An interpretable Deep Learning Framework for predict the amount of energy produced and consumed from renewable energy for a specific period of time by using IOT system.

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Abstract

Energy is the backbone of complete production activity; no productive activity can function without energy because it is an important aspect of the development process. It offers faster life for everyone, which means faster transportation, a speedy manufacturing process for industries, and faster communication, all these things that have been mentioned are part of the things that lead us to increase the demand for electricity day by day. But despite the extreme importance of energy, the possibility of it destroying the world would be great, if we did not know how to produce it. Most factories and homes use fossil fuels to obtain energy, which leads to many environmental problems.

Energy and environmental problems are closely linked, as it is almost impossible to produce, transport or consume energy without a significant environmental impact. Environmental problems directly related to energy production and consumption include air pollution, climate change, water pollution, thermal pollution, and solid waste disposal. The emission of air pollutants from fossil fuel combustion is the main cause of air pollution in urban areas. The burning of fossil fuels is also a major contributor to greenhouse gas emissions, there are multiple types of clean energy to be harnessed, such as solar, wind, geothermal, biomass, and hydropower. There are many factors that influence the successful integration of renewable energy into the grid. One such factor is whether the load can extract high enough energy from the renewable source to maintain high energy conversion efficiency. However, there are several nonlinear interactions between multiple parameters that control the integration of RE into the grid. Artificial intelligence (AI) technologies are becoming more popular as an alternative approach to traditional technologies in solving problems such as availability prediction, forecasting, and control of renewable energy systems.

Another important factor is the production of renewable energy, as it is highly dependent on the weather. Although we have effective weather forecasting technologies, there will be sudden changes in the climate that can affect the flow of energy. Therefore, the growing demand for renewable energy makes it important to invest in machine learning and other emerging technologies to make data-driven decisions. The implementation of new methods based on artificial intelligence will add further improvement to the performance of renewable energy systems.

1. Introduction

The world is going through a critical turning point when it comes to energy. However, most places still rely on non-renewable energy such as fossil fuels as their main source of energy. It is a non-renewable resource that takes hundreds of millions of years to form. And when fossil fuels are burned to produce energy, they eliminate harmful greenhouse gases, such as carbon dioxide, replacing non-renewable energy sources with renewable energy sources is essential, renewable energy is energy derived from natural sources that are replenished at a rate that exceeds what is consumed. For example, sunlight and wind are constantly replenishing sources, renewable energy sources are abundant and are all around us, and the emissions from them are much lower than those from burning fossil fuels.

This is why the shift from fossil fuels, which currently represent the lion's share of emissions, to renewable energy is necessary to face the climate crisis, as it is possible to rely heavily on renewable energy to reduce the damage resulting from the use of energy generated from fossil fuels, the most important of which is global warming, Which turns out to be very dangerous, and the odds of it happening are closer. The way to mitigate these risks is to immediately reduce the emissions that cause this phenomenon.

With all these advantages offered by renewable energy, our project aims to provide innovative solutions using advanced technologies such as the Internet of Things and artificial intelligence, especially deep learning, to promote the use of renewable energy and accelerate the transition to a more sustainable future and an environment free of environmental pollution, our project provides renewable energy to places using a set of advanced devices and sensors, solar cells generate electrical energy from solar energy, and sensors read the temperature and humidity and calculate the intensity of the current and the voltage difference to know the amount of energy generation and the amount of consumption, and when collecting data about the readings of the amount of generation and consumption, artificial intelligence is used, specifically deep learning models, to enhance the importance of using renewable energy, as Artificial Intelligence (AI) technologies are becoming more and more popular as alternative approaches to conventional techniques in solving problems such as availability prediction, forecasting, and control of renewable energy systems, thus by using AI we can predict the amount of energy that will be generated and consumed in the future, thus enabling the user to make informed decisions and save financial expenses.

Renewable energy sources, such as solar and wind power, play a vital role in meeting the global energy challenges we face today, they provide many benefits, including reducing greenhouse gas emissions, mitigating climate change, and promoting energy independence, as the world shifts increasingly towards sustainable energy solutions, accurate forecasting of energy production and consumption becomes critical.

Importance of Renewable Energy:

Renewable energy sources are intermittent in nature and fluctuate based on various factors such as weather conditions, time of day, and seasonal changes. This asymmetry poses challenges for power grid operators, policymakers, and energy-intensive industries that depend on stable and reliable energy supplies. To take full advantage of the potential of renewable energy, it is necessary to accurately forecast and plan its production and consumption.

1- Grid Integration and Stability:

Renewable energy sources, unlike traditional fossil fuel-based power plants, are decentralized and dispersed. Their integration into the existing power grid requires careful coordination to maintain grid stability and prevent disturbances. Accurate forecasting of power production helps grid operators balance supply and demand, optimize grid operations, and reduce the need for backup power sources.

2- Optimal Resource Allocation:

Effective planning and deployment of renewable energy infrastructure requires accurate forecasts of energy production. Through accurate forecasts, policymakers and investors can locate suitable locations for wind farms or solar installations, optimize resource allocation, and ensure optimal use of renewable energy potential.

3- Energy Management and Cost Efficiency:

For energy-intensive industries and companies, knowing in advance the expected energy production and consumption is crucial for efficient energy management. Accurate forecasts enable proactive load management, demand response strategies, and optimal power procurement decisions, resulting in cost savings and improved operational efficiency.

4- Environmental Impact:

Accurate prediction of renewable energy production and consumption facilitates better integration of renewable sources into the energy mix, reducing reliance on fossil fuels. This, in turn, helps reduce greenhouse gas emissions, air pollution, and dependence on finite and non-renewable energy resources, thus contributing to a more sustainable and environmentally friendly energy sector.

significance of using an interpretable deep learning framework:

Deep learning models, such as neural networks, have shown remarkable success in various fields, including energy prediction. However, their complexity and black-box nature often hinder understanding how predictions are made. This lack of interpretability raises concerns about the trustworthiness, reliability, and potential biases of the model. By utilizing an interpretable deep learning framework for energy prediction, Interpretable deep learning models provide insights into the decision-making process and the factors influencing predictions.

Using an interpretable deep learning framework for energy prediction enhances the understanding, confidence, and acceptability of the model's predictions. The transparency and interpretability it provides enable stakeholders to validate, interpret, and refine the model, leading to improved decision-making, error analysis, compliance, and energy knowledge discovery. By incorporating interpretability, your senior project aims to bridge the gap between complex deep-learning models and actionable insights, ensuring the practicality and reliability of your energy forecasting system.

The utilization of an IoT system:

In our project, we will make use of an IoT (Internet of Things) system to collect relevant data to analyze and forecast energy production and consumption. An IoT system consists of interconnected devices equipped with sensors and network connectivity, enabling data collection, transmission, and analysis in real time.

The utilization of an IoT system in our project enables the collection of real-time, diverse, and comprehensive data related to energy production and consumption. The system ensures data availability, scalability, and flexibility while facilitating data integration and fusion. By leveraging the data collected through the IoT system, you can develop accurate and dynamic energy prediction models, contributing to the optimization of renewable energy utilization and efficient energy management.

The project's key components include:

1- Deep Learning Framework:

The project involves the development and implementation of a deep learning framework for energy prediction. The selected deep learning techniques or models will be designed to deal with the complexities and dynamics associated with renewable energy sources. The focus will be on developing an interpretable model that provides transparency and insights into the forecasting process.

2- IoT System Integration:

The IoT system will be used to collect relevant data for analysis and forecasting. The system will consist of devices with sensors that are deployed within the energy ecosystem. These devices will collect data on various parameters, including weather conditions, solar panel performance, power consumption levels, and other relevant factors.

3- Data Analysis and Prediction:

The data collected will be processed and analyzed to identify patterns, relationships, and dependencies within the energy ecosystem. This analysis will serve as the basis for developing accurate prediction models. The deep learning framework will be trained using the integrated data to predict the amount of energy produced and consumed over a specified period.

4- Website Development:

Design and development of a website to provide users with access to project functionality.
Create an intuitive and user-friendly interface to navigate and interact with ease, integrate data visualization techniques to deliver forecasts of energy production and consumption in a clear and understandable manner.

2. Related Work

2.1. Time series forecasting using deep learning

Deep learning is a subfield of ML that uses algorithms called artificial neural networks (ANNs), which are inspired by the structure and function of the brain and are capable of self-learning. ANNs are trained to “learn” models and patterns rather than being explicitly told how to solve a problem. The building block of an ANN is called the perceptron, which is an algorithm inspired by the biological neuron. Deep learning neural networks, or artificial neural networks, attempts to mimic the human brain through a combination of data inputs, weights, and bias. These elements work together to accurately recognize, classify, and describe objects within the data.

Deep neural networks consist of multiple layers of interconnected nodes, each building upon the previous layer to refine and optimize the prediction or categorization. The input and output layers of a deep neural network are called visible layers. The input layer is where the deep learning model ingests the data for processing, and the output layer is where the final prediction or classification is made. Time series data is data collected on the same subject at different points in time, such as the GDP of a country by year, a stock price of a particular company over some time, or your heartbeat recorded at each second, any data that you can capture continuously at different time intervals is a form of time series data.

Time series forecasting is exactly what it sounds like, predicting unknown values, time series forecasting involves the collection of historical data, preparing it for algorithms to consume, and then predicting future values based on patterns learned from the historical data, time series forecasting use cases are certainly the most common time series use cases, as they can be found in all types of industries and various contexts. Whether it is forecasting future sales to optimize inventory, predicting energy consumption to adapt production levels, or estimating the number of airline passengers to ensure high-quality services, time is a key variable.

The future is forecast or estimated based on what has already happened. Time series adds a time order dependence between observations. This dependence is both a constraint and a structure that provides a source of additional information.

Deep learning methods offer a lot of promise for time series forecasting, such as the automatic learning of temporal dependence and the automatic handling of temporal structures like trends and seasonality. Traditionally, time series forecasting has been dominated by linear methods because they are well-understood and effective on many simpler forecasting problems.
Deep learning neural networks can automatically learn arbitrary complex mappings from inputs to outputs and support multiple inputs and outputs, Several deep learning models have been used to time series forecasting from their examples:

1- Multilayer Perceptrons or MLPs:

which provide capabilities that are offered by a few algorithms, such as:

- **Robust to noise**: Neural networks are robust to noise in input data and in the mapping function and can even support learning and prediction of the presence of missing values.

- **Nonlinear:** Neural networks do not make strong assumptions about the mapping function and readily learn linear and nonlinear relationships.

- **Multivariate Inputs:** An arbitrary number of input features can be specified, providing direct support for multivariate forecasting.

- **Multi-step Forecasts:** An arbitrary number of output values can be specified, providing direct support for multi-step and even multivariate forecasting. For these capabilities alone, feedforward neural networks may be useful for time series forecasting.

2- Convolutional Neural Networks or CNNs

which applies the basic concept of the Neural Network (NN) algorithm with more layers. CNN is popular in computer vision and image processing for being efficient, CNN uses a convolution layer that can handle spatial information available in images, while fully connected layers have a memory to store information in time-series data. The only difference between computer vision problems and time-series ones is the input given to the model, image matrix for computer vision, and 1D array for time-series forecast. The observation sequence can treat the raw input data as a 1D array that can be read and filtered by the CNN model. Thus, this principle can be implemented in time-series analysis.

CNN is suitable for forecasting time series because it offers dilated convolutions, in which filters can be used to compute dilations between cells. The size of the space between each cell allows the neural network to understand better the relationships between the different observations in the time series. CNN deals with time-series problems effectively. Recent studies which applied CNN to time-series forecasting tasks, mainly involving financial data, show promising results. Many CNN models can solve various time-series data, such as univariate, multivariate, multi-step, and multivariate multi-step models.

3- Long Short-Term Memory network or LSTM

processes input data by looping over time steps and updating the RNN state. The RNN state contains information remembered over all previous time steps. You can use an LSTM neural network to forecast subsequent values of a time series or sequence using previous time steps as input. To train an LSTM neural network for time series forecasting, train a regression LSTM neural network with sequence output, where the responses (targets) are the training sequences with values shifted by a one-time step. In other words, at each time step of the input sequence, the LSTM neural network learns to predict the value of the next time step. The LSTM rectifies a huge issue that recurrent neural networks suffer from short memory. Using a series of ‘gates,’ each with its own RNN, the LSTM manages to keep, forget or ignore data points based on a probabilistic model and many other models have been used in this area.

2.2. Forecasting Renewable Energy

Renewable energy research and development have gained significant attention due to a growing demand for clean and sustainable energy in recent years. Many researchers have looked at the application of ML and DL algorithms for the forecasting of solar radiation, a significant element influencing the output power of solar systems.

2.2.1 Machine Learning-Based Forecasting of Renewable Energy

Machine learning-based forecasting has become an increasingly popular approach for predicting renewable energy output due to its ability to handle large and complex datasets. This section covers the two main categories of machine learning algorithms, supervised and unsupervised learning, and their various subcategories. It also explores reinforcement learning and its applications in renewable energy forecasting.

2.2.1.1 Supervised Learning

ML is a subset of artificial intelligence that seeks to enable machines to learn from data and improve their ability to perform a particular task. The process involves developing statistical models and algorithms that enable computers to identify patterns in data and utilize them to make decisions or predictions. In essence, ML involves teaching a computer to identify and react to specific types of data by presenting it with extensive examples, known as “training data.” This training procedure helps the computer identify patterns and make predictions or decisions based on fresh data that it has not encountered previously. The applications of ML span diverse industries such as healthcare, finance, e-commerce, and others. The algorithms of ML can be categorized into three primary groups: supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning refers to an ML method that involves training a model using data that has been labeled. The labeled data comprises input-output pairs, where the input is the data on which the model is trained, and the output is the expected outcome. The model learns to map inputs to outputs by reducing the error between the predicted and actual outputs during training. Once trained, the model can be applied to generate predictions on new, unlabeled data. Regression and classification are the two basic sub-types of supervised learning algorithms.

Regression: Regression is a supervised learning approach that forecasts a continuous output variable based on one or more input variables. Regression aims to identify a mathematical function that can correlate the input variables to a continuous output variable, which may represent a single value or a range of values.
Linear and Polynomial Regression: Linear regression is a prevalent and straightforward approach used to forecast a continuous output variable utilizing one or more input variables. It uses a straight line to indicate the correlation between the input variables and the output variables. on the other hand, polynomial regression, a type of linear regression, employs nth-degree polynomial functions to depict the connection between input features and the outcome variable. This can enhance the accuracy of predictions by enabling the model to capture more intricate correlations between the input data and the target variable. In renewable energy forecasting, both linear and polynomial regression can be used to

predict the power output of RES such as solar and wind power. Weather information such as temperature, humidity, and wind speed are frequently included in the input characteristics, along with historical power output data. The target variable is the power output of the renewable energy source, which can be predicted using the input features.

Classification: a form of supervised learning that involves using one or more input variables to anticipate a categorical output variable. Classification aims to find a function that can map the input variables to discrete output categories. The most widely used classification algorithms for predicting RES include logistic regression, decision trees, random forests, and support vector machines.

2.2.1.2 Unsupervised Learning

Another form of ML is unsupervised learning, where an algorithm is trained on an unlabeled dataset lacking known output variables, to uncover patterns, structures, or relationships within the data.

2.2.1.3 Reinforcement Learning Algorithms

Reinforcement learning (RL) is a branch of ML in which an agent learns to make decisions in an environment to maximize a cumulative reward signal. The agent interacts with its surroundings by taking actions and receiving responses in the form of rewards or penalties that are contingent on its actions.
Renewable energy forecasting is among the many tasks for which RL has been utilized. One approach to applying RL to renewable energy forecasting is to use it to control the operation of energy systems. For example, Sierra-García J. and S. Matilde (2020) developed an advanced yaw control strategy for wind turbines based on RL. This approach uses a particle swarm optimization (PSO) and Pareto optimal front (PoF)-based algorithm to find optimal actions that balance power gain and mechanical loads, while the RL algorithm maximizes power generation and minimizes mechanical loads using an ANN. The strategy was validated with real wind data from Salt Lake City, Utah, and the NREL 5-MW reference wind turbine through FAST simulations.

2.3 Deep Learning-Based Forecasting of Renewable Energy

2.3.1 ANN for Renewable Energy Forecasting

Artificial neural networks (ANNs) belong to a category of ML models that imitate the arrangement and operation of the human brain. They are designed to learn from data and utilize that knowledge to produce predictions or decisions. At a high level, ANNs consist of three main components: input layers, hidden layers, and output layers. The input layer receives the data, which is usually represented as a vector of numbers. The output layer produces the desired output of the network, The hidden layers are where most of the “computation” happens in the network. They consist of one or more layers of neurons that perform nonlinear transformations on the input data. Each neuron in an ANN receives input from other neurons or directly from the input layer. Then, the neuron processes an activation function on the weighted sum of its inputs, which generates an output. This output can serve as the input for another neuron, and this process repeats until the final output of the output layer is obtained output and the actual output, and the primary objective of the training is to lessen this discrepancy.

ANNs have been employed in renewable energy forecasting, such as solar energy, wind energy, and multi-renewable energy forecasting, for several years, demonstrating their efficacy in this application. For instance, Rehman and Mohandes used ANN to estimate global solar radiation in Abha, Saudi Arabia, by incorporating air temperature and relative humidity as inputs.

2.3.2 RNN for Renewable Energy Forecasting

Recurrent neural networks (RNNs) are an artificial neural network category that is specifically engineered to manage sequential data by analyzing every element in a sequence while retaining an internal state or memory of previous elements. RNNs are particularly useful for natural language processing, speech recognition, time series prediction, and other applications that involve sequential or temporal data. The key feature of RNNs is the use of recurrent connections, which allow information to be passed from one-time step to the next. Recurrent connections are established in the network through the inclusion of loops, which permit the output of the prior time step to be utilized as input for the current time step. Like other neural networks, an RNN consists of layers of neurons with learnable weights. RNNs have shown remarkable success in tasks involving sequential data, such as speech recognition, sentiment analysis, machine translation, and even time series forecasting, including renewable energy forecasting. Several research studies have investigated the use of RNNs for predicting renewable energy. One such study by Kisvari et al. (2021) suggests a data-driven method for wind power prediction that involves pre-processing, anomaly detection, feature engineering, and hyperparameter tuning using gated recurrent DL models [135]. They also compare a new DL neural network of GRU with LSTM. The approach achieves high accuracy at lower computational costs, and GRU outperforms LSTM in predictive accuracy.

2.2.3 RBM for Renewable Energy Forecasting

Restricted Boltzmann Machines (RBM) is a type of unsupervised neural network that can learn complex probability distributions over input data. They are composed of two layers, a hidden layer and a visible layer, with each layer consisting of binary nodes that are either activated or deactivated. The training process of RBM involves contrastive divergence, a technique that works towards reducing the dissimilarity between the input data and the model’s depiction of the data. Through training, the RBM adapts the weights connecting the visible and hidden layers to model the probability distribution of the input data. RBMs have several unique features that make them useful for a variety of applications. Their capacity to learn high-level representations of input data without labels or supervision is one of their key strengths. This makes them ideal for unsupervised learning tasks like feature learning and dimensionality reduction. Another strength of RBMs is their ability to model complex dependencies between input features, which makes them effective in modeling data with multiple interacting factors. They have been effectively employed in a wide range of fields, including image recognition, voice recognition, and natural language processing. Finally, RBMs have also been used as building blocks for more complex neural networks, such as deep belief networks and deep neural networks. In these architectures, RBMs are used to pre-train the network’s layers before fine-tuning them for a specific task.

2.3.4 Auto Encoder for Renewable Energy Forecasting

One of the most effective unsupervised learning models in recent decades is the autoencoder based on a deep neural network. The unsupervised model allows for the extraction of effective and discriminative features from a large unlabeled data set, making this approach extensively suitable for feature extraction and dimensionality reduction. Essentially, an autoencoder can be described as a neural network consisting of three fully connected layers, with the encoder containing input and hidden layers and the decoder containing hidden and output layers. The encoder converts higher-dimensional input data into a lower-dimensional feature vector. The data is then converted back to the input dimension by the decoder. Building a complex nonlinear relationship between the input data and the output data is one of the deep neural network's top priorities since it enables the autoencoder to successfully recreate the decoder's output. As a result, throughout the entire training period, the reconstruction error will decrease simultaneously, and important features will be stored in the hidden layer.

In renewable energy forecasting, autoencoder models have been used to extract features from input data such as weather data, historical energy production data, and other relevant variables. These features are then used to train ML models for energy forecasting. For example, Dairi et al. (2015) propose a variational autoencoder (VAE) model for short-term solar power forecasting. The study compares the performance of the VAE-based method with seven DL methods and two ML methods using data from two PV systems. Results indicate that the VAE consistently outperforms the other methods in forecasting accuracy, highlighting the superiority of DL techniques over traditional ML methods.

Problem specification

Global warming is one of the biggest challenges facing our planet today. It is caused by an increase in greenhouse gases, particularly carbon dioxide, in the atmosphere because of human activities such as burning fossil fuels, deforestation, and industrial processes. This increase in greenhouse gases traps more heat in the Earth's atmosphere, causing global temperatures to rise. The negative impact of global warming is far-reaching and can be seen in various aspects of our environment, economy, and health. One of the most obvious effects of global warming is sea level rise. Melting glaciers and ice caps due to rising temperatures is causing the oceans to expand, causing sea levels to rise, this has led to the loss of coastal areas and caused flooding in many parts of the world, islands, and low-lying towns are at risk of being submerged, and millions of people are at risk of being displaced. The economic impact of this is significant, Arduino. Current-voltage parameters are measured using sensors, and the current and voltage values are shown on the LCD screen. The IoT device is also connected to the sensors with which parameters can be displayed on the screen from anywhere using an available network.

The main goal is to get the maximum power output from the solar panels. In addition, if there is any improper performance of the solar panels it will be shown and parameters like voltage and current are monitored using sensors and displayed using IoT technology. This model is explained using solar radiation, i.e., sunlight from the sun is trapped by solar panels and then these solar panels capture sunlight and convert it into useful energy forms of energy such as heat and electricity. Then the electric power obtained by the sensors such as the voltage sensor is sensed to sense the voltage generated by the solar panels with the help of the voltage divider principle and the current is obtained using the mathematical formula. The designed structure of the proposed monitoring system is shown in Figure 1. This has a huge economic impact, driving up costs for insurance and disaster relief, and it can also affect agriculture and food production. In addition, extreme weather events can spread disease and have a negative impact on public health.

Global warming also has a significant impact on wildlife and ecosystems. As temperatures rise, many species struggle to adapt, and some are at risk of extinction. Corals, for example, are very sensitive to changes in temperature and acidity levels, and many are dying because of global warming. This has a ripple effect on the entire ecosystem, as many other species depend on coral reefs to survive.
Global warming also has a significant impact on our health. High temperatures can lead to heatstroke and other heat-related illnesses and can aggravate respiratory conditions such as asthma. In addition, the prevalence of diseases such as malaria and dengue fever is increasing as warmer temperatures allow disease-carrying insects to thrive in new areas. This has a disproportionate impact on vulnerable populations such as the elderly, children, and low-income communities.

The increasing impact of global warming is a serious problem that requires urgent action, as highlighted in the Special Report issued by the Intergovernmental Panel on Climate Change (IPCC) in late 2018. The report indicates that two-thirds of greenhouse gas emissions originate from the energy sector, which is an indicator. The need for increased renewable energy and increased energy efficiency is evident immediately. as the cost of rebuilding and resettling communities is prohibitive.

Another effect of global warming is the increase in extreme weather events, heat waves, droughts, floods, and hurricanes are becoming more frequent and intense, causing loss of life and damage to infrastructure.

In society, the demand for energy is rapidly increasing as we depend on it to run our daily lives, energy is essential for transportation, and as the world's population rises, the demand for transportation continues to increase. In addition, we depend on energy to communicate, as we need electricity to power our devices and keep our networks functioning, we also need energy to keep our homes and businesses running, as we need heating and cooling systems to maintain a comfortable working and living environment.

In industries, energy is essential to drive manufacturing processes and operate heavy machinery, the industrial sector is one of the largest consumers of energy, and without access to reliable and affordable energy, many businesses will not be able to operate efficiently, energy is essential to many industries, including manufacturing, mining, and agriculture, all of which depend on power to carry out their operations.

Renewable energy has become a crucial aspect of our daily lives, it is essential for economic growth and environmental sustainability. In the past, energy production relied mainly on fossil fuels such as coal, oil, and natural gas. These energy sources are limited and nonrenewable and emit harmful greenhouse gases into the environment causing climate change. As a result, there has been a significant shift towards renewable energy sources, such as solar energy, wind energy, hydropower, and geothermal energy. Renewable energy is vital to environmental sustainability, burning fossil fuels releases harmful emissions that contribute to air pollution, respiratory diseases, and climate change, transitioning to renewable energy sources can help reduce these emissions, thus mitigating the negative impact of climate change on our environment and health.

Renewable energy has economic benefits as well. The installation and maintenance of renewable energy systems lead to the creation of new jobs. Renewable energy systems and reduce the impact of global warming, energy plays a critical role in modern society and industries, as it is required for many essential tasks. Without energy, we would not be able to power our homes, operate our transportation systems, or operate our factories. Energy is vital to society because it provides us with basic services such as lighting, heating, cooling, and cooking. Industries rely heavily on energy to carry out their operations, including manufacturing, mining, and agriculture.

opportunities that contribute to economic growth. In addition, renewable energy is becoming increasingly cost-effective, making it a viable alternative to fossil fuels. Investing in renewable energy can also help reduce our dependence on foreign energy sources, which contributes to energy security.

Renewable energy is generated from natural sources such as the sun, wind, and water, and is considered a solution to the negative impact of regular electricity production on the global climate. However, there are many factors that influence the successful integration of renewable energy into the grid. One such factor is the ability to extract high enough energy from a renewable source to maintain high energy conversion efficiency.

In addition, the nonlinear interactions between multiple parameters control the integration of RE into the grid, this means that it is important to develop alternative approaches to traditional techniques in solving problems such as availability forecasting, prediction, and control of renewable energy systems, artificial intelligence (AI) technologies are becoming as popular as this approach, given their potential to add significant performance improvements to renewable energy systems.

One of the biggest challenges in producing renewable energy is that it is highly dependent on weather patterns, this makes it imperative to invest in machine learning and other emerging technologies to make data-driven decisions, using artificial intelligence and machine learning, it is possible to predict the weather and adjust the production of renewable energy, thus reducing the impact of global warming. Using renewable energy is a solution that can help mitigate this effect. However, the successful integration of renewable energy into the grid requires the use of artificial intelligence and other emerging technologies to make data-driven decisions.

Our project aims to address the growing concern about the negative impact of fossil fuels on the environment, aims at reducing the use of fossil fuels, promoting the use of renewable energy sources, and reducing consumption in areas where fossil fuels are used heavily. We believe that our project will make a significant contribution to the fight against climate change and help create a more sustainable future for all.

To address these issues, we need to adopt new technologies that help integrate renewable energy into our power grids. For example, artificial intelligence (AI) and machine learning (ML) technologies are becoming popular as an alternative approach to traditional technologies in solving problems such as availability prediction, forecasting, and control of renewable energy systems, by harnessing these emerging technologies, we can predict energy demand, reduce costs, and improve the efficiency of renewable energy production and storage, to successfully integrate renewable energy into our energy networks, these technologies can help us forecast energy demand, reduce costs, and improve the efficiency of renewable energy production and storage, ensuring a stable energy supply and mitigating the harmful effects of climate change.

IoT technologies can also play an important role in promoting sustainable energy development. By monitoring and optimizing the performance of solar panels, energy production can be maximized, and the longevity of the system can be ensured. IoT devices can detect and diagnose potential issues or inefficiencies in real time, allowing for timely maintenance and repairs. Additionally, IoT systems can facilitate the integration of renewable energy sources into the grid, enabling better management of energy distribution and demand. Overall, IoT technologies offer valuable tools for enhancing the efficiency, reliability, and sustainability of renewable energy systems.

To highlight the advantages of renewable energy and its potential as a sustainable alternative to fossil fuel energy, the following table presents a comparison between the two energy sources:

Aspect	**Fossil Fuel Energy**	**Renewable Energy**
Availability	Limited and finite	Inexhaustible and abundant
Environmental Impact	High emissions of greenhouse gases, air pollution, water pollution, habitat destruction	Low or zero greenhouse gas emissions, minimal air and water pollution, minimal habitat disruption
Climate Change Impact	Major contributor to climate change due to CO2 emissions	Minimal contribution to climate change, helps reduce greenhouse gas emissions
Energy Source	Non-renewable (coal, oil, natural gas)	Renewable (solar, wind, hydro, geothermal)
Resource Dependence	Vulnerable to price fluctuations and geopolitical tensions	Less vulnerable to price fluctuations, promotes energy independence
Fuel Costs	Can be volatile and subject to price fluctuations	Generally stable, long-term cost savings
Energy Efficiency	Less efficient in energy conversion and transmission	Increasingly efficient with advancements in technology
Job Creation	Moderate job creation, but often in extractive industries	Significant job creation potential in manufacturing, installation, and maintenance of renewable energy systems
Sustainability	Unsustainable in the long run, contributes to resource depletion	Sustainable, reduces reliance on finite resources
Health Impacts	Associated with air pollutionrelated health problems	Generally cleaner and healthier, improves air quality
Grid Resilience	Centralized systems vulnerable to disruptions	Distributed systems enhance grid resilience
Research and Development	Limited innovation due to established infrastructure	Rapid advancements and ongoing research and development
Government Support	Historical subsidies and incentives, but declining	Increasing support and incentives to accelerate transition

Table 1: Comparison between Fossil Fuel Energy and Renewable Energy

3 Implementation

Keeping pace with the development witnessed by the country and achieving Egypt's sustainable vision for 2030, we decided to contribute and participate in the continuous development and reduce global warming, and with the emergence of artificial intelligence technologies (AI) and (IoT devices) as an alternative approach to traditional technologies in solving problems such as forecasting availability, predicting, and controlling renewable energy systems, another important factor is renewable energy production, as it is highly dependent on the weather, although we have effective weather forecasting technologies, there will be changes in the climate that can affect the flow of energy, therefore, the growing global demand for renewable energy has highlighted the urgent need for innovative solutions that can make this sector more efficient and cost-effective, one promising avenue for achieving this goal is the integration of machine learning and other emerging technologies into renewable energy systems, investing in these emerging technologies is critical to the long-term success and sustainability of the renewable energy sector, the implementation of new methods based on artificial intelligence will add further improvement to the performance of renewable energy systems, it is imperative that we take advantage of every tool available to make renewable energy production more efficient, cost-effective and environmentally friendly.

3.1 Framework

Artificial Intelligence (AI) is a field of computer science that focuses on the development of computer programs that can perform tasks that would typically require human intelligence. One of the most popular and widely used techniques in AI is deep learning, which uses neural networks to learn patterns and make predictions based on data, in recent years, deep learning has been applied to many different fields, including renewable energy. Researchers have developed frameworks that use deep learning to predict the amount of renewable energy that will be generated in the future at a given location.

This framework is built using Python, a popular programming language for data analysis and scientific computing, the framework consists of different models, which are trained to predict the amount of renewable energy that will be generated under different conditions, the models use a variety of data sources, including weather data, and historical energy generation data, by analyzing this data and learning from patterns, the models can predict how much renewable energy will be generated in the future.

One of the main advantages of using deep learning for renewable energy prediction is that it can consider complex interactions between different factors. For example, the models can analyze how weather patterns affect solar panel output, or how wind speeds affect the performance of wind turbines. Another advantage is that the models can adapt and improve over time, as more data is collected and more patterns are learned, the models can be retrained to improve their accuracy and make better predictions.

The use of deep learning for renewable energy prediction is an exciting development that has the potential to help us transition to a more sustainable and environmentally friendly energy system. By accurately predicting renewable energy output, we can better plan and manage our energy systems, reduce our reliance on fossil fuels, and work towards a cleaner, greener future.

The frameworks consist of 21 models and one of the most powerful models is LSTM, or Long Short-Term Memory, which is a type of neural network that is particularly good at analyzing time-series data. Time-series data is data that changes over time, such as stock prices, weather patterns, or renewable energy generation, the reason LSTM is so good at analyzing time-series data is that it can remember past data points and use them to make better predictions, this is important because time-series data often has patterns and trends that can be difficult to spot without considering past data.

The basic idea behind LSTM is to have a network of "memory cells" that can store and retrieve information. Each memory cell has a "gate" that controls how much information is stored or retrieved at each time step. There are three types of gates: input gates, forget gates, and output gates, the input gate controls how much new information is added to the memory cell at each time step, and the forget gate controls how much old information is removed from the memory cell, and the output gate controls how much information passes to the next layer in the network, by adjusting the strength of each gate, the LSTM network can learn to remember or forget certain patterns in the time-series data. This allows it to make more accurate predictions than other types of neural networks that don't consider the time dependency of the data.

In the context of renewable energy prediction, LSTM can be used to analyze historical energy generation data and make predictions about future energy generation. By considering past energy generation patterns and trends, the LSTM model can make more accurate predictions than other models that don't consider the time dependency of the data, Overall, LSTM is a powerful tool for analyzing time-series data and making accurate predictions. Its ability to remember past data points and use them to make better predictions makes it particularly well-suited for renewable energy prediction, where past data is often a strong predictor of future performance.

- There are many other powerful models used in the framework such as:

  1. BiLSTM (Bidirectional Long Short-Term Memory):

     - BiLSTM combines bidirectionality with the power of LSTM.
     - It consists of two LSTM layers, processing the input sequence in both forward and backward directions.
     - BiLSTM captures comprehensive temporal dependencies, considering the influence of both past and future context on renewable power generation forecasting.
     - This model is effective in capturing complex patterns, seasonality, and trends in renewable power generation data.

  2. GRU (Gated Recurrent Unit):

     - GRU is a type of RNN that addresses the vanishing gradient problem and captures temporal dependencies.
     - It has fewer gates compared to LSTM, making it computationally efficient while still maintaining strong performance.
     - GRU is suitable for modeling renewable power generation data, learning patterns and dynamics over time to make accurate predictions.

3. BiGRU (Bidirectional Gated Recurrent Unit):

- BiGRU extends GRU by incorporating bidirectionality.
- It consists of two GRU layers, one processing the input sequence in the forward direction and the other in the backward direction.
- BiGRU captures past and future context simultaneously, enhancing its understanding of sequential data and improving prediction capabilities.
- This model is effective in capturing dependencies and patterns in renewable power generation time series.

4. CNN (Convolutional Neural Network):

- CNN is primarily used for image and signal processing tasks but can be applied to sequential data.
- In the context of renewable power generation, a 1D CNN applies filters across the time series to capture local patterns and dependencies.
- CNNs are effective for feature extraction in renewable power generation data, contributing to accurate forecasting.

5. CNN-LSTM:

- CNN-LSTM combines CNN and LSTM to leverage their complementary strengths.
- CNN layers extract relevant features from the input time series data, capturing local patterns and representations.
- These features are then fed into LSTM layers, which capture long-term dependencies and temporal dynamics.
- CNN-LSTM is a robust model for forecasting renewable power generation, utilizing hierarchical representations from CNNs and sequential modeling from LSTMs.

6. ConvLSTM (Convolutional LSTM):

- ConvLSTM combines the spatial processing capabilities of convolutional neural networks (CNNs) with the temporal modeling abilities of LSTMs.
- It applies convolutional operations on the input sequence, enabling the model to capture spatial features and patterns.
- The LSTM component captures temporal dependencies within the convolutional feature maps, incorporating memory and gating mechanisms.
- ConvLSTM is effective in forecasting renewable power generation by jointly capturing spatial and temporal information.

7. LstNet (Long- and Short-Term Time-series Network):

- LstNet is a deep learning architecture designed specifically for time series forecasting tasks.
- It incorporates a combination of long-term components (such as a skip-rnn) and short-term components (such as a point-wise feed-forward neural network).
- LstNet captures both global trends and local dynamics in the time series data.

- The model incorporates residual connections and attention mechanisms to enhance its forecasting capabilities.

8. TCN (Temporal Convolutional Network):

    - TCN is a type of deep neural network architecture specifically designed for sequence modeling and forecasting.
    - It uses dilated convolutions, allowing the network to capture long-term dependencies while maintaining a large receptive field.
    - TCN operates on the entire sequence simultaneously, enabling parallel processing and efficient modeling of temporal relationships.
    - The model's depth and receptive field make it effective for capturing patterns and trends in renewable power generation data.

9. Time Distributed:

    - Time Distributed is a wrapper or layer that can be applied to any recurrent or convolutional neural network architecture.
    - It applies the same set of weights to each time step of the input sequence, treating them independently.
    - Time Distributed enables the model to make predictions at each time step separately, producing a sequence of outputs.
    - It is often used in tasks such as sequence labeling or forecasting where predictions need to be made at each time step.

10. MLP (Multilayer Perceptron):

    - MLP is a type of feed-forward neural network architecture consisting of multiple layers of interconnected neurons.
    - It is a versatile model that can be used for a variety of tasks, including forecasting renewable power generation.
    - MLPs are effective in capturing non-linear relationships and patterns in the input data.
    - They typically consist of an input layer, one or more hidden layers, and an output layer, with each layer composed of multiple neurons.

11. Informer:

    - Informer is a deep learning model specifically designed for time series forecasting tasks.
    - It incorporates a hybrid architecture that combines transformer-based self-attention mechanisms with convolutional and recurrent neural networks.
    - Informer captures both global and local dependencies in the time series data, allowing it to model long-term patterns and short-term dynamics effectively.
    - The model incorporates various attention mechanisms, including encoder-decoder attention and cross-attention, to enhance its forecasting capabilities.

12. Performer:

- Performer is a variant of the transformer model that improves the computational efficiency of self-attention mechanisms.
- It replaces the standard self-attention mechanism with a faster and memory-efficient method called the FAVOR+ algorithm.
- Performer is capable of handling long sequences more efficiently, making it suitable for time series forecasting tasks with large input lengths.
- The model maintains the advantages of transformers, such as capturing global dependencies and modeling complex patterns.

13. Transformer:

- Transformer is a powerful deep learning model architecture originally proposed for machine translation tasks.
- It utilizes self-attention mechanisms to capture global dependencies and context in the input data.
- Transformers are effective for modeling sequences, including time series data, by considering interactions between different time steps.
- The model consists of encoder and decoder layers that allow for both encoding historical data and generating future predictions.

14. Autoformer:

- Autoformer is a variant of the transformer model that incorporates automatic model design and optimization techniques.
- It uses a search algorithm to automatically discover the optimal architecture and hyperparameters for the transformer layers.
- Autoformer leverages neural architecture search (NAS) to improve the performance and efficiency of the transformer model for time series forecasting.
- The model adapts the architecture dynamically, making it suitable for handling different types of time series data.

15. BERT (Bidirectional Encoder Representations from Transformers):

- BERT is a popular language representation model that utilizes transformers.
- While primarily designed for natural language processing (NLP) tasks, BERT can also be applied to time series forecasting.
- BERT captures contextual information and learns representations by training on large amounts of unlabeled data.
- It can be fine-tuned on time series data to extract meaningful features and make accurate predictions for renewable power generation.

16. DeepAR:

- DeepAR is a probabilistic forecasting model specifically designed for time series data.
- It is based on a recurrent neural network (RNN) architecture, typically using LSTM or GRU cells.
- DeepAR captures temporal dependencies and learns the distribution of future values given the past observations.
- The model is trained to output probabilistic forecasts, providing a range of possible future scenarios along with their associated probabilities.

17. FNN (Feedforward Neural Network):

- FNN, also known as a multi-layer perceptron (MLP), is a classic neural network architecture.
- It consists of multiple layers of interconnected neurons, with each neuron in a layer connected to all neurons in the next layer.
- FNNs are well-suited for forecasting renewable power generation when the data exhibits non-linear patterns and dependencies.
- The model learns to map the input sequence to the target variable using hidden layers with non-linear activation functions.

18. N-BEATS (Neural basis expansion analysis for interpretable time series forecasting):

- N-BEATS is a deep learning architecture designed for interpretable time series forecasting.
- It consists of a stack of fully connected (FC) layers with learnable weights.
- N-BEATS uses a mechanism called the gating mechanism to combine the outputs of the FC layers and generate predictions.
- The model is trained to optimize a loss function that balances accuracy and interpretability.

19. RBFN (Radial Basis Function Network):

- RBFN is a type of feedforward neural network where the hidden layer neurons use radial basis functions as activation functions.
- Radial basis functions are centered at specific points in the input space, capturing local patterns and dependencies.
- RBFNs are effective for forecasting renewable power generation when the data exhibits spatial or localized patterns.
- The model learns the relationship between the input sequence and the target variable through the weighted combination of radial basis functions.

20. Seq2Seq (Sequence-to-Sequence):

- Seq2Seq is an architecture consisting of an encoder and a decoder, typically implemented using recurrent neural networks (RNNs) like LSTM or GRU.
- It is commonly used for tasks such as machine translation and text generation, but it can also be applied to time series forecasting.

- Seq2Seq models encode the input sequence into a fixed-length representation, which is then used to generate the output sequence.
- The model can be trained in a teacher-forcing manner or using techniques like attention mechanisms to capture relevant temporal dependencies.

Model	**Architecture**	**Strengths**	**Weaknesses**
LSTM	Recurrent Neural Network (RNN)	Captures temporal dependencies	May struggle with capturing long-term dependencies and complex patterns
BiLSTM	Recurrent Neural Network (RNN)	Captures comprehensive temporal dependencies	May struggle with capturing complex patterns
GRU	Recurrent Neural Network (RNN)	Addresses vanishing gradient problem, computationally efficient	May not capture long-term dependencies as effectively as LSTM
BiGRU	Recurrent Neural Network (RNN)	Captures past and future context simultaneously	Computationally more expensive
CNN	Convolutional Neural Network (CNN)	Effective for local pattern detection	May not capture long-term dependencies as effectively as recurrent models
CNN-LSTM	Combination of CNN and LSTM	Captures hierarchical representations and sequential dependencies	Requires more computational resources
ConvLSTM	Combination of CNN and LSTM	Captures spatial and temporal dependencies	Requires more computational resources
LstNet	Hybrid architecture	Captures both global trends and local dynamics	May require careful hyperparameter tuning
TCN	Temporal Convolutional Network	Captures long-term dependencies, parallel processing	May struggle with capturing complex temporal patterns
Time Distributed	Wrapper for recurrent/CNN models	Enables sequential prediction at each time step	Requires models with temporal dependencies or local patterns
MLP	Multilayer Perceptron (Feedforward NN)	Captures non-linear relationships in the input data	May not capture temporal dependencies as effectively as recurrent models
Informer	Transformer-based hybrid architecture	Captures global and local dependencies, attention mechanisms	May require longer training times due to complex architecture

Model	Architecture	Strengths	Weaknesses
Performer	Transformer variant	Improved computational efficiency, captures global dependencies	May require more training data to achieve optimal performance
Transformer	Transformer architecture	Captures global dependencies and interactions between time steps	May struggle with capturing fine-grained local patterns
Autoformer	Transformer variant	Automatic architecture design and optimization, adaptable	May require longer search times for optimal architecture
BERT	Transformer-based language model	Captures contextual information and learns representations	May require pretraining on large amounts of unlabeled data
DeepAR	RNN-based probabilistic model	Provides probabilistic forecasts, captures temporal dependencies	May require more training data for accurate probabilistic forecasting
FNN	Feedforward Neural Network	Captures non-linear patterns in the input data	May not capture temporal dependencies as effectively as recurrent models
N-BEATS	Fully connected layers	Interpretable forecasting, captures patterns with gating mechanism	May require longer training times to achieve desired interpretability
RBFN	Radial Basis Function Network	Captures spatial or localized patterns	Requires manual selection and placement of radial basis functions
Seq2Seq	Encoder-Decoder architecture	Captures temporal dependencies, suitable for sequence generation	May require careful attention mechanism design for accurate forecasting

Table 2: Comparison of all framework models in terms of (Architecture | Strengths | Weaknesses)

- Building a model can seem like a daunting task, but with a little guidance, it is possible to build a simple model even with limited experience in artificial intelligence. Here are the basic steps to build a model:

  - **Gather and preprocess data:** The first step in building a model is to gather and preprocess data. In the case of renewable energy prediction, this might involve gathering historical energy generation data. Preprocessing might involve scaling the data, filling in missing values, and creating time-series data sets.
  - **Split the data into training and testing sets:** Once you have preprocessed the data, the next step is to split it into training and testing sets. The training set is used to train the model, while the testing set is used to evaluate the model's performance.
  - **Build the model:** The next step is to build the model. This involves defining the number of layers in the network, the number of memory cells in each layer, and the number of input features. You can also choose the activation functions for each layer and the loss function for training the model.
  - **Train the model:** Once the model is defined, the next step is to train it using the training set. This involves feeding the training data into the model and adjusting the weights and biases of the network to minimize the loss function.
  - **Evaluate the model:** After training the model, the next step is to evaluate its performance using the testing set. This involves feeding the testing data into the model and comparing the model's predictions with the actual data.
  - **Fine-tune the model:** Finally, you can fine-tune the model by adjusting the hyperparameters and retraining the model. Hyperparameters are the settings that define the structure of the model and can be adjusted to improve its performance.

- **Matrices (RSME, MSE, R2 & MAE):** to evaluate the framework models' performance.

1- **Root Mean Square Error or Root Mean Square Deviation:** this is one of the most used measures for evaluating the quality of predictions. It shows how far predictions fall from measured true values using Euclidean distance. To compute RMSE, calculate the residual (difference between prediction and truth) for each data point, compute the norm of residual for each data point, compute the mean of residuals, and take the square root of that mean. RMSE is commonly used in supervised learning applications, as RMSE uses and needs true measurements at each predicted data point, Root Mean Square Error can be expressed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \|y(i) - \hat{y}(i)\|^2}{N}},$$

2- Mean Squad Error MSE

Mean squared error (MSE) measures the amount of error in statistical models. It assesses the average squared difference between the observed and predicted values. When a model has no error, the MSE equals zero. As model error increases, its value increases. The mean squared error is also known as the mean squared deviation (MSD).

The calculations for the mean squared error are like the variance. To find the MSE, take the observed value, subtract the predicted value, and square that difference. Repeat that for all observations. Then, sum all those squared values and divide them by the number of observations.

MSE Formula

The formula for MSE is the following.

$$MSE = \frac{\sum(y_i - \hat{y}_i)^2}{n}$$

3- R2

The coefficient of determination, or R2, is a measure that provides information about the goodness of fit of a model. In the context of regression, it is a statistical measure of how well the regression line approximates the actual data. It is therefore important when a statistical model is used either to predict future outcomes or in the testing of hypotheses.

$$R^2 = 1 - \frac{\text{sum squared regression (SSR)}}{\text{total sum of squares (SST)}}, \\ = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}.$$

4- Mean Absolute Error (MAE)

is a measure of errors between paired observations expressing the same phenomenon. Examples of Y versus X include comparisons of predicted versus observed, subsequent time versus initial time, and one technique of measurement versus an alternative technique of measurement. MAE is calculated as the sum of absolute errors divided by the sample size:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n}.$$

We will integrate deep learning models into the system to enhance its sustainability and predict future energy generation and consumption, such as LSTM, CNN, TCN, Transformer, GRU, and others, we have trained these models on real public historical datasets to ensure their accuracy and performance.

3.2 Designing an IoT-based renewable energy generation system

The Internet of Things (IoT) is one of the most important technologies of everyday life, helping people live smarter. The Internet of Things is a device used to enable communication between a device and the cloud. This technology helps in exchanging data between the connected devices on the available network. Through the internet, the user can get data and control devices from anywhere around the world.

It is an ecosystem that consists of web-enabled gadgets that use processors, sensors, and other communication hardware devices to fetch and send data, with the Internet of Things, we can establish machine-to-machine or machine-to-machine communication without human intervention, they also use computing facilities and software systems to process information, the need to use IoT technology in this solar energy monitoring system is because the range of sunlight ions is not fixed and may vary according to the location, time, and climatic conditions, solar panels that are exposed to sunlight always need to be monitored.

Solar panels can be monitored from anywhere using IoT technology, solar energy is said to be an incorruptible energy source. Therefore, to overcome the problems related to the scarcity of electricity, a solar energy monitoring system based on the Internet of Things has been proposed. Solar energy has become very fashionable because it is available in abundance and solar energy generation is cheaper in conversion technology, in this technology, light energy is converted into electrical energy, which is known as the photoelectric effect, and this energy is called solar energy. By using solar energy, pollution will be reduced and by monitoring it to predict energy, households, and communities, productivity can also be increased. By monitoring this system, we can know its status and show there is a very helpful problem. The system describes an Internet of Things-based solar energy monitoring system. In this system, sunlight is converted into electricity by the solar cells in the solar panels.
We will need to design and develop an IoT-based renewable energy generation system, which will include sensors and devices to collect data on solar energy, we will use this data to improve system performance and ensure that it generates as much renewable energy as possible, our experimental prototype is a small-scale model of a solar energy system consists mainly of :

1. **PV panel:** The PV panels consist of a set of parallel and series PV cells that convert sunlight into DC electrical energy.
2. **Regulator TP4056:** To harvest the maximum generated PV energy and reduce power losses, a stage of adaptation is necessary. For this reason, a dc-dc converter is placed between the PV generator and the load to adjust the maximum power point (MPP) using an MPPT control. However, it's important to note that the associated commercial regulator TP4056, used with a lithium-ion battery as a load, incorporates protection features but does not include the MPPT algorithm.

3. **DC load:** The lithium-ion battery, commonly used in mobile phone applications, is employed as a load in this monitoring prototype. This battery, with a nominal voltage of 3.7V, is protected by a regulator that controls the charging current (maximum of 1A). Additionally, it is equipped with an overload protection circuit (charging stops at 4.3V), excessive discharge protection, and overcurrent detection at the battery output level to prevent damage in case of a short circuit.
4. **Measurement Sensors:** The measurement sensor network in this application involves three main sensors that sense four physical signals: current, voltage, irradiation, and temperature.
5. **Current/voltage sensor:** This smart sensor not only senses but also filters and performs analog-to-digital conversion. The INA219 sensor is a current and power sensor that provides the total power consumed by the shunt load and delivers respective readings in digital form. It can handle high-side current measuring up to +26V and up to 3.2A of current, even though it is powered with 3.3V or 5V. Equipped with an I2C bus, it facilitates measurement retrieval using a microcontroller. 4.2
6. **Temperature sensor:** The DHT11 sensor is a low-cost temperature and humidity sensor widely used in embedded projects. It has a temperature range of 0 to 50 degrees Celsius with ±2 degrees accuracy. The DHT11 sensor offers good quality, fast response time, and high stability. It includes a thermistor for temperature measurement. To ensure measurement accuracy, this sensor has been calibrated using another trustworthy thermometer.
7. **ESP32-based controller:** The ESP32 is a low-cost, low-power consumption system-on-chip (SoC) microcontroller with integrated Wi-Fi, dual-mode Bluetooth, and support for low power. This single-chip solution is chosen to reduce the cost of the monitoring system while providing high processing performance. The ESP32 board is based on the Ten silica 32-bit dual-core CPU Extensa, LX6 microcontroller. One of its major advantages is that it can be coded using many open-source platforms and languages. The ESP32 leverages the advantages of Linux-based IoT boards like Raspberry Pi and Beagle bone, which support operating systems (OS). However, unlike those boards, it eliminates the need for external ADC devices to acquire analog measurements. Furthermore, the ESP32 offers the advantages of low-cost boards like Arduino, which require additional components and shields for internet connectivity. The ESP32 supports real-time operating systems (RTOS) like free RTOS to manage all the required tasks optimally. It integrates 16 ADC channels of 10 bits for acquiring analog information and has built-in Wi-Fi connectivity and other features. Moreover, the ESP32 chip provides high flexibility in software development, offering three easy-to-understand programming and open-source environments for researchers, engineers, and PV owners.

3.3 User Interface

As a final phase of the project, we have developed a user interface that enables users to interact with the renewable energy system in a user-friendly way, we used Flask, a Python web framework, to develop the interface, and integrated the deep learning models that we developed in earlier stages of the project, these models enable the system to accurately predict future energy generation or consumption, based on the data collected from the various sensors in the system, by deploying these models, users can plan their energy usage more effectively, and ensure that they are maximizing their use of renewable energy sources.

Due to the time required to collect appropriate data for deep learning models, we have temporarily implemented a feature on the website that allows users to upload their energy consumption data in CSV format, this feature allows users to start using the system right away and gain insights into energy consumption and generation patterns, once we have collected enough data to train the deep learning models, we will store the data in the cloud and configure the website to access and use this data directly. By storing data in the cloud, we can also ensure that the system remains scalable and can handle large amounts of data without affecting its performance. This will be especially important as more users start to use the system and generate greater amounts of data.

In general, the user interface is an essential component of a renewable energy system, as it allows users to fully utilize the capabilities of the system and make informed decisions about their energy use, providing users with a comprehensive view of their energy consumption and generation, by displaying real-time and historical data in clear visualizations, users can easily monitor their energy usage and receive alerts when their energy consumption exceeds certain thresholds.

3.3 Dataset Description

Dataset #1 (Household power consumption dataset)

Context:

Measurements of electric power consumption in one household with a one-minute sampling rate over a period of almost 4 years. Different electrical quantities and some sub-metering values are available.

Dataset information:

This archive contains 2075259 measurements gathered between December 2006 and November 2010 (47 months). Notes:

1.(global_active_power*1000/60 - submetering1 - submetering2 - submetering3) represents the active energy consumed every minute (in watt hour) in the household by electrical equipment not measured in sub-meterings 1, 2 and 3.

2.The dataset contains some missing values in the measurements (nearly 1,25% of the rows). All calendar timestamps are present in the dataset but for some timestamps, the measurement values are missing: a missing value is represented by the absence of value between two consecutive semi-colon attribute separators. For instance, the dataset shows missing values on April 28, 2007.

Attribute Information:

1.date: Date in format dd/mm/yyyy

2.time: time in format hh:mm: ss

3.global_active_power: household global minute-averaged active power (in kilowatt)

4.global_reactive_power: household global minute-averaged reactive power (in kilowatt)

5.voltage: minute-averaged voltage (in volt)

6.global_intensity: household global minute-averaged current intensity (in ampere)

7.sub_metering_1: energy sub-metering No. 1 (in watt-hour of active energy). It corresponds to the kitchen, containing mainly a dishwasher, an oven and a microwave (hot plates are not electric but gas powered).

8.sub_metering_2: energy sub-metering No. 2 (in watt-hour of active energy). It corresponds to the laundry room, containing a washing-machine, a tumble-drier, a refrigerator and a light.

9.sub_metering_3: energy sub-metering No. 3 (in watt-hour of active energy). It corresponds to an electric water-heater and an air-conditioner.

Dataset #2 (Wind power dataset)

context:

Here's data of a certain windmill. The aim was to predict the wind power that could be generated from the windmill for the next 15 days. A long-term wind forecasting technique is thus required.

content:

It contains various weather, turbine, and rotor features. Data has been recorded from January 2018 till March 2020. Readings have been recorded at 10-minute intervals.

Dataset #3 (Appliances energy prediction dataset)

The data set is at 10 min for about 4.5 months. The house temperature and humidity conditions were monitored with a ZigBee wireless sensor network. Each wireless node transmitted the temperature and humidity conditions around 3.3 min. Then, the wireless data was averaged for 10 minutes periods. The energy data was logged every 10 minutes with m-bus energy meters. Weather from the nearest airport weather station (Chievres Airport, Belgium) was downloaded from a public data set from Reliable Prognosis (rp5.ru) and merged with the experimental data sets using the date and time column. Two random variables have been included in the data set for testing the regression models and to filter out non-predictive attributes (parameters).

Dataset #4 (Predicting wind and solar generation from weather data)

The European Meteorological and Renewable Energy Generation dataset is a comprehensive collection of meteorological data and renewable energy generation values aggregated by country, control area, or bidding zone. The dataset covers the European Union (EU) and selected neighboring countries. All variables in the dataset are provided at an hourly resolution, enabling detailed analysis and modeling of meteorological conditions and renewable energy generation patterns.

With 84 columns dedicated to meteorological parameters, the dataset offers a wide range of variables essential for understanding weather patterns across Europe. These variables include temperature, humidity, atmospheric pressure, wind speed and direction, cloud cover, precipitation, and solar radiation. The inclusion of neighboring countries extends the geographical coverage, ensuring a comprehensive representation of weather conditions in the region.

In addition to the meteorological parameters, the dataset includes the last two columns that capture the hourly generation of energy from solar and wind sources. These values represent the actual renewable energy produced and serve as the target variables for deep learning-based prediction models. By studying the relationship between meteorological parameters and renewable energy generation, the dataset enables the prediction of the global total of renewable energy generation.

3.4 Result

3.4.1 Deep learning models:

We tested these time series forecasting models (CNN, TCN, GRU, Transformer, LSTM, Informer, BI-LSTM, etc.) on public datasets such as household electricity consumption, wind dataset, solar dataset, solar and wind dataset together that at first, we get 0.9 of loss than when we change in the format of the model by create structured layers and change in parameters of the models we got a loss rate between 0.01 and 0.002, which approve that our package has different models which can make accurate predictions on a different type of powers whether on one-step in figure 1 or multi-step forecasting in figure 2

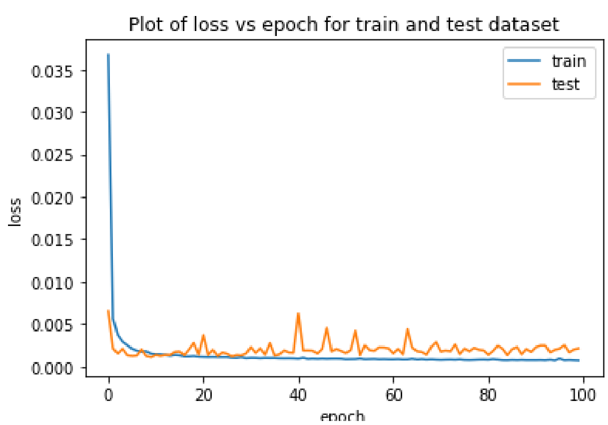


Figure1

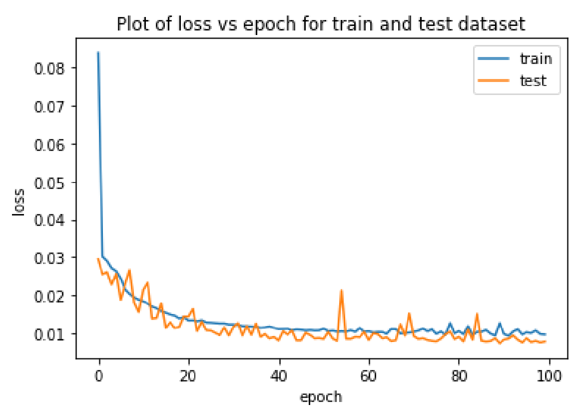


Figure2

The results presented in Figure 3 confirm the implementation of our models using Dataset #4

		RMSE	MSE	R2	MAE
LSTM	Train	0.041	0.002	0.985	0.022
	test	0.039	0.002	0.987	0.022
GRU	Train	0.023	0.001	0.996	0.008
	test	0.022	0.000	0.996	0.008
Bidirection GRU	Train	0.039	0.002	0.987	0.026
	test	0.038	0.001	0.987	0.027
Bidirection Lstm	Train	0.030	0.001	0.992	0.015
	test	0.028	0.001	0.992	0.015
CNN	Train	0.047	0.002	0.981	0.038
	test	0.046	0.002	0.982	0.038
Time Distributed	Train	0.032	0.001	0.991	0.017
	test	0.030	0.001	0.992	0.017
Transformer	Train	0.030	0.001	0.992	0.016

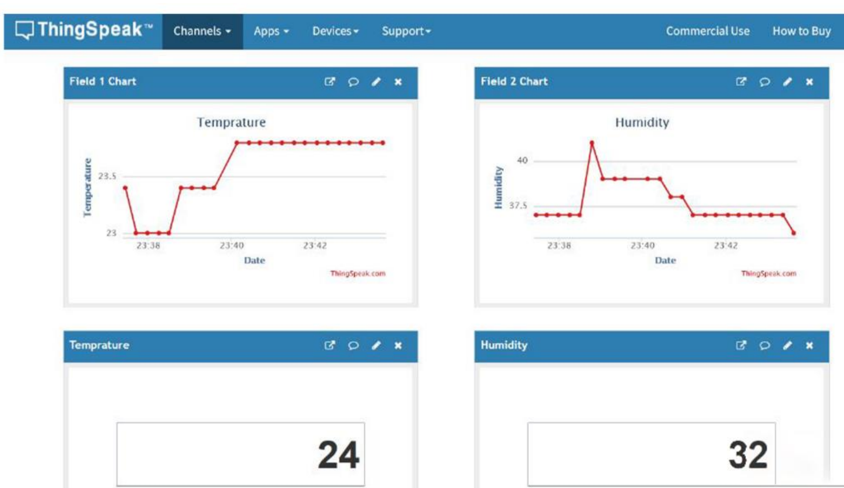
		RMSE	MSE	R2	MAE
TCN	Train	0.186	0.035	0.696	0.147
	test	0.186	0.034	0.701	0.147
Performer	Train	0.336	0.113	0.000	0.288
	test	0.337	0.114	0.000	0.289
CNN-LSTM	Train	0.338	0.114	-0.001	0.286
	test	0.340	0.116	-0.002	0.288
Autoformer	Train	0.338	0.114	0.225	0.290
	test	0.340	0.115	0.226	0.292
Bert	Train	0.079	0.006	0.946	0.069
	test	0.079	0.006	0.946	0.070
convlstm	Train	0.094	0.001	0.990	0.018
	test	0.032	0.001	0.991	0.018
DeepAR	Train	0.030	0.001	0.992	0.010
	test	0.027	0.001	0.994	0.010

		RMSE	MSE	R2	MAE
FNN	Train	0.044	0.002	0.983	0.015
	test	0.040	0.002	0.986	0.015
Bert	Train	0.031	0.001	0.992	0.014
	test	0.028	0.001	0.993	0.014
Lsnet	Train	0.036	0.001	0.989	0.021
	test	0.035	0.001	0.989	0.021
MLP	Train	0.038	0.001	0.988	0.022
	test	0.035	0.001	0.989	0.022
N-beats	Train	0.065	0.004	0.963	0.028
	test	0.061	0.004	0.967	0.028
RBFN	Train	0.338	0.114	0.322	0.290
	test	0.339	0.115	0.325	0.292
Seq2Seq	Train	0.338	0.114	0.345	0.290
	test	0.339	0.115	0.225	0.292

Figure3

3.4.2 IOT renewable energy generation System:

After we created the IOT generation system, to test the system's performance, we exposed it to sunlight which is our renewable energy source, and found that the system is working well and giving the right readings of the temperature, current intensity, and other weather factors, then by using the ThingSpeak website as a cloud which we stored the data on it as a CSV file to let the user use this dataset to make their prediction and make their decision, also by using ThingSpeak.Through these processes, we obtained a new dataset that we could use to replace the public dataset. This new dataset is based on real-time readings from our IOT generation system, providing users with accurate and up-to-date information about their energy generation.



	A	B	C	D	E	F	G	H
1		created_a	entry_id	field1	field2	field3	field4	field5
2	0	2023-03-2	1	24.1	34	3.792	5.256	1.386
3	1	2023-03-2	2	24.1	34	3.523	6.338	1.799
4	2	2023-03-2	3	24.1	34	3.159	3.623	1.147
5	3	2023-03-2	4	24.1	34	3.52	5.667	1.61
6	4	2023-03-2	5	24.1	34	3.226	5.297	1.642
7	5	2023-03-2	6	24.1	34	3.098	3.262	1.053
8	6	2023-03-2	7	24.1	34	3.81	7.395	1.941
9	7	2023-03-2	8	24.1	34	3.36	4.566	1.359
10	8	2023-03-2	9	24.1	34	3.292	4.675	1.42
11	9	2023-03-2	10	24.1	34	3.947	6.986	1.77
12	10	2023-03-2	11	24.1	34	3.244	4.36	1.344
13	11	2023-03-2	12	24.1	34	3.462	3.926	1.134
14	12	2023-03-2	13	24.1	34	3.611	4.662	1.291
15	13	2023-03-2	14	24.1	34	3.346	4.306	1.287
16	14	2023-03-2	15	24.1	34	3.305	3.973	1.202
17	15	2023-03-2	16	24.1	34	3.651	6.353	1.74
18	16	2023-03-2	17	24.1	34	3.651	6.481	1.775
19	17	2023-03-2	18	24.1	34	3.89	4.411	1.134
20	18	2023-03-2	19	24.1	34	3.177	5.995	1.887
21	19	2023-03-2	20	24.1	34	3.716	3.831	1.031
22	20	2023-03-2	21	24.1	34	3.821	5.625	1.472
23	21	2023-03-2	22	24.1	34	3.028	5.738	1.895
24	22	2023-03-2	23	24.1	34	3.225	3.606	1.118
25	23	2023-03-2	24	24.1	34	3.549	5.334	1.503
26	24	2023-03-2	25	24.1	34	3.818	4.013	1.051
27	25	2023-03-2	26	24.1	34	3.622	6.672	1.842

Figure4

4. conclusion

The project focused on developing an interpretable deep-learning framework for predicting the amount of energy produced and consumed from renewable energy sources over a specific period. By leveraging the power of IoT technologies, we integrated data collection and analysis, allowing for accurate predictions and optimization of renewable energy utilization, throughout the project, we emphasized the importance of renewable energy and the need for accurate prediction models in supporting its widespread adoption. By harnessing renewable energy sources, we can mitigate the environmental impact of fossil fuel energy and work towards a more sustainable future.

The development of a user-friendly website provided a platform for users to interact with the system, explore energy predictions, and provide valuable feedback. The website enhanced accessibility and usability, making the project more practical and user oriented.

By combining the power of deep learning, Internet of Things technologies, and an easy-to-use website, our project has demonstrated the potential for accurate energy prediction and optimization in the renewable energy sector. The project outcomes and outputs contribute to the advancement of sustainable energy development and provide valuable insights to decision-makers in the energy industry.

Overall, the project's outcomes highlight the significance of interpretable deep learning frameworks, IoT systems, and user-centric approaches in enabling effective energy prediction, fostering sustainable energy practices, and shaping a greener future.

Future works aim to further advance the project's capabilities, enhance the accuracy of energy prediction models, and enable more efficient and effective utilization of renewable energy resources. By exploring these areas, we can continue to contribute to the field of sustainable energy development and pave the way for a greener and more sustainable future.

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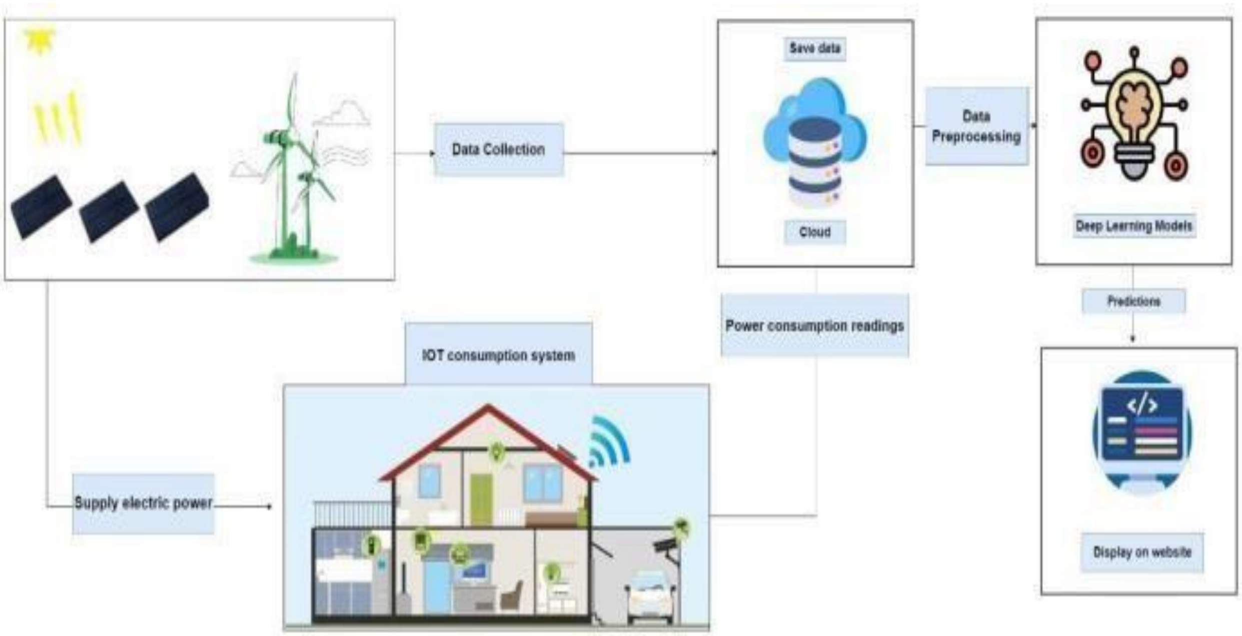
Appendix

- **System architecture diagram**



- **The prototype:**