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Power Factor Prediction in Three Phase Electrical Power Systems Using Machine Learning

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Abstract: The power factor in electrical power systems is of paramount importance because of the influence on the economic cost of energy consumption as well as the power quality requested by the grid. Low power factor affects both electrical consumers and suppliers due to an increase in current requirements for the installation, bigger sizing of industrial equipment, bigger conductor wiring that can sustain higher currents, and additional voltage regulators for the equipment. In this work, we present a technique for predicting power factor variations in three phase electrical power systems, using machine learning algorithms. The proposed model was developed and tested in medium voltage installations and was found to be fairly accurate thus representing a cost reduced approach for power quality monitoring. The model can be modified to predict the variation of the power factor, taking into account removable energy sources connected to the grid. This new way of analyzing the behavior of the power factor through prediction has the potential to facilitate decision-making by customers, reduce maintenance costs, reduce the probability of injecting disturbances into the network, and above all affords a reliable model of behavior without the need for real-time monitoring, which represents a potential cost reduction for the consumer.

Keywords: power factor; prediction; three phase systems; machine learning

1. Introduction

The economic growth of a country is closely related to its electrical energy consumption as depicted in Figure 1, where the relationship between the Gross Domestic Product (GDP) compared to the energy consumption of the countries belonging to the Organization for Economic Cooperation and Development is clearly visible. There is a clear correlation between these two variables [1]. However, this relationship is not always maintained when GDP decreases because, during a slowdown in the economy, power plants need to remain operational and this situation prevents electricity consumption from decreasing at the same rate as economic activity slows down.

The constant use of electricity is one of the main methods for economic development. A regular problem is the poor power quality in the supply network; this issue implies a large economic investment from the supplier side due to the need of high efficiency equipment, expensive devices for transitory events suppression inside the load center and through the general electricity system. It also causes an important economical investment from the user who is forced to hire highly qualified personnel to measure, identify, and provide an optimal solution to correct the potential problems that may arise due to a poor quality of electrical power. Electric power consumers are usually classified under three categories defined as residential, commercial and industrial. Additionally, the consumed power in any of the three categories mentioned above will vary according to electrical load type connected; the highly inductive loads as well as the nonlinear loads are the most important, as they are closely related to harmonic events in voltage and current as well as high losses in the efficiency and poor quality of electrical energy [2].

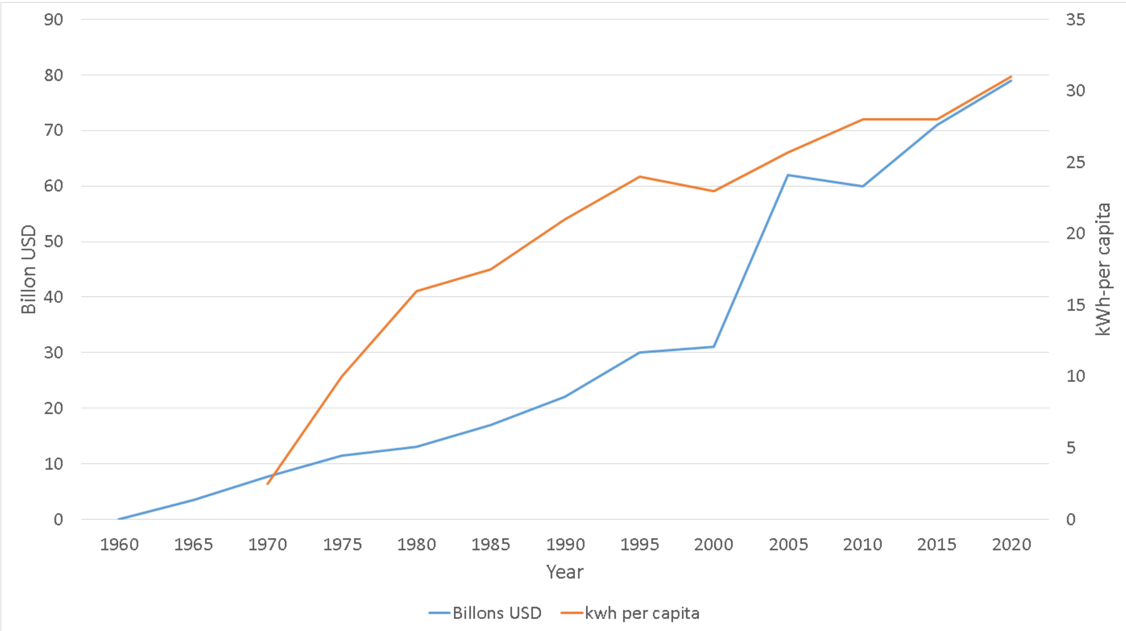


Figure 1. Total energy consumption vs. GDP for OCDE/AIE, adapted from Ref. [1].

One of the fundamental parameters to assess the quality of power in a load center along with harmonic content is the power factor (PF); this parameter indicates the efficiency in the use of supplied electrical power from the grid to the facility. Ideally, the PF should be equal to 1 and any deviation from this value implies loss of electrical power. The expression for calculating the PF is shown in Equation (1) describing the dependence of this parameter on the active power and the apparent power [3].

$$\text{PowerFactor} = \frac{\text{Total active power input (W)}}{\text{Total apparent power input (VA)}} \tag{1}$$

Having a low PF value [4,5] can cause numerous disadvantages like bigger sizing in industrial equipment, additional voltage regulators and larger conductor wiring to withstand higher currents to name a few. A low PF value therefore represents a higher economical cost for the user as much as for the supplier because it implies that consumed power from grid is very inefficiently converted in useful work (energy wastage). A low PF usually could have two different origins namely high harmonic content in current waveform or phase voltage-current shift, being by far the latest the most common. Therefore, in order to improve a low PF value, a power factor compensation (PFC) system is usually applied [6–8] consisting of an electrical circuit that supplies reactive power to the grid. Because of the voltage-current phase shift is caused by high inductive loads, a capacitor bank or power electronics converters (STATCOMs) are usually utilized to compensate and improve the PF. Operation of these PFC is based on the connection/disconnection of the PFC from the grid depending on real-time measurements of phase current and voltages waveforms. As a consequence, this implies an increased complexity and cost for the PFC system due to the need for a full sensor network required to monitor the phase currents, voltages, and powers. Indeed, in order to detect and eventually improve low PF values, it will be usually necessary to request at the supplier company the installation of smartmeters [9], which are devices capable of measuring and recording in real time the key parameters of electrical consumption as phase voltages and currents, consumed active and apparent power, power factor, harmonics content (THD), etc. From the consumer side, it can be necessary to use power quality analyzers for monitoring and recording in real time the PF [10] implying high economical costs.

Nevertheless, usually PF variations show a cyclical behavior as they are related to activation/deactivation of the inductive or non-linear loads. Thus, if these cyclic variations could be predicted on a daily, basis it could be very appealing, as no sensor network would be required for PF compensation and the number of recorded electrical variables it could be minimized. This minimization would simplify the monitoring procedure and reduce the investment cost for the consumer. Evidently, this alternative implemented by the consumer can prevent and correct present and potential failures in the electrical installation that also has important costs for the supplier.

The artificial intelligence (AI) could provide a valid option to solve issues concerning power quality and in particular about PF because in the past few years it has been widely documented its influence in multiple domains such as image processing [11], power electronics [12], medical [13], and many other domains.

Artificial intelligence can be classified into different disciplines as Computer Vision (CV), Machine Learning (ML), Neural Networks (NN), Deep Learning (DL) and Natural Language Processing (NLP) as depicted in Figure 2.

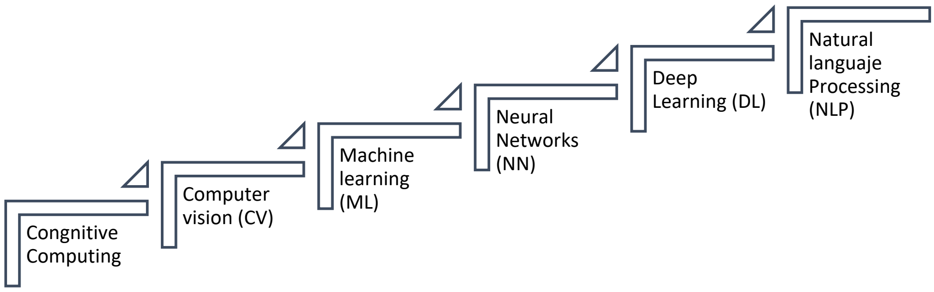


Figure 2. Artificial intelligence fields.

In Figure 3, a classification for machine learning domain is shown accordingly to the learning process—namely, supervised, unsupervised, and reinforcement learning.

Due to the nature of our data, which is tabular type, we decided to use a supervised ML technique. Moreover, supervised ML techniques have two options; the first are regression methods and the second classification methods. The use of one of them depends on the nature of the analyzed data. In our case, power factor data are continuous type therefore it is recommended to use the regression methods, which in turn is divided into different algorithms being OLS, Poly and RF the most important. Below, a brief description of each algorithm is provided.

Decision Trees (RF) are used for both regression and classification problems. They visually flow like trees, hence the name, and in the regression case, they start with the root of the tree and follow splits based on variable outcomes until a leaf node is reached and the result is given. Random Forest algorithm combines ensemble learning methods with the decision tree framework to create multiple randomly drawn decision trees from the data, averaging the results to output a new result that often leads to strong predictions/classifications.

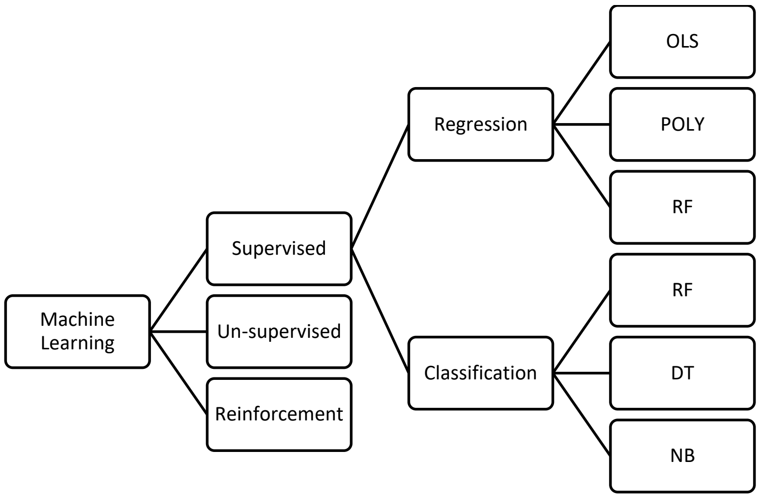


Figure 3. Machine learning classification according to learning algorithm type.

Ordinary Least Squares regression (OLS) is a common technique for estimating coefficients of linear regression equations which describe the relationship between one or more independent quantitative variables and a dependent variable (simple or multiple linear regression).

Polynomial Regression (Poly) is a form of regression analysis in which the relationship between the independent variables and dependent variables are modeled in the nth degree polynomial. Polynomial Regression models are usually fit with the method of least squares. This algorithm is a special case of Linear Regression where we fit the polynomial equation on the data with a curvilinear relationship between the dependent and independent variables.

In particular, AI in electrical power systems has been used in several areas such event detection as flickers and surge voltage transients [14], frequency regulation, distribution system control [15], power factor correction [8], voltage sag and swell problems [16], and power quality disturbances detection and classification [17].

In this work, a model for PF prediction using only phase currents (no phase voltages measurements required) is proposed. This solution provides a reliable prediction of PF fluctuations by using (ML) techniques, in particular linear regression models have been used. The results obtained from model deployment are very promising although for PF variations predictions in installations where renewable energy systems are operating it should be further optimized.

2. Materials and Methods

For this work, four electric load centers (ELC) were selected (listed in Table 1) based on the requirement for electrical local regulations for each site specified by Mexico's network code [18]. All ELCs analyzed have the same business division (gas stations); therefore, the type of electrical equipment is more or less similar between them. However, there are other important differences among these sites such frequency of service, contracted load, neighboring electrical installations, brands and characteristics of the installed equipment, years of service, maintenance scheme, geographical site, and infrastructure of the supplier company as well as installed load.

Obtaining data from the selected centers (ELC) was performed with a MYeBox 1500® three phase power quality analyzer from Circutor®. Data is stored in a 25 GB external SD memory card. Each selected ELC was monitored for a 7-day time period by using demand period storage rate of 5 min and recording current measurements for each phase along with real-time PF calculations [19]. Figure 4 shows the connection diagram of the analyzer in a 3F + N system [20].

Table 1. List of selected sites (ELC) for quality power monitoring.

Site	ID	Geographical Location
ALSA	ELC-1	Zacatecas, México
Centro-Sahuayo	ELC-2	Michoacán, México
Yerbabuena	ELC-3	Michoacán, México
Castellanos 2	ELC-4	Michoacán, México

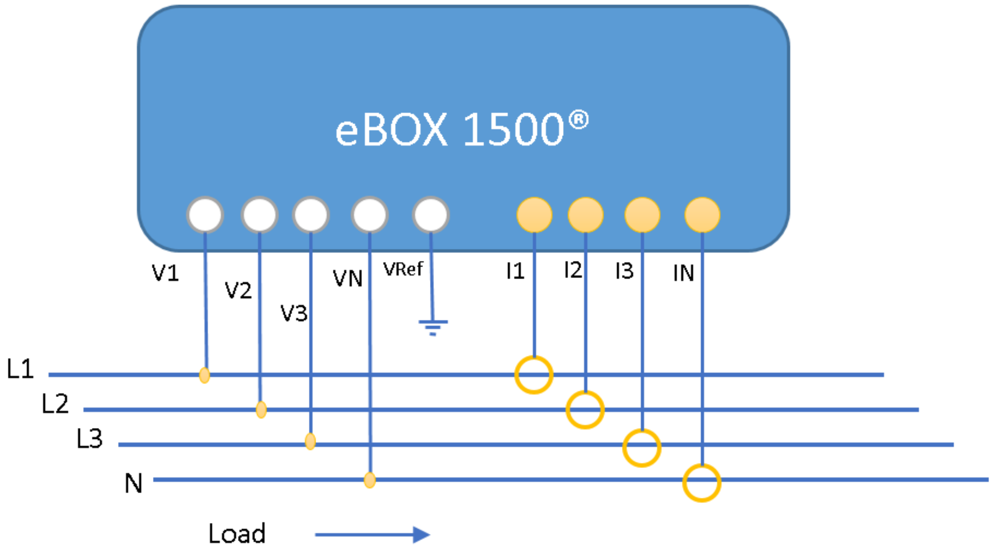


Figure 4. Power quality analyzer connection in a three phase facility, adapted from Ref. [20].

Once the data for each site was acquired, the procedure for ML analysis could be performed. Procedure for ML model building, testing and evaluating is graphically depicted in Figure 5 and is the typical used in the literature [21]. First, datasets are preprocessed (cleaning and tabular formatting), secondly site selection is performed based on statistical results and data splitting for model training using 70% of data for training and 30% of data for testing. Next, several linear regression algorithms are used for training and the statistical results are used to evaluate their performance. Finally, the model is tested in other selected sites, and statistical results are analyzed for final model evaluation.

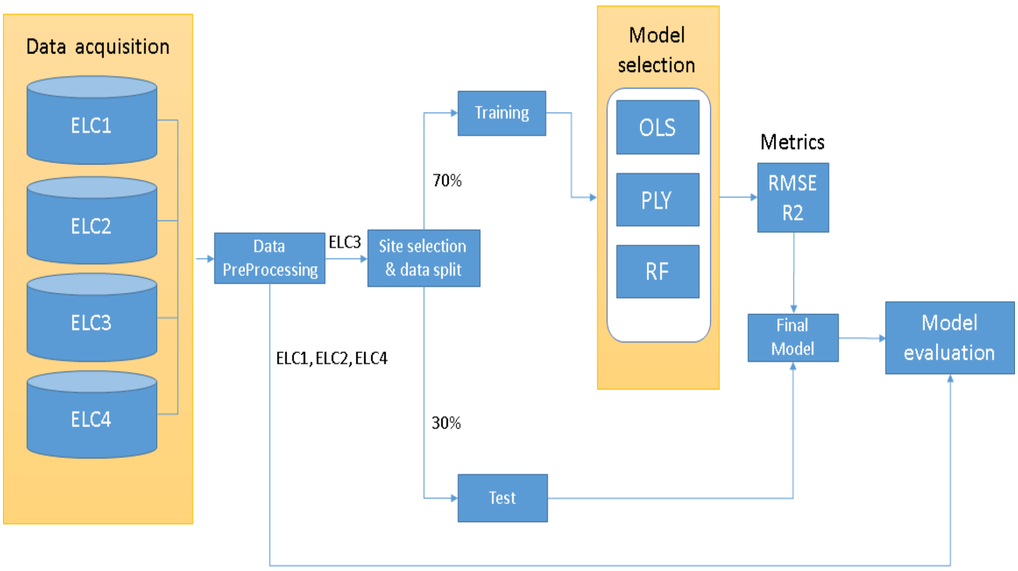


Figure 5. Block diagram describing the data processing for ML model selection and evaluation.

3. Results and Discussion

All data processing and display as well as ML model training and test were performed with Python environment [22]. As described above in Section 2, a total of 4 sites belonging to gas stations business category were analyzed. Figure 6 shows monitored PF data plotted as a function of measurement time.

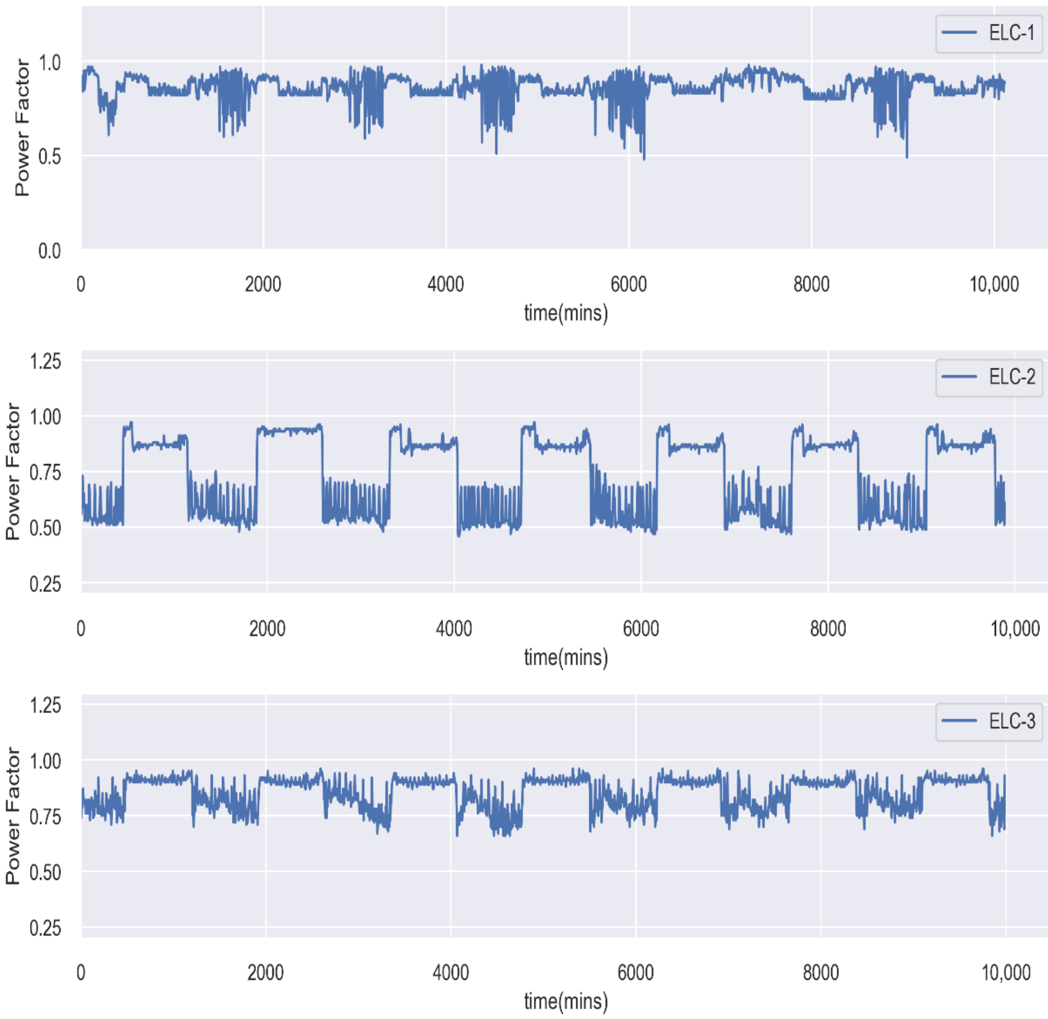


Figure 6. Time evolution of power factor in selected sites. All four sites show important power factor variations due to large inductive loads operation.

Figure 6 depicts the behavior of PF for a defined period of time (10,000 min i.e., 7 days). As it can be observed, each site shows cyclic variations of PF, but they are different between them because the equipment connected to the electrical grid in each site has different specifications. The cyclic variation of PF can be related to highly inductive loads operating at certain daily hours. For example, for site ELC-2 it can be seen that PF diminishes down to 0.5 between 8:00 p.m. and 8:00 a.m. corresponding to the night-shift when big equipment (high inductive loads) is operated.

The purpose of any supervised ML model is to establish a function of the predictors; that best explains the response variable (target). In this case, the predictors are the phase currents and the target variable will be the power factor value as depicted in Table 2.

Table 2. Predictors and target variables identification.

X1	X2	X3	Y
Current phase A	Current phase C	Current phase B	Power Factor

For this function to be stable and to be a good and reliable estimate of the target variable, it is very important that these predictors are correlated with it. Therefore, the first step would be to perform a correlation analysis between these variables. The correlation is a statistical measure that indicates the extent to which two or more variables move together. A positive correlation indicates that the variables increase or decrease together. A negative correlation indicates that if one variable increases, the other decreases, and vice versa. The correlation coefficient (r) indicates the strength of the linear relationship that might be existing between two variables. A correlation map involving the phase voltages, currents and power factor for every location was performed, and the results are shown in Figure 7. It can be observed that the highest correlation was obtained between phase currents and power factor whereas a weak correlation factor is observed between phase voltages and PF. Therefore, the use of only phase currents to predict PF is justified.

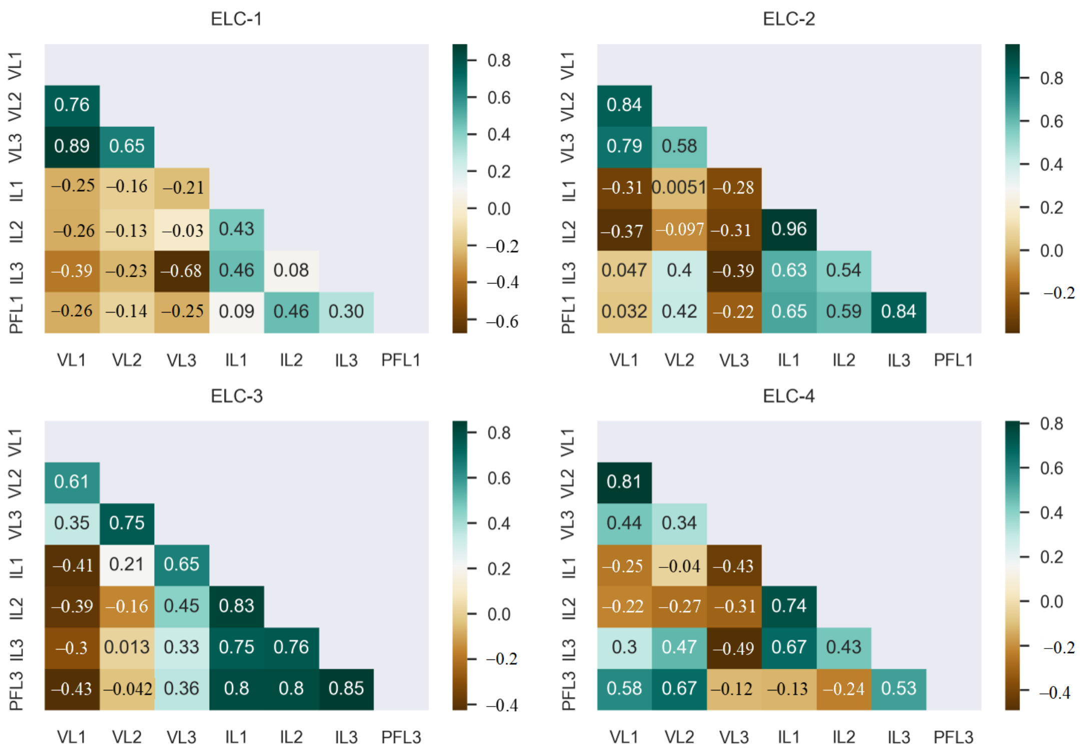


Figure 7. Correlation map between power factor, phase voltages and phase currents. It can be observed the strong correlation between PF and phase currents whereas concerning phase voltages the correlation is rather poor.

Once the correlation has been stablished for all sites, it is necessary to carefully select the site that will be used for ML model training. At first glance, site ELC-3 seems appealing for selection as is the one showing the higher correlation factors between phase currents (IL1, IL2, IL3) and PF being 0.8, 0.8, and 0.85, respectively.

However, this decision should be validated by exploring in detail the characteristics of the dataset. Specifically, the good performance of any ML model relies upon data distribution and for linear regression models four main characteristics should be taken into account: additivity and linearity of effects, constant error variance, normality of errors and zero correlation between errors. Therefore, for ML applications it is always preferable to have a normal (gaussian) distribution as described by Equation (2):

$$y = \frac{1}{\sqrt{2\pi}} e^{-(x-\mu)^{\frac{2}{2\sigma}}} \quad (2)$$

However, it is not mandatory that data should always follow normality. As a matter of fact, some ML models work very well in the case of non-normally distributed data like decision tree models which don't assume any normality and work fairly well. In order to analyze data distribution for each site histograms and Kernel Distribution Estimation (KDE) plots are very useful. Histogram plots give an estimate of the probability distribution of a continuous variable whereas KDE plots depict the probability density function of the continuous or non-parametric data variables. Figure 8 displays the histograms and KDE plots for the 4 sites showing that for ELC-1, ELC-2, and ELC-4 a broad data dispersion along with multimodal-type distribution is observed. Conversely, for ELC-3 site a bimodal-type distribution and a slightly narrower data dispersion was detected thus becoming a more suitable option for ML model training.

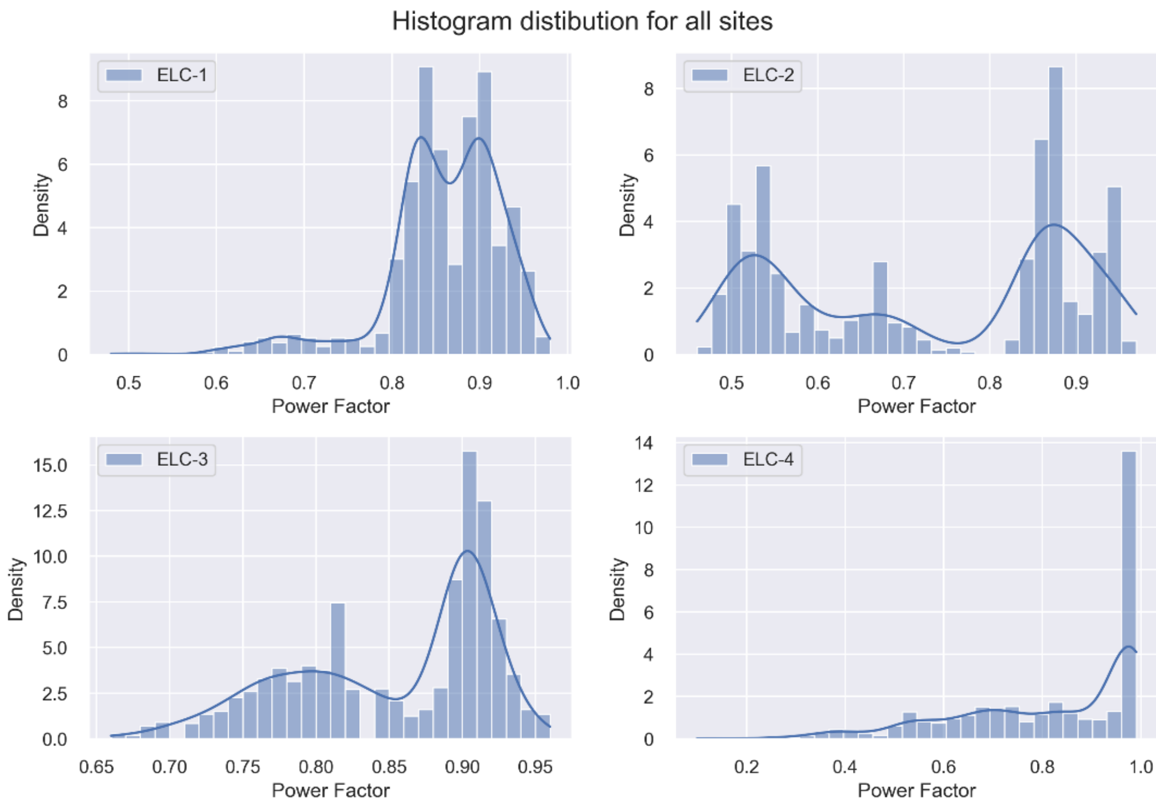


Figure 8. Histogram distribution and kernel density estimation for each monitored location. Bimodal and multimodal distributions can be observed.

Following and to confirm that ELC-3 site is the most suitable for model training a test-train split for each dataset was performed using sizes adjusted at 70% for training and 30% for testing, setting random_state = 101.

The Mean Squared Error, Mean absolute error, Root Mean Squared Error, and R-Squared or Coefficient of determination metrics are the evaluation metrics used in regression analysis.

The Mean absolute error (*MAE*) represents the average of the absolute difference between the actual and predicted values in the dataset. This parameter is calculated with Equation (3):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \tag{3}$$

Mean Squared Error (*MSE*) represents the average of the squared difference between the original and predicted values in the data set. This parameter is calculated with Equation (4):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \tag{4}$$

Root Mean Squared Error is the square root of Mean Squared error. This parameter is calculated with Equation (5):

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{5}$$

MSE and *RMSE* penalizes the large prediction errors vi-a-vis *MAE*. However, *RMSE* is widely used than *MSE* to evaluate the performance of the regression model with other random models, as it has the same units as the dependent variable (*Y*-axis).

The coefficient of determination or *R*-squared represents the proportion of the variance in the dependent variable which is explained by the linear regression model. This parameter is calculated with Equation (6):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \overline{y})^2} \tag{6}$$

The lower value of *MAE*, *MSE*, and *RMSE* implies higher accuracy of a regression model. However, a higher value of R^2 is considered desirable.

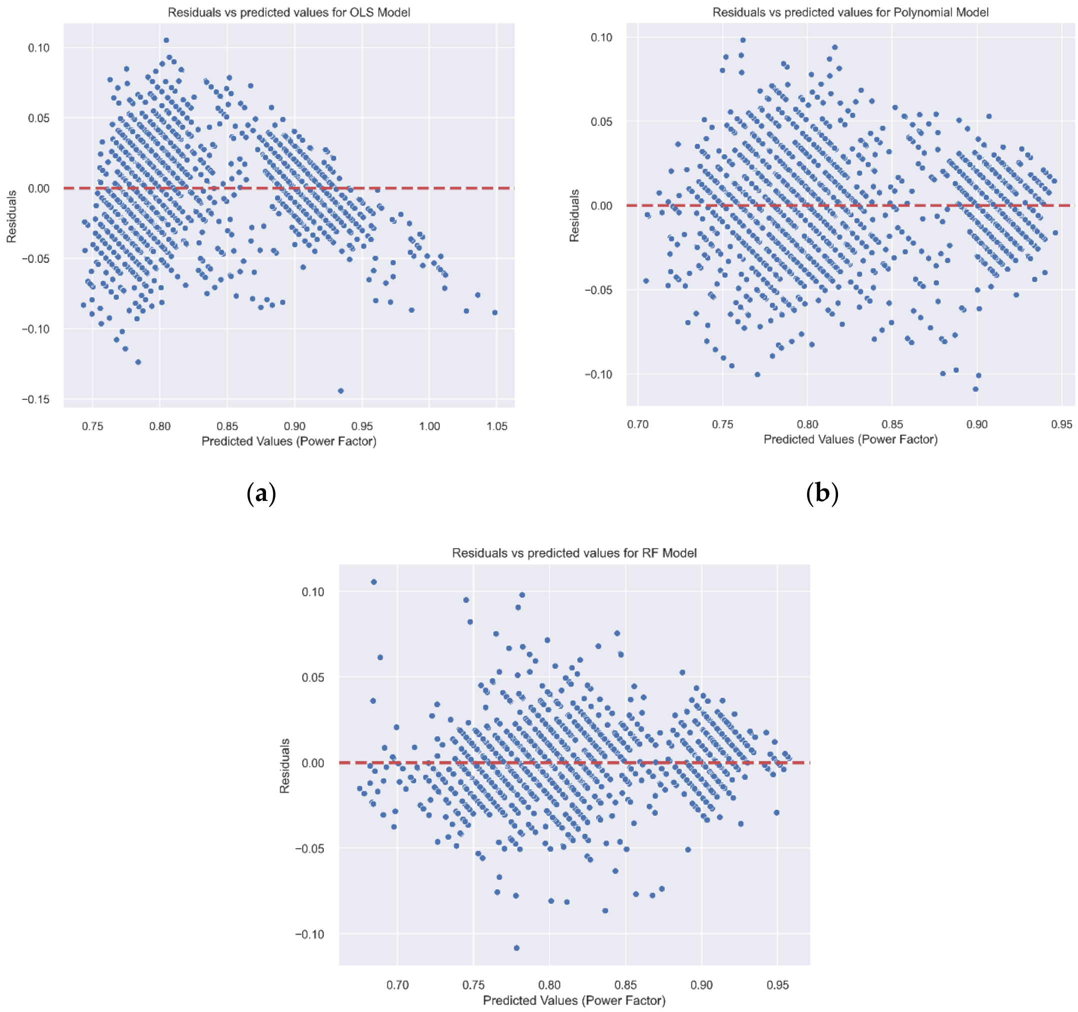
An ordinary least square regression (OLS) algorithm was algorithm was used and the evaluation metrics as *MAE*, *MSE*, *RMSE* and R^2 were calculated for each site. As observed from results depicted in Table 3, ELC-3 site showed the lowest *RMSE* as well as the higher R^2 value.

Table 3. Statistical parameters comparison using OLS algorithm.

	MAE	MSE	RMSE	R^2
ELC-1	0.159	0.031	0.175	0.70
ELC-2	0.052	0.007	0.087	0.73
ELC-3	0.023	0.001	0.029	0.82
ELC-4	0.072	0.009	0.096	0.73

Once the site for model training was confirmed, the next step was to compare the statistical parameters with the three main linear regression ML models, specifically ordinary least square regression (OLS), polynomial regression (Poly), and random forest regression (RF). The hyperparameters configuration setting for Poly regression was (degree = 2) whereas for RF algorithm setting was (n_estimators = 100, random_state = 101, criterion = "absolute_error", max_depth = 19).

In Figure 9, an error residuals (calculated errors between observed and predicted values) plot is depicted. In this type of plot, a random distribution of error residuals should be observed in order to consider linear regression as suitable technique for prediction. Consequently, the results obtained from Figure 9 confirm that for all three models the random behavior in the residuals distribution is present. Furthermore, it can be observed that RF model has the most compact residuals distribution (fewer spread) implying that calculated errors between observed and predicted values are lower than the other two models (OLS and polynomial).

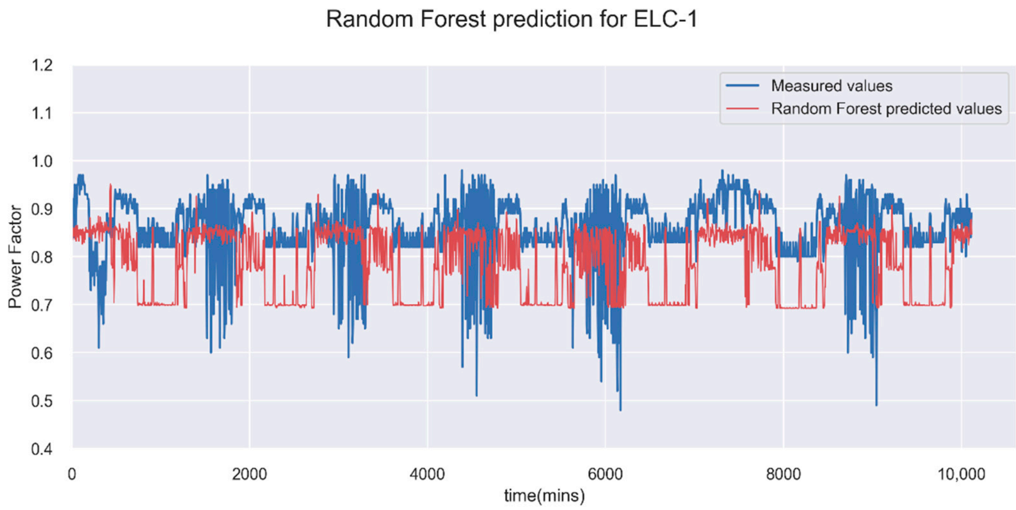


(**a**) (**b**) (**c**)

Figure 9. Residuals plot obtained for ELC-3 using the three main linear regression algorithms Ordinary Least Squares (OLS), Polynomial (Poly) and Random Forest (RF). (**a**) Residual plot for OLS algorithm; (**b**) Residual plot for Polynomial algorithm; (**c**) Residual plot for Random Forest algorithm.

Finally, last step was to predict the PF variations for the remaining three sites (ELC-1, ELC-2, and ELC-4) using the previously trained and adjusted RF model. Figure 10 shows the fitting results for each of these locations while Table 3 displays the statistical parameters for each site.

The plots in Figure 10 show a rather good fit between model predicted data and actual measured PF values. These results validate the satisfactory performance of the proposed model where only phase currents were taken into account. Moreover, as observed from Table 4, most of the sites show a fairly high R^2 coefficient (0.85) along with a low RMSE error except for ELC-4 where RMSE error is slightly bigger (0.175). The higher discrepancy obtained for site ELC-4 could be associated to a weaker correlation observed between phase currents and PF for this particular site (see Figure 7). Therefore, a different approach should be considered like taking into account also the phase voltages or consider only one phase current (i.e., IL3) for model prediction.



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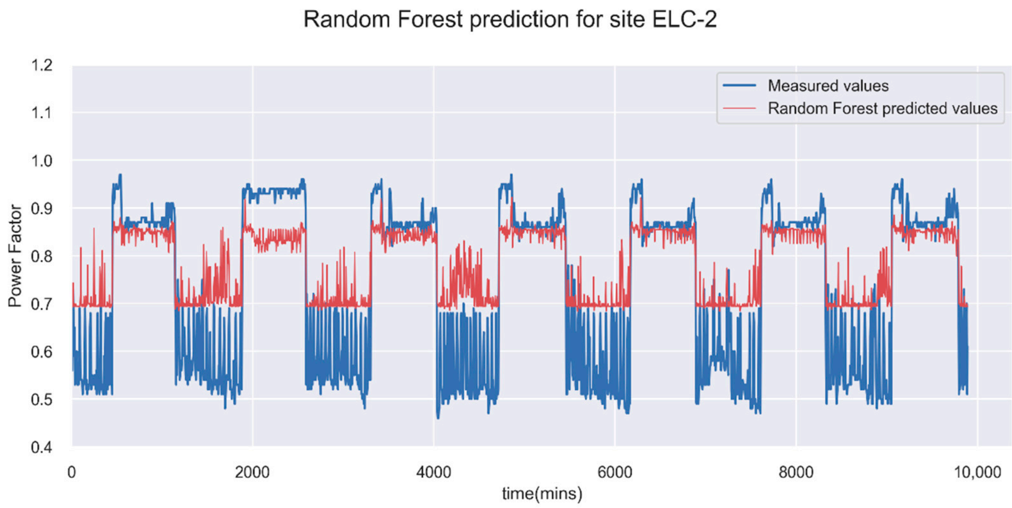

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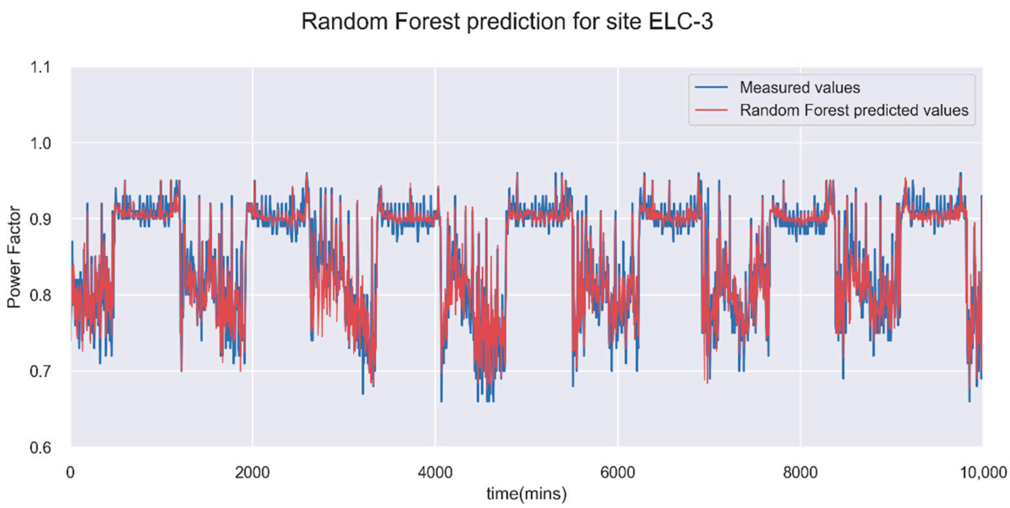

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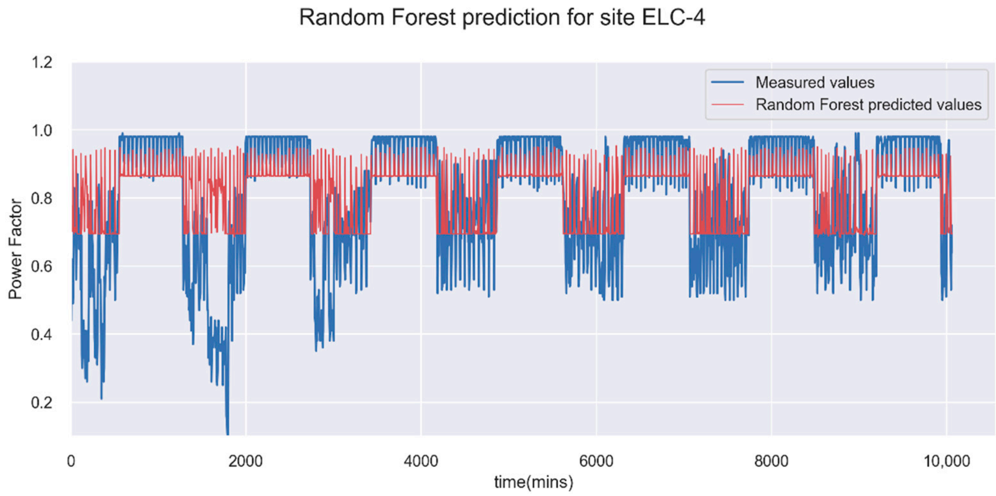
Figure 10. *Cont*.



(**d**)

Figure 10. RF predictions results for al monitored sites. It can be observed that model underestimates the PF variations in most cases. (**a**) RF prediction vs. actual measured data for site ELC-1; (**b**) RF prediction vs. actual measured data for site ELC-2; (**c**) RF prediction vs. actual measured data for site ELC-3; (**d**) RF prediction vs. actual measured data for site ELC-4.

Table 4. Statistical parameters obtained after RF prediction results.

	MAE	MSE	RMSE	R^2
ELC-1	0.099	0.012	0.110	0.85
ELC-2	0.091	0.014	0.117	0.85
ELC-3	0.012	0.0003	0.018	0.85
ELC-4	0.135	0.031	0.175	0.85

4. Conclusions

In this work a new approach to predict power factor variations has been proposed relaying only on phase currents (without considering phase voltages) thus simplifying the data acquisition procedure and consequently reducing the time and costs for a simplified power quality analysis at consumer facilities. It also was shown that Random Forest model gives a very good result for different sites (with different electrical loads). The root Mean Square Error and the coefficient of determination obtained were quite acceptable. The prediction results demonstrate the viability for use this model for PF variations prediction using only phase currents as input variables in power systems where the PF reflects the power consumption from the grid. Finally, the developed model can be modified to adequately predict PF variations when phase currents do not show a high correlation as a result of specific installation conditions and to consider the presence of grid-connected renewable energy sources.

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Nomenclature

1. (GDP)	Gross Domestic Product
2. (OCDE)	Organization for Economic Co-operation and Development
3. (AIE)	International Energy Agency
4. (PF)	Power Factor
5. (PFC)	Power Factor Compensation
6. (STATCOMs)	Static synchronous compensator
7. (THD)	Total Harmonic Distortion
8. (AI)	Artificial Intelligence
9. (CV)	Computer Vision
10. (ML)	Machine Learning
11. (NN)	Neural Networks
12. (DL)	Deep Learning
13. (NLP)	Natural Language Processing
14. (ELC)	Electric Load Centers
15. (ID)	Identification
16. (OLS)	Ordinary Least Squares
17. (PLY)	Polynomial
18. (RF)	Random Forest Regression
19. (MAE)	Mean Absolute Error
20. (MSE)	Mean Square Error
21. (RMSE)	Root Mean Square Error
22. (KDE)	Kernel Distribution Estimation
23. (NB)	Naive Bayes
24. (IL1)	Line Current 1
25. (IL2)	Line Current 2
26. (IL3)	Line Current 3

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