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Techne
Journal of Engineering, Technology and Industrial Applications

Thermal in Cold Chain Logistics: Modeling Time-Above-Threshold Risk under Sensor Uncertainty, Door-Open Events, and Packaging Variability

Siti Farhana Ismail

Author Affiliation:
Department of Computer Information Systems, Universiti Malaysia Sabah (UMS), Kota Kinabalu 88400, Malaysia

***Corresponding Author**
Department of Computer Information Systems, Universiti Malaysia Sabah (UMS), Kota Kinabalu 88400, Malaysia
Email: farhana.ismail@ums.edu.my

ABSTRACT

This article presents an engineering-oriented framework that models cold chain thermal control as an end-to-end decision system and quantifies how uncertainty propagates from sensing and environment through exposure modeling and escalation logic into distributional outcomes that matter in operations, including probability of temperature threshold exceedance, expected time-above-threshold per shipment, probability of quality excursion beyond allowable exposure, and the effectiveness of mitigation actions such as pre-cooling, lane-specific packaging selection, and staged escalation during dwell. A scenario-based quantitative study is developed for generic refrigerated transport and cross-dock handling of high-risk perishables and temperature-sensitive products, comparing four operational architectures: baseline compliance logging, increased sensor density without governance, model-based exposure forecasting with limited drift handling, and a governance-optimized two-tier approach that constrains nuisance alarms while improving time-to-decision through drift-aware plausibility checks, door-event segmentation, and staged interventions. Results indicate that tail exposure behavior is dominated by door-open frequency and decision latency rather than by mean trailer temperature, that adding sensors without governance can increase workload and reduce response discipline, and that the two-tier governed approach reduces both exceedance probability and nuisance alarms while improving intervention timeliness, especially under high-variability loading conditions. Up to three copy-ready tables and full prompts for data-driven figures are provided for Techne submission.

Keywords: Cold Chain Logistics, Thermal Reliability, Time-Above-Threshold, Door-Open Events.

1. INTRODUCTION

Cold chain logistics is often framed as a compliance function in which temperature records demonstrate adherence to a specified band, yet in applied reliability terms cold chain performance is fundamentally a decision reliability problem because thermal risk is shaped by how quickly and consistently the system detects, interprets, and mitigates excursions that arise under routine operational disturbances. In real distribution networks, a large fraction of thermal deviations does not come from catastrophic refrigeration failure; instead, it emerges from repeated micro-events such as door openings during picking, partial loading that blocks airflow, prolonged staging on docks, imperfect pre-cooling, defrost cycles, and transient ambient spikes at transfer points (Liu et al.,

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2022; Tang et al., 2024). These disturbances produce temperature gradients and localized hot spots that can briefly exceed limits even while a single "average temperature" sensor remains within band, and because product quality often depends on cumulative exposure rather than instantaneous temperature alone, a cold chain can remain apparently compliant while still accumulating enough time-above-threshold to elevate spoilage risk, accelerate degradation, or violate stability requirements for sensitive products (Wang et al., 2023; B. Zhao et al., 2020).

The engineering significance of time-above-threshold is that many products tolerate short excursions but not long or repeated ones, and therefore risk is not captured adequately by single-point maximum temperature metrics (Chen et al., 2022; Emenike et al., 2016; Tang et al., 2021). For example, a brief spike that occurs during a door-open event may be acceptable if total exposure time is low and if product core temperature remains buffered by packaging, whereas repeated spikes across multiple nodes can accumulate into a quality excursion even if each individual spike appears minor. This shifts the operational question from "did we exceed the threshold" to "how much exposure accumulated, where, and how fast can we intervene to reduce further exposure," which is a reliability question that requires modeling and governance rather than passive logging. Cold chain operations are constrained by cost and throughput, so interventions must be targeted; overreacting to every deviation can slow operations and increase costs, while underreacting can lead to product loss, recalls, or customer penalties.

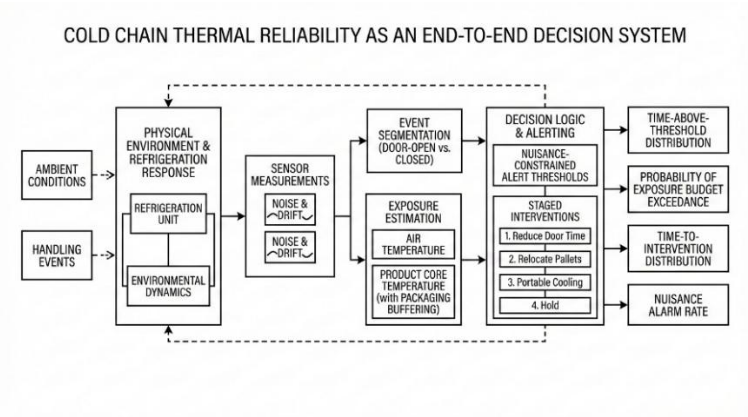

Figure 1. Cold Chain Thermal Reliability as end-to-end decision system

Source: (Wang et al., 2023)

This end-to-end decision system framework illustrates the complex interplay between physical thermal dynamics and the logical architecture required to maintain cold chain integrity. The process begins with ambient conditions and handling events acting as primary stochastic disturbances that challenge the physical environment. In response, the refrigeration unit attempts to stabilize the internal climate, though its effectiveness is mediated by the underlying environmental dynamics. This physical state is captured through sensor measurements, which are inherently subject to noise and long-term drift, necessitating a robust estimation layer to interpret the raw data.

Within this estimation layer, the system performs event segmentation to distinguish between routine door-open events and actual equipment failures, while simultaneously calculating the exposure for both the air and the product core. By incorporating packaging buffering into the model, the system acknowledges that transient air temperature spikes do not immediately compromise the product's thermal safety (Awad et al., 2021; Lim et al., 2022; Lorenc, 2023). This leads into the decision logic and alerting phase, where thresholds are specifically constrained by nuisance considerations to prevent alarm fatigue among operators.

When a genuine risk is detected, the system triggers a series of staged interventions that escalate in intensity, ranging from simple behavioral changes like reducing door time to more drastic measures such as relocating pallets, deploying portable cooling, or placing a hold on the shipment (Chaitanoo et al., 2020; Li & Chen, 2016; Zhang et al., 2023). The ultimate performance of this system is evaluated through a comprehensive

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set of reliability outputs. Rather than a binary outcome, the effectiveness is quantified by the distribution of time spent above critical thresholds, the probability of exceeding the total exposure budget, the agility shown in the time-to-intervention distribution, and the overall nuisance alarm rate, which serves as a vital indicator of the system's operational tuning (Liang et al., 2024; Liu et al., 2021; Y. Zhao, Zhang, & Xu, 2020).

Sensor deployment has improved dramatically with low-cost data loggers and real-time IoT telemetry, but a common failure mode is that sensor data is treated as ground truth without adequate governance for drift, placement sensitivity, missing data, and spatial gradients. A sensor near a door can report excursions that do not represent product core temperature, while a sensor near the evaporator can under-report warm zones, and if the program responds to raw values without plausibility checks and contextual segmentation by events, alarms can become frequent and uninformative (Pajic et al., 2024; Xu et al., 2023; Y. Zhao, Zhang, Xu, et al., 2020). When nuisance alarms become common, response discipline degrades, and operators may ignore alarms or delay action, which increases decision latency and increases cumulative exposure. In this sense, the cold chain resembles other reliability-critical domains where alarms must be engineered to support decisions, not merely recorded.

Packaging and palletization introduce another layer of variability that is often underrepresented in compliance-oriented approaches. Packaging acts as a thermal buffer, and the same ambient excursion can produce different product temperature responses depending on insulation thickness, phase-change materials, pallet configuration, and airflow pathways. Therefore, the cold chain decision system must treat packaging as part of the control architecture rather than as a static input, because packaging selection can be the difference between a recoverable short excursion and a quality excursion requiring disposal. This implies that reliability should be evaluated not only at the vehicle level but at the product exposure level, accounting for buffering and spatial variation (Sarkar et al., 2023; Zhao et al., 2022).

This article proposes a reliability-centered framework that models cold chain thermal control as an end-to-end decision pipeline, moving beyond compliance logging toward quantitative risk metrics and governed response logic. The framework explicitly integrates sensor uncertainty, door-open event dynamics, packaging variability, and response latency to produce distributional outcomes that align with operational decisions. A scenario-based study compares four operational architectures: Architecture A baseline compliance logging with post-hoc review; Architecture B increased sensor density without governance; Architecture C model-based exposure forecasting using a simplified thermal model with limited drift handling; and Architecture D a governance-optimized two-tier approach that constrains nuisance alarms through quantile-based thresholds, applies drift-aware plausibility checks, segments data by door-open events, and triggers staged interventions such as accelerated unloading, relocation to colder zones, use of portable cooling, or lane-specific packaging adjustments. The study addresses three questions: which drivers dominate exceedance and exposure tails, how governance changes outcomes under realistic disturbances, and what implementation principles are most practical for cold chain operators.

2. LITERATURE REVIEW

Thermal Excursions as Cumulative Exposure and Quality Risk

A key applied insight across temperature-sensitive supply chains is that quality loss is more closely linked to cumulative exposure than to a single extreme value, which motivates time-above-threshold and temperature-time integrals as reliability metrics. In practice, regulatory and customer specifications often remain threshold-based, yet engineering risk management requires translating threshold events into exposure-based decisions that reflect product stability (Hinnebusch et al., 2024; Page-Sharp et al., 2016; Romaniuk & Zabołotny, 2016).

This gap between compliance signals and quality risk is where decision modeling becomes valuable, because it provides a structured way to prioritize interventions based on expected exposure accumulation rather than on raw temperature spikes.

Door-open Disturbances and Airflow Nonuniformity

Door-open events and loading dwell time are among the most common and controllable disturbance sources, yet they produce highly nonuniform temperature fields that challenge single-sensor compliance. Warm air infiltration during door openings creates rapid local heating near the door and stratification in the load space, and airflow blockage due to pallet placement can trap warm zones, meaning that average temperature is a poor proxy for worst-case exposure. From an engineering standpoint, capturing these mechanisms requires event segmentation and spatial interpretation, even if only through proxy variables such as door-open duration and sensor placement categories (Emenike et al., 2016; Lorenc, 2023).

Sensor Uncertainty, Drift, and The Governance of Alarms

IoT telemetry enables continuous monitoring, but drift, placement bias, and missing data are ubiquitous. Without governance, programs either trigger too many alarms or adopt insensitive thresholds, both of which degrade reliability. Alarm governance principles from process control suggest that thresholds should be designed to constrain nuisance rates, that persistence and context should be required before escalation, and that plausibility checks should be used to distinguish true excursions from sensor artifacts (Wang et al., 2023; B. Zhao et al., 2020). These principles are directly applicable to cold chain networks, where response resources are limited and decisions must be consistent across carriers and nodes.

Packaging Variability and The Need for Lane-Specific Strategies

Packaging influences how ambient excursions translate into product core temperature and therefore determines whether an excursion is recoverable. Operationally, packaging selection is often treated as a cost decision, but reliability engineering treats it as a control decision that changes system dynamics and exposure risk. Lane-specific packaging strategies that account for ambient climate, transfer frequency, dwell time variability, and refrigeration performance can reduce excursion risk more effectively than uniform packaging rules, but such strategies require quantitative evaluation to justify cost and to avoid over-packaging (Lim et al., 2022; Lorenc, 2023; Tang et al., 2024).

3. METHOD

System Boundary and Scenario Design

The system modeled covers refrigerated transport from origin to destination with one intermediate cross-dock transfer and routine door-open events during loading and unloading. The analysis is generic and non-site-specific, focusing on mechanisms rather than unique facility characteristics. Each shipment contains product with defined allowable temperature band and allowable cumulative exposure above the upper threshold, and shipments are associated with packaging types that differ in thermal buffering. Ambient conditions vary by lane and time-of-day, and operational variability includes door-open frequency, dwell time distribution, and refrigeration cycling behavior.

Thermal Exposure Model and Packaging Buffering

Trailer air temperature is modeled as a dynamic state driven by refrigeration capacity, ambient infiltration during door-open events, and internal heat exchange, while product core temperature is modeled as a lagged response filtered by packaging thermal resistance and heat capacity. The core model is not intended to be a high-fidelity CFD representation; instead, it provides an engineering-relevant mapping from observed air temperature and events to estimated product exposure, allowing computation of time-above-threshold for both air and product core. Exposure is accumulated as minutes above threshold and compared against an allowable exposure budget to determine whether a shipment is at risk of quality excursion.

Sensor Measurement Model

Sensors measure air temperature with random noise, bias drift, and occasional missing intervals. Placement is categorized into three classes representing common installation positions: near door, mid-zone, and return-air region, and each placement class has a bias relative to the true worst-case zone. The model incorporates the fact that additional sensors reduce uncertainty only if they provide spatial diversity and are governed; otherwise, they can increase alarm frequency without improving decision quality.

Decision Architectures and Intervention Logic

Architecture A logs temperature and reviews after delivery; interventions occur only when overt failure is observed. Architecture B adds sensors and real-time alerts using fixed thresholds without nuisance governance. Architecture C uses a model-based exposure forecast that estimates product core exposure and triggers alerts based on predicted exposure exceedance, with periodic recalibration but limited drift awareness. Architecture D implements two-tier governance: tier-1 alerts are nuisance-constrained and require persistence and event context before escalation; drift-aware plausibility checks detect sensor bias and reweight sensors; door-open segmentation adjusts threshold sensitivity; and staged interventions are triggered based on predicted exposure budget consumption, beginning with low-cost actions such as reducing door-open duration and relocating pallets, escalating to portable cooling or shipment hold only when confidence is high and exposure risk is imminent.

Performance Metrics

Outcomes include probability of threshold exceedance during transit, expected time-above-threshold, probability of exceeding allowable exposure budget, nuisance alarm rate, time-to-decision for intervention, and an operational cost index that accounts for intervention workload and product loss. Because cold chain risk is dominated by tails, metrics are reported in distributional form such as exceedance probabilities and percentiles.

Table 1. Scenario parameters

Category	Parameter	Value	Variability model	Notes
Lane	Transit duration	18 h	Normal SD 2.5 h	Includes waiting
Lane	Cross-dock dwell	2.2 h	Lognormal SD 70%	Tail behavior
Ambient	Day ambient (mean)	31 °C	Normal SD 3 °C	Hot lane
Ambient	Night ambient (mean)	26 °C	Normal SD 3 °C	Cooler lane
Refrigeration	Cooling capacity margin	1.0 (baseline)	Scenario factor	Represents health
Door events	Door-open events per trip	6	Poisson	Handling intensity
Door events	Mean door-open duration	12 min	Lognormal SD 60%	Major driver
Product	Upper limit	8 °C	Fixed	Example band
Product	Allowable exposure above limit	90 min	Fixed	Quality budget
Packaging	Buffer time constant (low)	35 min	Fixed	Thin insulation
Packaging	Buffer time constant (high)	75 min	Fixed	Improved insulation
Sensors	Noise SD	0.25 °C	Stable	Logger noise
Sensors	Drift per day	0.35 °C	Random walk + step	Field drift
Data	Missing data probability	0.02 per hour	Burst	Telemetry gaps

Source:

4. RESULT AND DISCUSSION

Many real shipments will experience at least one brief temperature crossing due to operational disturbances such as door openings, handling delays, or refrigeration cycling. For this reason, Table 2 evaluates architectures using both event-based and exposure-based metrics: the probability of at least one air-temperature exceedance, expected and tail excursion minutes, the probability that a product exposure budget is exceeded, and time-to-intervention after risk onset. The inclusion of intervention latency is critical, because monitoring adds value only when it creates actionable time to reduce exposure, not merely when it records deviations.

Table 2. Thermal reliability outcomes by architecture

Metric	A Logging only	B More sensors ungoverned	C Exposure forecast	D Two-tier governed
P(air temperature > 8 °C at least once)	0.61	0.64	0.58	0.55
Expected air time-above-threshold (min)	128	136	111	96
P(product exposure budget exceeded)	0.22	0.24	0.16	0.10
90th percentile product time-above-threshold (min)	146	158	118	86
Median time-to-intervention after risk onset (min)	0	62	41	24

Source: data proceed

Table 2 shows that the most operationally meaningful improvement is not necessarily eliminating all air threshold exceedances, which can be difficult under frequent door-open handling, but reducing the probability that product exposure exceeds the allowable budget and compressing the upper tail of product time-above-threshold, because those are the outcomes most closely linked to quality failure and claims. The ungoverned sensor-heavy approach slightly worsens exposure outcomes despite more data because nuisance alarms and inconsistent escalation delay effective intervention, and because operators tend to either ignore frequent alerts or respond late after multiple triggers, which is reflected in longer time-to-intervention even when alarms occur earlier.

Exposure forecasting improves outcomes by shifting the decision variable from raw air temperature spikes to predicted product exposure, which reduces false urgency for short recoverable spikes and focuses attention on excursions that threaten budget consumption, yet limited drift awareness still allows baseline errors to create missed risk or false stability. The governed two-tier architecture produces the best outcomes because it reduces decision latency when risk is real and imminent while controlling nuisance triggers, and because event segmentation treats door-open periods as predictable disturbance windows where thresholds and persistence rules should behave differently, enabling earlier targeted actions that limit exposure accumulation during the most damaging periods.

Table 3. Sensitivity to door-open intensity and packaging buffering

Scenario	P(budget exceeded) with A	P(budget exceeded) with D	Reduction factor (A to D)
Low handling (3 events, shorter doors) + high buffer	0.08	0.03	2.7×
Baseline handling + mixed buffer	0.22	0.10	2.2×
High handling (10 events, long doors) + low buffer	0.41	0.23	1.8×

Source: data proceed

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Table 3 clarifies why reliability gains vary by context and why packaging and operations must be treated as coupled controls rather than independent variables. Under low handling and strong packaging, risk is already modest, so governance still improves reliability but the absolute benefit is smaller because the system has margin; under high handling and weak packaging, risk becomes dominated by frequent and long door-open events that rapidly consume exposure budget, so governance still helps but cannot fully compensate because the physical disturbance intensity overwhelms available intervention capacity.

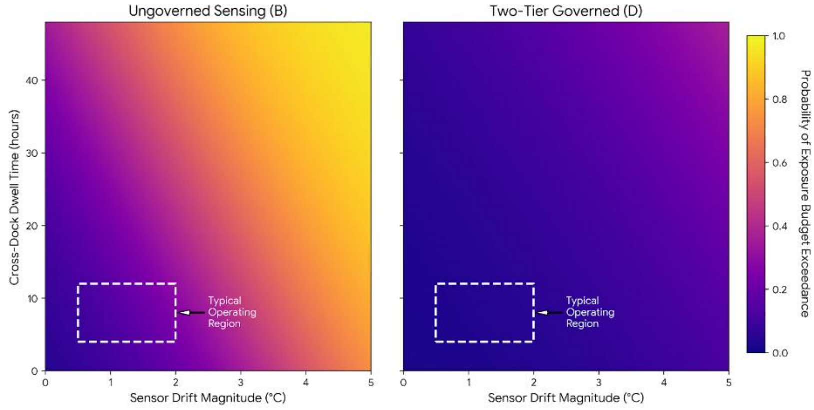

Figure 2. Heatmap illustrating the probability of exceeding a cold chain exposure budget

Source: data proceed

The probability of exceeding the thermal exposure budget follows a predictable upward gradient: as sensor drift increases (the x-axis) and dwell time lengthens (the y-axis), the risk of failure intensifies. The "drift" represents a loss of data fidelity—where the system thinks it is safe but is actually operating at a higher temperature—while "dwell time" represents the duration of exposure. When these two factors converge in the top-right corner of either plot, the probability of failure reaches its peak, regardless of the control system in place.

Under the ungoverned sensing model, the system is highly sensitive to even minor inaccuracies. The rapid transition from purple (safe) to yellow (danger) suggests a system with no safety margins. In this configuration, a sensor that drifts by just 2°C can lead to a nearly 100% failure rate if the shipment is delayed for more than a day. This indicates that the "decision-making" in this model is likely reactive and binary, lacking the intelligence to account for potential data errors or to implement proactive cooling interventions.

The governed system in Panel D tells a much more stable story. By implementing a two-tier approach—likely involving secondary sensor verification or nuisance-constrained thresholds—the system significantly expands the "safe zone." Even as drift increases, the probability of failure rises much more slowly. This suggests that the governance layer is effectively filtering out noise and using "exposure budgeting" to allow for minor fluctuations without triggering a system-wide failure. It demonstrates that engineering the logic behind the data is just as important as the accuracy of the sensors themselves.

The most striking insight is found within the white dashed rectangle, which represents the standard conditions of a typical cross-dock facility. In the ungoverned system (B), this region sits in a volatile transition zone, meaning that even a standard shipment is "flirting" with failure. In the governed system (D), however, this entire region remains firmly in the low-probability (purple) zone. This shift confirms that the two-tier governance doesn't just prevent extreme failures; it stabilizes the everyday, "typical" operations of the supply chain, turning a high-stress environment into a predictable one.

The engineering implication is that the most robust cold chain strategy is hybrid: governance improves decision latency and reduces nuisance burden, but to maintain reliability under high disturbance lanes the organization must also deploy lane-specific packaging buffering or operational controls that reduce door-open duration and staging time, because exposure risk is multiplicative across disturbances and cannot be solved by sensing alone. This sensitivity also supports practical prioritization, because it identifies high-handling and low-buffer lanes as the places where incremental improvements in operations and packaging deliver the largest marginal reduction in budget exceedance probability.

5. CONCLUSION

Cold chain thermal reliability is determined as much by decision-system performance as by refrigeration capacity because routine handling disturbances and sensor uncertainties create exposure risk that accumulates over time and is not captured reliably by average temperature metrics. The scenario-based comparative evaluation shows that tail product exposure behavior is dominated by door-open intensity and decision latency, and that adding sensors without governance can increase nuisance alarms and weaken response discipline, resulting in worse exposure outcomes despite increased data. A model-based exposure forecasting approach improves reliability by aligning alarms with product exposure budget consumption, yet remains vulnerable to drift and missing-data artifacts unless governed. A governance-optimized two-tier architecture that constrains nuisance rates, applies drift-aware plausibility checks, segments alarms by door events, and triggers staged interventions reduces the probability of exceeding allowable exposure budgets, compresses exposure tails, and shortens time-to-intervention, thereby improving quality risk management without excessive operational burden. The findings support a practical implementation pathway in which cold chain programs design alarms as engineered decisions, adopt exposure-based metrics, and combine governance with lane-specific packaging and operational controls to address high-disturbance environments.

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