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An Effective Prediction of Power Consumption Using Deep Learning Models

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Abstract
Effective prediction of electric power consumption is vital for accurate energy management systems, particularly in growing urban regions. Conventional statistical techniques usually fail to capture the complicated patterns and non-linear tendencies in time-series energy data. The development of deep learning models has demonstrated encouraging findings in a variety of prediction tasks. Therefore, this paper concentrates on the application of diverse deep learning models, comprising One-dimensional Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Bidirectional LSTM, and a hybrid model for power consumption prediction based on a dataset gathered from January 1, 2017, until January 1, 2018, in Tetouan, Morocco. These applied models were assessed utilizing diverse robust assessment metrics, and the findings demonstrated that the hybrid model (One-dimensional CNN with LSTM) reached superior performance with a Mean Squared Error (MSE) of 0.42548, Root-MSE of 0.65228, Mean Absolute Error (MAE) of 0.54395, and Median-AE of 0.51401, surpassing the other standalone and relevant models. The attained findings emphasize the merits of incorporating recurrent and convolutional structures to obtain more effective and accurate predictions of energy consumption time series.

Keywords: Power Consumption Prediction, Deep Learning, One-dimensional CNN, LSTM, Bidirectional LSTM, hybrid model

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1. Introduction

Electricity represents an essential component of the basic energy sources needed in various sectors to promote social evolution and maintain economic growth models. It has many benefits encompassing enhanced health, productivity, and mobility [1]. The dynamics of global electric consumption growth have remained stable over thirty years, and there are no preconditions for lowering electric consumption in the future. At the current stage of human evolution, electricity represents an essential resource, without which human professional and domestic activities are impossible [2].

Accurately predicting power consumption represents a vital task to ensure that electric power systems operate effectively and reliably. With the increasing reliance on electric power for industrial, commercial, and residential purposes, accurate consumption prediction is becoming progressively essential for diverse stakeholders. Enhanced electricity demand prediction enables effective resource allocation, power trading, and grid stability. It can also assist in integrating renewable energy production (such as solar, tidal, hydro, or wind) into

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the grid, which may often not be accessible when energy is required [3], [4].

With the increasing availability of historical consumption data, there is a growing need for advanced modeling techniques capable of learning complicated patterns and improving prediction accuracy [5]. Many have predicted that artificial neural networks, inherently prepared to address non-linear datasets and diverse input sources, will form the basis for developing machine and deep learning models. Nowadays, the extensive deployment of smart sensors and meters across the grid creates a favorable environment for improving these models [6], and [7].

In recent decades, many feasible works have been presented for predicting electric power consumption, which can be principally incorporated into data-driven approaches that in turn include various models of machine learning and deep learning. Machine learning algorithms work on predicting power consumption using data analysis, which has the merit of being speedy and simple to perform. Nevertheless, algorithms' limitations and data complexity make it tough to mine large amounts of complex data in deep. Thus, it is not possible to achieve a highly accurate prediction of power consumption [8]. Deep learning algorithms have the ability to solve the deficiencies of simple machine learning algorithms and attain more effective and accurate prediction findings over deeper data mining [9].

This work handles the issue of elevating short-term electric power consumption prediction via investigating the effectiveness of diverse deep learning models. The essential contributions of this deep learning-based power consumption prediction system are as follows:

1. Implementing four deep learning models (One-dimensional CNN, Long Short-Term Memory (LSTM), Bidirectional LSTM, and Hybrid model) for electric power consumption prediction utilizing a real dataset from Titouna.
2. Incorporating a one-dimensional CNN with LSTM to yield a hybrid model for extracting spatial features and modeling temporal sequences, reaching superior prediction performance compared to other applied models.
3. Providing a practicable reference for energy suppliers and researchers seeking to implement deep learning models to reach more accurate predictions.

2. Related Works

Diverse researchers have concentrated on determining the most effective approaches to predict electric power consumption for many years.

Kesornsit and Sirisathitkul [10], the authors proposed a hybrid system in which several dimensional diminution and feature selection methods (Random Forest, Stepwise Regression, and Principal Component Analysis) were incorporated with a backpropagation-NN for predicting power consumption. This system was trained and validated utilizing a real-world geospatial dataset gathered from 2018 to 2019 in Thailand. Among the implemented models, the incorporation of Random Forest and backpropagation-NN surpassed the other models with the lowest error (0.0416 of Root-MSE) in predicting electricity consumption.

Gonçalves et al. [11] proposed a one-dimensional convolution-LSTM model with a two-dimensional convolution-attention mechanism and roll padding to predict the power consumption. The French household power consumption dataset (gathered from 2006 to 2010) was utilized in this work. This dataset encompasses time-stamped measurements (reactive/active power, present intensity, voltage, and submetering) in one-minute intervals. The proposed model outperformed alternative models (like LSTM with standard attention mechanism, Auto-regressive Integrated Moving Average (ARIMA), and a temporal convolution network) in predicting irregular tendencies in electrical consumption. The findings of the proposed model recorded minimal prediction error (0.0140 of MSE, and 0.0875 of Root-MSE). However, the complexity of this model may inhibit deployment in resource-limited settings.

Kim et al. [12] implemented an LSTM model utilizing monthly data of electric power consumption (gathered from 2011 to 2020) with additional features (throughput, details of terminal operation, alternative power, and other weather circumstances) to predict the future consumption of the largest container port in South Korea (Busan). This model outperformed the baseline models like deep neural network and

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seasonal ARIMA, with root-MSE of 1.0711, but it did not take into account sudden disruptions (such as policy changes and epidemics).

Zhou et al. [13] the authors combined TrAdaBoost as a transfer learning with LSTM to predict daily electricity consumption. This incorporation is applied on the data (gathered from May-November 2021) of a primary school in China, including several features (average and maximum temperatures, humidity, solar radiation, and some weather parameters). This data was combined with auxiliary data (gathered from 2016 to 2023). The presented model exceeded several baseline models, with 7.8% of MAPE, 1.8077 of Root-MSE, and 0.2747 of MAE. However, this system needs frequent weight updates and fine-tuning for hyper-parameters, and mismatched source buildings lead to negative transmission.

Islam et al. [14] utilized a Tetouan City's power consumption dataset out of the Smir, Boussafou, and Quads zones, which encompasses power consumption proportions documented every ten minutes, as well as environmental features like wind speed, humidity, temperature, and diffusion and general diffusion flows. In the pre-processing phase, the average power consumption of these zones is first calculated to produce a composite target variable for prediction. The environmental features are then converted to hourly time intervals by utilizing the highest consumption and average environmental data values. Two machine learning models were utilized for prediction; the first model (FB-Prophet), which is a tool evolved via Facebook for predicting time series, and the second model (Neural Prophet) represents an expansion of FB-Prophet, which integrates neural network abilities to strengthen prediction performance. This presented system provided a 23.33% lowering in Root-MSE for ten minutes and an 88% lowering for hourly time intervals compared to other relevant works. However, the utilized models might need considerable computation resources to be applied effectively.

Tona et al. [15] presented an encoder-decoder LSTM-based future electricity demand prediction system for individual households, which has been extended to include different combinations of future and past exogenous variables. The French household power consumption dataset was utilized, and the presented model was compared with several models, causing a decrease in the MAE up to 8%.

Palaniyappan and Ramu [16] presented a fine-tuned LSTM-based system to predict short-term power consumption in a dedicated electrical distribution substation. In other words, the presented system worked on selecting the optimal hyper-parameters to enhance the prediction accuracy. This system enables customers to effectively regulate loads and charging sessions of electric vehicles based on pricing by incorporating predicted power consumption into the dynamic electricity pricing for the next day. The utilized dataset holds present and previous information for electric meters, renewable power generation, and weather circumstances. The attained findings were 0.3224 for MAE, 0.1984 for MSE, and 0.4454 for Root-MSE, highlighting the usefulness of using the fine-tuned LSTM model in power consumption prediction.

3. Proposed Power Prediction System

This section involves several phases, starting from the dataset preparation, preprocessing, and finally prediction, as illustrated in Figure 1.

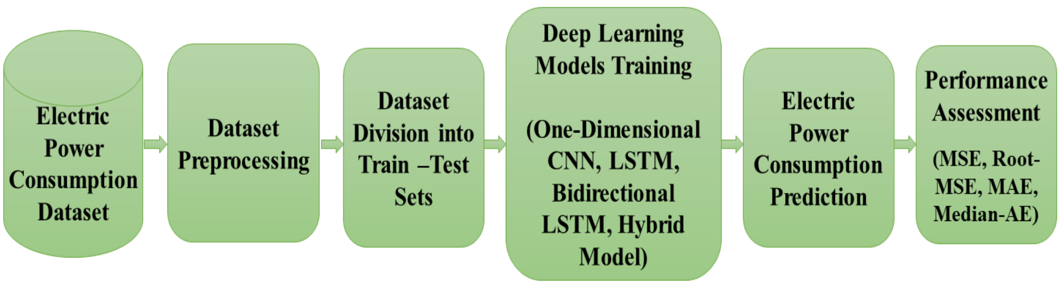

Fig. 1 Diagram of the proposed consumption prediction system

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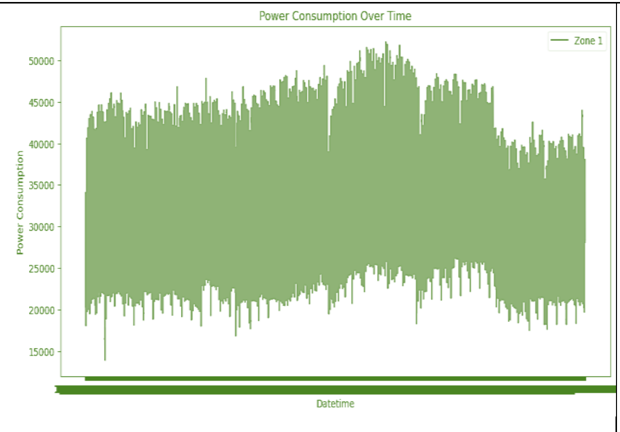
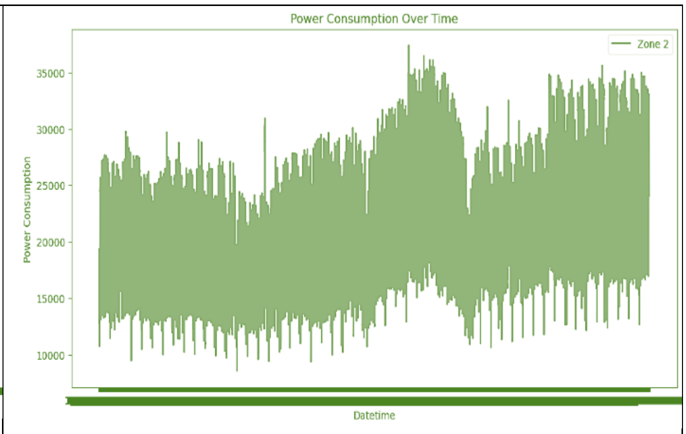
3.1 Dataset Preparation

The dataset utilized in this proposed power consumption system was historical data gathered every ten minutes for the interval from January 1, 2017, to January 1, 2018 [17]. This dataset contains no missing data and includes date, time, and consumption for three zones (Boussafou, Smir, and Quads distribution networks). Additionally, further data (humidity, temperature, wind speed, and diffuse & general diffuse flows) were gathered every five minutes and resampled to correspond to the intervals of ten minutes [18]. Fig. 2 illustrates the graph of the power consumption time series concerning the zones.

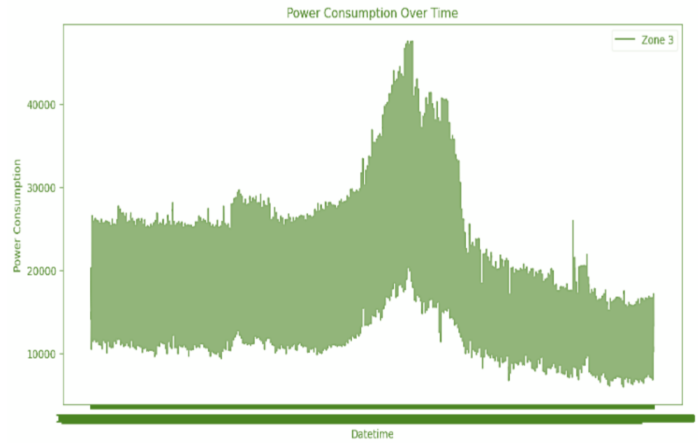
To increase the value of data analysis, further features are generated from time stamps (season, quarter, week of the year, day of the year, minute, day, month, and year). These features are utilized to achieve a more complicated data perspective and are essential feature variables for applying deep learning models.



a) Zone 1



b) Zone 2



c) Zone 3

Fig. 2 Power consumption time-series graph

After that, the target variables are generated by moving the consumption of the next point to the present date and time. Deep learning models utilize present consumption as the feature variable and the consumption of the succeeding point as the target variable in the phase of model training. Therefore, utilizing this training variable generation process, the next point (the subsequent ten minutes) is obtained as the production value (output) at a specific moment.

3.2 Dataset Preprocessing

In the pre-processing phase, the average power consumption of the three zones Pc_{Avg} is calculated to produce a composite target variable for prediction. The mathematical formulation can be given as follows:

$$Pc_{Avg}(t) = Pc_1(t) + Pc_2(t) + Pc_3(t)/3 \qquad (1)$$

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Where $Pc_1(t)$, $Pc_2(t)$, and $Pc_3(t)$ denote the power consumption in the first, second, and third zones at "t" time, respectively.

Additionally, in this phase, the dataset is split into train/test sets and is not subject to random shuffling. Here, time (chronological) splits are used to avoid data leakage during time series preprocessing, which appears when future information inadvertently affects the process of training. This data splitting process involves separating datasets into train/test sets, which strictly relies on chronological order. The train set involved data from earlier periods, while the test set involved data from later periods.

3.3 Deep Learning Models

In this proposed power consumption system, four models are implemented, having the following hyper-parameters: 50 epochs, 256 batches, 0.0001 learning rate, and Adam optimizer. The utilization of a fixed number of epochs (50 epochs) across various implemented models works on offering a consistent basis for performance assessment, simplifying the training process, fairly controlling training effort, and assisting in comprehending comparative learning behavior. Counts of parameters for each model are illustrated in Table 1.

Table 1: Counts of parameters per model

Models	Total	Trainable	Non-Trainable
One-Dimensional CNN	98,947	98,947	0
LSTM	10,553	10,553	0
Bidirectional LSTM	21,103	21,103	0
Hybrid Model	60,913	60,913	0

- The first model implemented is a “one-dimensional CNN" that encompasses many layers: first, a one-dimensional convolution (128 kernels and 384 parameters) with ReLU; second, a one-dimensional max pooling (without parameters); third, a one-dimensional flattening (without parameters), followed by two densest (fully connected layers), the first is dense with 64 units and 98,368 parameters, and the second is dense with 3 units and 195 parameters.
- The second model implemented is an “LSTM" that takes sequential input, handles it over an LSTM (with 50 units) to learn temporal patterns, and makes predictions using one dense layer (with 3 units).
- The third model implemented is a “Bidirectional LSTM" in which the Bidirectional layer acquires patterns from forward and backward sequential input, and makes output using one dense layer (with 3 units).
- The fourth model implemented is a “Hybrid model" in which the one-dimensional CNN is combined with LSTM to take out local features from the entry time series and learn temporal addictions and tendencies in electric power consumption, accompanied by a one dense output layer to produce the last prediction, as illustrated in Figure 3.

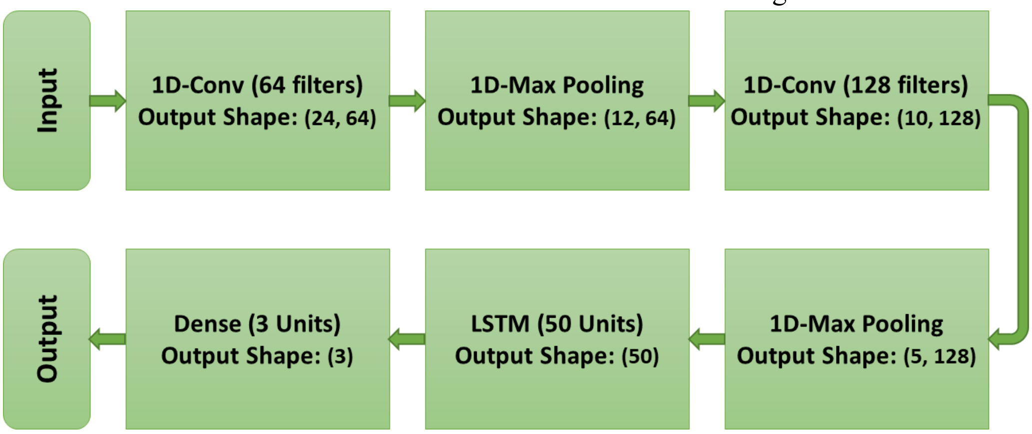
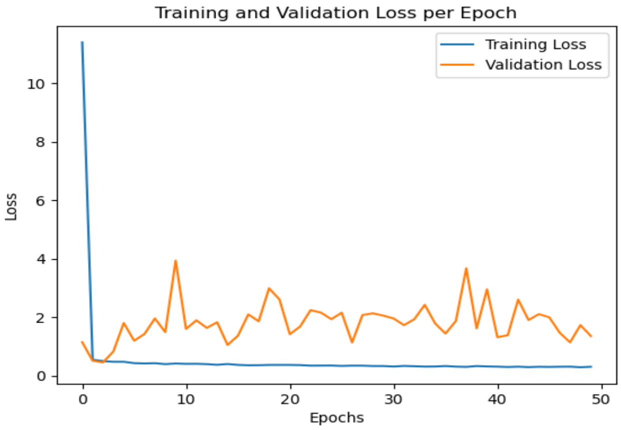


Fig. 3 Architecture of the proposed hybrid model.

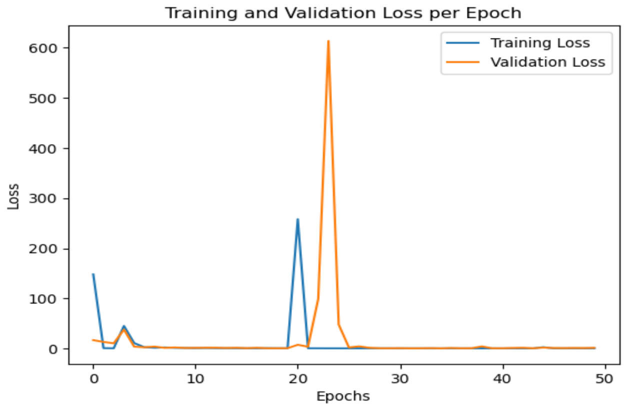
4. Results and Discussion

The applied models are assessed utilizing diverse robust assessment metrics (Mean Square Error

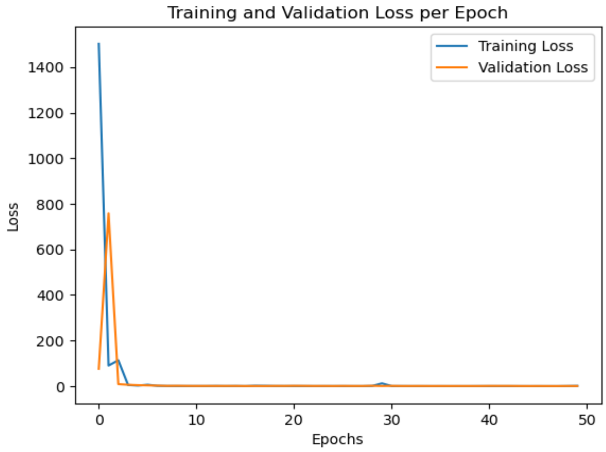
(MSE), Root-MSE, Mean Absolute Error (MAE), and Median-AE) and supplying a quantitative comparison of predictions. The obtained findings were (MSE: 1.35255 and MAE: 0.90154) for one-dimensional CNN, MSE: 1.29964 and MAE: 0.91223 for LSTM, MSE: 0.51879 and MAE: 0.56311 for Bidirectional LSTM, and MSE: 0.42548 and MAE: 0.54395 for the proposed hybrid model. It is noted from these results that the hybrid model achieved superior prediction performance compared to other applied models. Figure 4 illustrates the training and validation losses for each Epoch for (A) One-dimensional CNN, (B) LSTM, (C) Bidirectional LSTM, and (D) the proposed hybrid model.



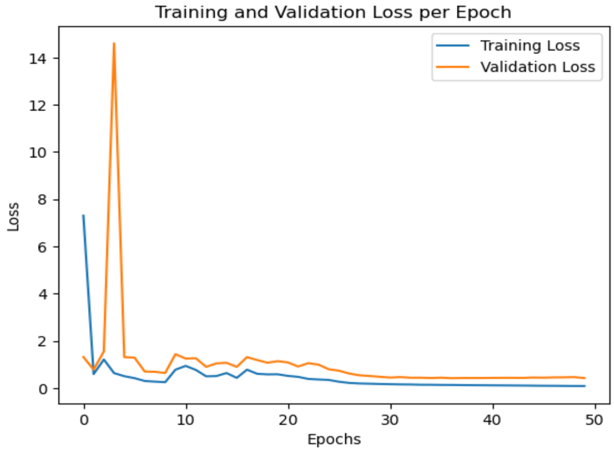
a) One-dimensional CNN



b) LSTM



c) Bidirectional LSTM



d) Proposed hybrid model

Fig. 4 Losses of training and validation for each Epoch

The Bidirectional LSTM model reached minimal MSE and MAE compared to the one-dimensional CNN model and the LSTM model. It works on capturing dependencies (forward and backward) in the sequence, and gives a deeper comprehension of the temporal context.

The LSTM model performed superior to the one-dimensional CNN model on the MSE metric, but somewhat worse on the MAE metric. Although the one-dimensional CNN model is trained faster than the LSTM, it misses the long-term sequence memory provided by the LSTM model. The whole set of findings for each implemented model are illustrated in Table 2.

Table 2: Comparison between implemented models

Metrics	One-dimensional CNN	LSTM	Bidirectional LSTM	Hybrid Model
MSE	1.35255	1.29964	0.51879	0.42548
Root-MSE	1.16299	1.14001	0.72027	0.65228

MAE	0.90154	0.91223	0.56311	0.54395
Median-AE	0.87238	0.85647	0.52151	0.51401

The hybrid model achieved Root-MSE of 0.65228, demonstrating competitive performance compared to the rescaled findings from FB-Prophet and Neural Prophet models [14]. The attained RMSE for the hybrid model is lower than the rescaled FB-Prophet Root-MSE (0.7304) and Neural Prophet Root-MSE (0.7696). This indicates that the hybrid model is able to make a more accurate prediction of the composite power consumption, emphasizing its efficacy in capturing the complicated temporal dependencies in the Tetouan energy demand data.

5. Conclusion

Accurately predicting power consumption is a crucial problem for energy suppliers and urban architects, specifically in regions experiencing speedy growth and dynamic desire patterns. In this paper, the implementation of diverse deep learning models was explored to predict electric power consumption utilizing a dataset gathered in Tetouan, Morocco. These deep learning models are assessed, and the findings demonstrate that the hybrid model (one-dimensional CNN with LSTM) exceeded the other models, reaching the minimal MSE (0.42548) and MAE (0.54395), signifying its outstanding capability of capturing local features and temporal addictions in the historical data. Consequently, the integration of recurrent and convolutional layers could considerably improve prediction accuracy in energy-relevant time series issues.

In the future, it is possible to utilize other datasets of various regions to evaluate generalizability and incorporate external variables like holidays, weather circumstances, and social and economic indices to enhance the robustness of power consumption prediction. Additionally, utilizing recent optimization algorithms, transformer-based approaches, or attention mechanisms can be leveraged to further improve the performance of deep learning models. Furthermore, these models can be extended to include long-term prediction (weeks or even months) to produce deeper perceptions into strategic energy plans.

Conflict of interest

The authors declare that there are no conflicts of interest concerning the publication of this paper.

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