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Natural Gas Price Prediction Using Machine Learning

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Abstract

Around the world, natural gas has been proposed as a means of reducing environmental pollution and increasing energy supply security. Machine learning algorithms like regressions and decision tree algorithms play a significant role in predicting natural gas prices. The R2 score is also used to compare the prices we have with our predictions. After training and testing the model, we can move on to the next step, which is evaluation. Natural gas price prediction has gradually gained popularity thanks to machine learning algorithms. In this paper, we investigate linear regression and decision tree algorithms as predictive methods for predicting the price of natural gas. The outcomes indicate the precise month, year, and day natural gas price in dollars.

1. Introduction

The world total primary energy supply (TPES) by fuel in 2016 was as follows: oil (31.9%), coal (27.1%), natural gas (22.1%), biofuels and waste (9.8%), nuclear (4.9%), hydro (1.8%), and other (0.1%) [1]. Natural gas thus has the third-largest share among the TPES. Furthermore, natural gas production continues to grow at a higher pace, most notably with a 3.6% increase in 2017 compared to 2016 that constitutes the largest increase since 2010. In today's world, concerns about air quality and climate change are growing, but renewable energy is expanding at a limited rate and low-carbon energy sources are hard to find in some areas. Natural gas offers many potential benefits as a solution to environmental problems. Natural gas generates heat, power, and mobility with fewer emissions, including both carbon-dioxide (CO2) emissions and air pollutants, than the other fossil fuels, helping to address widespread concerns over air quality. Because the natural gas energy causes less pollution to the environment than other kinds of energy resource, it has received much more recognition recently.

Natural gas exploitation has significantly helped many countries to reduce CO2 emissions nationally and globally since 2014 [2]. Natural gas, which is one of the most important energy resources, is going to play an expanded role in the future of global energy due to its significant environmental benefits.

Forecasting natural gas prices is a powerful and essential tool which has become more important for different stakeholders in the natural gas market, allowing them to make better decisions for managing the potential risk, reducing the gap between the demand and supply, and optimizing the usage of resources based on accurate predictions.

Accurate natural gas price forecasting not only provides an important guide for effective implementation of energy policy and planning, but also is extremely significant in economic planning, energy investment, and environmental conservation.

The aim of this project is to build data-driven machine learning models for natural gas price forecasting. The proposed Intelligent alert system for forest tribal people model is based on neural networks(CNN) incorporated with an alerting system. Several million of areas of forest destroyed every year due to they facing forest fire then we will notified and we can detect forest tribal people like wild animals. Forest is fire one of the major causes to the tribal people then we use this method to save wild animals with help of alerting to the higher authorities.There are so many problem faced by these people out of which human-wildlife is a serious problem.Hence early and effective testing and detection of wild animals can save forest tribal people.The main purpose of this project to save the lives of tribal people by notifying about wildlife predation with help Deep learning. Forest survey of higher authorities has been alerting when forest are detected and wild animals are in danger places.

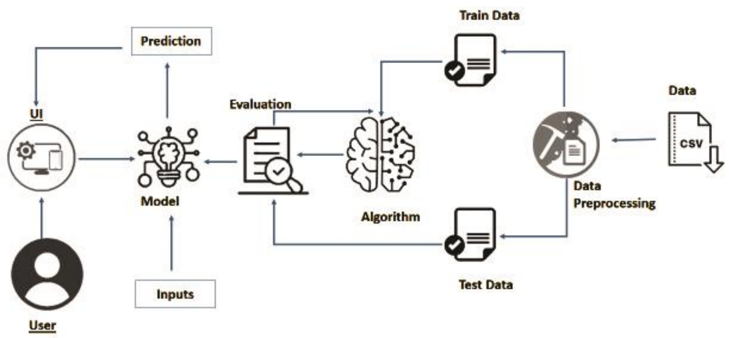

Fig.1 Architecture

2. Literature Review

Machine learning (ML) is the study of computer algorithms that improve automatically through experience and by the use of data.[1] It is seen as a part of artificial intelligence. Machine learning algorithms build a model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do so.[2] Machine learning algorithms are used in a wide variety of applications, such as in medicine, email filtering, and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.[3]

A subset of machine learning is closely related to computational statistics, which focuses on making predictions using computers; but not all machine learning is statistical learning. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning.[5][6] In its application across business problems, machine learning is also referred to as predictive analytics

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Linear regression is a linear approach to modelling the relationship between a scalar response and one or more explanatory variables (also known as dependent and independent variables). The case of one explanatory variable is called simple linear regression; for more than one, the process is called multiple linear regression.[1] This term is distinct from multivariate linear regression, where multiple correlated dependent variables are predicted, rather than a single scalar variable.[2]

In linear regression, the relationships are modeled using linear predictor functions whose unknown model parameters are estimated from the data. Such models are called linear models.[3] Most commonly, the conditional mean of the response given the values of the explanatory variables (or predictors) is assumed to be an affine function of those values; less commonly, the conditional median or some other quantile is used. Like all forms of regression analysis, linear regression focuses on the conditional probability distribution of the response given the values of the predictors, rather than on the joint probability distribution of all of these variables, which is the domain of multivariate analysis.

Linear regression was the first type of regression analysis to be studied rigorously, and to be used extensively in practical applications.[4] This is because models which depend linearly on their unknown parameters are easier to fit than models which are non-linearly related to their parameters and because the statistical properties of the resulting estimators are easier to determine.

Linear regression has many practical uses. Most applications fall into one of the following two broad categories:

If the goal is prediction, forecasting, or error reduction,[clarification needed] linear regression can be used to fit a predictive model to an observed data set of values of the response and explanatory variables. After developing such a model, if additional values of the explanatory variables are collected without an accompanying response value, the fitted model can be used to make a prediction of the response.

If the goal is to explain variation in the response variable that can be attributed to variation in the explanatory variables, linear regression analysis can be applied to quantify the strength of the relationship between the response and the explanatory variables, and in particular to determine whether some explanatory variables may have no linear relationship with the response at all, or to identify which subsets of explanatory variables may contain redundant information about the response.

Decision Trees are a type of Supervised Machine Learning (that is you explain what the input is and what the corresponding output is in the training data) where the data is continuously split according to a certain parameter. The tree can be explained by two entities, namely decision nodes and leaves. The leaves are the decisions or the final outcomes. And the decision nodes are where the data is split. An example of a decision tree can be explained using above binary tree. Let’s say you want to predict whether a person is fit given their information like age, eating habit, and physical activity, etc. The decision nodes here are questions like ‘What’s the age?’, ‘Does he exercise?’, ‘Does he eat a lot of pizzas’? And the leaves, which are outcomes like either ‘fit’, or ‘unfit’. In this case this was a binary classification problem (a yes no type problem)

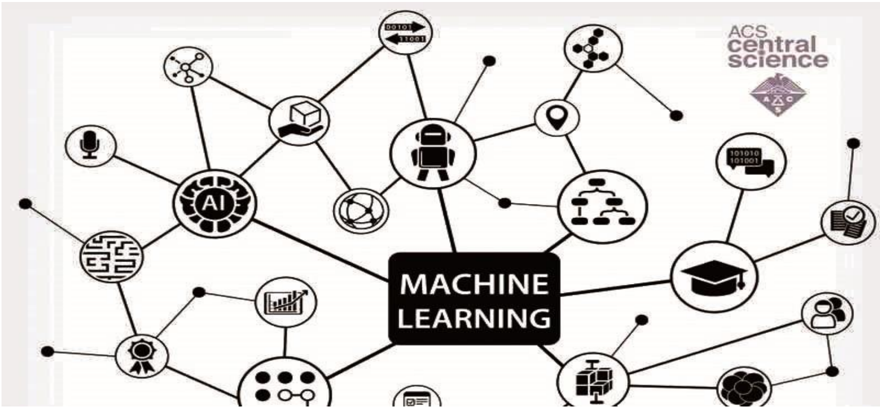

Fig.2 Parameter

3. Proposed System

In fact, we use models like ANN, SVM, GBM, and GPR to predict and forecast natural gas prices. utilizing graphs to represent the prices that were different from one year to the next.

Compare intuitively the 214 observed values in the prediction suitcases of four machine learning methods from January 2001 to October 2018. Beginning in March 2001, ANN delays two values. It is possible to obtain because all of the methods' predicted natural gas spot prices approximate the characteristics of the Henry Hub natural gas spot price time series and are close to the actual prices. In terms of overall tendency, ANN outperforms the competition, particularly when it comes to predicting abnormal values at the beginning of 2009 and the second half of 2010.

As a result, we proposed Simple Machine Learning Natural Gas Price Prediction. The goal of this project is to use standard machine learning algorithms to determine the prices for a specific year, month, and day. The results of this prediction, which are used to determine the prices of previous years, are accurate.

This shows how much money was spent on natural gas on a specific day, month, or year.

Using straightforward machine learning algorithms, this results in dollars.

Instead of relying heavily on complex machine learning models, we can easily find the results by utilizing HTML and CSS.

In addition to predicting the price of natural gas, this kind of project can also be used to predict the prices of crude oil and other petroleum products. This is used to predict how much natural gas will cost per liter in the future. By anticipating the price of the previous year, the cost is increased for this year. With last year's budget, we can use less natural gas. The current study is used to make life easier. because the task is completed and the price is predicted in dollars using straightforward algorithms.

To make life much simpler, the current study recommends using more powerful methods to predict the price of natural gas.

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Predicts the price from the previous year in this study. as well as imply the price of natural gas for the upcoming year. After falling from a three-month high in February, the price of natural gas has increased in April. What is the cause of the most recent rise, and can gains be sustained? Is it a good idea to start trading the commodity right now?

We examine the market's driving forces and analysts' predictions for natural gas in this article. The New York Mercantile Exchange (NYMEX) is used to trade natural gas contracts in the United States. The Henry Hub is the benchmark price, and its name comes from a gas pipeline in Louisiana that is used as the delivery point for NYMEX contracts.

Prices for natural gas are influenced by the weather and, as a result, by changes in demand. When it is cold, customers use gas-fired heating systems; They seek relief from the heat in the air conditioning, which is powered by electricity generated by gas-fired power plants. Spot prices are more affected by weather than futures prices are. The unseasonably cold weather in North America and northwest Europe has increased demand for heating, which has led to strong spot natural gas prices at the Henry Hub in April. The surplus in gas production that is typically injected into storage during the spring for withdrawal during the winter has decreased as a result of this rise in gas consumption.

The Energy Information Agency (EIA) reports that the week ending April 16 saw 38 billion cubic feet (Bcf) of gas injected into US storage facilities, down from 47 Bcf for the same week last year. Analyst estimates ranged from 37 to 59 Bcf, with a median of 48 Bcf. The week's working natural gas stocks were 1,883 Bcf, which is 251 Bcf less than they were during the same time last year. The linear regression method is used in the majority of studies. These techniques are known to be effective in certain circumstances. In some instances, combining methods may result in a breakthrough. Utilizing a combination of existing methods in such instances is correct

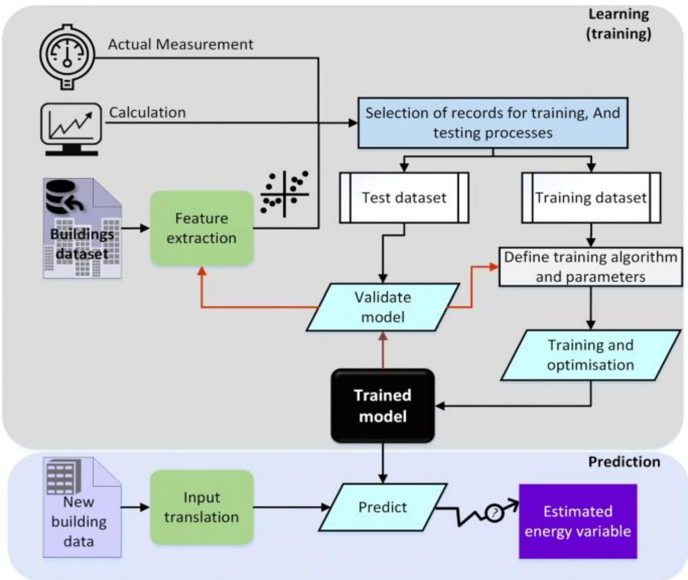

Fig.3 Proposed Method

4. Conclusion

The aim of the present study is to investigate Natural Gas Price Prediction using Machine Learning. Linear regression, decision tree algorithm are mostly used simple algorithms, which be used here. The models like pickle and packages like numpy, panda were very well used to make the project effective to predict. For prediction, evaluation criteria included R2 score. Hence we conclude that, this study supports and very much helpful to every user's of Natural Gas.Implementation of Neural network as described in this project was successful.We were able to build a network to save forest tribal people.Detection of wild animal was functional.Data Transmission through the network was efficient and reliable. The villages and the authorities is getting alerted via SMS. The Sms software programs for the network proved to be accurate.It capture the image data and send alert to higher authorities. This system detect the wildanimals and send warning message to the authorities and the villagers has been implemented.Wildlife is a precious gift of God to this planet. The term ‘wildlife’ not only caters to wild animals but also takes into account all undomesticated lifeforms including birds, insects, plants, fungi and even microscopic organisms. For maintaining a healthy ecological balance on this earth, animals, plants and marine species are as important as humans. Each organism on this earth has a unique place in food chain that helps contribute to the ecosystem in its own special way.

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