A Deep Learning Approach for Electric Vehicle Charging Duration Prediction at Public Charging Stations: The Case of Morocco

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Abstract—**The adoption of electric vehicles (EVs) is increasing worldwide as it may help reduce reliance on fossil fuels and greenhouse gas emissions. However, the large-scale use of charging stations for electric vehicles poses some challenges to the power grid and public infrastructure. To overcome the problem of extended charging time, the simple solution of increasing the charging station and increasing the charging capacity does not work due to the load and space limitation of the power grid. Therefore, researchers focused on developing intelligent planning algorithms to manage the demand for public charging based on predicting the charging time of electric vehicles. As a result, this paper proposes a deep learning approach for predicting the duration of charging sessions. These approaches are validated using a real-world dataset of charging processes collected at public charging stations in Morocco. Numerical results show that the gated recurrent units (GRU) regression method slightly outperforms the other methods in predicting the charging sessions duration. Accurate prediction of electric vehicles charging duration has many potential applications for utilities and charging operators, including grid reliability, scheduling, and smart grid integration. In the case of Morocco, the massive deployment of EVs can cause a variety of problems to the electrical system due to the considerable charging power and stochastic charging behaviors of electric vehicle drivers. Thanks to this study's results, we can assess the expected impact of additional EVs on the grid, considering specific characteristics of the Moroccan power system.**

Keywords—electric vehiclest; deep learning; charging duration; predection; Morocco

I. INTRODUCTION

To reduce harmful carbon emissions from burning fossil fuels, most countries worldwide have proposed keeping the global average temperature below 2 degrees Celsius [1]. To do so, all regulations and policies must meet the 100% clean energy target [2-3]. Replacing internal combustion engine vehicles (ICEV) with electric vehicles are among the most promising options for reducing fossil energy use and Carbon emissions (EVs). In fact, road transportation accounted for 23% of total CO2 emissions in 2020 [4]. As a result, plug-in electric vehicles (PEVs) are viewed as one solution for reducing the transportation sector's reliance on oil imports and greenhouse gas emissions [5-6]. Confidence in the reliability of electric vehicles has increased, and satisfaction among EVs owners has become higher [7]. As a result, the number of electric vehicles on the road is expected to reach 140 million by 2030, generating an additional power demand of 550 TWh [8]. Driver flexibility has also increased along with the addition of charging stations in different parts of the world, driven by various government initiatives encouraging further adoption of EVs [9-11]. These factors have placed electric vehicles to be in a pole position with regards to providing a clean source of transportation. Despite promising pote, several challenges remain, most notably the charging time and public charging requirements.

Although EVs charging time has decreased significantly over the last few years, it is still much longer than the refueling time for ICE vehicles, on average. New charging technologies such as ultra-fast charging [12] and wireless charging [13] are promising, but they still overcome various challenges and require more years before being widely adopted. The constraints from charging infrastructure mean that most EVs owners rely on public charging stations, which strain the power distribution grid due to the high-power demand from electric vehicles batteries [14]. To avoid power grid degradation and failure, un-coordinated charging behavior must be avoided. The best solution is to better manage the scheduling of charging stations. Although predictions of EVs charging behavior can have various categories, the focus of this work will be on the session duration.

In this context, many studies in the literature have used artificial intelligence tools to provide accurate predictions of the future charging time of electric vehicles. Xiong et al. [15] predicted the start time and session duration using mean estimation. The session duration was also used to predict energy consumption using linear regression. To predict session duration from two charging datasets, the authors of [16] used several Machine Learning models, including DT, K-NN, and RF. The first dataset contains charging sessions from the university campus of California, Los Angeles (UCLA), representing non-residential charging behavior. The second dataset contains residential charging data from EV drivers in the United Kingdom. Support Vector Regression outperformed LR (Liner Regression) in terms of session duration (SMAPE 10.54 percent) (SMAPE 11.05 percent). Zachary et al. [17] used Gaussian Mixture Model to predict charging duration from a public charging space in California, USA. By considering the distribution of the known arrival times.

Although the previous works from the literature have successfully predicted session durations, they mainly focus on liberalized electricity markets. This has motivated us to conduct the current study and investigate the charging duration prediction using deep learning methods in regulated (non-liberalized) electricity markets.

The rest of the paper is structured as follows. Section II provides an overview of electric vehicles and charging infrastructures in Morocco. Section III contains a detailed explanation of the used methodology, including the dataset description and experimental setup. Section IV presents and discusses the findings of this study, and Section VI concludes the paper and offers some suggestions for future research.

II. Electrci vehicles and charging infrastructures in Morocco

A. EVs in Morocco

Much research has been done in Morocco to analyze and outline the impact of the large-scale development of electric vehicles on the transportation sector. Jelti al, [18] this study discussed in detail the assessment of Morocco's transition to electric vehicles using an approach known as the A3 report. El Harouti et al, [19] demonstrate the diverse interests of electric vehicles in Morocco and describe the stages of contribution and change to pure electric vehicles. Chachdi et al, [20] reveal why it influences Morocco's choice of transportation based on electric vehicle technology. This paper also explores possible options for integrating this green mode of transport in Morocco. While Boulakhbar et al [21] highlights the actual situation of electric mobility in the Kingdom and proposes key recommendations for EV adoption acceleration in the Kingdom.

During COP21 in Paris, Morocco committed to a strategy to reduce greenhouse gas emissions by 42% by 2030 [22] by encouraging various participants to achieve energy savings of 48% in the industry, 23% in transport, 19% in the residential sector, and 10% in the service sector and reduce the cumulative CO_2 emissions in the transportation sector by 9.5% (50 million tons) [23].

The transportation sector is the priority, accounting for 29.3 percent of Morocco's ultimate energy consumption [24] in 2020. It also accounts for more than 23.23 percent of total greenhouse gas emissions. Morocco offers many incentives to boost the country's adoption of electric vehicle technology as the first step in the search for green and sustainable transportation. In this regard, all-electric and hybrid electric vehicles have been exempted from taxes and customs since 2017 add more [25]. This has created public demand for electric vehicles that have attracted automakers like China's BYD (Build Your Dream) and encouraged the commercialization of the technology alongside the country's political stability. In addition to promoting private electric vehicles, the Moroccan Government is actively participating in this transition by replacing 30% of its fleet (35,400 vehicles) with electric/hybrid vehicles by 2030 [26].

As a result, 1,400 electric and hybrid vehicles were sold only in the first half of 2021. according to the association of vehicle importers in Morocco (AVIM) [27] (see Figure 1). According to a study carried out by the Moroccan Federation of energy [28], these numbers are expected to skyrocket are estimated to reach 425,704 by 2030.

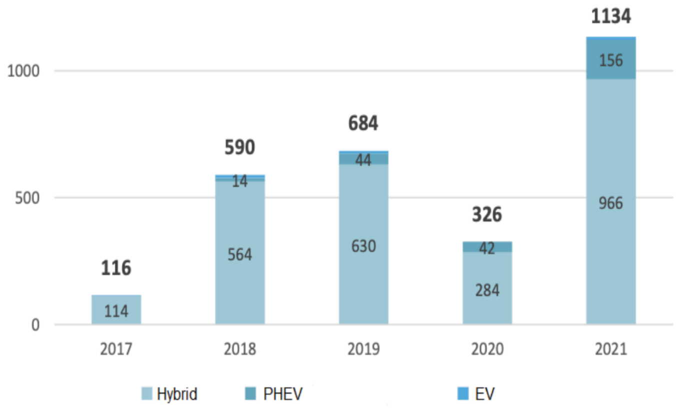

FIGURE I. SALES VOLUMES COMPARISON OF HYBRID/ELECTRIC VEHICLES FROM THE FIRST HALF OF 2017 TO THE FIRST HALF OF 2021 [27]

In this regard, Morocco falls behind the global EV trend. The EV sales in Morocco are still very low with an integration of less than 1%. Tab.2 shows the part of EVs and HEVs sales in Morocco between 2016 and the first half of 2021.

TABLE I. PART OF EVs AND HEVs SALES BETWEEN 2016 AND H1 2021

Year	Number of Hybrid EVs	Number of EVs	Total
2016	130	54	184
2017	461	66	527
2018	800	93	893
H1 2019	630	54	684
H1 2020	284	42	326
H1 2021	966	168	1134

Driven by its commitment to implementing energy reforms and major orientations necessary for the protection of the environment and sustainable development, the Moroccan government is rolling out strategies to support its goals in several areas. However, despite some progress, the introduction of electric vehicles in Morocco is still in the start-up phase and its implementation and development remains poor compared to the announced goals.

B. Charging infrastructures in Morocco

To provide a robust and reliable infrastructure for charging electric vehicles, the government is working with energy companies, automakers, and corporate investors on a hybrid approach to installing charging stations along roads and strategic points in major cities. In this regard, EVBox has partnered with Vivo Energy Morocco to launch its first EVs charging station in Morocco in 2016, laying the foundation for domestic charging. infrastructure [29]. To accelerate the use of electric vehicles, Moroccan authorities have also launched several projects, including the Green Mile Program, which offers the construction of 37 charging stations with 74 fast and regular charging points [30]. IRESEN (Institute of Research in Solar Energy and New Energies) conducted a project in collaboration with Schneider Electric on the Agadir-Tangier Highway (800 km).

Other public charging stations could also be implemented in hotels, restaurants, shopping malls, and parking lots so that EVs users can perform other daily activities while charging. Figures 2 and 3 show the various charging stations deployed in Morocco by December 2021.

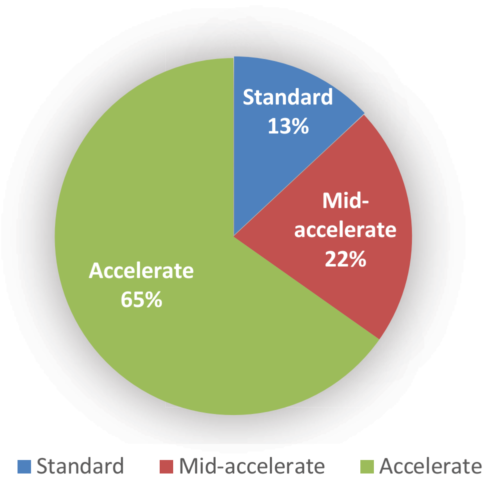

FIGURE II. DISTRIBUTION OF CHARGE POINTS BY CHARGING SPEED [31]

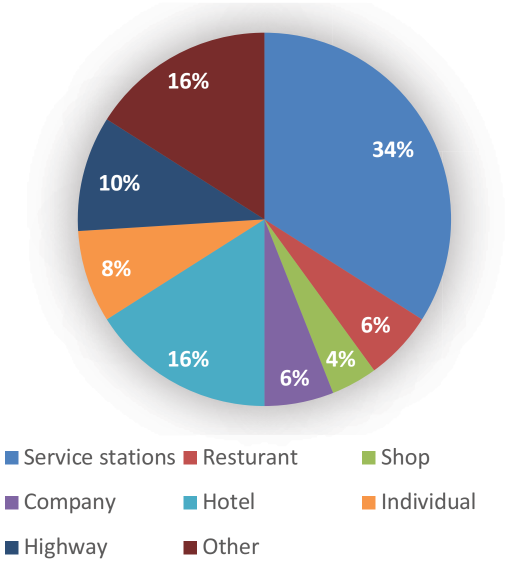

FIGURE III. DISTRIBUTION OF CHARGE POINTS BY LOCATION TYPE SOURCE [31]

While it is a solid start, there is still a need for more charging stations, as the already existing ones aren't enough to match the 425,704 EV forecasted for 2030.For that, the government will have to encourage each region to establish a roadmap to facilitate and accelerate the deployment of EV charging infrastructures on a regional scale.

III. DATA DESCRIPTION AND ANALYSIS

The data consists of a file that contains observations from two public charging stations in Morocco. Data were collected and analyzed from available Level 2 public charging stations throughout the city of Rabat from February 2019 to February 2021. The first charging station is a 22KW charging station, three phases, 32 A, 400 V with dual charging ports, and the second is an 11 KW charging station, three-phase, 16A, 400V with two charging ports. The total dataset has 2044 charging sessions. For each session, the following information is considered: the station identification number and location of the station, connection port, start and end time, charging duration, kWh consumed, and the driver ID.

Sessions that lasted less than 4 minutes without recharging were removed from the record. Most of these cases are believed to be due to technical issues that the PEVs (Plug-in electric vehicles) users were unable to connect to the charging point properly. These cases make up 9.03% of the total dataset. A total of 1841 charging processes are analyzed over a period of more than 4 minutes to determine charging requirements.

A. Charging duration prediction

Our analysis is based on the charging sessions duration and datetime data from two of the more used public charging stations in Morocco. We assess the feasibility of predicting the future charging sessions time of EVs in public charging stations in Morocco, using real information and deep learning algorithms.

We evaluate the proposed approach on multiple case studies and demonstrate its effectiveness by simulation analysis. The dataset was divided into a test set, validation set, and training set during the training process, with the ratio selected as 0.2/0.2/0.6. This approximated function (model) can then be used to predict the duration of future sessions based on the input parameters of those sessions. The overall framework is illustrated in figure 4.

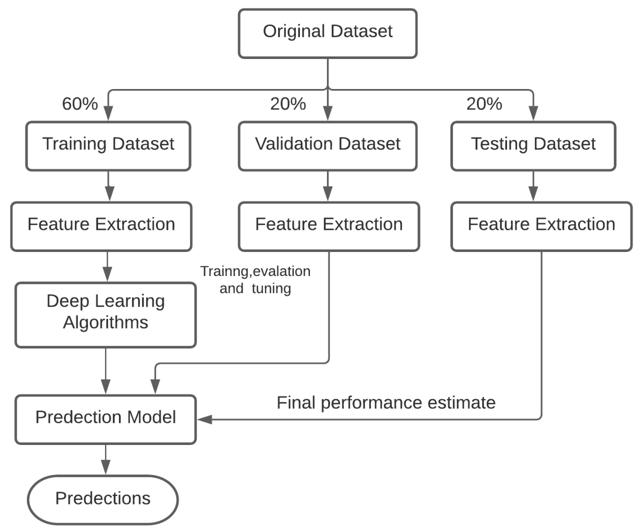

FIGURE IV. CHARGING DURATION PREDICTION FRAMEWORK

There are many established regression techniques with various advantages and disadvantages. Because the prediction of session duration has possible real-time applications, tree deep learning algorithms with a balance of accuracy and computational speed are investigated: Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). The following section outlined the deep learning methods used in this research paper.

B. Deep learning models

With the development of artificial intelligence technology and tools. Deep learning algorithms are widely used in a variety of fields, especially in the field of prediction. Intelligent algorithms, primarily including recurrent neural networks (RNNs), long short-term memory (LSTM), and gated recurrent units (GRU), have gradually proven to be very efficient in case of predictive problems

a) Recurrent Neural Network

RNN is a very popular Deep Learning model. RNNs have proven to be very effective in many other areas, such as load forecasting [32] and automatic speech recognition [33]. Thanks to its dynamic nature and instinctive structure, the RNN model has a better understanding of the properties of the input data. The structure is shown in Figure 5.

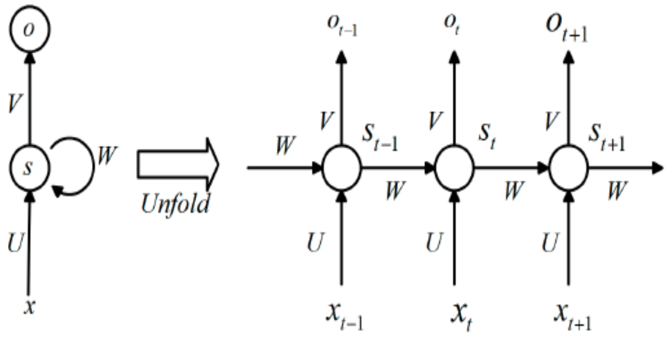

FIGURE V. BASIC LONG RNN STRUCTURE [34]

For time t:

$$S_t = \phi(\mathcal{U}x_t + \mathcal{W}S_{t-1} + b1) \quad (1)$$

$$o_t = \phi(VS_t + b2) \quad (2)$$

$$\widehat{y}_t = \phi(o_t) \quad (3)$$

Where xt and St denote the input and the hidden unit, while ot is the output at t. Moreover, V, W, U are network connection weights. In addition, b is bias, and yˆt is the model predicted output, is activation, function, and tanh are well adapted as activation function shown as follows:

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (4)$$

b) Long Short-term Memory (LSTM)

LSTM is a type of periodic neural network capable of studying order dependence on sequence prediction problems. This helps keep errors that can spread over time and in layers. By maintaining a more consistent error, the iterative network can continue to learn in stages. The structure of LSTM is shown in Figure 6.

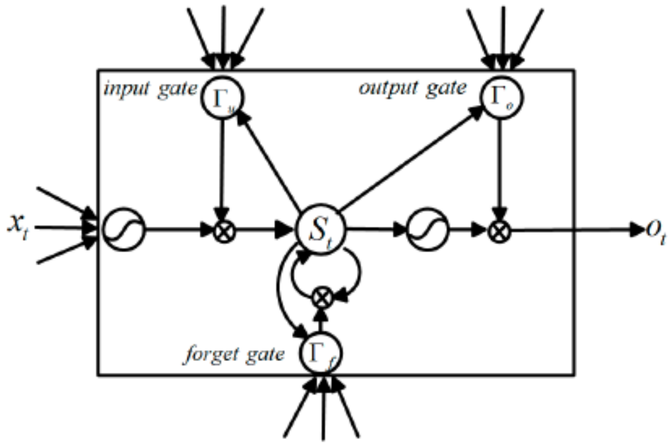

FIGURE VI. BASIC LONG SHORT-TERM MEMORY STRUCTURE [35]

The LSTM manipulates the input time series by recursively passing a transfer function and adding an input gate (Gu), a forgetting gate (Gf), and an exit gate (Go) to store valuable information for them. The gateway causes the hidden layer information to be updated, while the forgetting gateway determines if the updated information contains the latest information. The output gateway determines which data segment is selected. Finally, the formula for updating status and cell parameters is as follows:

$$\Gamma_f = \sigma\big(\mathcal{W}_f[o_{t-1}, x_t] + b_f\big) \quad (5)$$

$$\Gamma_f = \sigma(\mathcal{W}_i[o_{t-1}, x_t] + b_i) \quad (6)$$

$$\Gamma_f = \sigma(\mathcal{W}_o[o_{t-1}, x_t] + b_o) \quad (7)$$

$$\tilde{S}_t = tanh(\mathcal{W}_s[o_{t-1}, x_t] + b_s) \quad (8)$$

$$S_t = \Gamma_i * \tilde{S}_t + \Gamma_f * S_{t-1} \quad (9)$$

Where ot-1 is the output at t-1 time slot, and xt is the input at the current moment, St is the new candidate values, and St is the memory from the current block, St-1 is the memory from the previous block, w is the weights, b is the bias, and symbol * is the element-wise multiplier. σ is another activation function as follows:

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (10)$$

c) Gated Recurrent Units (GRU)

The Gated Recurrent Unit (GRU) is an efficient and functional variant of the LSTM. This makes the structure simpler while maintaining the introduced LSTM effect [35]. The GRU combines the input gate and the forget gate of LSTM into an update gate *Γ*u-1, and the output gate in LSTM is named a reset gate (*Γ*r-1) in GRU. *Γ*u-1 determines how to combine the new input with the previous memory, and *Γ*r-1 determines how much of the previous memory can pass through. Figure 7 shows the GRU model structure.

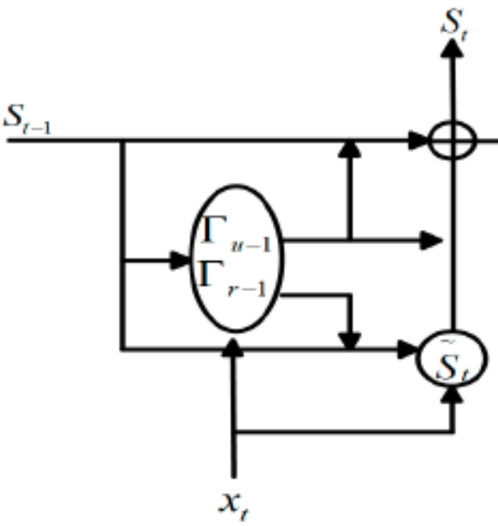

FIGURE VII. GRU MODEL STRUCTURE [37]

The formulation for updating the cell states of gated recurrent unit and parameters as follows:

$$\Gamma_{r-1} = \sigma(\mathcal{W}_{r-1}[S_{t-1}, x_t] + b_{r-1}) \quad (11)$$

$$\Gamma_{u-1} = \sigma(\mathcal{W}_{u-1}[S_{t-1}, x_t] + b_{u-1}) \quad (12)$$

$$\tilde{S}_t = tanh(\mathcal{W}_s[\Gamma_{r-1} * S_{t-1}, x_t] + b_s) \quad (13)$$

$$S_t = (1 - \Gamma_{u-1}) * S_{t-1} + \Gamma_{u-1} * \tilde{S}_t \quad (14)$$

$$\hat{y}_t = \sigma(\mathcal{W}_o S_t) \quad (15)$$

The symbols share the same meaning as Long Short-Term Memory except for *Γ*u-1 and *Γ*r-1 GRU has fewer parameters and thereby benefit from a faster training speed than LSTM.

d) Results and discussions

This section evaluates the proposed approach on multiple case studies and demonstrates its effectiveness by simulation analysis. The processed data was fed into tree deep learning models for comparison and performance evaluation. All training processes for EV charging duration prediction were implemented in a desktop PC with 8.0 GHz Intel I5 and 64GB memory. The Keras library runs all python codes with TensorFlow backend [38].

First, we measure the accuracy and the effectiveness of the models using the Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The reason behind using this four metrics is that we will be able to deduce how well the models can predict the future with more confidence. The equation of this metrics is given as follows:

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(A_j - F_j)^2 \quad (16)$$

$$RMSE = \sqrt{\left(\frac{1}{N}\right)\sum_{j=1}^{N}(A_j - F_j)^2} \quad (17)$$

$$MAE = \frac{\sum_{j=1}^{N}|A_j - F_j|}{N} \quad (19)$$

Generally, lower scores of RMSE, MAE and SMAPE indicate accurate predictions, and this occurs when the predicted value, Fj is very close to the actual value Aj.

TABLE II. PERFORMANCE COMPARISON OF DEEP LEARNING-BASED METHODS. MSE: MEAN SQUARED ERROR, RMSE: ROOT MEAN SQUARED ERROR AND MAE: NORMALIZED MEAN ABSOLUTE ERROR, RNN: RECURRENT NEURAL NETWORKS, LSTM: LONG SHORT-TERM MEMORY; GRU: GATED RECURRENT UNITS.

Model	MSE (%)	RMSE (%)	MAE (%)
RNN	6.981	2.642	2.570
LSTM	1.523	1.234	1.130
GRU	0.474	0.688	0.686

The tree models' actual values and predicted values are given in Figures 8-10. Figure 8 shows more gaps between predicted values and charging duration in min in the RNN, indicating that the prediction is clustered around certain values for high predicted charging duration sessions. These values are the average duration of the small number of users charged for long times, indicating this mothed does not predict far from the user means.

In Figure 9, the LSTM regression model had a mean squared error of 1.523%. This shows that the accuracy of the LSTM model is extremely high compared to the RNN model. LSTM shows potential for providing the best results for the regression problem. It is seen that the real and predicted values are significantly close, and the model can provide accurate results following the trend shown by the real values.

Figure 10 illustrates the results using the GRU model, Gated Recurrent Unit has the best performance with a mean squared error of 0.474%. The predicted and observed values are too close compared to RNN and LSTM. The high accuracy obtained by the GRU model is explained by its ability to detect time series and time-dependent patterns, which are inherent in the used dataset.

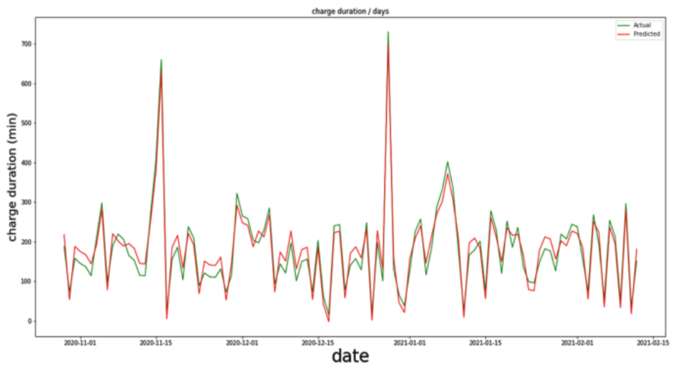

FIGURE VIII. OBSERVED AND PREDICTED CHARGING TIME RESULTS WITH RNN

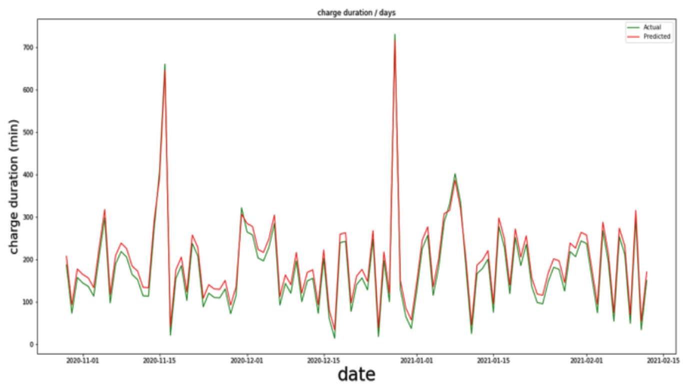

FIGURE IX. OBSERVED AND PREDICTED CHARGING TIME RESULTS WITH LSTM

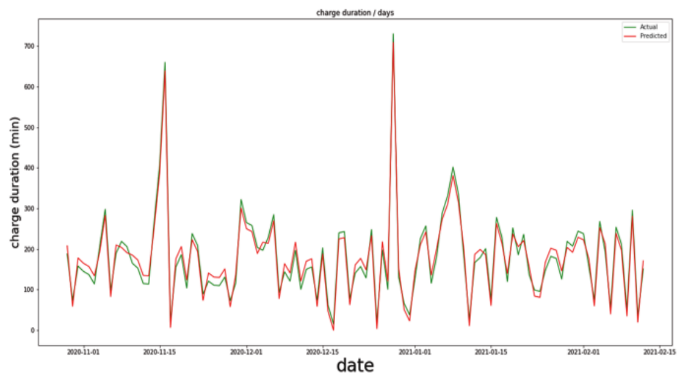

FIGURE X. OBSERVED AND PREDICTED CHARGING TIME RESULTS WITH GRU

Results show that the deep learning model effectively predicts the PEV charging time and provides an accurate prediction curve for dynamic grid planning. The rapid and mass adoption of PEVs at various levels of the Moroccan power grid provides significant economic and social benefits by accurately predicting PEV charging times. The proposed deep learning model is an important tool paving the way for widespread adoption of integrated PEVs in energy systems and represents a competitive demonstration of artificial intelligence in low-carbon energy systems in the regulated electricity market.

IV. CONCLUSION

In this paper, we conducted a case study of the Moroccan electricity market and we have used tree deep learning models to predict the charging duration of a public charging station. Analysis of the results shows that the tree pattern is found to be valid in the dataset. GRU (Gated Recurrent Unit) model performs better than other models. This work will serve as a decision-making tool for authorities responsible for electricity regulation and for public utility companies in Morocco. Nonetheless, this work has provided highly accurate results that will enable medium and short-term planning of energy systems and charging infrastructures deployment in this type of market. This will also facilitate the creation of additional public charging stations, increase the popularity of electric vehicles, and rise the social awareness about the importance of electric vehicles as well as reduce the maintenance and optimize the operation of public charging stations.

New deep learning models are promising to improve prediction speed and forecasting accuracy. An extension to this work can be done by analyzing the impact of uncoordinated charging. Therefore, smart charging algorithms that prevent such problems will become necessary as uptake of EVs increases and they become more popular. Smart charging offers the potential for electric vehicles (EVs) to use renewable energy more efficiently, lowering costs and improving the electricity grid's stability. Our future research focuses on implementing a smart charging methodology for economical electric vehicle charging and guarantees grid stability based on an innovative deep learning model.

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