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Enhancing Smart Grids for Sustainable Energy Transition and Emission Reduction with Advanced Forecasting Techniques

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ABSTRACT

Smart grids are modernized, intelligent electricity distribution systems that integrate information and communication technologies to improve the efficiency, reliability, and sustainability of the electricity network. However, existing smart grids only integrate renewable energies when it comes to active demand management without taking into consideration the reduction of greenhouse gas emissions. This paper addresses this problem by forecasting CO_2 emissions based on electricity consumption, making it possible to transition to renewable energies and thereby reduce CO_2 emissions generated by fossil fuels. This approach contributes to the mitigation of climate change and the preservation of air quality, both of which are essential for a healthy and sustainable environment. To achieve this goal, we propose a transformer-based encoder architecture for load forecasting by modifying the transformer workflow and designing a novel technique for handling contextual features. The proposed solution is tested on real electricity consumption data over a long period. Results show that the proposed approach successfully handles time series data to detect future CO_2 emissions excess and outperforms state-of-the-art techniques.

INTRODUCTION

The load demand for electrical energy is gradually increasing as the number of Electrical appliances in different fields such as Heating, lighting, washing, and many more vital daily life activities is rising (Hernandez et al. 2014). However, the misuse of this energy resource makes it a double-edged sword. How people generate electricity is a crucial issue at a time when environmental issues and the struggle against climate change are taking on more and more importance in our daily lives (Harper & Snowden 2017). Many countries, such as the United States, China, and Russia, rely heavily on fossil fuels for electricity generation, mainly due to the availability of fossil resources on their territory and the existing capacity of their power stations (Schulz & AQAL Group 2019). Power generation from fossil fuels such as natural gas or coal has long been an important source of energy but is now coming under scrutiny due to its environmental implications (Zou et al. 2016). It is essential to keep in mind that although this method of generating electricity from natural gas is efficient in terms of energy output, it still has a major negative impact on the environment and significantly increases carbon dioxide (CO_2) emissions, which are one of the main causes of global environmental problems. Rising sea levels, more extreme weather conditions, and the devastation of ecosystems are just some of the effects of climate change caused by CO_2 emissions related to electricity generation (Slingo & Slingo 2024). In addition to CO_2, the combustion of fossil fuels releases other atmospheric pollutants such as nitrogen oxides (NOx), sulfur dioxide (SO_2), and fine particles. These pollutants have adverse effects on air quality and can cause serious health problems for local populations. The use of fossil fuels also leads to the destruction of ecosystems, deforestation, water pollution, and the disruption of biodiversity. Cooling fossil fuel power plants requires large quantities of water, which can lead to conflicts over water use and the disruption of aquatic ecosystems (Wu et al. 2023). Furthermore, in 2022, global CO_2 emissions from energy combustion and industrial processes reached a new historical record of 36.8 billion metric tons (Gt) (Wang & He 2023). This represents an increase of 0.9%, equivalent to 321 million metric tons (Mt) in the previous year (Scott et al. 2000).

Smart grids are an emerging technology aiming to optimize energy usage by enabling precise management of electricity production, distribution, and consumption. This can reduce energy losses and maximize system efficiency (Mishra & Singh 2023). Additionally, smart grids facilitate the efficient integration of renewable energy sources, such as solar and wind, into the electricity grid (Kataray et al. 2023). However, existing smart grids transition to renewable energy to address fluctuations in demand, environmental constraints, and seasonal variations without adequately considering air pollution. Consequently, it has become essential to develop accurate forecasting systems to anticipate future demand and effectively manage these energies, ultimately leading to a reduction in CO_2 emissions.

This study presents a novel adaptation of the transformer architecture specifically tailored for load forecasting. The focus of this research is on improving forecast accuracy for real-time data streams by incorporating modifications to the encoder component. In contrast to many charge forecasting studies that assess proposed solutions based on short-term data, our investigation delves into the adaptability and performance of our solution across extended periods of data flow.

Introducing a 4-space transformation module with a revamped workflow, this approach aims to bolster the efficiency of load forecasting tasks. The evaluation of the proposed method utilizes real data streams, demonstrating that the adapted transformer consistently outperforms existing state-of-the-art methods.

RELATED WORKS

Forecasting is a very important challenge for electricity providers and has received considerable attention in the existing literature. The ability to accurately forecast electricity demand is crucial for efficient resource planning, grid management, and ensuring a reliable and sustainable electricity supply, which automatically implies a reduction in CO_2 emissions in order to preserve society's health and its environment. By managing electricity demand more effectively, it is possible to reduce the use of fossil fuel power stations. This translates into lower CO_2 emissions, helping to fight climate change and its harmful effects. Many studies have focused on developing forecasting models and techniques specifically tailored to the unique characteristics of electricity consumption. These models have been developed to capture the complex and dynamic nature of electricity demand, taking into account factors such as temporal patterns, seasonality, weather conditions, economic indicators, and consumer behavior.

Researchers have used a wide range of approaches to forecast electricity demand, including statistical methods, machine learning algorithms, time series analysis, artificial neural networks, and hybrid models. These techniques continue to evolve and improve with advances in data availability, computing power, and predictive analysis. The studies on electricity demand forecasting offer valuable perspectives, methodologies, and empirical results that help to understand the complexities of the problem. This knowledge forms the basis for the development of accurate and robust forecasting models, which support decision-making processes within the electricity industry.

Recent studies in electrical process management include several techniques in an attempt to analyze, understand, and predict electrical consumption, ranging from conventional ones such as CNN (Kim & Cho 2019), to statistical approaches to modern machine learning (Solyali 2020, Ahmad & Chen 2018) and deep learning methods [Bedi & Toshniwal 2019, Rahman et al. 2018] such as Long Short Term Memory (LSTM) based deep framework and deep Recurrent Neural Network (RNN). Process analysis, which is an evaluation of time series (Singh & Yassine 2018) by taking into account historical relationships between occurrences of electrical data, is used in a substantial part of the aforementioned methodologies.

The most traditional electrical consumption predictions are Artificial neural networks (ANN) (Deo & Şahin 2017, Jetcheva et al. 2014), which have determined that ANN is a high-performance model that generates good results in the case of energy prediction, whether for an entire region or a single building., Support vector machine (SVM) (Guo et al. 2006, Daut et al. 2017), which has proven its effectiveness in various fields, regression that offers a modeling of the relationships between the independent variables and the dependent variable (Yildiz et al. 2017, Kavousi-Fard et al. 2014), random forest (RF) known to reduce overfitting (Dudek 2015) that uses the seasonal cycles of time series to simplify the forecasting problem. The use of Convolution neural networks (CNN) architecture for their performance of feature extraction (Levi & Hassner 2015, He 2017) by using more than one feature to estimate electrical demand, including temperature (Deo & Şahin 2017), weather (Chow & Leung 1996), and many other exogenous variables (Jetcheva et al.2014, Roldán-Blay et al. 2013). In the aforementioned related works, as well as the recent advancement architectures: Support vector regression with modified firefly algorithm (SVR-MFA) (Kavousi-Fard & Marzbani 2014) and Support vector regression (SVR) combined with swarm optimization algorithms (SVR-PSO) (Jiang et al. 2016). In various traditional modeling approaches, the processing analysis of input data is handled independently, without taking into account the temporal nature of the data. This implies that each data point is used as separate information, regardless of its relationship to all the other occurrences of the data. However, considering time-series data, as in this paper, energy consumption, the temporal aspect plays a crucial role. Values are interdependent, interconnected, and influenced by previous or subsequent ones. The most important information to use are patterns, trends, and dependencies, which are essential for an accurate analysis and prediction.

To address this issue, (RNN) (Huang et al. 2021, Elsaraiti & Merabet 2021) and (LSTM) architecture can catch temporal dependencies in energy consumption data (Memarzadeh & Keynia 2021, Le et al. 2019) are frequently employed in the prediction of nonlinear time series as a neural network that integrates time dependency, and their usefulness has been demonstrated in the field of building energy consumption. The use of RNN in the field of building energy consumption prediction has been expanded to more complex LSTM (Chen et al. 2018) and generative adversarial networks (GAN) which are an advanced deep learning method (Zhang & Guo 2020). Baasch et al. (2021) and Bendaoud et al. (2021) demonstrated that GAN offers an innovative approach to electric charge prediction by generating new realistic electric charge time series and improving prediction despite their complexity. One way to explore the Attention Mechanism and Transformer Model power in comparison to the classic machine-learning (ML) approach is to identify the processing mode for previously known information and forecast future known or unknown information. Encoders and decoders are extensively employed in natural language processing and were originally utilized for sequence-to-sequence encoding and processing (Wu et al. 2021, Giuliari et al. 2021), with the use of historical data.

Traditionally, machine learning algorithms are the root of artificial intelligence techniques that have been used in electrical forecasting for decades, exploiting their capacity to capture complicated non-linear data correlations. The advancement of deep learning techniques is used to address a wide range of more complex applications, especially applied to electricity usage.

From these models, Recurrent neural networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN), in particular, have demonstrated their usefulness in dealing with time series (Fu et al. 2022).

Due to the irregular nature of the market, forecasting electricity consumption has shown to be a tricky task; it may be classified as a non-linear time series problem (Clements et al. 2004) since future values cannot be represented as linear combinations of previous ones. Several researchers employed statistical or machine learning-based time series forecasting models to anticipate the near future electrical load to solve this issue. However, extracting important features from the large quantities of data collected from different sources is a difficult task that remains largely unsolved. To this end, processing and analyzing these data represents a major challenge that still requires significant advances to achieve complete resolution (Bello-Orgaz et al. 2016).

The most recent studies underline the need to accurately forecast energy demand, a key element in optimizing power grid management and reducing CO_2 emissions. This research takes place in a global context where the transition to renewable energies is becoming an imperative in the fight for a healthier environment.

ve in the fight for a healthier environment. Focusing on consumption forecasting, the researchers aim to facilitate the efficient integration of renewable energies, such as solar and wind power (Kamani & Ardehali 2023), into the power grid. To achieve their goals, various research projects have focused on the Internet of Things (IoT), and a number of studies have focused on connected sensors to observe load, temperature, humidity, or energy consumption in real-time. To observe changes and decide whether they should be shifted towards renewable energies (Raju & Laxmi 2020). Venkatesan et al. (2022) provided an effective solution for managing agricultural energy. The smart farm system described in this study is based on the ability to regulate the growing environment with sensors, which are designed to regulate their internal power levels according to the temperatures they observe. A prediction model based on the Internet of Things (IoT) and artificial intelligence (AI) to monitor IAQ in real time using CO_2 measurement data has been modeled (Zhu et al. 2022). It highlights the importance of monitoring indoor air quality (IAQ), particularly in response to the COVID-19 pandemic, as poor IAQ can have an impact on health.

This research will not only optimize the use of clean energy but also reduce CO_2 emissions into the air by comparing several ML approaches such as Transformer, CNN, LSTM, and RNN. A more precise and accurate prediction of electricity consumption will lead to a significant reduction in power losses, particularly by limiting the overproduction of electricity, which is the source of pollution due to CO_2 emissions. In addition, this prediction will alert us to consumption peaks before they occur, enabling us to switch quickly to renewable energies.

PROPOSED APPROACH

This section is divided into two parts. First, the theoretical background was introduced, including numerous essential time-series concepts and the deep learning models used in this work. The proposed approach is then presented following the suggested transformer model validation technique.

Theoretical Background

This section highlights the importance of deep learning in predicting power generation to reduce CO_2 emissions. Deep learning neural networks, in particular the transformer, are proving effective in processing indexed temporal data. These networks are capable of learning complex correspondences between inputs and outputs and excel in the automatic processing of a wide range of temporal data. In the context of this study, the processor is considered a forecaster. Unlike traditional approaches such as CNN, RNN, and LSTM, which encounter difficulties in modeling complex long-term relationships in data sequences due to problems such as "gradient disappearance and explosion" in RNNs and the limitations of convolutional filters, the transformer offers a novel solution. It introduces a revolutionary model of long-term memory, as described in the article Attention Is All You Need (Vaswani et al. 2017). The practical application of this technology lies in the accurate prediction of electricity demand. Once the prediction reaches a certain threshold, the system automatically switches to using renewable energies rather than more polluting sources such as gas for power generation. This proactive strategy optimizes the use of renewable energies and significantly reduces CO_2 emissions, thus contributing to a more sustainable and environmentally friendly transition in the power generation sector. In a nutshell, transformers represent a cutting-edge approach to Natural Language Processing (NLP). They leverage the Multi-head Self-Attention (MSA) mechanism to gather information and build dynamic contextual understanding by comparing each token in an input sequence to every other token. The Transformer model establishes an information-passing graph among its inputs. Unlike sequential processing, transformers circumvent the issue of vanishing gradients commonly encountered by RNNs during long-term predictions. As a result, transformers have been successfully employed in datasets containing extensive historical data to derive optimal models for time-series forecasting (Zeng et al. 2023).

Encoder-Decoder Transformer-Based Prediction Model

The Transformer-based forecasting model (Vaswani et al. 2017) is based on the original Transformer architecture, which consists of encoder and decoder layers. The architecture of an encoder-decoder transformer is made up of many significant components and steps.

The principal element of the model is the encoder, which is in charge of processing inputs and transforming them into representations helpful for prediction. A number of encoder layers are stacked on top of one another. The two primary sub-modules that compose up each encoder layer are the forward propagation neural network and the multi-headed attention. The input layer transforms the time series data into a vector of dimension d using a fully connected network, as shown in Fig. 1.

Transforms the time series data into a vector of dimension using a fully connected network, as shown in Fig. 1. The usage of a multi-head attention mechanism requires this transition. The multi-head attention assists the model in identifying the relations between various elements of the input sequence. The positional encoding helps the model to identify temporal dependencies and the relationship between the various values across time. The position vectors can be added to electrical charge value embedding using position encoding using sine and cosine functions. Then, the four encoder layers receive the generated vector. A d-dimensional model vector created by the encoder is then supplied to the decoder.

The decoder inputs are created using the last data point of the encoder outputs. A decoder input layer is employed to process these inputs, converting them into a d-dimensional vector representation suitable for further processing. Multi-

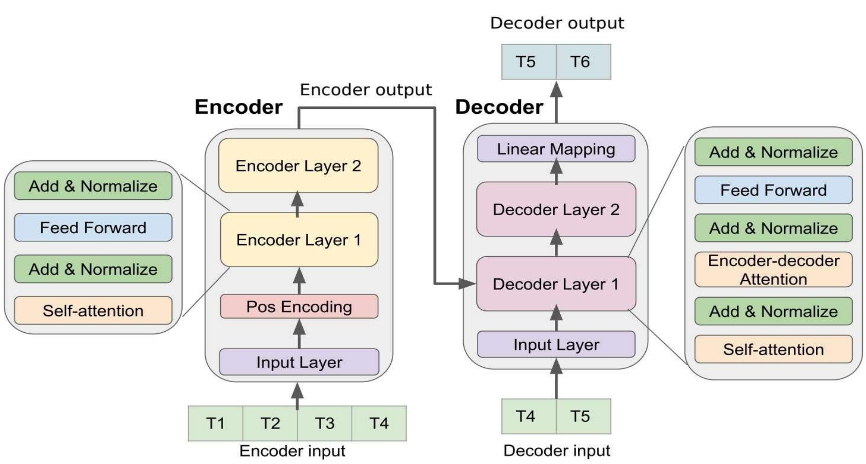

Fig. 1: Encoder-decoder transformer-based prediction model (Vaswani et al. 2017).

head attention is also employed in the decoder; however, it differs slightly from the attention used in the encoder. Multi-head attention considers both the outputs from the encoder and the outputs from the previous decoders for each place in the decoder. This enables the decoder to focus on both the information coming from the encoder that is pertinent and the data that the decoder has already produced. The output layer is responsible for generating the target time sequence based on the results of the preceding decoding layers. It combines the data from earlier layers to create the desired output. A method known as look-ahead masking is used to ensure that decoder predictions only depend on previous positions. This masking forces the decoder to rely solely on historical data by preventing access to future data throughout the prediction process. Additionally, the decoding module introduces a one-position offset between the decoder input and the target output.

Encoder Transformer-Based Prediction Model

Transformers have often been developed as encoder-decoder neural networks. The encoder-decoder configuration is frequently used in a variety of unsupervised tasks, including anomaly detection (Huang et al. 2020), translation (Vaswani et al. 2017), language and vision (Zhu et al. 2021), and more, which is necessary for this specific usage of transformer topology. The basic structure has been modified in the suggested modeling approach to use only the Encoder module. The global complexity of the model is reduced when the model is limited to the encoder, which facilitates learning and inference.

The main goal of these prediction tasks is to produce output that reflects the input data. However, consumption prediction is a supervised activity in which the model is trained using known inputs and corresponding outputs. Identifying the complicated, non-linear relationship between inputs (such as historical consumption habits, time of day, and weather conditions) and outputs (future consumption) is challenging. Transformers have proved effective in detecting these relationships in a variety of tasks, but their direct use for supervised prediction problems can be challenging. The considered approach focuses on obtaining the most pertinent information from the input data using only the encoder part of the transformer.

SYSTEM ARCHITECTURE

The study used a dataset of 4,380 days of quarter-hourly electricity consumption from Algerian electricity supplier "Sonalgaz," covering the years 2008 to 2020. (Bendaoud et al. 2021) The survey showed that a number of variables, such as climate and seasonal fluctuations, have a significant impact on electricity consumption. The Min-Max normalization procedure was used to ensure data stability for the analysis of daily consumption. This normalization method improves data stability, which facilitates model learning and convergence. The model aimed to meet the challenge of forecasting daily electrical energy consumption using multivariate data collected at 24-hour intervals in order to switch to renewable energies during periods of high consumption and reduce CO_2 emissions, as shown in Fig. 2. The figure describes the impact of electricity consumption prediction on CO_2 emissions, renewable energy use, and intelligent grid management, which relies on a complex symbiosis between different players in the energy system. Initially, the gas-fired power plant generates electricity while emitting CO_2, revealing the environmental implications associated with this traditional production method. Electricity consumption prediction is emerging as a key enabler of this process. It draws on historical data and sophisticated predictive models to anticipate future electricity demand. This forecast guides Prediction Response, triggering adjustments in generation and prompting a transition to renewable energy sources. This last aspect is essential, as it marks a turning point

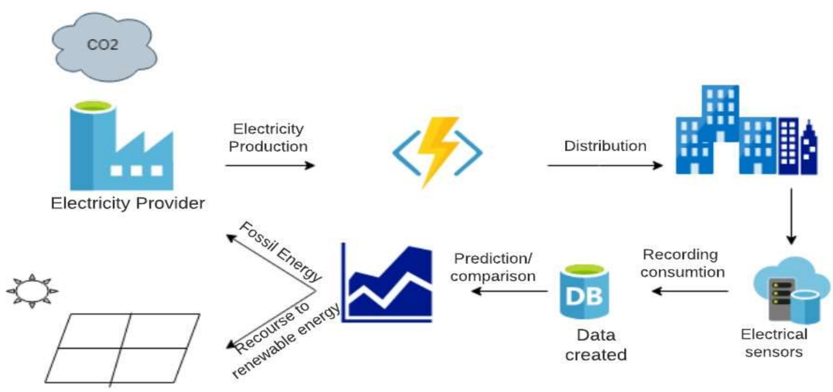

Fig. 2: Architecture of the proposed system.

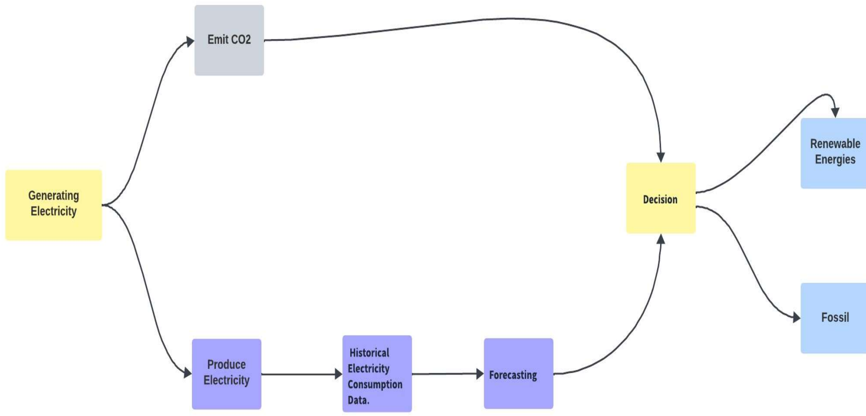

Fig. 3: Conceptual chart of the proposed system.

towards cleaner production and a consequent reduction in CO_2 emissions.

System Planning Proposed

The process of converting gas into electricity in a power plant is usually handled by a gas-fired power station. In a gas-fired power plant, gas (often natural gas) is burned in a combustion chamber to produce heat. This heat is used to vaporize a heat-transfer fluid, usually water, creating high-pressure steam that is directed toward a turbine, causing it to rotate. The rotation of the turbine drives a generator that converts mechanical energy into electricity. The electricity generated is then distributed via the power grid to homes or housing estates, which are equipped with electrical sensors that measure electricity consumption in real-time, recording consumption data and creating a dynamic database containing information on consumption patterns as shown in Fig. 3. From these data, different prediction models are tested and compared in order to choose the best possible predictor. First of all, the results of these predictions are of crucial importance, as they offer valuable insights to guide electricity suppliers in their strategic decisions. In particular, if the forecasts indicate an excessively high CO_2 emission rate, this can guide the supplier towards greater integration of renewable energies. These results can be used as a compass to take proactive measures to reduce the carbon footprint, adjusting power generation for more sustainable sources where necessary. Using this data, several prediction models are rigorously tested and compared to select the best-performing predictor. The results of these predictions are of crucial importance, as they offer valuable insights to guide electricity suppliers in their strategic decisions. In particular, if the forecasts indicate an excessively high CO_2 emission rate, this can guide the supplier towards greater integration of renewable energies. These results can be used as a compass to take proactive measures to reduce the carbon footprint, adjusting power generation in favor of more sustainable sources where necessary. In addition, prediction results provide crucial indications for optimal power generation planning. With an understanding of expected demand trends, the supplier can adjust production accordingly, optimizing available resources and improving operational efficiency. This iterative process of prediction, model evaluation and strategic adjustment helps to establish proactive management of power generation, aligned with environmental sustainability objectives, while ensuring efficient planning and agile response to changing energy needs.

Transformer-Based Encoder

The basic Transformer encoder architecture and a number of additional models were trained and compared to predict

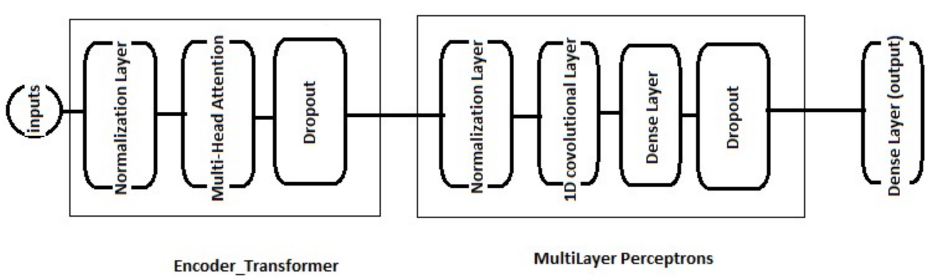

Fig. 4: The Transformer-Encoder framework.

load data for the next day using data divided into 24-hour intervals. The encoder presented in this research paper is based on the Transformer architecture and will be compared with other models in the following section, as shown in Fig. 4.

The Transformer model is a neural network design that is frequently employed in Natural language processing. Nevertheless, its applications are not limited to language-related tasks. One such application is electrical load prediction, where the Transformer model can be effectively utilized. The Transformer Encoder design is a stack of residual encoder blocks in a more formal sense. During training, the transformer-based encoder maps the input sequence to a contextualized encoding sequence.

The encoder block begins with a bidirectional self-attention layer, followed by two feedback layers. Various implementations have been explored to optimize performance on time-series data, each customizing its methods to meet specific needs. A crucial adaptation has been introduced to the attention map to effectively capture short-term patterns. This adjustment involves incorporating a window that confines backward attention, allowing focused analysis on nearby time sequences. Following a normalization step, the input sequence is transformed into a fixed-dimension vector for each element, ensuring uniform data preparation for consistent analysis. In the instance of electric charge prediction, each element represents a specific temporal value of electric charge, contributing to a meaningful representation for a more nuanced understanding of temporal patterns. Maintaining the chronological order of power consumption times is facilitated by positional encoding. Assigning a specific value to each element in the time sequence based on its relative position is essential for the model to capture temporal dynamics and accurately interpret variations in power consumption over time. Position-dependent cyclic patterns are made using the sin in eq. 1 and cos functions eq. 2. The embedding of the sequence elements is then enhanced using these cyclic patterns. In doing so, it is possible for each element to have a distinct vector representation that includes both information and position.

$$PE(pos2I) = \sin(pos/2i/(10000 d_{model})) \quad \dots(1)$$

$$PE(pos2i + 1) = \cos(pos/2I/(10000 d_{model})) \quad \dots(2)$$

with PE: the calculated positional encoding.

Once the position vectors have been generated, they are combined with their respective elements in the sequence. This step involves summing the position vectors with the existing embedding. This allows position information to be combined with the characteristics of each element with the eq. 3. The addition of position vectors enables the model to distinguish elements according to their relative position in the sequence, which is essential for understanding the temporal order of electric charge values and capturing the dependencies between them.

$$PE = PV + EV \quad \dots(3)$$

with PV: the positional vector and

EV: the embedding vector.

Each data point in the electric charge sequence will be converted by the encoding process of the Transformer into a context-dependent vector representation, taking into account any previous and potential future data points. The complex interactions between the numerous electric charge features are subsequently captured by the encoding blocks, which further enhance this contextual representation. This procedure is repeated until the last encoding block generates the contextual coding, which contains the crucial data required to make precise projections regarding future electric charges. Consequently, the model can identify the temporal correlations and patterns in the electrical charge data and then can make predictions of the future electrical charge demand.

After merging the inputs with the positional encoding eq. (3), the model will utilize a linear layer to create a collection of query vectors (key/value) for these features. Multi-headed attention employs a particular attention process known as self-attention.

V, K, and Q will just be identical copies of the embedding vector in the encoder case (plus positional encoding).

$Batchsize * seql_{en} * d_{model}$ will be the sequence length. The integration vector is divided into N heads in multihead attention; giving them the dimensions batch and d_k will be the dimension of the queries and keys of the attention Eq.(4)

$$Size * N * seqlen * (dmodel/N) \quad \dots(4)$$

After the scalar product between the queries and the keys, a score matrix is formed to determine the significance and the relevance of various input sequence elements Eq. (5)

$$Q * K = Scorematrix \quad \dots(5)$$

Then, the scalar products are subjected to a softmax function eq. (6) to generate the score matrix. In order to create a weighting distribution over the keys in the sequence, the softmax function normalizes the scores so that the sum of all scores for each query is equal to 1.

$$softmax(Q * K/sqrt(dk)) = attention(q,k,v) * V \quad \dots(6)$$

where $Softmax$ is a function that normalizes attention scores, and $sqrt(d_k)$ is the square root of the dimension.

After this, all attention head outputs are concatenated and multiplied by a projection weight matrix W_o of size ($dmodel * dmodel$) to obtain the final multi-head attention output

$$Attention\ i = Concatenate(O1, O2, \dots, Oh) * Wo \dots(7)$$

Where i_o is the output of the head attention i.

The neural network layer can learn to combine and transform input features to capture the complex patterns and non-linear relationships that influence target values. During model training, weights are iteratively adjusted using optimization techniques, such as gradient backpropagation, to minimize the gap between model predictions and actual target values. The representation that results from this contextual encoding will then be run through a fully linked layer to calculate the amount of electricity used.

MATERIALS AND METHODS

Settings

It is essential to introduce in this subsection the setting parameters that lead to the experimental results of the paper.

Event-Cause Analysis

Different events show that consumption is not a linear and constant process; it can range from a political speech, a football match, an abrupt climate change, or simply a change of seasons. It is essential to find which are the most influencing factors and to understand them, and this allows our prediction system to be as efficient as possible. Accurate forecasts of electricity consumption enable service providers to better manage energy resources, savings, and maintenance operations and guarantee a stable, reliable power supply. Anticipating the demand will avoid a lack of production and subsequent load shedding since overproduction is simply a huge economic loss and a major source of pollution. Maintenance operations will be easier to do, and distribution will be more efficient. Good forecasting will have a positive effect on the environment and, therefore, on human health. Anticipating and effectively controlling these fluctuations in electricity consumption not only ensures reliable service but also contributes to energy efficiency and sustainable development while keeping CO_2 levels acceptable enough to protect air quality. This enables service providers to choose wisely and deploy resources more effectively, which ultimately benefits suppliers, customers, and the environment.

An inventive strategy was used to achieve the objectives of forecasting energy consumption and maximizing the use of renewable energy sources and battery storage. To achieve this, the data were divided into 24-hour segments to represent days. This division allows a comprehensive examination of the correlations between energy consumption and various important factors. In order to give a clear picture of the temporal relationships and patterns present in the data, the aim is to assess the influence of past values in the time series on current or future values. Prediction plays a central role in the process of managing electricity consumption. Using machine learning algorithms, the system analyzes historical data to accurately anticipate electricity demand. A critical threshold is determined, which triggers a transition to renewable energy sources, such as solar or wind power, as soon as the prediction indicates that electricity consumption is close to or exceeds this threshold. This proactive strategy minimizes the use of polluting sources and reduces the CO_2 emissions associated with electricity production. In addition, in the event of excess production from renewable sources, excess electricity is efficiently stored in batteries. These batteries act as energy stores, enabling demand to be satisfied during periods of insufficient renewable production or peak consumption. In this way, the system ensures optimal use of

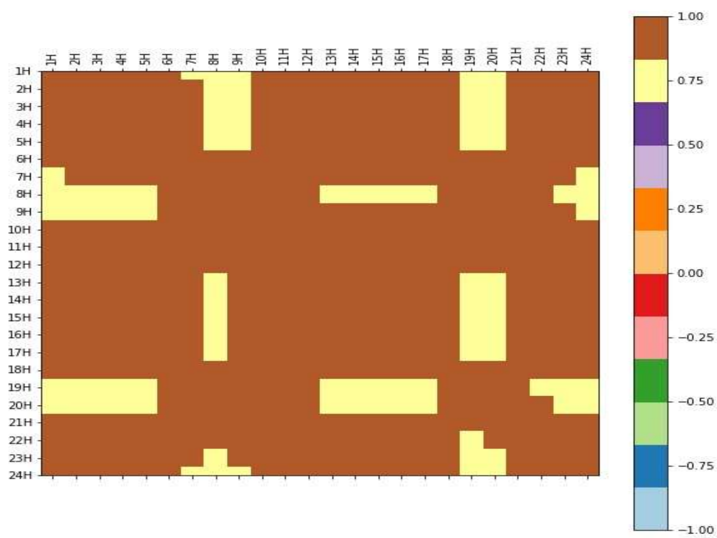

Fig. 5: The correlation results.

renewable energies, avoiding overproduction and responding dynamically to fluctuations in demand. Integrating prediction, transition to renewable energies, and electricity storage, this process offers a comprehensive approach to reducing CO_2 emissions from electrical consumption while guaranteeing a reliable and sustainable energy supply.

The outcome in Fig. 5 amply demonstrates that there is a very strong correlation between the database's variables. A linear link and a strong relationship between the variables were discovered through this statistical investigation, which can be used to reduce the amount of data needed for future research and make forecasting easier. Electricity consumption patterns vary according to the day, season, and year. In summer, when temperatures rise, demand increases in the afternoon, as residential and commercial spaces rely heavily on air conditioning. This translates into a higher overall hourly electrical load.

Conversely, during the winter months, the hourly electrical load is relatively stable but peaks in the morning and evening. These distinct patterns reflect the fluctuation in electricity consumption across different time periods, driven by factors such as climatic conditions and consumer usage habits. Understanding these dynamics is essential for effectively managing energy resources and implementing strategies to optimize power generation and distribution.

In addition, electricity consumption follows a daily cycle, with peak demand occurring at a given time of day *(depending on the season)* and then declining in the late evening. This fluctuation in electricity demand is due to daily habits of energy use by households and companies but is also influenced by weather conditions. Due to variations in weather conditions and the types of electrical equipment used, the overall quantity and trend of total electricity demand fluctuates from year to year.

Here are some curves of average consumption during the seasons to back up these claims.

Winter: The Fig. 6 shows the consumption trends during the winter months. This season is characterized by lower daylight hours and longer evenings. Consequently, the peak in electricity use happens around 8 p.m., reflecting the higher demand in the evening.

Summer: Fig. 7 represents the summer consumption pattern, which is characterized by the habits and life routines of Algerian citizens compared to other seasons. As a result, consumption curves show significant variations. In the morning, there is a significant drop in electricity consumption, probably due to reduced activity in the early hours of the day. However, around 12 o'clock, consumption rises significantly, probably because it is too hot. Another interesting observation is a minor shift in the peak, which occurs at 10 p.m., indicating a higher demand for electricity during the evening hours. These variations highlight the unique consumption behavior during the summer season, reflecting the specific needs and routines of Algerian citizens during this period.

Spring: With more daylight hours than in winter, spring brings a remarkable change in peak electricity consumption. This change is illustrated by Fig. 8, which shows that the peak is at 10 p.m. This change in peak time reflects the shift in energy consumption trends due to the lengthening of the day and the beginning of night-time activities. Spring's longer days allow for more outdoor activities and later working hours, shifting the peak consumption period to later in the day.

Autumn: In autumn, electricity consumption peaks at 8 pm. This is because the days gradually resemble those of winter, as illustrated in Fig. 9. Shorter daylight hours and colder temperatures lead to changes in consumer behavior, resulting in higher electricity consumption during the evening hours. The combination of winter and summer factors influences the consumption profile during autumn, resulting in a peak at 8 pm.

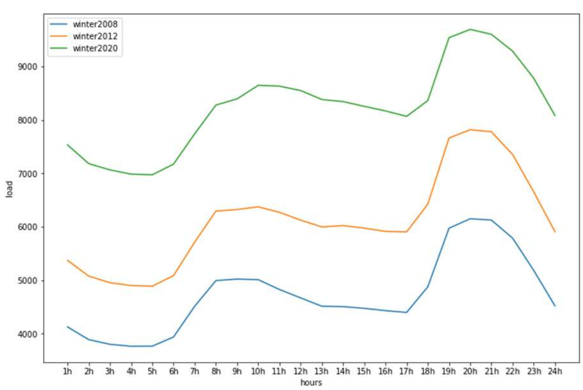

Fig. 6: The average consumption curve in winter.

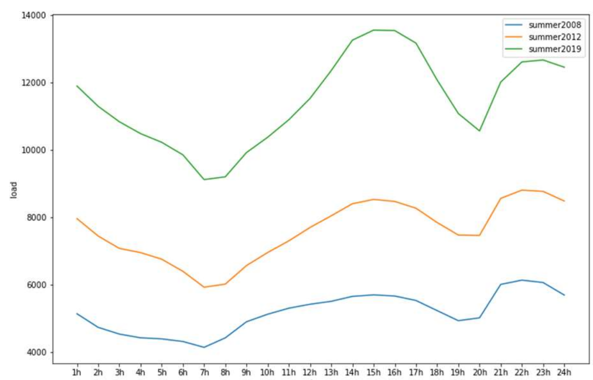

Fig. 7: The average consumption curve in summer.

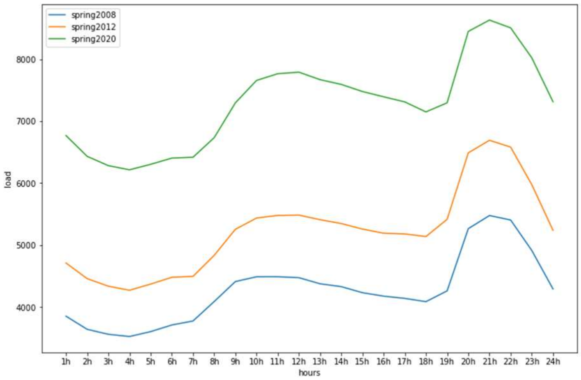

Fig. 8: The average consumption curve in spring.

As a result, seasonal influence becomes a key element to consider. Detailed observation of electricity consumption profiles for each season demonstrates the significant impact of seasonal variations. These seasonal differences, clearly visible in electricity consumption patterns, are crucial for refining predictive models. Taking these seasonal variations into account, the models can more accurately anticipate fluctuations in demand, enabling more efficient energy management and a consequent reduction in the CO_2 emissions associated with electricity generation.

RESULTS AND DISCUSSION

The Transformer-Encoder model is compared to many other models in this study to evaluate its performance, particularly in predicting electricity consumption while using and considering the influence of historical data. The models were evaluated using metrics frequently used in time series analysis, including mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and accuracy (100- (mean absolute percentage error (MAPE) (Boylan 2011))). These parameters serve as standard metrics for estimating model performance in catching and predicting the patterns of time series data. MAPE measures the average percentage deviation between predicted and actual values. Subtracting MAPE from 100 gives the precision measure, which represents the proportion of accurate predictions in percentage terms. This formulation enables a better interpretation of accuracy. The results are resumed in Table 1 and Fig. 10, respectively.

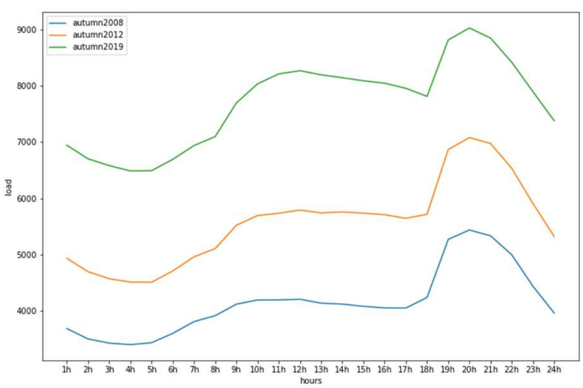

Fig. 9: The average consumption curve in autumn.

Table 1: Obtained model results.

Models	Accuracy	MAE	MSE	RMSE
RNN	0.89	1.34	3.20	1.72
Transformer-Encoder	0.98	0.71	0.26	0.53
CNN	0.98	0.09	0.09	0.099
LSTM	0.98	0.28	0.62	0.8

The comparison presented in Table 1 and Fig. 10 highlights the significant relationship between accurate power consumption forecasts and the use of appropriate forecasting models. As with any deep learning model, various factors, such as data quality and quantity, as well as model parameters, contribute to model performance and results. It is important to note that the Transformer-Encoder model achieves a remarkably high level of accuracy during training. Consequently, it highlights the potential for the Transformer model to be applied and adapted to meet such forecasting challenges.

Comparing this time series model with other architectures, it is interesting to note that transformers and CNNs achieved similar results. While CNNs are reputed for their ability to extract relevant features, transformers performed equally well in predicting power consumption. This finding highlights the ability of transformers to capture the complex temporal relationships inherent in time series.

On the other hand, when comparing RNNs with transformers, the main differentiating factor is the presence of parallelism in RNNs. Transformers may process several input sequences at once in contrast to RNNs, which only process one input sequence at a time in a sequential fashion. Transformers have more ability to recognize and represent complicated relationships due to this parallelism. In RNNs, the learned representation of the input sequence must be compressed into a single state vector before processing subsequent sequences. The model may not be able to accurately capture long-term dependencies due to this compression. RNNs can also experience gradient explosion issues, which further limits their capacity to manage long-term dependencies, even when using cutting-edge methods like LSTMs. Transformers, on the other hand, have a much wider bandwidth, enabling them to efficiently capture long-term dependencies and model relationships across the entire sequence. When it comes to managing long-

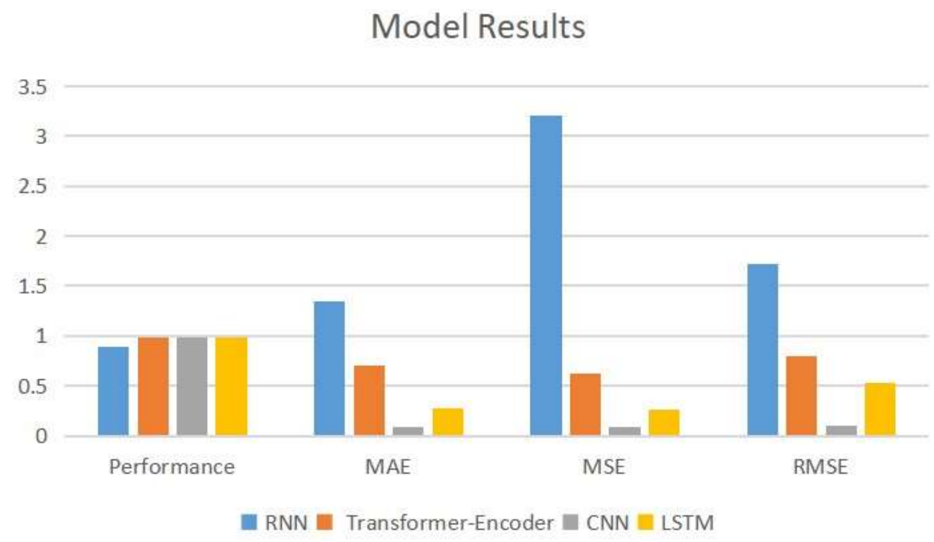

Fig. 10: Representation of the Model's results.

term dependencies and processing information effectively, transformers clearly outperform RNNs due to their parallel processing and capacity to handle all tokens directly. Transformers can effectively model complicated patterns and relationships within sequences, making them a powerful alternative for applications involving time-series data.

According to all that has been discussed, it becomes evident that transformers, both in their general form and through customized architectures, have a profound impact on the forecast of electrical consumption. Their attention and parallel processing mechanisms enable them to effectively understand the overall context and interrelationships within time series. This enables processors to make accurate forecasts and provide valuable information on future consumer trends. Overall, transformers are emerging as a transformational method for predicting energy use. Their ability to take advantage of the temporal aspect of the problem and their global modeling capabilities make them an effective tool for correctly forecasting future consumption patterns and supporting informed decision-making in the energy sector. This capability becomes crucial in the context of reducing CO_2 emissions linked to electricity production. Accurate forecasting of electricity consumption enables more precise planning of energy activities. The electricity production process has a significant impact on the relationship between electricity consumption forecasts and CO_2 emissions. In other words, accurate forecasting of energy needs has a direct impact on carbon dioxide emissions by improving the production, delivery, and use of electricity. Table 2 shows the CO_2 emission results, illustrating predicted values of the Transformer over a few hours of a day, as an example.

A significant observation emerges regarding the direct link between calculated CO_2 emissions and predicted values: an increase in consumption is directly correlated with an increase in CO_2 emissions. To illustrate this mathematically, the relationship between electricity consumption (E), CO_2 emissions (CO_2), and greenhouse gases can be represented by the following equation:

$$CO_2 = E * EF \quad \ldots(8)$$

where CO_2 represents carbon dioxide emissions, E represents electricity consumption, and EF (Emission Factor) represents the emissions conversion factor specific to the electricity source.

The EF depends on the source of electricity used to produce the energy. For example, if the electricity is mainly produced from gas, the emission factor will be high due to the high CO_2 emissions associated with gas combustion. On the other hand, if the electricity comes from renewable sources, the emission factor will be close to zero. Focusing on Algeria, the EF for gas use in the country was set at 548 gCO_2/kWh for this study. Although this value seems modest on a global scale, it is of significant importance for the country's environmental health. It is essential to recognize that all production has an impact on the global environment, as evidenced by global pollution reaching 32,252 Mt in 2020, according to the International Energy Agency (IEA) (Palaian Premalalitha & Balraj 2024). Even if these values are

Table 2: CO_2 Emission results.

Hours	1h	6h	12h	17h	21h
Predicted Values	7250	6250	6877	7145	7840
CO_2 Emission	3973	3768	3916	3739	4296

expressed in grams, the commitment to reducing greenhouse gas emissions is crucial, particularly through the increased integration of renewable energies. It is important to note, however, that countries are not isolated entities. Without the exceptional growth in renewable energies, electric vehicles, heat pumps, and energy efficiency technologies, the increase in CO_2 emissions would have been almost three times higher. These advances, therefore, play a crucial role in the fight against rising global emissions, demonstrating the importance of sustainable initiatives. Awareness of these emissions specific to Algeria provides a crucial basis for developing more sustainable energy policies aimed at minimizing environmental impact while improving health on a national scale.

CONCLUSIONS

Energy is the most important resource in the economy. There can be no economic development without energy control, and wasting energy is a disaster for the economy and the environment. One of the ways of controlling electrical energy is to forecast its consumption, which not only optimizes production and allows us to anticipate equipment maintenance but also helps us to move towards a more sustainable energy future. To achieve these objectives, it is necessary to apply statistical processing techniques to consumption data, enabling historical trends to be understood and interpreted. These findings enable a range of models, including linear and non-linear approaches, to be used to accurately explain and predict electricity consumption patterns that will play a fundamental role in reducing CO_2 emissions and promoting renewable energies. Through statistical processing, companies can gain a better understanding of their energy consumption patterns, enabling them to make informed decisions about energy management strategies. Accurate prediction of electricity demand enables production to be adapted in real-time, consequently reducing the use of CO_2-emitting energy sources, particularly during peak hours. This method will encourage more efficient management of energy resources and will also directly reduce greenhouse gas emissions, thus making an active contribution to the fight against climate change. The proposed models are deep learning models such as CNN, RNN, LSTM, and the transformer. The different used profiles are known as well as daily, seasonal, and yearly can catch the Algerian behavior. However, the obtained results are very promising, with up to 98 percent of good prediction for CNN, 98% for RNN, 98% for LSTM, and 98% for Transformers. The integration of renewable energies into the energy mix is a crucial step towards a sustainable future. By anticipating energy needs, accurate prediction of electricity consumption makes it possible to optimize the use of these clean sources. A deeper transition to renewable energies becomes feasible when forecast reliability reaches a defined threshold. The transition is accompanied by a significant reduction in dependence on fossil fuels. Intelligent management of surplus energy is another essential pillar. The use of batteries to store surplus electricity during periods of low demand offers a practical solution for smoothing out variations in production. This approach guarantees a stable supply of clean energy. This fusion of capabilities enables a more comprehensive and powerful approach to forecast electricity consumption, enabling informed decisions to optimize this energy, reduce costs, and contribute to a greener, more sustainable future.

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