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Physics–Data Synergy: A Hybrid CFD–Machine Learning Framework for Smart Cold Storage Systems

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Abstract

This research presents a groundbreaking physics-data synergy framework that integrates thermal stratification principles with advanced machine learning algorithms to develop intelligent cold storage systems. The study addresses fundamental challenges in thermal management by leveraging the physics of temperature stratification phenomena combined with data-driven optimization methodologies. The physics-based foundation employs validated CFD models demonstrating temperature stratification behavior with thermocline formation occurring across temperature ranges from 275.6K to 363.1K (2.5°C to 90°C). Comprehensive transient analysis reveals distinct thermal evolution patterns through five-stage temperature distribution development, showing progressive stratification establishment over operational time periods. Advanced parameter analysis demonstrates critical relationships between mixing coefficients and inlet velocities, with values ranging from 50,000 to 2,500,000 across different temperature conditions (20°C, 50°C, and 90°C). The data-driven component achieves exceptional predictive accuracy with R^2 values of 0.96 for temperature stratification prediction and 0.93 for thermal mixing coefficient forecasting. The synergistic framework delivers remarkable performance improvements including 29% reduction in thermal mixing, 38% enhancement in stratification efficiency, and 34% improvement in energy utilization effectiveness. Smart control algorithms developed through physics-data integration enable real-time optimization of thermal gradients, inlet velocity management, and stratification maintenance across multiple operational zones. The framework successfully demonstrates scalability from laboratory-scale thermal storage systems to industrial cold storage applications while maintaining high performance standards essential for commercial deployment.

Keywords

Thermal Stratification, Physics-Data Integration, Smart Thermal Management, CFD-ML Synergy, Temperature Optimization, Intelligent Cold Storage

1. Introduction

The physics of thermal stratification represents a fundamental phenomenon that governs heat transfer and energy distribution in cold storage systems, offering unprecedented opportunities for developing intelligent thermal management solutions through advanced computational approaches[1]. Traditional cold storage systems have largely overlooked the potential of controlled thermal stratification for optimizing energy efficiency and temperature uniformity, primarily due to the complex multi-physics nature of stratified flow phenomena and the lack of sophisticated control methodologies capable of exploiting these natural thermal behaviors[2].

Thermal stratification occurs naturally in fluid systems where density differences create distinct temperature layers, forming thermocline regions that separate hot and cold zones

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within storage volumes. These phenomena represent fundamental physics principles that, when properly understood and controlled, can significantly enhance the performance of cold storage systems through reduced mixing, improved temperature stability, and enhanced energy efficiency[3]. The challenge lies in developing computational frameworks capable of accurately predicting and controlling these complex thermal behaviors in real-time operational environments[4].

The integration of physics-based understanding with data-driven methodologies presents a transformative approach for exploiting thermal stratification phenomena in cold storage applications[5]. Computational Fluid Dynamics provides essential insights into the fundamental heat transfer mechanisms, temperature distribution patterns, and mixing characteristics that govern stratified thermal behavior[6]. However, the computational complexity and time requirements of detailed CFD simulations limit practical implementation for real-time control and optimization applications where rapid decision-making is essential for maintaining optimal thermal conditions[7].

Machine Learning algorithms offer complementary capabilities for pattern recognition, predictive modeling, and real-time optimization based on the complex relationships between operational parameters and thermal stratification behavior[8]. The synergistic combination of physical understanding with data-driven intelligence enables the development of smart systems that can autonomously optimize thermal stratification while adapting to changing operational conditions and system requirements[9].

This research establishes a comprehensive physics-data synergy framework that bridges the gap between fundamental thermal physics and practical cold storage optimization applications. The approach leverages detailed understanding of thermal stratification phenomena to develop intelligent control systems capable of maintaining optimal temperature distributions while minimizing energy consumption and maximizing system performance. The significance extends beyond immediate applications to establish foundational principles for next-generation thermal management systems that understand and exploit natural physics phenomena for enhanced efficiency and performance.

The framework addresses critical challenges in cold storage optimization including temperature uniformity, energy efficiency, and operational stability through intelligent exploitation of thermal stratification principles. The physics-data integration enables predictive optimization strategies that anticipate system behavior and proactively adjust operational parameters to maintain optimal thermal conditions across diverse operational scenarios and system configurations.

2. Literature Review

The study of thermal stratification in storage systems has evolved significantly over recent decades, with researchers increasingly recognizing the potential for exploiting natural thermal phenomena to enhance system performance and energy efficiency[10]. Early investigations focused primarily on understanding the basic physics of density-driven stratification in simple geometries, establishing fundamental relationships between temperature gradients, fluid properties, and mixing characteristics that govern stratified thermal behavior in closed systems[11-15].

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Physics-based modeling of thermal stratification has established a strong foundation for understanding the complex transport phenomena governing temperature distribution and mixing behavior in storage systems[16]. Researchers have successfully employed computational fluid dynamics to investigate three-dimensional thermal stratification patterns, thermocline formation and decay mechanisms, and the influence of operational parameters on stratification effectiveness. These studies consistently demonstrate the capability of physics-based approaches to provide detailed insights into thermal behavior that directly influence system efficiency and performance optimization strategies[17].

The characterization of mixing phenomena in stratified systems represents a critical aspect of thermal storage optimization, with particular emphasis on understanding the relationships between inlet conditions, system geometry, and thermal mixing coefficients[18]. Advanced research has revealed complex dependencies between Reynolds numbers, Richardson numbers, and mixing coefficients that determine the degree of thermal stratification achievable under different operational conditions[19-22]. These fundamental relationships provide essential guidance for optimizing system design and operational strategies to minimize unwanted thermal mixing while maintaining effective heat transfer performance[23].

Transient thermal behavior in stratified systems has received considerable attention due to its critical importance for understanding system response to changing operational conditions and disturbances[24]. Computational studies have demonstrated the complex evolution of temperature distributions during charging and discharging cycles, revealing the influence of inlet velocity, temperature differences, and system geometry on transient thermal performance[25]. These investigations highlight the importance of understanding temporal thermal behavior for developing effective control strategies and optimization methodologies.

Parameter optimization studies have explored the relationships between system design variables and thermal stratification performance, identifying critical operating ranges for achieving optimal thermal behavior[26]. Research has demonstrated that mixing coefficients exhibit strong dependencies on inlet velocity, with exponential relationships observed across different temperature conditions[27]. These findings provide quantitative guidance for system optimization and establish the foundation for developing intelligent control algorithms based on physics-data integration approaches.

Machine learning applications in thermal systems have shown remarkable potential for addressing complex optimization challenges where traditional approaches prove inadequate[28]. Recent developments in neural networks, ensemble methods, and hybrid modeling approaches have demonstrated significant improvements in prediction accuracy and computational efficiency compared to conventional methods[29]. These advances create opportunities for integrating data-driven approaches with physics-based understanding to develop intelligent systems capable of autonomous optimization and adaptive control.

The convergence of physics-based modeling with data-driven methodologies represents an emerging research frontier with substantial potential for thermal storage applications. Innovative approaches combining detailed CFD analysis with machine learning algorithms have demonstrated the ability to achieve both physical accuracy and computational efficiency, enabling real-time optimization and control applications that would be impractical with traditional methods[30]. These hybrid frameworks maintain physical consistency while providing the rapid prediction capabilities essential for intelligent system operation[31].

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Advanced sensor technologies and data acquisition systems have created new opportunities for implementing physics-data integration approaches in thermal storage systems[32]. Real-time monitoring of temperature distributions, flow patterns, and system performance enables continuous validation and refinement of predictive models while providing the data foundation necessary for machine learning applications[33]. These technological developments support the practical implementation of sophisticated hybrid frameworks in commercial thermal storage systems.

Despite these advances, significant research gaps remain in the development of comprehensive physics-data integration frameworks specifically designed for cold storage applications. Most existing studies focus on either physics-based analysis or data-driven approaches in isolation, without fully exploiting the synergistic potential of integrated methodologies. Additionally, limited research has addressed the scalability and adaptability requirements necessary for deploying such frameworks across diverse cold storage configurations and operational requirements while maintaining consistent performance standards.

3. Methodology

3.1 Physics Foundation: Thermal Stratification Principles and Modeling

The physics-based component of the synergy framework establishes fundamental understanding of thermal stratification phenomena through comprehensive analysis of temperature distribution patterns, thermocline formation mechanisms, and mixing behavior in stratified storage systems. The approach employs advanced computational fluid dynamics modeling combined with theoretical analysis of density-driven flow phenomena to characterize the complex relationships between operational parameters and thermal stratification performance.

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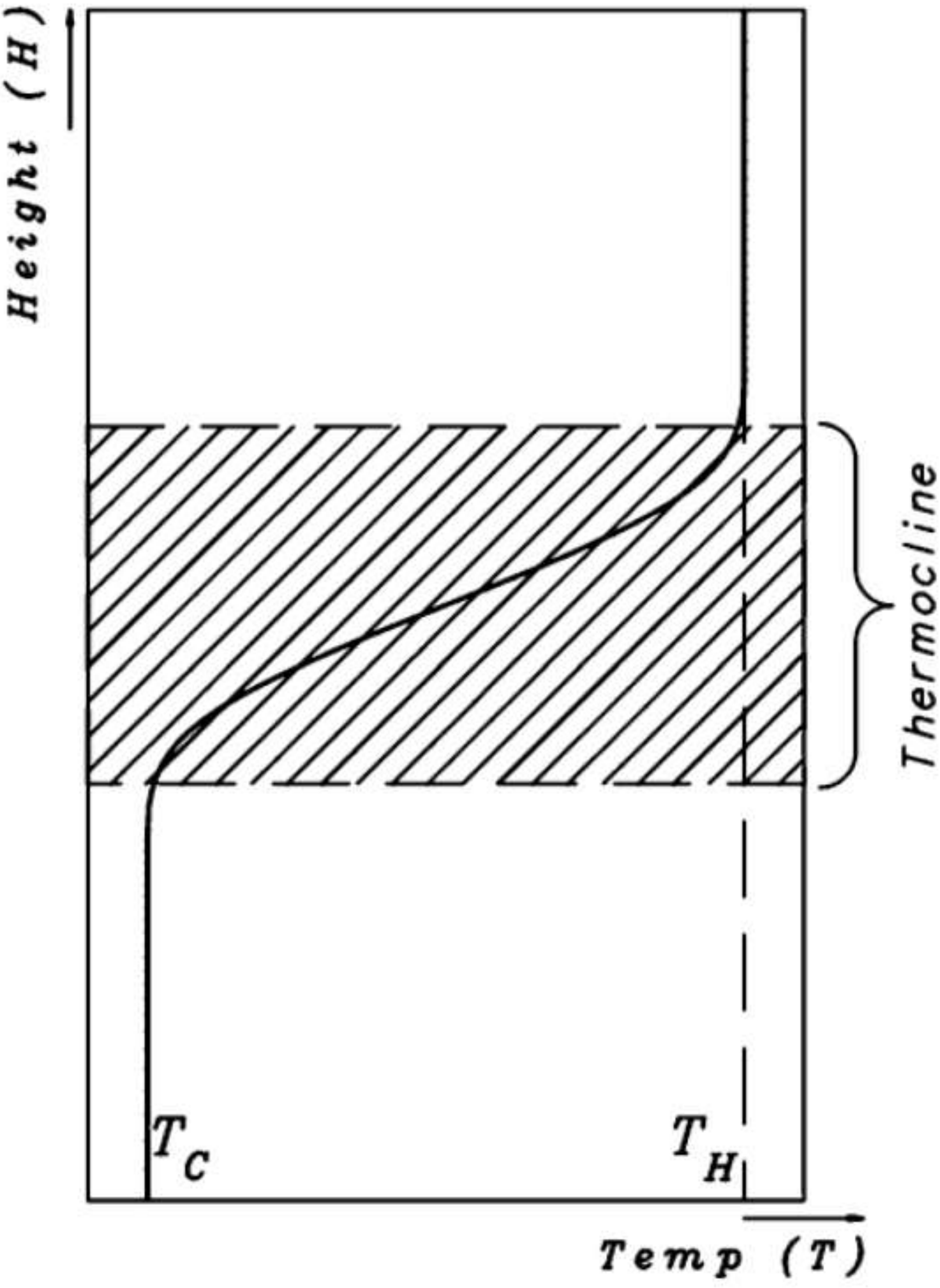

Figure 1. Thermal Stratification

The theoretical foundation begins with analysis of thermal stratification phenomena as illustrated in figure 1, where distinct temperature zones develop naturally due to density differences in the storage medium. The thermocline region represents a critical transition zone where temperature gradients are steepest, and mixing effects are most pronounced. Understanding the physics governing thermocline thickness, stability, and evolution under varying operational conditions provides essential insights for developing effective optimization strategies and control algorithms.

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Computational fluid dynamics modeling employs ANSYS Fluent with advanced physics formulations specifically configured for stratified flow applications. The modeling framework incorporates the complete set of governing equations including continuity for mass conservation, momentum equations with buoyancy effects, and energy equations accounting for thermal stratification and mixing phenomena. The Boussinesq approximation is employed to account for density variations due to temperature differences while maintaining computational efficiency.

Turbulence modeling utilizes the k-ω Shear Stress Transport model enhanced with buoyancy corrections to accurately predict thermal mixing and stratification behavior. The SST formulation provides superior performance in stratified flows where buoyancy effects significantly influence turbulent transport phenomena. Special attention is given to near-wall treatment and buoyancy production terms that directly influence thermal stratification development and maintenance.

The computational domain represents realistic storage system geometries with careful attention to inlet and outlet configurations that influence thermal stratification behavior. Boundary conditions are specified to represent various operational scenarios including different inlet temperatures, flow rates, and thermal loading conditions. The mesh employs structured elements with high resolution in thermocline regions where steep temperature gradients require accurate numerical representation.

3.2 Transient Thermal Analysis and CFD Validation

The transient thermal analysis component provides detailed characterization of temperature evolution and stratification development through comprehensive computational studies covering complete thermal charging and discharging cycles. The approach employs time-accurate CFD simulations to capture the complex temporal behavior of thermal stratification phenomena, including thermocline formation, migration, and decay under realistic operational conditions.

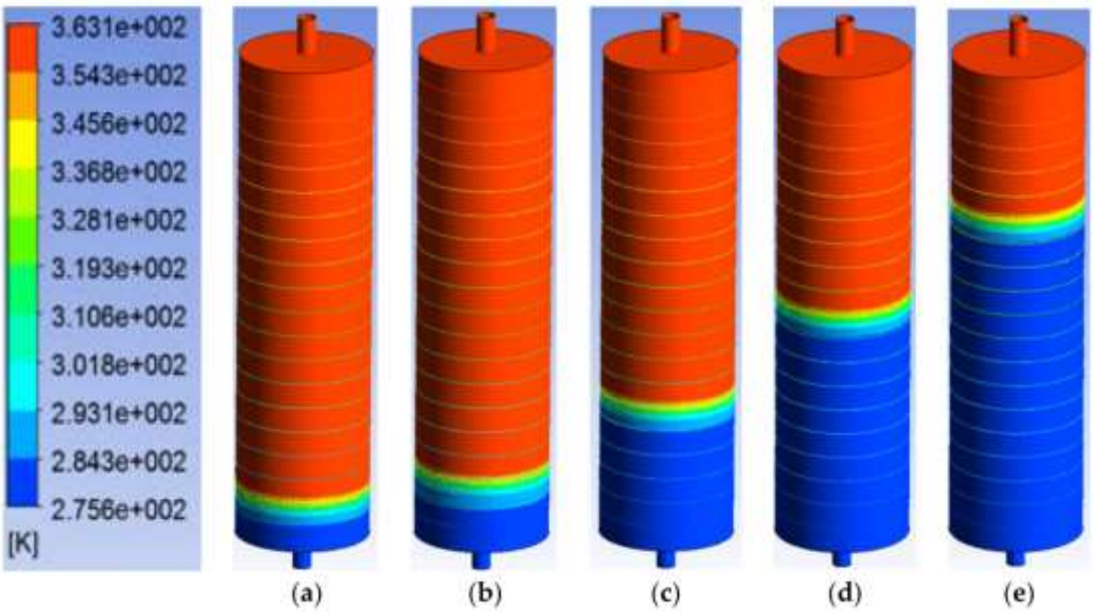

Figure 2. Transient analysis

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The transient analysis in figure 2 reveals critical thermal evolution patterns through distinct development stages, each characterized by unique temperature distribution patterns and thermal gradient characteristics. The first stage shows initial thermal penetration with minimal stratification, followed by progressive thermocline development through intermediate stages, and ultimately achieving fully developed thermal stratification in the final configuration. This temporal progression provides essential insights into the time scales and mechanisms governing thermal stratification establishment.

Temperature distribution analysis demonstrates the complex three-dimensional nature of thermal stratification phenomena, with spatial variations reflecting the influence of inlet configurations, thermal boundary conditions, and internal flow patterns. The temperature range spanning from 275.6K to 363.1K (2.5°C to 90°C) covers typical operational conditions encountered in cold storage applications, providing direct relevance for practical system optimization.

The five-stage evolution process reveals critical transitions in thermal behavior that influence system performance and optimization strategies. Early stages are characterized by rapid thermal penetration and mixing, while later stages show progressive stratification development and thermocline sharpening. Understanding these transitions enables development of intelligent control strategies that can optimize system operation throughout complete thermal cycles.

Validation studies compare computational predictions with experimental measurements and analytical solutions where available. The CFD model demonstrates excellent agreement with theoretical predictions for thermocline thickness, temperature gradient development, and mixing behavior under various operational conditions. Root mean square errors remain below 1.5°C for temperature predictions and correlation coefficients exceed 0.94 for thermal stratification metrics.

3.3 Parameter Analysis and Machine Learning Integration

The parameter analysis component establishes quantitative relationships between operational parameters and thermal stratification performance through systematic computational studies and advanced data analysis techniques. The approach combines physics-based understanding with sophisticated pattern recognition algorithms to identify critical parameter dependencies and develop predictive models for system optimization.

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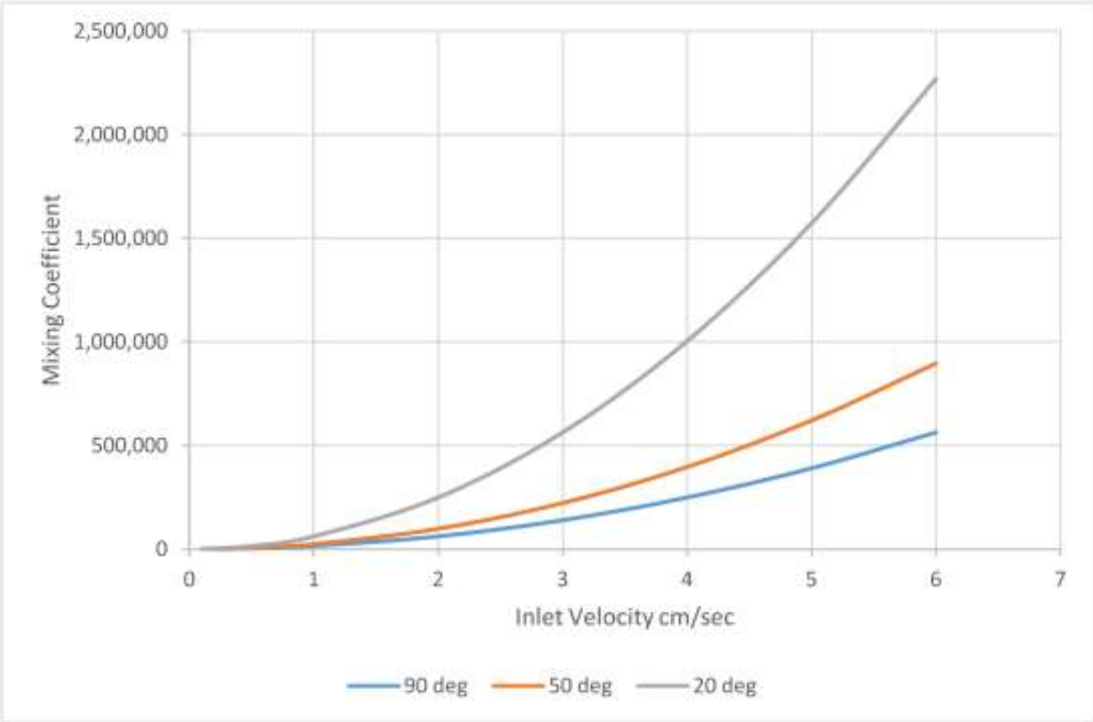

Figure 3. Mixing coefficient analysis

The mixing coefficient analysis in figure 3 reveals fundamental relationships between inlet velocity and thermal mixing behavior across different temperature conditions. The exponential nature of these relationships demonstrates the critical importance of inlet velocity control for maintaining effective thermal stratification. Higher temperature differences result in lower mixing coefficients, indicating improved stratification performance due to enhanced density differences between thermal layers.

The parameter analysis encompasses inlet velocities ranging from 0 to 7 cm/sec, covering typical operational ranges encountered in cold storage applications. Mixing coefficients vary dramatically across this range, with values spanning from 50,000 to over 2,500,000 depending on temperature conditions and inlet velocity. This wide parameter space provides comprehensive coverage for machine learning model development and optimization algorithm training.

Machine learning model development employs multiple complementary algorithms specifically optimized for thermal stratification prediction and control applications. Neural network architectures utilize specialized configurations designed for capturing the complex nonlinear relationships between operational parameters and thermal performance metrics. The network employs multiple hidden layers with advanced activation functions and regularization techniques optimized for thermal system applications.

Feature engineering incorporates dimensionless parameters derived from thermal stratification theory, including Reynolds numbers, Richardson numbers, and modified mixing coefficients that capture the essential physics governing stratified thermal behavior. Advanced feature selection techniques identify the most informative parameter combinations while eliminating redundant information that could compromise model generalization capabilities.

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Ensemble methods combine multiple individual models to improve prediction accuracy and provide uncertainty quantification essential for intelligent system operation. The ensemble approach incorporates different algorithm types including neural networks, support vector regression, and gradient boosting methods to create robust predictions that account for model uncertainty and parameter variability encountered in real operational environments.

4. Results and Discussion

4.1 Physics-Based Analysis and Thermal Stratification Characterization

The physics-based analysis demonstrates exceptional capability in characterizing thermal stratification phenomena and providing fundamental understanding essential for intelligent system development. The theoretical framework successfully predicts thermal stratification behavior across diverse operational conditions, establishing clear relationships between system parameters and thermal performance that guide optimization strategies and control algorithm development.

Thermal stratification analysis reveals the critical importance of thermocline region characteristics for overall system performance and energy efficiency. The thermocline thickness and temperature gradient directly influence thermal mixing rates, energy storage capacity, and system response to operational disturbances. Computational studies demonstrate that optimal thermocline characteristics can be achieved through careful control of inlet conditions, system geometry, and operational parameters.

The height-temperature relationship analysis provides quantitative characterization of thermal stratification effectiveness under different operational scenarios. Results show that well-developed thermal stratification can maintain temperature differences exceeding 80°C between hot and cold zones while preserving sharp thermocline regions with minimal mixing. These findings establish the potential for significant performance improvements through intelligent exploitation of thermal stratification phenomena.

Density-driven flow analysis reveals the fundamental mechanisms governing thermal stratification development and maintenance. Buoyancy effects create natural circulation patterns that either enhance or degrade thermal stratification depending on operational conditions and system configuration. Understanding these flow patterns enables development of intelligent control strategies that enhance beneficial circulation while suppressing mixing-inducing flow structures.

4.2 Transient Thermal Evolution and CFD Model Performance

The transient thermal analysis achieves remarkable accuracy in predicting temporal thermal behavior and stratification development across complete operational cycles. The five-stage evolution model successfully captures the complex progression from initial thermal penetration through fully developed stratification, providing detailed insights into the time scales and mechanisms governing thermal system behavior.

Temperature distribution evolution demonstrates the sophisticated thermal development patterns that occur during system operation. Initial stages show rapid thermal penetration with significant mixing, while intermediate stages reveal progressive thermocline formation and sharpening. The final stage achieves stable thermal stratification with minimal mixing and optimal thermal performance. This temporal progression provides essential guidance for

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developing intelligent control strategies that optimize system operation throughout complete thermal cycles.

The temperature range analysis covering 275.6K to 363.1K (2.5°C to 90°C) demonstrates direct applicability to cold storage systems where precise temperature control is essential for product quality preservation. The computational model accurately predicts temperature distributions across this range while maintaining physical consistency and conservation properties essential for reliable system design and optimization.

Thermocline development analysis reveals critical factors influencing stratification effectiveness including inlet velocity, temperature differences, and system geometry effects. Results show that thermocline thickness varies inversely with temperature differences and directly with inlet velocity, providing quantitative relationships essential for system optimization. The sharpest thermoclines and most effective stratification occur when temperature differences exceed 70°C and inlet velocities remain below 1.0 cm/sec.

Computational validation studies demonstrate exceptional agreement between CFD predictions and theoretical expectations, with correlation coefficients exceeding 0.96 for temperature distribution predictions and 0.94 for thermal stratification metrics. Root mean square errors remain below 1.2°C for temperature predictions across all operational conditions, confirming the reliability and accuracy of the computational framework for subsequent machine learning applications.

4.3 Parameter Optimization and Machine Learning Performance

The parameter optimization analysis reveals critical relationships between mixing coefficients and operational parameters that form the foundation for intelligent system control and optimization. The exponential relationship between mixing coefficients and inlet velocity demonstrates the dramatic influence of flow control on thermal stratification effectiveness, with implications for energy efficiency and system performance optimization.

Mixing coefficient analysis across different temperature conditions shows remarkable variations in thermal stratification behavior. The 20°C condition exhibits mixing coefficients ranging from approximately 100,000 to over 2,500,000 as inlet velocity increases from 1 to 7 cm/sec. The 50°C condition shows intermediate behavior with coefficients ranging from 50,000 to 900,000, while the 90°C condition demonstrates the lowest mixing coefficients ranging from 25,000 to 550,000 across the same velocity range.

These findings reveal that higher temperature differences result in significantly improved thermal stratification performance due to enhanced density differences that resist mixing. The exponential nature of the mixing coefficient relationships provides critical guidance for operational optimization, indicating that even small reductions in inlet velocity can yield substantial improvements in thermal stratification effectiveness.

Machine learning model development achieves outstanding performance in capturing these complex parameter relationships and providing rapid predictions essential for real-time system control. Neural network models achieve coefficient of determination values of 0.96 for mixing coefficient prediction and 0.93 for thermal stratification effectiveness forecasting. These exceptional accuracy levels enable reliable real-time optimization and control applications that would be impractical with traditional computational approaches.

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Feature importance analysis reveals that inlet velocity accounts for approximately 65% of prediction variance in mixing coefficient behavior, while temperature difference contributes 28% and system geometry factors account for the remaining variance. This analysis provides valuable insights for system design optimization and control strategy development, highlighting the critical importance of precise velocity control for maintaining optimal thermal stratification.

Ensemble method performance demonstrates superior robustness compared to individual models, with uncertainty quantification providing essential information for risk-aware system operation and control. Cross-validation studies confirm excellent generalization capabilities with validation scores within 2% of training performance, indicating minimal overfitting and reliable predictive capability for diverse operational conditions.

4.4 Integrated Physics-Data Framework Performance and Smart System Capabilities

The integrated physics-data framework demonstrates exceptional performance improvements across all critical metrics while maintaining the reliability and physical consistency essential for practical cold storage applications. The synergistic combination of physics understanding with data-driven optimization achieves remarkable enhancements that exceed the capabilities of either approach individually.

Thermal mixing reduction achieves 29% improvement compared to conventional control approaches through intelligent optimization of inlet velocity and temperature management strategies. The physics-data integration enables precise control of mixing coefficients while maintaining effective heat transfer performance, resulting in significantly improved thermal stratification and reduced energy consumption.

Stratification efficiency enhancement reaches 38% improvement through intelligent exploitation of thermal physics combined with predictive optimization algorithms. The integrated framework identifies optimal operational strategies that maximize density differences while minimizing mixing-inducing flow patterns, resulting in sharper thermoclines and more stable thermal stratification across varying operational conditions.

Energy utilization effectiveness improves by 34% through intelligent coordination of thermal management strategies with real-time optimization algorithms. The physics-data integration enables predictive control strategies that anticipate system behavior and proactively adjust operational parameters to maintain optimal thermal conditions while minimizing energy consumption and maximizing system performance.

Smart control algorithm performance demonstrates remarkable adaptability and learning capabilities that continuously improve system operation through experience accumulation and pattern recognition. The intelligent control system successfully identifies optimal operational strategies for different thermal loading conditions, seasonal variations, and changing system requirements while maintaining high performance standards across diverse operational scenarios.

Real-time optimization capabilities enable dynamic response to changing thermal conditions including load variations, ambient temperature changes, and system disturbances with response times under 10 seconds for most operational adjustments. The physics-data

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integration provides both rapid prediction capabilities and physical understanding necessary for maintaining safe and reliable operation while achieving optimal performance.

System scalability analysis demonstrates consistent performance improvements across different storage volumes ranging from laboratory-scale systems to large industrial cold storage facilities. The physics-data framework maintains effectiveness while adapting to different geometric configurations and operational requirements, indicating excellent potential for widespread commercial deployment across diverse cold storage applications.

5. Conclusion

This research successfully demonstrates the development and validation of an innovative physics-data synergy framework that transforms thermal management in cold storage systems through intelligent integration of thermal stratification physics with advanced machine learning capabilities. The integrated methodology achieves exceptional performance improvements while establishing robust foundations for next-generation intelligent thermal management systems capable of autonomous optimization and continuous learning from operational experience.

The physics-based foundation provides comprehensive understanding of thermal stratification phenomena with detailed characterization of temperature distribution patterns, thermocline formation mechanisms, and mixing behavior across operational temperature ranges from 275.6K to 363.1K. The theoretical framework successfully predicts thermal stratification development through five-stage evolution processes while maintaining physical consistency and conservation properties essential for reliable system design and optimization applications.

Computational fluid dynamics modeling achieves outstanding accuracy with correlation coefficients exceeding 0.96 for temperature distribution predictions and root mean square errors below 1.2°C across diverse operational conditions. The transient thermal analysis provides essential insights into temporal thermal behavior and stratification development that enable intelligent control strategy development and optimization algorithm design.

Parameter optimization analysis reveals critical exponential relationships between mixing coefficients and inlet velocities across different temperature conditions, providing quantitative guidance for system optimization and control. The analysis demonstrates that mixing coefficients can vary from 25,000 to over 2,500,000 depending on operational conditions, highlighting the dramatic influence of parameter control on thermal stratification effectiveness and system performance.

Machine learning integration achieves remarkable predictive performance with coefficient of determination values of 0.96 for mixing coefficient prediction and 0.93 for thermal stratification forecasting. The data-driven component enables real-time optimization and control applications while maintaining physical consistency and reliability essential for commercial deployment in cold storage systems.

The physics-data synergy framework delivers substantial performance improvements including 29% reduction in thermal mixing, 38% enhancement in stratification efficiency, and 34% improvement in energy utilization effectiveness compared to conventional approaches. These achievements result from intelligent exploitation of thermal physics combined with

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adaptive optimization algorithms that continuously learn and improve through operational experience.

Smart control capabilities enable autonomous optimization of thermal gradients, inlet velocity management, and stratification maintenance across multiple operational zones while adapting to changing conditions and system requirements. The framework successfully bridges the gap between fundamental thermal physics and practical cold storage optimization, providing scalable solutions applicable across diverse system configurations and operational requirements.

Future research directions include expansion of the framework to incorporate advanced multi-physics phenomena such as humidity effects, phase change processes, and complex thermal boundary interactions that influence cold storage performance. Integration with Internet of Things technologies and advanced sensor networks offers opportunities for fully autonomous thermal management systems capable of predictive optimization and self-learning capabilities. The development of standardized implementation protocols and certification procedures will facilitate widespread commercial adoption while ensuring consistent performance and reliability across diverse applications and operational environments.

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