IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ≋ Impact Factor 7.918 ≋ Vol. 11, Issue 11, November 2022

DOI: 10.17148/IJARCCE.2022.111136

PREDICTION OF ELECTRICITY POWER CONSUMPTION USING MACHINE LEARNING APPROACH

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Abstract: discipline about computer architecture has long researched electricity consumption in great detail. While energy acquisition as a machine learning metric is starting to gain traction, majority about experiments are still primarily focused on achieving extremely high levels about accuracy among no computational constraints. We think that one about reasons for this lack about interest is because people don't easily have access to information on energy consumption. major goal about this research is to evaluate helpful regulations for machine learning community, enabling them to use & develop energy estimation techniques for machine learning algorithms. LSTM, linear regression, random forest regression, & other ensemble models are used to forecast electricity & produce precise results. We also provide two use cases that support investigation about energy exhaustion in machine learning, as well as most recent software tools that provide electricity estimating methods. through using updated smart metres that allow everyone to see who is consuming more energy in what appliances, we are able to accurately estimate future energy that will be very useful to grid in determining when we will need more & less energy.

Keywords: Machine Learning, Lstm.

I. INTRODUCTION

Because about residential & industrial uses such motor vehicles, large-scale generators, mobile devices, & home appliances, energy consumption is increasing today. Similarly, infrastructure for smart metres (SMI) is constantly expanding [1].

foundation was set globally to include active energy systems in intelligent metres. This introduction opened door for energy usage forecasting or modelling, & time has come to apply for a greener environment, particularly for domestic energy consumers [2].

market for electricity is impacted through consumer behaviour & use about electrical equipment. power grid administrators are also aware about necessity to adapt & find fresh approaches to successfully manage power use in commercial & residential structures that manage energy demand. While residents about intelligent residential complexes can operate multiple electrical gadgets remotely via mobile applications, sensors require a significant amount about energy. An ensemble regression model utilising linear & SVR prediction methods was developed[3] to improve accuracy about electricity forecasts. This type about bad administration commonly results in misuse about household equipment, which results in annual resource losses about a sizable amount[3]. through accurately forecasting demand for future use, it is especially crucial to reduce this energy loss in order to maintain it. field about energy management employs a number about forecast algorithms to predict future electricity consumption in order to produce capacity[3].

However, there are other factors related to building structure that could affect energy use, such as climate, building materials, & sub-level structures for heating, lighting, & ventilation. [4] Customers can modify load about their appliances or occupants, which permits them to subsidise energy use. [5] sophistication & instability about building's infrastructure play a role in crucial duty about projecting this energy.

To facilitate effective use & deployment, historical data among reported household values from 2006 to 2010 are used to predict electricity use. [6].

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II. LITERATURE REVIEW

Using support vector machine to predict next day electricity load about public buildings among sub-metering devices

Precise transient electrical burden estimating is fundamental for empowering request side administration in development industry. It is doable to conjecture complete power interest and loads about unambiguous structure administration frameworks for structures among introduced power sub-metering frameworks (cooling, lighting, power, and other gear). In this exploration, a Support Vector Machine (SVM)- based approach is recommended to estimate framework level burdens. 24 SVM models (one model each hour) were created and used to conjecture hourly power load for each kind about framework. Straightforward weather conditions conjectures and hourly electrical interest from going before two days act as just contributions for expectation calculation. proposed strategy beats three other notable information mining methods (ARIMAX, Decision Tree, and Artificial Neural Network) in both CV RMSE and N MBE, as per a contextual analysis. To conjecture framework level electrical burdens for public structures, SVM approach is suggested.

Low-voltage power demand forecasting using K-nearest neighbors approach

It has every now and again been proposed to involve request reaction in low-voltage area to supply lessen whimsical nature about sustainable power. Consequently, around here, an exact interest figure is fundamental for overseeing adjusting power. By the by, load profile-based estimating strategies, for example, run of the mill circulation matrix load profiles that are characterized, are inadequate for this assignment. In this paper, we present a spic and span K-closest neighbors-based transient guaging model. It predicts load for following day without buyer's information utilizing just authentic savvy meter information. Thus, our model is naturally parametrized and doesn't need manual arrangement. For various examples about low voltage end-buyers and their conglomeration about any gathering size, it is exhibited that its precision is unrivaled than individual burden profile strategy. This makes recommended model functional for boundless low-voltage application.

BelbounaguiaShort-term load forecasting using machine learning & periodicity decomposition

To successfully control energy interest, it is urgent for energy arranging that projections about power use are exact. Through deterioration about verifiable time series in regard to verifiable development about every hour about day, we offered a heap figure in this review. results about these deteriorations were utilized as contributions for a few AI strategies. We put our model to test utilizing five AI procedures, and we saw results utilizing three about most utilized anticipating assessment measurements. results were truly fulfilling.

Machine learning models for electricity consumption forecasting: a review

Energy supply firms can change in accordance with specific propensities through foreseeing energy use. Knowing client conduct to fit costs to utilization, foreseeing when there will be a spike in energy interest, and arranging production network versatility are a few about undertakings that organizations can do. In such manner, a survey about approaches that empower foreseeing future energy utilization in view of past utilization designs and other client explicit qualities is significant. This article surveys essential AI calculations that can estimate energy use utilizing a shoe store's one-year worth about information. investigation directed took into account perception that best outcomes got for informational collection utilizing straight relapse and backing vector relapse were 85.7% achievement.

Optimal household appliances scheduling under day-ahead pricing & load-shaping demand response strategies

To distinguish best machine booking for a brilliant home under hourly evaluating and top power-restricting (hard and delicate power impediment)- based request reaction methodologies, a total home energy the executives framework structure is inherent this article. Thermostatically controllable (like forced air systems and water warmers) and nonthermostatically controllable (like clothes washers and dishwashers) apparatuses, as well as electric vehicles, have all been officially demonstrated (EVs).

At end-client area, circulated age and an energy stockpiling framework (ESS) are additionally thought about. Through better decisions for EV and ESS activity, bidirectional energy stream is additionally thought about. To completely evaluate viability about model, a veritable experiment among an adequately diminished time granularity is given and examined. Results about thorough reenactments are accounted for.

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III. METHODOLOGY

In view of weather conditions estimates and hourly power load input, Fu et al. (2015) proposed using one about ML procedures, Support Vector Machine (SVM), to expect load at a structure's framework level (cooling, lighting, power, and others). among a mean inclination blunder (MBE) around 7.7% and a root mean square mistake (RMSE) around 15.2%, SVM approach had the option to figure all out power load.

As part about Smart City Demo Aspern (SCDA) project, Valgaev et al. (2016) fostered a power utilization conjecture utilizing k-Nearest Neighbor (k-NN) model at a brilliant structure. We utilized a set about verifiable perceptions (everyday burden bends) and their relatives to move toward k-NN determining technique. k-NN approach just distinguishes comparable occasions in a wide component space, which makes it restricted in its capacity to gauge future worth. Thus, it should be joined among fleeting data ID, among conjecture being created for following 24 hours during working hours.

The LSTM & LR machine learning algorithms will be used in prediction technique. dataset's 2075259 rows & 9 columns about electrical power usage data will be used as feature attributes for this prediction. consisting about global reactive power, global intensity, global voltage, global active power, & global sub metering, where demand is intended output.

STEPS for Proposed Approach-

- Normality testing about dataset
- Data pre-processing
- Model development (training)
- Model evaluation (testing)

Advantages

- Each appliance does not require a separate measuring device.
- It is reasonably priced.
- It is a monitoring system without intrusion.
- Calculates whether an appliance is on or off, including an inverter.

Disadvantages

- Models can be used only for short term predictions.
-

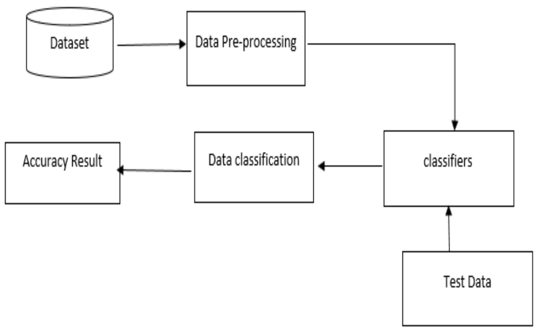

Fig.1: System architecture

Modules description

- Data collection
- Data pre-processing
- Data splitting
- Evaluation model

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Data collection:

The data set used in this article consists about metre data from several appliances.
A multivariate time series dataset called dataset describes how much electricity a household uses.
The attributes used include global active power, global reactive power, voltage, global intensity, ST, ET, etc.
The training set & test set are randomly selected from dataset.
For datasets, mean absolute errors (MAE) & root mean squared errors (RMSE) are determined.
The accuracy about an algorithm is measured through its lowest mistake rate.
Ideally, ML challenges begin among a large amount about data (examples or observations) for which you already know desired solution. Labeled data is information for which you already know desired outcome.

IV. IMPLEMENTATION

Linear Regression:

An AI calculation in light of directed learning is straight relapse. It executes a relapse activity. Relapse utilizes free factors to demonstrate an objective expectation esteem.

It is generally used to decide how factors and anticipating connect with each other. Relapse models change as indicated by sum about autonomous factors they use, type about relationship they consider between subordinate and free factors, and different variables.

The undertaking about foreseeing a reliant variable's worth (y) in light of a free factor is done utilizing straight relapse (x). Subsequently, x (the info) and y (the result) are viewed as straightly related through this relapse method (yield). Accordingly, term "straight relapse" was begat.

X (the information) is a dataset among a couple of sections, and Y (yield). relapse line accommodates our model best.

As we train gave model:
Input preparing information (one information variable, or boundary), x
Names to information, y (supervised learning)

LSTM model:

Profound learning utilizes counterfeit intermittent brain organization (RNN) engineering known as lengthy transient memory (LSTM).

LSTM highlights input associations rather than ordinary feedforward brain organizations. It can handle total information arrangements as well as individual data of interest, (for example, photographs, (for example, discourse or video inputs).

LSTM Layer: To choose whether to keep or dispose of information through considering latest information, yield, and memory. In LSTM, there are not many pivotal components.

Disregard Gate, picks whether to keep or dispose of data.

By taking care of past result and current contribution to sigmoid enactment capability, input door refreshes cell state.

Compute another cell state, increase it through a fail to remember vector (which drops esteem on the off chance that it is duplicated through a number near nothing), and add it to yield from input entryway to refresh cell state esteem.

Yield Gate decides ensuing secret state and is utilized in gauging

Thick Layer:

work out input utilizing an enactment capability, a weight grid, and a predisposition (if material). Since yield is just 0 or 1, I use Sigmoid enactment capability in this venture.

Adam is enhancer, and Binary Crossentropy is misfortune capability since yield is just 0 or 1, which is a paired number.

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V. EXPERIMENTAL RESULTS

Training

It is clear for preparing. Just our x train (input) and y train (yield/mark) information should be fitted. I utilize a small-scale group learning procedure among a cluster size around 128 and 5 ages for this preparation.

Moreover, I incorporated a designated spot callback to save model locally for every age on the off chance that its exactness expanded from past age.

Testing:

Utilizing our x test information to figure feeling and y test (expected yield) information to contrast expectations and, we can evaluate model. exactness about model not entirely settled through isolating number about right expectations through aggregate sum about information. achieved a misfortune around 0.0092

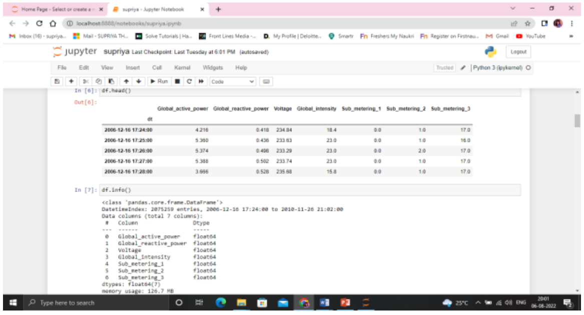

Fig.2: Dataset Columns & Data Types

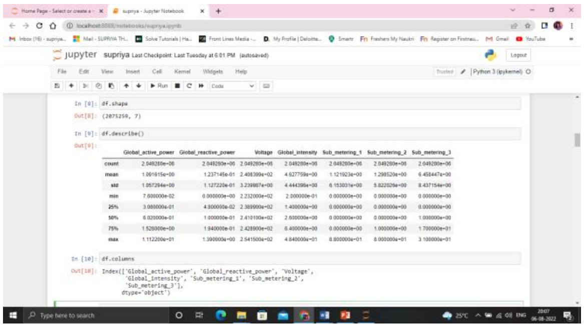

Fig.3: Describing dataset

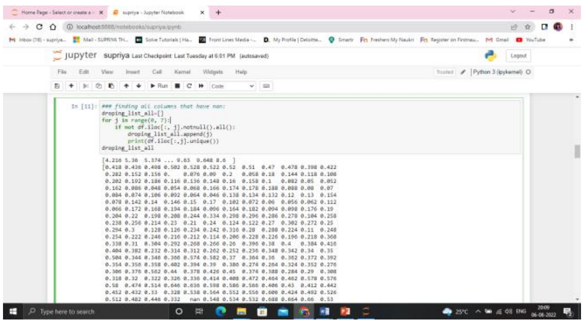

Fig.4: Finding Nan Values in columns

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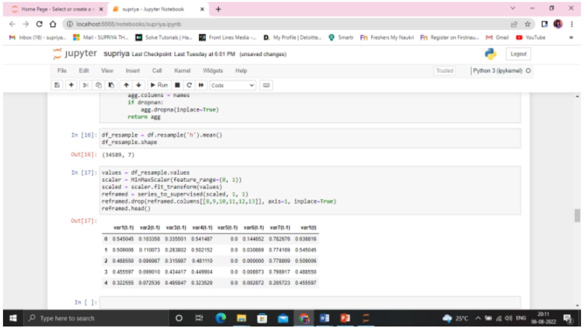

Fig.5: LSTM algorithm

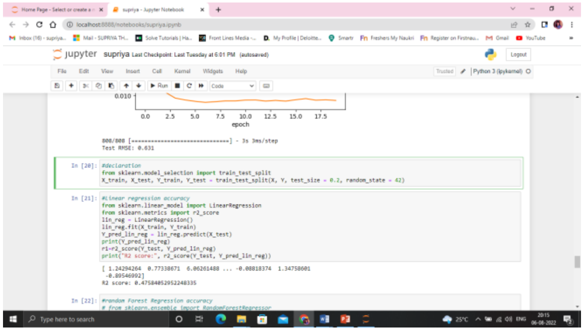

Fig.6: Linear regression algorithm

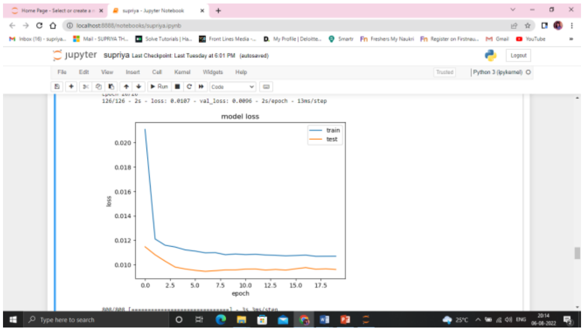

Fig.7: Training & testing Model

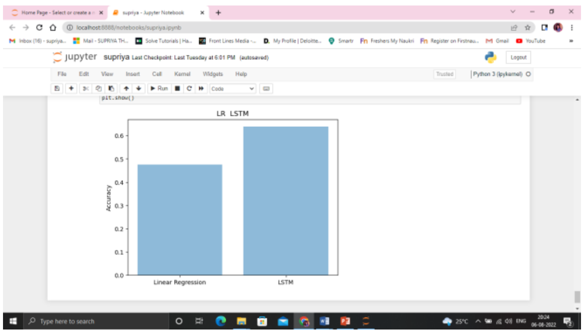

Fig.8: Accuracy graph

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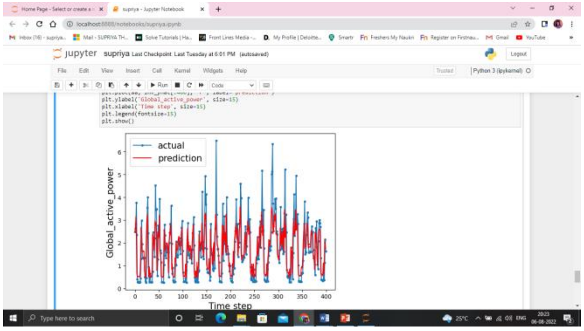

Fig.9: Actual prediction

VI. CONCLUSION

Recently, machine learning (ML) techniques have made significant advancements in power consumption prediction models. These models significantly boost traditional time series forecasting tools' precision, accuracy, & generalizability. Future power usage can be predicted using historical data. Here, we applied linear regression & random forest regression on electric power consumption data about a single household, achieving a 72% accuracy, & then we utilised LSTM to forecast future.

VII. FUTURE WORK

For our nation's sustainable economic & social development, growth about energy industry, wise use about energy resources, development about a society that values conservation, & formulation about a national energy strategy, it is crucially practical to conduct research on & develop scientific models about energy use & accurately predict future energy supply & demand gap.

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