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June 1, 2025

[1]:
```python
# Load Required Libraries
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.ensemble import IsolationForest
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, LSTM, RepeatVector, TimeDistributed,␣
↪Dense
import matplotlib.pyplot as plt

# Load the Dataset
df = pd.read_csv("C:/Users/Varun/OneDrive/Desktop/DATASET/merged_cleaned_data.
↪csv",parse_dates=['SETTLEMENTDATE'])

# Feature Engineering
# Ensure datetime conversion
df['SETTLEMENTDATE'] = pd.to_datetime(df['SETTLEMENTDATE'], errors='coerce')

# Create lagged price
df['lagged_RRP'] = df['RRP'].shift(1).bfill()

# Calculate percentage price change
df['price_change_pct'] = df['RRP'].pct_change().fillna(0) * 100

# Calculate demand forecast error
df['demand_error'] = df['TOTALDEMAND'] - df['DEMANDFORECAST']

# Extract temporal features
df['hour_of_day'] = df['SETTLEMENTDATE'].dt.hour
df['day_of_week'] = df['SETTLEMENTDATE'].dt.dayofweek

# Define Selected Features
features = [
    'RRP', 'lagged_RRP', 'price_change_pct', 'demand_error',
    'TOTALDEMAND', 'AVAILABLEGENERATION', 'DISPATCHABLEGENERATION',
    'TRADING_RRP', 'TEMPERATURE', 'SOLAR_RADIATION', 'RAINFALL',
    'hour_of_day', 'day_of_week'
```

```
]
```

[2]:
```
df
```

[2]:
```
              SETTLEMENTDATE REGIONID        RRP  MARKETSUSPENDEDFLAG  \
0       2022-01-01 00:05:00     QLD1  118.73008                  0.0
1       2022-01-01 00:10:00     QLD1  119.10000                  0.0
2       2022-01-01 00:15:00     QLD1  118.73008                  0.0
3       2022-01-01 00:20:00     QLD1  109.20000                  0.0
4       2022-01-01 00:25:00     QLD1  117.61542                  0.0
…                       …      …        …                  …
220660 2023-12-31 23:40:00     QLD1   85.55000                  0.0
220661 2023-12-31 23:45:00     QLD1   85.55000                  0.0
220662 2023-12-31 23:50:00     QLD1   85.75000                  0.0
220663 2023-12-31 23:55:00     QLD1   85.55000                  0.0
220664 2024-01-01 00:00:00     QLD1   85.55000                  0.0

        RAISE6SECRRP  RAISE60SECRRP  RAISE5MINRRP  RAISEREGRRP  LOWER6SECRRP  \
0               5.00           2.29          0.75        19.94          0.18
1               5.00           2.29          0.75        19.94          0.18
2               5.00           1.98          0.75        19.94          0.18
3               5.00           2.29          0.75        19.94          0.18
4               5.00           2.29          0.75        19.94          0.18
…                …            …           …           …            …
220660          0.39           0.39          0.39         1.00          0.01
220661          0.39           0.39          0.39         1.00          0.03
220662          0.39           0.39          0.39         2.64          0.01
220663          0.39           0.39          0.38         0.91          0.03
220664          0.39           0.39          0.39         1.17          0.03

        LOWER60SECRRP  …  TRADING_RRP        DATE  RAINFALL  TEMPERATURE  \
0                0.90  …       118.73  2022-01-01       NaN         26.6
1                0.90  …       119.10  2022-01-01       NaN         26.6
2                0.90  …       118.73  2022-01-01       NaN         26.6
3                0.90  …       109.20  2022-01-01       NaN         26.6
4                0.90  …       117.62  2022-01-01       NaN         26.6
…                  …  …          …         …       …          …
220660           0.07  …        85.55  2023-12-31       5.8         30.4
220661           0.17  …        85.55  2023-12-31       5.8         30.4
220662           0.08  …        85.75  2023-12-31       5.8         30.4
220663           0.15  …        85.55  2023-12-31       5.8         30.4
220664           0.17  …        85.55  2024-01-01       NaN          NaN

        SOLAR_RADIATION  lagged_RRP  price_change_pct  demand_error  \
0                  10.1   118.73008          0.000000    5994.84561
1                  10.1   118.73008          0.311564    6040.45600
2                  10.1   119.10000         -0.310596    6025.94813
```

```
3                    10.1   118.73008        -8.026677    5942.65281
4                    10.1   109.20000         7.706429    5924.75816
…                     …         …             …             …
220660               28.3    85.55000         0.000000    6438.64000
220661               28.3    85.55000         0.000000    6391.79000
220662               28.3    85.55000         0.233781    6399.35000
220663               28.3    85.75000        -0.233236    6343.06000
220664                NaN    85.55000         0.000000    6344.38000

       hour_of_day  day_of_week
0                0            5
1                0            5
2                0            5
3                0            5
4                0            5
…            …          …
220660          23            6
220661          23            6
220662          23            6
220663          23            6
220664           0            0

[220665 rows x 27 columns]
```

[3]:
```python
df.columns
```

[3]:
```
Index(['SETTLEMENTDATE', 'REGIONID', 'RRP', 'MARKETSUSPENDEDFLAG',
       'RAISE6SECRRP', 'RAISE60SECRRP', 'RAISE5MINRRP', 'RAISEREGRRP',
       'LOWER6SECRRP', 'LOWER60SECRRP', 'LOWER5MINRRP', 'LOWERREGRRP',
       'TOTALDEMAND', 'DEMANDFORECAST', 'AVAILABLEGENERATION',
       'DISPATCHABLEGENERATION', 'NETINTERCHANGE', 'TRADING_RRP', 'DATE',
       'RAINFALL', 'TEMPERATURE', 'SOLAR_RADIATION', 'lagged_RRP',
       'price_change_pct', 'demand_error', 'hour_of_day', 'day_of_week'],
      dtype='object')
```

[4]:
```python
# Drop NaNs, handle inf values, and scale the features
X = df[features].replace([np.inf, -np.inf], np.nan).dropna()
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
```

[8]:
```python
# ---------------------------------
# Isolation Forest Anomaly Detection
# ---------------------------------
# Train Isolation Forest on full scaled feature set
iso_model = IsolationForest(n_estimators=100, contamination=0.02,␣
 ↪random_state=42)
df_iso = X.copy()
```

```python
df_iso['iso_anomaly'] = iso_model.fit_predict(X_scaled)
# Convert output: -1 = anomaly → 1, 1 = normal → 0
df_iso['iso_anomaly'] = df_iso['iso_anomaly'].map({1: 0, -1: 1})
```

[9]:

```python
df_iso
```

[9]:

```
              RRP  lagged_RRP  price_change_pct  demand_error  TOTALDEMAND  \
575      91.20000    91.20000          0.000000    5963.68545      5931.35
576     109.20000    91.20000         19.736842    5963.01764      5939.19
577     109.09998   109.20000         -0.091593    5902.69941      5875.05
578     107.42242   109.09998         -1.537635    5872.74354      5851.37
579     109.10000   107.42242          1.561667    5888.37908      5853.82
…             …           …               …            …            …
220659   85.55000    60.60896         41.150747    6466.49000      6441.49
220660   85.55000    85.55000          0.000000    6438.64000      6384.64
220661   85.55000    85.55000          0.000000    6391.79000      6374.79
220662   85.75000    85.55000          0.233781    6399.35000      6386.35
220663   85.55000    85.75000         -0.233236    6343.06000      6296.06

        AVAILABLEGENERATION  DISPATCHABLEGENERATION  TRADING_RRP  TEMPERATURE  \
575              9525.71501                 5733.61        91.20         30.2
576              9529.07401                 5622.78       109.20         30.2
577              9523.92301                 5528.22       109.10         30.2
578              9524.36201                 5500.82       107.42         30.2
579              9533.37801                 5494.25       109.10         30.2
…                         …                       …            …            …
220659           9324.73916                 5912.86        85.55         30.4
220660           9315.29446                 5857.84        85.55         30.4
220661           9115.39488                 5848.00        85.55         30.4
220662           9126.19154                 5858.87        85.75         30.4
220663           9388.81190                 5767.10        85.55         30.4

        SOLAR_RADIATION  RAINFALL  hour_of_day  day_of_week  iso_anomaly
575                23.4       0.0            0            0            0
576                23.4       0.0            0            0            0
577                23.4       0.0            0            0            0
578                23.4       0.0            0            0            0
579                23.4       0.0            0            0            0
…                     …         …            …            …            …
220659             28.3       5.8           23            6            0
220660             28.3       5.8           23            6            0
220661             28.3       5.8           23            6            0
220662             28.3       5.8           23            6            0
220663             28.3       5.8           23            6            0

[217122 rows x 14 columns]
```

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

```
<class 'pandas.core.frame.DataFrame'>
Index: 217122 entries, 575 to 220663
Data columns (total 14 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   RRP                     217122 non-null  float64
 1   lagged_RRP              217122 non-null  float64
 2   price_change_pct        217122 non-null  float64
 3   demand_error            217122 non-null  float64
 4   TOTALDEMAND             217122 non-null  float64
 5   AVAILABLEGENERATION     217122 non-null  float64
 6   DISPATCHABLEGENERATION  217122 non-null  float64
 7   TRADING_RRP             217122 non-null  float64
 8   TEMPERATURE             217122 non-null  float64
 9   SOLAR_RADIATION         217122 non-null  float64
 10  RAINFALL                217122 non-null  float64
 11  hour_of_day             217122 non-null  int32
 12  day_of_week             217122 non-null  int32
 13  iso_anomaly             217122 non-null  int64
dtypes: float64(11), int32(2), int64(1)
memory usage: 23.2 MB
```

[11]:
```
# Count and print number of anomalies detected by Isolation Forest
num_iso_anomalies = df_iso['iso_anomaly'].sum()/len(df_iso)
print(f"Number of anomalies detected by Isolation Forest: {num_iso_anomalies}")
```

```
Number of anomalies detected by Isolation Forest: 0.0200025791951069
```

[12]:
```
# Create Sliding Windows for LSTM
window_size = 96
X_seq = []
for i in range(len(X_scaled) - window_size):
    X_seq.append(X_scaled[i:i+window_size])
X_seq = np.array(X_seq)

# Build LSTM Autoencoder Model
input_dim = X_seq.shape[2]
inputs = Input(shape=(window_size, input_dim))
encoded = LSTM(64, return_sequences=False)(inputs)
bottleneck = RepeatVector(window_size)(encoded)
decoded = LSTM(64, return_sequences=True)(bottleneck)
outputs = TimeDistributed(Dense(input_dim))(decoded)

model = Model(inputs, outputs)
model.compile(optimizer='adam', loss='mse')
```

```python
# Train the LSTM Autoencoder
model.fit(X_seq, X_seq, epochs=30, batch_size=64, validation_split=0.1,
 ↪verbose=1)
```

```
Epoch 1/30
3052/3052                329s 106ms/step
- loss: 0.0088 - val_loss: 0.0013
Epoch 2/30
3052/3052                301s 99ms/step
- loss: 0.0010 - val_loss: 8.6527e-04
Epoch 3/30
3052/3052                249s 82ms/step
- loss: 8.4124e-04 - val_loss: 8.1116e-04
Epoch 4/30
3052/3052                265s 87ms/step
- loss: 6.1090e-04 - val_loss: 5.9193e-04
Epoch 5/30
3052/3052                267s 87ms/step
- loss: 5.2574e-04 - val_loss: 5.4852e-04
Epoch 6/30
3052/3052                271s 89ms/step
- loss: 4.6558e-04 - val_loss: 4.5584e-04
Epoch 7/30
3052/3052                255s 84ms/step
- loss: 4.3536e-04 - val_loss: 3.9063e-04
Epoch 8/30
3052/3052                257s 84ms/step
- loss: 4.0428e-04 - val_loss: 3.8401e-04
Epoch 9/30
3052/3052                253s 83ms/step
- loss: 3.6473e-04 - val_loss: 3.7030e-04
Epoch 10/30
3052/3052                263s 86ms/step
- loss: 3.5127e-04 - val_loss: 4.2261e-04
Epoch 11/30
3052/3052                263s 86ms/step
- loss: 3.3407e-04 - val_loss: 3.4077e-04
Epoch 12/30
3052/3052                245s 80ms/step
- loss: 3.1965e-04 - val_loss: 3.1861e-04
Epoch 13/30
3052/3052                246s 80ms/step
- loss: 3.1448e-04 - val_loss: 3.4746e-04
Epoch 14/30
3052/3052                247s 81ms/step
- loss: 3.0350e-04 - val_loss: 2.9992e-04
Epoch 15/30
3052/3052                246s 81ms/step
```

```
- loss: 2.9553e-04 - val_loss: 3.2844e-04
Epoch 16/30
3052/3052            247s 81ms/step
- loss: 3.0602e-04 - val_loss: 3.1831e-04
Epoch 17/30
3052/3052            246s 81ms/step
- loss: 3.1669e-04 - val_loss: 3.0301e-04
Epoch 18/30
3052/3052            247s 81ms/step
- loss: 2.8562e-04 - val_loss: 2.6665e-04
Epoch 19/30
3052/3052            246s 81ms/step
- loss: 2.6990e-04 - val_loss: 4.7265e-04
Epoch 20/30
3052/3052            267s 88ms/step
- loss: 2.7615e-04 - val_loss: 2.5319e-04
Epoch 21/30
3052/3052            272s 89ms/step
- loss: 2.7147e-04 - val_loss: 2.8716e-04
Epoch 22/30
3052/3052            250s 82ms/step
- loss: 2.7016e-04 - val_loss: 2.3558e-04
Epoch 23/30
3052/3052            250s 82ms/step
- loss: 3.1250e-04 - val_loss: 2.4728e-04
Epoch 24/30
3052/3052            248s 81ms/step
- loss: 2.7019e-04 - val_loss: 2.8995e-04
Epoch 25/30
3052/3052            269s 83ms/step
- loss: 2.5757e-04 - val_loss: 2.5405e-04
Epoch 26/30
3052/3052            252s 83ms/step
- loss: 2.4842e-04 - val_loss: 2.4629e-04
Epoch 27/30
3052/3052            251s 82ms/step
- loss: 2.3661e-04 - val_loss: 2.2292e-04
Epoch 28/30
3052/3052            251s 82ms/step
- loss: 3.1688e-04 - val_loss: 4.3981e-04
Epoch 29/30
3052/3052            251s 82ms/step
- loss: 3.0490e-04 - val_loss: 3.6510e-04
Epoch 30/30
3052/3052            252s 83ms/step
- loss: 2.6952e-04 - val_loss: 2.5410e-04
```

[12]: <keras.src.callbacks.history.History at 0x20b6f100d50>

[13]:
```
# Reconstruct and Compute Reconstruction Error
X_pred = model.predict(X_seq)
reconstruction_errors = np.mean(np.square(X_seq - X_pred), axis=(1, 2))

# Set Threshold and Flag Anomalies
threshold = np.percentile(reconstruction_errors, 95)
anomalies = reconstruction_errors > threshold

# Attach LSTM Anomaly Labels to Data
anomaly_df = X.iloc[window_size:].copy()
anomaly_df['reconstruction_error'] = reconstruction_errors
anomaly_df['lstm_anomaly'] = anomalies.astype(int)

# Combine Both Anomaly Flags
anomaly_df['iso_anomaly'] = df_iso.iloc[window_size:]['iso_anomaly'].values
```

```
6783/6783            124s 18ms/step
```

[14]:
```
anomaly_df.tail(10)
```

[14]:

	RRP	lagged_RRP	price_change_pct	demand_error	TOTALDEMAND	\
220654	65.47628	61.87869	5.813940	6616.48	6589.48	
220655	64.98145	65.47628	-0.755739	6574.99	6575.99	
220656	65.45639	64.98145	0.730886	6613.07	6601.07	
220657	65.35098	65.45639	-0.161039	6582.44	6555.44	
220658	60.60896	65.35098	-7.256234	6510.98	6492.98	
220659	85.55000	60.60896	41.150747	6466.49	6441.49	
220660	85.55000	85.55000	0.000000	6438.64	6384.64	
220661	85.55000	85.55000	0.000000	6391.79	6374.79	
220662	85.75000	85.55000	0.233781	6399.35	6386.35	
220663	85.55000	85.75000	-0.233236	6343.06	6296.06	

	AVAILABLEGENERATION	DISPATCHABLEGENERATION	TRADING_RRP	TEMPERATURE	\
220654	9570.58009	6127.72	65.48	30.4	
220655	9579.74810	6135.83	64.98	30.4	
220656	9575.39208	6132.63	65.46	30.4	
220657	9568.80508	6125.14	65.35	30.4	
220658	9581.54185	6187.67	60.61	30.4	
220659	9324.73916	5912.86	85.55	30.4	
220660	9315.29446	5857.84	85.55	30.4	
220661	9115.39488	5848.00	85.55	30.4	
220662	9126.19154	5858.87	85.75	30.4	
220663	9388.81190	5767.10	85.55	30.4	

	SOLAR_RADIATION	RAINFALL	hour_of_day	day_of_week	\
220654	28.3	5.8	23	6	

```
220655                28.3       5.8           23             6
220656                28.3       5.8           23             6
220657                28.3       5.8           23             6
220658                28.3       5.8           23             6
220659                28.3       5.8           23             6
220660                28.3       5.8           23             6
220661                28.3       5.8           23             6
220662                28.3       5.8           23             6
220663                28.3       5.8           23             6

        reconstruction_error  lstm_anomaly  iso_anomaly
220654              0.000115             0            0
220655              0.000110             0            0
220656              0.000108             0            0
220657              0.000107             0            0
220658              0.000105             0            0
220659              0.000105             0            0
220660              0.000105             0            0
220661              0.000106             0            0
220662              0.000110             0            0
220663              0.000114             0            0
```

[15]:

```
# Print anomaly percentages from LSTM and Isolation Forest
lstm_count = anomaly_df['lstm_anomaly'].sum()
lstm_percent = lstm_count / len(anomaly_df) * 100

iso_count = anomaly_df['iso_anomaly'].sum()
iso_percent = iso_count / len(anomaly_df) * 100

print(f"LSTM Anomalies: {lstm_count} ({lstm_percent:.2f}%)")
print(f"Isolation Forest Anomalies: {iso_count} ({iso_percent:.2f}%)")
```

```
LSTM Anomalies: 10852 (5.00%)
Isolation Forest Anomalies: 4343 (2.00%)
```

[16]:

```
# Compare agreement between LSTM and Isolation Forest
anomaly_df['both_agree'] = (anomaly_df['lstm_anomaly'] == 1) &␣
↪(anomaly_df['iso_anomaly'] == 1)
both_agree_count = anomaly_df['both_agree'].sum()
print(f"Both models agree on {both_agree_count} anomalies ({(both_agree_count/
↪len(anomaly_df))*100:.2f}%)")
```

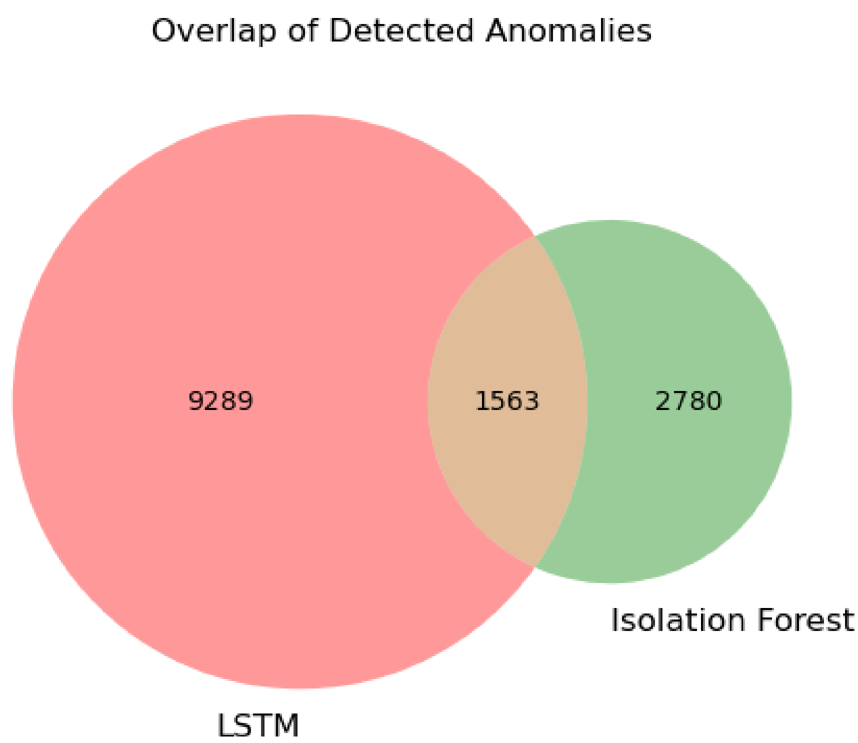
```
Both models agree on 1563 anomalies (0.72%)
```

[17]:

```
# Save final combined anomaly output for future use
anomaly_df.to_csv("anomaly_detected_combined.csv", index=False)
```

[18]:

```
from matplotlib_venn import venn2
from matplotlib import pyplot as plt

plt.figure(figsize=(6,6))
venn2(subsets = (
    ((anomaly_df['lstm_anomaly'] == 1) & (anomaly_df['iso_anomaly'] == 0)).
 ↪sum(),
    ((anomaly_df['iso_anomaly'] == 1) & (anomaly_df['lstm_anomaly'] == 0)).
 ↪sum(),
    ((anomaly_df['lstm_anomaly'] == 1) & (anomaly_df['iso_anomaly'] == 1)).sum()
), set_labels=('LSTM', 'Isolation Forest'))
plt.title("Overlap of Detected Anomalies")
plt.show()
```



[19]:

```
# Top anomalies by LSTM reconstruction error
top_anomalies = anomaly_df.sort_values(by='reconstruction_error',␣
 ↪ascending=False).head(10)
print(top_anomalies[['RRP', 'reconstruction_error', 'lstm_anomaly',␣
 ↪'iso_anomaly']])
```

```
            RRP  reconstruction_error  lstm_anomaly  iso_anomaly
9237  70.81522              0.030475             1            0
9236  70.81522              0.030418             1            1
```

```
9238 -999.99417              0.030147            1            0
9235 -999.99171              0.030082            1            1
9239 -999.99417              0.029818            1            1
9234 -999.99171              0.029789            1            0
9233   86.04854              0.029560            1            0
9240  300.10000              0.029533            1            1
9232   86.04854              0.029168            1            0
9241  300.10000              0.029159            1            0
```

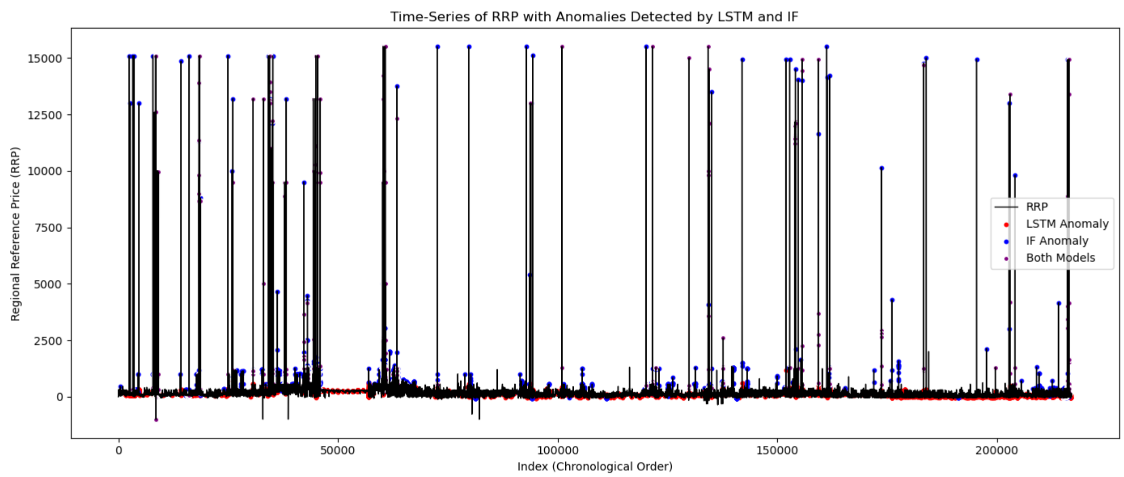
[20]:
```
# Check for RRP values equal to -999.99 in the original dataset
invalid_rrp_rows = df[df['RRP'] == -999.99]

# Display results
print(f"Number of rows with RRP = -999.99: {len(invalid_rrp_rows)}")
invalid_rrp_rows.head()
```

```
Number of rows with RRP = -999.99: 0
```

[20]:
```
Empty DataFrame
Columns: [SETTLEMENTDATE, REGIONID, RRP, MARKETSUSPENDEDFLAG, RAISE6SECRRP,
RAISE60SECRRP, RAISE5MINRRP, RAISEREGRRP, LOWER6SECRRP, LOWER60SECRRP,
LOWER5MINRRP, LOWERREGRRP, TOTALDEMAND, DEMANDFORECAST, AVAILABLEGENERATION,
DISPATCHABLEGENERATION, NETINTERCHANGE, TRADING_RRP, DATE, RAINFALL,
TEMPERATURE, SOLAR_RADIATION, month]
Index: []

[0 rows x 23 columns]
```

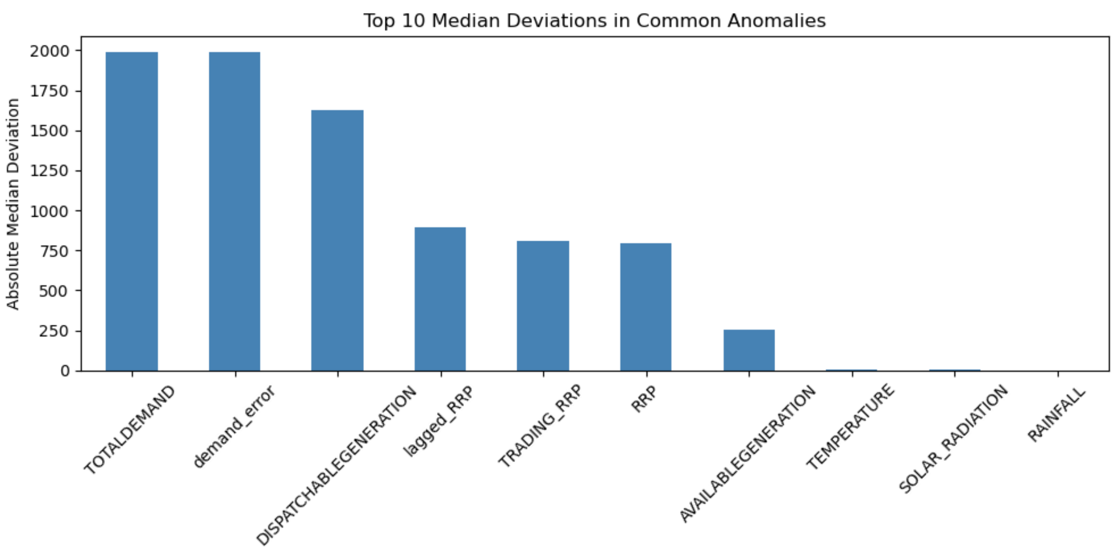
[21]:
```
# Load the dataset
df = pd.read_csv("anomaly_detected_combined.csv")

# Create 'both_agree' column if not present
df['both_agree'] = (df['lstm_anomaly'] == 1) & (df['iso_anomaly'] == 1)

# Create index for plotting (since no timestamp column)
df['index'] = range(len(df))

# Plot RRP time-series
plt.figure(figsize=(14, 6))
plt.plot(df['index'], df['RRP'], label='RRP', color='black', linewidth=1)

# Overlay anomalies
plt.scatter(df[df['lstm_anomaly'] == 1]['index'], df[df['lstm_anomaly'] ==␣
↪1]['RRP'],
            color='red', label='LSTM Anomaly', s=10)
plt.scatter(df[df['iso_anomaly'] == 1]['index'], df[df['iso_anomaly'] ==␣
↪1]['RRP'],
            color='blue', label='IF Anomaly', s=10)
```

```
plt.scatter(df[df['both_agree'] == True]['index'], df[df['both_agree'] ==␣
↪True]['RRP'],
            color='purple', label='Both Models', s=20, edgecolor='white')

# Formatting
plt.title("Time-Series of RRP with Anomalies Detected by LSTM and IF")
plt.xlabel("Index (Chronological Order)")
plt.ylabel("Regional Reference Price (RRP)")
plt.legend()
plt.tight_layout()
plt.show()
```



[22]:
```
# Load your data
df = pd.read_csv("anomaly_detected_combined.csv")

# Confirm both_agree column exists
df['both_agree'] = (df['lstm_anomaly'] == 1) & (df['iso_anomaly'] == 1)

# Keep only original (unscaled) meaningful features
core_features = [
    'RRP', 'lagged_RRP', 'price_change_pct', 'demand_error', 'TOTALDEMAND',
    'AVAILABLEGENERATION', 'DISPATCHABLEGENERATION', 'TRADING_RRP',
    'TEMPERATURE', 'SOLAR_RADIATION', 'RAINFALL'
]

# Calculate median deviation
normal_median = df[df['both_agree'] == False][core_features].median()
anomaly_median = df[df['both_agree'] == True][core_features].median()
deviation = (anomaly_median - normal_median).abs().sort_values(ascending=False)
```

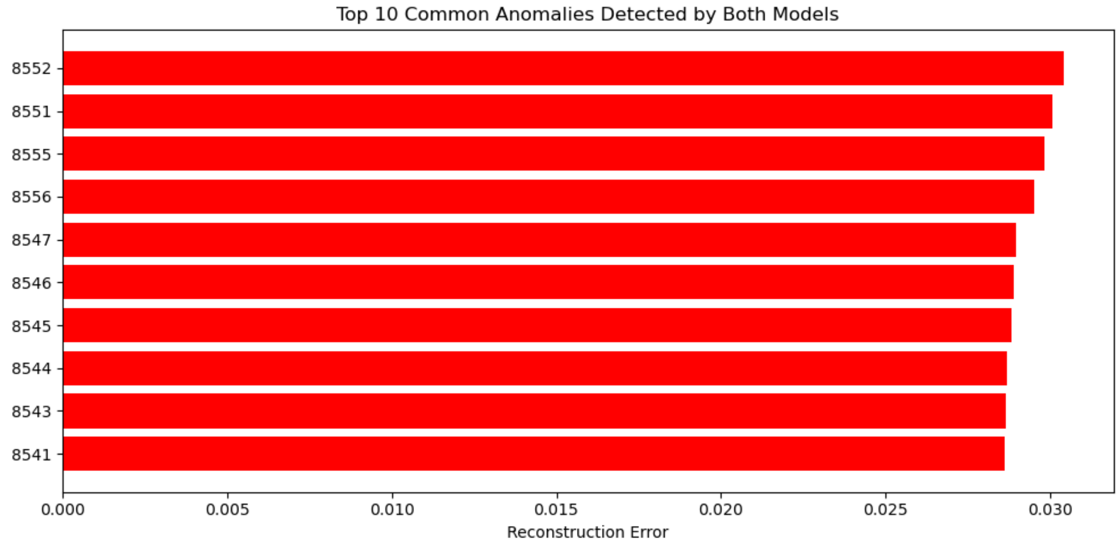
```python
# Plot top 10
plt.figure(figsize=(10, 5))
deviation.head(10).plot(kind='bar', color='steelblue')
plt.title("Top 10 Median Deviations in Common Anomalies")
plt.ylabel("Absolute Median Deviation")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



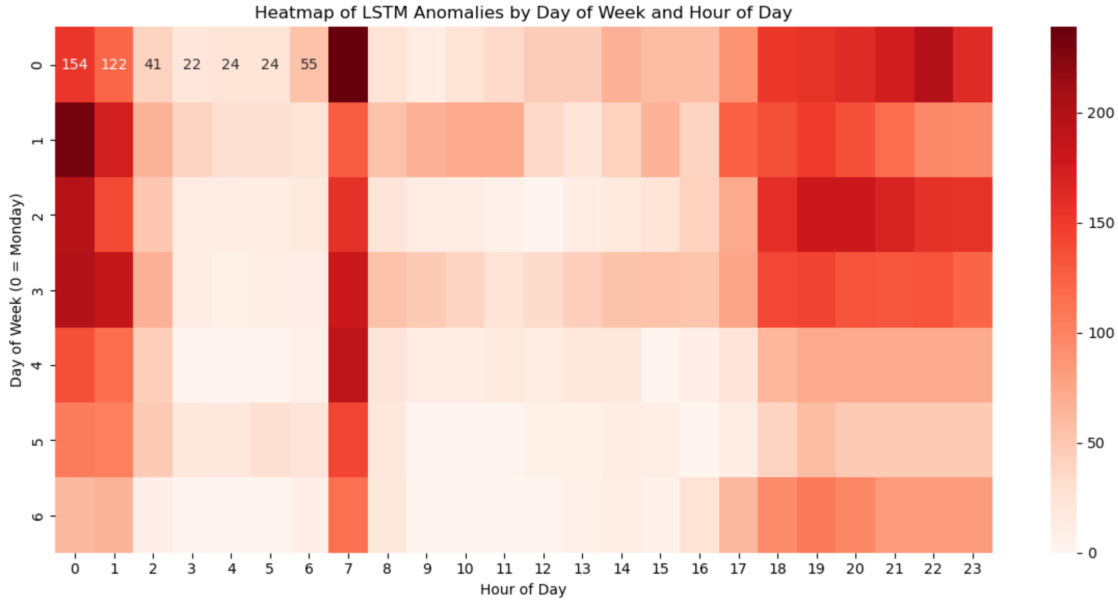
[23]:
```python
import pandas as pd
import matplotlib.pyplot as plt

# Load your anomaly detection results (no date column to parse)
df = pd.read_csv("anomaly_detected_combined.csv")

# Create the both_agree column
df['both_agree'] = (df['lstm_anomaly'] == 1) & (df['iso_anomaly'] == 1)

# Filter where both models agree
common_anomalies = df[df['both_agree'] == True]

# Sort by reconstruction error and pick top 10
top_common = common_anomalies.sort_values(by='reconstruction_error',␣
↪ascending=False).head(10)

# Display the top anomalies
print("Top 10 High-Confidence Anomalies (LSTM + IF):")
```

```python
print(top_common[['RRP', 'reconstruction_error', 'TOTALDEMAND', 'TEMPERATURE',␣
↪'demand_error']])

# Visualize as a bar chart
plt.figure(figsize=(10, 5))
plt.barh(top_common.index.astype(str), top_common['reconstruction_error'],␣
↪color='red')
plt.xlabel("Reconstruction Error")
plt.title("Top 10 Common Anomalies Detected by Both Models")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```

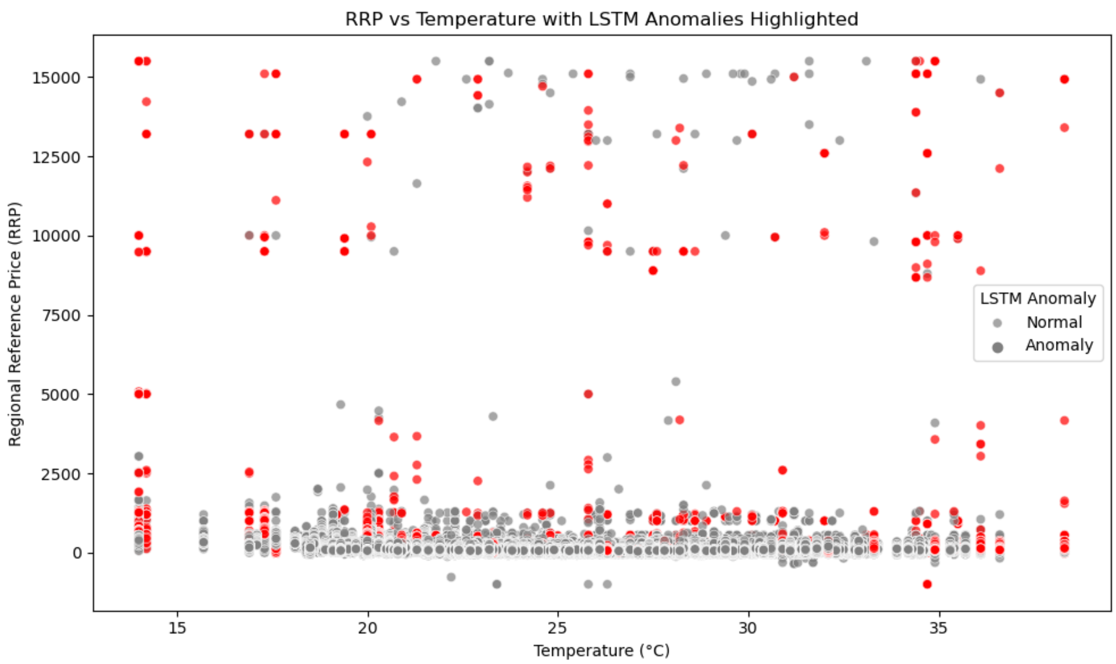
```
Top 10 High-Confidence Anomalies (LSTM + IF):
              RRP  reconstruction_error  TOTALDEMAND  TEMPERATURE  \
8552     70.81522              0.030418      9068.35         34.7
8551   -999.99171              0.030082      9149.24         34.7
8555   -999.99417              0.029818      9068.35         34.7
8556    300.10000              0.029533      9086.19         34.7
8547     77.07020              0.028984      9268.48         34.7
8546     77.07020              0.028890      9268.48         34.7
8545  15100.00000              0.028829      9268.48         34.7
8544  15100.00000              0.028698      9268.48         34.7
8543     11.00008              0.028667      9205.84         34.7
8541  12594.00000              0.028637      9205.84         34.7

      demand_error
8552    9112.66738
8551    9157.56813
8555    9112.66738
8556    9119.83648
8547    9244.11867
8546    9244.11867
8545    9244.11867
8544    9244.11867
8543    9223.27262
8541    9223.27262
```



[24]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load anomaly file
df = pd.read_csv("anomaly_detected_combined.csv")

# Create time-based features if not already present
df['hour_of_day'] = df.get('hour_of_day', pd.Series(range(len(df))) % 24)
df['day_of_week'] = df.get('day_of_week', pd.Series(range(len(df))) % 7)

# Create a pivot table showing count of LSTM anomalies by hour and day
heatmap_data = df[df['lstm_anomaly'] == 1].pivot_table(
    index='day_of_week',
    columns='hour_of_day',
    values='RRP',
    aggfunc='count',
    fill_value=0
)

# Plot the heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(heatmap_data, cmap="Reds", annot=True, fmt='d')
plt.title("Heatmap of LSTM Anomalies by Day of Week and Hour of Day")
plt.xlabel("Hour of Day")
plt.ylabel("Day of Week (0 = Monday)")
plt.tight_layout()
plt.show()
```



[25]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load your data
df = pd.read_csv("anomaly_detected_combined.csv")

# Scatter plot: RRP vs Temperature, colored by LSTM anomaly
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='TEMPERATURE', y='RRP', hue='lstm_anomaly',
                palette={0: 'gray', 1: 'red'}, alpha=0.7)

plt.title("RRP vs Temperature with LSTM Anomalies Highlighted")
plt.xlabel("Temperature (°C)")
plt.ylabel("Regional Reference Price (RRP)")
plt.legend(title="LSTM Anomaly", labels=["Normal", "Anomaly"])
plt.tight_layout()
plt.show()
```


RRP vs Temperature with LSTM Anomalies Highlighted
Regional Reference Price (RRP)
Temperature (°C)
LSTM Anomaly
Normal
Anomaly
15000
12500
10000
7500
5000
2500
0
15
20
25
30
35

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