4222-SURYA GROUP OF INSTITUTION

VIKRAVANDI-605 652

NAAN MUDHALVAN PROJECT

MEASURE ENERGY CONSUMPTION

PREPARED BY:

J.DINESH KUMAR

REGNO:422221106302

ECE DEPARTMENT

3RD YEAR 5TH SEM

OBJECTIVE:

The purpose of this research was to predict energy consumption using the data of Finland's transmission system operator. The objective of this project was to test if a machine learning model can yield good enough results in a complex forecasting problem, exploring machine learning techniques and developing a data-driven model for forecasting energy.

DATA SOURCE:

To predict the total energy consumption of a data center, we calculated the PUE according to different internal and external parameters, and estimated the IT equipment energy consumption. The overall energy consumption, carbon emissions, and electricity cost of the data center were obtained directly.

DATA PREPROCESSING:

Data preprocessing is an important step before applying machine learning methods for energy or load prediction. The common steps include data imputation, data resolution processing, data normalization, outlier detection and data smoothing. Data smoothing could reduce the influence of noisy data and improve data quality, which contributes to the improvement of model performance. There are several approaches of data smoothing widely used in the field of energy consumption prediction, such as moving average approach seasonal exponential smoothing model Gaussian kernel density estimation exponential moving average filter neighbor-averaging interpolation and Savitzky-Golay filter. Most studies either have no data smoothing or only choose one method for data smoothing according to their experience.

FEATURE EXTRACTION:

Features should be selected and determined before model construction and they are important to the model performance. Engineering knowledge or statistical methods are two main methods to determine model inputs . According to engineering knowledge, HVAC energy consumption relates to outdoor weather and occupancy so the dry-bulb temperature, dew point temperature and occupant schedules are widely used as model inputs. With the availability of system operation data from building management systems, many studies consider historical energy consumption data as model inputs because they can reflect the delay of weather influence and similar operation patterns on the dynamic HVAC energy consumption. When the historical data are used as inputs, the length of historical data can affect the model performance. Existing studies adopt historical data to predict future energy consumption according to their experience and these models can achieve accurate prediction results.

```
#features about the hour of the day, day of the week type things
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['weekoftheyear'] = df.index.isocalendar().week
    return df
```

MODEL DEVELOPMENT:

The model performance of load prediction models based on de learning methods is closely related to training sets used to map t relationship between inputs and outputs. Large training set volum contribute to more accurate results but the computation time is long Sometimes it is hard to collect sufficient data in practical projects. Smal training set volumes use fewer calculation resources but the model m produce worse prediction results Therefore, a suitable training set volu

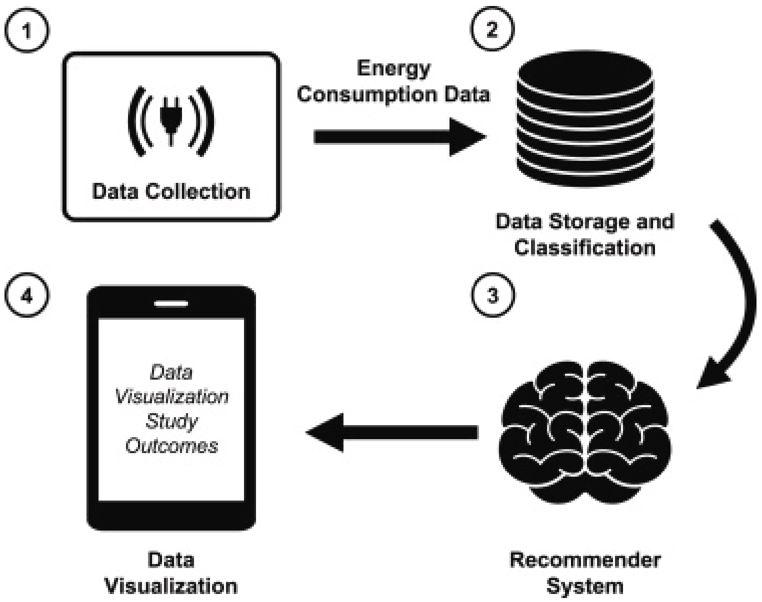
should be selected to ensure model performance with less computing co
The training sets are usually selected in a certain proportion from the who
dataset in most research, ignoring the balance of accuracy and computation
time in practice . As a result, guidance lacks in the applications of predicti
models. Therefore, it is necessary to address how to select suitable traini
set volumes in practical applications to ensure reasonable computing tin
and accuracy.

VISUALIZATION:

With data visualization, consumers can acquire a bett
understanding of their appliances' consumption, showing how th
contribute to the whole energy consumption. Thus, with the right incentiv
consumers can become more aware and more energy-efficient. For instanc
some studies have already shown interest in energy consumpti
visualization inside buildings, where the former is interested in lig
commercial buildings' energy consumption visualization, and the latter
focused on domestic consumption visualization and human behavi
simulation. In addition, augmented reality is also utilized to enhance t
consumers' awareness regarding electronic devices/appliances consumption

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.metrics import mean_squared_error
```

```
from sklearn.model_selection import train_test_split
import pickle


import xgboost as xgb
from xgboost import plot_importance
```



1.To identify consumption trends which will enable them to reduce the consumption. For example, the trends might show that the consumption is at its highest in the evening between when the user’s family is back from work/school.

2.To determine the energy consumed by individual appliances so that the users can identify which appliances are responsible for high energy consumption

AUTOMATION:

The dataset is obtained by combining the two data sources. It is classified by probe measurement channel, where each channel corresponds to a server connection. The analysis focuses on power consumption and the types of tests performed. The seven tests carried out are described in Section This categorization enables a detailed impact analysis of the system charging tests according to energy consumption and system process usage.

The no charge test was developed as a baseline for future analysis and comparison. Using this approach, it is possible to isolate the system processes from the benchmark techniques applied to stimulate the machines. Therefore, the no charge test served as a benchmark for comparison of the energy consumption of the other tests.

Graphical analysis helps to understand the relationship between the different identified characteristics. The conclusions drawn thanks to the evaluation enable the creation of a correct and reliable dataset. Data are analyzed with a special focus on finding possible information patterns of interest. Additionally, the evolution of measurements throughout the benchmarks is considered, taking into account the CPU progression for each test.