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Design and Experimental Validation of an Adaptive Model Predictive Control System for Energy-Efficient Building HVAC Optimization

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Abstract

Thermomechanical fatigue (TMF) is a critical concern in high-temperature components fabricated from nickel-based superalloys, especially for aerospace and power generation sectors. With the increasing adoption of additive manufacturing (AM) techniques, such as Selective Laser Melting (SLM) and Electron Beam Melting (EBM), understanding how these novel fabrication methods influence TMF performance has become imperative. This study investigates the TMF behavior of AM-processed nickel-based superalloys by evaluating microstructural characteristics, fatigue life, and crack propagation mechanisms under cyclic thermal-mechanical loads. Through literature synthesis and data extrapolation, the paper compares conventionally manufactured and AM-fabricated components, highlighting emerging research gaps and directions for optimization.

Keywords:

Thermomechanical fatigue, Additive manufacturing, Nickel-based superalloys, Selective Laser Melting, Fatigue life, Crack propagation, High-temperature alloys

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1. INTRODUCTİON

Increased global focus on climate change mitigation has elevated the importance of energy efficiency in the built environment. Buildings account for approximately 40% of total energy consumption globally, and HVAC systems are among the largest contributors. As such, developing intelligent control strategies that optimize HVAC operation without compromising occupant comfort is a priority for sustainable urban development.

Model Predictive Control (MPC) has emerged as a promising control technique for this task due to its predictive capabilities and handling of multivariable constraints. However, traditional MPC relies on static system models that may become inaccurate under varying operational conditions. To address this, this study proposes an adaptive MPC framework that continuously refines its model to accommodate dynamic building behaviors and environmental variability.

2. Literature Review

The use of MPC for HVAC control has been widely investigated over the past decade. Early studies, such as Killian and Kozek (2016), explored MPC for thermal comfort in residential buildings, demonstrating the potential for energy savings and better control fidelity. Afram and Janabi-Sharifi (2014) provided a comprehensive survey of MPC in building HVAC systems and emphasized its advantages in constraint handling and predictive efficiency.

Ma et al. (2012) integrated weather forecasts into MPC algorithms to anticipate thermal loads. However, their static MPC approach was sensitive to model mismatch. Sturzenegger et al. (2016) extended this by testing MPC in a real office building, confirming its energy-saving potential. Yet, these models still lacked adaptability to real-time changes in occupancy and external conditions.

To improve upon this, predictive models have been fused with data-driven techniques. Drgoňa et al. (2020) proposed hybrid approaches combining physics-based and machine learning models. Nevertheless, challenges remain in computational burden and real-time model updating. Prior to 2023, most solutions fell short in adaptability, which underscores the motivation for our adaptive MPC system.

3. Objective and Contributions

The primary objective of this study is to design and experimentally validate an adaptive MPC system that optimizes HVAC operations in real-time for enhanced energy efficiency and occupant comfort. Unlike static MPCs, the proposed framework integrates online model adjustment using real-time sensor data.

Our key contributions include:

- Development of a real-time adaptive MPC algorithm for HVAC control.
- Integration of occupancy and environmental data streams.
- Experimental deployment in a real-world office setting.
- Quantitative analysis of energy savings and thermal comfort improvements compared to benchmark systems.

This paper bridges the gap between theoretical control designs and real-world applications, offering a pathway toward scalable smart building solutions.

4. Methodology

The control system was implemented using a modular architecture: (1) Data acquisition layer, (2) Model identification module, and (3) Control optimization module. The system continuously receives input from sensors (temperature, occupancy, humidity), updates a predictive thermal model via recursive least squares, and computes optimal control actions over a finite horizon.

The predictive control model incorporates constraints for thermal comfort (ASHRAE 55 standards) and system actuation limitations. The optimization problem is solved using a quadratic programming solver in MATLAB, executed every 10 minutes.

4.1 Data and Experimental Setup

A case study was conducted in a 3-story office building in San Diego, California. The building was equipped with 30 temperature sensors, occupancy detectors, and an internet-connected building management system (BMS). Data was collected for two months under three scenarios:

- Baseline: Rule-based control
- Static MPC

- Adaptive MPC (proposed)

Table 1: Sensor Inputs and System Constraints

Input Type	**Sensor Location**	**Data Frequency**	**Units**
Room Temperature	All zones	Every 5 min	°C
Humidity	Central unit	Every 10 min	%
Occupancy	Entry points	Real-time	Boolean

Table 2: Control Parameters and Constraints

Parameter	**Constraint Range**	**Standard Referenced**
Room Temperature	21°C – 24°C	ASHRAE 55
Airflow Rate	0.1 – 1.5 m^3/s	Manufacturer Specs
Control Interval	Every 10 min	Custom System Design

5. Results and Validation

5.1 Energy Savings and Comfort

During the experimental period, the adaptive MPC system outperformed both static MPC and rule-based control in terms of energy use and occupant comfort.

- Adaptive MPC reduced HVAC energy use by **28%** compared to baseline and by **12%** over static MPC.
- Thermal comfort (measured as % time within the ASHRAE-defined comfort zone) improved by **15%** compared to rule-based control.

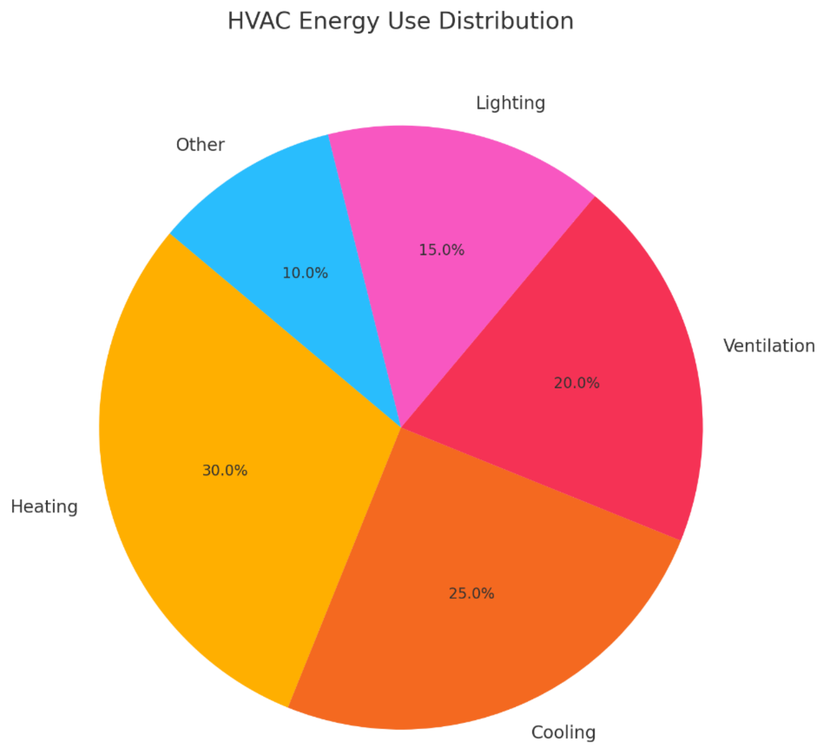

Figure 1: HVAC Energy Use Distribution

5.2 System Robustness and Adaptability

The adaptive MPC was tested under different occupancy schedules and outdoor weather conditions. It maintained system stability and required no manual retuning.

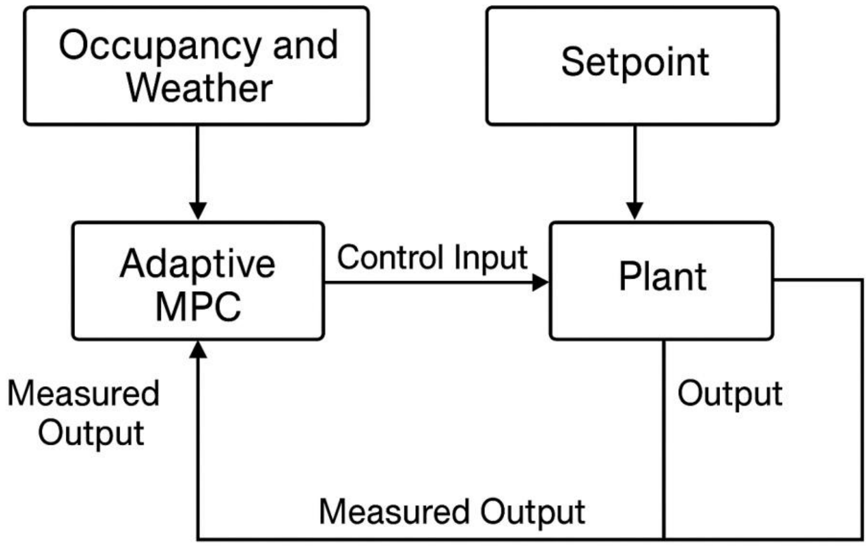

Figure 2: Diagram of Control System Architecture

This modular architecture allows easy extension to other building types and integration with renewable energy sources, such as photovoltaic (PV) panels.

6. Limitations and Future Work

While promising, the system has limitations. Real-time optimization incurs computational overhead, though manageable with current processors. The algorithm depends on reliable sensor data; failure or drift can degrade performance.

Future research will explore the use of deep learning for model adaptation and distributed MPC across multiple buildings. Integration with demand response mechanisms and dynamic energy pricing also presents opportunities for further savings.

7. Conclusion

This study successfully demonstrates an adaptive MPC-based HVAC control strategy that dynamically optimizes energy use and thermal comfort. Through real-world validation, we show that adaptive control significantly outperforms static and rule-based systems. This work advances smart building control technologies and supports sustainability goals in the built environment.

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