Three-Phase Load Balancing Optimization using Mixed Integer-Linear Programming Model: A Case Study at Electrical Engineering Building, University of Lampung

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Abstract

Load imbalance in a three-phase low voltage distribution system is a significant operational challenge and can result in voltage drops and reduced efficiency. Based on the daily three-phase load profile of the electrical engineering academic building at the University of Lampung, particularly during operating hours, the R-phase overloaded (+13.64% deviation). Meanwhile, the S-phase underloaded (-1.70% deviation), and the T-phase underloaded (-11.94% deviation). This study implements an optimization model to balance loads by relocating load units between phases. This model was developed using Mixed-Integer Linear Programming (MILP) framework to produce practical and implementable recommendations. An innovative approach to dynamic load identification is introduced, where the model intelligently determines which loads are active at each time interval based on aggregate power data from the power meter data acquisition system. The optimal solution involved relocating six air conditioning units from the overloaded Phase R (three to Phase S and three to Phase T). This implementation successfully achieved a near-perfectly balanced system, validated by an 11.83% reduction in the aggregate load imbalance metric.

Keywords: *Load Optimization, Mixed-Integer Linear Programming (MILP), Dynamic Load Identification, Energy Efficiency, Data Acquisition System*

I. INTRODUCTION

Three-phase electrical power distribution systems are the global standard for power transmission and distribution in the commercial and industrial sectors due to their high efficiency. Optimal operating conditions for this system are achieved when the total load is distributed evenly across all three phases [1]. However, in practice, most connected loads, such as lighting, office equipment, and air conditioning (AC) units, are single-phase. The unplanned placement of these loads often leads to severe load imbalance [2].

Load imbalance has widespread negative effects. Fundamentally, it causes current to flow through the neutral conductor, which should be close to zero under balanced conditions. This neutral current causes excessive heating and additional power losses [3]. Furthermore, imbalance causes overloading on one phase while the other phases are underloaded, which reduces the effective capacity of the transformer and can trigger premature circuit tripping [4]. Long-term impacts include a decrease in overall energy efficiency and accelerated degradation of equipment insulation, which shortens its service life [5].

With the development of monitoring technology, data acquisition systems have become the main platform for recording operational data of electricity distribution systems more accurately and in real time. Granular data obtained from the data acquisition system forms the basis for the application of mathematical optimization methods, including Linear Programming, which is effective for formulating load distribution models with an objective function of minimizing load deviation between phases [6]. Linear Programming can optimize load allocation by considering phase capacity constraints, actual load profiles, and imbalance reduction targets. The application of mathematical programming-based optimization can improve distribution system efficiency by 8–15% compared to manual approaches [7]. Mixed-Integer Linear Programming (MILP) is one of the most popular and powerful methods due to its ability to handle binary decisions (load allocation) and continuous variables (power flow) simultaneously, as well as guaranteed convergence to a global optimal solution [8]. MILP has been widely applied in the context of Demand-Side Management (DSM) and even for the optimal scheduling of household appliances to minimize electricity costs [9]. In the context of direct load balancing, the MILP model is used for distribution network reconfiguration, although the focus is more on network topology than load relocation at the consumer level [10]. MILP can also be used for phase balancing by considering the uncertainty of renewable energy sources [11].

With the increasing urgency of efficient and reliable energy consumption management, particularly in the education sector, the development of real-time monitoring systems and the application of load distribution optimization models have become strategic efforts. This is in line with national efforts in energy conservation and reduction of distribution losses. Therefore, this research is designed to fill the gap in knowledge and practice by integrating real-time monitoring technology, Linear Programming optimization modeling, and unbalance load analysis based on actual data. The case study at the Electrical Engineering Building of the University of Lampung will be an example of the application of innovative monitoring technology and electrical load distribution optimization that is applicable, relevant, and replicable in similar facilities in other higher education environments.

II. METHODS

A. Power Data Acquisition System Architecture

To obtain an accurate time-series load profile, a power data acquisition system was designed and implemented in this study. The architecture of data acquisition system, illustrated in figure 1, consists of several layers, from the physical sensor to the data storage on a campus server.

The data acquisition process begins at the main distribution panel in the Electrical Engineering Academic Building as shown in figure 2. A Schneider PM2230 power meter is installed in this panel to continuously measure the essential electrical parameters, including voltage (V), current (A), active power (kW), and reactive power (kVAR) for each phase.

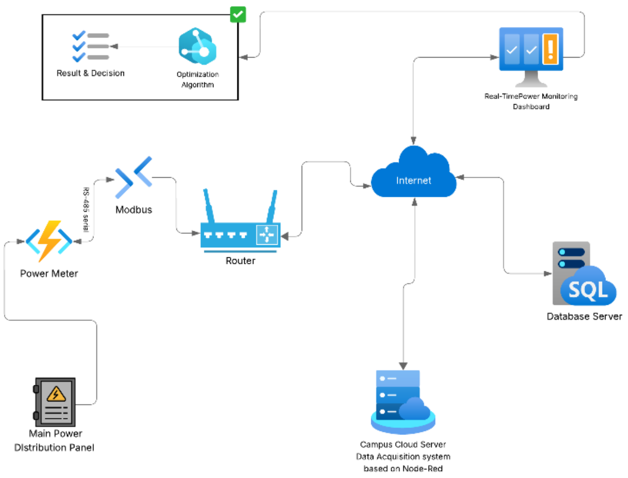


Figure 1. Power Data Acquisition System Architecture

The power meter is connected to a gateway device through RS-485 serial communication line using Modbus RTU protocol. This protocol is a reliable industry standard for communication between electronic instruments. Regarding the serial-to-network gateway, a USR-TCP232-304 serial ethernet converter serves as the system's gateway. Its function is to convert the Modbus RTU serial data from the power meter into Modbus TCP packets, making the data accessible over the campus Local Area Network (LAN).

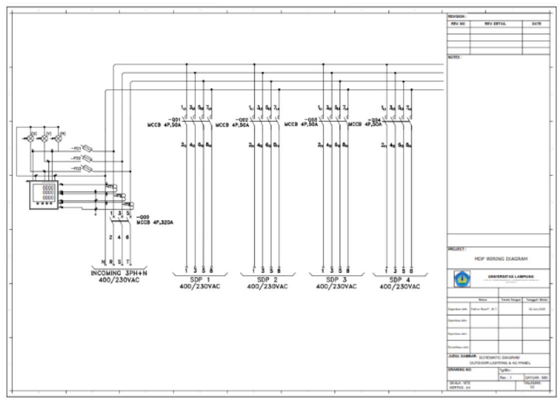


Figure 2. Power Meter Wiring Diagram in Main Distribution Panel

Data processing and orchestration are handled by a Node-RED flow deployed on a Campus Cloud Server. Acting as the central data processor, this flow is programmed to periodically poll the USR-TCP232 device by sending Modbus TCP requests to its static IP address. It then parses the response packets to extract the relevant active power values for each phase (R, S, and T) and formats the extracted data into a structure suitable for database insertion, typically an SQL insertion statement. Data storage is managed by a MySQL Server hosted within the campus cloud infrastructure. The time-series data is structured within a relational table, where each record is composed of a precise timestamp and the corresponding active power values for all three phases. Subsequently, this data is visualized on a monitoring dashboard to facilitate real-time analysis as shown in figure 3. To facilitate the optimization process, the historical load profile data stored in the MySQL database serves as the primary input source. Mixed Integer-Linear Programming developed in this study queries, this database to retrieve data for a specified time range which is subsequently used for the load balancing analysis.

Figure 3. Power Data Monitoring Dashboard

B. Mathematical Optimization Model

Once the load profile data is acquired, the balancing process is performed using a Mixed-Integer Linear Programming (MILP) model. This model is designed to be executed for each time interval 't', after dynamically identifying the likely active loads.

The model is formulated using two primary sets. The set of electrical phases is denoted by $P = \{R, S, T\}$, indexed by j. Concurrently, the set of discrete loads identified as active during a specific time interval t is denoted by K_t, indexed by k. Three key parameters, derived from the acquired data, serve as inputs for the model at each time interval t. First, $B_{j,t}$ represents the base (non-movable) load on phase j, which is calculated by subtracting the power of all active loads initially assigned to that phase from the total measured power. Second, the power rating of each active movable load k is given by the parameter W_k. Finally, $L_{avg,t}$ defines the target average load each phase, calculated as the mean of the total measured power across all three phases, where $L_{avg,t} = \frac{1}{3}\sum_{j\in P} P_{total,j,t}$.

To determine the optimal load distribution, the model employs three types of decision variables. The core decision is captured by the binary variable x_{kj}, which is defined as $x_{kj} = 1$, if active load k is allocated to phase j, and $x_{kj} = 0$ for otherwise.

The resulting state of the system is then described by two continuous variables. The variable $S_{j,t}$ represents the final total load on phase j after optimization. Assisting this, $d_{j,t}$ is a non-negative continuous variable that quantifies the absolute deviation of the final load on phase j from the average load.

The objective of the model is to minimize the sum of total deviations from the average load across all phases as shown in equation (1).

$$Min. Z_t = \sum_{j\in P} d_{j,t} \qquad (1)$$

subject to:

- Unique assignment constraint as shown equation (2). Each active load k must be allocated to exactly one phase j.

$$\sum_{j\in P} x_{k,j} = 1 \quad \forall k \in K_t \qquad (2)$$

- Final load calculation constraint as shown equation (3). The final load on each phase $(S_{j,t})$ is the sum of its base load $(B_{j,t})$ and the total power of all active loads allocated to it.

$$S_{j,t} = B_{j,t} + \sum_{k\in K_t} W_k \cdot x_{kj} \quad \forall j \in P \qquad (3)$$

- Deviation Constraint as shown equation (4) and ewuation (5). The following up constraints is used to define $d_{j,t}$ as the absolute value of $|S_{j,t} - L_{avg,t}|$.

$$S_{j,t} - L_{avg,t} \le d_{j,t} \quad \forall j \in P \qquad (4)$$

$$-(S_{j,t} - L_{avg,t}) \le d_{j,t} \quad \forall j \in P \qquad (5)$$

C. Dynamic Load Identification

The distribution of electrical load in the H building of the Electrical Engineering Department at Lampung University, there are 10 air conditioning units, each with a capacity of 2 hp, which function as variable loads with relocatable phase connections. The purpose of this reallocation is to achieve a balanced load distribution between phases, thereby minimizing voltage drop in specific phases. The load distribution is as shown in figure 4.

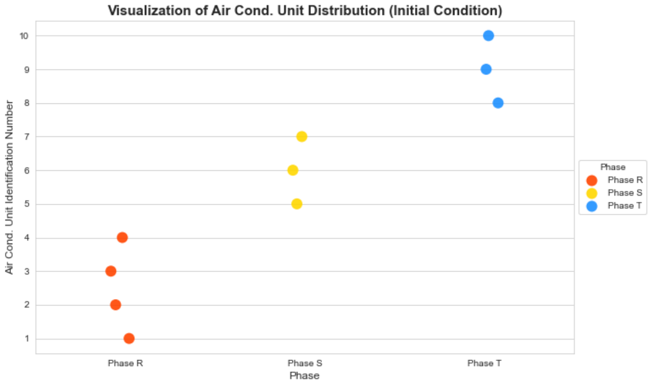


Figure 4. Air conditioning distribution as a control variable for electrical load

III. Results and Discussions

A. Acquisition Data Testing Using PQA

A fundamental stage preceding the implementation of the mathematical optimization model is the accuracy validation of the real-time data acquisition system. This validation aims to ensure the reliability and precision of the data acquired from the power meter. The validation method employed involves simultaneous data comparison against a reference instrument, specifically a Power Quality Analyzer (PQA). Measurements were conducted in parallel, involving both the data acquisition system and the PQA, to evaluate any reading deviations or discrepancies.

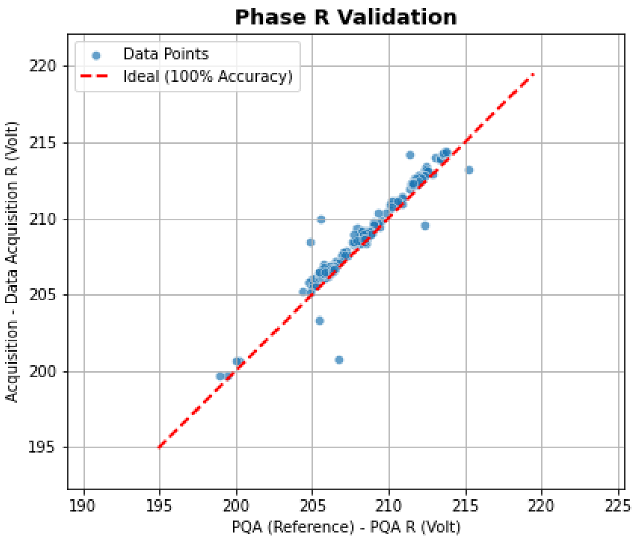
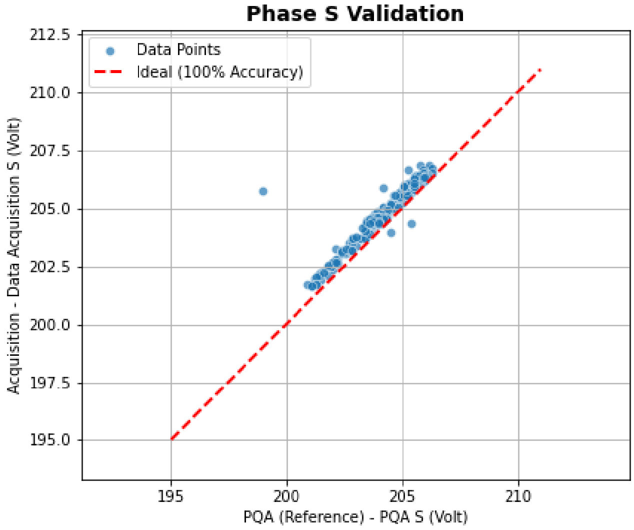


Figure 5. Voltage measurement validation on Phase R (PQA vs Data Acquisition System)

A detailed per-phase review reveals minimal performance variation, which reinforces the system's overall reliability. Phase R exhibited the highest precision, achieving 99.80% accuracy with the lowest Mean Absolute Percentage Error (MAPE) at just 0.20% as shown in figure 5. Conversely, Phase S recorded the highest deviation with a 0.22% MAPE, resulting in a 99.78% accuracy; however, this 0.02% difference from the other phases is practically negligible, confirming no significant weakness in this measurement channel as shown in figure 6.

Figure 6. Voltage measurement validation on Phase S



(PQA vs Data Acquisition System)

Phase T performed with stable, intermediate results, showing 99.79% accuracy and 0.21% MAPE. This highly uniform and consistent performance across all three phases confirms that the data acquisition system operates without any channel-specific bias or anomalies as shown in figure 7.

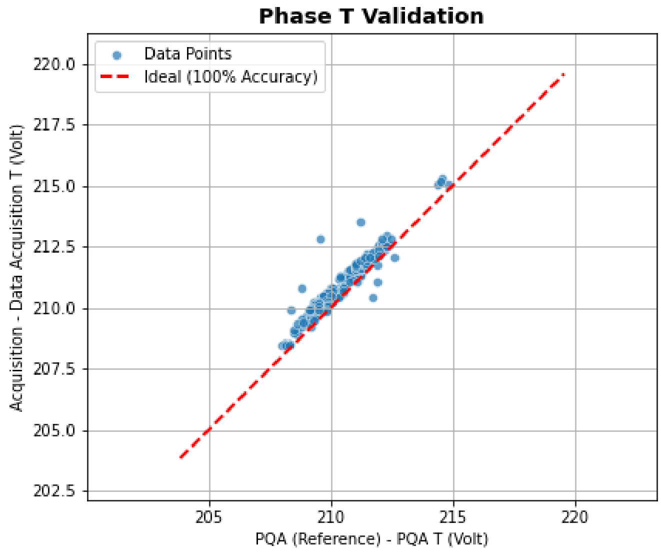


Figure 7. Voltage measurement validation on Phase T (PQA vs Data Acquisition System)

B. Initial Load Profile Analysis

Analysis of the daily load profile from real-time data reveals a chronic load imbalance as shown figure 8. The graph illustrates that Phase R operates with a significantly higher power consumption compared to Phase S and Phase T. This gap becomes particularly evident during the building's operational hours (approximately 08:00 to 16:00), where Phase R carries most of the variable load (such as air conditioning and lighting), while Phase S and Phase T operate at relatively lower levels. This persistent load disparity creates a non-ideal *unbalanced* condition, which serves as the primary justification for performing load reallocation to achieve a more balanced and efficient system.

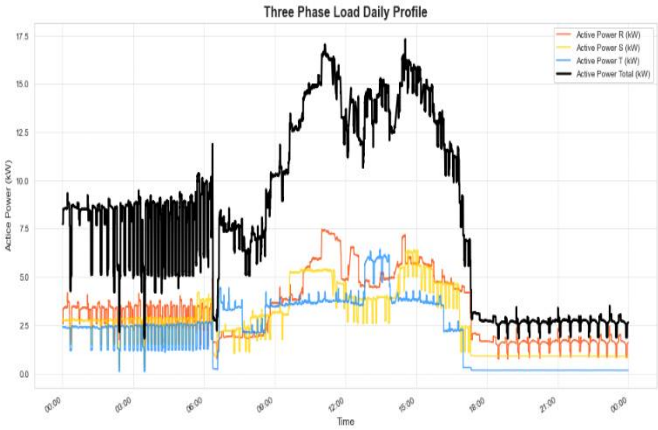


Figure 8. Three phase loads daily profile data capture by Data Acquisition System

Analysis of the captured data shows that the average peak load for H-Building, Electrical Engineering, University of Lampung is 13.83 kW. This data also reveals a significant load imbalance between the phases. Phase R is identified as the heaviest phase, operating at 5.24 kW, which is a positive deviation of +13.64% from the ideal average load. Conversely, Phase T is the lightest phase at 4.06 kW (a -11.94% deviation). Phase S operates closest to equilibrium at 4.53 kW (a -1.70% deviation). This wide gap between Phase R and Phase T, also Phase R and Phase S confirm the need for a load-balancing strategy.

C. *Three Phase Load Balancing Optimization Result*

The implementation of the mathematical optimization model successfully achieved a near-ideal load condition through the reallocation of 6 air conditioning (AC) units. This reallocation strategy specifically moved 3 units from Phase R to Phase S and 3 units from Phase R to Phase T. Although the total average peak load remains 13.83 kW, its distribution among the phases has now reached an equilibrium point, as summarized in table-1. The post-optimization data demonstrates a remarkable convergence of the load. The most drastic improvement occurred in Phase R; previously severely overloaded (a +13.64% deviation), it now operates at 4.60 kW with a negligible deviation of -0.18%.

Table-1. Comparative Analysis of Phase Load Deviation (Pre- and Post-Optimization)

Phase	Initial Load	Initial Deviation	Post-Optimization Load	Post-Optimization Deviation	Number of Load Reallocation
R	5.24 kW	+13.64%	4.06 kW	-0.18%	▲ 6-unit of Air Cond.
S	4.53 kW	-1.70%	4.62 kW	+0.22%	▼ 3-unit of Air Cond.
T	4.06 kW	-11.94%	4.61 kW	-0.04%	▼ 3-unit of Air Cond.

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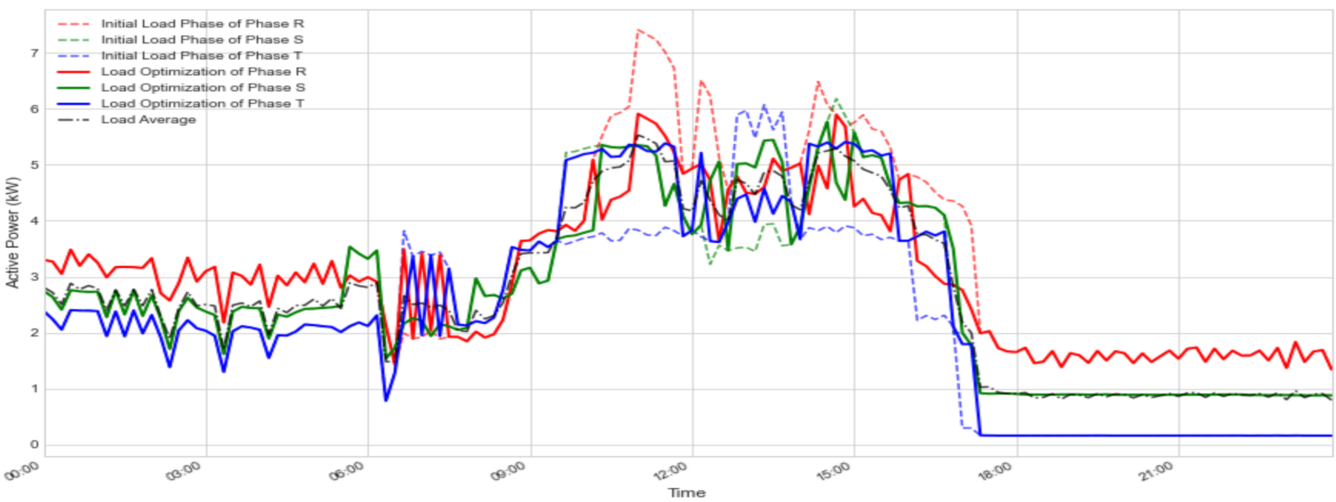

Figure 9. Comparative of Phase Load Deviation (Pre- and Post-Optimization)

Similarly, Phase T, which was the most underloaded phase at a -11.94% deviation, had its load successfully increased to 4.61 kW, reducing its deviation to just -0.04%. Phase S remains stable near the ideal point, shifting to 4.62 kW (a +0.22% deviation).

Based on the analysis in table-1, the implementation of the Mixed-Integer Linear Programming (MILP) optimization model has been proven to reduce load imbalance in a system with daily load variations. This analysis shows that this model could achieve an average reduction in the aggregate load imbalance metric percentage of 11.83% as shown in table-2.

Table-2. Aggregate Load Imbalance Reduction Summary

Unbalance Load Average (Pre-Optimization)	41.51%
Unbalance Load Average (Post-Optimization)	36.60%
Unbalance Load Reduction	11.83%

Visually, this result represents a total transformation of the daily load profile. The Phase R load curve, which was previously isolated far above the other phases, has now dropped and converged with the Phase S and Phase T curves as shown in figure 9. All three load traces (kW) now appear nearly identical and overlapping across the 24-hour period. This success validates the proposed optimization model as an effective solution for mitigating load disparity, resulting in a balanced, efficient, and reliable three-phase system.

IV. CONCLUSIONS

The *Mixed-Integer Linear Programming* (MILP) optimization model implemented in this study proved effective for minimizing load imbalance in a system with variable daily load profiles. The model generated a specific reallocation strategy: moving 6 units of Air Conditioning each with capacity of 2 Hp from Phase R, with 3 units transferred to Phase S and 3 units to Phase T. This post-optimization configuration successfully created a near-balanced load condition over 24 operational hours, with Phase R (4.60 kW), Phase S (4.62 kW), and Phase T (4.61 kW) operating at nearly identical levels. Overall, the application of this model resulted in an average reduction of 11.83% in the aggregate load imbalance metric

V. ACKNOWLEDGMENT

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