MEASURE ENERGY CONSUMPTION USING AI

Phase 3 Project

INTRODUCTION

In today's world, with the growing emphasis on sustainability and efficient resource utilisation, the need to accurately measure and manage energy consumption is paramount. This is where Artificial Intelligence (AI) plays a pivotal role. Our AI model, which we've developed to address this challenge, leverages cutting-edge technology to revolutionise the way we monitor and optimise energy usage.

Key Features:

Real-time Data Analysis: Our AI model continuously collects and analyses real-time data from various sources, including smart metres, IoT devices, and building management systems, providing a comprehensive view of energy usage.

Predictive Analytics: By employing machine learning algorithms, our model can forecast energy consumption patterns, helping organisations plan for peak demand and optimise energy usage during off-peak hours.

Anomaly Detection: The AI model is capable of identifying unusual energy consumption spikes or irregularities, enabling quick response to potential issues or energy wastage.

Energy Efficiency Recommendations: It offers actionable insights and suggestions to improve energy efficiency, reducing costs and environmental impact.

Customization: The AI model can be tailored to specific industries, buildings, or energy systems, making it a versatile solution for a wide range of applications.

Integration: Seamlessly integrates with existing energy management systems and platforms, allowing for a smooth transition to AI-driven energy monitoring.

Benefits:

Cost Savings: By optimising energy usage, businesses can significantly reduce their operational costs.

Sustainability: Effective energy management supports sustainability goals by minimising carbon footprint.

Data-Driven Decision Making: The AI model empowers organisations with data to make informed decisions about energy consumption.

Improved Reliability: Preventing energy wastage and identifying issues proactively enhances the reliability of energy supply.

Phase 3: Development Part 1

In this technology project you will begin building your project by loading and preprocessing the dataset. Start building the energy consumption model by loading and preprocessing the dataset.

DataSource

A model for measuring energy consumption should encompass several essential features to be effective. Here's how such a model should be designed:

Data Collection: The model should gather data from various sources, including smart meters, IoT devices, sensors, and historical records. Data accuracy is crucial for reliable measurement.

Real-Time Monitoring: It should provide real-time monitoring of energy consumption, enabling immediate response to changes and anomalies.

Machine Learning Algorithms: Incorporate machine learning algorithms to analyse and process data, allowing for predictive analytics and pattern recognition.

Customization: The model should be adaptable to different environments, industries, and energy systems, with the ability to fine-tune parameters to match specific needs.

Anomaly Detection: Implement anomaly detection mechanisms to identify irregular patterns or sudden spikes in energy usage, which could indicate inefficiencies or issues.

Predictive Analytics: Utilize historical data and machine learning to predict future energy consumption, aiding in demand forecasting and resource planning.

Visualization: Provide user-friendly dashboards and data visualization tools to present energy consumption data in a clear and comprehensible manner.

Recommendations: Offer actionable insights and recommendations for optimizing energy usage and reducing costs, including suggestions for adjusting equipment settings, improving insulation, or scheduling operations during off-peak hours.

Integration: Ensure seamless integration with existing energy management systems, building management systems, and other related platforms to streamline operations.

Energy Efficiency Metrics: Calculate key performance indicators like energy intensity, efficiency ratios, and carbon emissions, allowing organizations to track their progress toward sustainability goals.

Cloud-Based or On-Premises: The model can be hosted on the cloud or on-premises, depending on the organisation's preferences and requirements.

Security: Prioritise data security and privacy to safeguard sensitive energy consumption information from unauthorised access or breaches.

Reporting: Generate comprehensive reports and alerts to keep stakeholders informed about energy consumption trends and deviations from set targets.

Scalability: Ensure the model can handle growing datasets and the addition of new sensors or devices as an organization's needs evolve.

Dataset Link:
https://www.kaggle.com/datasets/robikscube/hourly-energy-consumption

CODE:

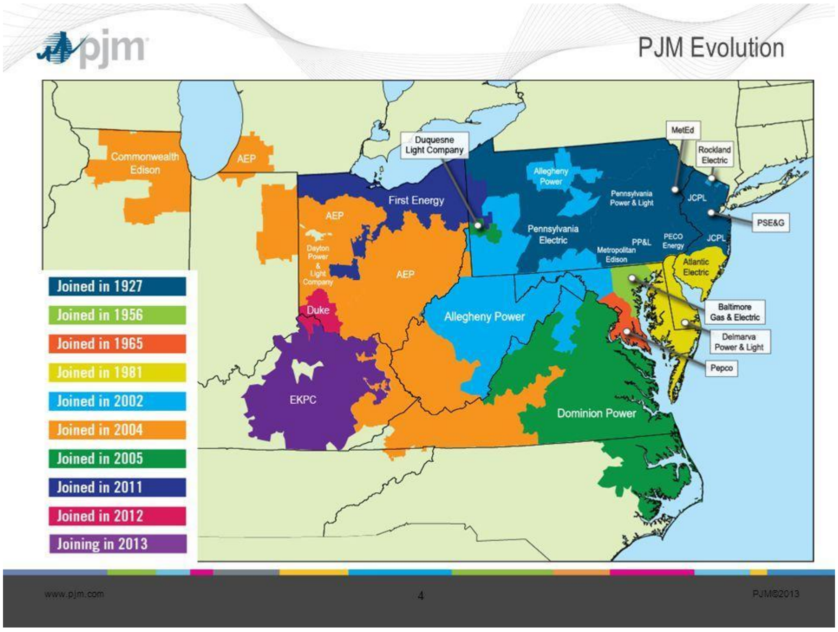
HOURLY ENERGY CONSUMPTION

```
import matplotlib.pyplot as plt # plotting
import numpy as np # linear algebra
import os # accessing directory structure
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
plt.style.use('ggplot') # Make it pretty
# Data is saved in parquet format so schema is preserved.
df = pd.read_parquet('../input/est_hourly.paruqet')
```

Data index is the date/hour, columns are for different regions within PJM.

Regions joined at different times, so not all have data for all dates. Regions also split (PJM_Load split to East and West)

```
#Show PJM Regions
from IPython.display import Image
Image(url= "http://slideplayer.com/4238181/14/images/4/PJM+Evolution.jpg")
```



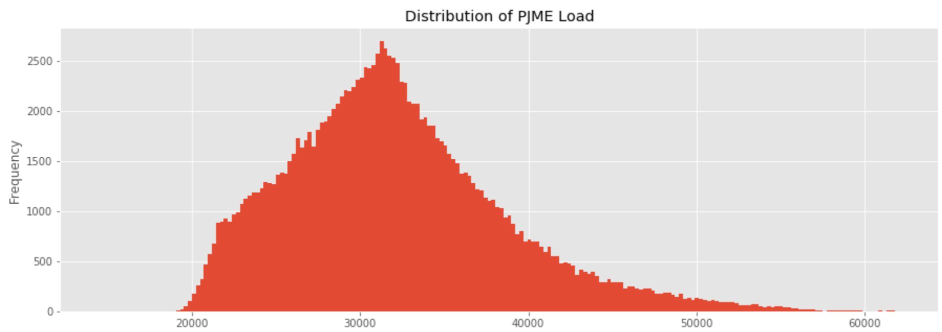

```
df.head()
```

	AEP	COMED	DAYTON	DEOK	DOM	DUQ	EKPC	FE	NI	PJME	PJMW	PJM_Load
Datetime												
1998-12-31 01:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	29309.0
1998-12-31 02:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	28236.0
1998-12-31 03:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	27692.0
1998-12-31 04:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	27596.0
1998-12-31 05:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	27888.0

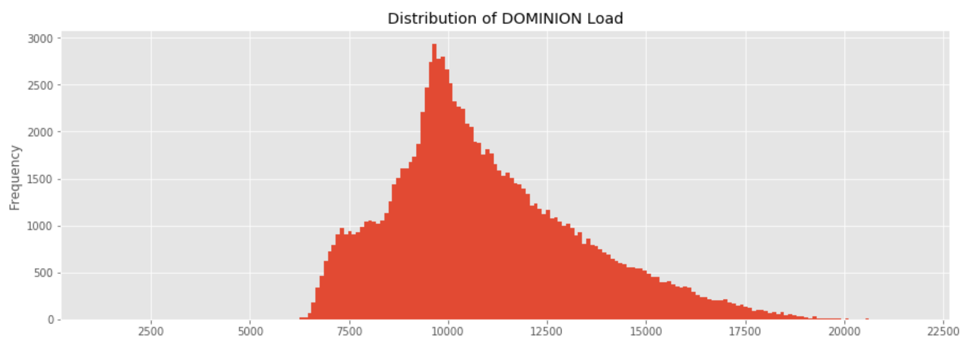
df.describe().T

	count	mean	std	min	25%	50%	75%	max
AEP	121273.0	15499.513717	2591.399065	9581.0	13630.0	15310.0	17200.00	25695.0
COMED	66497.0	11420.152112	2304.139517	7237.0	9780.0	11152.0	12510.00	23753.0
DAYTON	121275.0	2037.851140	393.403153	982.0	1749.0	2009.0	2279.00	3746.0
DEOK	57739.0	3105.096486	599.859026	907.0	2687.0	3013.0	3449.00	5445.0
DOM	116189.0	10949.203625	2413.946569	1253.0	9322.0	10501.0	12378.00	21651.0
DUQ	119068.0	1658.820296	301.740640	1014.0	1444.0	1630.0	1819.00	3054.0
EKPC	45334.0	1464.218423	378.868404	514.0	1185.0	1386.0	1699.00	3490.0
FE	62874.0	7792.159064	1331.268006	0.0	6807.0	7700.0	8556.00	14032.0
NI	58450.0	11701.682943	2371.498701	7003.0	9954.0	11521.0	12896.75	23631.0
PJME	145366.0	32080.222831	6464.012166	14544.0	27573.0	31421.0	35650.00	62009.0
PJMW	143206.0	5602.375089	979.142872	487.0	4907.0	5530.0	6252.00	9594.0
PJM_Load	32896.0	29766.427408	5849.769954	17461.0	25473.0	29655.0	33073.25	54030.0

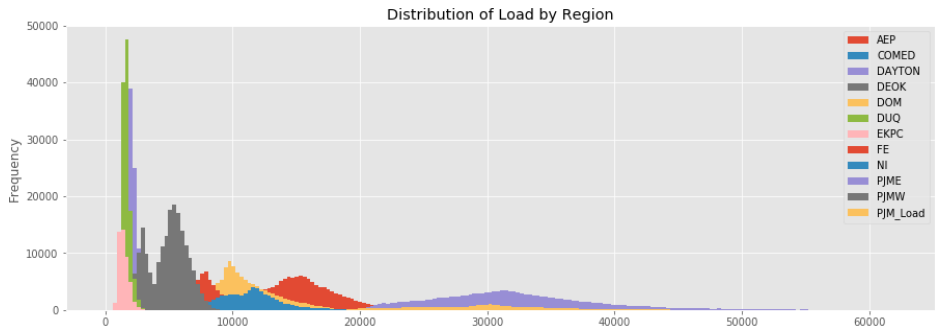
```
_ = df['PJME'].plot.hist(figsize=(15, 5), bins=200, title='Distribution of PJME Load')
```



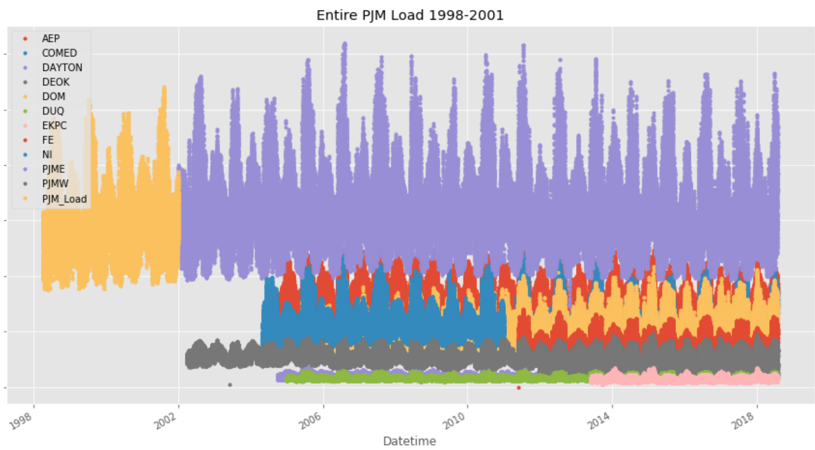

```
_ = df['DOM'].plot.hist(figsize=(15, 5), bins=200, title='Distribution of DOMINION Load')
```



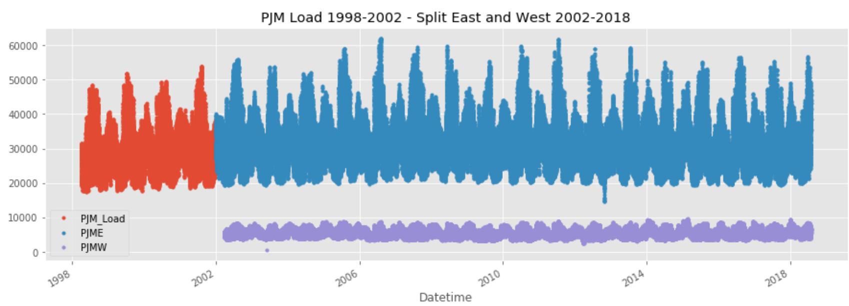

```
_ = df.plot.hist(figsize=(15, 5), bins=200, title='Distribution of Load by Region')
```



Plot Time Series
plot = df.plot(style='.', figsize=(15, 8), title='Entire PJM Load 1998-2001')



Plotting Regions
_ = df[['PJM_Load','PJME','PJMW']] \
.plot(style='.', figsize=(15, 5), title='PJM Load 1998-2002 - Split East and West 2002-2018')

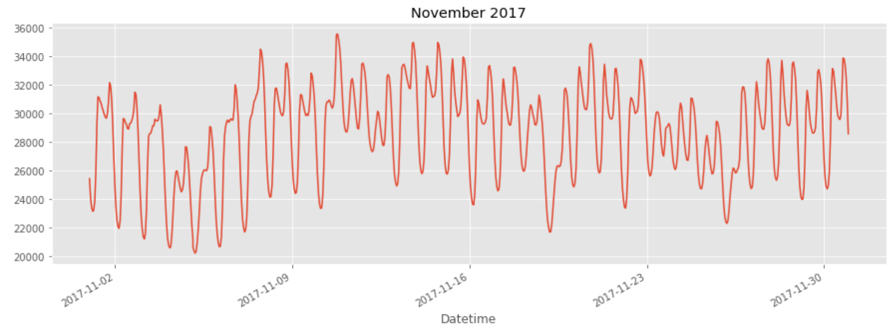


<u>Summer Demand vs Winter Demand</u>

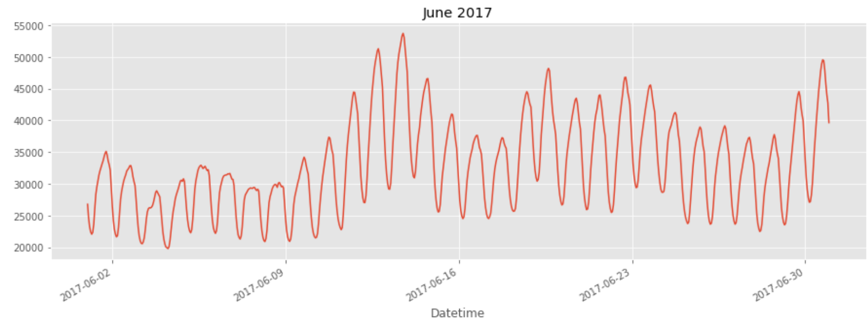
Note the dips mid-day in the winter months. Conversely in summer months the daily load is more bell shaped. This is due to high mid-day energy consumption by air conditioning. In winter months people tend to use less energy mid-day.

_ = df['PJME'].loc[(df['PJME'].index >= '2017-11-01') &

```
              (df['PJME'].index < '2017-12-01')] \
    .plot(figsize=(15, 5), title = 'November 2017')
```

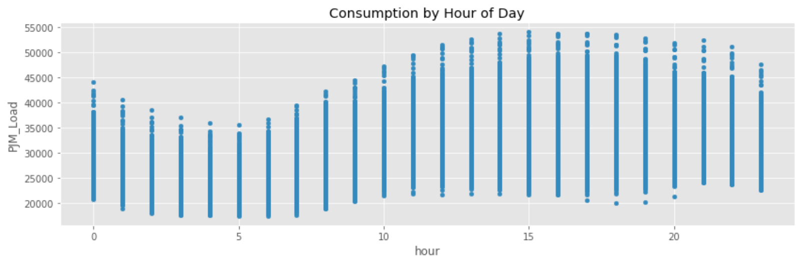



```
_ = df['PJME'].loc[(df['PJME'].index >= '2017-06-01') &
              (df['PJME'].index < '2017-07-01')] \
    .plot(figsize=(15, 5), title = 'June 2017')
```



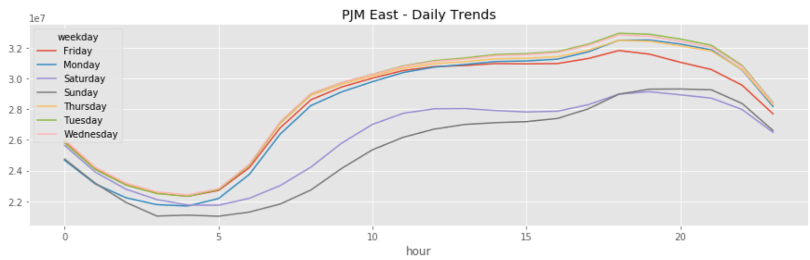
Create Time Series Features

```
df['dow'] = df.index.dayofweek
df['doy'] = df.index.dayofyear
df['year'] = df.index.year
df['month'] = df.index.month
df['quarter'] = df.index.quarter
df['hour'] = df.index.hour
df['weekday'] = df.index.weekday_name
df['woy'] = df.index.weekofyear
df['dom'] = df.index.day # Day of Month
df['date'] = df.index.date
_ = df[['PJM_Load','hour']].plot(x='hour',
                                  y='PJM_Load',
                                  kind='scatter',
                                  figsize=(14,4),
                                  title='Consumption by Hour of Day')
```



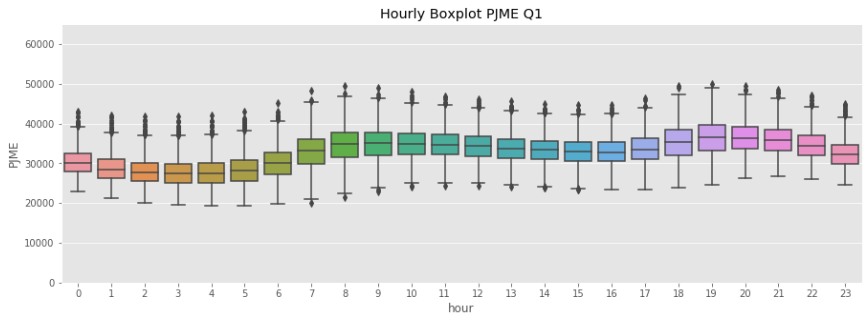
Note Saturday and Sunday demand is much less than during a work week. This is also true for holidays.

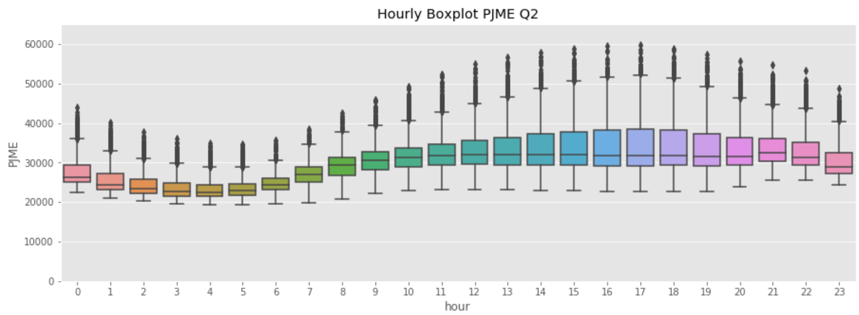
```
_ = df.pivot_table(index=df['hour'],
                   columns='weekday',
                   values='PJME',
                   aggfunc='sum').plot(figsize=(15,4),
                   title='PJM East - Daily Trends')
```

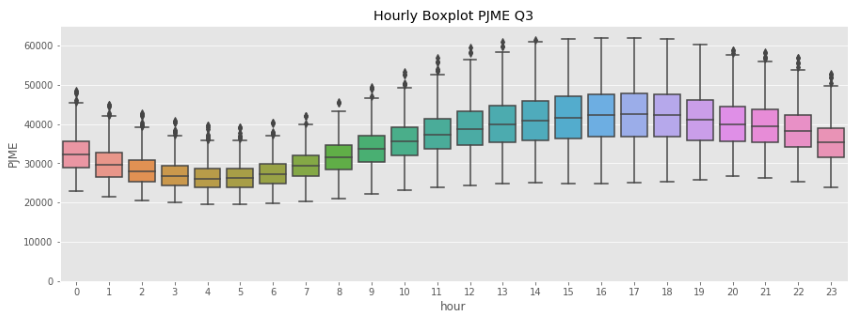


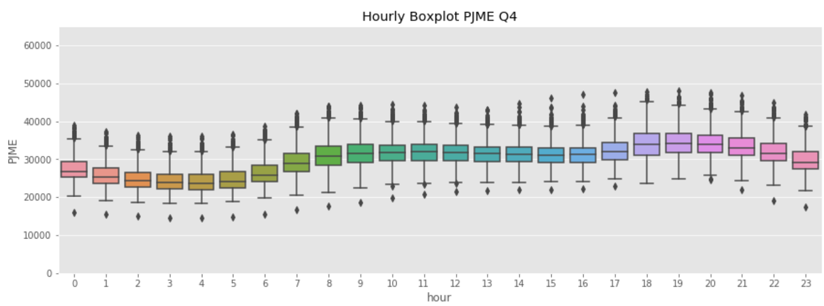
Trends change depending on time of year

```
fig, ax = plt.subplots(figsize=(15,5))
sns.boxplot(df.loc[df['quarter']==1].hour, df.loc[df['quarter']==1].PJME)
ax.set_title('Hourly Boxplot PJME Q1')
ax.set_ylim(0,65000)
fig, ax = plt.subplots(figsize=(15,5))
sns.boxplot(df.loc[df['quarter']==2].hour, df.loc[df['quarter']==2].PJME)
ax.set_title('Hourly Boxplot PJME Q2')
ax.set_ylim(0,65000)
fig, ax = plt.subplots(figsize=(15,5))
sns.boxplot(df.loc[df['quarter']==3].hour, df.loc[df['quarter']==3].PJME)
ax.set_title('Hourly Boxplot PJME Q3')
ax.set_ylim(0,65000)
fig, ax = plt.subplots(figsize=(15,5))
sns.boxplot(df.loc[df['quarter']==4].hour, df.loc[df['quarter']==4].PJME)
ax.set_title('Hourly Boxplot PJME Q4')
_ = ax.set_ylim(0,65000)
```









CONCLUSION

In conclusion, monitoring hourly energy consumption is a valuable practice for individuals and organisations alike. It enables better understanding of energy usage patterns, facilitates cost savings, and promotes sustainability. By analyzing the data and making informed decisions, we can reduce energy waste, lower carbon footprints, and contribute to a more efficient and eco-friendly future.

Additionally, hourly energy consumption data empowers us to identify peak usage times, aiding in load management and preventing grid overloads during high-demand periods. This can enhance grid stability and reliability, reducing the risk of power outages. Furthermore, the insights gained from hourly energy consumption monitoring can drive innovations in energy-efficient technologies and inform policies for a more sustainable and energy-responsible society. It's a crucial tool in our journey towards a greener and more resilient energy future.

Leveraging AI models in hourly energy consumption monitoring takes this practice to a whole new level. AI can provide predictive analytics, real-time adjustments, and anomaly detection, optimising energy usage. Machine learning algorithms can forecast energy demands, enabling better resource planning and allocation. AI can also help consumers receive personalised insights on how to reduce energy consumption, ultimately saving money and reducing their environmental impact. Moreover, by continuously learning and adapting, AI systems can make our energy infrastructure smarter and more responsive, contributing to a more sustainable and efficient energy ecosystem.