ECE 445

SENIOR DESIGN LABORATORY

FINAL REPORT

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# Advanced Modeling and Display of International Campus Power System

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# Abstract

We have developed a sophisticated modeling and display system for the Campus Power System, meticulously crafted to enhance electricity management and monitoring at Zhejiang University's Haining International Campus. This system utilizes hourly data collected from the campus's support and security departments to perform accurate power flow calculations. The results, which include metrics such as current, voltage, and active power, are dynamically displayed using multicolored LED beads on a meticulously detailed 1:1600 scale 3D printed model of the campus.By incorporating advanced technologies such as machine learning to improve grid behavior monitoring and management, and by deploying event-driven fault simulations for emergency scenarios, the project lays the groundwork for a proactive approach to energy efficiency. These enhancements are crucial for pushing forward sustainable energy objectives. Our system, with its modeling and visualization tools, is strategically designed to steer the campus towards a more sustainable and environmentally friendly future.

**Keywords:** Campus Power System, Energy Management, Load Forecasting, Power Event Detection, Power Flow Calculations

# Contents

# 1 Introduction

## 1.1 Background

As an open and modern campus, Zhejiang University Haining International Campus has state-of-the-art infrastructure and cozy single dormitories. However, this also leads to a relatively high electricity consumption. In 2023, the Haining campus spent tens of millions of RMB on electricity. High electricity consumption is also common in campus around the world [1].

The following problems have been identified with the campus' electricity consumption:

- **Lack of Awareness and Sensitivity:** There is a noticeable lack of awareness and sensitivity among students and faculty regarding electricity consumption and energy conservation practices.
- **Insufficient Visualization Tools:** The current visualization tools for power data lack intuitiveness, which hinders effective management and understanding of energy usage.
- **Inadequate Emergency Response Capabilities:** There is a need for improved responsiveness and expanded treatment options to effectively manage emergencies such as over-voltage and short circuits.

Addressing these issues is essential for advancing sustainable energy goals. By integrating advanced modeling and visualization tools, our system is designed to guide the campus towards a more eco-friendly future.

## 1.2 Objective

Our proposed solution to address the situation is to develop an Advanced Modeling and Display system for the campus power system.

**1. Comprehensive Data Visualization**

The raw power data undergoes accurate power flow calculations using a power flow solver, which extracts relevant information vital for understanding power distribution and load balancing across the campus. The resulting information, including current, voltage, power, and other relevant data, will be visually represented using LED strips with varying brightness and colors on a physical model.

**2. Advanced Load Forecasting and Strategic Anomaly Simulation**

The system utilizes machine learning-based algorithms to forecast and monitor diverse grid behaviors. The project leverages these algorithms for remote data analysis, scrutinizing historical power consumption patterns to facilitate accurate forecasting. Moreover, the system incorporates power anomaly simulation techniques to anticipate potential disruptions in the power supply. These simulations are instrumental in assisting stakeholders to assess contingency plans and refine response strategies effectively.

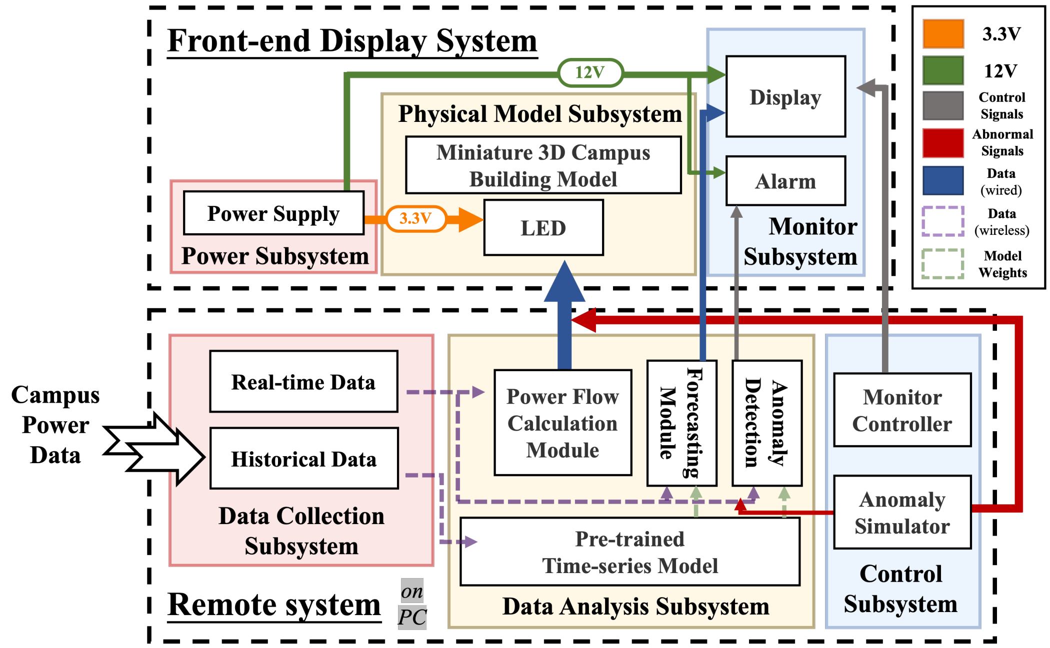



Figure 1: Block Diagram

**3. User-friendly GUI**

The development of the Data Interaction Monitor equips users with an intuitive tool to engage effectively with electricity data. This tool enables access to power data for all buildings in the database, facilitating the observation of trends and comparisons between buildings. Furthermore, the monitor is equipped to control LED strips for dynamic displays of power changes, offering a more intuitive visualization of evolving electricity usage across the campus.

## 1.3 High-level Requirement

- **Quantitative criteria for the front-end display.** The envisioned physical model must possess the capability to visually represent power consumption data across the entire campus accurately. It should offer detailed representations of individual buildings or substations, allowing users to discern usage patterns easily. In the case of state changes, the LEDs are expected to exhibit the desired state within a delay of **2** seconds.
- **Quantitative criteria for the machine-learning model.** The machine learning model, should be able to accurately forecast electricity consumption trends. Specifically, the average MAPE should be **10%** or less.
- **Quantitative criteria for the event-driven power accident simulation.** For a simulated power anomaly event, e.g., simulating a two-phase short circuit to ground in North Building A, the anomaly detection module should react and trigger an alarm within **5** seconds, and the macro-F1 score is expected to be no less than **0.95**.

### 1.4 Block Diagram

Figure 1 demonstrates the workflow and data flow of the entire system. The system first collects and analyzes real-time and historical power data from substations. The Data Analysis Subsystem processes this data to forecast usage, identify anomalies, and generate metrics like voltage and current. The Control Subsystem manages data display settings and simulates anomalies for testing. The Physical Model and Monitor Subsystems visualize the processed data, with the former using LEDs to show building usage and the latter displaying numerical data, forecasts, and anomaly alerts. The Power Subsystem provides electricity to the visualization components.

# 2 Design

## 2.1 Front-end Display System

#### 2.1.1 Power Subsystem

The Power Subsystem powers the Physical Model and the Monitor subsystems, providing the proper voltage to both through a transformer.

The Power Subsystem is responsible for supplying power to the LED strips of the Physical Model Subsystem and the monitor subsystem through transformers in order to obtain different required voltages. First of all, for the light strips of the Physical Model Subsystem, the LED strips must be supplied with a continuous current of at least **500**mA and a stabilized voltage of about **5**V to ensure the stability of the LED strips. LED strips in our project are controlled by a Raspberry Pi, which fails to provide such an amount of power. We hence use a DC power supply to support the LED strips. We will also use the Raspberry Pi to provide power to our display. The display needs a power supply of **220V** AC, which is also included in our Power Subsystem.

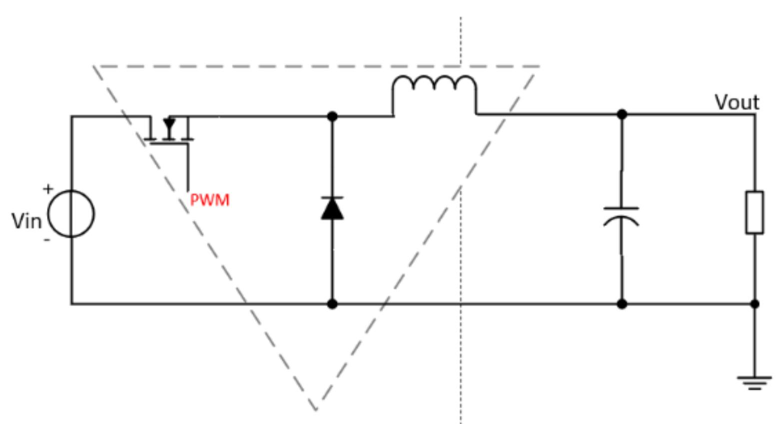



Figure 2: The Circuit of Power Subsystem

#### 2.1.2 Physical Model Subsystem

The Physical Model Subsystem visualizes the real-time electrical usage of each building on campus. It receives display commands from the Control Subsystem and uses LED strips of various colors to display electrical data such as voltage and power.

The Physical Model Subsystem will receive display commands from the Control Subsystem within **500** milliseconds to ensure the timeliness of the visualized power data presented. The subsystem is equipped with WS2812 LED strips to display voltage, power, and other data. The use of LED strips to display power data allows for a more intuitive display of power data for individual buildings and zones by color. We use a Raspberry Pi to control the LEDs on the LED strips. Since it's hard for human eyes to distinguish LED with different brightness, we choose to use different colors to represent different levels of quantity of the data for each building.

Meanwhile, the campus building model needs to be as realistic as possible to facilitate real-time troubleshooting and processing. So we created a more detailed electronic model of the campus, as shown in Figure 3a and Figure 3b. The Physics International Campus sandbox will be a square with **1** meter sides and a height of less than **30** centimeters. This ensures the fineness of the individual buildings and leaves enough space for the placement of the LED strips and their wiring, as shown in Figure 4a and Figure 4b. For the base plate of the solid sand table model we use wood to ensure the strength of the model. On top of that we used blue acrylic glass for the water and different colors of ABS plastic for the pavement and green areas. For each building of the school we use architectural modeling and 3D printing with different colors of ABS plastic to get a detailed and accurate model of the building. The models were scaled to the actual distances and pasted onto the plots of land. Based on this, some small models such as trees are pasted to make the overall model more complete and close to reality. In addition, the Physical Model Subsystem needed to include fail-safe mechanisms to deal with issues such as LED strip failures in a timely manner.

(a) Electrical model  (b) Local electrical model

Figure 3: Electrical model

(a) Physical model (b) Local physical model

Figure 4: Physical model

### 2.1.3 Monitor Subsystem

To display the power data and make detailed analysis, we implement a Monitor Subsystem with GUI support, which responds to commands from the Control Subsystem. The GUI for the Monitor subsystem is implemented based on PyQt5. As shown in Figure 5, the background of the window is a photo of the campus, and the three main functions of the subsystem are at the top of the window, which can be switched by clicking.

The Data Monitor page within the Monitor subsystem, depicted in Figure 5a, functions as a dashboard that presents essential information about the campus power system. It displays the number of campus buildings, the total electricity consumption of these buildings over the past week, and the current status of the campus power system, with green indicating normal conditions. To give users a clear numerical understanding of trends and changes in the campus power data, the Data Monitor enables the selection of a specific time range to plot a line graph for a designated building. This graph not only illustrates power usage over the selected period but also displays exact values adjacent to each data point for enhanced clarity. Table 1 presents the selection of display times available on this page, which encompasses both the historical data retrieved from the school's electricity database and the predicted values for the upcoming 24 hours, as forecasted by the data analysis subsystem.

Figure 5b demonstrates the anomaly simulation function. Given that power anomalies are typically rare, brief, and challenging to record in real-world scenarios, this module has been developed to enable users to test the anomaly detector's capabilities. Users can select a specific building and the type of fault they wish to simulate. Upon clicking 'Apply', the test results and fault analysis will be displayed on the right side of the screen. Concurrently, if the system successfully detects the fault, the three-phase voltage and current for the selected building will be graphically represented on the left side of the screen. Detailed information about the anomaly simulation module is further discussed in Section 2.2.2.


(a) Data Monitor

(b) Error Simulation

Figure 5: Monitoring System GUI

The Monitor subsystem is required to receive display commands from the Control Subsystem within **500** milliseconds. In anomaly simulation, the subsystem needs to trigger an alarm within **5** second after detecting a power failure and record the time of the failure, so as to facilitate timely handling of power failures and post-inspection. To facilitate collaboration with the Data Collection Subsystem and the Physical Model Subsystem, our monitoring system was implemented on a Raspberry Pi. An external screen was utilized to display the interface described above.

## 2.2 Remote System

### 2.2.1 Data Collection Subsystem

The Data Collection Subsystem collects and stores power usage data from each substation provided by the Engineering Department. This subsystem then transfers the collected data to the Data Analysis Subsystem for further analysis and utilization.

Table 1: The range of optional data displays, the meaning of the horizontal axis coordinates and the data sources in the Data Monitor .

| Timescale | Frequency | Data sources |
|---|---|---|
| **Yesterday** | Hourly | System database |
| **Last Week** | Uniform sampling at 4 points / day | System database |
| **Last Month** | Daily (average of hours) | System database |
| **Forecast(24h)** | Hourly | ML model outputs |

Following extensive consultations with the Support and Assurance as well as Engineering departments, we have successfully secured authorization to access real-time data housed within the database. This invaluable resource offers a granular perspective, with data points recorded at hourly intervals, detailing the power consumption in kilowatt-hours (kWh) over the preceding hour.

Furthermore, considering the unreliability of data within the distribution network, we have expanded our dataset by obtaining detailed electricity use records for the entire year 2023. These extra statistics include the aggregate energy usage within the campus, which is thoroughly documented on a monthly basis, giving us a comprehensive view of consumption trends and patterns over the course of the year.

To facilitate the collection of real-time data, a Python script has been developed to query the campus database. Considering that the targeted data is stored within the database and updated on an hourly basis, we have opted to execute the data collection process daily. The Python script is hosted on the database server and is scheduled to activate at 2 a.m. each day. It performs queries to gather power usage data for each building. Upon retrieval, the data is compiled into CSV files. Subsequently, these files are transmitted to our server, enabling us to archive daily data for further analysis.

### 2.2.2 Data Analysis Subsystem

The Data Analysis Subsystem is the central hub for processing, calculating, and managing data flows (see Figure 6), and serves as the primary data source for the front-end presentation system. It preprocesses power consumption data from each campus substation, converting it into active electricity consumption for individual buildings. This data is then used by the automatic power flow calculation model to generate key metrics like voltage and current. Additionally, real-time power usage data is fed into machine learning models, which leverage historical consumption data to forecast power usage and detect anomalies in individual buildings. The processed data is subsequently transmitted to the Physical Model and Monitor subsystems for visualization.

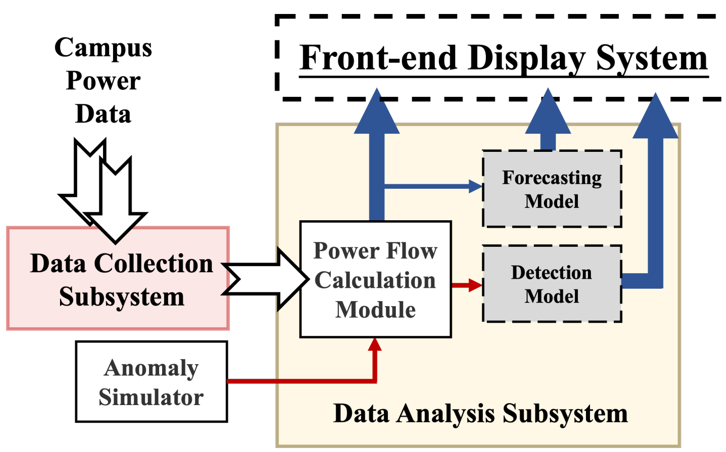
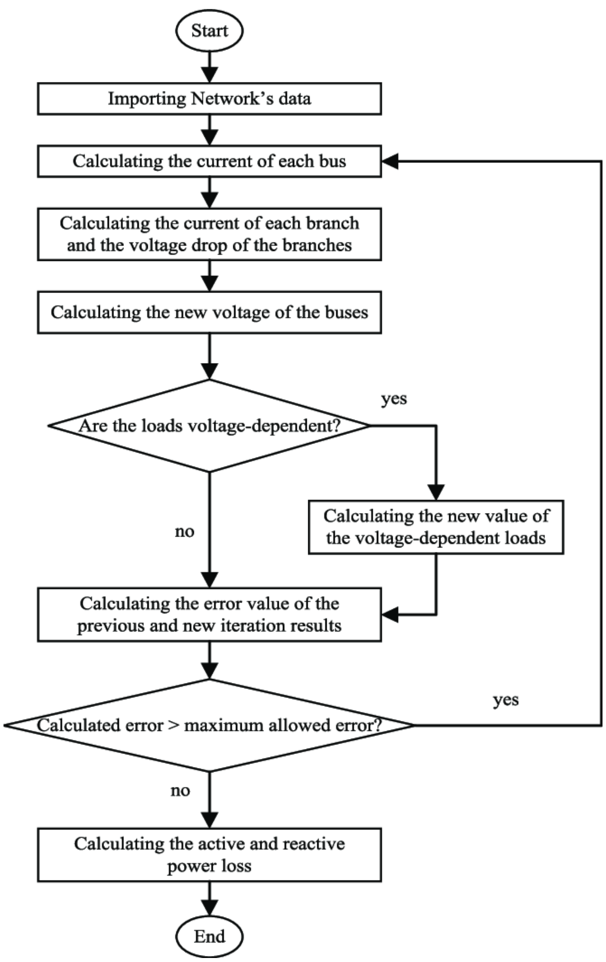



Figure 6: Data Flow in the Data Analysis System

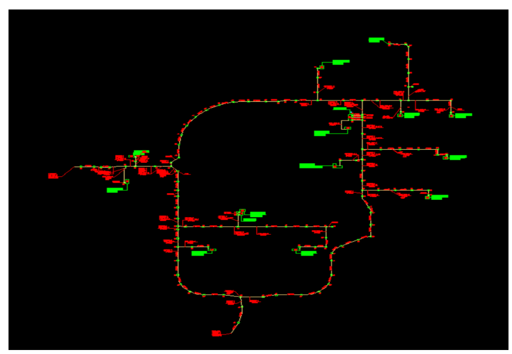
### Automatic power flow calculation for distribution networks

The subsystem utilizes OpenDSS, an open-source software effective for simulating electrical power distribution networks. By leveraging its advanced power flow calculation capabilities, we aim to thoroughly analyze the dynamics of our distribution network, capturing detailed power data for each building at every time node. This data includes key parameters like active power, voltage, and current, providing deep insights into the operational complexities of our infrastructure. OpenDSS enables detailed modeling and simulation, allowing for comprehensive analysis of power flow, voltage regulation, and fault analysis. The flowchart of this process is displayed in Figure 7a.

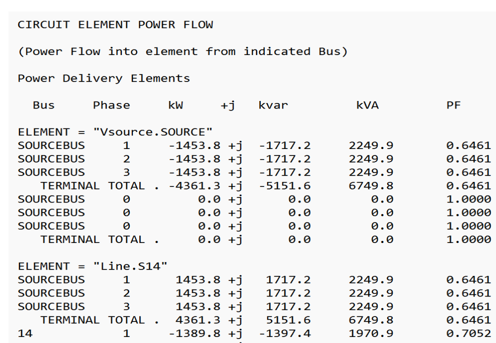
To calculate the input power data, we first construct the campus distribution network. The modeling and simulation results are depicted in Figure 7b and 7c. Furthermore, to improve the real-time monitoring capabilities of our system, we have integrated OpenDSS seamlessly into our project framework. Utilizing OpenDSS's versatile API interface, the subsystem facilitate smooth data exchange, ensuring fast and efficient communication between our simulation environment and external applications.




(a) Flowchart of Power Flow Calculation



(b) Distribution Grid Modeling



```
CIRCUIT ELEMENT POWER FLOW

(Power Flow into element from indicated Bus)

Power Delivery Elements

  Bus      Phase     kW     +j   kvar          kVA          PF

ELEMENT = "Vsource.SOURCE"
SOURCEBUS      1      -1453.8 +j  -1717.2     2249.9       0.6461
SOURCEBUS      2      -1453.8 +j  -1717.2     2249.9       0.6461
SOURCEBUS      3      -1453.8 +j  -1717.2     2249.9       0.6461
   TERMINAL TOTAL . -4361.3 +j  -5151.6     6749.8       0.6461
SOURCEBUS      0          0.0 +j      0.0        0.0       1.0000
SOURCEBUS      0          0.0 +j      0.0        0.0       1.0000
SOURCEBUS      0          0.0 +j      0.0        0.0       1.0000
   TERMINAL TOTAL .       0.0 +j      0.0        0.0       1.0000

ELEMENT = "Line.S14"
SOURCEBUS      1       1453.8 +j   1717.2     2249.9       0.6461
SOURCEBUS      2       1453.8 +j   1717.2     2249.9       0.6461
SOURCEBUS      3       1453.8 +j   1717.2     2249.9       0.6461
   TERMINAL TOTAL .  4361.3 +j   5151.6     6749.8       0.6461
14             1      -1389.8 +j  -1397.4     1970.9       0.7052
14             2      -1389.8 +j  -1397.4     1970.9       0.7052
```

(c) Power Flow Calculation

Figure 7: Overview of the power flow calculation process

### Machine learning-based load forecasting

To enhance energy savings on campus, developing accurate short-term load forecasting models for the electrical system is essential. Machine learning techniques can be used to train models with historical power usage data from individual campus buildings, enabling predictions of future load data for specific time periods.

Based on thorough research and careful evaluation, we have selected the Long short-term memory (LSTM) [2] algorithm as our base model. This decision to choose LSTM models is influenced by three primary factors. First, LSTM is highly effective in capturing time-dependent and seasonal variations in power system load data. It can autonomously learn feature representations from input data, which is advantageous for load forecasting where data is influenced by complex factors and nonlinear relationships. Second, LSTM models are robust against noisy and outlier-ridden input data, with techniques such as dropout and regularization helping to mitigate overfitting and enhance generalization. Lastly, compared to more complex models recently used in time series analysis, LSTM offers a simpler implementation and adaptation process. This simplicity, coupled with reasonable training times, makes LSTM well-suited for continuous predictions on real-time data, fulfilling our needs for developing online prediction schemes.

As shown in Figure 8, LSTM uses a memory unit to store information from past time steps and decides whether to discard or retain specific information based on the current input. The memory unit consists of three gates: input, forget, and output. The input gate controls the amount of fresh information that enters the memory unit, whereas the forget gate controls how much old information is maintained. Furthermore, the output gate controls the use of information throughout the prediction process.

The LSTM model is tasked with generating power consumption predictions for the next 24 hours using data inputs. For a balance of accuracy and efficiency, we opted for a single-step rolling prediction approach, which utilizes the previous week's data and the previous outputs to sequentially predict 24 future data points on a rolling basis.

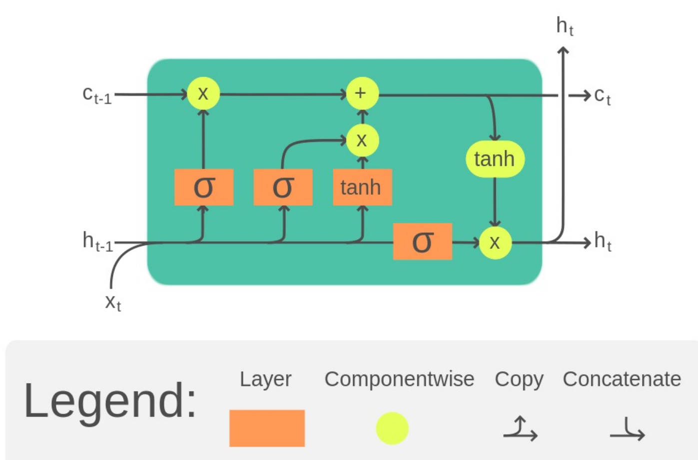



Figure 8: Flowchart of the LSTM algorithm, from Wikipedia [3]

**Power system data-driven event detection**

Anomaly detection (or event detection), on the other hand, plays a critical role in addressing the overall problem. With the detection of faults (or events) in power system, managers can promptly respond to issues, preventing potential losses and mitigating further complications.

Power system events are classified into major physical events and power quality phenomena. Major events, such as line trips, short circuits, generation-load imbalances, equipment failures, and islanding, impact the bulk power system significantly, leading to power quality issues, large disturbances, and potential cascading failures. Conversely, power quality phenomena involve deviations in voltage, current, frequency, and power, often due to minor factors like weather, contamination, equipment issues, or maintenance. Major events can also precipitate severe power quality issues. These phenomena are defined and analyzed according to IEEE power quality standards [4], [5].

In the campus electrical network, many of the scenarios described above are highly improbable or unlikely to occur. Therefore, we focus on several more common types of anomalies: single-phase ground faults, two-phase ground faults, two-phase shorts, and three-phase ground faults. Table 2 shows the current and voltage outputs of the simulation of the aforementioned events using OpenDSS. We performed event simulations for Building 1A, and all buildings experienced changes in voltage and current conditions from normal, with the most significant changes at the event location, which is the basis for the model's determination of where the event occurred.

Table 2: Simulation Results for Various Short Circuit Conditions in Building 1A on March 15, 2024, at 14:00 CST: Magnitudes and Phase Angles of Three-Phase Voltage and Current

| Type | Voltage Magnitude | Voltage Phase Angle | Current Magnitude | Current Phase Angle |
|---|---|---|---|---|
| **Original** | [226, 226, 226] | [-1.6, -122, 118] | [53, 53, 53] | [-20, -140, 100] |
| **Single-phase grounded short circuit** | [0.56, 279, 243] | [-51, -131, 131] | [38, 64, 59] | [-13, -129, 86] |
| **Two-phase short circuit** | [111, 110, 220] | [-62, -63, 119] | [37, 37, 74] | [-80, -80, 100] |
| **Two-phase grounded short circuit** | [0.65, 0.74, 263] | [-32, -177, 121] | [29, 28, 57] | [-77, -78, 102] |
| **Three-phase grounded short circuit** | [0.74, 0.77, 0.72] | [-42, -167, 75] | [0.23, 0.24, 0.22] | [-60, 176, 56] |

The four types of faults are considered common due to their potential occurrence from everyday activities and conditions in a school setting. For example, a single-phase ground fault might happen due to aging or damaged insulation on wiring, which can occur over time as building materials wear out. Two-phase ground faults and two-phase shorts can result from accidental contact between wires during maintenance or construction activities, a situation that might arise during upgrades to school facilities or repairs. Lastly, three-phase ground faults, while less frequent, can occur due to severe weather conditions such as lightning strikes or heavy rain infiltrating electrical systems, both of which are plausible in a school environment. Each of these faults impacts the stability and safety of the power supply, necessitating their prioritization in our monitoring efforts.

Statistical based methods can be used for anomaly detection in power usage. Research in related fields has shown that certain time series features can be used to determine the occurrence of events. Using these features, we can develop a model that can automatically categorize events.

The 3-Sigma method can be utilized for anomaly detection in power data, such as current and voltage measurements. This method is based on the principle that normal variations in the data should fall within three standard deviations from the mean. For three-phase current and voltage data, we analyze 12 inputs from a given building at any specific moment. By comparing this data with the statistical model derived from all historical data, we can determine whether an event has occurred and identify its type.

### 2.2.3 Control Subsystem

The control subsystem acts as the crucial link between the front-end system and the back-end data and models. It corresponds directly to the Monitor subsystem and facilitates its back-end operations.

For the Data Monitor module, the control subsystem is tasked with retrieving the appropriate data from the database or invoking the load forecasting model for predictions.

For the Error Simulation module, it is responsible for generating random anomalies or processing user-specified anomalies, which are then integrated into the power flow computation model. This data is subsequently analyzed by the Data Analysis subsystem and relayed back to the Monitor subsystem.

For LED Show requests from the Monitor subsystem, the control subsystem retrieves and forwards the relevant data to the Physical Model subsystem.

By transmitting control signals to the Monitor Subsystem and the Physical Model Subsystem, the Control Subsystem swiftly switches the power data display, with a response time of less than **100** milliseconds. Additionally, effective communication with other subsystems is established through standardized protocols.

# 3 Requirements and Verifications

Our testing is divided into three main components: power data processing (which includes data acquisition, grid modeling, and both offline and online testing), physical model testing, and data analysis model testing. Table 3 outlines our testing schedule.

- Distribution Grid Modeling Testing: Conducted during the first two weeks, this phase tests the system's capability to accurately and reliably model the distribution grid from the substation level to specific buildings, covering various grid components.
- Power Flow Calculation Testing: This phase evaluates both offline and online power flow calculations, assessing the accuracy and efficiency of the power flow calculation module using simulated data offline and real-time data online.
- API Interface Testing: Scheduled for the fourth week, this test focuses on the online capabilities of the power flow solver API interface, checking its ability to access real-time data and its responsiveness in delivering power flow solutions.
- Physical Model Testing: On the fifth week, this phase tests the LED and monitor components of the physical model, which may involve visualizing the results of power flow calculations or other system parameters on a physical display.
- Load Forecasting and Event Simulation Testing: Conducted in the last weeks, this testing evaluates the system's time series prediction functions and its ability to simulate faults within the distribution system, aiming to verify the system's predictive accuracy and its response to simulated real-world events.

Table 3: Test Plans with Timelines

| Date | Test Name |
|---|---|
| 3.25 - 3.31 | Distribution grid modeling to substation level offline data testing |
| 4.1 - 4.7 | Distribution grid modeling to specific buildings offline data testing |
| 4.8 - 4.14 | Real data online power flow calculation testing |
| 4.15 - 4.21 | Power flow solver API interface access to real-time data testing |
| 4.22 - 4.28 | Physical model: LED and monitor testing |
| 4.29 - Demo | Load forecasting and event detection models testing |

## 3.1 Result of Physical Model

**Reliability of the Power Subsystem.**

The power supply needs to provide continuous power to the LED strips of the Physical Model Subsystem and the monitor subsystem. Any failure or interruption of the power supply may result in the loss of the visual display and alarm functions. At the same time, the voltage and current supplied to multiple LED strips after passing through the transformer may be unstable, which may lead to damage or malfunction of the strips. Therefore, we have a backup power supply in case the main power supply fails. When a mains failure is detected, the backup power supply activates within 1 second, which ensures a seamless transition and avoids interruption of the LED strip operation.

**The visual effect of the LED strips.**

To enhance the clarity and intuitiveness of the LED display in the physical model subsystem, we developed a color cross-reference table, as illustrated in Figure 9, to correlate power levels with specific colors. According to Table 10, the distribution of values in this table is non-uniform, intentionally designed based on historical observations of power usage across campus. Power consumption varies significantly from one building to another, influenced by different activities and usage patterns. Thus, this color comparison table effectively utilizes a range of colors to visually represent variations in power usage.

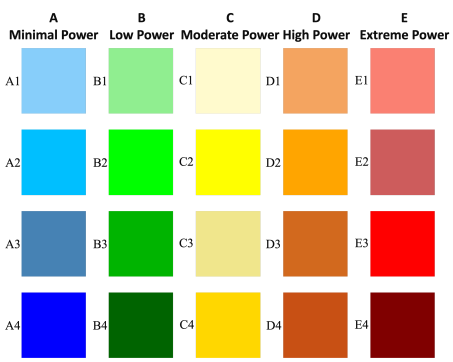



Figure 9: Color Reference Table

Figure 10: Power Reference Table

| | Minimal Power | Low Power | Moderate Power | High Power | Extreme Power |
|---|---|---|---|---|---|
| Level1 | [0,1) | [10,12) | [20,25) | [50,60) | [100,120) |
| Level2 | [1,3) | [12,15) | [25,30) | [60,70) | [120,150) |
| Level3 | [3,6) | [15,18) | [30,40) | [70,80) | [150,250) |
| Level4 | [6,10) | [18,20) | [40,50) | [80,100) | [250,$\infty$) |

## 3.2 Result of data collection and processing

**Reasonableness of input data.**

By examining and contrasting the statistical attributes of historical power consumption data for each building, we have initially validated the reliability of the data sources. The Gymnasium (Building 23) and the Student Center (Building 16) exhibit the highest average power consumption. Building 23, being larger in size, encompasses various sports facilities such as the swimming pool, basketball court, and table tennis area, while Building 16 hosts the cafeteria, supermarket, and other bustling venues. Hence, it is reasonable for these buildings to register the highest power consumption. Conversely, the lowest average power consumption is recorded in buildings 4 and 8, both of which are yet to be inaugurated, and the multi-purpose hall (Building 7), which sees infrequent use aside from large conferences. Additionally, we noticed consistent statistical patterns and power usage behaviors across several symmetrical buildings. This includes the three inaugurated college (Buildings 11, 12, and 15), North Academic Buildings A and B (Buildings 19 and

20), and the East and West Lecture Halls (Buildings 5 and 6). These buildings within each cluster share comparable dimensions, foot traffic, and electricity usage patterns, thereby further validating the dataset.

**Reliability of Distribution Grid Modeling.**

For the substation level offline data test, we modeled each substation as a load. we used 80% of the capacity of each substation as the total power of each load. Power Factor 0.95 was used for modeling. The current calculation converged successfully and the active power and voltage values were within a reasonable range.

```
CIRCUIT ELEMENT POWER FLOW

(Power Flow into element from indicated Bus)

Power Delivery Elements

  Bus      Phase     kW     +j   kvar         kVA         PF

ELEMENT = "Vsource.SOURCE"
SOURCEBUS     1     -1453.8 +j  -1717.2     2249.9       0.6461
SOURCEBUS     2     -1453.8 +j  -1717.2     2249.9       0.6461
SOURCEBUS     3     -1453.8 +j  -1717.2     2249.9       0.6461
   TERMINAL TOTAL . -4361.3 +j  -5151.6     6749.8       0.6461
SOURCEBUS     0         0.0 +j      0.0        0.0       1.0000
SOURCEBUS     0         0.0 +j      0.0        0.0       1.0000
SOURCEBUS     0         0.0 +j      0.0        0.0       1.0000
   TERMINAL TOTAL .     0.0 +j      0.0        0.0       1.0000

ELEMENT = "Line.S14"
SOURCEBUS     1      1453.8 +j   1717.2     2249.9       0.6461
SOURCEBUS     2      1453.8 +j   1717.2     2249.9       0.6461
SOURCEBUS     3      1453.8 +j   1717.2     2249.9       0.6461
   TERMINAL TOTAL .  4361.3 +j   5151.6     6749.8       0.6461
14            1     -1389.8 +j  -1397.4     1970.9       0.7052
14            2     -1389.8 +j  -1397.4     1970.9       0.7052
```

(a) Power Flow Test 3.25

```
NODE-GROUND VOLTAGES BY CIRCUIT ELEMENT

Power Delivery Elements

Bus       (node ref)  Phase    Magnitude, kV (pu)    Angle

ELEMENT = "Vsource.SOURCE"
SOURCEBUS  (  1)    1          4.4483 (       0) /_  112.7
SOURCEBUS  (  2)    2          4.4483 (       0) /_   -7.3
SOURCEBUS  (  3)    3          4.4483 (       0) /_ -127.3
------------
SOURCEBUS  (  0) 24114              0 (       0) /_    0.0
SOURCEBUS  (  0) 24114              0 (       0) /_    0.0
SOURCEBUS  (  0) 24114              0 (       0) /_    0.0

ELEMENT = "Line.S14"
SOURCEBUS  (  1)    1          4.4483 (       0) /_  112.7
SOURCEBUS  (  2)    2          4.4483 (       0) /_   -7.3
SOURCEBUS  (  3)    3          4.4483 (       0) /_ -127.3
------------
14         ( 43)    1          3.8966 (       0) /_  108.1
14         ( 44)    2          3.8966 (       0) /_  -11.9
14         ( 45)    3          3.8966 (       0) /_ -131.9
```

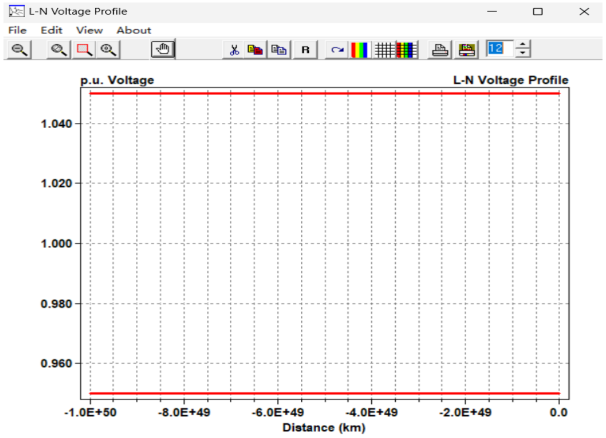
(b) Voltage Test 3.25

Figure 11: Offline Power Flow Test

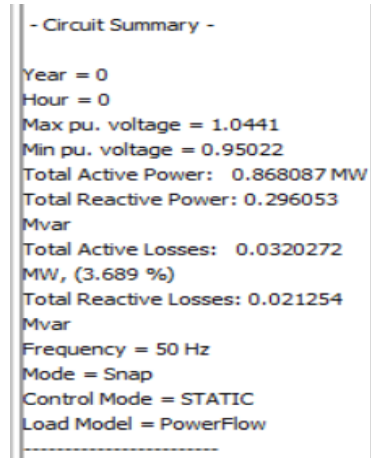
In the building offline data test, all the in-use buildings on the campus were successfully connected to their respective substations. For the real data online power flow calculation test, we accessed the OpenDSS dssdirect API interface and developed a working python version. In the test, the convergence of the trend results is very good, the missing data is not obvious, and the test results are basically in line with the actual situation of power consumption on the campus.

After that, our main focus has been to continuously improve the DSSDirect API interface, which serves as the gateway to interact with OpenDSS. This key component enables seamless communication and integration between external systems and the OpenDSS platform, facilitating efficient data exchange and streamlining operations within the power system domain.

As a result of the development of this API interface, the following functions were implemented by me: input period and time automated distribution network modeling, bad data filling and data optimization, voltage and current calculation and data analysis, and event-driven fault simulation. The current obtained from the API interface is shown in Figure 13a and the voltage is shown in Figure 13b, both of which are at the normal level of the distribution grid.

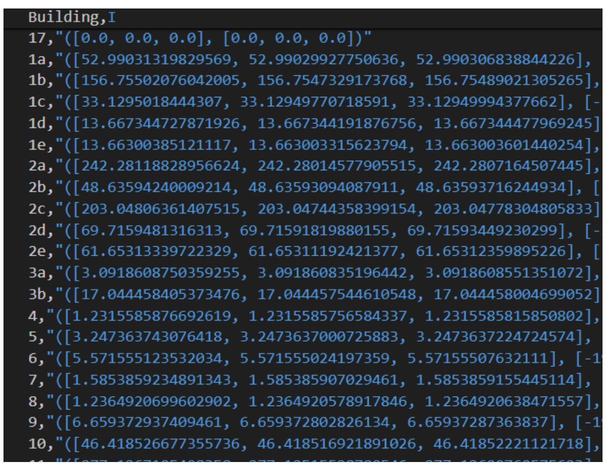



(a) Voltage Profile 4.8

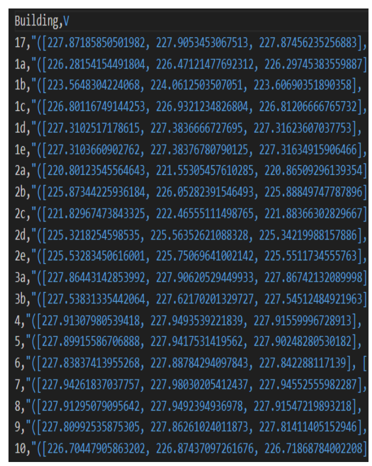



(b) Circuit Summary 4.8

Figure 12: Online Power Flow Test




(a) Current Data




(b) Voltage Data

Figure 13: API interface Test

## 3.3 Result of Load Forecasting and Event Detection Models

### The Load Forecasting Model

The error in the Load Forecasting model is the difference between the power value predicted by the model and the actual power value. The metric used to measure model performance is MAPE (Mean Absolute Percentage Error).

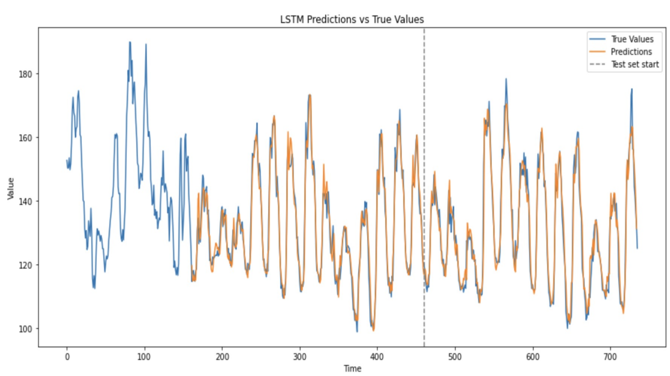
$$\mathbf{MAPE} = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{\hat{\mathbf{x}}^i - \mathbf{x}^i}{\mathbf{x}^i}\right| \times 100$$

where $\hat{\mathbf{x}}^i$ represents the predicted value, $\mathbf{x}^i$ represents the true value, and $M$ is the number of samples. According to our Design Document, the forecasting model is required to achieve a maximum MAPE of 10%. This stipulates that for each test, the average MAPE across all buildings must be less than 10%.

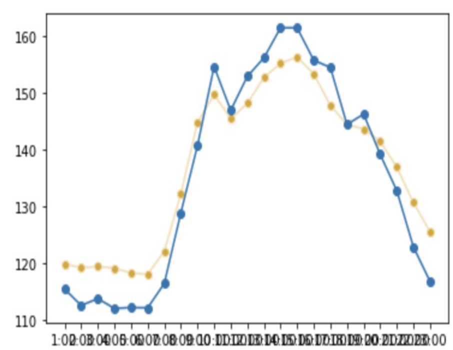
Table 4 displays the average MAPE outcomes for 32 distinct load forecasting models. The "Single-step Forecast" column denotes the MAPE associated with predicting data at the subsequent time point using a time series input, while the "One Day Rolling Forecast" column indicates the MAPE for forecasting data over a consecutive day by iteratively rolling the previous forecast output into the input. It is evident that both approaches meet the error tolerance, albeit the latter exhibits a larger error magnitude. This disparity arises from the accumulation of errors over successive forecasting steps. Furthermore, the results underscore the critical role of timely data access in achieving forecasting accuracy. Figure 14 provides a specific case study, and it can be seen that both capture the trend of the data, with Single-step's predictions being more accurate.

Table 4: Average MAPE of the LSTM load forecasting models

| | **Single-step Forecast** | **One Day Rolling Forecast** |
|---|---|---|
| **MAPE** | 7.68% | 9.90% |




(a) Single-step Forecast example



(b) One Day Rolling Forecast example

Figure 14: Load Forecasting results of Single-step Forecast and One Day Rolling Forecast for Building 2B

**Errors in the Event Detection**

In our design, the task of event detection in power systems can be conceptualized as a classification problem. The verification tasks encompass (1) detecting events, (2) accurately categorizing four types of short-circuit events, and (3) ensuring precise categorization down to the three-phase level. These tasks correspond to 2-classification, 5-classification, and 11-classification scenarios, respectively. Precision and recall stand as commonly utilized metrics for evaluating the effectiveness of classification models.

Precision measures the proportion of correctly predicted positive samples out of all the samples predicted as positive. Recall measures the proportion of correctly predicted positive samples out of all the actual positive samples.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

where TP represents True Positives and FP represents False Positives. A higher precision indicates a higher accuracy in predicting positive samples.

where TP represents True Positives and FP represents False Positives. A higher precision indicates a higher accuracy in predicting positive samples. A higher recall indicates a better ability to capture true positive samples.

In anomaly detection tasks, the macro-F1 score is commonly used as the primary evaluation metrix. This is because anomaly detection problems typically involve highly imbalanced classes, with the normal class vastly outnumbering the anomaly class. Macro-F1 effectively captures the performance on the anomaly class, which is of greater interest, by computing the F1 score for each class independently and then taking the average. Precision and recall alone may not provide a comprehensive assessment, while micro-F1 can be skewed by the dominant normal class. Macro-F1 strikes a balance, ensuring that the model's performance on the rare but crucial anomaly class is adequately represented.

$$\text{macro-F1} = \frac{1}{2}\left(\frac{2 \times \text{precision}_p \times \text{recall}_p}{\text{precision}_p + \text{recall}_p} + \frac{2 \times \text{precision}_n \times \text{recall}_n}{\text{precision}_n + \text{recall}_n}\right)$$

We performed experiments on 160 sets of simulated data, where anomalies were randomly generated, and the probabilities were uniformly distributed across different event types. The experimental findings are depicted in Table 5. Notably, the results of the latter two tasks exhibit complete consistency. This is primarily attributable to the classification of short-circuit types being heavily reliant on individual phase anomalies. Consequently, once a phase is identified as anomalous, the short-circuit anomalies are essentially determined, and vice versa.

Table 5: Results of Precision, Recall, and Macro-F1 Experiments for Three Tasks

| | 2-classes | 5-classes | 11-classes |
|---|---|---|---|
| precision | 0.9917 | 0.975 | 0.975 |
| recall | 1.0 | 0.9832 | 0.9832 |
| Macro-F1 | 0.9979 | 0.9721 | 0.9721 |

# 4 Cost and Schedule

## 4.1 Cost Analysis

Table 6: Cost Analysis

| **Category** | **Item** | **Price** |
|---|---|---|
| Microprocessor | RaspberryPi 4B | 600RMB |
| Physical Model | Campus Building Model | 800RMB |
| | Display | 400RMB |
| | Display Bracket | 300RMB |
| | LED*80 | 160RMB |
| Power Supply | 36V DC Power Supply | 300RMB |
| GPU | RTX 3080 Ti(Rental servers) | 650RMB |
| Labor | 4 people * 100hours * 100RMB/hour | 40000RMB |
| **Total** | | 43210RMB |

## 4.2 Schedule

Table 7: Schedule - 1

| Date | Erkai Yu | Yilang Feng | Tiantong Qiao | Jiahe Li |
|---|---|---|---|---|
| **3/11** | Write Python scripts to make database queries and send power consumption data to local server | Construct a digital model for the physical model and made data usage requirements to verify compliance. | Confirm data types with Support and Assurance to prepare for access to the database | Researching Power Forecasting and Anomaly Detection Algorithms |
| **3/18** | Learn how to control the LEDs with single-chip microcomputers | Modeled the campus based on the physical campus landscape | Confirming the connection of each substation in the distribution network and starting modeling | Selecting alternatives for the algorithm; designing the UI for the Monitor Subsystem |
| **3/25** | Implement scripts for Raspberry Pi board to control LEDs | 3D printing and sandboxing from already built 3D models and electronic models | Modeling the campus distribution network down to the substation level | Conducting selected algorithms on historical data and testing for acceptable errors |
| **4/1** | Test and debug the script for Raspberry Pi to control LED, install Raspberry Pi with LED | 3D printing and sandboxing from already built 3D models and electronic models | Completing modeling of the school district's distribution network and completing testing of the offline version of the model | Selection based on data characteristics and adapting existing algorithms |
| **4/8** | Test the connection between Raspberry Pi and the data server, implement local script to receive and store data on Raspberry Pi | 3D printing and sandboxing from already built 3D models and electronic models | Preparing python version of online modeling using OpenDSS API interface | Completing the code for the final time-series model and designing interfaces with other subsystems |

Table 8: Schedule - 2

| Date | Erkai Yu | Yilang Feng | Tiantong Qiao | Jiahe Li |
|---|---|---|---|---|
| **4/15** | Design database on Raspberry Pi to store the power data | Finish the sandbox and put LED strips around the building and connect the wiring | Completing python version of online modeling using OpenDSS API interface | Interfacing with real-time data, testing code on real-time data, checking for errors |
| **4/22** | Integrate real-time data power flow calculation on Raspberry Pi, feed it with data stored locally | Connect the wiring between the display and the sandbox so that the display can control the display state of the sandbox | Completing the online version of the real-time data power flow calculation test | Interfacing Model, Data and Monitor |
| **4/29** | Design user interaction interface with screen on Raspberry Pi | Connecting the sandbox to the siren so that the siren can give a timely alert in case of power data failure | completing power flow calculations for successful interfacing with led displays | |
| **5/6** | Integrate monitor subsystem on Raspberry Pi, help with installing the final model | Check all circuit connections, add LEDs and a circuit fault alarm system, and add a backup power supply to prevent failures | Prepare final demo and design testing cases | Prepare final demo and design testing cases |

# 5 Conclusion

## 5.1 Accomplishments

Driven by a commitment to innovation and efficiency, our team has achieved remarkable progress in constructing a campus power management system.

One significant achievement involved the accurate display of power data. Utilizing the advanced OpenDSS power flow solver in conjunction with the DSSDirect API interface, our system now precisely calculates and analyzes power distribution and load balancing throughout the campus. This critical data is vividly represented on a physical model using LED strips. These strips vary in brightness and color to visually depict different power metrics, enhancing both understanding and engagement.

In terms of predictive capabilities, our team has successfully implemented machine learning algorithms to monitor and forecast various behaviors of the campus grid. We have meticulously analyzed historical power usage patterns, enabling the development of highly accurate forecasting models. Furthermore, our system now includes power anomaly simulations that anticipate potential error events in power system. These simulations are invaluable, allowing stakeholders to assess and refine contingency plans, thereby elevating our response strategies.

Lastly, the development of the Data Interaction Monitor represents a notable enhancement in our ability to interact with electricity data. This intuitive tool offers straightforward access to power data across all campus buildings, enabling users to easily observe trends and make comparisons. While primarily a data access point, the monitor also supports the dynamic control of LED strips. This feature subtly enhances the visualization of power level changes, providing a clearer, albeit simplified, depiction of energy usage across the campus.

## 5.2 Uncertainties

Our project confronts certain uncertainties in the realm of prediction accuracy and anomaly detection. One significant challenge involves the diminishing accuracy of our forecasting models during rolling predictions. Additionally, our current anomaly detection system cannot monitor anomalies in real-time. These issues could be notably improved by increasing the frequency of data acquisition. By capturing data more frequently, we can enhance the responsiveness and precision of our models, allowing for more accurate predictions and timely detection of anomalies.

Moreover, the integration of our system with the smart campus infrastructure presents a potential advancement in how energy data is utilized. Currently, our system retrieves data indirectly through a database. However, if our project gains further recognition, there is an opportunity to connect directly with electricity meters across the campus. This direct connection would enable a more comprehensive display, monitoring, and management of energy usage, aligning seamlessly with the objectives of a smart campus. Such integration would not only streamline operations but also enhance the effectiveness of our energy management strategies, making them more adaptive and efficient.

## 5.3 Ethics and Safety

**Privacy.** The data displayed by our system should not reflect any individual's electricity usage, as we highly value the data privacy of each individual. Thus, our system takes each building as our measuring object, to exclude any sensitive personal data while maintaining the purpose of displaying meaningful power usage data of the campus.

**Social Benefits.** According to IEEE Code of Ethics, we are obligated to prioritize the safety, health, and well-being of the public [6]. Furthermore, we should make diligent efforts to adhere to ethical design principles and promote sustainable development practices. Our system is designed to achieve two main goals. Firstly, it monitors the power usage of the campus to provide a safe and efficient electricity system. Secondly, it also plays a role in educating people about the value of electricity we use every day. With the model we built, we can vividly display how electricity power runs inside our campus, which urges us to use it appropriately.

**Data Safety.** The power usage of each building can be highly sensitive data, especially for those involving experiments. To realize our goal of power usage model display and power usage data analysis, we will preprocess the data before displaying it with our model, thus making sure that no one can reverse engineer the model to get the sensitive data. Meanwhile, the data we collected will be carefully stored to avoid any information leaks. In our project, we adhere to high standards of integrity, responsible behavior, and ethical conduct, ensuring the use of legal data sources and preventing harm to others according to [6].

**Electricity Usage Safety.** As our system uses a large number of LEDs to display the power consumption of the campus, it's important to monitor the functionality of the circuits and avoid potential safety issues such as fire hazards. The LEDs we use should be capable of not only long-term functioning but also smooth voltage adjustment. We will also add monitoring components for our system, in case of any unpredicted accidents.

## 5.4 Future Work

The potential of our project hinges on its ability to integrate and interoperate with other intelligent systems, particularly within smart campus infrastructures. We envision multiple applications where our system enhances and synergizes with existing technologies.

#### 1. Integration with Smart Campus Management Systems

One scenario envisages the system's ability to interface with HVAC in dormitories and classrooms. By utilizing real-time electricity consumption data, our system could potentially automate adjustments in environmental controls. This proposed capability would go beyond mere monitoring, actively optimizing energy efficiency and comfort based on current usage patterns.

**2. Advanced Data Analytics and Predictive Capabilities**

Another application utilizes collected electrical data along with factors like weather to develop more precise predictive models for managing campus energy. These models assist in forecasting energy needs and analyzing usage patterns, which supports strategic planning. Moreover, the system proactively informs administrators of any anomalies based on existing functionalities, enabling timely maintenance and enhancing operational reliability.

**3. A Resource for Education and Research**

Additionally, the system is proposed as a valuable educational tool. By providing students with access to real-time energy data, it could significantly enhance learning opportunities in energy management and sustainability.

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# A Requirement and Verification Table

Table 9: Overall Requirements & Verifications List

| | Requirements | Verifications | Results |
|---|---|---|---|
| **Remote System** | For power data, historical data must be accessible for at least 1 year. | The front-end display system needs to have the ability to display data from the past 1 year. | Yes |
| | The forecasting model must achieve a maximum MAPE of 10% | The historical data can be used as a test basis. | Yes |
| | The event detection model must achieve an F1 score of 0.95 or higher. | Each abnormal simulation and its neighboring normal conditions are counted from which the F1 score can be calculated. | Yes |
| | The remote system must maintain an update response time of $\leq$ 1s and an operation update response time of $\leq$ 100 ms | The control subsystem calculates these times, and the front-end display system shows them on the display. | Yes |
| **Front-end Display System** | The LED voltage must be 3.3V, the display voltage should be 12V. Tolerance should be within 5%. | Measure the output voltages with an oscilloscope to ensure that they remain stable. | Yes |
| | Color changes to the LED and display on the monitor must maintain a response time of $\leq$ 500ms | The front-end display system can calculate and show these times on the display. | Yes |
| | The physical model needs to include all the 26 significant buildings on campus that are electrified | Physical model will be displayed. | Yes |