Forecasting Needs for Improving Grid Resilience in Shore Power Infrastructures

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Abstract

Energy transition is a major goal for humanity to mitigate climate change. Transportation is one of the sectors that should contribute the most to the reduction of greenhouse gas emissions. Shore Side Energy is proposed as one of the main approaches to reduce the emissions of vessels when they are docked. Nevertheless, several improvements should be made in ports to achieve optimal management of energy, considering the needs of vessels. To achieve this goal, accurate forecasting tools need to be used. In the present paper, a forecasting framework to be used in ports is described, and some results are presented. The proposed framework will be used in a European project, Shift2DC.

1. INTRODUCTION

In the European Union, maritime transport was responsible for the emission of 124.3 million tonnes of CO2 in 2021 [1]. In July 2023, the International Maritime Organization (IMO) defined new targets for reducing greenhouse gas (GHG) emissions in maritime transportation, formulating and adopting a set of measures by 2025 to achieve these reduction targets [2]. According to the FuelEU Maritime regulation [3], by 2030, container and passenger ships (including cruise ships) with a gross tonnage equal to or exceeding 5,000 must utilize shore power connections when docked at major EU ports designated within the trans-European transport network (TEN-T) [4].

In the Shift2DC project[1], a digital twin of the Port of Madeira will be developed, allowing the assessment of the impact of shore power on the global energy system of Madeira Island. The proposed architecture includes several layers, from data acquisition, consumption monitoring, and cruise power consumption monitoring to DC grid simulation, intelligent control strategies, and AI tools. Beyond the implemented framework, several scenarios will be tested, considering the global management of the port, the possibility of providing grid services supporting the system operator, the possibility of operating the port as a microgrid, and finally, the development of a scenario where the port is considered an energy hub with multiple energy vectors. In all the proposed scenarios, grid reliability will be taken into account.

All the mentioned scenarios will be tested, considering the use of alternating current (AC) grids and the assessment of using direct current (DC) grids. The use of DC distribution grid solutions in ports can bring several advantages to improve both flexibility and energy efficiency. There are numerous applications in ports where DC systems can offer various advantages. One of the most important points in ports is that the ships can operate at 50 Hz, 60 Hz, or in DC. This means that several levels of conversion will be required. Considering the installation of photovoltaic (PV) and battery storage systems in the port, the DC solution is seen as an interesting alternative.

The use of DC systems in ports can significantly enhance port operation efficiency by eliminating conversion losses between AC and DC. DC grids should primarily be used to connect shore-side power, batteries, charging stations, and PV systems. However, some loads can also operate directly on DC.

In the present paper, forecasting needs to simulate the ports are described. The main challenge can be the forecasting of the power needs of the ships that will be docked in the Port. Afterwards, some results obtained from the proposed forecasting framework are presented. Beyond the need to forecast the power demand of the ports and the PV generation, it is important to forecast the power consumption of the ships. Considering the characteristics of the Port of Madeira, most of the ships are large cruise ships that are docked for an average period of 12 hours. To develop the power consumption forecast for these ships, a transfer learning methodology has been developed, considering the behavior of previous cruises and some features of the cruises that will be docked in the port the following day.

2. FORECASTING FRAMEWORK

The forecasting framework for the Shift2DC project involves several crucial steps to ensure accurate and reliable predictions of power demand and generation.

[1] https://shift2dc.eu/

This framework encompasses data acquisition, preprocessing, feature engineering, feature selection, forecasting methods, and validation.

2.1. Data Acquisition

Data acquisition is the foundational step of the forecasting process. In the Shift2DC project, data will be collected from various sources, including historical power consumption of ships, PV generation data from installed systems, and environmental factors such as weather data. This data is sourced from sensors, smart meters, and external open-source datasets, ensuring comprehensive coverage of all variables influencing the energy dynamics at the port.

2.2. Pre-processing

The raw data obtained through acquisition often contains noise, missing values, and inconsistencies. The preprocessing will include data cleaning, handling missing values through imputation techniques, and normalizing data to a common scale. This ensures the data is in a suitable format for further analysis and modeling.

2.3. Feature Engineering and Selection

Feature engineering involves creating new features from the existing data to improve the performance of forecasting models. In the context of the port's energy system, relevant features might include date-time features like the hour, day of the week, or season, ship characteristics, and historical power usage patterns (lag features). These features are crafted to capture the underlying patterns and relationships in the data.

Afterwards, it is needed to identifying the most relevant features that contribute to forecasting accuracy (Feature selection). Techniques such as correlation analysis and feature importance scores from tree-based models will be employed to select the number and subset of features that provide the best performance in forecasting.

2.4. Forecasting Methods

Various forecasting methods will be implemented to predict power consumption and generation. The project utilizes traditional machine learning algorithms such as Random Forest and XGBoost, as well as advanced neural network architectures. Transfer learning is employed to enhance the model's ability to generalize from one domain to another, leveraging knowledge from previous cruise ships' power consumption patterns.

2.5. Transfer Learning

Transfer learning is particularly useful in scenarios where the target data is limited [5]. By using a pre-trained model on a related task, it is possible to transfer learned features to improve the forecasting of power consumption for new ships docking at the port. This approach significantly enhances prediction accuracy by leveraging the behavioral patterns of previously docked ships.

2.6. Validation

Model validation is crucial to ensure the reliability of the forecasting models. Cross-validation techniques, such as k-fold validation, will be used to assess the model's performance. Metrics like Mean Absolute Error (MAE) and Normalized Root Mean Square Error (RMSE) will be calculated to evaluate the accuracy of the predictions.

3. FORECASTING NEEDS FOR SHORE POWER INFRASTRUCTURES

Forecasting needs in ports can be divided into electric power consumption and electric power generation. Concerning power consumption, it is possible to split it into three main categories: the power consumption of buildings, the power consumption of electric vehicles, and the power consumption of boats. Power generation will depend on the type of technology installed in the ports. Finally, considering the impact of ports on the global power systems, it can be interesting to estimate the global power profiles of the ports. A short description of each type of forecasting is presented in the following subsections.

3.1. Port Power Consumption

Ports can present different organizations depending on the type and size of vessels that will be docked. One of the main challenges is the lack of monitoring systems allowing the use of historical data. In the SHIFT2DC project, all the distribution boards in Madeira Port will be monitored through the use of smart meters. Alongside a detailed characterization of the loads installed in each distribution board, it will be possible to create a historical dataset and to estimate the available flexibility in each board.

3.2. Electric Vehicles Consumption

Beyond the 'natural' power consumption of the buildings, electric vehicles (EVs) can have a significant impact on the consumption profiles of ports in the near future. EVs exhibit specific behavior, primarily depending on the power installed in each charging station. Another interesting characteristic of EVs is their capability to provide flexibility to the system, which is greater if vehicle-to-grid technology is available [6].

3.3. Ships

Finally, it is important to consider the forecasting of the power demand of ships. Depending on the type of ports and vessels, the power consumption of a ship can vary greatly [7]. For example, when ports are used for electric ferries, the power consumption will depend on the ferry scheduling. In such cases, high accuracy in the forecasting process is expected due to the predictable nature of ferry operations. On the other hand, ports used for cruises may face challenges due to varying ship sizes, technical characteristics, and passenger numbers, even for the same cruise line. To address these challenges, innovative methods based on transfer learning and federated learning will be tested.

3.4. Electric Power Generation in Ports

The main aim of a port is not only to supply energy to vessels but mainly to provide green energy. This means that the port should have (or buy) electricity generated through renewable technologies such as photovoltaic or wind generators. In both cases, forecasting will be used based on several features, mainly related to historical data and weather forecast data. The accuracy of forecasting is typically higher for photovoltaic systems.

3.5. Port Power Demand Profiles

The estimation of global power demand profiles will be critical not only for the operators of the port but mainly for the system operators. These profiles will integrate all the other forecast results but also intelligent scheduling algorithms that will be used to take advantage of the existing flexibility in the port. This flexibility can be provided by different loads, as already mentioned, but also by energy storage systems such as batteries or boilers.

4. RESULTS

To provide an initial overview of the forecasting framework and implementation, a preliminary study on PV power production forecasting was conducted for a residential house in Madeira. This initial effort demonstrates some of the steps and methodologies that will be applied to the port's energy system once specific data have been collected.

The available data for the analyzed house includes power consumption records spanning two and a half years (2019-2021). In addition to power consumption data, weather data including temperature, Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI), etc., was obtained for the same period based on the house's coordinates.

For feature engineering, date time features such as hour, day of the week, month, and season and lag features (past values of power) for one day, seven days (week), and 30 days (month) were extracted.

Figure 1 present the Pearson correlation obtained for each feature. After feature selection, the final set of features used for the forecasting include the radiation features, the three lag features and the hour.

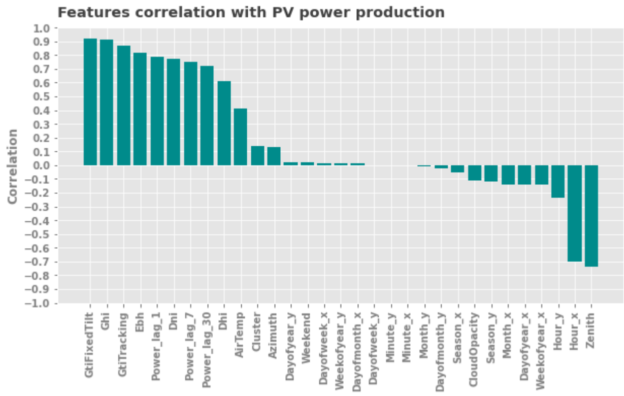

Figure 1: Feature correlation with PV power production

For training and testing the models, the data was split into training and testing sets. Since the forecast horizon defined corresponds to the day ahead, the training set consists of data from 2019 up to January 13, 2021, while the testing set includes the data for January 14, 2021. This split ensures that the models are trained on historical data and evaluated on future data, mimicking real-world forecasting scenarios. Figure 2 shows the time series of PV power production in the residential house, and illustrates the train and test split used in this case.

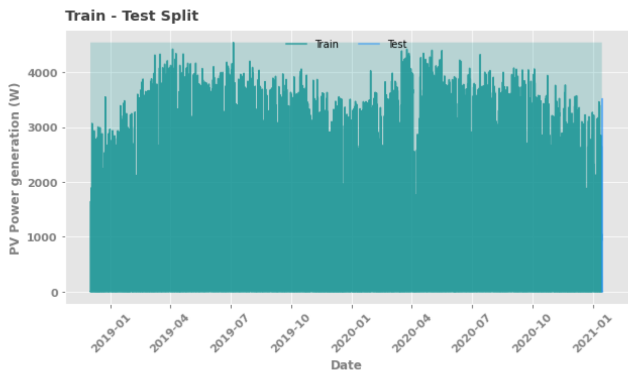

Figure 2: Train and Test Split for PV Power Forecasting

Two machine learning methods were implemented to predict the PV power production: Random Forest (RF) and XGBoost. The models were evaluated using Mean Absolute Error (MAE) and Normalized Root Mean Square Error (NRMSE). The results obtained indicate that XGBoost outperformed Random Forest in both MAE and NRMSE metrics, in fact XGBoost achieved a MAE of 108.09 W and an NRMSE of 5.91%, while Random Forest achieved a MAE of 116.50 W and an NRMSE of 6.88%.

Figure 3 and Figure 4 present the comparison between the predictions (in blue) and the actual values (in red) achieved by Random Forest and XGBoost, respectively.

One possible reason for XGBoost's superior performance is its ability to handle complex relationships and

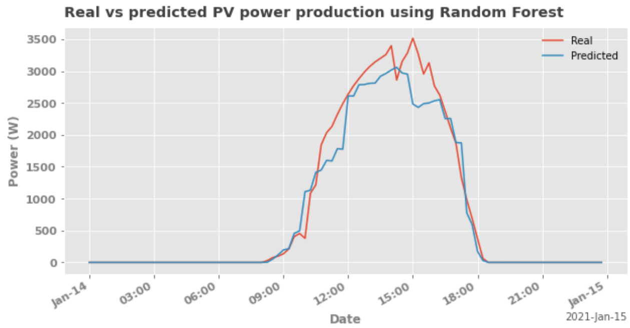

Figure 3: Predicted vs actual PV power generation for Random Forest

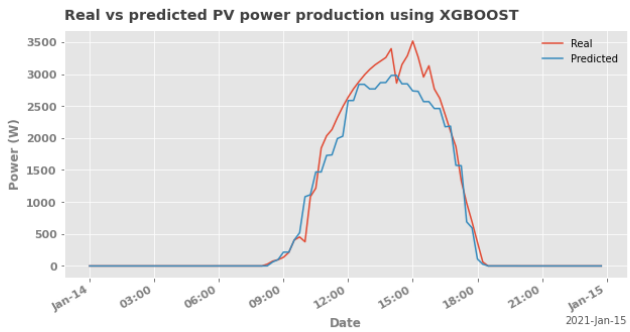

Figure 4: Predicted vs actual PV power generation for XGBoost

interactions between features through gradient boosting. This method incrementally builds an ensemble of trees, where each tree corrects the errors of the previous one. This can lead to better capture of non-linear patterns in the data, which is crucial for accurate PV power production forecasting. Random Forest, on the other hand, builds multiple decision trees independently and averages their results. While it is robust and effective for many applications, it might not capture intricate dependencies as well as XGBoost, leading to slightly higher prediction errors.

These initial results illustrate the effectiveness of the forecasting approach and provide a blueprint for the process that will be followed for the port's energy system. Once the specific data for the port is acquired, it will be implemented a similar methodology to forecast the power consumption of ships and overall energy demand at the port. The integration of different methods such as Random Forest, XGBoost, and neural networks will be evaluated, and their performance will be compared to determine the optimal forecasting method for the port's energy hub scenario.

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6. CONCLUSION

The present paper introduces a forecasting framework intended for use in ports. The main aim of this tool is to generate accurate information to enable better management of electric energy through optimal scheduling of the port's power resources. The proposed framework includes all components of machine learning, such as data acquisition, feature selection, forecasting, and validation. This process is applied independently for different forecasting needs. Subsequently, features and forecasting algorithms are selected based on the characteristics of each requirement. The final outcome of this process will be an accurate estimation of the global power demand of the port for the next hours/days.

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