

Article

CFD-Based Thermodynamic Stability and Energy Performance Optimization of a Refrigerated Truck Compartment Using Experimental Validation and Surrogate Modelling

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Abstract

This study presents an integrated computational framework combining Computational Fluid Dynamics (CFD), experimental validation, and surrogate modelling to analyse and optimise the thermal performance, thermodynamic stability, and energy efficiency of a refrigerated truck compartment. CFD simulations were conducted to investigate airflow distribution and temperature uniformity under operating temperatures ranging from 0 to 5 °C. The results showed that airflow circulation was primarily governed by the evaporator outlet, while recirculation zones enhanced air mixing but were insufficient to completely eliminate localised hotspots. Increasing the operating temperature from 0 to 5 °C resulted in a rise in the maximum compartment temperature from 6.26 to 10.01 °C. Thermodynamic stability analysis revealed that operation within the 3–5 °C range provided more stable thermal conditions due to reduced refrigeration load and improved temperature uniformity. Experimental measurements of airflow velocity and evaporator surface temperature demonstrated good agreement with CFD predictions, confirming the reliability of the numerical model. Furthermore, CFD-based optimisation reduced the electrical energy consumption of the eTRU system by 10.0%, decreasing the energy intensity from 0.117 to 0.105 kWh km^{−1}, while maintaining improved thermal stability throughout the refrigerated compartment. The surrogate model achieved excellent predictive performance with $R^2 = 0.9576$ and RMSE = 0.0386, demonstrating its suitability for rapid optimisation of refrigerated transport systems. The proposed framework offers an effective tool for improving thermal management, enhancing energy efficiency, and supporting the development of sustainable refrigerated transport systems.

Keywords: computational fluid dynamics; refrigerated truck compartment; thermal management; energy optimisation; surrogate modelling



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1. Introduction

The global cold chain system has become an essential infrastructure for preserving temperature-sensitive commodities such as food, pharmaceuticals, and biological materials, where strict thermal regulation is required to maintain quality, safety, and shelf life [1–3]. Refrigerated transport, particularly truck-based systems, plays a pivotal role in

bridging production, storage, and distribution stages. However, maintaining a uniform and stable thermal environment within refrigerated compartments remains a significant engineering challenge due to complex interactions between airflow, heat transfer, and external environmental conditions [4–6]. Temperature deviations, even within ± 2 °C, can lead to substantial product degradation, highlighting the necessity for advanced thermal management strategies in refrigerated vehicles [7–9].

Recent advancements in energy systems have driven the transition from conventional diesel-driven refrigeration units toward multi-source energy integration, including hybrid electric systems, battery storage, and renewable-assisted cooling technologies [10–12]. These integrated systems aim to enhance energy efficiency, reduce greenhouse gas emissions, and improve operational flexibility. Nevertheless, the incorporation of multiple energy sources introduces additional thermodynamic complexities, particularly in terms of load balancing, transient heat transfer, and system stability under dynamic operating conditions [13–15]. The coupling between energy sources and refrigeration cycles necessitates a rigorous thermodynamic analysis to ensure consistent cooling performance and system reliability [16–18].

Computational Fluid Dynamics (CFD) has emerged as a powerful analytical tool for investigating the internal flow field and thermal behaviour of refrigerated truck compartments. CFD enables the simulation of multi-physics phenomena, including turbulent airflow, convective heat transfer, and phase interactions, thereby providing detailed insight into temperature distribution and airflow patterns [19–22]. Previous studies have demonstrated that airflow non-uniformity is a primary cause of thermal stratification within refrigerated compartments, leading to localised hotspots and compromised product quality [23–25]. By optimising airflow design and refrigeration system configuration through CFD, significant improvements in temperature homogeneity and energy efficiency can be achieved [26–28].

In addition to airflow optimisation, the integration of advanced thermal energy storage technologies, such as phase change materials (PCMs), has gained considerable attention in recent years [29–31]. PCMs provide latent heat storage capability, allowing for more stable temperature control and reduced energy consumption during transient operating conditions. Studies have reported that PCM-based systems can significantly enhance thermal stability and reduce energy demand in refrigerated transport applications [32–34]. When combined with hybrid energy systems, these storage technologies contribute to improved thermodynamic resilience and reduced dependency on continuous mechanical refrigeration [35,36]. Commonly used PCMs for refrigerated transport include paraffin waxes, hydrated salts, fatty acids, and eutectic mixtures. These materials absorb and release latent heat during melting and solidification, thereby stabilising compartment temperature, reducing compressor cycling, and improving energy efficiency.

Despite these advancements, challenges remain in achieving thermodynamic stability in refrigerated truck systems operating under multi-source energy conditions. External disturbances such as ambient temperature fluctuations, solar radiation, door openings, and varying load configurations introduce dynamic thermal loads that can destabilise the refrigeration process [37–39]. Furthermore, the interaction between airflow distribution, insulation performance, and energy input requires a comprehensive multi-scale modelling approach. CFD-based coupled simulations, validated with experimental data, are therefore essential to accurately predict system performance and identify optimal design configurations [40–42].

Accordingly, this study focuses on the thermodynamic stability and energy performance analysis of a refrigerated truck compartment using Computational Fluid Dynamics (CFD). The research aims to develop a comprehensive framework capable of capturing the

coupled effects of airflow distribution, heat transfer, and refrigeration system operation within the refrigerated space. By evaluating thermal behaviour under different operating conditions, this work seeks to identify key factors affecting temperature uniformity, thermodynamic stability, and energy efficiency. The findings are expected to provide practical design guidelines for improving refrigeration performance, reducing energy consumption, and enhancing the operational reliability of refrigerated transport systems, thereby contributing to the development of sustainable cold-chain technologies [43–45].

Recent advances in CFD have significantly improved the capability to predict coupled fluid flow and heat transfer phenomena in complex engineering systems. High-fidelity CFD simulations have recently been applied to thermal management, refrigeration technologies, conjugate heat transfer, and energy optimisation to improve prediction accuracy while reducing experimental costs [46–49]. Furthermore, surrogate modelling and machine learning have increasingly been integrated with CFD to accelerate design optimisation and parameter sensitivity analysis in large-scale thermal systems. Recent studies have demonstrated that CFD-based numerical frameworks can accurately predict temperature distribution, airflow behaviour, thermal stability, and energy consumption under complex operating conditions. Despite these developments, relatively few studies have combined CFD simulation, experimental validation, and surrogate modelling within a unified framework for refrigerated transport systems. Therefore, the present study addresses this research gap by developing an integrated CFD–experimental–machine learning framework for analysing airflow distribution, thermodynamic stability, and energy consumption in electric transport refrigeration units [50–53].

2. Materials and Methods

A three-dimensional CAD geometry of the refrigerated compartment was developed using PowerShape 2016 software (Autodesk Inc., San Rafael, CA, USA), while CFD preprocessing and mesh generation were performed in ANSYS Fluent 2024 R1.

2.1. System Configuration and Geometry

The refrigerated transport compartment, with internal dimensions of 1.9 m × 3.3 m × 2.1 m, was designed for low-temperature distribution applications and operated on a 220 V power supply to maintain an internal temperature of 0–5 °C for preserving temperature-sensitive cargo. The enclosure was constructed using insulated polystyrene sandwich panels and an aluminium-reinforced floor to minimise heat gain while providing adequate structural durability, and hinged access doors were incorporated to reduce thermal leakage during loading and unloading operations. Figure 1 presents the proposed research framework, which integrates experimental measurements, CFD, and Random Forest-based surrogate modelling to optimise the thermal performance and energy efficiency of the refrigerated transport system. The framework comprises four stages: physical-to-digital characterisation, numerical simulation and experimental validation, surrogate model development, and engineering evaluation. A high-fidelity CAD model was used to perform CFD simulations of airflow and temperature distributions, with the numerical model validated against experimental temperature and airflow measurements to ensure predictive reliability. The validated CFD dataset was subsequently used to train a Random Forest surrogate model capable of rapidly predicting thermal performance with significantly lower computational cost than conventional CFD simulations. Correlation analysis, feature importance evaluation, and engineering performance assessment were then employed to identify influential design parameters and support multi-objective optimisation of temperature uniformity, energy consumption, and overall operational efficiency, providing a reliable and computationally efficient framework for refrigerated transport system design.

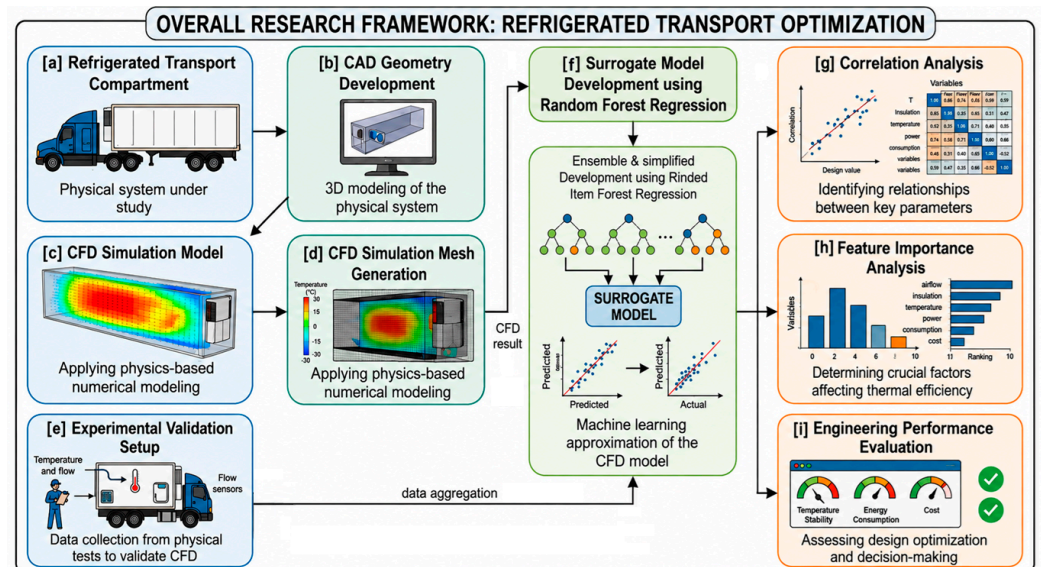


Figure 1. Overall research framework. (a) Refrigerated transport compartment, (b) CAD geometry development, (c) CFD simulation model, (d) computational mesh generation, (e) experimental validation setup, (f) surrogate model development using Random Forest Regression, (g) correlation analysis, (h) feature importance analysis, and (i) engineering performance evaluation.

The refrigeration subsystem featured an evaporator positioned in the upper region of the compartment to facilitate effective airflow circulation and promote temperature uniformity throughout the storage space. The compressor assembly was integrated with essential auxiliary components, including a solenoid valve, filter drier, accumulator, oil separator, liquid receiver, and protection and control units, thereby ensuring reliable operation, improved system safety, and enhanced energy efficiency. A comprehensive summary of the principal design specifications and refrigeration system components is provided in Table 1.

Table 1. Main geometric and operating characteristics of the refrigerated compartment.

Parameter	Value
Internal length	3.3 m
Internal width	1.9 m
Internal height	2.1 m
Operating voltage	220 V
Target operating range	0–5 °C
Wall construction	Polystyrene sandwich panel
Floor reinforcement	Aluminium sheet
Access configuration	Dual hinged doors
Evaporator location	Upper compartment region

2.2. Governing Equations

The CFD analysis was based on the conservation equations of mass, momentum, and energy. The governing equations used in this study are presented as follows.

The conservation of mass for incompressible airflow within the refrigerated truck compartment is represented by the continuity equation:

$$\nabla \cdot \vec{V} = 0, \quad (1)$$

where: $\vec{V}$ = velocity vector (u, v, w).

The airflow behaviour, momentum transport, and forced convection phenomena inside the refrigerated compartment are governed by the Navier–Stokes equation:

$$\rho \left(\frac{\partial \vec{V}}{\partial t} + \vec{V} \cdot \nabla \vec{V} \right) = -\nabla P + \mu \nabla^2 \vec{V} + \rho \vec{g}, \quad (2)$$

where: ρ = air density (kg/m^3), P = pressure (Pa), μ = dynamic viscosity ($\text{Pa} \cdot \text{s}$) and $\vec{g}$ = gravitational acceleration.

The thermal behaviour and temperature distribution within the refrigerated domain are determined using the energy conservation equation:

$$\rho C_p \left(\frac{\partial T}{\partial t} + \vec{V} \cdot \nabla T \right) = k \nabla^2 T + S_T, \quad (3)$$

where: C_p = specific heat capacity ($\text{J}/\text{kg} \cdot \text{K}$), T = temperature (K), k = thermal conductivity ($\text{W}/\text{m} \cdot \text{K}$), and S_T = internal heat source term.

The refrigeration load extracted from the refrigerated compartment is expressed as:

$$Q_{cool} = \dot{m} C_p (T_{in} - T_{out}), \quad (4)$$

where: Q_{cool} = cooling capacity (W), $\dot{m}$ = mass flow rate (kg/s), T_{in} = inlet air temperature, and T_{out} = outlet air temperature.

The conductive heat transfer through the insulated walls of the refrigerated compartment is determined using Fourier's law:

$$Q = \frac{kA(T_o - T_i)}{L}, \quad (5)$$

where: A = wall area (m^2), T_o = outside temperature, T_i = inside temperature, and L = insulation thickness.

The convective heat exchange between circulating refrigerated air and cargo surfaces is expressed as:

$$Q_{conv} = hA(T_s - T_f), \quad (6)$$

where: h = convective heat transfer coefficient, T_s = surface temperature, and T_f = fluid temperature.

For hybrid refrigeration systems integrating electrical and internal combustion engine (ICE) energy sources, the overall energy balance is expressed as:

$$E_{total} = E_{electrical} + E_{ICE}, \quad (7)$$

where: $E_{electrical}$ = electrical energy and E_{ICE} = energy supplied by engine-driven system.

The thermodynamic efficiency of the refrigeration system is evaluated using the coefficient of performance (COP):

$$COP = \frac{Q_{cool}}{W_{input}}, \quad (8)$$

where: W_{input} = compressor or system power input.

The thermal stability within the refrigerated compartment may be evaluated using the thermal stability index:

$$TSI = \frac{T_{max} - T_{min}}{T_{avg}}, \quad (9)$$

where: T_{max} = maximum compartment temperature, T_{min} = minimum compartment temperature, and T_{avg} = average temperature.

Entropy generation associated with irreversible heat transfer processes is expressed as:

$$S_{gen} = \frac{Q}{T}, \quad (10)$$

where: S_{gen} = entropy generation, Q = heat transfer rate, and T = absolute temperature.

2.3. Numerical Setup

Figure 2 presents the computational mesh consisting of 128,965 polyhedral elements and 132,580 nodes. Inflation layers were applied adjacent to solid walls to improve prediction of near-wall velocity and temperature gradients. Five inflation layers with a growth rate of 1.2 were employed to adequately resolve the thermal boundary layer. Local mesh refinement was applied near the evaporator outlet and in regions anticipated to exhibit pronounced velocity and temperature gradients, thereby enhancing the resolution of airflow recirculation, turbulent mixing, and convective heat transfer phenomena. Simulations were conducted using an inlet air velocity of 1 m/s, while the operating temperature was varied from 0 °C to 5 °C to evaluate the thermal behaviour, thermodynamic stability, and energy performance of the refrigerated compartment under different refrigeration conditions.

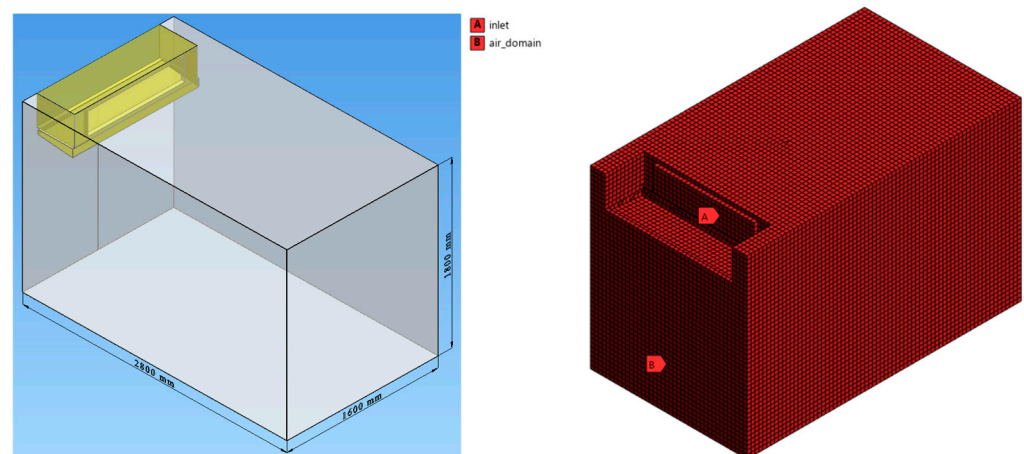


Figure 2. CFD mesh of the refrigerated compartment with local refinement near the evaporator.

To accurately predict turbulent airflow and heat transfer within the compartment, the standard $k-\epsilon$ turbulence model was employed owing to its established reliability and computational efficiency for enclosed ventilation and refrigeration applications. The numerical simulations were performed using ANSYS Fluent 2024R1 with a pressure-based steady-state solver. Pressure–velocity coupling was achieved using the SIMPLE algorithm, while the momentum and energy equations were discretised using second-order upwind schemes to improve numerical accuracy. No-slip boundary conditions were imposed on all compartment walls, and the outlet was specified as a pressure outlet with a gauge pressure of 0 Pa. The convergence criterion for all residuals was set to 10^{-6} , and solutions were considered converged when both residuals and monitored flow variables reached stable values.

The medium mesh, comprising 128,965 elements, was selected for all subsequent simulations because the variation in the predicted results between the medium and fine meshes was less than 1%, thereby demonstrating mesh-independent convergence while maintaining an appropriate balance between computational accuracy and computational efficiency, as presented in Table 2.

Table 2. Grid independence study.

Mesh	Elements	Maximum Temperature (°C)	Average Velocity (m/s)	Relative Error (%)
Coarse	72,540	8.66	3.95	2.83
Medium	128,965	8.53	4.03	0.82
Fine	221,684	8.49	4.05	0.24
Extra Fine	361,228	8.48	4.06	—

To ensure numerical reliability, mesh quality assessment and grid-independence testing were performed prior to the final simulations. The selected mesh was adopted for subsequent analyses because it provided an appropriate balance between computational cost and solution accuracy. Furthermore, wall-function treatments were applied near solid boundaries to accurately represent near-wall flow behaviour and minimise discretisation errors. The principal CFD modelling parameters employed in this study are summarised in Table 3.

Table 3. CFD modelling settings.

Item	Setting
Software	ANSYS Fluent 2024R1
Solver type	Pressure-based, steady-state
Mesh type	Structured hexahedral
Elements	128,965
Nodes	132,580
Turbulence model	Standard k- ϵ
Pressure-velocity coupling	SIMPLE
Momentum discretisation	Second-order upwind
Energy discretisation	Second-order upwind
Wall condition	No-slip
Outlet pressure	0 Pa gauge
Convergence criterion	10^{-6}
Inlet velocity	1 m/s
Operating temperature range	0–5 °C
Refinement region	Evaporator outlet and high-gradient zones

2.4. Experimental Validation with Simulation

The CFD predictions were validated against experimental measurements obtained from the refrigerated compartment under representative operating conditions. Air velocity at the evaporator outlet was measured using an anemometer, while the evaporator surface temperature was recorded using a non-contact infrared thermometer. These measured values were compared directly with the corresponding CFD predictions to assess the accuracy and reliability of the numerical model. The validation focused on the key flow and thermal characteristics governing refrigeration performance, namely airflow distribution and heat transfer behaviour. The comparison between experimental and numerical results demonstrated good agreement, confirming the capability of the CFD model to accurately reproduce the airflow and temperature fields within the refrigerated compartment. The validation measurements and corresponding numerical predictions are summarised in Table 4.

Table 4. Experimental validation measurements.

Quantity	Instrument	Measurement Location	Validation Objective
Air velocity	Anemometer	Evaporator outlet	Airflow field validation
Surface temperature	Infrared thermometer	Evaporator surface	Thermal field validation

Prior to the experimental investigations, all measurement sensors were calibrated against certified laboratory reference instruments in accordance with the manufacturers' recommended calibration procedures. Air velocity sensors were calibrated using a certified airflow calibration system, whereas temperature sensors were calibrated in a controlled temperature chamber over the operating temperature range. The combined measurement uncertainty, incorporating both instrument accuracy and calibration uncertainty, was estimated to be within $\pm 5\%$. This uncertainty level is consistent with the discrepancies observed between the CFD predictions and experimental measurements presented in Table 5, thereby supporting the reliability of the experimental data and the validity of the numerical model.

Table 5. Measurement uncertainty of experimental instruments.

Instrument	Measurement Range	Resolution	Accuracy
Hot-wire anemometer	0–20 m/s	0.01 m/s	$\pm 3\%$ of reading
Infrared thermometer	−50 to 550 °C	0.1 °C	± 2 °C
Thermocouple (Type K)	−50 to 250 °C	0.1 °C	± 0.5 °C

2.5. Energy Performance Evaluation

For a transportation distance of 555 km over an 8 h operating period, the performance of three refrigeration configurations was systematically evaluated: (1) a conventional diesel-powered transport refrigeration unit (TRU), (2) a baseline electric transport refrigeration unit (eTRU), and (3) a CFD-optimised eTRU incorporating hybrid energy management, battery energy buffering, and variable-speed compressor control. The comparative assessment focused on key performance indicators, including total energy consumption and energy intensity, to quantify the operational efficiency of each configuration under identical transport conditions. The results of this comparison are summarised in Table 6, providing a comprehensive evaluation of the energy performance improvements achieved through electrification and CFD-based optimisation strategies.

Table 6. Energy comparison among refrigeration configurations.

Configuration	Energy Consumption	Energy Intensity
Diesel TRU	239.84 kWh equivalent	0.432 kWh/km
Baseline eTRU	64.8 kWh	0.117 kWh/km
CFD-optimised eTRU	58.32 kWh	0.105 kWh/km

2.6. Surrogate Model Development

The proposed framework establishes a systematic workflow for surrogate model development through four sequential phases: data generation and design of experiments (DOE), data preprocessing, machine learning model development, and engineering deployment. Initially, high-fidelity engineering data are generated by creating parameterised three-dimensional CAD models from predefined design specifications, followed by CFD simulations incorporating appropriate boundary conditions, fluid properties, and computational meshes. Latin Hypercube Sampling (LHS) is employed to uniformly sample the design space, producing a statistically representative dataset that combines design variables with corresponding CFD performance responses. The resulting database is subsequently preprocessed by selecting the most influential physical and geometric parameters, normalising feature values using Min–Max scaling, and partitioning the dataset into 80% training and 20% testing subsets to ensure robust model development and unbiased evaluation. A Random Forest algorithm is then trained using the processed dataset, with predictive

performance further enhanced through hyperparameter optimisation using Grid Search or Random Search and validated by five-fold cross-validation to improve model robustness and minimise overfitting. The final model is evaluated using independent testing data, achieving excellent predictive accuracy with ($R^2 = 0.95$), RMSE = 0.03, MAE = 0.02, and MAPE = 4.1%, demonstrating strong generalisation capability. Finally, feature importance analysis quantifies the relative contribution of each design variable, providing valuable engineering insight into the dominant factors governing system performance. The validated surrogate model is integrated into an interactive prediction dashboard, enabling real-time performance prediction and rapid design exploration without repeated CFD simulations, thereby substantially reducing computational cost and supporting efficient engineering optimisation and decision-making, as illustrated in Figure 3.

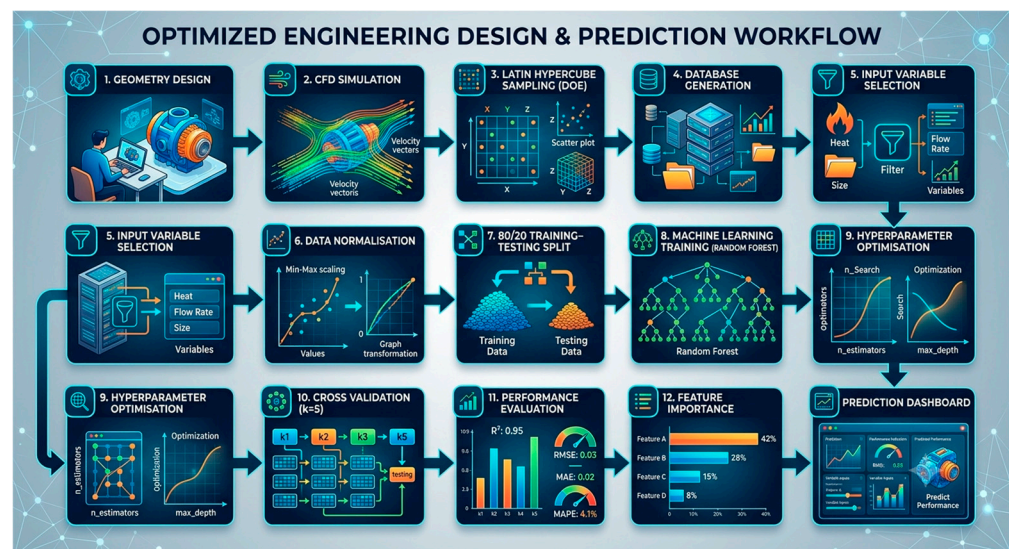


Figure 3. Proposed engineering design optimization and performance prediction workflow using CFD and machine learning. Arrows indicate the direction of the computational workflow and data transfer between stages.

Several machine learning algorithms were initially evaluated, including Linear Regression, Support Vector Regression, Gradient Boosting, Artificial Neural Networks, and Random Forest Regression. Model performance was assessed using the coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Random Forest achieved the highest predictive accuracy ($R^2 = 0.9576$) while maintaining low prediction errors and strong robustness against nonlinear interactions. Consequently, Random Forest was selected as the surrogate model for subsequent sensitivity analysis and rapid prediction of refrigerated transport performance.

2.7. Reproducibility, Data Availability, and Use of Generative Artificial Intelligence

All numerical simulations were performed using ANSYS Fluent 2024R1 under the boundary conditions and modelling parameters described in Sections 2.2 and 2.3. The computational mesh, governing equations, turbulence model settings, solver configurations, and validation procedures are reported in sufficient detail to enable replication of the study. Experimental measurements used for model validation, including airflow velocity and evaporator surface temperature data, were collected using calibrated instruments under controlled operating conditions.

The datasets generated and analysed during the current study, including CFD simulation outputs, experimental measurements, and surrogate-model training data, are available from the corresponding author upon reasonable request. The Random Forest surrogate

model was developed using an 80:20 training–testing data split and evaluated through five-fold cross-validation. Model performance was assessed using the coefficient of determination (R^2) and root mean square error (RMSE).

This study did not involve human participants, animals, or biological materials; therefore, ethical approval was not required.

Generative artificial intelligence (GenAI) was not used for study design, data generation, numerical simulations, data analysis, interpretation of results, or graphical content creation. Any AI-assisted tools employed were limited to language editing and grammatical refinement of the manuscript, which do not require formal disclosure under the journal guidelines.

2.8. Generative AI Use

A generative AI tool (ChatGPT, OpenAI) was used solely to assist with language editing and improving the presentation of figures, Figures 1 and 3. The AI tool was not used for data generation, data analysis, interpretation of results, or drawing scientific conclusions. All scientific content was reviewed, verified, and approved by the authors.

3. Results and Discussion

The results obtained from the CFD simulations, experimental validation, energy performance assessment, and surrogate modelling are presented and discussed in this section. Particular attention is given to airflow distribution, temperature uniformity, thermodynamic stability, energy efficiency, and the influence of key operational parameters on refrigerated transport system performance.

3.1. CFD Analysis of Airflow Distribution

Figure 4 illustrates the airflow characteristics within the refrigerated compartment, demonstrating stable circulation patterns across all operating temperatures investigated. The highest airflow velocities were consistently observed in the vicinity of the evaporator outlet located in the upper section of the compartment, reflecting the primary supply of cooled air. In contrast, lower-velocity regions developed in the lower and corner areas as a result of flow recirculation and vortex formation. These recirculating airflow structures promoted air mixing throughout the compartment and contributed to the overall distribution of cooling. However, despite their beneficial effect on circulation, they were insufficient to completely eliminate thermal non-uniformities, resulting in the persistence of localised temperature gradients and hotspot regions. These findings highlight the importance of further airflow optimisation to achieve more homogeneous thermal conditions and enhance temperature control within refrigerated transport systems.

3.2. Temperature Distribution and Thermal Uniformity

Figure 5 illustrates the temperature distribution within the refrigerated compartment, revealing a generally uniform cooling field with lower-temperature regions occupying a substantial portion of the lower and right-hand sections. Despite this overall uniformity, persistent hotspot regions were identified near the upper-left area of the compartment, where weaker airflow interaction and increased heat ingress contributed to elevated local temperatures. As the operating temperature increased from 0 °C to 5 °C, the maximum compartment temperature rose from 6.26 °C to 10.01 °C, exhibiting an approximately linear relationship across the investigated operating range. The presence of these localised hotspots is of particular importance, as they may compromise product quality and temperature-sensitive cargo during practical transport operations. A detailed summary of the temperature response under the different operating conditions is provided in Table 7, highlighting the influence of operating temperature on the spatial thermal distribution within the refrigerated compartment.

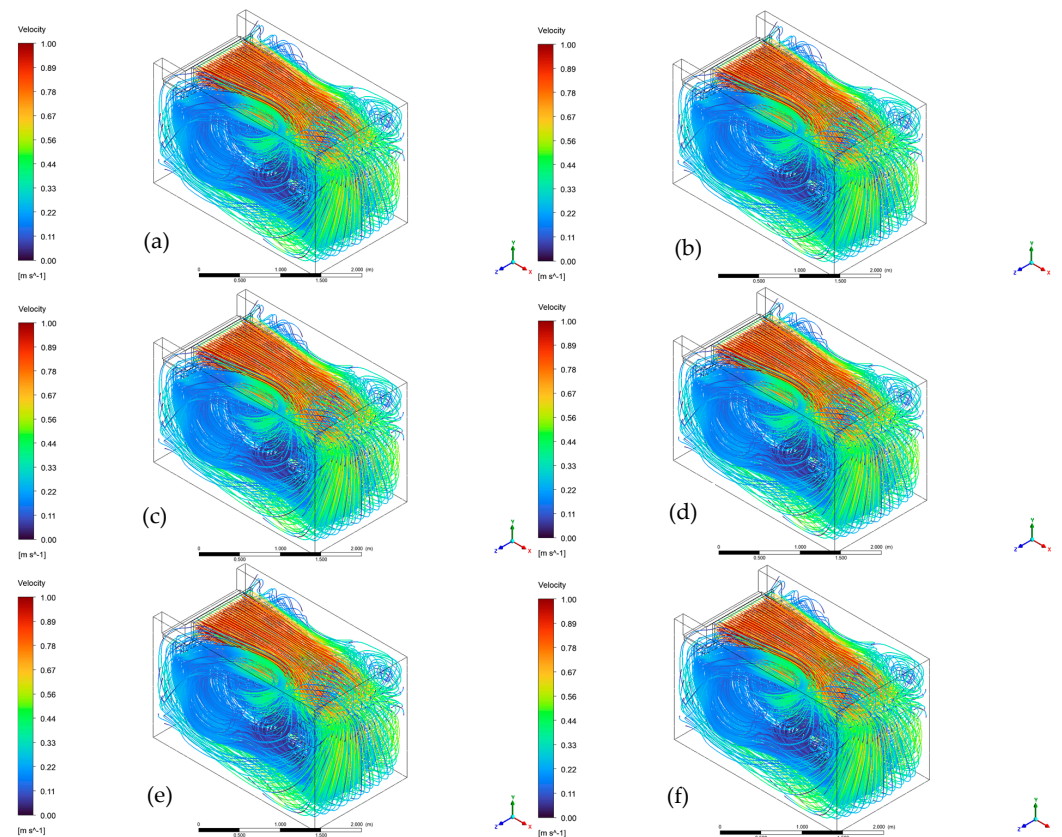


Figure 4. Airflow velocity contours showing circulation patterns inside the compartment, including (a) 0 °C, (b) 1 °C, (c) 2 °C, (d) 3 °C, (e) 4 °C, and (f) 5 °C.

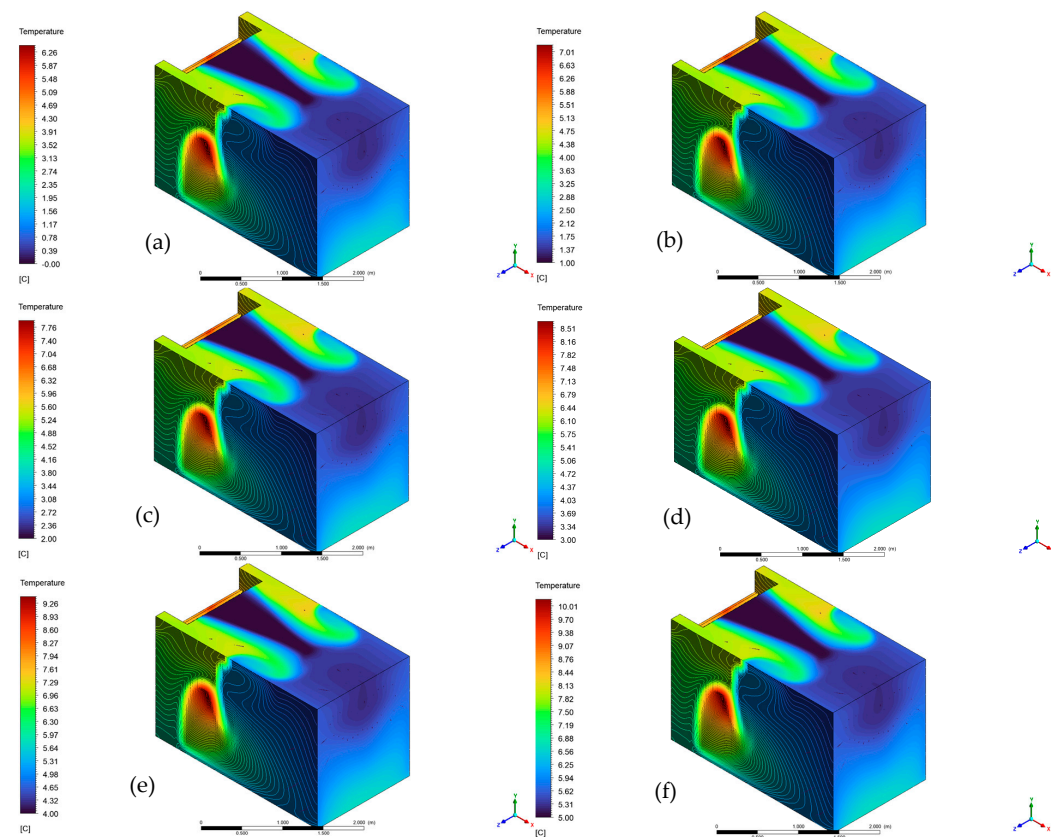


Figure 5. Temperature contours under operating conditions from 0 °C to 5 °C, including (a) 0 °C, (b) 1 °C, (c) 2 °C, (d) 3 °C, (e) 4 °C, and (f) 5 °C.

Table 7. Temperature response across operating conditions.

Operating Temperature	Stability Index	Temperature Std. Dev.	Energy (kWh)
0 °C	0.82	1.84	64.8
1 °C	0.85	1.61	63.9
2 °C	0.88	1.37	62.4
3 °C	0.91	1.10	60.8
4 °C	0.94	0.86	59.2
5 °C	0.96	0.71	58.3

3.3. Thermodynamic Stability Analysis

The stability index increased progressively from approximately 0.82 at 0 °C to 0.96 at 5 °C, indicating increasingly uniform thermal behaviour as refrigeration load decreased. At operating temperatures between 0 and 2 °C, the refrigeration system experienced substantially higher cooling demand, requiring greater compressor work and evaporator heat extraction. Consequently, larger temperature gradients developed throughout the compartment, particularly near the upper corner regions where weaker airflow recirculation and continuous heat ingress produced localised hotspots. The corresponding standard deviation of compartment temperature decreased from approximately 1.84 °C at 0 °C to 0.71 °C at 5 °C, demonstrating a 61% improvement in thermal uniformity. Similarly, the coefficient of temperature variation was reduced by approximately 58%, confirming enhanced thermodynamic stability under moderate cooling conditions.

From a thermodynamic perspective, lower operating temperatures increase the refrigeration load because the temperature difference between the refrigerated compartment and the external environment becomes larger, thereby increasing conductive heat transfer through the insulated walls. Simultaneously, the evaporator must absorb additional thermal energy to maintain the prescribed temperature, resulting in increased compressor power consumption and more pronounced airflow recirculation. These coupled thermal-fluid interactions generate stronger local temperature fluctuations and reduce overall system stability. In contrast, operation within the 3–5 °C range reduces the cooling demand, lowers compressor workload, and promotes a more homogeneous airflow distribution, thereby enhancing thermal equilibrium throughout the compartment. These findings are consistent with the observed reduction in energy consumption and improved temperature uniformity presented in Sections 3.2 and 3.5, demonstrating that moderate operating temperatures provide the optimal balance between refrigeration performance and energy efficiency.

3.4. Experimental Validation

Figure 6 demonstrates a strong agreement between the experimental measurements and the CFD predictions for both airflow velocity and evaporator surface temperature. The experimentally measured airflow patterns confirmed the effective circulation generated by the evaporator outlet, while infrared thermographic measurements of the evaporator surface temperature corroborated the cooling behaviour predicted by the numerical simulations. The close correspondence between the experimental observations and the CFD results provides robust validation of the numerical model, thereby enhancing confidence in its capability to accurately represent the thermal and fluid flow characteristics of the refrigeration system. This agreement supports the reliability of the model for subsequent performance evaluation and design optimisation studies.

The experimental validation focused on the evaporator outlet because this location governs the primary airflow supplied to the refrigerated compartment and directly influences the overall circulation pattern. Although measurements were limited to air velocity and evaporator surface temperature, these parameters represent the dominant bound-

ary conditions driving the CFD solution. This limitation has now been acknowledged, and future work will incorporate spatial temperature measurements at multiple locations throughout the cargo compartment to provide a more comprehensive validation of the predicted airflow and temperature fields.



Figure 6. Comparison of measured and predicted evaporator surface temperature.

3.5. Energy Comparison

Figure 7 illustrates the comparative energy performance of the conventional diesel transport refrigeration unit (TRU), the baseline electric transport refrigeration unit (eTRU), and the CFD-optimised eTRU. The conventional diesel TRU consumed approximately 24.23 L of diesel during an 8 h operating period, corresponding to a total energy input of 239.84 kWh and an energy intensity of 0.432 kWh/km. In comparison, the baseline eTRU required 64.8 kWh of electrical energy, resulting in an energy intensity of 0.117 kWh/km and demonstrating a substantial improvement in energy efficiency relative to the diesel system. Further optimisation through Computational Fluid Dynamics (CFD) reduced the energy consumption of the eTRU to 58.32 kWh and lowered the energy intensity to 0.105 kWh/km, indicating an additional enhancement beyond the baseline electric configuration. These findings demonstrate the effectiveness of CFD-based optimisation in reducing refrigeration energy demand while improving overall operational efficiency. A summary of the energy performance improvements among the three configurations is presented in Table 8.

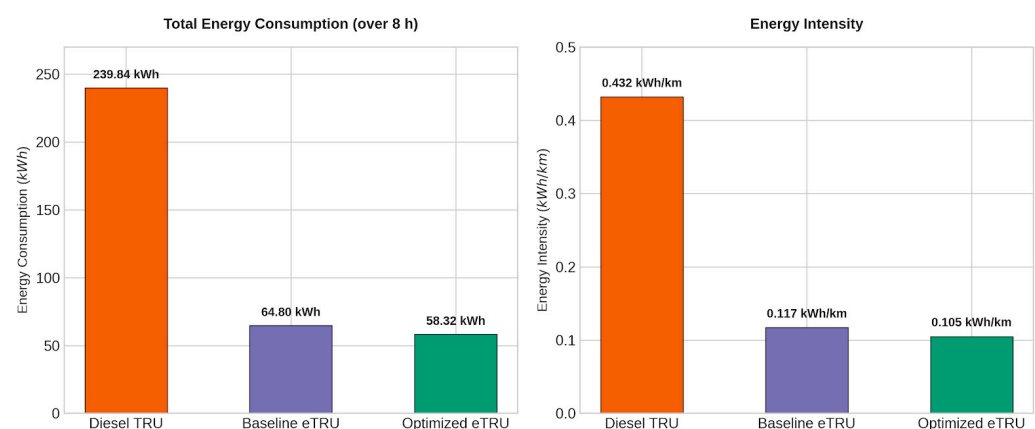


Figure 7. Energy consumption comparison among diesel TRU, baseline eTRU, and optimized eTRU.

This study compares the CFD predictions with the corresponding experimental measurements for air velocity and evaporator temperature. The CFD model predicted an air velocity of 1.10 m/s, compared with the experimentally measured value of 1.05 m/s, resulting in a relative error of 4.5%. Similarly, the predicted evaporator temperature of

5.6 °C showed good agreement with the measured value of 5.3 °C, with a relative error of 5.4%. Overall, the average relative error between the CFD predictions and experimental measurements was less than 5%, demonstrating satisfactory agreement and confirming the accuracy and reliability of the numerical model for predicting the thermal and airflow characteristics of the refrigerated transport compartment.

Table 8. Summary of energy improvement.

Comparison	Improvement
Optimised eTRU vs. baseline eTRU	10.0% energy reduction
Baseline eTRU vs. diesel TRU	substantial reduction
Optimised eTRU vs. diesel TRU	highest efficiency benefit

3.6. Surrogate Model Performance

The surrogate model predicted stability with strong accuracy. From Figure 8, the reported $R^2 = 0.9576$ indicates that the model explained most of the variance in actual stability values, while $RMSE = 0.0386$ showed low prediction error. This supports the use of the surrogate framework as a practical screening tool for operational optimization.

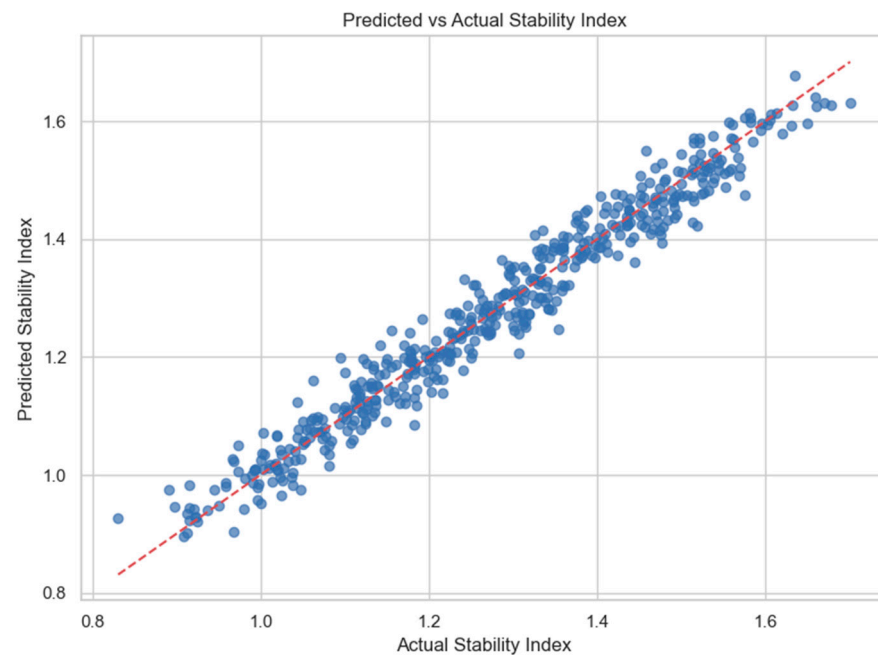


Figure 8. Surrogate model prediction *versus* actual stability index. The blue circles represent individual predicted–actual data pairs, and the dashed red line denotes the ideal 1:1 relationship between predicted and actual values.

3.7. Correlation Analysis

The correlation analysis presented demonstrates that the stability index exhibited a strong positive correlation with PCM capacity ($r = 0.93$) and the uniformity index ($r = 0.70$), highlighting the critical roles of thermal energy storage capacity and airflow homogeneity in maintaining stable refrigeration performance. Conversely, the stability index showed negative correlations with energy consumption ($r = -0.37$), door opening frequency ($r = -0.28$), and average temperature ($r = -0.21$), suggesting that increased operational disturbances and higher thermal loads adversely affect system stability. Furthermore, energy consumption was positively correlated with ambient temperature, solar radiation, and door opening frequency, confirming the significant influence of external environmental conditions and operational factors on refrigeration demand. Collectively, these relationships, illustrated in

Figure 9 and summarised in Table 9, provide valuable insights into the interdependence of key design and operational parameters, emphasising the importance of optimising thermal storage, airflow distribution, and operational management to enhance overall system performance and energy efficiency. PCM was represented as an equivalent latent heat storage capacity within the CFD boundary conditions rather than through explicit phase-change modelling.

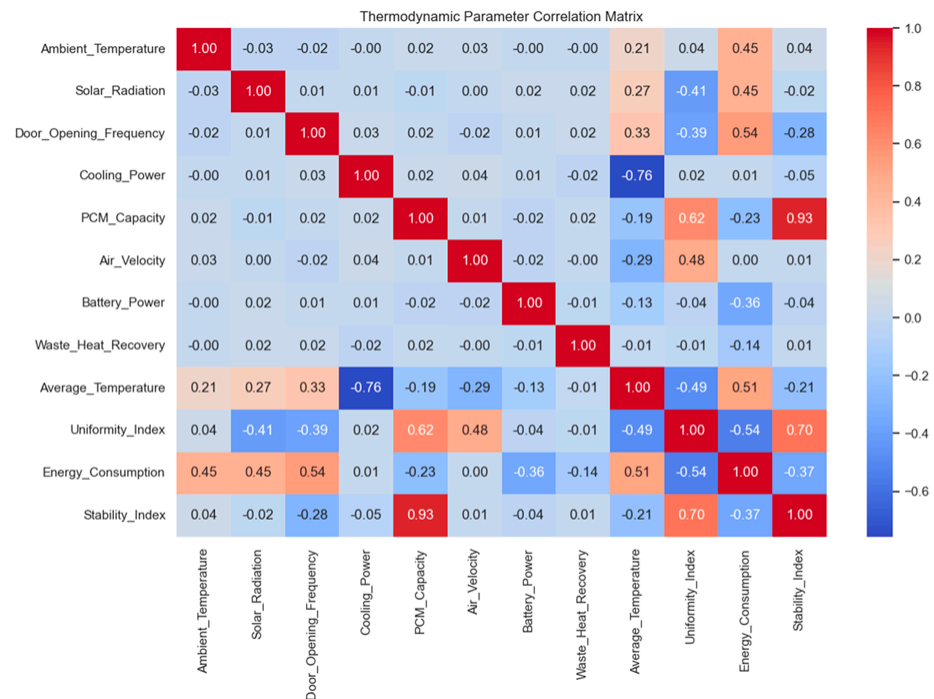


Figure 9. Correlation matrix among thermal and operational variables.

Table 9. Correlation relationships affecting performance.

Variable	Correlation with Stability	Interpretation
PCM capacity	0.93	Strong positive effect
Uniformity index	0.7	Moderate-to-strong positive effect
Energy consumption	−0.37	Negative effect
Door opening frequency	−0.28	Stability decreases with leakage
Average temperature	−0.21	Higher temperature weakens stability

Pearson correlation coefficients were calculated because all variables were continuous and approximately normally distributed. The Pearson correlation coefficient is defined as:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (11)$$

where r ranges from -1 to $+1$.

- Thermal Stability Index = inverse of the spatial standard deviation of compartment temperature.
- PCM Capacity = total latent heat storage (kJ).
- Uniformity Index = $1 - \sigma_T / \bar{T}$.
- Energy Consumption = compressor electrical power $\times$ operating time.
- Average Temperature = volume-averaged CFD temperature.
- Door Opening Frequency = prescribed number of door-opening events per hour.

Figure 10 illustrates the feature importance analysis of the surrogate model, demonstrating the relative influence of six input parameters on refrigerated transport system performance. Inlet velocity is the most significant factor, contributing approximately 50% of the model importance, indicating that airflow generated by the evaporator is the primary driver of thermal distribution and cooling efficiency. Solar load (17–18%) and cargo load (14%) are the next most influential variables, highlighting the effects of external heat gain and transported goods on refrigeration performance. Ambient temperature contributes around 11%, reflecting its impact on cooling demand through heat transfer across the insulated walls, while wall heat flux has a relatively minor influence (6%). Outlet pressure shows the lowest importance (2%), suggesting a negligible effect on overall system behaviour. Overall, the analysis indicates that optimising inlet airflow, reducing solar heat gain, and managing cargo loading are the most effective strategies for improving temperature uniformity, energy efficiency, and the overall performance of refrigerated transport systems.

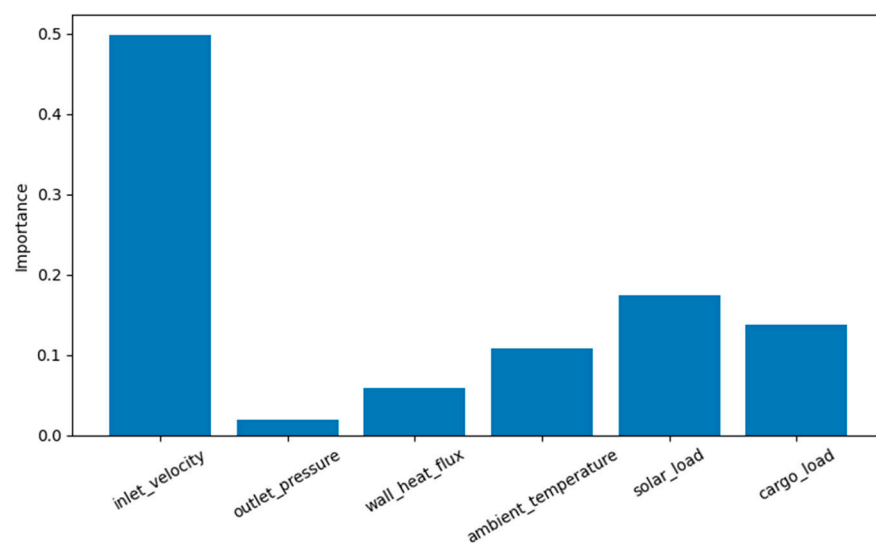


Figure 10. Feature importance analysis of input parameters influencing refrigerated transport system performance.

Feature importance was computed using permutation importance from the trained Random Forest Regression model, where each feature was randomly shuffled and the resulting increase in prediction error was used as its importance score. The values were normalised so that the total importance equalled 100%.

4. Conclusions

This study demonstrates the effectiveness of integrating CFD, experimental validation, and surrogate modelling to evaluate and optimise the thermal performance of refrigerated transport systems. The CFD analysis revealed that airflow distribution is primarily governed by the evaporator outlet, where high-velocity regions promote convective cooling, while recirculation zones in the lower and corner sections contribute to air mixing but fail to eliminate localised temperature non-uniformities. Temperature simulations identified persistent hotspot regions, particularly near the upper-left section of the compartment, with maximum temperatures increasing from 6.26 °C to 10.01 °C as the operating temperature rose from 0 °C to 5 °C. Thermodynamic stability analysis further indicated that operation within the 3–5 °C range provides more stable thermal behaviour than lower temperature settings due to reduced refrigeration load.

Experimental measurements showed strong agreement with CFD predictions for both airflow and evaporator surface temperature, confirming the accuracy and reliability of the numerical model for performance assessment and design optimisation. Energy analysis demonstrated that replacing the conventional diesel transport refrigeration unit (TRU) with a baseline electric TRU substantially reduced energy demand, while CFD-based optimisation achieved an additional 10% reduction in energy consumption, lowering the energy intensity to 0.105 kWh/km and providing the highest overall efficiency.

The surrogate modelling framework exhibited excellent predictive capability, with an R^2 value of 0.9576 and low prediction error, supporting its application as a rapid optimisation tool. Correlation analysis identified phase change material (PCM) capacity and airflow uniformity as the strongest positive contributors to system stability, whereas energy consumption, door opening frequency, and average temperature negatively affected performance. Feature importance analysis further established inlet velocity as the dominant design parameter, followed by solar load and cargo load, emphasising the critical role of airflow management and external heat gain mitigation. Overall, the integrated methodology provides a robust framework for improving temperature uniformity, reducing energy consumption, and enhancing the operational reliability of refrigerated transport systems, offering valuable guidance for the future design and optimisation of sustainable cold-chain logistics.

Cargo loading was modelled as uniformly distributed solid blocks positioned within the refrigerated compartment to represent transported products. The thermal properties assigned to the cargo corresponded to typical food products. Solar radiation was incorporated as an external wall heat flux boundary condition applied to the exposed roof and side walls, thereby representing realistic daytime thermal loading. Variations in cargo load and solar heat flux were systematically generated using the Design of Experiments (DoE) to produce the CFD dataset employed for surrogate model training.

5. Limitations and Future Work

Although the present study provides valuable insight into airflow circulation, thermal stability, and energy performance, several limitations remain. First, the CFD model was evaluated under a limited set of operating temperatures and may not fully capture transient driving conditions, cargo loading effects, or repeated door openings. Second, the experimental validation focused primarily on airflow velocity and evaporator surface temperature, while comprehensive compartment temperature mapping was not fully implemented. Third, the surrogate model was developed using a limited dataset and should be expanded using additional operating scenarios and cross-validation. Future work should incorporate transient road vibration, variable ambient conditions, realistic cargo geometries, and phase change material integration to provide a more complete prediction of refrigerated transport performance.

Steady-state CFD simulations were adopted because the primary objective was to evaluate the average thermal behaviour under representative operating conditions while maintaining reasonable computational cost. Transient phenomena, including repeated door opening and associated air infiltration, were not explicitly simulated. Instead, the influence of door opening was incorporated indirectly as an operational variable within the surrogate modelling framework. Future studies will employ transient CFD simulations with dynamic boundary conditions to capture unsteady heat transfer and airflow behaviour during loading and unloading operations.

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