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Research Article

Feature Analysis of Current Unbalance in Electrical Distribution Systems Using Random Forest

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ABSTRACT

The building sector accounts for more than 130 exajoules (EJ) of global energy consumption, representing approximately 30% of the total energy demand, with a continuous upward trend. Notably, energy demand in buildings surged during the COVID-19 crisis and increased by approximately 20% between 2000 and 2007. A significant portion of this energy consumption is attributed to lighting and air-conditioning systems. The rising electricity demand in buildings adversely impacts power quality, leading to issues such as harmonic distortion, voltage unbalance, and current unbalance in electrical distribution systems. This study investigates the application of the Machine Learning-based Random Forest Regressor model to analyze the causes of current unbalance in a building's power distribution system. A case study was conducted using electricity consumption data from a facility at the College of Industrial Technology and Management, Rajamangala University of Technology. The analysis results indicate that power features significantly influence current unbalance, with Power Phase A contributing the most at 74.73%, followed by Power Phase C at 10.98% and Power Phase B at 9.55%. These findings provide valuable insights for optimizing maintenance strategies and improving the efficiency of building power distribution systems.

1. Introduction

The building sector accounts for more than 130 exajoules (EJ) of global energy consumption, representing approximately 30% of total energy demand, with a continuously increasing trend. During the COVID-19 crisis, energy consumption in this sector surged beyond typical levels. Historical data from 2000 to 2007 indicate an approximate 20% increase in energy demand (Santamouris and Vasilakopoulou, 2021). A significant portion of this energy is utilized for lighting and air-conditioning systems, including heating, cooling, and ventilation (Melo *et al*., 2023). The growing deployment of such systems has significantly contributed to the increasing electricity demand in buildings.

The rise in electricity demand negatively impacts power quality, leading to issues such as harmonic distortion, voltage unbalance, and current unbalance in electrical systems (Drovtar *et al.*, 2012). The degradation of power quality can result in increased energy losses in power transmission, excessive heat buildup in electrical components, and a reduced lifespan of connected equipment. Additionally, power quality disturbances may cause operational errors in industrial control devices such as Programmable Logic Controllers (PLC) and Variable Frequency Drives (VFD). To mitigate power quality issues in electrical distribution systems, previous studies have proposed various analytical approaches. For instance, Jove *et al.* (2021) applied machine learning techniques, including Principal Component Analysis (PCA), k-nearest neighbor (KNN), and Gaussian classifiers, to detect harmonic distortions in wind generator systems. Their results indicate that PCA demonstrated the highest detection efficiency, particularly for harmonic distortion variations ranging from 10% to 40% total harmonic distortion

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(THD) and exceeding 90% THD. In another study, Vinayagam *et al.* (2021) analyzed the impact of integrating renewable energy sources, such as solar power, into the electrical grid. Their comparison of two models one combining Bayesian networks with multilayer perceptron classifiers (Model 1) and another incorporating Bayesian networks, multilayer perceptrons, and J48 decision tree classifiers (Model 2) revealed that Model 2 achieved a classification accuracy of up to 100%. Furthermore, Wang and Chen (2019) introduced a convolutional neural network (CNN)-based system for power quality classification within multi-energy integration systems. Their results demonstrated that CNN achieved an accuracy of approximately 99.5% on validation data, with a training time of 191 minutes, outperforming long short-term memory (LSTM), ResNet50, and stacked autoencoder (SAE) models.

A review of existing research suggests that most power quality disturbance classification techniques rely on machine learning models combined with feature extraction methods based on signal processing (Chawda *et al.*, 2020). However, these approaches often focus on classification rather than identifying the root causes of power quality issues. Therefore, this study presents the application of the Random Forest Regressor model, a machine learning technique well-suited for analyzing nonlinear datasets of medium to large sizes (Schonlau and Zou, 2020). The proposed approach aims to identify the key factors contributing to current unbalance in building power distribution systems. The analysis is conducted using real-world electricity consumption data from the College of Industrial Technology and Management, Rajamangala University of Technology. The findings of this study will contribute to the development of optimized maintenance strategies for electrical distribution systems, ultimately improving energy efficiency and system reliability.

2. Theoretical Framework

2.1 Unbalanced Current

In a three-phase power supply system, the system is considered to be in a balanced current state when the current magnitudes in all three phases are equal and the phase shift between them is precisely 120°. However, any deviation from these conditions results in an unbalanced current state (Mahmoud, 2021). The degree of current unbalance is typically quantified by evaluating the ratio of the maximum deviation of phase currents from the average phase current to the total average current across all phases. This is commonly expressed as the Percentage Current Unbalance (PCU) in accordance with the IEEE 45-2002 standard (Sinuraya *et al.*, 2022). The general formulation for PCU is defined as follows: (1)

$$PCU = \frac{I_{Max}Dev}{I_{avg}} \times 100 \qquad (1)$$

From (1), the Percentage Current Unbalance *PCU* is defined as the ratio of the maximum current deviation to the total average current across all phases. The maximum current deviation $I_{Max}Dev$ from the average current in each phase is determined using (2), while the total average current I_{avg} across all phases is calculated as shown in (3).

$$I_{Max}Dev = \max\left(\left|I_A - I_{avg}\right|, \left|I_B - I_{avg}\right|, \left|I_C - I_{avg}\right|\right) \qquad (2)$$

$$I_{avg} = \frac{I_A + I_B + I_C}{3} \qquad (3)$$

2.2 Correlation Matrix

The Correlation Matrix serves as a fundamental statistical tool for analyzing relationships among multiple features or variables (Wang *et al.*, 2022). The relationship between features is quantified using the Correlation Coefficient (R), which ranges from -1 to 1. When $R \approx 1$, it indicates a strong positive correlation, meaning the features change in the same direction. Conversely, when $R \approx -1$, the features exhibit an inverse relationship, changing in opposite directions. If R=0, it signifies no correlation, implying that changes in one feature do not correspond to changes in another (Hadd and Rodgers, 2020). The Correlation Coefficient (R) is computed using (4)–(6).

$$X = \begin{bmatrix} X_{1,1} X_{1,2} \cdots X_{1,m} \\ X_{2,1} X_{2,2} \cdots X_{2,m} \\ \vdots \\ X_{n,1} X_{n,2} \cdots X_{n,m} \end{bmatrix} \qquad (4)$$

From (4), let X represent the dataset under analysis, where Observations are denoted as n and Variables as m. Each data point in the dataset is evaluated to determine the Correlation Coefficient (r) using the Pearson correlation coefficient equation, as defined in (5). In this context, $X_{i,j}$ represents the data at the i^{th} Observation and the j^{th} Feature within the dataset.

$$r_{x_i,x_j} = \frac{\sum (X_i - \bar{X}_i)(X_j - \bar{X}_j)}{\sqrt{\sum (X_i - \bar{X}_i)^2} \cdot \sqrt{\sum (X_j - \bar{X}_j)^2}} \qquad (5)$$

From (5), let X_i and X_j represent the data points within the dataset at the specified positions, while $\bar{X}_i$ and $\bar{X}_j$ denote their respective mean values. Since equation (5) analyzes the relationship of a single feature within the dataset, the computation of the Correlation Coefficient (R) for all features within the dataset follows the matrix representation in equation (6).

$$R = \begin{bmatrix} r_{X_1,X_1} r_{X_1,X_2} \cdots r_{X_1,X_m} \\ r_{X_2,X_1} r_{X_2,X_2} \cdots r_{X_2,X_m} \\ \vdots \\ r_{X_m,X_1} r_{X_m,X_2} \cdots r_{X_m,X_m} \end{bmatrix} \qquad (6)$$

From equation (6), r_{X_i,X_j} represents the Correlation Coefficient between X_i and X_j indicating the degree of relationship between the respective feature positions within the dataset.

2.3 Random Forest Regressor (RFR) Algorithm

The Random Forest Regressor (RFR) is a Machine Learning Model commonly employed for decision-making processes and target prediction based on independent and uncorrelated decisions. It operates using the Bagging Technique, incorporating Boot-strapping and Aggregation principles (Breiman, 2001). In the context of Feature Importance analysis using the RFR Algorithm, two primary approaches are utilized: Mean Decrease in Impurity (MDI) and Permutation Importance. The MDI value, defined in equation (7), quantifies the extent to which a feature contributes to reducing the model's variance. Meanwhile, Permutation Importance, as described in equation (9), measures the effect of randomly shuffling features on model performance (Hastie *et al*., 2009).

$$FI(X_j) = \frac{1}{T}\sum_{t=1}^{T}\sum_{s\hat{I}S_t,X_a=X_j}\Delta Var_s \qquad (7)$$

As presented in equation (7), $FI(X_j)$ is defined as the Mean Decrease in Impurity (MDI), where S_t represents the set of nodes in tree T that utilize the corresponding feature. Additionally, ΔVar_s is defined based on Decision Tree Regression, which is computed using equation (8).

$$\Delta Var_s = Var(D) - \left[\frac{|D_L|}{|D|}Var(D_L) + \frac{|D_R|}{|D|}Var(D_R)\right] \qquad (8)$$

As presented in equation (8), $Var(D)$ represents the variance of the parent node, while $Var(D_L)$ and $Var(D_R)$ denote the variances of the left and right child nodes, respectively.

$$FI(X_i) = R(X) - R(X_{shuffled}) \qquad (9)$$

From equation (9), Permutation Importance $FI(X_i)$ is defined as the difference between the model error before random shuffling $R(X)$ and the model error after random shuffling of features $R(X_{shuffled})$.

3. Materials and Methods

3.1 Installation of Electrical Energy Meters in the Building Power Distribution System

To measure electrical energy consumption within the building, a Clamp Meter (CM) is installed to monitor the current in the range of 0.6–120 A (AC) with a measurement resolution of 0.03 A. The CM supports a maximum alternating current voltage of 600 V and includes the capability to measure the temperature of the transmission line. The device is integrated into the power transmission line within the Main Distribution Board (MDB) cabinet. The installation layout of the measuring device within the MDB cabinet is illustrated in Figures 1 and 2, which depict the experimental setup utilized in this study. Once the electrical energy measurement system acquires the current flowing through the power transmission line, the signal undergoes quality enhancement via a Signal Conditioner. Subsequently, all recorded electrical energy consumption data are transmitted via Bluetooth 4.1, operating in the 2.402 GHz to 2.48 GHz frequency band, to the Gateway for data logging and further analysis.

Figure 1 The Main Distribution Board (MDB) used for analyzing the relationship between features influencing the occurrence of unbalanced current.

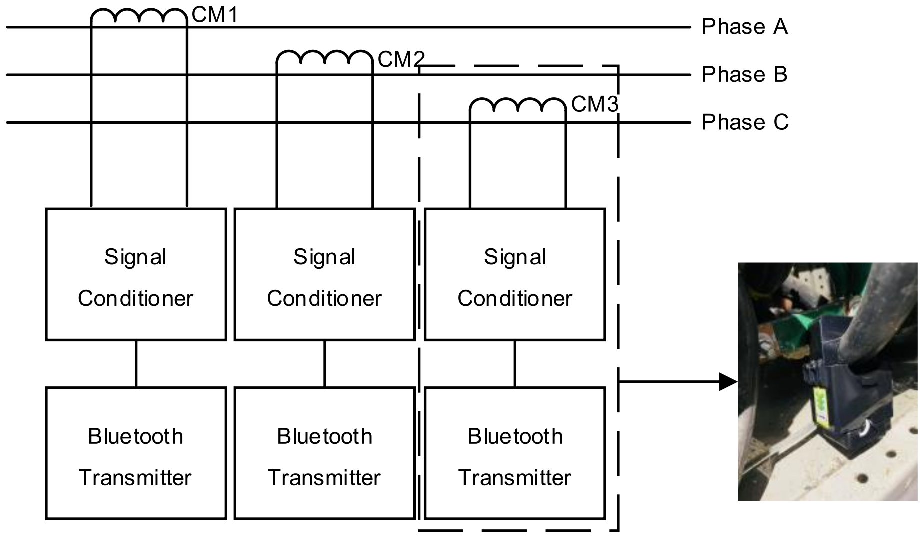


Figure 2 Diagram illustrating the installation of the Clamp Meter (CM) in the power transmission line inside the Main Distribution Board (MDB).

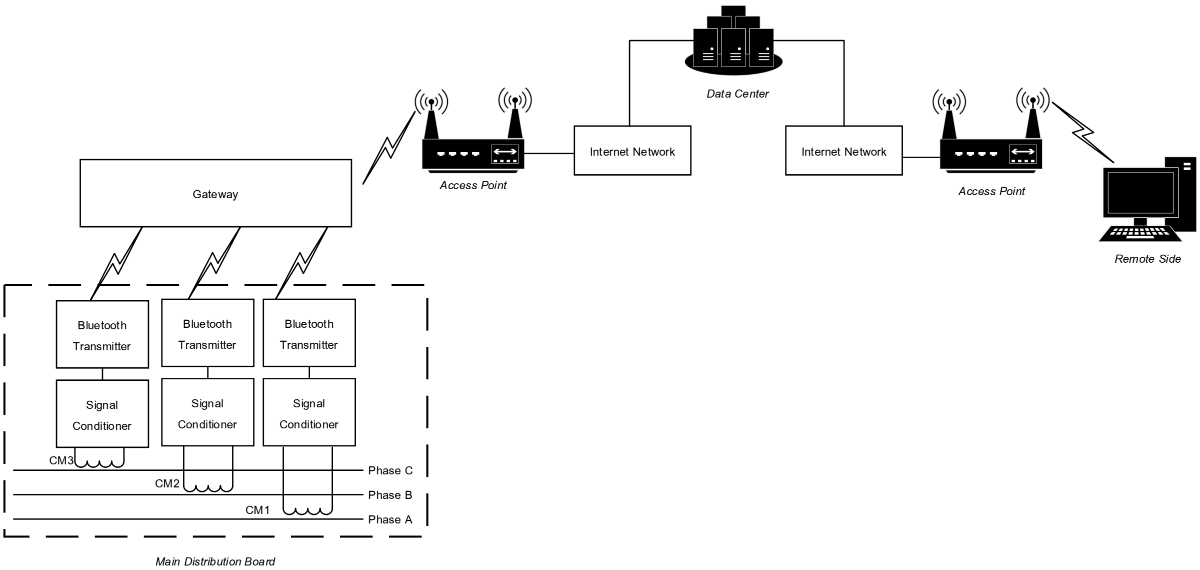


Figure 3 Overview diagram of the electrical energy usage recording system installed in the Main Distribution Board (MDB)

3.2 Electricity Usage Data Recording Process

The recording of electrical energy usage data from the Main Distribution Board (MDB) involves multiple stages. After the Clamp Meter (CM) measures the electrical parameters and undergoes the Signal Conditioning process, the processed data is transmitted to the Gateway. The Gateway serves as an intermediary, facilitating communication between field devices, specifically the Clamp Meter (CM), and the Internet via Bluetooth 4.1 operating within the 2.402 GHz to 2.48 GHz frequency range. The recorded electrical energy usage data is uploaded to the Data Center at one-minute intervals. The overall system architecture for data recording is illustrated in Figure 3. Access to the recorded electrical energy usage data is provided in CSV format, allowing for direct downloads from the Data Center. Remote-side equipment connected to the Internet, in conjunction with a Browser Engine, is utilized to retrieve and analyze the recorded data. The graphical user interface for data access and retrieval via the Browser Engine is depicted in Figure 4. For this study, electrical energy usage data was recorded continuously over one month, from December 1, 2024, to December 31, 2024. This dataset was sub-sequently used to analyze the relationship between various features influencing the occurrence of Un-balance Current.

3.3 Feature Extraction

After downloading the electrical power usage data in CSV format from the Data Center, the data is grouped into features for model training and analysis to identify relationships influencing the occurrence of Unbalance Current. The features used in this study are categorized into two groups. The first group consists of 12 features obtained from direct measurements inside the Main Distribution Board, as presented in Table 1. The second group includes a single feature derived using an analytical equation for Unbalance Current, as defined in equation (1).

Table 1 Features of Measured Energy Consumption in the MDB Cabinet

Feature	**Unit**
Power Phase A	W
Energy Phase A	kWh
Current Phase A	A
Temperature Phase A	Celsius
Power Phase B	W
Energy Phase B	kWh
Current Phase B	A
Temperature Phase B	Celsius
Power Phase C	W
Energy Phase C	kWh
Current Phase C	A
Temperature Phase C	Celsius

Figure 4 Illustrating the electrical energy usage recording system.

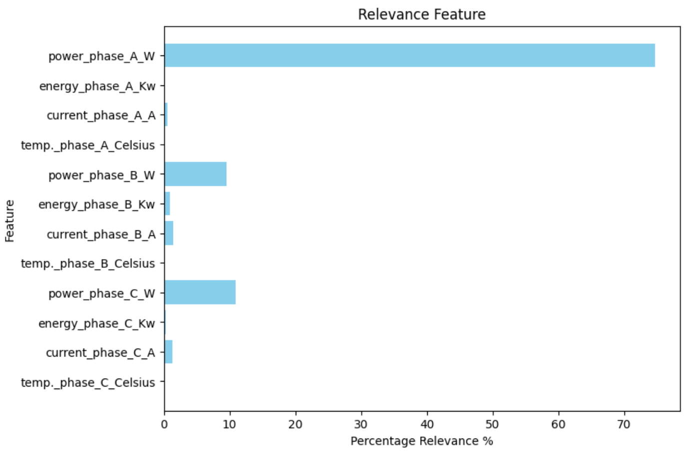


Figure 5 Comparison of relevance score percentages for each feature analyzed using the Random Forest Regressor.

4. Results and Discussion

4.1 Power

As shown in Figure 5, the power feature exerts the most significant influence on unbalanced current compared to other parameters. Phase A power alone accounts for approximately 74.73% of the observed unbalance, while Phases C and B contribute only 10.98% and 9.55%, respectively. Interestingly, the average power of Phase A is 1.56 kW, which is considerably lower than the values of Phase B (3.76 kW) and Phase C (1.80 kW), as depicted in Figure 6. This suggests that unbalanced current is not merely a function of absolute power magnitude but is strongly associated with the disproportionate loading conditions in Phase A. Further analysis of the unbalanced current distribution using histogram plots Figure 7 highlights this difference. The Phase A data exhibit a broader spread, indicating greater variability, while Phases B and C follow narrower, near- normal distributions with similar statistical characteristics. The estimated mean unbalance current in Phase A is 52.58%, significantly exceeding the 36.87% observed for Phases B and C. This wider distribution combined with the higher mean value confirms that the load imbalance in Phase A dominates the overall system unbalance. Therefore, the results demonstrate that although Phase A operates with lower average power than the other two phases, its disproportionate loading condition drives the highest unbalanced current. This finding emphasizes the importance of phase balancing in power distribution networks, as the concentration of load in a single phase can introduce substantial current imbalance, even when the overall system power is relatively low.

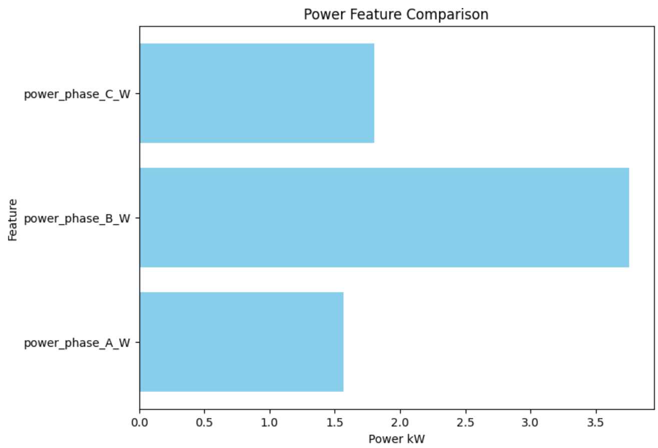
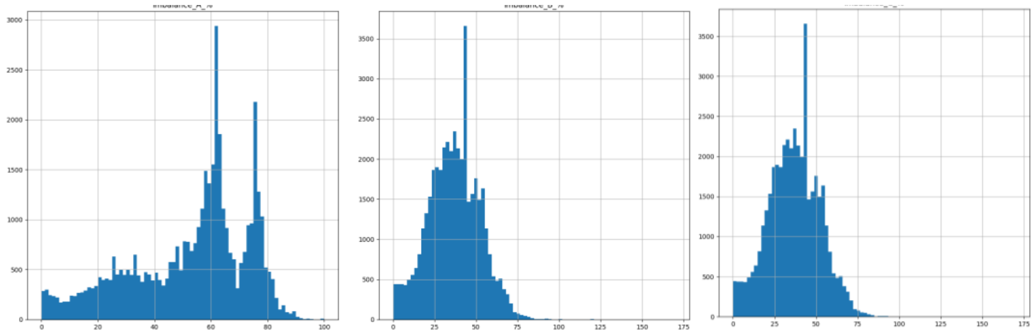


Figure 6 Comparison of power across each phase.



A) Unbalance current Phase A B) Unbalance current Phase B C) Unbalance current Phase C

Figure 7 Histogram of unbalance current in the power distribution system

4.2 Current

Figure 5 illustrates the contribution of electric current to the unbalance current, with Phases A, B, and C contributing 0.58%, 1.37%, and 1.21%, respectively. These results demonstrate that electric current has a minimal impact on the unbalance current compared to electric power. However, changes in electric current directly influence changes in electric power, as evidenced by the correlation matrix in Figure 8.

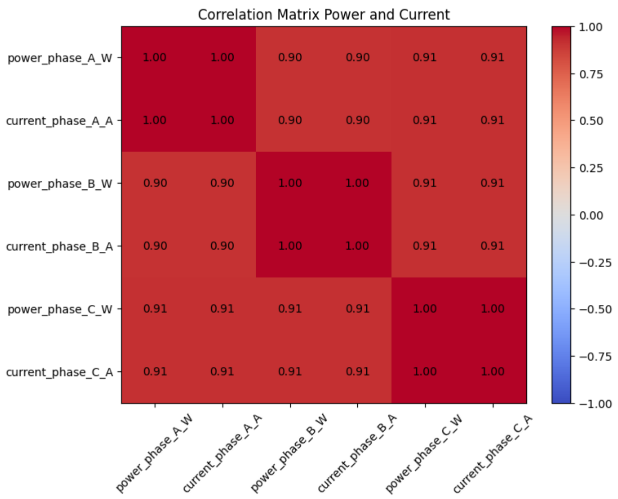


Figure 8 Correlation matrix of power and current.

The correlation matrix in Figure 8 demonstrates a perfect positive correlation (correlation coefficient = 1) between power and current across all three phases, indicating that changes in these features are directly proportional. Analysis of the current data reveals that Phase A contributes 75.17% to the unbalance current, significantly higher than Phase B (12.10%) and Phase C (12.72%). Figure 8 illustrates the percentage relevance scores of the current feature in influencing the unbalance current state.

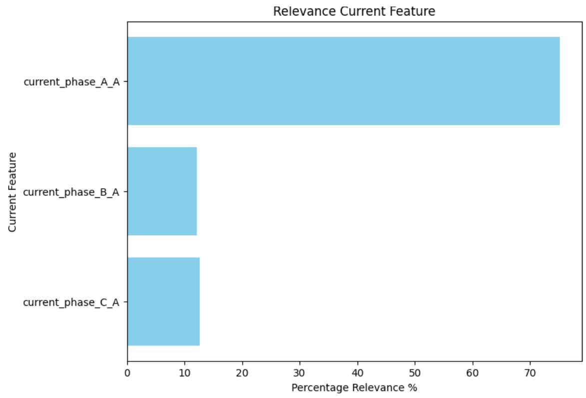


Figure 9 Comparison of relevance score percentages for the current feature analyzed using the Random Forest Regressor.

Phase A current has the highest impact on the unbalance current in the power distribution system, with an average current consumption of 4.12 A, lower than Phase C (4.74 A) and Phase B (9.89 A). Consequently, Phase A contributes the most to the unbalance current, as reflected in its higher weight in the three-phase current feature analysis. These results align with the histogram presented in Figure 7.

4.3 Energy

Analysis of the energy feature using the Random Forest Regressor indicates contributions to the unbalance current of 0.23%, 1.02%, and 0.39% for Phases A, B, and C, respectively. These values are significantly lower than those of the power and electric current features. The relationships between these features are further explored using the correlation matrix, as shown in Figure 10.

Figure 10 demonstrates that the energy feature directly influences changes in the power and current features, which are the primary drivers of the unbalance current in the power distribution system. The correlation coefficient between energy, power, and current is 1 for all phases (A, B, and C), reflecting a perfect positive relationship. This relationship arises because energy is a function of power and time, causing its variation to align directly with changes in power and current. Thus, while the energy feature does not directly impact the unbalance current, it indirectly affects it by influencing the power and current features.

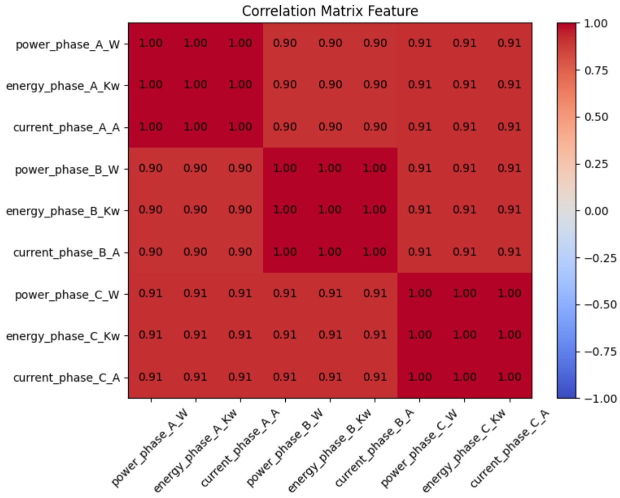
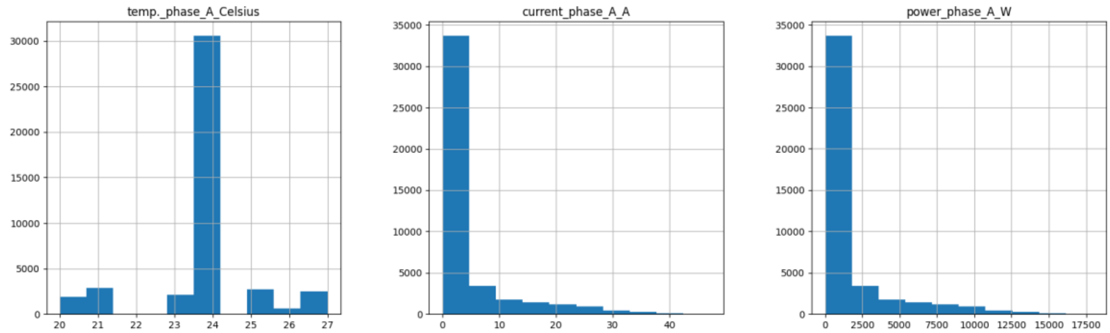
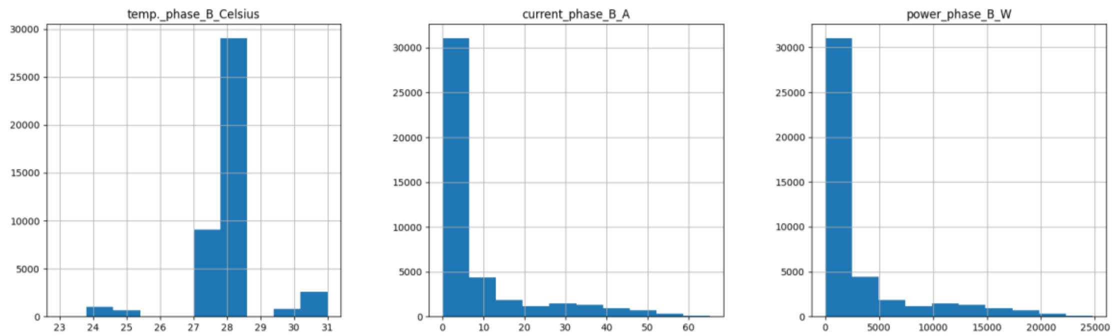


Figure 10 Correlation matrix of power, current, and energy features.



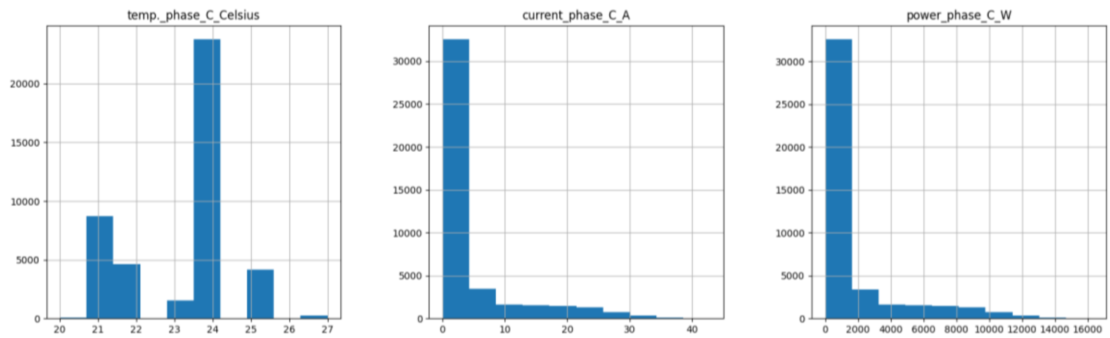
A) Temperature Phase A B) Current Phase A C) Power Phase A

Figure 11 Histogram of temperature, current, and power for Phase A.



A) Temperature Phase B B) Current Phase B C) Power Phase B

Figure 12 Histogram of temperature, current, and power for Phase B.



A) Temperature Phase C B) Current Phase C C) Power Phase C

Figure 13 Histogram of temperature, current, and power for Phase c.

4.4 Temperature

Temperature was identified as the feature with the least contribution to unbalanced current in the power distribution system when analyzed using the Random Forest Regressor model. As shown in Figure 5, the effect of temperature was quantified at approximately 0.07% in Phases A and C, and only 0.02% in Phase B. Compared to electrical power and current, which exhibited significantly higher contributions, temperature was determined to be a secondary factor in the development of unbalanced current conditions. A closer inspection of the histogram data provides further insight into this observation. For Phase B Figure 12, the system recorded a maximum power demand of 24.78 kW and a maximum current of 65.20 A. These operating conditions resulted in a peak conductor temperature of approximately 31 °C, which was higher than in the other phases. In contrast, Phase A Figure 11 reached a maximum power demand of 17.93 kW and a maximum current of 47.20 A, corresponding to a maximum temperature of about 27 °C. Phase C showed similar behavior, with a maximum power demand of 16.30 kW, a maximum current of 42.90 A, and a peak temperature of 27 °C, as illustrated in Figure 13. These results are consistent with findings reported in Beňa *et al.* (2021), which emphasize that conductor temperature is primarily driven by current loading. Although temperature had the smallest statistical contribution to unbalance prediction, it remains a valuable diagnostic parameter. Thermal variation across phases reflects differences in electrical loading and provides indirect information about conductor losses and efficiency. For example, elevated temperatures in Phase B suggest that this phase experiences higher energy stress, which may accelerate insulation aging and reduce equipment lifespan. Furthermore, localized heating can increase resistive losses, contributing to overall system inefficiency. This interpretation is supported by Moon and Lee (2019), who demonstrated that temperature rise in large electrical machines is strongly correlated with electromagnetic and copper losses. Therefore, while temperature by itself is not a dominant predictor of unbalanced current, its monitoring enhances the understanding of phase imbalance from a thermal perspective. Integrating temperature data with electrical features allows for improved condition monitoring, better prediction of component degradation, and more effective energy management strategies. From a system-level perspective, these insights contribute to optimizing load distribution, reducing technical losses, and enhancing the long-term reliability of power distribution networks.

5. Conclusion

The case study on the analysis of factors influencing Unbalance Current in the power distribution system at the College of Industrial Technology and Management, Rajamangala University of Technology, utilized a dataset comprising four key features: Power, Current, Energy, and Temperature. The Machine Learning Model Random Forest Regressor was employed to examine the relationship between these features and Unbalance Current. The analysis results indicate that electrical power has the highest impact on the occurrence of Unbalance Current, with Phase A Power contributing 74.73%, followed by Phase C Power (10.98%) and Phase B Power (9.55%). The primary cause of this imbalance is the significantly lower power consumption in Phase A, where small loads, such as lighting systems, are connected. In contrast, Phase B and Phase C are linked to large loads, including motors and air conditioning systems, leading to higher power demand in Phases B and C and contributing to the unbalance in Phase A. Other features, such as Current and Energy, have a relatively lower impact, contributing less than 1.5% in all cases, but show a direct correlation with the Power feature. The Temperature feature has the least impact, with values of 0.07% in Phases A and C and 0.02% in Phase B. The study concludes that Power is the most influential factor in Unbalance Current, and the application of Machine Learning for predictive analysis can support maintenance planning to mitigate power quality issues in building power systems, as highlighted by Popa *et al.* (2020). However, this approach has limitations due to the small dataset used for model training and testing, which may lead to miscalculations in practical applications. Additionally, the need to download data from Cloud systems for analysis adds complexity to the data processing workflow. To address these limitations, future research should focus on developing real-time Machine Learning models capable of running on embedded control devices or Cloud Computing systems. This would enable real-time anomaly detection, improve the accuracy of predictive models by increasing the training dataset size, and enhance the efficiency of power quality management in building and industrial applications.

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7. References

Beňa, Ľ., Gáll, V., Kanálik, M., Kolcun, M., Margitová, A., Mészáros, A. and Urbanský, J. 2021. Calculation of the overhead transmission line conductor temperature in real operating conditions. **Electrical Engineering** 103: 769-780.

Breiman, L. 2001. **Random forest, Machine Learning.** Statistics Department, University of California, Berkeley.

Chawda, G.S., Shaik, A.G., Shaik, M., Padmanaban, S., Holm-Nielsen, J.B., Mahela, O.P. and Kaliannan, P. 2020. Comprehensive review on detection and classification of power quality disturbances in utility grid with renewable energy penetration. **IEEE Access** 8: 146807-146830.

Drovtar, I., Niitsoo, J., Rosin, A., Kilter, J. and Palu, I. 2012. Electricity consumption analysis and power quality monitoring in commercial buildings, pp. 1-6. *In* **Electric Power Quality and Supply Reliability.** Department of Fundamentals of Electrical Engineering and Electrical Machines, Tallinn, Estonia.

Hadd, A. and Rodgers, J.L. 2020. **Understanding correlation matrices.** Sage Publications.

Hastie, T., Tibshirani, R., Friedman, J., Hastie, T., Tibshirani, R. and Friedman, J. 2009. **The elements of statistical learning: data mining, inference, and prediction.** springer, New York.

Jove, E., González-Cava, J.M., Casteleiro-Roca, J.L., Alaiz-Moretón, H., Baruque, B., Leitão, P., Pérez, J.A.M. and Calvo-Rolle, J.L. 2021. An intelligent system for harmonic distortions detection in wind generator power electronic devices. **Neurocomputing** 456: 609-621.

Mahmoud, R.A.A. 2021. Detection and assessment scheme of voltage and current unbalance for three phase synchronous generators using dual numerical techniques based on correlation and deviation percentage concepts. **The Journal of Engineering** 2021(9): 477-495.

Melo, F.C., da Graça, G.C. and Panão, M.J.O. 2023. A review of annual, monthly, and hourly electricity use in buildings. **Energy and Buildings** 293: 113201.

Moon, S. and Lee, S. 2019. High-reliable temperature prediction considering stray load loss for large induction machine. **IEEE Transactions on Magnetics** 55(6): 1-5.

Popa, G.N., Iagăr, A. and DiniȘ, C.M. 2020. Considerations on current and voltage unbalance of nonlinear loads in residential and educational sectors. **Energies** 14(1): 102.

Santamouris, M. and Vasilakopoulou, K. 2021. Present and future energy consumption of buildings: Challenges and opportunities towards decarbonisation. **e-Prime-Advances in Electrical Engineering, Electronics and Energy** 100002(1): 1-14.

Schonlau, M. and Zou, R.Y. 2020. The random forest algorithm for statistical learning. **The Stata Journal** 20(1): 3-29.

Sinuraya, E., Soemantri, M. and Rafif, I. 2022. Evaluation and Mitigation of Voltage and Current Unbalance at MSTP Undip Jepara. **Journal of Physics: Conference Serie** 2406(1): 012013. 1-9.

Vinayagam, A., Veerasamy, V., Radhakrishnan, P., Sepperumal, M. and Ramaiyan, K. 2021. An ensemble approach of classification model for detection and classification of power quality disturbances in PV integrated microgrid network. **Applied Soft Computing** 106: 107294.

Wang, C., Du, J. and Fan, X. 2022. High-dimensional correlation matrix estimation for general continuous data with Bagging technique. **Machine Learning** 111(8): 2905-2927.

Wang, S. and Chen, H. 2019. A novel deep learning method for the classification of power quality disturbances using deep convolutional neural network. **Applied Energy** 235: 1126-1140.