# Weather-Adaptive Power Factor Management: A Machine Learning Approach

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***Abstract*—The low power factor condition is influenced by various aspects one of the main being weather and load variations, a clever and sophisticated solution is necessary. With suboptimal power factors leading to penalties as well as due to the weather changes, the consumption will also vary, a single policy won't solve all problems. We hope to study the effect of weather conditions on power factors and develop an auto-corrective system. Through supervised learning, using Logistic Regression, Support Vector Machine (SVM), Decision Trees, and Random Forest Models, we have attained a high precision of 93 %. Cross-validation further strengthens the reliability by more than 99.7 %. This solution adjusts capacitors in real time based on weather data, which optimizes the power factor as precisely as possible. This study paves the way for an intelligent method to resolve power factor problems, improving efficiency and avoiding financial penalties.**

***Keywords—machine learning, logistic regression, support vector machine, decision trees, random forest models, weather conditions, power factor correction***

## I. INTRODUCTION

The power factor plays a vital role in the Electrical Power Distribution System. It can vary depends on the load variation and weather conditions. In such case, Real Power (P) is a wattful power that is used to do work and measured in kW. Reactive power (Q) is a wattless power or imaginary power that flow from load to source and vice versa. But it is also very important for the electrical system within the limit. In volt-amperes, Apparent power (S) is the sum of real and reactive power [1]. These definitions guide power factor enhancement for improved system efficiency and correction tactics. Power factor affects costs, equipment performance, and energy efficiency [2]. Due to low power factor operation, the maximum demand will be increased drastically, which leads to penality in the monthly billing as well as affects equipements life span. For maximum system reliability, a high power factor must be maintained [3]. K. D. Sekaran et.al [4] have highlighted inefficiencies in inductive loads and their effects on losses and utility costs, emphasizing energy efficiency for resource and environmental benefits with the help of IoT.

M. Callies et.al [5] has examined the use of capacitor banks, synchronous condensers, static VAR compensators (SVCs), and sophisticated power factor correction devices are just a few of the various power factor correction options. M. S. Rahman et.al [6] have developed case studies to explore how each solution is actually put into practice and how well it works to maximize power factor and raise overall system efficiency. Power factor correction is frequently achieved through the use of capacitor banks. To improve the power factor, they function by providing reactive power to counteract the reactive power drawn by inductive loads. To shed light on the benefits and efficiency of the capacitor bank [7]. S. S. Dhruvanth et.al [8] have found the problem of non-linear, inductive loads influencing system efficiency, quality, and power factor. The main objective is to investigate power factor correction techniques that can improve stability and lower electricity costs across various consumer segments. Additionally, it demonstrates how it affects equipment performance, financial costs, and energy efficiency. It addresses how advancements in power factor correction technologies can improve the overall stability and reliability of a system. M. Kolcun et.al [9] has promoted the use of capacitors at load centers for efficient reactive power supply to reduce power losses and enhance voltage profiles in distribution networks. The study highlights the significance of optimal placement by demonstrating a positive effect on power factor, voltage levels, and system losses through strategic capacitor bank installations.Y. Soluyanov et.al [10] have highlighted the proposal to update residential building electrical loads through the introduction of a correction factor to existing national standards. This initiative aims to enhance cost efficiency, optimize land use, and ensure a reliable and economical energy supply. The need for changes is underscored by an analysis of actual electrical loads in Moscow and the Moscow Region.

A. Alkhalifah and M. Khalid [11] have concluded that power factor correction, harmonics filtering, and voltage stability are highlighted as ways to improve network power quality. Benefits are shown mathematically, with case studies

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on harmonic filtering and power factor enhancement to bolster the argument. J.Ramesh et.al [12]-[19] have discussed the different control techniques to improve the power factor in the distribution system with various load disturbances. R. S. Jagzap et.al [20] have come up with automated power factor improvement using a microcontroller. This approach results in overall energy savings and improved system performance. Our research adopts a novel approach by including weather parameters as significant variables, acknowledging the critical influence of weather on power factor. Our goal is to create a model that takes weather into account to maximize power factor by utilizing machine learning techniques. Achieving a unity power factor is the ultimate objective since it guarantees effective energy use and system performance under a range of weather conditions.

## II. Methodology

### A. Dataset Description

The ZigBee wireless sensor and energy consumption dataset covers 4.5 months, with sensors monitoring house conditions at 10-minute intervals through the use of a ZigBee network. Energy data is recorded every 10 minutes [21]. The dataset is enriched by integrated weather information from Chievres Airport, Belgium. Timestamps enable smooth weather integration. The following two random variables help in testing the regression model. The dataset provides a look at how these house conditions, energy usage, and external weather factors interact with one another. It is especially suitable for predictive analysis as depicted in Fig.1.

| | date | reactive power | active power | apparent power | power factor | t1 | rh_1 | t2 | rh_2 | t3 | ... | t9 | rh_9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 2016-01-11 17:00:00 | 24 | 66 | 70.228199 | 0.939793 | 19.89 | 47.596667 | 19.2 | 44.790000 | 19.79 | ... | 17.033333 | 45.53 |
| 1 | 2016-01-11 17:10:00 | 24 | 66 | 70.228199 | 0.939793 | 19.89 | 46.693333 | 19.2 | 44.722500 | 19.79 | ... | 17.066667 | 45.56 |
| 2 | 2016-01-11 17:20:00 | 20 | 60 | 63.245553 | 0.948683 | 19.89 | 46.300000 | 19.2 | 44.626667 | 19.79 | ... | 17.000000 | 45.50 |
| 3 | 2016-01-11 17:30:00 | 20 | 70 | 72.801099 | 0.961524 | 19.89 | 46.066667 | 19.2 | 44.590000 | 19.79 | ... | 17.000000 | 45.40 |
| 4 | 2016-01-11 17:40:00 | 24 | 76 | 79.699435 | 0.953583 | 19.89 | 46.333333 | 19.2 | 44.530000 | 19.79 | ... | 17.000000 | 45.40 |

5 rows × 31 columns

Fig.1. Energy consumption dataset

### B. Dataset Preparation

In the first stage of data cleaning, care was taken to deal with missing values in the dataset. Cases with null values, after careful examination as shown in Fig.2, either carried out imputation using statistically sound methods or were removed from the dataset. This process is very strict; it's trying to make sure that there are no gaps in the dataset, and ensure its completeness and accuracy. Then we have a firm foundation for later analysis and modeling.

```
reactive power    0
active power      0
apparent power    0
power factor      0
t1                0
rh_1              0
t2                0
rh_2              0
t3                0
rh_3              0
t4                0
rh_4              0
t5                0
rh_5              0
t6                0
```

Fig.2. Elimination of null values for enhanced dataset integrity

At the same time, we looked for gaps in this dataset by drawing box plots as depicted in Fig.3. This helps us to find outliers and sudden changes described in Fig.4. Many notable changes were discovered by visual inspection. This multi-stage, combined approach toward addressing both null values and discontinuities allows for a fuller picture to be obtained by future analyses in terms of information accumulation and decision reference [22].

| date | reactive power | active power | apparent power | power factor | t1 |
|---|---|---|---|---|---|
| 2016-01-16 18:50:00 | 432 | 678 | 803.932833 | 0.843354 | 21.930000 |
| 2016-01-21 18:50:00 | 428 | 672 | 796.723289 | 0.843455 | 19.600000 |
| 2016-01-14 17:00:00 | 364 | 546 | 656.210332 | 0.832050 | 21.463333 |
| 2016-04-04 15:40:00 | 360 | 540 | 648.999230 | 0.832050 | 23.000000 |
| 2016-01-21 19:00:00 | 356 | 554 | 658.522589 | 0.841277 | 19.730000 |

5 rows × 37 columns

Fig.3. Identification of discontinuities

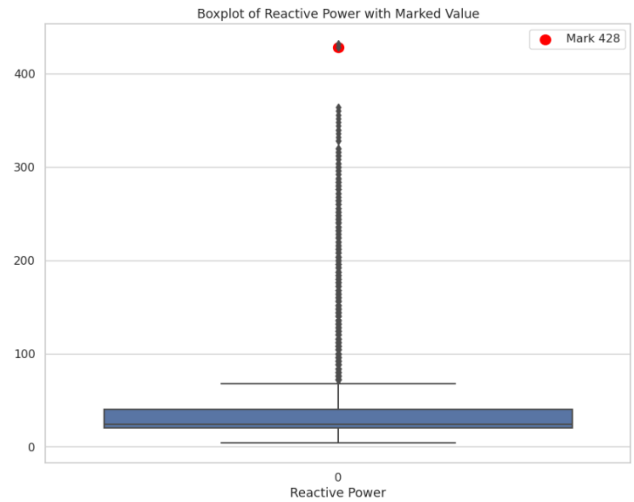


Fig.4 Box plot analysis revealing anomalies and shifts in the dataset

## C. Dataset Exploration

Fig.5 shows histogram plots depicting the distribution of key dataset parameters such as active power, reactive power, room temperature, and humidity. Visualizing the frequency distribution and patterns offers a preliminary dive into this dataset.

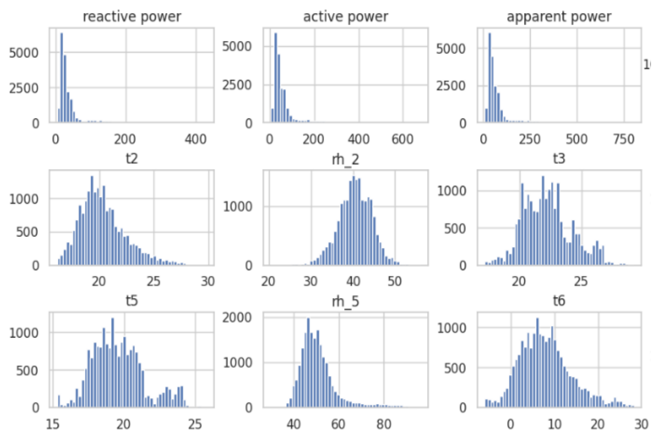


Fig.5. Histograms illustrating parameter distributions in the dataset

Fig.6 shows the correlation of mean reactive power values month by month from January to May, with each day on the horizontal axis (x-axis). The vertical axis (y-axis) represents the months shown in Fig. 6. This correlation chart makes it possible to appreciate how mean reactive power changes day by day over the observed months.

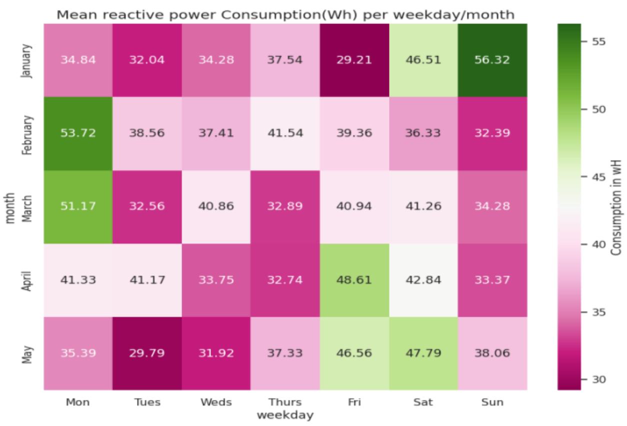


Fig.6 .Matrix representation of data variation across days and months

## D. Data Splitting

The train_test_split function from sci-kit-learn's library is used here to divide a dataset into training and testing sets. The feature matrix X and target vector Y2 are split into x_train,x test y train, and y test. Training a machine learning model on 80 % of the data used to create as shown in Fig.7. The other 20 % is a test set to see if it works. The random_state=42 parameter ensures reproducibility. Doing this standardizes practice, which is very important in building reliable models for machine learning.

```
x2_train.describe()
```

| | t1 | rh_1 | t2 | rh_2 |
|---|---|---|---|---|
| count | 15788.000000 | 15788.000000 | 15788.000000 | 15788.000000 |
| mean | 21.688684 | 40.266486 | 20.345215 | 40.428811 |
| std | 1.609561 | 3.957219 | 2.196357 | 4.067871 |
| min | 16.790000 | 27.023333 | 16.100000 | 20.463333 |
| 25% | 20.775937 | 37.399167 | 18.823333 | 37.900000 |
| 50% | 21.600000 | 39.663333 | 20.000000 | 40.500000 |
| 75% | 22.600000 | 43.060000 | 21.500000 | 43.290000 |
| max | 26.260000 | 57.423333 | 29.856667 | 54.766667 |

8 rows × 21 columns

```
y2_train.describe()

count    15788.000000
mean         3.388986
std          0.656777
min          1.386294
25%          2.995732
50%          3.178054
75%          3.688879
max          6.068426
Name: log_reactive_power
```

Fig.7 Description of x_train and y_train

## E. Random Forest Algorithm

While performing regression tasks, Random Forest is an exceptionally powerful algorithm for predicting continuous variables with numerical values as shown in Fig.8. In the context of regression, the algorithm starts with a training set that contains instances each having associated with it some numerical target value [23]. By way of bootstrapping, random subsets of the data are sampled with replacements for each tree. The individual predictors end up being quite diverse. Furthermore, at every decision node of each tree, a random subset of features is considered for splitting to ensure model diversity and reduce overfitting. The process of tree-building continues until a predefined stopping criterion is reached. The difference is that in classification, where a majority vote decides the final prediction; in regression the algorithm averages predictions from all trees. Therefore, this yields an ongoing prediction and gives a stable but accurate estimate of the target variable. Random Forest regression uses those out-of-bag samples to evaluate the model so that there is no need for a separate validation set to test performance [24]. In addition, the algorithm provides information about feature importance; it indicates which features contribute noticeably to the decrease of variance across the ensemble.

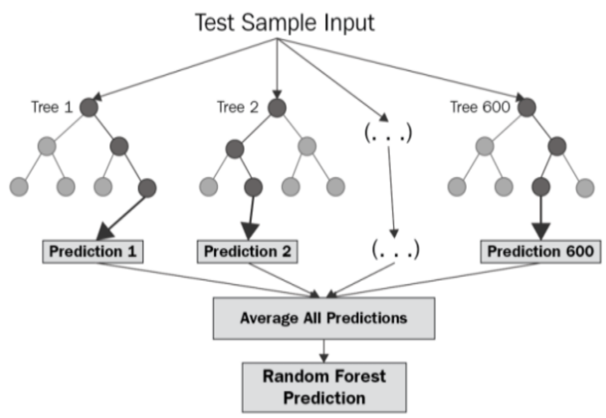


Fig.8 Random forest workflow

## III. Block Diagram

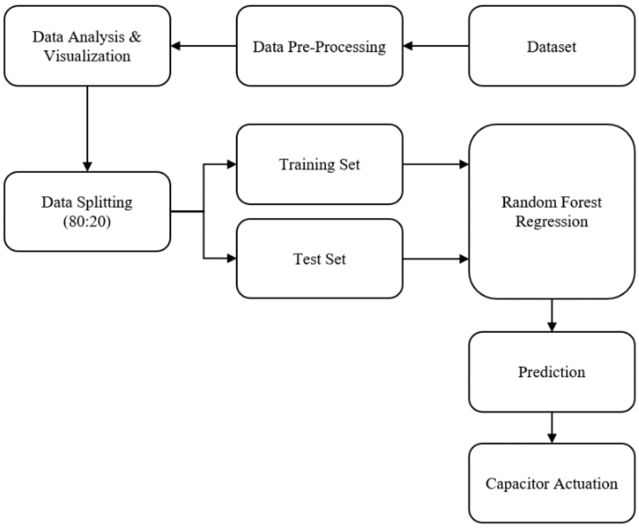


Fig.9. Block diagram for prediction

Fig. 9 describes the flow of work on this project--the process begins with a preprocessing step, in which null values are removed from the dataset. Later, this dataset is subject to a visual inspection in the form of box plot analysis for discontinuous values that need elimination from the data set. After this, the preprocessed data set is split into training and testing sets, 80 % for training and 20 % for testing. Use the chosen machine learning algorithm to train a model with the training set. Then, after being trained it is performance-tested on the test data to check that has been well learned and how well it generalizes[25]. These preliminary steps using data preparation, visualization, and model training/testing build a strong scheme for the construction of machine learning models.

## IV. Results and Discussion

These advantages include the normalization of skewed distributions, stabilizing variance, and handling wide value ranges. The logarithmic transformation conforms with statistical assumptions, especially in linear regression models, making it a convenient way of avoiding overfitting and improving the interpretability shown in Fig.10.

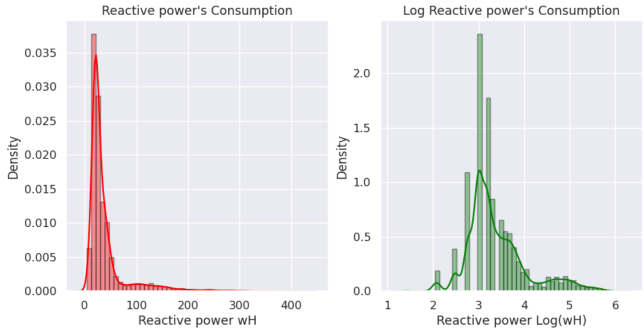


Fig.10. Log reactive power

Among the evaluated models—linear regression, SVM, decision tree, and random forest—the last turns out to be champion with an astonishingly high 93 % accuracy. This indicates its superior ability to pick up underlying patterns in the data shown in Fig.11. Even the assessment of variance and mean absolute error further confirms Random Forest's reliability in predicting. Briefly, the Random Forest model turns out to be the best of all in terms of robustness and efficiency.

```
LinearRegression()

Average Error (Mean Absolute Error)    : 0.4064 degrees
Variance score R^2                     : 23.04%
Accuracy                               : 88.07%

SVR()

Average Error (Mean Absolute Error)    : 0.3040 degrees
Variance score R^2                     : 46.66%
Accuracy                               : 91.32%

DecisionTreeRegressor()

Average Error (Mean Absolute Error)    : 0.2782 degrees
Variance score R^2                     : 49.18%
Accuracy                               : 91.86%

RandomForestRegressor(random_state=42)

Average Error (Mean Absolute Error)    : 0.2231 degrees
Variance score R^2                     : 72.85%
Accuracy                               : 93.45%
```

Fig.11. Regression models comparison

After post-cross-validation, the models' accuracies (as represented by mean values) improved slightly to 99.59 % for the Linear Model; 98.60 % for the SVR Model; and both Decision Tree and Random Forest achieved a score of exactly 100 %.

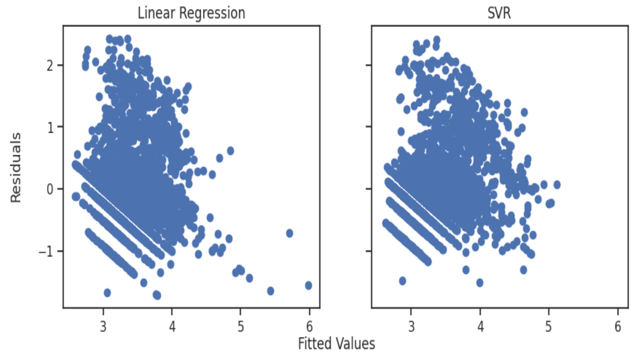


Fig.12. LR vs SVM - Fitting values and residuals comparison.

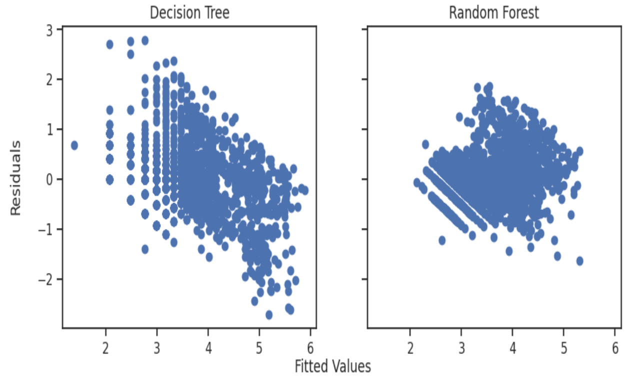


Fig.13. DT vs. RF - Fitting values and residuals comparison.

This indicates the increased power with which models handle data patterns, indicating greater robustness and reliability. Cross-validation has been vital in fine-tuning the models 'predictive capability, producing a more representative appraisal of performance. The figures offer a graphic understanding of how things are working in getting model-fitting values and residuals. Also, worth noting is that in the Random Forest model, residuals remain almost zero across all data points shown in Fig. 12 & 13. In other words, this indicates the model's forecasting capability is extremely good. However, others may have larger residuals indicating greater differences between predicted and actual values. That the residuals are close to zero in Random Forest is evidence that it captures well underlying tendencies. Given this predictive task, Random Forest makes an excellent choice with which to work.

Fig.14-15 shows a visual comparison of the target values (actual measurements) and predictions for the random forest model. The horizontal axis shows time, measured in 10-minute intervals; the vertical axis represents the log active power and reactive power. The blue line represents the target values (the actual log active and reactive power measurements). The red dashed line indicates predictions using the random forest method.

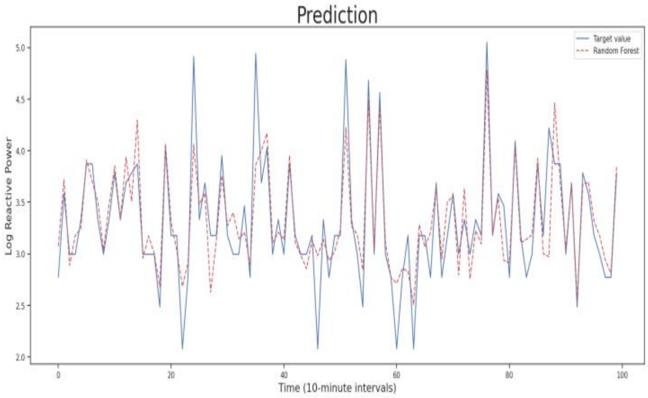


Fig.14. Random forest active power predictions

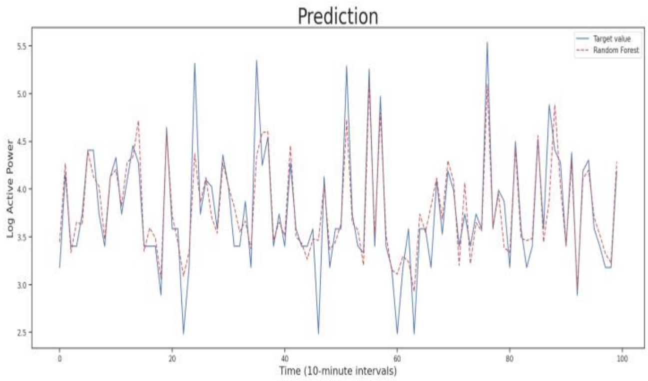


Fig.15. Random forest reactive power predictions

The anticipated active and reactive power from the Random Forest model helps inform how much capacitance is required in an electrical system. The system's electrical characteristics can be used to calculate the required capacitances, based on the predicted reactive power values. After the main power values are derived from the logarithmic predicted values of active and reactive power for this dataset by exponentiating them back to their original scale. Active and reactive power are well worth the effort of correct measurement shown in Fig.16.

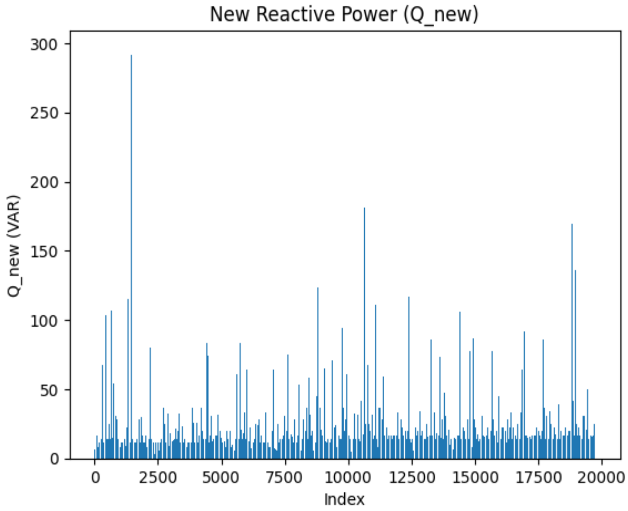


Fig.16. Additional reactive power needs to be injected

Later, the additional reactive power needed to maintain a unity power factor for all runs in the dataset is calculated. Since this reactive power injection is a very important step toward balancing the distribution system, real to apparent power level become optimal.

TABLE I. COMBINATIONS OF CAPACITORS AND TIMES REPEATED

| S.No | Target Reactance Value | Combination | No of Times Repeated |
|---|---|---|---|
| 1 | 13.9 | (3.0, 4.7, 6.2) | 3995 |
| 2 | 16.6 | (7.5, 9.1) | 2663 |
| 3 | 11.1 | (2.0, 9.1) | 1814 |
| 4 | 19.4 | (4.7, 5.6, 9.1) | 1093 |
| 5 | 22.2 | (5.6, 7.5, 9.1) | 876 |
| 6 | 25.0 | (1.5, 6.2, 8.2, 9.1) | 684 |
| 7 | 8.3 | (1.5, 6.8) | 658 |
| 8 | 27.8 | (1.0, 4.3, 6.8, 7.5, 8.2) | 454 |
| 9 | 30.6 | (1.0, 6.2, 6.8, 7.5, 9.1) | 326 |

These figures are the extra values of reactive power required to make system PF equal unity, and we take them one step further by only keeping those occurring most frequently with a high probability. We retain only 9 of these numbers These are the most common and important magnitudes of reactive power that a system might need. Afterward, an optimization process is used to find the optimum values for these capacitors given this maximum possible required reactive power shown in Table 1. The optimal set is derived containing capacitor values [1.0, 1.5, 2.0, 3.0, 4.3, 4.7, 5.6, 6.2, 6.8, 7.5, 8.2, 9.1]. These capacitor values are additionally. need to be in the capacitor set because most of the time these values are repeating so this helps in high power factor combining with the existing capacitor set. Thus, these resulting capacitors are indeed suited to that system's need for reactive power.

## V. CONCLUSION

In general, a random forest regression model together with the optimal capacitance actuation technique is an effective means of controlling reactive power for electrical systems. Forecasting reactive power accurately, the model makes it possible to more precisely determine capacitance requirements. This not only results in a better power factor but can also improve system stability. However, an important factor is that weather conditions affect reactive power dynamics. But meteorological differences, such as temperature and humidity can indeed result in major changes in the system's reactive power needs. Changing climate conditions further means that the model's adaptability and capacitance adjustments then become key to power quality. The employment of machine learning in power system operation not only deals with the current headaches but also cultivates an electric installation that will be able to work towards a more flexible and efficient tomorrow when weather-related changes in reactive energy can be foreseen.

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