MEASURE ENERGY CONSUMPTION

PROJECT SUBMISSION PHASE 5

TOPIC

Project documentation and submission

MEASURE ENERGY CONSUMPTION

INTRODUCTION

Measuring energy consumption is a critical aspect of managing and optimizing energy use, both at the individual and societal levels. It involves quantifying the amount of energy consumed by various devices, systems, or processes. This measurement is essential for several reasons, including

Resource Management:

Efficient energy consumption helps conserve valuable natural resources and reduce the environmental impact associated with energy production and consumption.

Cost Savings:

Accurate measurement of energy consumption allows individuals and organizations to identify areas where energy efficiency improvements can lead to cost savings on utility bills.

Environmental Impact:

Understanding energy consumption is crucial for assessing and mitigating the environmental impact of energy use, including greenhouse gas emissions and air pollution.

Regulatory Compliance:

Many regions have regulations and standards in place that require the measurement and reporting of energy consumption for businesses and industries. Compliance with these regulations is necessary to avoid penalties.

Performance Monitoring:

In industrial and commercial settings, monitoring energy consumption helps evaluate the performance of equipment and processes, identifying areas for optimization and maintenance.

Energy Conservation:

Tracking energy consumption provides insights into patterns and trends, which can inform energy conservation efforts and promote sustainability.

To measure energy consumption effectively, the following steps are typically involved:

Instrumentation:

Install energy meters or monitoring equipment at the point of consumption, such as utility meters for homes or sub-meters for specific appliances or systems in commercial and industrial settings.

Data Collection:

Collect data from these meters and sensors to record energy usage over time. This can be done manually or automatically through smart meters and IoT devices.

Data Analysis:

Analyze the data to identify consumption patterns, peak usage times, and areas of high energy consumption.

Benchmarking:

Compare energy consumption data to industry standards or historical data to assess performance and efficiency.

Reporting:

Present the data in a clear and understandable format, often through graphical charts and reports, to help individuals and organizations make informed decisions.

Optimization:

Based on the analysis, take action to optimize energy consumption, which might involve upgrading equipment, implementing energy-efficient technologies, adjusting user behavior, or making other changes.

Verification:

Periodically verify the results of optimization efforts to ensure that they are effective and sustainable.

Methods of measuring energy consumption can vary, depending on the context. Common units of measurement include kilowatt-hours (kWh) for electrical energy and British thermal units (BTUs) or joules for other forms of energy like heat. The choice of measurement method and equipment depends on the specific application, such as residential, commercial, or industrial.

In summary, measuring energy consumption is a fundamental practice for responsible energy management, cost savings, and environmental sustainability. It enables individuals and organizations to understand, monitor, and control their energy usage, ultimately leading to more efficient and sustainable energy systems.

MEASURE ENERGY CONSUMPTION USING ARTIFICIAL INTELLIGENCE

Measuring energy consumption in the context of artificial intelligence (AI) is becoming increasingly important as AI technologies are deployed in a wide range of applications, from data centers to edge devices. Efficient energy consumption in AI is crucial for various reasons, including sustainability, cost savings, and performance optimization. Here's an introduction to measuring energy consumption in AI:

AI in Modern Computing:

AI algorithms, especially deep learning models, have gained popularity in recent years due to their ability to perform complex tasks, such as image recognition and natural language processing. These AI applications often require significant computational power, which can result in high energy consumption.

Importance of Energy Efficiency:

As AI systems are integrated into various industries, energy efficiency has become a top priority. In data centers and cloud computing environments, energy costs can be a significant part of operational expenses. Moreover, the environmental impact of energy consumption in data centers has drawn attention, making it essential to monitor and optimize AI-related energy use.

Energy Measurement in AI:

Hardware-Level Measurement: Measuring energy consumption at the hardware level is a fundamental approach. This involves using power meters, smart sensors, or specialized hardware components to measure the power draw of the computing equipment (e.g., CPUs, GPUs, TPUs).

Software-Level Measurement:

Monitoring and profiling software at the application level can provide insights into how efficiently AI algorithms are implemented. Profiling tools can identify resource-intensive sections of code, helping developers optimize energy consumption.

Data Center and Cloud Environments:

In data center and cloud settings, energy-efficient infrastructure and cooling systems are vital. Monitoring energy usage in these environments involves measuring server power consumption, cooling systems, and data center facilities as a whole.

Edge Devices:

On the edge, where AI is deployed on mobile devices, IoT sensors, and embedded systems, energy efficiency is critical for extending battery life and reducing the need for frequent recharging or maintenance. Power-efficient AI algorithms and hardware accelerators are key components.

Machine Learning for Energy Optimization:

AI can be used to optimize energy consumption itself. Machine learning models can be trained to predict and manage energy usage in real-time, helping to balance workloads and allocate resources efficiently.

Benchmarking and Standards:

Standardized benchmarks and metrics are important for comparing the energy efficiency of different AI systems. Organizations like MLPerf provide benchmarks to evaluate AI system performance, including energy efficiency.

Sustainability and Green AI:

The concept of "Green AI" focuses on developing AI technologies and practices that are environmentally sustainable. This includes reducing energy consumption, using renewable energy sources, and minimizing the carbon footprint of AI systems.

Measuring energy consumption in AI is not only about understanding the energy usage but also optimizing it. It requires collaboration between hardware designers, software developers, and data center managers to create more energy-efficient AI systems. As AI continues to grow in importance and scale, monitoring and improving energy consumption will play a significant role in the sustainable and cost-effective deployment of AI technologies.

DESIGN THINKING AND INNOATION

Design thinking and innovation are closely intertwined concepts that play a significant role in problem-solving, product development, and organizational growth. Let's explore both of these concepts and how they relate to each other:

Design Thinking:

Design thinking is a human-centered approach to problem-solving and innovation that places empathy for the end-users at its core. It is characterized by the following key principles:

Empathy:

Design thinking begins with a deep understanding of the needs, desires, and challenges of the people who will use the product or service. This involves engaging with users, conducting interviews, and observing their behaviors.

Define:

Once empathy is established, the problem is clearly defined. This involves identifying the pain points, challenges, and opportunities that need to be addressed.

Ideate:

During the ideation phase, cross-functional teams brainstorm a wide range of creative solutions to the defined problem. This is a divergent thinking process aimed at generating innovative ideas.

Prototype:

Ideas are then turned into tangible prototypes or mock-ups. These prototypes are used to quickly test and iterate on possible solutions.

Test:

Prototypes are tested with real users to gather feedback. This iterative process helps refine the solution based on user insights.

Innovation:

Innovation refers to the process of introducing new, creative, and valuable ideas, products, services, or processes. It encompasses a broad range of activities and can manifest in various ways, such as technological advancements, business model innovations, or improvements in customer experiences. Key elements of innovation include:

Creativity:

Innovation often starts with creative thinking and the generation of novel ideas. These ideas can be incremental improvements or disruptive breakthroughs.

Risk-Taking:

Innovation involves a degree of risk, as new ideas and approaches may not always succeed. A culture that encourages calculated risk-taking is often associated with successful innovation.

Market Orientation:

Innovations should meet the needs and demands of the market. Understanding customer preferences and staying attuned to market trends is essential for successful innovation.

Implementation:

Innovation is not limited to idea generation; it also involves the effective implementation of those ideas to create value, whether through new products, services, or processes.

Relationship between Design Thinking and Innovation:

Design thinking is a powerful approach for driving innovation because it prioritizes empathy and user-centric problem-solving. Here's how they are connected:

Human-Centered Innovation:

Design thinking ensures that innovations are rooted in a deep understanding of user needs and pain points, increasing the likelihood that new solutions will be relevant and valuable.

Iterative and User-Validated:

Design thinking emphasizes the iterative nature of problem-solving and innovation. It encourages the rapid prototyping and testing of ideas, reducing the risk of developing solutions that don't resonate with users.

Creative Problem-Solving:

Design thinking's ideation phase promotes creative problem-solving, fostering the generation of novel ideas and potential innovations.

Cross-Disciplinary Collaboration:

Design thinking often involves cross-functional teams, which can lead to a diversity of perspectives and expertise, driving innovation through collaboration.

Focus on User Experience:

Innovation is not just about creating something new; it's about creating something that enhances the user experience. Design thinking helps ensure that innovation is user-centric.

PYTHON PROGRAM

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

df.head()

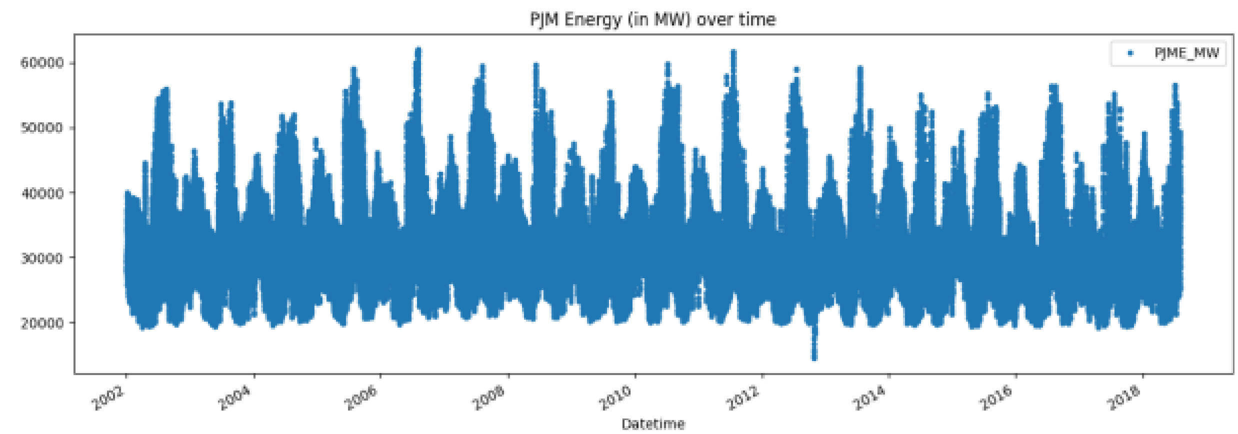
	AEP	COMED	DAYTON	DEOK	DOM	DUQ	EKPC	FE	NI	PJME	PJMW	PJM_LOAD
DATETIME												
1998 12-31 01-00-00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	29309.0
1998 12-31 02-00-00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	28236.0
1998 12-31 03-00-00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	27692.0
1998 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
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

DATA VISUALIATION

```
df = df.set_index('Datetime')
df.index = pd.to_datetime(df.index)
 # create the plot
 df.plot(style='.',figsize=(15, 5), title='PJM Energy (in MW) over time')
plt.show()
```



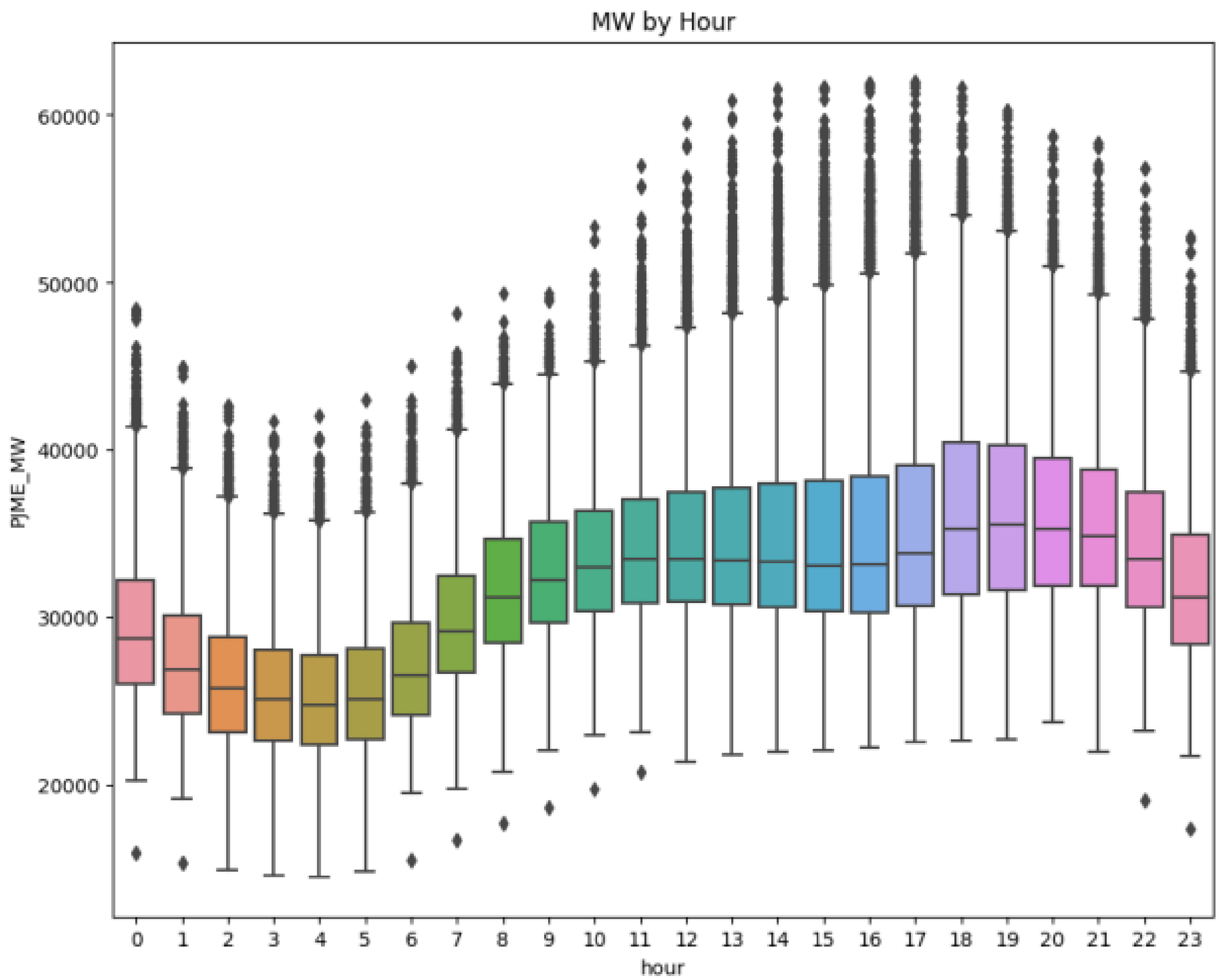
Feature Engineering

```
 # feature creation
def create_features(df):
      df = df.copy()
      df['hour'] = df.index.hour
      df['dayofweek'] = df.index.dayofweek
      df['quarter'] = df.index.quarter
      df['month'] = df.index.month
      df['year'] = df.index.year
      df['dayofyear'] = df.index.dayofyear
      df['dayofmonth'] = df.index.day
      df['weekofyear'] = df.index.isocalendar().week
     return df

 df = create_features(df)

 # visualize the hourly Megawatt fig,
```

```
ax = plt.subplots(figsize=(10, 8))
sns.boxplot(data=df, x='hour', y='PJME_MW')
ax.set_title('MW by Hour')
plt.show()
```



Modelling

```
# preprocessing
train = create_features(train)
test = create_features(test)
```

```
features = ['dayofyear', 'hour', 'dayofweek', 'quarter', 'month', 'year']
target = 'PJME_MW'
X_train = train[features]
y_train = train[target]
X_test = test[features]
y_test = test[target]
```

Build the model

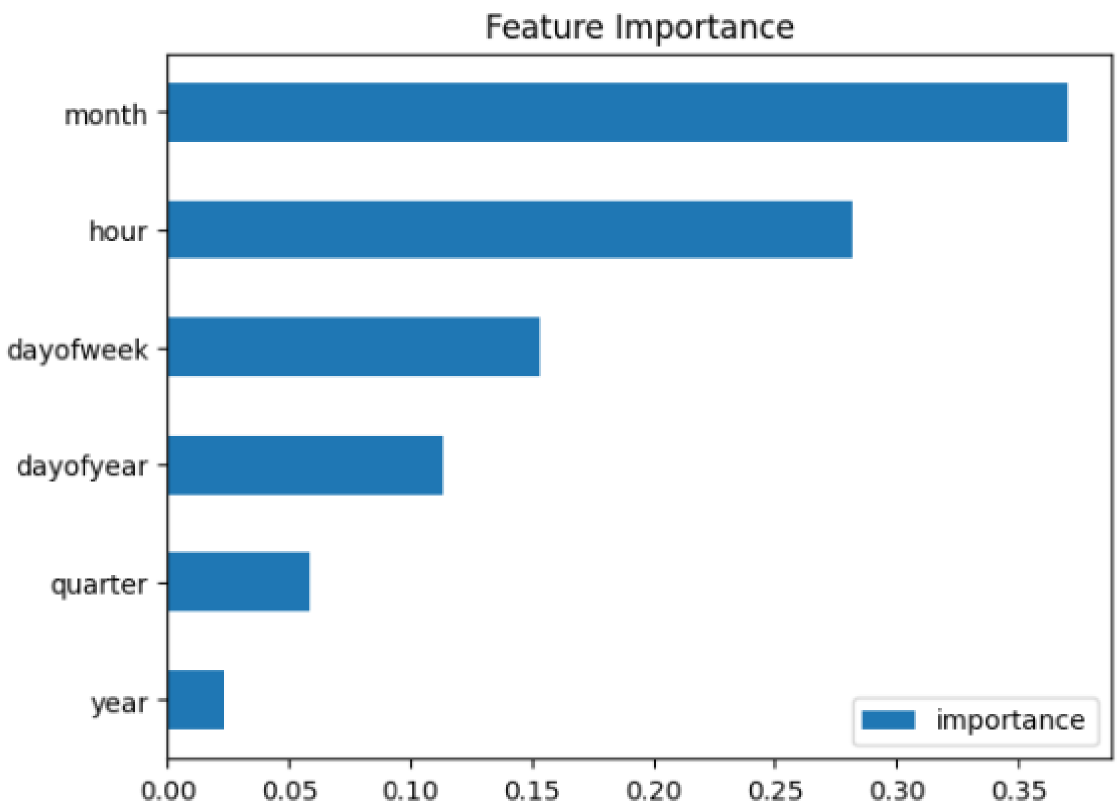
```
import xgboost as xgb from sklearn.metrics
import mean_squared_error

# build the regression model
reg = xgb.XGBRegressor(base_score=0.5,
booster='gbtree',
                       n_estimators=1000,
                       early_stopping_rounds=50,
                       objective='reg:linear',
                       max_depth=3,
                       learning_rate=0.01)
reg.fit(X_train, y_train, eval_set=[(X_train, y_train), (X_test, y_test)]
verbose=100)
```

Features importance

```
fi = pd.DataFrame(data=reg.feature_importances_,
index=reg.feature_names_in_, columns=['importance'])
```

fi.sort_values('importance').plot(kind='barh', title='Feature Importance')
plt.show()



defload_data(stock,seq_len):
X_train=[]
y_train=[]
foriinrange(seq_len,len(stock)):
X_train.append(stock.iloc[i-seq_len:i,0])
y_train.append(stock.iloc[i,0])

# 1 last 6189 days are going to be used in test
X_test=X_train[110000:]
y_test=y_train[110000:]

```
# 2 first 110000 days are going to be used in training
X_train=X_train[:110000]
y_train=y_train[:110000]

# 3 convert to numpy array
X_train=np.array(X_train)
y_train=np.array(y_train)

X_test=np.array(X_test)
y_test=np.array(y_test)

# 4 reshape data to input into RNN models
X_train=np.reshape(X_train,(110000,seq_len,1))

X_test=np.reshape(X_test,(X_test.shape[0],seq_len,1))

return[X_train,y_train,X_test,y_test]



#create train, test data

seq_len=20#choose sequence length
X_train,y_train,X_test,y_test=load_data(df,seq_len)

print('X_train.shape = ',X_train.shape)
print('y_train.shape = ',y_train.shape)
print('X_test.shape = ',X_test.shape)
print('y_test.shape = ',y_test.shape)


X_train.shape =  (110000, 20, 1)
```

```
y_train.shape =  (110000,)
X_test.shape =  (6169, 20, 1)
y_test.shape =  (6169,)


#RNN model

rnn_model=Sequential()
rnn_model.add(SimpleRNN(40,activation="tanh",return_sequences=True,input_shape=(X_train.shape[1],1)))
rnn_model.add(Dropout(0.15))
rnn_model.add(SimpleRNN(40,activation="tanh",return_sequences=True))
rnn_model.add(Dropout(0.15))
rnn_model.add(SimpleRNN(40,activation="tanh",return_sequences=False))
rnn_model.add(Dropout(0.15))
rnn_model.add(Dense(1))
rnn_model.summary()
rnn_model.compile(optimizer="adam",loss="MSE")
rnn_model.fit(X_train,y_train,epochs=10,batch_size=1000)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
simple_rnn (SimpleRNN)	(None, 20, 40)	1680
dropout (Dropout)	(None, 20, 40)	0
simple_rnn_1 (SimpleRNN)	(None, 20, 40)	3240
dropout_1 (Dropout)	(None, 20, 40)	0

```
simple_rnn_2 (SimpleRNN)    (None, 40)            3240
_________________________________________________________________
dropout_2 (Dropout)         (None, 40)            0
_________________________________________________________________
dense (Dense)               (None, 1)             41
=================================================================
Total params: 8,201
Trainable params: 8,201
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
2022-08-19 16:26:37.061384: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:185] None of the MLIR Optimization Passes are enabled (registered 2)
110/110 [==============================] - 10s 73ms/step - loss: 0.0820
Epoch 2/10
110/110 [==============================] - 9s 81ms/step - loss: 0.0178
Epoch 3/10
110/110 [==============================] - 8s 74ms/step - loss: 0.0096
Epoch 4/10
110/110 [==============================] - 8s 73ms/step - loss: 0.0065
Epoch 5/10
110/110 [==============================] - 8s 74ms/step - loss: 0.0050
Epoch 6/10
110/110 [==============================] - 8s 73ms/step - loss: 0.0040
Epoch 7/10
110/110 [==============================] - 9s 81ms/step - loss: 0.0035
Epoch 8/10
110/110 [==============================] - 8s 73ms/step - loss: 0.0030
Epoch 9/10
110/110 [==============================] - 8s 74ms/step - loss: 0.0027
Epoch 10/10
110/110 [==============================] - 8s 75ms/step - loss: 0.0024
```

ADVANTAGES

Measuring energy consumption using machine learning offers several advantages, including:

Granular Insights:

Machine learning allows for the collection and analysis of fine-grained data, enabling you to understand energy consumption patterns at a much more detailed level. This can help identify specific areas of inefficiency and pinpoint opportunities for improvement.

Predictive Analytics:

Machine learning models can predict future energy consumption based on historical data and various factors such as weather, occupancy, and equipment usage. This predictive capability can help organizations plan better and optimize their energy usage.

Anomaly Detection:

Machine learning can identify abnormal energy consumption patterns, potentially indicating equipment malfunctions, leaks, or other issues that may lead to energy wastage. Early detection of anomalies can prevent costly problems and reduce energy costs.

Optimization:

By continuously monitoring and analyzing energy consumption data, machine learning can suggest optimization strategies to reduce energy usage. This might include adjusting equipment settings, optimizing schedules, or implementing energy-efficient technologies.

Cost Savings:

The insights gained from machine learning can result in significant cost savings by reducing energy waste, optimizing energy usage, and avoiding peak demand charges.

Sustainability and Environmental Benefits:

Lowering energy consumption through machine learning can help organizations reduce their carbon footprint and contribute to sustainability goals.

Real-Time Monitoring:

Machine learning systems can provide real-time monitoring and alerts, allowing organizations to respond promptly to energy-related issues or inefficiencies as they arise.

Customization:

Machine learning models can be tailored to specific industries, building types, or energy sources, making them adaptable to a wide range of applications.

Data Integration:

Machine learning can integrate data from various sources, such as IoT sensors, energy meters, weather data, and historical usage data, to provide a holistic view of energy consumption and its drivers.

Compliance and Reporting:

Machine learning can assist in meeting regulatory requirements by providing accurate and auditable data on energy consumption, emissions, and efficiency measures.

Scalability:

Machine learning systems can scale with the size and complexity of energy management needs, making them suitable for both small-scale and large-scale applications.

Continuous Improvement:

Machine learning can adapt and improve its predictions and recommendations over time as it gains more data and experience, leading to ongoing energy efficiency gains.

Overall, measuring energy consumption using machine learning not only helps organizations save money but also contributes to environmental sustainability and can enhance operational efficiency. It offers a powerful tool for addressing the growing demand for energy management and sustainability initiatives in various industries.

DISADANTAGES

While measuring energy consumption using machine learning offers numerous advantages, there are also some disadvantages and challenges to consider:

Complexity and Cost:

Implementing machine learning solutions can be complex and costly. It often requires specialized expertise, infrastructure, and ongoing maintenance, which can be expensive for some organizations.

Data Quality:

Machine learning models are highly dependent on the quality of data. Inaccurate or incomplete data can lead to flawed insights and recommendations. Ensuring data accuracy and consistency is a critical challenge.

Data Privacy and Security:

Handling energy consumption data may raise privacy and security concerns, especially in residential or commercial settings. Protecting this data from breaches and ensuring compliance with data privacy regulations is a significant challenge.

Energy Source Variability:

Different energy sources and their associated consumption patterns can be complex to model accurately. Renewable energy sources, for example, may introduce variability that's difficult to predict.

Model Interpretability:

Some machine learning models, especially deep learning models, can be challenging to interpret. Understanding why a model makes a particular recommendation or prediction can be a barrier to acceptance, especially in critical applications like energy management.

Energy Storage and Grid Management:

Machine learning models may not account for the complexities of energy storage and grid management in some scenarios. For example, in a smart grid environment, predicting energy demand and supply can be challenging.

Initial Setup and Training:

Training machine learning models requires historical data and can take time. Organizations may need to invest resources into this process before realizing benefits.

Maintenance and Updates:

Machine learning models may need constant monitoring and updates as conditions change. This ongoing maintenance can be resource-intensive.

Overfitting:

Machine learning models can overfit the data, meaning they become too specific to historical patterns, which might not generalize well to changing conditions.

Ethical Considerations:

The use of machine learning in energy management may raise ethical questions, such as bias in decision-making, especially in situations where energy consumption affects vulnerable communities.

Dependency on External Factors:

Predicting energy consumption often depends on external factors, like weather or economic conditions. If these factors change unpredictably, it can impact the accuracy of machine learning models.

Resistance to Change:

Organizations and individuals may be resistant to adopting machine learning solutions for energy management due to unfamiliarity or fear of job displacement in cases where automation is involved.

Scalability:

Scaling machine learning solutions across a large organization or an entire city can be challenging, especially when dealing with a wide variety of energy sources and consumption patterns.

Regulatory and Compliance Challenges:

Meeting regulatory requirements related to data collection, energy management, and privacy can be complicated and may vary by region.

Overall, while machine learning offers significant benefits for energy consumption management, it's essential to be aware of these disadvantages and challenges to plan for successful implementation and mitigate potential issues

BENEFITS

Measuring energy consumption using machine learning offers several benefits:

Improved Accuracy:

Machine learning models can provide more accurate and granular insights into energy consumption patterns compared to traditional methods. They can account for various variables and factors that affect energy usage, leading to more precise predictions and recommendations.

Energy Efficiency:

Machine learning can identify inefficiencies and opportunities for energy savings. By optimizing equipment usage, scheduling, and other factors, organizations can reduce energy waste and lower operational costs.

Cost Reduction:

Optimizing energy consumption can lead to significant cost savings. Machine learning models can help organizations avoid peak demand charges, reduce energy bills, and minimize maintenance costs through predictive maintenance.

Environmental Sustainability:

Lowering energy consumption contributes to reduced greenhouse gas emissions and environmental sustainability. It aligns with green initiatives and corporate social responsibility goals.

Predictive Maintenance:

Machine learning can predict when equipment is likely to fail or require maintenance based on energy usage patterns. This enables proactive maintenance, reducing downtime and maintenance costs.

Customization:

Machine learning models can be tailored to specific industries, building types, or energy sources, making them adaptable to various applications and requirements.

Real-Time Monitoring and Alerts:

Machine learning systems can provide real-time monitoring and alerts, allowing organizations to respond promptly to energy-related issues, inefficiencies, or anomalies.

Data Integration:

Machine learning can integrate data from various sources, such as IoT sensors, energy meters, weather data, and historical usage data, providing a comprehensive view of energy consumption and its drivers.

Regulatory Compliance:

Machine learning can assist in meeting regulatory requirements by providing accurate and auditable data on energy consumption, emissions, and efficiency measures.

Energy Load Forecasting:

Machine learning models can forecast energy demand and supply, helping grid operators and energy providers better manage resources and avoid overloads or shortages.

Behavioral Insights:

Machine learning can analyze human and equipment behavior to identify usage patterns and recommend changes that lead to energy savings.

Continuous Improvement:

Machine learning models can adapt and improve their predictions and recommendations over time as they gain more data and experience, leading to ongoing energy efficiency gains.

Remote Management:

Machine learning systems can be accessed and managed remotely, allowing organizations to control energy consumption across multiple sites or facilities from a centralized location.

Operational Efficiency:

Energy optimization can lead to improved operational efficiency and productivity by ensuring that equipment and systems are operating at their peak performance.

Asset Management:

Machine learning can help organizations manage and maintain their energy assets more effectively, extending the lifespan of equipment and reducing the need for replacements.

Resilience:

By optimizing energy consumption and reducing waste, organizations can become more resilient to energy price fluctuations and supply disruptions.

In summary, measuring energy consumption using machine learning provides a range of benefits, including cost savings, environmental benefits, improved accuracy, and the ability to make data-driven decisions for better energy management and sustainability. These advantages are particularly important in today's world, where energy efficiency and sustainability are critical concerns for organizations and communities.