distribución de Parameter2_9am',
    'Distribución de Parameter2_3pm'
]

# Crear la figura y los subplots polares
fig, axs = plt.subplots(1, 3, subplot_kw=dict(polar=True), figsize=(18, 6))

for i, (col_rad, col_name) in enumerate(param_cols):
    direcciones_radianes = df[col_rad]
    frecuencias, bins = np.histogram(direcciones_radianes, bins=16)
    axs[i].bar(bins[:-1], frecuencias, width=np.diff(bins), align='edge',␣
↪edgecolor='black')
    axs[i].set_theta_zero_location("N")
    axs[i].set_theta_direction(-1)
    axs[i].set_title(titulos[i], va='bottom')

plt.tight_layout()
plt.show()
```



[207]:
```
# Asegúrate de que 'Date' es datetime
df['Date'] = pd.to_datetime(df['Date'])

# Agrupar por semanas y calcular la suma de fallas semanales
df['Week'] = df['Date'].dt.to_period('W').apply(lambda r: r.start_time)
```

```
fallas_semanales = df.groupby('Week')['Failure_today'].sum().reset_index()

# Agrupar por meses y calcular la suma de fallas mensuales
df['Month'] = df['Date'].dt.to_period('M').apply(lambda r: r.start_time)
fallas_mensuales = df.groupby('Month')['Failure_today'].sum().reset_index()

# Graficar las fallas mensuales
plt.figure(figsize=(10,5))
plt.plot(fallas_mensuales['Month'], fallas_mensuales['Failure_today'],
 ↪label='Fallas Mensuales', color='#ff6361', alpha=0.7)
plt.xlabel('Mes')
plt.ylabel('Cantidad de Fallas')
plt.title('Fallas Mensuales en Función del Tiempo')
plt.legend()
plt.grid(True)
plt.show()
```



Exploración de los datos

[208]:
```
dfrelevante = df[['Min_Temp', 'Max_Temp','Evaporation', 'Electricity',
 ↪'Parameter1_Speed', 'Parameter1_Dir_sin', 'Parameter1_Dir_cos',
 ↪'Parameter2_9am_sin', 'Parameter2_9am_cos', 'Parameter2_3pm_sin',
 ↪'Parameter2_3pm_cos',
                  'Parameter3_9am', 'Parameter3_3pm', 'Parameter4_9am',
 ↪'Parameter4_3pm', 'Parameter5_9am', 'Parameter5_3pm','Parameter6_9am',
 ↪'Parameter6_3pm','Parameter7_9am','Parameter7_3pm',
 ↪'Failure_today','Leakage','Date']]
```

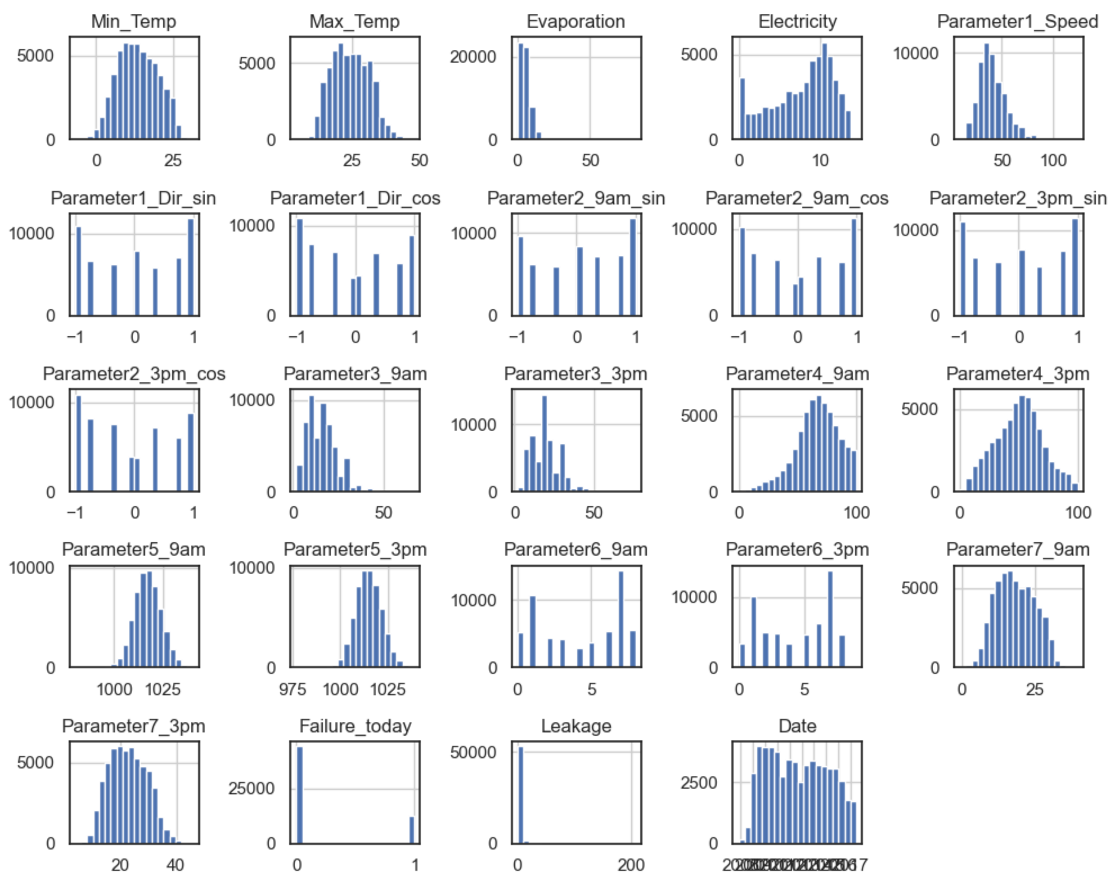
```python
print(dfrelevante.describe()) #estadisticas descriptivas de los datos
```

```
          Min_Temp      Max_Temp   Evaporation   Electricity  \
count  56420.000000  56420.000000  56420.000000  56420.000000
mean      13.464770     24.219206      5.503135      7.735626
min       -6.700000      4.100000      0.000000      0.000000
25%        8.600000     18.700000      2.800000      5.000000
50%       13.200000     23.900000      5.000000      8.600000
75%       18.400000     29.700000      7.400000     10.700000
max       31.400000     48.100000     81.200000     14.500000
std        6.416689      6.970676      3.696282      3.758153

       Parameter1_Speed  Parameter1_Dir_sin  Parameter1_Dir_cos  \
count      56420.000000        5.642000e+04        5.642000e+04
mean          40.877366        1.856414e-02       -5.689761e-02
min            9.000000       -1.000000e+00       -1.000000e+00
25%           31.000000       -7.071068e-01       -7.071068e-01
50%           39.000000        1.224647e-16       -1.836970e-16
75%           48.000000        7.071068e-01        7.071068e-01
max          124.000000        1.000000e+00        1.000000e+00
std           13.335232        7.213366e-01        6.900067e-01

       Parameter2_9am_sin  Parameter2_9am_cos  Parameter2_3pm_sin  …  \
count        5.642000e+04        5.642000e+04        5.642000e+04  …
mean         5.737015e-02        8.993245e-03        1.354252e-02  …
min         -1.000000e+00       -1.000000e+00       -1.000000e+00  …
25%         -7.071068e-01       -7.071068e-01       -7.071068e-01  …
50%          1.224647e-16        6.123234e-17        1.224647e-16  …
75%          7.071068e-01        7.071068e-01        7.071068e-01  …
max          1.000000e+00        1.000000e+00        1.000000e+00  …
std          7.041894e-01        7.076459e-01        7.184015e-01  …

       Parameter4_3pm  Parameter5_9am  Parameter5_3pm  Parameter6_9am  \
count    56420.000000    56420.000000    56420.000000    56420.000000
mean        49.601985     1017.239505     1014.795580        4.241705
min          0.000000      980.500000      977.100000        0.000000
25%         35.000000     1012.700000     1010.100000        1.000000
50%         50.000000     1017.200000     1014.700000        5.000000
75%         63.000000     1021.800000     1019.400000        7.000000
max        100.000000     1040.400000     1038.900000        8.000000
std         20.197040        6.909357        6.870892        2.797162

       Parameter6_3pm  Parameter7_9am  Parameter7_3pm  Failure_today  \
count    56420.000000    56420.000000    56420.000000   56420.000000
mean         4.326515       18.204961       22.710333       0.220879
min          0.000000       -0.700000        3.700000       0.000000
25%          2.000000       13.100000       17.400000       0.000000
```

```
50%          5.000000      17.800000      22.400000      0.000000
75%          7.000000      23.300000      27.900000      0.000000
max          9.000000      39.400000      46.100000      1.000000
std          2.647251       6.567991       6.836543      0.414843

            Leakage                          Date
count  56420.000000                         56420
mean       2.130397  2012-09-17 06:16:13.952498944
min        0.000000            2007-11-01 00:00:00
25%        0.000000            2010-07-19 00:00:00
50%        0.000000            2012-07-28 00:00:00
75%        0.600000            2014-10-10 00:00:00
max      206.200000            2017-06-25 00:00:00
std        7.014822                           NaN

[8 rows x 24 columns]
```

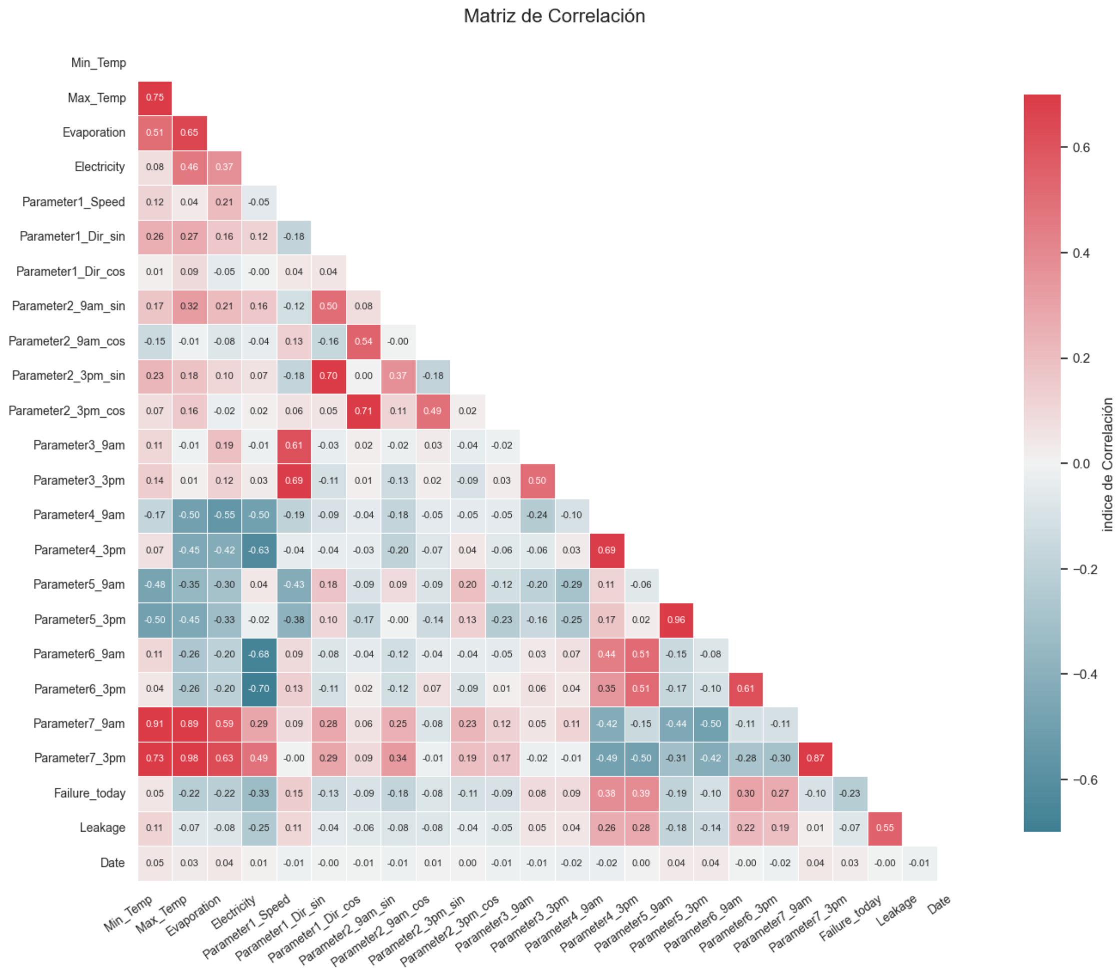
[209]:

```python
import matplotlib.pyplot as plt
dfrelevante.hist(figsize=(10,8), bins=20)
plt.tight_layout()
plt.show()
```



[210]:
```
#exploración de datos
# for column in dfrelevante.select_dtypes(include=['float64', 'int64']).columns:
#     sns.kdeplot(dfrelevante[column], shade=True, label=column)
#     plt.legend()
#     plt.show()
```

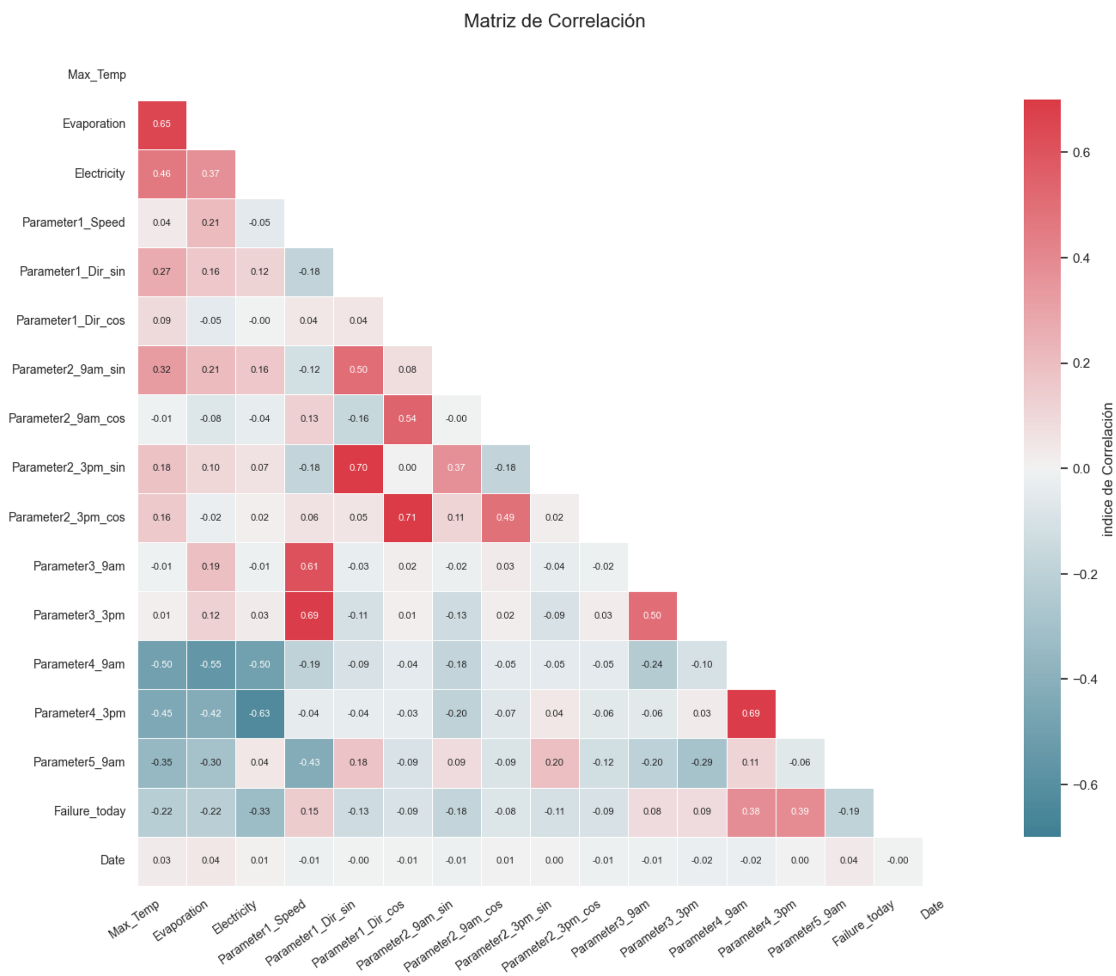
[211]:
```
# Calcula la matriz de correlación

df4=dfrelevante
corr = df4.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))

# Estilo de seaborn
sns.set(style="white")

# Tamaño del gráfico
f, ax = plt.subplots(figsize=(14, 12))

# Paleta de colores mejorada
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Mapa de calor
sns.heatmap(
    corr, mask=mask, cmap=cmap, vmax=0.7, vmin=-0.7, center=0, square=True,␣
 ↪linewidths=0.4,
    cbar_kws={"shrink": 0.8, 'label': 'indice de Correlación'}, annot=True,␣
 ↪fmt=".2f",annot_kws={"size": 8}
)
plt.xticks(rotation=35, ha='right', fontsize=10)
plt.yticks(fontsize=10)
plt.title("Matriz de Correlación", fontsize=16, pad=20)
plt.tight_layout()
plt.show()
```



En función de esta matriz de correlación, podemos ver que el parametro 7 (9am y 3pm) presentan una correlación alta con otras variables. También asi el parametro 6 (esto sumado a que la variable 6 presnta un gran numero de valores nulos). Otra variable que presenta redundancia al momento de enriquecer el modelo es la de min_Temp, que está altamente correlacionada con su variable alterna que es Max_Temp, Y por ultimo, el parametro5_3pm tiene una alta correlación con parametro5_9am, por lo que se quita para disminuir la multicolinealidad. Tambien es necesario quitar la variable leakage ya que esta esta directamente relacionada con la falla y hasta cierto punto predice el futuro, lo que genera problemas en modelos como Probit.

[212]:
```
df5 = dfrelevante.drop(columns=[col for col in␣
↪['Parameter7_9am','Parameter7_3pm','Parameter6_9am','Parameter6_3pm','Min_Temp','Parameter5
↪'Leakage'] if col in df.columns])

corr = df5.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))
```

```python
# Estilo de seaborn
sns.set(style="white")

# Tamaño del gráfico
f, ax = plt.subplots(figsize=(14, 12))

# Paleta de colores mejorada
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Mapa de calor
sns.heatmap(
    corr, mask=mask, cmap=cmap, vmax=0.7, vmin=-0.7, center=0, square=True,␣
 ↪linewidths=0.4,
    cbar_kws={"shrink": 0.8, 'label': 'indice de Correlación'}, annot=True,␣
 ↪fmt=".2f",annot_kws={"size": 8}
)
plt.xticks(rotation=35, ha='right', fontsize=10)
plt.yticks(fontsize=10)
plt.title("Matriz de Correlación", fontsize=16, pad=20)
plt.tight_layout()
plt.show()
#eliminar la variable dependiente para el analisis de correlacion
```




```
[213]: df7=df5
#Se calcula el percentil 99 para cada columna
percentil_99 = df7.quantile(0.99)

# Filtrar las filas que están por debajo del percentil 99 en todas las columnas
df7_cleaned = df7[(df7 <= percentil_99).all(axis=1)]

# Verificar la cantidad de datos restantes
print(f"Datos originales: {len(df7)}")
print(f"Datos después de eliminar outliers: {len(df7_cleaned)}")
```

```
Datos originales: 56420
Datos después de eliminar outliers: 51948
```

0.3 2.-

calculamos la regresión para ver los parametros con la data hasta este punto

[214]:

```python
import statsmodels.api as sm

# Definir la variable dependiente
y = df7_cleaned['Failure_today']
df6=df7_cleaned.drop(columns=['Failure_today'])
# Definir las variables independientes
X = df6[['Max_Temp', 'Evaporation', 'Electricity', 'Parameter1_Speed',␣
↪'Parameter1_Dir_sin', 'Parameter1_Dir_cos', 'Parameter2_9am_sin',␣
↪'Parameter2_9am_cos', 'Parameter3_9am', 'Parameter3_3pm', 'Parameter4_9am',␣
↪'Parameter4_3pm', 'Parameter5_9am']]
# Agregar una constante al modelo
X = sm.add_constant(X)

# Ajustar el modelo OLS
model = sm.OLS(y, X).fit(cov_type='HC0')

# Mostrar el resumen del modelo
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Failure_today   R-squared:                       0.259
Model:                            OLS   Adj. R-squared:                  0.259
Method:                 Least Squares   F-statistic:                     1428.
Date:                Thu, 24 Apr 2025   Prob (F-statistic):               0.00
Time:                        23:21:12   Log-Likelihood:                -20005.
No. Observations:               51948   AIC:                         4.004e+04
Df Residuals:                   51934   BIC:                         4.016e+04
Df Model:                          13
Covariance Type:                  HC0
================================================================================
======
                         coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
------
const                 10.8452      0.355     30.564      0.000      10.150
11.541
Max_Temp               0.0019      0.000      4.546      0.000       0.001
0.003
Evaporation           -0.0185      0.001    -23.044      0.000      -0.020
-0.017
Electricity           -0.0072      0.001    -12.315      0.000      -0.008
-0.006
Parameter1_Speed       0.0053      0.000     23.833      0.000       0.005
0.006
Parameter1_Dir_sin    -0.0065      0.003     -2.504      0.012      -0.012
-0.001
```

```
Parameter1_Dir_cos    -0.0349      0.003    -12.897      0.000      -0.040
-0.030
Parameter2_9am_sin    -0.0257      0.003     -9.849      0.000      -0.031
-0.021
Parameter2_9am_cos    -0.0457      0.003    -16.588      0.000      -0.051
-0.040
Parameter3_9am         0.0050      0.000     19.370      0.000       0.005
0.006
Parameter3_3pm        -0.0041      0.000    -14.881      0.000      -0.005
-0.004
Parameter4_9am         0.0058      0.000     42.983      0.000       0.006
0.006
Parameter4_3pm         0.0022      0.000     17.084      0.000       0.002
0.002
Parameter5_9am        -0.0110      0.000    -32.395      0.000      -0.012
-0.010
==============================================================================
Omnibus:                     4691.412   Durbin-Watson:                   1.783
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6056.900
Skew:                           0.833   Prob(JB):                         0.00
Kurtosis:                       2.843   Cond. No.                     2.12e+05
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC0)
[2] The condition number is large, 2.12e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

en función de estos datos obtenidos, podemos ver que en este modelo con un coef R2 del 0.259 con un F=1438 y un p-value <0,001 es globalmente significativo por lo que las variables independientes aportan información al comportamiento del sistema y a la predicción de falla.

en función de los coeficientes obtenidos, podemos veer que la tempeeratura maxima, la velocidad y los parametros 3__9am, 4__9am, 4__3pm aumentan la probabilidad de falla, mientras que las otras variables la disminuyen.

0.4 3.-

Ahora para tener otro enfoque, aplicamos el modelo probit que se ajusta mejor a la variable binaria

[215]:
```python
X2 = X
model = sm.Probit(y, X2)
probit_model = model.fit(cov_type='HC0')
print(probit_model.summary())

mfxp = probit_model.get_margeff()
print(mfxp.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.372519
         Iterations 7
                          Probit Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                51948
Model:                         Probit   Df Residuals:                    51934
Method:                           MLE   Df Model:                           13
Date:                Thu, 24 Apr 2025   Pseudo R-squ.:                  0.2906
Time:                        23:21:12   Log-Likelihood:                -19352.
converged:                       True   LL-Null:                       -27277.
Covariance Type:                  HC0   LLR p-value:                     0.000
================================================================================
======
                         coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
------
const                 40.8697      1.459     28.011      0.000      38.010
43.729
Max_Temp               0.0050      0.002      2.857      0.004       0.002
0.008
Evaporation           -0.0904      0.004    -22.785      0.000      -0.098
-0.083
Electricity           -0.0055      0.003     -2.054      0.040      -0.011
-0.000
Parameter1_Speed       0.0205      0.001     21.904      0.000       0.019
0.022
Parameter1_Dir_sin    -0.0158      0.013     -1.226      0.220      -0.041
0.009
Parameter1_Dir_cos    -0.1340      0.013    -10.459      0.000      -0.159
-0.109
Parameter2_9am_sin    -0.1417      0.012    -11.422      0.000      -0.166
-0.117
Parameter2_9am_cos    -0.2438      0.013    -18.753      0.000      -0.269
-0.218
Parameter3_9am         0.0196      0.001     15.944      0.000       0.017
0.022
Parameter3_3pm        -0.0128      0.001    -10.074      0.000      -0.015
-0.010
Parameter4_9am         0.0322      0.001     45.959      0.000       0.031
0.034
Parameter4_3pm         0.0127      0.001     22.152      0.000       0.012
0.014
Parameter5_9am        -0.0444      0.001    -31.614      0.000      -0.047
-0.042
================================================================================
======
```

```
       Probit Marginal Effects
=====================================
Dep. Variable:          Failure_today
Method:                          dydx
At:                           overall
================================================================================
======
                        dy/dx    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
------
Max_Temp               0.0010      0.000      2.859      0.004       0.000
0.002
Evaporation           -0.0188      0.001    -23.239      0.000      -0.020
-0.017
Electricity           -0.0012      0.001     -2.054      0.040      -0.002
-5.27e-05
Parameter1_Speed       0.0043      0.000     22.256      0.000       0.004
0.005
Parameter1_Dir_sin    -0.0033      0.003     -1.226      0.220      -0.009
0.002
Parameter1_Dir_cos    -0.0279      0.003    -10.483      0.000      -0.033
-0.023
Parameter2_9am_sin    -0.0295      0.003    -11.439      0.000      -0.035
-0.024
Parameter2_9am_cos    -0.0508      0.003    -19.002      0.000      -0.056
-0.046
Parameter3_9am         0.0041      0.000     16.066      0.000       0.004
0.005
Parameter3_3pm        -0.0027      0.000    -10.100      0.000      -0.003
-0.002
Parameter4_9am         0.0067      0.000     49.502      0.000       0.006
0.007
Parameter4_3pm         0.0026      0.000     22.377      0.000       0.002
0.003
Parameter5_9am        -0.0093      0.000    -32.535      0.000      -0.010
-0.009
================================================================================
======
```

Considerando que el modelo probit converge y tiene un p-value 0, este es significativo para interpretaciones

Con esto vemos que los valores con mayor magnitud son los asociados a la dirección del viento, donde tenemos ordenes de hasta el 5% de disminución de probabilidad de falla.

Tambien podemos ver que la temperatura aumenta la probabilidad de falla junto con la velocidad de salida.

[216]:
```python
X3= X2
model = sm.Logit(y, X3)
logit_model = model.fit(cov_type='HC0')
print(logit_model.summary())

mfxl = logit_model.get_margeff()
print(mfxl.summary())

params = logit_model.params
conf = logit_model.conf_int()
conf['Odds Ratio'] = params
conf.columns = ['Odds Ratio', '5%', '95%']
print("Odds Ratios")
print(np.exp(conf).iloc[1:17 , ])
```

```
Optimization terminated successfully.
         Current function value: 0.372308
         Iterations 7
                           Logit Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                51948
Model:                          Logit   Df Residuals:                    51934
Method:                           MLE   Df Model:                           13
Date:                Thu, 24 Apr 2025   Pseudo R-squ.:                  0.2910
Time:                        23:21:13   Log-Likelihood:                -19341.
converged:                       True   LL-Null:                       -27277.
Covariance Type:                  HC0   LLR p-value:                     0.000
================================================================================
======
                         coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
------
const                 71.1818      2.587     27.514      0.000      66.111
76.252
Max_Temp               0.0101      0.003      3.307      0.001       0.004
0.016
Evaporation           -0.1656      0.007    -23.034      0.000      -0.180
-0.152
Electricity           -0.0073      0.005     -1.555      0.120      -0.017
0.002
Parameter1_Speed       0.0357      0.002     21.656      0.000       0.032
0.039
Parameter1_Dir_sin    -0.0250      0.023     -1.090      0.276      -0.070
0.020
Parameter1_Dir_cos    -0.2272      0.023    -10.052      0.000      -0.271
-0.183
Parameter2_9am_sin    -0.2476      0.022    -11.199      0.000      -0.291
```

```
-0.204
Parameter2_9am_cos    -0.4479      0.023    -19.385      0.000      -0.493
-0.403
Parameter3_9am         0.0340      0.002     15.572      0.000       0.030
0.038
Parameter3_3pm        -0.0211      0.002     -9.352      0.000      -0.026
-0.017
Parameter4_9am         0.0580      0.001     46.781      0.000       0.056
0.060
Parameter4_3pm         0.0224      0.001     22.246      0.000       0.020
0.024
Parameter5_9am        -0.0776      0.002    -31.106      0.000      -0.082
-0.073
================================================================================
======
        Logit Marginal Effects
=====================================
Dep. Variable:          Failure_today
Method:                          dydx
At:                           overall
================================================================================
======
                        dy/dx    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
------
Max_Temp               0.0012      0.000      3.310      0.001       0.000
0.002
Evaporation           -0.0195      0.001    -23.520      0.000      -0.021
-0.018
Electricity           -0.0009      0.001     -1.555      0.120      -0.002
0.000
Parameter1_Speed       0.0042      0.000     22.059      0.000       0.004
0.005
Parameter1_Dir_sin    -0.0029      0.003     -1.090      0.275      -0.008
0.002
Parameter1_Dir_cos    -0.0267      0.003    -10.069      0.000      -0.032
-0.022
Parameter2_9am_sin    -0.0292      0.003    -11.215      0.000      -0.034
-0.024
Parameter2_9am_cos    -0.0527      0.003    -19.692      0.000      -0.058
-0.047
Parameter3_9am         0.0040      0.000     15.707      0.000       0.004
0.004
Parameter3_3pm        -0.0025      0.000     -9.378      0.000      -0.003
-0.002
Parameter4_9am         0.0068      0.000     50.758      0.000       0.007
0.007
```

```
Parameter4_3pm          0.0026      0.000     22.492      0.000       0.002
0.003
Parameter5_9am         -0.0091      0.000    -32.131      0.000      -0.010
-0.009
================================================================================
======
Odds Ratios
                    Odds Ratio        5%       95%
Max_Temp              1.004136  1.016273  1.010186
Evaporation           0.835533  0.859414  0.847389
Electricity           0.983544  1.001916  0.992687
Parameter1_Speed      1.032971  1.039662  1.036311
Parameter1_Dir_sin    0.932545  1.020107  0.975344
Parameter1_Dir_cos    0.762267  0.832877  0.796790
Parameter2_9am_sin    0.747547  0.815228  0.780655
Parameter2_9am_cos    0.610706  0.668594  0.638995
Parameter3_9am        1.030144  1.038992  1.034558
Parameter3_3pm        0.974799  0.983459  0.979119
Parameter4_9am        1.057169  1.062322  1.059742
Parameter4_3pm        1.020622  1.024655  1.022637
Parameter5_9am        0.920842  0.929889  0.925355
```

0.4.1 5.-

Variable	OLS (coef)	Logit (dy/dx)	Probit (dy/dx)
Max_Temp	0.0018	0.0053	0.0053
Evaporation	-0.0183	-0.0177	-0.0171
Electricity	-0.0073	-0.0019	-0.0022
Parameter1_Speed	0.0053	0.0060	0.0061
Parameter1_Dir_sin	-0.0063	-0.0209	-0.0216
Parameter1_Dir_cos	-0.0358	-0.0210	-0.0222
Parameter2_9am_sin	-0.0258	-0.0322	-0.0334
Parameter2_9am_cos	-0.0457	-0.0507	-0.0488
Parameter3_9am	0.0050	0.0039	0.0040
Parameter3_3pm	-0.0041	-0.0027	-0.0029
Parameter4_9am	0.0058	0.0071	0.0070
Parameter4_3pm	0.0022	0.0033	0.0034
Parameter5_9am	-0.0111	-0.0011	-0.0011

Aunque los tres modelos presentan resultados consistentes en cuanto a la dirección e importancia relativa de las variables, el modelo Logit es el más adecuado para predecir fallas de máquinas en este contexto. Permite estimar probabilidades realistas, facilita la interpretación de los efectos a partir de los odds ratios y se ajusta mejor a la naturaleza binaria del problema. Por lo tanto, usar Logit como modelo de referencia para la interpretación del sistema y toma de desiciones sobre como mejorarlo.

0.5 6.-

[217]:
```
# Extrae año y mes
df7_cleaned['AñoMes'] = df7_cleaned['Date'].dt.to_period('M')

# Lista de variables numéricas EXCLUYENDO las categóricas como las de dirección␣
↪del viento
vars_numericas = [
    'Max_Temp', 'Evaporation', 'Electricity',
    'Parameter1_Speed','Parameter3_9am','Parameter3_3pm',
    'Parameter4_9am','Parameter4_3pm', 'Parameter5_9am'
    # agrega o ajusta según tu dataset
]

# Agrupa promediando las variables numéricas y contando fallos por mes
df_agregado = df7_cleaned.groupby('AñoMes')[vars_numericas].mean()
df_agregado['Fallos_mes'] = df7_cleaned.groupby('AñoMes')['Failure_today'].sum()

# Si no hubo fallos, Fallos_mes será 0, así que no hace falta más ajustes
df_agregado = df_agregado.reset_index()
```

[218]:
```
import statsmodels.api as sm

# Variables independientes
X = df_agregado[vars_numericas]
X = sm.add_constant(X)

# Variable dependiente: cantidad de fallos por mes (recuerda: debe ser int >= 0)
y = df_agregado['Fallos_mes']

# Modelo Poisson
poisson_model = sm.GLM(y, X, family=sm.families.Poisson())
poisson_results = poisson_model.fit()
print(poisson_results.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:             Fallos_mes   No. Observations:                  111
Model:                            GLM   Df Residuals:                      101
Model Family:                 Poisson   Df Model:                            9
Link Function:                    Log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -641.89
Date:                Thu, 24 Apr 2025   Deviance:                       590.03
Time:                        23:24:05   Pearson chi2:                     538.
No. Iterations:                     5   Pseudo R-squ. (CS):              1.000
Covariance Type:            nonrobust
================================================================================
====
```

```
                     coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
----
const             26.6680      7.113      3.749      0.000      12.727
40.609
Max_Temp           0.1299      0.011     11.926      0.000       0.109
0.151
Evaporation       -0.3343      0.032    -10.306      0.000      -0.398
-0.271
Electricity       -0.0560      0.040     -1.405      0.160      -0.134
0.022
Parameter1_Speed  -0.1025      0.012     -8.638      0.000      -0.126
-0.079
Parameter3_9am     0.2415      0.017     14.438      0.000       0.209
0.274
Parameter3_3pm     0.2218      0.019     11.587      0.000       0.184
0.259
Parameter4_9am     0.0088      0.006      1.473      0.141      -0.003
0.021
Parameter4_3pm     0.0259      0.007      3.730      0.000       0.012
0.040
Parameter5_9am    -0.0282      0.007     -4.263      0.000      -0.041
-0.015
================================================================================
====
```

[ ]: