AC With Predictive Control And Temperature Sensor

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Abstract—**Air Conditioners are a staple aspect in many common households of today especially for their capabilities to counteract extreme temperatures. However, ACs are also prone to malfunctions due to not only their high power consumption but also of basic control systems causing extreme fluctuations. This study addresses these problems by developing a simulation tool of an AC with temperature sensors and a controller based on Model Predictive Control. The main tool used to develop was with Python through Google Colab and the dataset used to test the model was taken from Kaggle. The study also modeled a standard On/Off controller with fixed deadband settings to be compared against. And the results showed that Model Predictive Control gained more stable results and less extreme fluctuations in power output compared to standard On/Off models. This shows that software modifications like Model Predictive Control can help ACs by actively optimizing their output based on temperature data recorded in realtime.**

Index Terms—**Air Conditioners, Model Predictive Control, Simulation, On/Off Controller, Temperature Control.**

I. Introduction

Air Conditioners have become a staple aspect in so many modern households of today especially in a country like Indonesia which is often classified as a tropical country and where the temperatures can get really hot in many times of the day. For example, Batam City in the Riau Islands province has an average temperature of 28 C and a maximum temperature of 34 C [1]. Having an AC in a moderately sized household is basically essential to main comfortable environment conditions. However many researchers such as Irshad et al., such tropical regions require more dynamic systems to maintain desirable air quality and temperatures [10].

The common problem is that most of the ACs in these households only use static On/Off (Hysterisis) Control logic. The way these systems work is simple as they use simple logic which tells them to turn on when the room gets too hot and to turn off the AC when the room temperature is cold enough. As analyzed by Pramono et al, these systems are static and don't optimize themselves to the real-time conditions as they are [5].

The operational simplicity of these standard systems results in considerable inefficiencies in energy usage and user comfort. Since the system cannot adjust its output, it needs to cycle between on and off phases very often which requires high electrical currents during each startup phase. Shamrat et al. recognize this inflexibility in conventional AC systems as a primary factor in energy loss and hardware fragility [2]. Additionally, this responsive control approach creates a ”sawtooth” temperature pattern, causing the room temperature to continually fluctuate above and below the intended setpoint.

In light of these problems, many modern research shift their focus to predictive control strategies. As the strategy name suggests, these intelligent systems can utilize the current temperature to predict the future temperature states. Wang et al. demonstrate that the performance of HVAC demand response systems is directly impacted by prediction accuracy, suggesting that better forecasting models lead to better control outcomes [11]. And Mostafavi et al. also proposed that dealing with unknown HVAC dynamics requires estimation techniques that go beyond simple linear feedback, allowing the system to handle constraints and disturbances more effectively [3].

This paper discusses a solution in the form of simulations of AC devices with predictive control and temperature detection system that can be analyzed to gain better understanding in applying real world solutions in the future. Where standard AC systems lack automatic environmental adaptability, AC devices with predictive control and temperature detection system will be able to respond to sudden temperature fluctuations much more effectively, making for a more sustainable and intelligent solution. This study specifically utilizes a Python-based simulation environment show that standard On/Off methods in tropical temperature profiles, quantifying the benefits in how well they stay close to the setpoint temperature target.

II. Literature Review

A. Limitations of Conventional Control Strategies

Traditional air conditioning systems predominantly utilize On/Off (hysteresis) control logic. While simple to implement, these systems are characterized by significant energy inefficiencies and thermal instability. Research by Shamrat et al. [2] identifies the lack of adaptability in these standard systems as a primary factor in energy waste and hardware fragility. Because these controllers operate reactively—toggling the compressor only when temperature thresholds are crossed—they result in frequent ”sawtooth” temperature fluctuations and high-current startup cycles that stress mechanical components. Pramono et al. [5] further emphasize that such static systems fail to optimize for real-time room conditions, operating continuously without regard for dynamic environmental changes.

B. IoT and Wireless Sensor Networks (WSNs)

To overcome the limitations of static feedback, modern HVAC research has shifted toward distributed sensing [5]. The integration of Wireless Sensor Networks (WSNs) allows for spatially distributed monitoring of temperature and humidity, providing granular data for control algorithms. Irshad et al [9] demonstrated an IoT-based framework specifically designed for tropical climates, utilizing cloud-connected platforms to manage thermoelectric cooling. These IoT-centric approaches provide the necessary data infrastructure for intelligent control, allowing systems to react to ”disturbance profiles” such as sudden heat loads from equipment or occupancy.

C. Model Predictive Control and Machine Learning

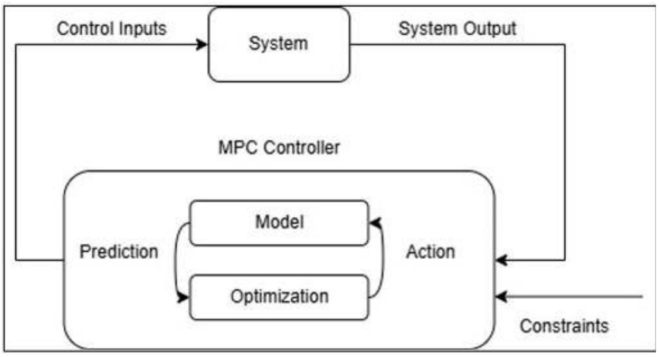

FIGURE 1
Model Predictive Control Process

The core advancement in HVAC automation is the transition from Proportional-Integral-Derivative (PID) logic to Model Predictive Control (MPC). MPC differs from traditional methods by utilizing a ”receding horizon” strategy to optimize future control actions based on predicted system states.

Recent studies have integrated Machine Learning (ML) to enhance these predictive capabilities. Mostafavi et al. [3] proposed a nonlinear MPC approach that estimates unknown HVAC dynamics using neural networks, allowing the system to handle constraints more effectively than linear feedback models. Similarly, Kargar and Bahamin [4] explored advanced MPC for multi-zone buildings, incorporating dynamic pricing and energy storage to reduce power peaks

D. Thermal Modeling and Heat Transfer

Accurate MPC implementation requires a precise mathematical model of the physical environment (The Plant). The characterization of passive heat transfer is critical for determining thermal inertia. Chew et al. [13] utilized Large Eddy Simulation (LES) to demonstrate that convective heat transfer coefficients in buildings are highly sensitive to local temperature differences. Simultaneously, the active cooling capacity of modern systems has been analyzed by Alghamdi and Krarti [14] [15], who noted that inverter-based and hybrid systems can significantly modulate cooling potential compared to fixed-speed DX systems. These physical parameters—specifically the heat transfer coefficient (α) and cooling coefficient (β)—form the mathematical backbone of the differential equations used in this study’s simulation.

Finally, the target setpoints for these models are grounded in established standards, such as ASHRAE Standard 55 [17], which defines the optimal thermal environmental conditions for human occupancy

E. Research Gap

While existing literature extensively covers MPC in commercial multi-zone buildings, there is limited focus on reducing hardware ”hard switches” in single-room environments using high-frequency real-world IoT datasets. This study bridges that gap by validating an MPC algorithm against a specific computer laboratory dataset to quantify improvements in both thermal stability (RMSE) and hardware longevity.

III. SYSTEM DESIGN AND METHODOLOGY

This study implements a closed-loop feedback control mechanism designed to maintain indoor thermal comfort while optimizing energy consumption through predictive logic. Unlike traditional open-loop systems, the proposed architecture continuously monitors the state of the system to dynamically adjust the compressor output of the air conditioner.

The system consists of three primary components: a Model Predictive Controller (MPC) that determines optimal actions, a Thermal Plant Model that simulates room thermodynamics, and a feedback loop that updates the controller with the new room temperature at every time step.

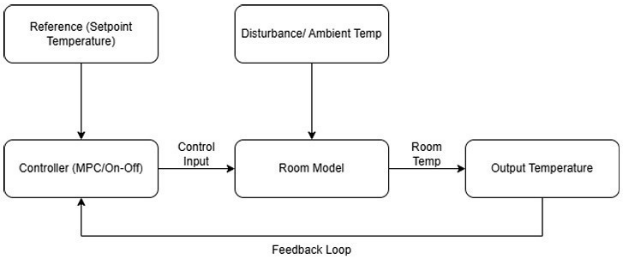

FIGURE 2
Block Diagram for AC Control System Using Model Predictive Control

A. Thermal Plant Modeling

To simulate the physical environment, the system utilizes a first-order differential equation based on Newton’s Law of Cooling. This mathematical representation calculates the room temperature for the next time step (T_{k+1}) by accounting for the thermal inertia relative to the ambient temperature ($T_{ambient}$) and the active cooling impact of the control input (u_k).

The thermal evolution of the room is governed by the following equation:

$$T_{k+1} = T_k + \alpha(T_{ambient} - T_k) + \beta \times u_k \tag{1}$$

Where:

- T_k: Current room temperature at step

- $k.T_{ambient}$: External environmental temperature acting as a disturbance.u_k: Control input (AC power) at step
- $k.\alpha$ (0.05): The heat transfer coefficient, representing the rate at which the room passively gains heat from the environment (thermal inertia).
- β (-0.2): The cooling coefficient, representing the AC's capacity to reduce temperature per unit of effort.

B. Model Predictive Control Formulation

The core of the proposed system is the MPC algorithm, which utilizes a "Receding Horizon" strategy. At every sampling step k, the controller solves a convex optimization problem to predict a sequence of future control actions, but only applies the first action to the system.

1) Cost Function Optimization: The controller seeks to minimize a multi-objective Cost Function (J) that balances three conflicting goals: maintaining thermal comfort (minimizing error), reducing energy consumption, and preventing hardware stress (minimizing rapid switching). The cost function is defined as:

$$J = \sum_{k=0}^{H} (T_k - T_{set})^2 + \lambda_{energy} \cdot u_k^2 + \lambda_{switch} \cdot (u_k - u_{k-1})^2 \quad (2)$$

The optimization is governed by the following parameters:

- Prediction Horizon (H): Set to 20 steps (minutes), determining how far the controller looks into the future.
- Setpoint (T_{set}): Fixed at $24^\circ C$, the target temperature for thermal comfort.
- Energy Penalty (λ_{energy}): Weighting factor (0.1) that penalizes high electricity usage.
- Switching Penalty (λ_{switch}): Weighting factor (5.0) that heavily penalizes rapid changes in compressor state to prevent short-cycling and extend hardware lifespan.

2) Constraints: To ensure the simulation remains physically realistic, the optimization is subject to hard constraints. The control signal u is bounded between 0 and 1, representing the AC compressor operating between off state and full power.

C. Baseline Control Strategy

For comparative analysis, a standard On/Off (Hysteresis) controller was also modeled. This baseline system operates on simple reactive logic: it activates the compressor ($u = 1$) when the room temperature exceeds an upper threshold ($T_{upper} = 25^\circ C$) and deactivates it ($u = 0$) when the temperature drops below a lower threshold ($T_{lower} = 23^\circ C$). This 2-degree deadband is designed to prevent immediate short-cycling while maintaining the temperature near the $24^\circ C$ target.

D. Data Acquisition and Preparation

The simulation utilized the "Modeling of Air-Conditioning for Energy Savings" dataset, authored by Marco Hernandez Cucei and available via the Kaggle public repository. This dataset was selected to ensure the controller was tested against a realistic thermal profile rather than a theoretical model.

1) Dataset Characteristics: The data originates from a computer laboratory environment equipped with a network of sensors connected to a Raspberry Pi. This specific environment was chosen because it provides a challenging "disturbance profile" characterized by sudden heat loads from computing equipment, which serves as a robust test for the controller's predictive capabilities. Furthermore, the data is logged at high-frequency 1-minute intervals, which is essential for simulating the real-time control loop required by the MPC algorithm.

2) Data Preprocessing: Before simulation, the raw dataset underwent specific preprocessing steps to ensure compatibility with the control logic:

- Resampling: The timestamped temperature readings were resampled to strict 1-minute intervals to match the simulation's control frequency ($dt = 1.0$ min).
- Duplicate Removal: Duplicate timeframes were identified and removed to ensure a continuous, linear time series.
- State Conversion: The categorical variable Ac_status (recorded as 'On' or 'Off') was converted into binary integers (1 or 0) to allow for numerical computation within the energy metrics.

E. Simulation Environment

The experimental simulation was developed and executed using Python within the Google Colab platform. The software architecture leveraged specific libraries to handle the mathematical modeling and optimization:

- CVXPY: Used to process the Model Predictive Control optimization and solve the cost function at every time step.
- NumPy and Pandas: Employed for vector calculations, thermal plant model updates, and formatting outputs into tabular data.
- Matplotlib: Used to generate visualization graphs for temperature trajectories and power input profiles.

F. Performance Metrics

To quantitatively evaluate the MPC algorithm against the baseline On/Off controller, the simulation outputs were mapped to three distinct performance indicators

1) Temperature Stability (RMSE): The Root Mean Square Error (RMSE) serves as the primary indicator of thermal comfort. It measures the standard deviation of the room temperature (T_t) relative to the target setpoint ($T_{set} = 24^\circ C$)14. Lower values indicate that the system successfully eliminated "sawtooth" fluctuations.

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (T_t - T_{set})^2} \quad (3)$$

2) Total Energy Usage (U_{total}): To analyze efficiency, "Energy Units" are used as a proportional proxy for electricity consumption. This metric is calculated as the cumulative sum of the compressor input (u_t) over the entire simulation horizon (N).

$$U_{total} = \sum_{t=1}^{N} u_t \quad (4)$$

3) Hard Switch Sum (N_{switch}): To evaluate the impact on hardware longevity, the study tracks "Hard Switches." These are defined as events where the compressor's power input changes drastically (e.g., toggling from 0 to 1) within a single time step. Minimizing this metric is critical, as frequent short- cycling is a primary cause of AC motor failure.

$$N_{switch} = \sum_{k=1}^{N} (|u_k - u_{k-1}| > 0.5) \quad (5)$$

IV. Results and Analysis

In this chapter, the performance of the proposed Model Predictive Control (MPC) system is evaluated against the baseline On/Off controller using the real-world IoT dataset. The analysis focuses on three key areas: thermal stability, energy efficiency, and hardware impact.

FIGURE 3
Visualization graphs of MPC Performance on Real Dataset

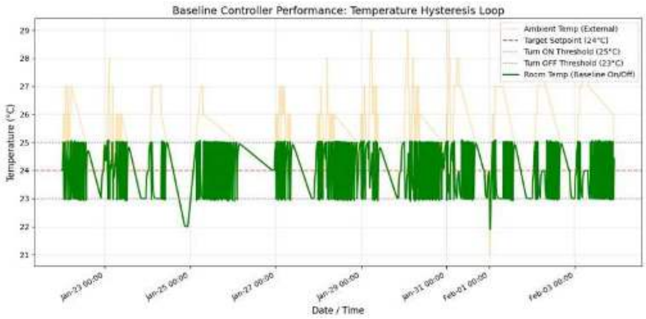

FIGURE 4
Visualization graphs of ON/OFF controller on Real dataset

A. Thermal Stability and Comfort

As shown in the simulation results, the Baseline Controller exhibited a characteristic "sawtooth" pattern, with temperature constantly oscillating between $23.2^{\circ}C$ and $25.2^{\circ}C$. In con- trast, the MPC System successfully stabilized the temperature with significantly less variance.

- Baseline RMSE: 0.6774
- MPC RMSE: 0.4435

Improvement: The MPC achieved a 34.53% reduction in RMSE, indicating a much higher level of thermal comfort and a reduction in the "overshooting" effect common in traditional systems.

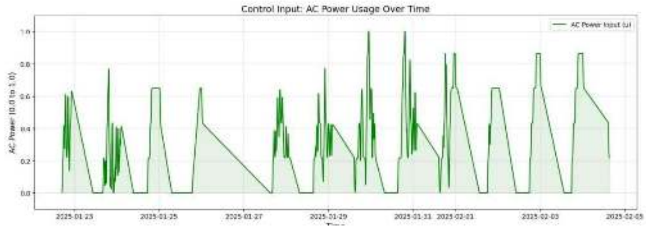

FIGURE 5
Visualization graphs of MPC Power Input on Real Dataset

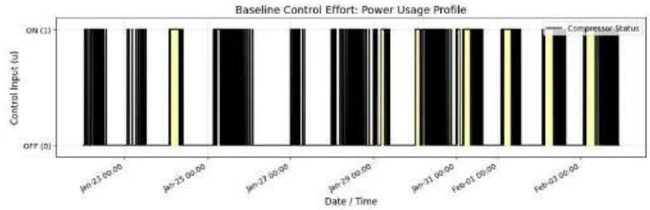

FIGURE 6
Visualization graphs of ON/OFF power input on Real dataset

B. Energy Consumption Analysis

Efficiency was measured by calculating the total energy units consumed by the compressor over the test period.

- Baseline Energy Units: 5628.00 units
- MPC Energy Units: 5283.33 units

Observation: While the energy consumption is nearly identical, the MPC provides much higher quality of cooling (stability) for the same "price" in energy. The MPC logic optimizes the distribution of power, using partial compressor loads (e.g., $u = 0.6$) rather than full-power bursts.

C. Hardware Longevity (Hard Switches)

The most significant disparity between the two systems was observed in the mechanical stress applied to the compressor.

- Baseline Hard Switches: 338
- MPC Hard Switches: 0

Analysis: The Baseline controller toggled the compressor fully on or off 338 times during the simulation. The MPC eliminated these "Hard Switches" entirely by utilizing its pre- dictive horizon to make smooth, incremental adjustments. By preventing short-cycling, the MPC-based system significantly extends the operational lifespan of the AC hardware.

TABLE I
Performance Comparison between the MPC controller and the baseline

Performance Metric	MPC	Baseline(On/Off)
RMSE	0.4435 °C	0.6774°C
Energy Units	5282.33	5628.00
Hard Switches	0	338.00

V. Discussion and Conclusion

After completing the project, a python-based Model Predic- tive Control simulation program was successfully developed and the desired objectives were met. The final comparison shows that the MPC Controller was able to improve upon several aspects compared to ad On/Off Controller such as target temperature RMSE, energy usage, and hard switching between on and off states.

The implementation of the many equations and functions such as the cost function helped with simulation's environment being close to realistic. In conclusion, the research verifies thagoing from a reactive On/Off controller to a predictive MPC strategy changes the air conditioning process from a high-variance, mechanically taxing operation into something more stable, energy-efficient, and longer lasting.

To enhance the validity and scope of future research, several key improvements should be prioritized to transition from theoretical modeling to real-world application. First, researchers should move toward physical hardware implementation by deploying systems on devices such as Raspberry Pis within actual room environments which ensures that current findings are validated against real-world variables. Furthermore, the modeling scope should be expanded beyond temperature to include a more holistic set of environmental data, such as humidity, light intensity, and CO_2 levels.

Finally, the system's efficiency can be refined by introducing adaptive weights within the cost function. By allowing these weights to adjust dynamically based on the time of day, the model can achieve significantly higher energy efficiency and better align with fluctuating environmental demands.

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