Learning-Based Model Predictive Control for Multi-Room Energy Incident Management in Smart Hospitals Using Cloud Services

Problem Statement:

Hospitals require reliable and efficient energy and thermal management to ensure patient safety, comfort, and uninterrupted operations. Traditional Energy Management Systems (EMS) lack adaptability, priority-based allocation, and cloud-based intelligence. Current approaches rely on static or data-intensive models, which reduce accuracy under dynamic conditions. These limitations make them unsuitable for real-time, scalable, and incident-aware energy management in multi-room hospital environments.

This project aims to design and implement a **Learning-Based Model Predictive Control (LB-MPC)** framework that dynamically optimizes HVAC and energy dispatch across multiple hospital zones with different criticality levels. The system will leverage real-time data acquisition, predictive modelling, and cloud integration to enable scalable, adaptive, and intelligent control.

Phase 1: Thermal and Electrical Modelling of Hospital Zones

The first phase focuses on building accurate mathematical models for the thermal and electrical behaviour of hospital rooms. Each hospital zone, such as ICU, OT, wards, and administrative offices, is modelled using **RC thermal networks**. The heat transfer in a room can be approximated using the **first-order differential equation**:

$$C\frac{dT_i(t)}{dt} = \frac{T_{out}(t) - T_i(t)}{R} + \eta P_{HVAC}(t)$$

The electrical load profile is modelled as a combination of **constant PQ loads** (for equipment and lighting) and dynamic loads for scenarios such as surgical operations. **Expected Output:** Verified RC model responses with HVAC ON/OFF control cycles maintaining setpoint limits.

Phase 2: Power Grid and EMS Simulation

In this phase, the thermal and electrical models are integrated with a **power distribution network** using the IEEE 14-Bus system. Hospital zones are mapped to selected buses to simulate realistic grid interactions. The EMS monitors real-time power flows and enforces **priority-based load shedding** during shortages.

The EMS optimization problem can be formulated as:

$$\min \sum_{i=1}^{N_z} \left[w_i (T_i(t) - T_{set,i})^2 + \lambda_i P_{HVAC,i}(t) \right]$$

Subject to: $P_{total}(t) \leq P_{grid}^{\max}, \quad T_i^{\min} \leq T_i(t) \leq T_i^{\max}$

Expected Output: Power flow analysis and temperature stability plots for normal and emergency conditions.

Phase 3: Data Acquisition and Forecasting

Accurate forecasting of **ambient temperature** and **grid power availability** enables predictive control decisions. This phase involves simulating sensor data and implementing forecasting models such as ARIMA or LSTM for time-series prediction.

The LSTM-based forecasting uses the update rule: $\hat{y}_{t+1} = f_{\mathrm{LSTM}}(y_t, y_{t-1}, \ldots, y_{t-n})$

Forecast outputs feed into the LB-MPC controller, reducing comfort violations and energy costs under uncertainty.
Expected Output: Good forecast accuracy for next intervals.

Phase 4: Cloud Integration

The cloud layer acts as a **centralized intelligence hub** for real-time data acquisition, visualization, storage, and control signal dispatch. It enables remote accessibility and scalable integration of multiple hospital zones, eliminating hardware dependency for on-site control.

The architecture consists of three main components:

1. **Data Ingestion Layer**
    - Sensor data (temperature, power usage, grid status) from each zone is transmitted at fixed intervals (e.g., every 30 seconds) to the cloud using MQTT/HTTP APIs.
    - The data is tagged with zone identifiers and timestamps to maintain synchronization across multiple hospital areas.

2. **Data Processing & Visualization**
    - The cloud platform (ThingSpeak or AWS IoT) aggregates the data and stores it in structured channels.
    - Real-time dashboards visualize **temperature trends, energy usage, and HVAC switching states** for each zone.
    - Forecasting models (executed in Python) can also run in the cloud, enabling disturbance-aware control updates.
3. **Control Signal Distribution**
    - After LB-MPC computes optimal setpoints (HVAC power, temperature limits), these are pushed back to local controllers through secure REST APIs.
    - Communication is bidirectional and encrypted using API keys or TLS for security.

The control pipeline can be expressed as:

$$\text{Zone Data} \xrightarrow{\text{API}} \text{Cloud Storage} + \text{Visualization} \xrightarrow{\text{LB-MPC Optimization}} \text{Control Commands} \xrightarrow{\text{Local HVAC Actuators}}$$

Expected Output:

- A functional **cloud-based dashboard** for real-time monitoring and control.
- **Alerts and notifications** for energy constraint incidents.
- **Scalability**, allowing additional hospital zones to be added without hardware reconfiguration.

Phase 5: LB-MPC Design and Implementation

Model Predictive Control is formulated as an optimization problem over a prediction horizon

$$\min_{u(t),\ldots,u(t+N_c-1)} \sum_{k=1}^{N_p} \left[(T(t+k) - T_{\text{ref}})^2 + \alpha P_{HVAC}(t+k)^2 \right]$$

subject to system dynamics and constraints.

To enhance adaptability, **reinforcement learning (RL)** is incorporated into the LB-MPC framework. The RL agent updates the MPC cost weights based on historical performance:

$$w_i^{\text{new}} = w_i^{\text{old}} + \gamma\delta, \quad \delta = r + \beta V(s') - V(s)$$

Expected Output: LB-MPC achieves **lower energy consumption** and **fewer comfort violations** compared to traditional MPC.

Expected Results and Performance Analysis:

The project is expected to deliver:

- **Priority-based HVAC scheduling** under grid limits.
- **Energy savings of 10–20%** compared to conventional MPC.
- **Comfort compliance rate > 80%** across zones.
- **Visualization** of LB-MPC vs MPC performance in terms of energy, temperature deviation, and response to disturbances.
- Performance will be measured using: $\text{Energy Efficiency (\%)} = \frac{E_{\text{MPC}} - E_{\text{LB-MPC}}}{E_{\text{MPC}}} \times 100$