MACHINE LEARNING BASED ENERGY MANAGEMENT SYSTEM

A Project report submitted in partial fulfilment

of the requirements for the degree of B. Tech in Electrical Engineering

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CERTIFICATE

To whom it may concern

This is to certify that the project work entitled **MACHINE LEARNING BASED ENERGY MANAGEMENT SYSTEM** is the bona fide work carried out by **SAMRAT CHOWDHURY (11701615040), SAYAN BANERJEE (11701615044), SAYIDA NAJM (11701615046)** a student of B.Tech in the Dept. of Electrical Engineering, RCC Institute of Information Technology (RCCIIT), Canal South Road, Beliaghata, Kolkata-700015, affiliated to Maulana Abul Kalam Azad University of Technology (MAKAUT), West Bengal, India, during the academic year **2018-19**, in partial fulfilment of the requirements for the degree of Bachelor of Technology in Electrical Engineering and that this project has not submitted previously for the award of any other degree, diploma and fellowship.

Signature of the Guide	**Signature of the HOD**
Name:	**Name:**
Designation:	**Designation:**

Signature of the External Examiner
Name:
Designation:

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Place:

Date:

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ABSTRACT

Energy management plays a crucial role in providing necessary system flexibility to deal with the ongoing integration of volatile and intermittent energy sources. Demand Response (DR) programs enhance demand flexibility by communicating energy market price volatility to the end-consumer. In such environments, home energy management systems assist the use of flexible end-appliances, based upon the individual consumer's personal preferences and beliefs. However, with the latter heterogeneously distributed, not all dynamic pricing schemes are equally adequate for the individual needs of households. We conduct one of the first large scale natural experiments, with multiple dynamic pricing schemes for end consumers, allowing us to analyze different demand behavior in relation with household attributes. We apply a spectral relaxation clustering approach to show distinct groups of households within the two most used dynamic pricing schemes: Time-Of-Use and Real-Time Pricing. The results indicate that a more effective design of smart home energy management systems can lead to a better fit between customer and electricity tariff in order to reduce costs, enhance predictability and stability of load and allow for more optimal use of demand flexibility by such systems.

Keywords: Energy management; Indoor environment; Reinforcement learning; Adaptive control; Energy efficiency.

INTRODUCTION

The energy business is going through a series of swift and radical transformations to meet the growing demands for sustainable energy. The future of the energy sector will, to a large extent, be formed by a transformation in the electricity sector, posing challenges for traditional electrical power systems. This shift is of a complex nature, but offers ample opportunities for business and information analytics to support the transition. The non-storability and volatile aspect of sustainable energy sources and the required shift from a demand-driven to a supply-driven market means the energy transition requires system flexibility from all market participants. The non-storability and volatile aspect of sustainable energy sources and the required shift from a demand-driven to a supply-driven market means the energy transition requires system flexibility from all market participants. The heterogeneity amongst customers ensures that EMS and the energy service provider have to learn from the customer’s individual preferences in order to make optimal recommendations in terms of dynamic tariff targeting, and ultimately, consumer welfare. We apply machine learning techniques in this paper, to show how such systems can recommend tariff schemes based upon the individual household’s attributes. With the growth of home energy management systems and smart meters, the volume, frequency and variety of information is growing exponentially. Business intelligence and machine learning techniques can provide utilities and energy-market-related companies with demand forecasts and customer usage patterns to support data-driven decision making.

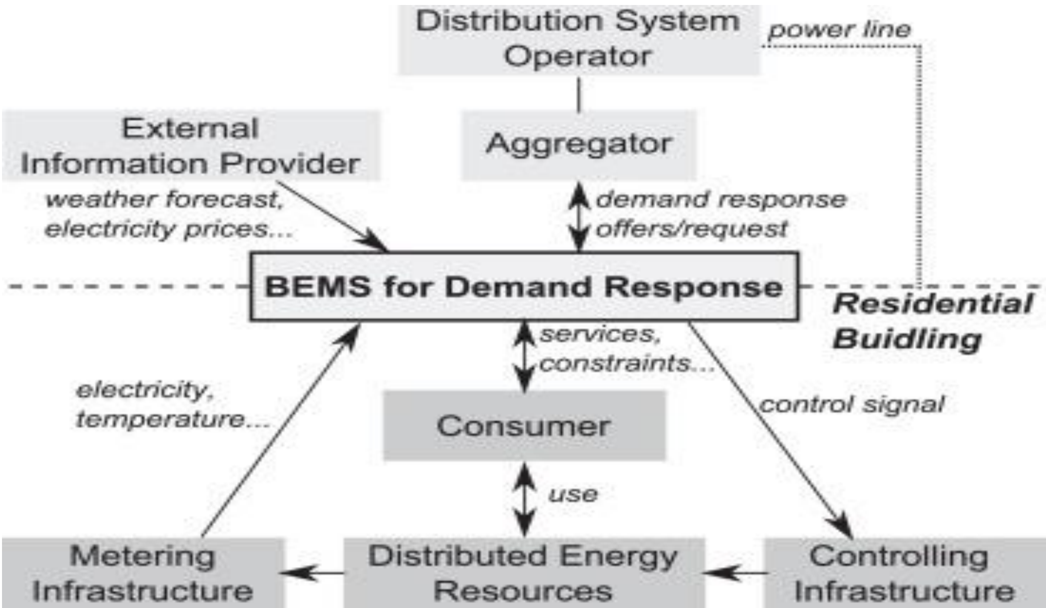
MACHINE LEARNING

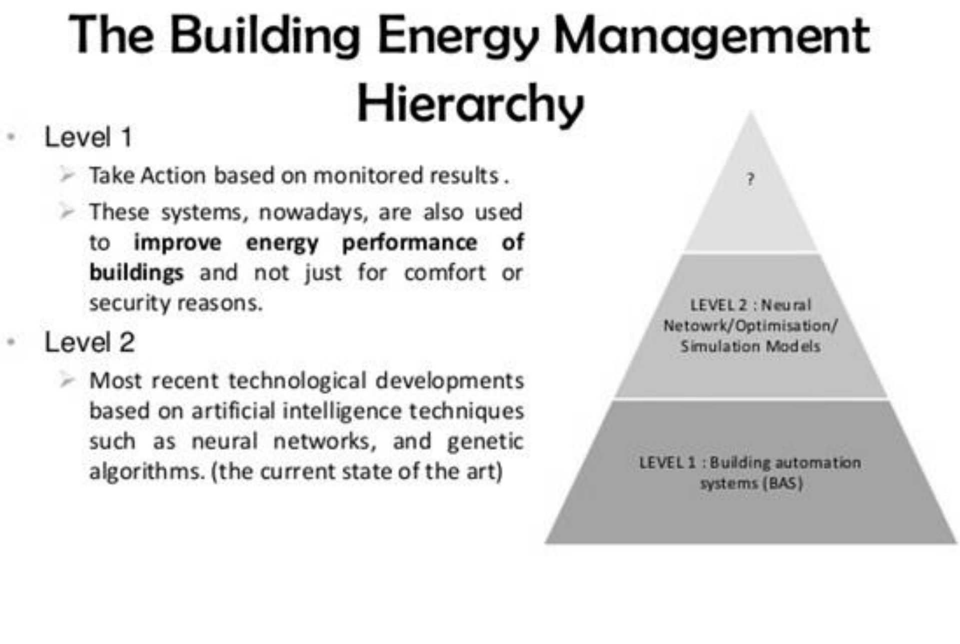
Energy management plays a crucial role in providing necessary system flexibility to deal with the ongoing integration of volatile and intermittent energy sources. The energy business is going through a series of swift and radical transformations to meet the growing demands for sustainable energy. The future of the energy sector will, to a large extent, be formed by a transformation in the electricity sector, posing challenges for traditional electrical power systems. This shift is of a complex nature, but offers ample opportunities for business and information analytics to support the transition. The electricity grid faces decentralized production from renewable sources, electric mobility, and related advances. These are at odds with traditional power systems, where central large-scale generation of electricity follows inelastic consumer demand. Energy Management Systems (EMS) can control the use of end-appliances and optimize the flexible range, based upon the end consumer’s personal preferences and beliefs. We apply machine learning techniques in paper, to show how such systems can recommend tariff schemes based upon the individual household’s attributes. Our setting is a natural experiment, involving real-world customers of a national utility company participating via dynamic pricing contracts. This allows us to reach high ecological validity in testing, whether the increase of household information influences demand for individual households, and how utilities can use machine learning techniques in designing their home energy management systems for better targeting of customers. With the growth of home energy management systems and smart meters, the volume, frequency and variety of information is growing exponentially. Business intelligence and machine learning techniques can provide utilities.

SCIKIT LEARNING (SKLEARN) FOR ML

Scikit-learn is a machine learning library for Python. It features various algorithms like support vector machine, random forests, and k-neighbours, and it also supports Python numerical and scientific libraries like NumPy and SciPy.

MECHANISM OF IDENTIFYING DEMAND PATTERNS

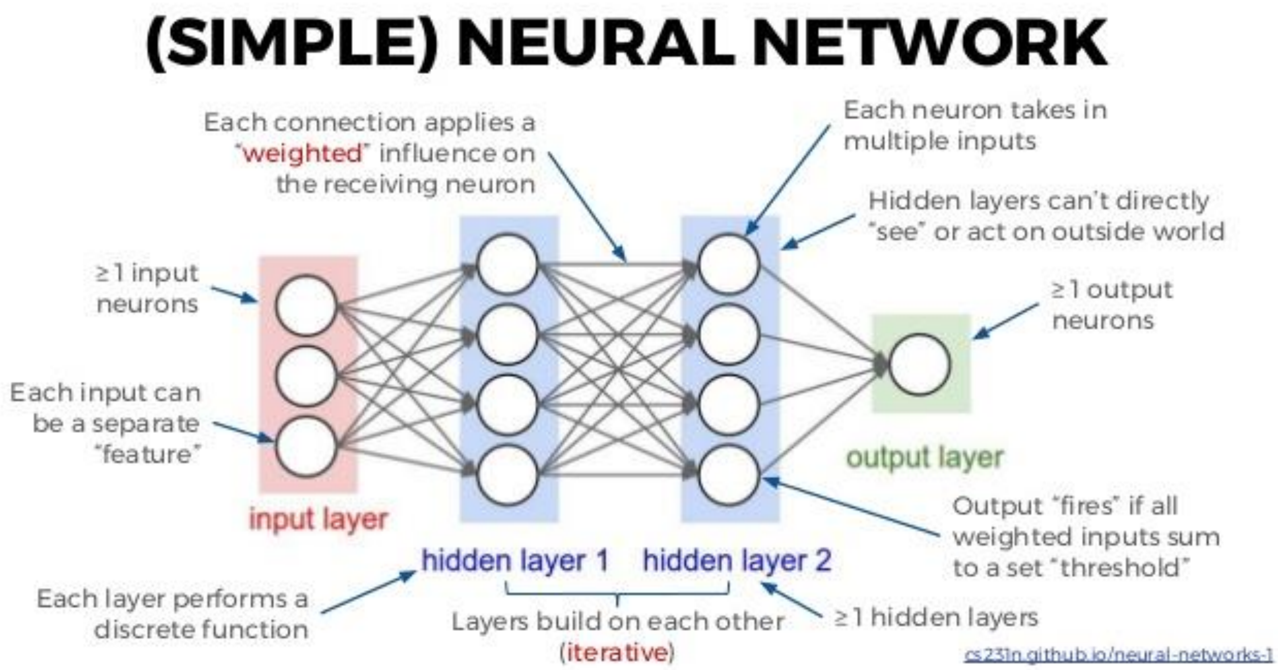




ARTIFICIAL NEURAL NETWORKS

Nowadays, Artificial Neural Networks (ANNs) are one of the most widely used solutions for energy prediction problem.

The general design of ANN is inspired by the model of the human brain. Overall, an ANN is composed by neurons, grouped in layers and the connection between them. In our specific case the ANN has three layers. More precisely, the ‘u’ layer represents the inputs, which encodes the last values of the energy consumption. The ‘v’ layer contains the output neurons, and the ‘h’ layer has hidden neurons to learn the characteristics of the time series. The connections between neurons are unidirectional, so that the model is able to compute the output values ‘v’ from the inputs ‘u’ by feeding information through the network.



PROPOSED OPTIMIZATION ALGORITHM

Let us consider a function as follows: $f(x_1, x_2, x_3, \ldots, x_k)$

Here $(x_1, \ldots, x_k)$ are the k parameters that function f depends on.

We assume the fact that function f is always concave or at least it has well-defined global minima to which **Gradient Descent** can converge. GD may converge to local minima.

The algorithm in this case would work as follows:

Repeat until convergence:

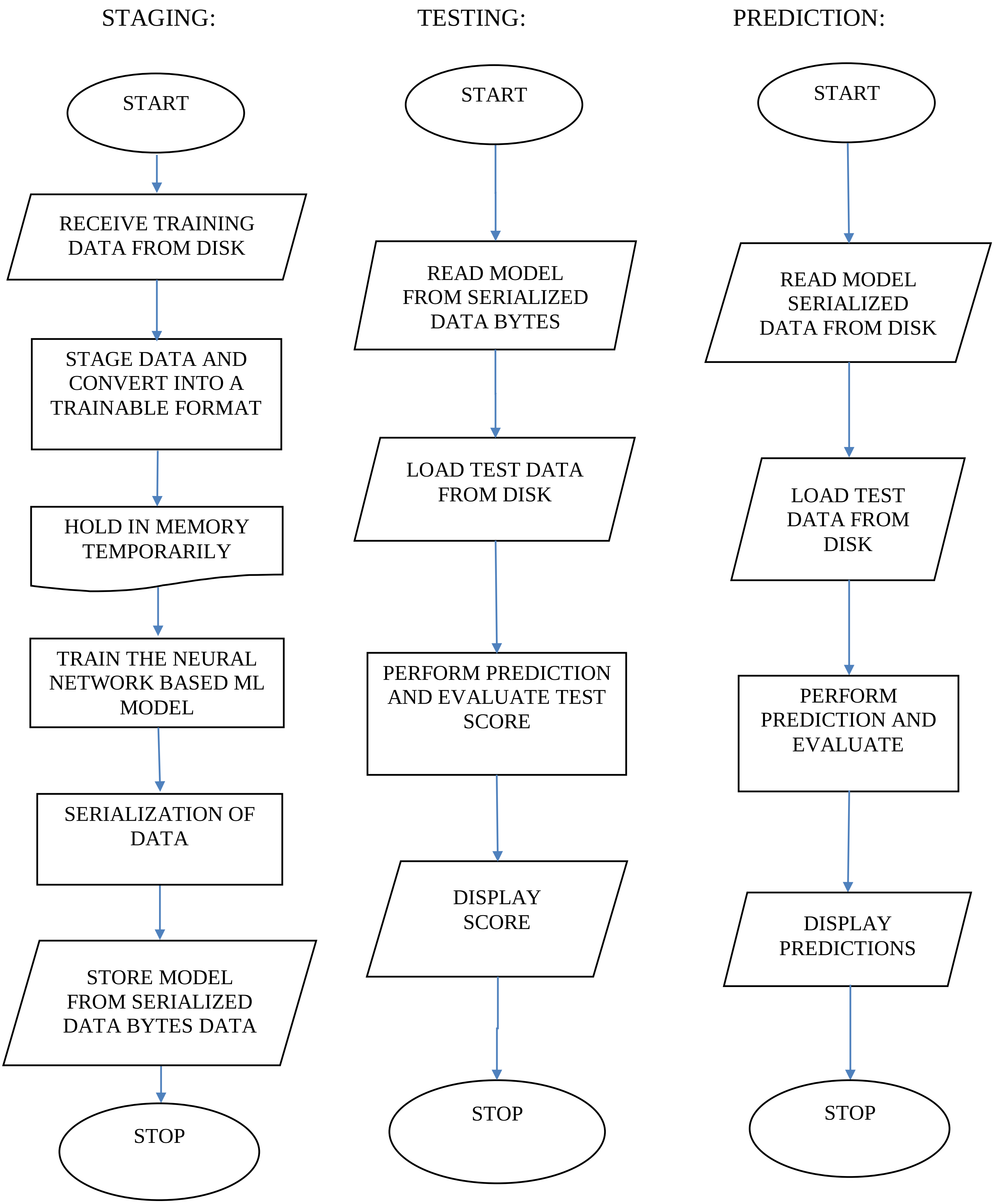
$$x_1^{(n+1)} := x_1^{(n)} - \alpha \frac{\partial f(x_1, \ldots, x_k)}{\partial x_1} \Big|_{x_i = x_i^{(n)}}$$

$$x_2^{(n+1)} := x_2^{(n)} - \alpha \frac{\partial f(x_1, \ldots, x_k)}{\partial x_2} \Big|_{x_i = x_i^{(n)}}$$

$$\ldots$$

$$x_k^{(n+1)} := x_k^{(n)} - \alpha \frac{\partial f(x_1, \ldots, x_k)}{\partial x_k} \Big|_{x_i = x_i^{(n)}}$$

PROPOSED FLOWCHART



DESIGN AND DEVELOPMENT OF PROGRAMMING

STAGING:

```
import pandas as pd
import datetime
from sklearn.neural_network import MLPRegressor
import pickle

PATH = 'data.csv'
OUT = 'context.nn'

def flatten_date(date_str):
    dt = datetime.datetime.strptime(date_str, '%d/%m/%y %H:%M')
    return [dt.month, dt.day, dt.hour, dt.minute]

def create_test(df, indices):
    master = []
    for i, row in df[indices].iterrows():
        it = []
        for index in indices:
            it.append(row[index])
        master.append(it)
    return master

#Read the data
print('Beginning to read CSV data from %s' % PATH)
df_all = pd.read_csv(PATH, header=None)
print('Data read successfully')
indices = [4, 5, 6, 9, 10, 13, 14, 15, 16]
```

```
# Pull timestamp from extracted dataframe
print('Processing and staging dataframe...')
df_input = df_all[0].tolist()
df_input = list(map(flatten_date, df_input))
df_output = create_test(df_all, indices)
print('Staging complete')

# Test code - Do not touch
# print(df_input[0], df_input[1])
# print(df_output[0], df_output[1])
# print(len(df_input))
# print(len(df_output))

print('Training a MLPRegressor - hold tight...')
nn = MLPRegressor(solver='adam',
                  alpha=1e-5,
                  learning_rate='adaptive',
                  learning_rate_init=0.001,
                  hidden_layer_sizes=(20, 15),
                  random_state=1,
                  max_iter=1000)
nn.fit(df_input, df_output)
print('Training complete')
print('Saving model')
pickle.dump(nn, open(OUT, 'wb'))
print('Model created, trained and saved successfully')
```

TESTING:

```
import pandas as pd
import datetime
```

```
from sklearn.neural_network import MLPRegressor
import pickle

PATH = 'data.csv'
IN = 'context.nn'

print('Using path %s for test data' % PATH)
print('Deserializing model from %s' % IN)
nn = pickle.load(open(IN, 'rb'))
print('Model deserialized and loaded...')

def flatten_date(date_str):
	dt = datetime.datetime.strptime(date_str, '%d/%m/%y %H:%M')
	return [dt.month, dt.day, dt.hour, dt.minute]

def create_test(df, indices):
	master = []
	for i, row in df[indices].iterrows():
		it = []
		for index in indices:
			it.append(row[index])
		master.append(it)
	return master

#Read the data
print('Beginning to read CSV data from %s' % PATH)
df_all = pd.read_csv(PATH, header=None)
print('Data read successfully')
indices = [4, 5, 6, 9, 10, 13, 14, 15, 16]

# Pull timestamp from extracted dataframe
```

```
print('Processing and staging dataframe...')
df_input = df_all[0].tolist()
df_input = list(map(flatten_date, df_input))
df_output = create_test(df_all, indices)
print('Staging complete')
result = nn.score(df_input, df_output)
print('------------------------------')
print('Training error (score) from generated model')
print(result)
```

PREDICTION:

```
import pandas as pd
import datetime
from sklearn.neural_network import MLPRegressor
import pickle
import matplotlib.pyplot as plt

PATH = 'predict.csv'
IN = 'context.nn'
AC_PATH = 'data.csv'

ins_names = ['Solar PV System            ']
ins_names.append('Heat Pump - Inside Unit     ')
ins_names.append('Heat Pump - Outside Unit    ')
ins_names.append('Hot Water Heater            ')
ins_names.append('Lights + fans + stair lights')
ins_names.append('Dryer                       ')
ins_names.append('Washing Machine             ')
ins_names.append('Human Generator - Kitchen   ')
ins_names.append('Remaining level 1 plus + DAS')
```

```
rate = input('Enter cost per unit of consumption: ')
try:
        rate = abs(float(rate))
except:
        print('Entered value is not a valid number')
        exit()

def create_test(df, indices):
        master = []
        for i, row in df[indices].iterrows():
it = []
for index in indices:
it.append(row[index])
master.append(it)
return master
def process(ll):
return list(map(lambda o: list(map(abs, o)), ll))
def print_pretty(ll, x):
for l in ll:
print()
print('%s \t\t %s \t %s \t %s \t\t %s' % ('EQUIPMENT NAME / INSTRUMENT', 'MEAN
CONSUMPTION', 'PRED. CONSUMPTION', 'MEAN COST', 'PREDICTED COST'))
print('-----------------------------------------------------------------------------------------------------------------')
show_list = []
for index in range(len(l)):
show_list.append((ins_names[index], l[index]))
show_list.sort(key=lambda o: o[1], reverse=True)
for i in range(9):
item = show_list[i]
```

```
print('%s \t\t %.6f \t\t %.6f \t\t %.4f \t\t %.4f' % (item[0], x[i], item[1], x[i] * rate, item[1] *
rate))
print('Using path %s for test data' % PATH)
print('Deserializing model from %s' % IN)
nn = pickle.load(open(IN, 'rb'))
print('Model deserialized and loaded...')
print('Reading test data (input) from %s' % PATH)
df = pd.read_csv(PATH, header=None)
df_all = pd.read_csv(AC_PATH, header=None)
indices = [4, 5, 6, 9, 10, 13, 14, 15, 16]
adf = create_test(df_all, indices)
print('Read test data')
adf = pd.DataFrame(adf)
adf = adf.mean(axis=0).tolist()

def listify(df):
master = []
for i, row in df.iterrows():
master.append(row.tolist())
return master

print('Staging input...')
input = listify(df)
print('Staging complete')
org = nn.predict(input)
print(len(adf))
print(len(org))
print_pretty(process(org), adf)
plt.plot(nn.loss_curve_)
plt.show()
```

TRAINING AND LEARNING OUTPUT

STAGING:

C:\Users\Sayan Banerjee\Desktop\Machine leraning\ml>python stage.py

Beginning to read CSV data from data.csv

sys:1: DtypeWarning: Columns (68,71,83,84,101) have mixed types. Specify dtype option on import or set low_memory=False.

Data read successfully

Processing and staging dataframe...

Staging complete

Training a MLPRegressor - hold tight...

Training complete

Saving model

Model created, trained and saved successfully.

TESTING:

C:\Users\Sayan Banerjee\Desktop\Machine leraning\ml>python test.py

Using path data.csv for test data

Deserializing model from context.nn

Model deserialized and loaded...

Beginning to read CSV data from data.csv

sys:1: DtypeWarning: Columns (68,71,83,84,101) have mixed types. Specify dtype option on import or set low_memory=False.

Data read successfully

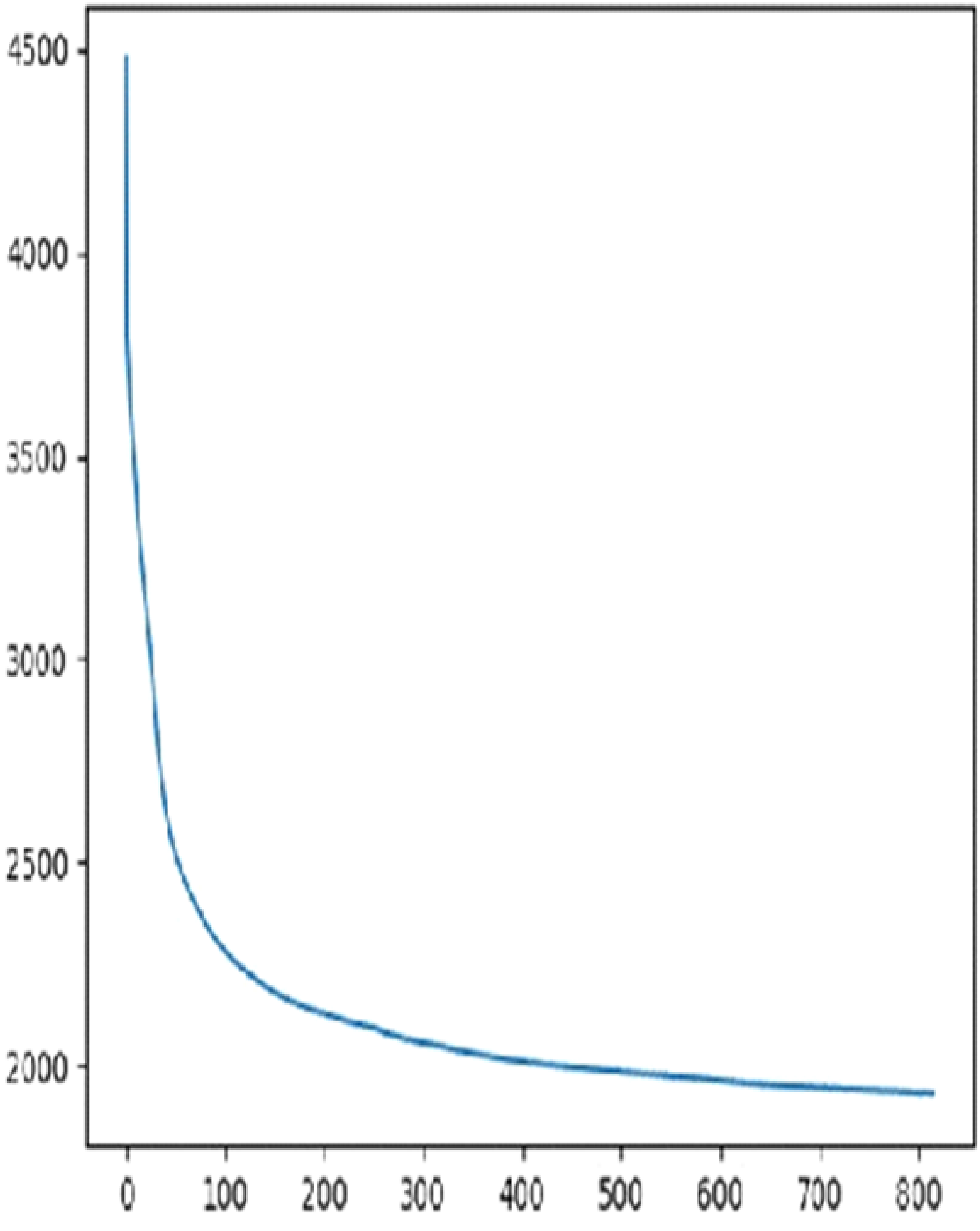
Processing and staging dataframe...

Staging complete

Training error (score) from generated model

0.48529420463554945.

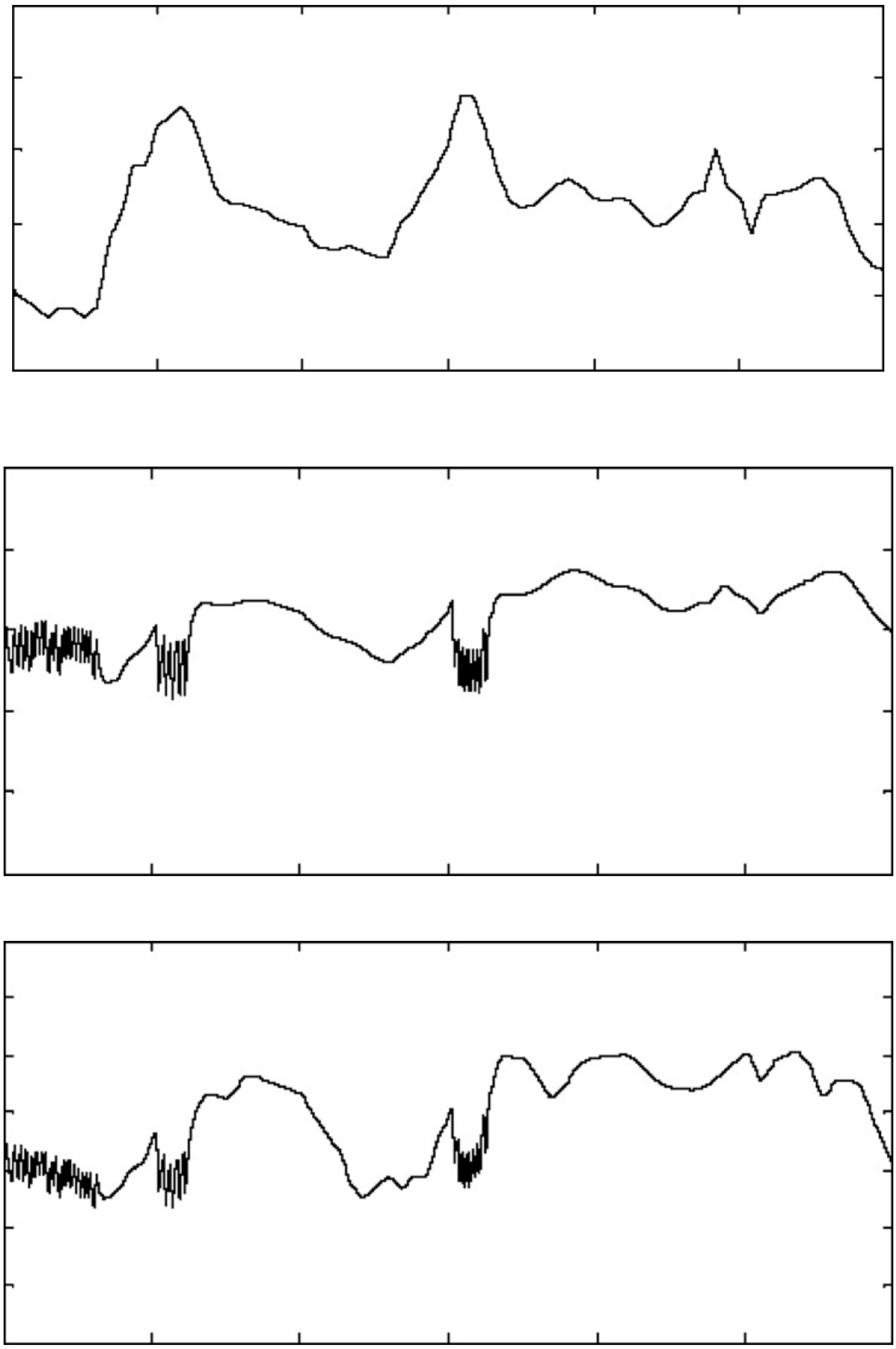
CURVE OF ROOT MEAN SQUARE ERROR VS EPOCH



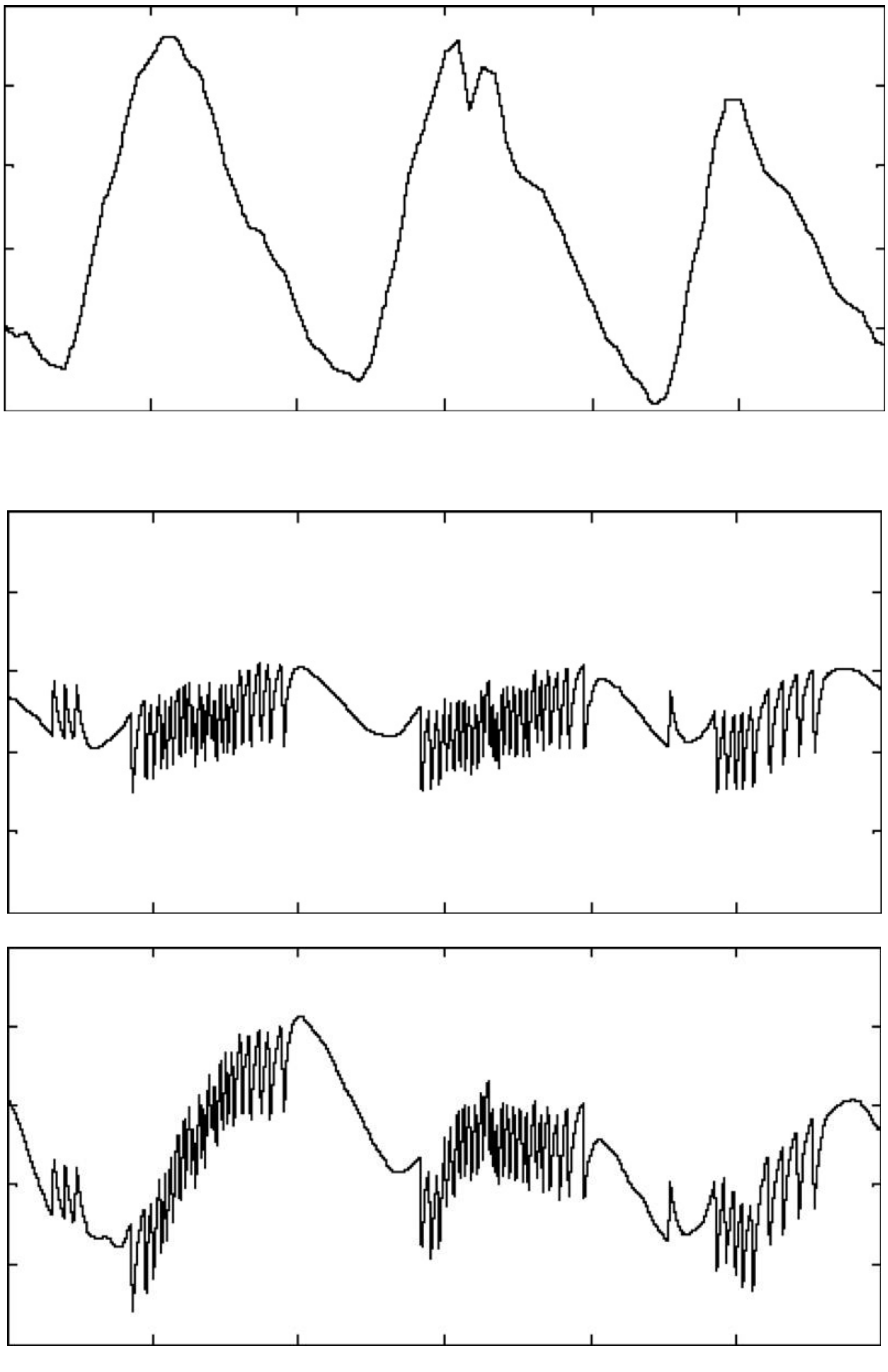
EVALUATION OF PREDICTIVE MODEL

```
C:\Users\Sayan Banerjee\Desktop\Machine leraning\ml>python predict.py
Enter cost per unit of consumption: 7.50
Using path predict.csv for test data
Deserializing model from context.nn
Model deserialized and loaded...
Reading test data (input) from predict.csv
sys:1: DtypeWarning: Columns (68,71,83,84,101) have mixed types. Specify dtype option on import or set low_memory=False.
Read test data
Staging input...
Staging complete
9
5

EQUIPMENT NAME / INSTRUMENT        MEAN CONSUMPTION    PRED. CONSUMPTION    MEAN COST    PREDICTED COST
---------------------------------------------------------------------------------------------------------
Solar PV System                    100.803335          273.973207           756.0250     2054.7990
Heat Pump - Outside Unit           33.328649           146.981727           249.9649     1102.3630
Heat Pump - Inside Unit            85.077901           35.103590            638.0843     263.2769
Hot Water Heater                   45.690611           35.051831            342.6796     262.8887
Remaining level 1 plus + DAS       3.197560            28.075189            23.9817      210.5639
Human Generator - Kitchen          18.608690           19.393563            139.5652     145.4517
Washing Machine                    2.465586            1.221336             18.4919      9.1600
Dryer                              42.233586           1.119229             316.7519     8.3942
Lights + fans + stair lights       31.749084           0.399026             238.1181     2.9927

EQUIPMENT NAME / INSTRUMENT        MEAN CONSUMPTION    PRED. CONSUMPTION    MEAN COST    PREDICTED COST
---------------------------------------------------------------------------------------------------------
Solar PV System                    100.803335          334.620230           756.0250     2509.6517
Heat Pump - Outside Unit           33.328649           109.562994           249.9649     821.7225
Hot Water Heater                   85.077901           63.967164            638.0843     479.7537
Dryer                              45.690611           34.728462            342.6796     260.4635
Remaining level 1 plus + DAS       3.197560            30.132667            23.9817      225.9950
Human Generator - Kitchen          18.608690           21.045705            139.5652     157.8428
Heat Pump - Inside Unit            2.465586            5.483146             18.4919      41.1236
Washing Machine                    42.233586           4.691663             316.7519     35.1875
Lights + fans + stair lights       31.749084           0.783134             238.1181     5.8735

EQUIPMENT NAME / INSTRUMENT        MEAN CONSUMPTION    PRED. CONSUMPTION    MEAN COST    PREDICTED COST
---------------------------------------------------------------------------------------------------------
Heat Pump - Inside Unit            100.803335          171.654509           756.0250     1287.4088
Heat Pump - Outside Unit           33.328649           104.335736           249.9649     782.5180
Remaining level 1 plus + DAS       85.077901           41.145906            638.0843     308.5943
Hot Water Heater                   45.690611           34.008952            342.6796     255.0671
Human Generator - Kitchen          3.197560            25.590491            23.9817      191.9287
Dryer                              18.608690           6.314871             139.5652     47.3615
Lights + fans + stair lights       2.465586            3.000246             18.4919      22.5018
Washing Machine                    42.233586           0.988354             316.7519     7.4127
Solar PV System                    31.749084           0.320201             238.1181     2.4015
```

EVALUATION OF PREDICTIVE MODEL PERFORMANCE



Temperature and PMV variations for a 3-day winter period of a trained LRLC



Temperature and PMV variations for a 3-day summer period of a trained LRLC.

LITERATURE SURVEY

Electric Power is the most flexible and broadly utilized type of vitality and worldwide request is developing persistently. In present day life all individuals are customer of Electric power. Electricity can be utilized to feel comfort at home, to cool, to warm, light them, wash garments, cook to eat, to engage and different purposes Currently electric energy distribution and deployment with in smart environment fairly and intelligently faces different challenges. Forecasting customer's electric energy consumption manages and handles challenges that result from currently unbalanced distribution of smart electric energy. Forecasting the electricity consumption by applying different machine learning mechanisms and models is the best approach to save energy as well as economy. Accurate forecasting will empower utility suppliers to design extra assets and furthermore take control activities to adjust the electricity supply and demand. Forecasting electric utilization is an imperative assignment to give insight to smart grid. It includes prediction of maximum power usage of appliance, peak demand and customers level of life style. Different researchers tried to address challenges of current electric consumption forecasting systems in which some of them are described below.

Implementing machine learning – What are the benefits for the energy ...

https://www.powel.com/.../implementing-machine-learning--what-are-the-benefits-for...

Implementing **machine learning** – What are the benefits for the **energy** sector? Through **machine learning**, companies can turn their data into insight and advanced analytics into foresight, in order to improve decision making. This enables them to achieve real and measurable improvements compared to traditional methods.

How Machine Learning Can Help With Energy Management - Buildings

https://www.buildings.com/article-details/.../machine-learning-energy-management

2 days ago - Facility managers and buildings owners can use **machine learning** to control and, eventually, predict **energy management** use. That can save ...

Implementation of Machine Learning Algorithm for predicting user ...

https://ieeexplore.ieee.org/document/8073480

by RG Rajasekaran - 2017 - Related articles
Implementation of **Machine Learning** Algorithm for predicting user behavior and smart **energy management**. ... To obtain appliance-specific **energy** consumption statistics that can further be used to formulate load scheduling strategies for optimal **energy** utilization, disaggregation of Load is essential.

Machine learning, IoT and big data for energy efficiency: a use case ...

https://www.engerati.com/energy-management/.../energy.../machine-learning-iot-and-...

Jul 16, 2018 - Reducing **energy** consumption with **machine learning** .... Enerbrain has leveraged IoT to control, **manage** and make buildings efficient. Ferraris ...

Efficient MIMO energy management with Machine Learning and AI

https://www.ericsson.com/.../augmenting-mimo-energy-management-with-machine-le...

Ericsson and Vodafone are collaborating to build advanced **Machine Learning** algorithms to improve MIMO **energy management** at radio sites.

How Machine Learning, Big Data, & AI are Changing Energy ...

https://rapidminer.com/blog/machine-learning-big-data-ai-energy/

Nov 13, 2018 - Learn how artificial intelligence (AI), **machine learning** (ML), and big ... One of the most interesting uses of AI in **energy** is grid **management**.

Machine learning for estimation of building energy consumption and ...

https://link.springer.com/article/10.1186/s40327-018-0064-7

by S Seyedzadeh - 2018 - Cited by 3 - Related articles
Oct 2, 2018 - On the other hand,efficient **energy management** and smart ... consumption Building energy efficiency Energy benchmarking **Machine learning** ...

ADVANTAGES OF ML BASED ENERGY MANAGEMENT SYSTEM

1. The home energy management system allows households to get a better overview of past usage behavior and future outlook in the form of next day prices by a dashboard visualizing consumption and production next to general functions, such as profile, metering, messages and a financial overview.
2. The users can examine the respective load profiles for electricity and gas for any given point in the past on daily, weekly or monthly levels.
3. Additionally, users can compare their load profile with the load profile of comparable households
4. The households have the option of exporting their usage data from the dashboard for a more in-depth analysis.
5. The hourly electricity tariffs are communicated on a day-ahead basis via the home energy management system.
6. It gives the consumers more control over their energy usage, and enabling the development and expansion of demand-side management programs, contributing to needed flexibility in volatile energy systems thus allows customers to get a better, real-time understanding.

DISADVANTAGES OF ML BASED ENERGY MANAGEMENT SYSTEM

1. Higher initial costs for design and installation.
2. Operation and maintenance costs might be higher compared to simpler management systems. However, it is also capable of reducing overall costs through improved energy efficiency and more efficient use of staff.
3. Requires commitment at all levels throughout its operational.

CONCLUSION

Home energy management systems are believed to play a crucial role in efficiently capturing the benefits of DR programs to ensure demand flexibility and peak load reduction. The effectiveness of such programs are however, largely affected by the willingness of end-users to be involved in such programs. The need for individual customer tariff targeting, as static building characteristics, such as building age, building size and building type, and demographic characteristics, such as the number of household occupants, make end-consumers act significantly different in the two dynamic pricing schemes. We are able to isolate groups that differ in their level of engagement with the respective dynamic pricing scheme. This indicates that home energy management systems do not perform equally over a varying set of households, with respect to reducing and shifting load.

FUTURE SCOPE OF ML BASED ENERGY MANAGEMENT SYSTEM

Based on the analysis of the surveyed and compared learning-based strategies, upcoming trends and open challenges are identified. The highlights of this survey are expected to advance in future due to potential of learning-based approaches, which will also help to address the open challenges. These advances will need to explore efficient machine learning strategies to take the learning-based approaches for multi/many-core systems into the next era of computing. Incorporating other energy sources like solar energy, heat and wind energy with electric energy for efficient forecasting and utilization is another part of future work. More stable and exact forecasting of power utilization is profoundly critical for reserving money vitality and decreasing carbon emanation. It is a reality that smart meters are digging in for the long haul and that the smart grid and smart metering will be a 'lifestyle' later on. This paper overviewed research works related to forecasting customer's electricity consumption using data from smart meter by applying various machine learning techniques. This paper has reviewed investigate works identified with determining client's power utilization utilizing information from brilliant meter by applying different machine learning procedures. The paper features different ideas of anticipating clients' electric utilization, distinctive techniques, algorithms, models and summary of results applied by various studies related to forecasting customer's electric consumption is clearly emphasized. The requirements of effective utilization of energy resources with the help of smart meter data needs brief study and deep analysis in the research area. Incorporating other energy sources like solar energy, heat and wind energy with electric energy for efficient forecasting and utilization is another part of future work.

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