Contextual prediction of electric vehicles charging using transfer learning

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***Abstract*—This study explores the use of transfer learning (TL) to improve electricity consumption forecasting for electric vehicle (EV) charging stations, particularly when faced with limited data and varying contextual factors. The main objective is to assess whether transfer learning can enhance forecasting accuracy for weekend predictions by leveraging knowledge from weekday data. Traditional models, including AutoRegressive Integrated Moving Average (ARIMA), Random Forest (RF), Gradient Boosting Machines (GBM), and Long Short-Term Memory (LSTM), were employed, with TL integrated to transfer insights from larger datasets to smaller ones. The results demonstrate that TL enhances weekend forecast accuracy by mitigating data irregularities through the application of knowledge gained from weekday data. The research underscores the potential of TL and machine learning in enhancing energy management for EV charging stations, contributing to more effective power system planning and operation in the context of the global energy transition including electric mobility.**

***Index Terms*—Charging Stations; Contextual Learning; Electric Vehicle; Electricity Consumption; Forecast; Transfer Learning**

I. Introduction

A. Motivation

In recent years, sustainability has emerged as a central focus across various sectors, particularly energy production and transportation, which are two of the main contributors to greenhouse gas emissions [1]. As the global community intensifies efforts to reduce emissions, electricity has become an increasingly vital energy source, driven by the ongoing shift toward renewable energy sources (RES) and greener technologies. The growing adoption of electric vehicles (EVs) exemplifies this transition, reflecting a commitment to global sustainability goals [2], [3]. However, the growing demand for electricity from sectors like transportation, along with traditional sectors, intensifies the need for advanced energy infrastructure and management systems [4]. This transformation is essential not only for ensuring a sustainable future but also for maintaining reliable energy systems that can meet future demand.

This dynamic landscape calls for advanced forecasting algorithms capable of accurately predicting power demand and production to optimize power grid operation, reduce energy waste (renewables curtailment), and enhance overall sustainability [4]. These forecasting techniques are critical in addressing the unique demands of EV charging infrastructure, where inconsistent patterns and varying consumption levels can present challenges. The need for forecasting, however, extends beyond the energy sector, impacting domains like healthcare for early diagnosis [5], finance for risk assessment and stock prediction [6], and city management for predicting traffic [7] and preparing for natural disasters [8]. In each case, forecasting tools empower decision-makers to optimize resources and improve quality of life.

Most forecasting algorithms rely on Machine Learning (ML) and statistical techniques and are adept at handling a wide range of scenarios. Yet, these methods often struggle in settings with limited data, leading to decreased forecast accuracy [9]. Additionally, as energy forecasting increasingly incorporates contextual and behavioral data, the need for algorithms that can adapt to varied, dynamic data inputs grows. To address these challenges, Transfer Learning (TL) has emerged as a promising complement. By leveraging pre-trained models, TL adapts learned insights to new scenarios, offering a robust solution when historical data is sparse. This approach is particularly relevant to EV infrastructure forecasting, where TL can help bridge data gaps and support the sustainable growth of electricity demand [10].

B. Use of Transfer Learning - Overview

The study presented in [11], based on [12], findings highlight that 90% of the top nine algorithms employed in electricity forecasting are AI-based, with Artificial Neural Networks (ANN) representing 28% of the AI models, predominantly used in Short-Term Load Forecasting (STLF). STLF is chosen

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due to its ability to handle intricate electrical energy consumption patterns compared to Long-Term Load Forecasting (LTLF). Traditional ARIMA models accounted for 17.5% , showcasing efficiency in LTLF, where load fluctuations and periodicity are less critical. Notably, a significant proportion of regression models are utilized for LTLF prediction. Furthermore, the study reveals the growing popularity of Support Vector Machines (SVM), Particle Swarm Optimization (PSO), and fuzzy logic in recent research, indicating increased attention from researchers towards these algorithms for Electricity Demand (ED) forecasting. This reflects a broader trend of applying artifitial intelligence (AI) across various economic sectors to enhance efficiency and profitability.

When implementing TL in electricity consumption forecasting, the primary models identified are predominantly ANNs. ANNs are a type of ML model that is inspired by the structure and function of the human brain. They are composed of layers of interconnected nodes, or neurons, that can learn to perform complex tasks by processing data. The ANN can model a complex non-linear problem without prior assumptions of the nature of the relationship using unsupervised training. This ANNs can be categorized in 4 different types: Deep Neural Network (DNN), Convolutional Neural Network (CNN), Feed-Forward Neural Network (FNN) and Recurrent Neural Network (RNN), all of which have been identified in studies on electricity consumption forecasting. DNN uses multiple hidden layers and a full connection between each layer and has been used on the article [13] to ensure better modeling of the non-linear problem and avoid the local optima problem.

C. Contributions

The main contribution of the present are:

- Propose TL methodologies introducing factors obtained from weekdays dataset (large dataset) in weekends dataset (small dataset).
- Compare the performance of the TL methodologies in different forecasting algoritms
- Assessment of the performance of the methods in a dataset of real charging stations.

D. Paper Organization

Following this section, Section II introduces the proposed TL methodology and its implementation in various forecasting algorithms. Section III presents the main results obtained by these algorithms when applied to a real charging station. Finally, Section IV highlights the key contributions of the work presented in this paper.

II. Federated Model applied to charging stations power demand forecast

This section presents the proposed FL methodology applied to forecasting the power demand of EV charging stations. It begins with a detailed description of the selected forecasting models, the evaluation metrics employed, and the implementation of transfer learning techniques within each forecasting method. The section concludes with an in-depth examination of the dataset, including its contents and any modifications made.

A. TL model

For the forecast, four methods are proposed for implementation: a statistical method, ARIMA; a neural network, LSTM; an ensemble learning method, RF; and a ML technique, GBM. The decision behind this choice was based on section I-B, since statistical methods, ANNs, Ensemble and ML techniques are the most used and effective algorithms in the universe of electricity forecast.

The ARIMA algorithm is a powerful method for time series forecasting. It combines AutoRegressive (AR), Integrated (I), and Moving Average (MA) components to model the underlying patterns in sequential data. The AR component captures past observations' influence, the 'I' component ensures stationarity by differencing, and the MA component accounts for the error term from a moving average of past observations. The model's parameters are fine-tuned to minimize the difference between predicted and observed values, making ARIMA effective for forecasting based on historical trends and patterns in time series data [14]. Mathematically, ARIMA can be written as:

$$y_t = c + \sum_{i=1}^{p} \phi_i \cdot y_{t-i} + \sum_{j=1}^{q} \theta_j \cdot \epsilon_{t-j} + \epsilon_t \tag{1}$$

where:

- y_t is the predicted value at the time t
- c is a constant,
- ϕ_i are the autoregressive coefficients,
- θ_j are the moving average coefficients,
- ϵ_t is the error term at time t.

LSTM is a type of RNN architecture designed to address the challenge of capturing long-range dependencies in sequential data. LSTM introduces memory cells that can store and retrieve information over extended sequences, facilitating the modeling of intricate temporal patterns. The key innovation lies in the incorporation of gating mechanisms, including input, forget, and output gates. These gates regulate the flow of information, allowing LSTM to selectively update and use the contents of the memory cell. This architectural design overcomes the vanishing gradient problem associated with traditional RNNs, enabling LSTM to effectively learn and retain complex temporal dependencies, making them particularly well-suited for time series forecasting and other tasks involving sequential data analysis [15]. Mathematically, the LSTM cell at time t can be expressed as:

1. Forget Gate (f_t): controls what information from the previous cell state (C_{t-1}) should be discarded.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$

where:

- σ is the sigmoid function,
- h_{t-1} is he hidden state from the previous timestep,
- x_t is the input at time t,

- W_f and b_f are the weight and bias for the forget gate.

2. Input Gate (i_t) and Candidate Cell State (C'_t): Controls what new information will be stored in the cell.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

$$C'_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{4}$$

3. Cell State Update: The new cell state C_t is updated based on the forget gate and input gate.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot C'_t \tag{5}$$

4. Output Gate (o_t) and Hidden State (h_t): Controls what part of the cell state is passed to the output.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

$$h_t = o_t \cdot tanh(C_t) \tag{7}$$

RF for forecasting involves preparing time series data, selecting relevant features, training the model, tuning hyper-parameters for optimal performance, and evaluating the model using appropriate metrics. The algorithm builds multiple decision trees and combines their predictions to make accurate forecasts. Hyper-parameter tuning is crucial for optimizing the RF model, and the final step involves using the trained model to make predictions on future data points [16]. The mathematical representation of RF is as follows:

The prediction y_t in RF is the average prediction across multiple decision trees $h_i(X)$, where X is the input data:

$$y_t = \frac{1}{N} \sum_{i=1}^{N} h_i(X) \tag{8}$$

where N is the number of decision trees in the forest, and $h_i(X)$ represents the prediction made by the i-th tree.

Similar to RF, GBM is also a powerful ML technique that can be used for forecasting [17], where the core idea of GBM is to improve the predictions of y by iteratively adding new decision trees $h_m(X)$ that focus on the residuals (errors) of the previous model. This methodology also involves preparing the data, identifying relevant features, selecting a GBM algorithm, training the model, tuning hyper-parameters, making predictions, evaluating performance, refining the model, and forecasting. GBM are effective for handling complex relationships and providing accurate predictions [18]. And mathematically, the prediction after m iterations can be described as follow:

$$y_m = y_{m-1} + \alpha h_m(X) \tag{9}$$

where α is a learning rate that controls the contribution of each tree, and $h_m(X)$ is the decision tree trained on the residuals.

Each model underwent extensive hyperparameter tuning and cross-validation across different chargers and datasets to ensure optimal forecast accuracy under various conditions. This rigorous approach aimed to achieve the best possible forecasting results for each charger across different scenarios.

1) Evaluation of the Methods: To evaluate the models, two metrics were consistently used: RMSE and MAE.

The evaluation was conducted for forecasting one day ahead, provided there was at least one instance of charger connection during that day. If additional time was necessary to observe charger activity, the evaluation was extended to two or more days ahead, until charging activity was verified.

2) TL Methods: After the implementation of forecast models and further evaluation, TL techniques are implemented across the different models, use cases, and scenarios to assess their potential in enhancing the performance of standard models.

In this approach, a model is trained using a data-rich dataset, and the trained model is then applied to a data-poor dataset [13]. Typically, the training dataset comes from a different source than the original dataset. However, as noted earlier, this exact scenario is not always feasible for every use case. Therefore, the TL technique was customized for each model, taking into account their unique architectures and principles.

To describe each TL technique more clearly, we can consider two charging stations: station a, which transfers knowledge, and station b, which receives and applies this knowledge to improve predictions. Both stations are divided into equally sized training and testing sets before the methods are applied.

In ARIMA, both datasets, from a and b are combined in just one dataset and an initial model ARIMA model is trained with this combined data and using the hyperparameters from a. Afterwards, we fine tune the model on charger b with the same hyperparameters and then we make the predictions for station b.

ARIMA posed the most challenges in applying TL techniques due to its fundamental architecture and methodology, which typically relies on historical time series data rather than direct knowledge transfer from other sources.

In RF, an initial model is trained based on the data from station a and with its hyperparameters. Subsequently, this model is employed to make predictions for charging station b, and these predictions are saved as new feature.

Next, a new model is trained based now on the data from station b , incorporating the new feature, which represents the predictions made by the model from station a. This enhanced model is then used to forecast the charging station b electricity consumption.

For GBM, an initial model is trained using the data and hyperparameters from station a. Subsequently, a new model is trained with the data from charging station b, initialized with the weights and structure of the previously trained model.

This approach allows the new model to leverage the knowledge acquired by the initial model, enhancing the forecast accuracy for charging station b.

In LSTM, the data from both charging stations a and b are reorganized to fit the expected input format of the LSTM model, where each sample is represented as a sequence of timestamps with multiple features.

First, an initial model is trained using the data and hyperparameters from station a over 100 epochs, and this model is saved for later use.

Next, the saved model is loaded and fine-tuned with data from charging station b for an additional 20 epochs, enhancing the forecast accuracy for electricity consumption at station b.

For all methods, the dataset was pre-divided into training and testing sets based on the forecasted time period.

B. Data

The dataset concerns to a single EV station located in Azores, Portugal, obtained under the project EV4EU, with data spanning from November 1, 2020, to November 28, 2022. This data, collected at 15- minute intervals, is organized in a time series format, providing two years' worth of information. The time series format is ideal for forecasting electricity consumption, and the 15-minute intervals are well-suited for making day-ahead, month-ahead, or year-ahead forecasts. The initial features of the dataset included Break Info, Date and Hour, Active Power Consumption [kW], Reactive Inductive Power [kvar], and Reactive Capacitive Power [kvar]. An example of the data for weekdays and weekends is presented in Figure 1 and Figure 2, respectively.

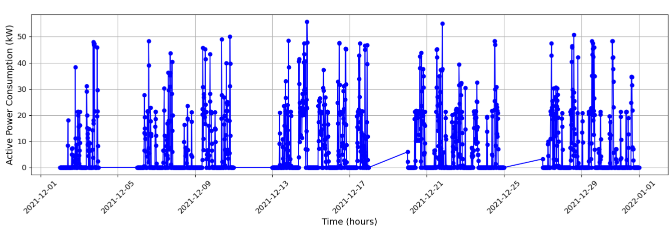

Fig. 1. Weekdays Dataset of Azores for the month of December

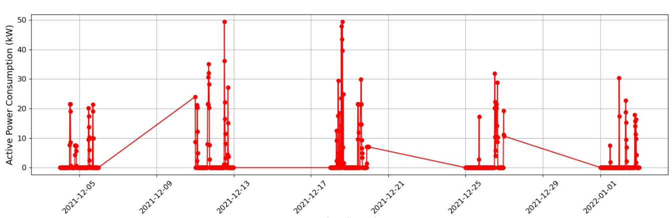

Fig. 2. Weekends Dataset of Azores for the month of December

The primary goal was to determine the final target for forecasting and identify which features were relevant. The target feature for forecasting is Active Power Consumption [kW]. Although, Reactive Inductive Power [kvar] and Reactive Capacitive Power [kvar] are not the primary targets for forecasting electricity consumption at an EV station, they were retained for further analysis as they could be relevant for the forecast models.

The Date and Hour feature, while no longer considered a feature, serves as the index for the dataset, indicating the time period. The Break Info feature, which was initially included to record the maximum, average, and minimum power consumption values, was considered neither useful nor meaningful in this context and was therefore removed from the dataset. Next, the dataset was examined for missing values, which were deleted as necessary. Potential outliers, consumption patterns, and irregularities in data collection were also analyzed. And three possible irregularities were identified, all occurring during the same time intervals. These irregularities corresponded to periods when the charger was either off for extended durations or exhibited constant consumption over a long period. These patterns were unusual compared to the overall dataset, with average values during these periods being significantly lower than those of corresponding periods in other parts of the dataset.

To address these irregularities, two versions of the dataset were created: one that retained the irregularities in Feature Active Power Consumption (kW) with no correction of irregularities and another that corrected them in feature Active Power Consumption (kW) with correction of irregularities. The correction involved replacing the irregular periods with data from the same time periods in different years, where no irregularities were observed. This approach allowed for an analysis of how these irregularities might influence the forecast values.

Given that only two potentially relevant features are available for inclusion in the forecast model, this is insufficient to create a robust method or perform effective feature selection. Therefore, additional relevant features were added to the dataset: weekends, weekdays, month, hour, and holidays. Additionally, was included another new feature, the Active Power Consumption for the day ahead (kW), which is actually the accurate forecast target. And the previously mentioned feature, Active Power Consumption (kW), was retained not as the forecast target but as a regular feature to enhance the forecast model's accuracy. Additionally, the feature ON/OFF was also included based on observed patterns during random days and weeks, indicating periods when the charger was consistently connected or disconnected.

III. Results

This section provides a detailed description of the forecasting scenario, along with the results obtained both with and without the implementation of transfer learning techniques.

A. Scenario description

Given that there is only one charging station, it is not feasible to distinguish between charging stations a and b as separate entities. Instead, it was decided to evaluate the effects of TL by dividing the dataset into weekdays and weekends. The primary assumption is that forecasting accuracy for weekends, which has less data, would benefit from the information gathered during weekdays. In this scenario, data collected on weekdays is designated as a, while data collected on weekends is designated as b.

B. Results

As the decision was made to apply TL techniques to enhance the accuracy of weekend forecasts by leveraging knowledge from weekday data, the results of the traditional forecast for both weekdays and weekends are presented in Table I and Table II, respectively.

TABLE I
WEEKDAYS DAY-AHEAD FORECAST USING THE FULL DATASET

	ARIMA	RF	GBM	LSTM
RMSE	12.20	11.47	11.36	11.58
MAE	9.48	7.37	7.31	7.24

TABLE II
WEEKENDS DAY-AHEAD FORECAST USING THE FULL DATASET

	ARIMA	RF	GBM	LSTM
RMSE	13.48	12.85	12.89	12.59
MAE	9.00	7.69	7.72	7.75

Tables II and I reveal that the forecasts for weekdays are slightly better than those for weekends. This aligns with expectations and indicates that applying TL techniques could be beneficial, as weekends have less data, which may contribute to more accurate forecasts when addressed effectively.

Given that weekend forecasts are less accurate compared to weekdays, the TL methods described in II-A2 were implemented to enhance these results. The results of these improvements are presented in Table III:

TABLE III
WEEKENDS DAY-AHEAD FORECAST USING THE FULL DATASET WITH THE APPLICATION OF TL TECHNIQUES

	ARIMA	RF	GBM	LSTM
RMSE	13.43	12.70	12.79	12.72
MAE	10.08	7.53	7.62	7.64

Comparing Tables II and III, it is possible to observe a slight improvement in the results mainly in RF and GBM. Nevertheless, in LSTM, the improvement was only verified in MAE with a small increase on RMSE of 0.13 p.p. The obtained results show that generally, TL can improve the accuracy of the methods but this increase is not very significant.

IV. CONCLUSIONS

The first notable insight from the case of a single charger in the Azores is that identifying and correcting irregularities in consumption patterns, based on prior observations of "normal" consumption, can significantly improve the accuracy of traditional forecasts. Therefore, an essential step to improve forecast performance is to check for and address any evident irregularities by leveraging historical consumption data from similar periods.

Additionally, it was observed that, among traditional forecasting methods, the LSTM model consistently outperformed others. This superior performance is likely due to LSTM's robustness and its ability to handle irregularities and complex consumption patterns more effectively.

Finally, the use of TL improved the performance of all the forecasting methods, though the significance of the improvements was limited. It is important to note that predicting the power demand of EV charging stations is a complex task due to the challenges in identifying charging patterns.

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