

# Intelligent Optimization of Fermentation and Freezing Parameters for High-Quality Frozen Dough Products

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## Abstract

Frozen dough products occupy a critical position in modern food supply chains because they reconcile centralized production, long-distance distribution, retail flexibility, and household convenience. Their quality, however, depends on tightly coupled fermentation and freezing processes whose optimal settings are difficult to determine through conventional trial-and-error methods. This paper develops a system-level analysis of intelligent optimization for fermentation and freezing parameters in frozen dough manufacturing. Rather than treating optimization as a narrow search problem, the discussion frames it as a socio-technical architecture that links sensing, data governance, process control, digital twins, predictive modeling, and policy constraints. The paper examines how machine learning and digital twin approaches can improve dough strength, gas retention, freeze tolerance, and baking performance while also introducing new trade-offs in robustness, interpretability, deployment cost, and fairness across small and large producers. It further considers how governance mechanisms, accountability requirements, and sustainability goals shape the design space of intelligent freezing and fermentation control. Through cross-domain comparisons with smart manufacturing and agricultural digital twins, the analysis identifies opportunities for adaptive control, infrastructure sharing, and resilient supply chain coordination. The central argument is that high-quality frozen dough products should be pursued not merely through better parameter tuning but through integrated institutional, technical, and environmental design. Such an approach can improve product consistency, reduce waste, and support more equitable food system outcomes, provided that optimization systems remain transparent, maintainable, and aligned with public-interest priorities.

## Keywords

frozen dough, intelligent optimization, fermentation control, freezing parameters, digital twin, food systems governance, sustainability.

## 1. Introduction

Frozen dough is a deceptively simple product whose industrial production depends on a complex sequence of biological, physicochemical, and logistical decisions. Fermentation determines the development of the gluten network, gas production, flavor precursors, and structural resilience, while freezing and frozen storage influence ice crystal formation, yeast viability, water redistribution, and the integrity of the dough matrix [1]. A dough that performs well immediately after mixing may fail after weeks of frozen storage if fermentation and freezing parameters are poorly aligned. Consequently, manufacturers have long sought to optimize fermentation time, temperature, humidity, pre-freezing conditions, freezing rate, frozen storage temperature, and thawing protocols. The search space is multidimensional, nonlinear, and sensitive to raw material variability, equipment differences, and environmental conditions [2]. This complexity makes frozen dough an instructive case for intelligent optimization in food systems.

The emergence of machine learning, cyber-physical systems, and digital twins has created new possibilities for process control in food manufacturing [9]. Instead of relying on fixed recipes or periodic manual adjustments, intelligent systems can use sensor data, historical batch records, and predictive models to recommend or autonomously enact process changes. In frozen dough production, such systems might adjust fermentation profiles according to flour quality, predict the effects of freezing rates on yeast survival, or reconfigure storage conditions when distribution delays occur [8]. These capabilities are attractive because they promise higher quality, lower waste, and more efficient energy use. Yet they also raise important questions about system architecture, data ownership, model reliability, infrastructure equity, and regulatory accountability. An intelligent optimization system is not simply a computational overlay on existing equipment; it redistributes decision rights, creates new dependencies, and changes how quality is defined and verified [12].

This paper argues for a system-level interpretation of intelligent optimization in frozen dough production. The objective is not to promote a single algorithm or control strategy but to analyze the structural trade-offs that arise when fermentation and freezing parameters are optimized through digital and data-driven means. The discussion proceeds from the material foundations of frozen dough quality to the architecture of intelligent control, then to data infrastructure, robustness, governance, sustainability, and policy. By linking technical optimization with institutional and environmental considerations, the paper aims to show that high-quality frozen dough products are best understood as outcomes of coupled technical and organizational systems. The analysis is especially concerned with how optimization can remain robust under uncertainty, fair across different scales of production, and compatible with long-term sustainability goals.

## **2. Conceptual Foundations of Frozen Dough Quality and Process Coupling**

The quality of frozen dough is shaped by a chain of coupled transformations. During fermentation, yeast metabolism produces carbon dioxide and ethanol while biochemical changes alter gluten proteins and starch structure. The dough gains gas retention capacity, extensibility, and a desirable internal structure. When freezing begins, water transitions into ice, and the rate and uniformity of that transition determine crystal size and location. Slow freezing tends to produce larger ice crystals that can damage gluten networks and yeast cells, while rapid freezing can reduce structural damage but may introduce thermal stress, uneven cooling, and energy penalties [3]. Frozen storage adds another layer of complexity because temperature fluctuations, recrystallization, and oxidative changes continue to affect dough performance. Thawing then partially reverses the process, but it cannot restore all lost

functionality. The final baking performance therefore reflects the cumulative history of fermentation, freezing, storage, and thawing.

Research on frozen dough has consistently shown that no single parameter can be optimized in isolation. Fermentation time interacts with freezing tolerance because over-fermented dough may be more vulnerable to ice damage, whereas under-fermented dough may not develop sufficient structure before freezing [4]. Rheological properties measured before freezing can predict some aspects of baking performance, but predictions weaken when storage duration and temperature variability are introduced [5]. Freezing treatments also affect viscoelastic behavior and structural organization in ways that depend on dough composition and moisture distribution [6]. Additives and hydrocolloids can improve freeze-thaw stability, but their effects are mediated by processing conditions and by interactions with native flour components [7]. A recent hydrocolloid study further indicates that cryoprotective sol-gel transitions can influence frozen dough behavior through structural mechanisms that are not fully captured by conventional quality metrics [17]. This finding reinforces the need for optimization systems that represent structural transitions rather than only correlating input parameters with final loaf volume.

From a systems perspective, frozen dough quality is a multi-objective problem. Producers seek consistent volume, desirable crumb structure, acceptable flavor, low breakage, long shelf life, and predictable thawing behavior. They also seek energy efficiency, low ingredient cost, high throughput, and minimal waste. These objectives can conflict. A slower freezing process may improve texture but increase energy use and reduce line capacity. A longer fermentation may improve flavor but increase sensitivity to freezing damage. A more aggressive additive strategy may improve stability but complicate clean-label positioning. Intelligent optimization must therefore make trade-offs explicit rather than hiding them inside a single objective. The most defensible systems are those that allow operators to adjust priorities according to product category, market segment, regulatory context, and sustainability commitments. This requires not only predictive accuracy but also interpretability, uncertainty communication, and mechanisms for human override.

### **3. Intelligent Optimization Architecture**

An intelligent optimization architecture for frozen dough production can be understood as a layered system. The physical layer includes mixers, fermenters, proofers, freezers, cold storage rooms, and packaging lines. The sensing layer includes temperature probes, humidity sensors, imaging devices, gas sensors, torque measurements, and inline rheology instruments. The data layer stores batch records, equipment states, raw material specifications, environmental conditions, and quality assessments. The modeling layer contains machine learning models, mechanistic simulations, and optimization routines. The control layer translates recommendations into setpoints, alarms, or automated adjustments. The governance layer defines who can access data, how models are validated, and how decisions are audited. This layered view helps clarify that intelligent optimization is not merely a model but an integrated capability dependent on physical infrastructure and organizational routines.

Machine learning can contribute in several ways. Supervised models can predict final dough quality from early process signals, allowing operators to intervene before a batch is fully committed. Reinforcement learning can, in principle, discover control policies that balance quality and energy use over repeated production cycles [10]. Deep learning can extract patterns from complex sensor streams, such as imaging data that reveal bubble structure or ice crystal proxies [11]. Optimization algorithms can search large parameter spaces more

efficiently than manual experimentation. However, these methods depend on data quality, stationarity, and representativeness. A model trained on one flour type or one freezer design may perform poorly when conditions change. In frozen dough production, seasonal variation in flour protein, damaged starch, and moisture content can shift the process landscape. An intelligent system must therefore detect distributional drift and update its recommendations without destabilizing production.

Cyber-physical systems provide a useful reference architecture because they tightly couple computation with physical processes [13]. In a cyber-physical frozen dough line, sensors and actuators are networked with computational models that monitor and control fermentation and freezing in real time. Digital twins extend this idea by maintaining a virtual representation of the product, process, or asset [14]. A digital twin of a freezer, for example, could simulate airflow, heat transfer, and product temperature history, while a digital twin of a dough batch could track fermentation state and predicted freeze tolerance. Digital twin-driven manufacturing has been explored in other sectors as a way to improve commissioning, diagnostics, and optimization [15]. Applying similar ideas to frozen dough requires attention to biological variability, food safety constraints, and the difficulty of measuring internal structural changes non-invasively. Nevertheless, the architecture is promising because it supports scenario analysis: operators can ask what would happen if fermentation were shortened, if storage temperature rose, or if a delivery were delayed.

#### **4. Data, Sensing, and Digital Twin Infrastructure**

The quality of intelligent optimization depends on the quality of its data infrastructure. Frozen dough production generates data at different time scales. Mixing and fermentation data arrive in minutes or hours, freezing data in minutes, storage data over days or weeks, and quality data after baking or sensory evaluation. These data are often held in separate systems, such as laboratory information management systems, manufacturing execution systems, and enterprise resource planning platforms. Integrating them requires common identifiers, time synchronization, semantic standards, and governance rules. Without such integration, models may learn spurious correlations or fail to account for confounding factors. For example, a model might attribute improved quality to a changed fermentation profile when the real cause was a new flour shipment or a maintenance intervention. Robust data infrastructure is therefore not a back-office concern but a precondition for trustworthy optimization.

Sensing is another critical constraint. Many important dough properties are internal and difficult to measure continuously. Inline temperature sensors can track surface and ambient conditions, but they may not capture core temperature accurately during rapid freezing. Imaging can reveal surface browning or shape, but not gluten network integrity. Near-infrared spectroscopy can estimate moisture and protein, but its calibration may drift. Soft sensors that infer unmeasured variables from correlated signals are useful, but they inherit the limitations of their training data. A digital twin can help by fusing mechanistic knowledge with data-driven estimates, but it must be validated against physical measurements. In this sense, intelligent optimization is not a replacement for laboratory analysis and sensory evaluation; it is a way to allocate analytical attention more effectively.

Infrastructure also has equity implications. Large manufacturers can invest in advanced sensors, cloud platforms, and dedicated data science teams. Smaller bakeries may lack the capital, skills, or bargaining power to implement comparable systems. If intelligent optimization becomes a competitive requirement, it could consolidate production further and marginalize smaller producers. Shared infrastructure, open standards, and third-party

validation services can mitigate this risk. Agricultural digital twins offer a useful comparison because they must operate across heterogeneous farms with different equipment, connectivity, and resource endowments [16]. Lessons from that domain suggest that modular, low-cost sensing and cooperative data pools can broaden access. For frozen dough, cooperatives, industry associations, and public research institutions could host shared models or anonymized benchmarks that allow smaller firms to benefit without bearing the full cost of infrastructure.

## **5. Trade-offs in Robustness, Quality, and Throughput**

Intelligent optimization inevitably confronts trade-offs between robustness and performance. A model that is finely tuned to average conditions may achieve excellent quality under normal operation but fail during disruptions. A more conservative model may sacrifice some quality or energy efficiency to maintain stability. In frozen dough production, disruptions include raw material variability, freezer malfunction, cold chain delays, labor shortages, and sudden demand shifts. Robust optimization seeks solutions that perform acceptably across a range of plausible conditions rather than optimally under one assumed condition. This may mean selecting fermentation and freezing parameters that are slightly suboptimal in the laboratory but more resilient in the factory. The choice depends on risk tolerance, product category, and contractual obligations. Premium artisan products may justify tighter control and higher cost, while commodity products may prioritize throughput and cost stability.

Throughput and quality also interact with energy use. Faster freezing can increase capacity but may require more powerful refrigeration and may create thermal gradients. Longer fermentation can improve flavor but occupy valuable floor space and increase scheduling complexity. Intelligent systems can help by dynamically balancing these factors, but they also create new dependencies. If the optimization model is unavailable because of a network outage or software failure, can the line continue safely? Resilient architectures require fallback modes, local control, and clear procedures for degraded operation. They also require operators to maintain tacit knowledge that may otherwise erode as automation increases. A system that is highly optimized but opaque may leave workers unable to diagnose problems when conditions fall outside the model's experience. This is both a technical and a labor issue.

Fairness is another dimension of trade-off. Optimization objectives often encode assumptions about what counts as quality. If models are trained primarily on data from large-scale white pan bread, they may undervalue the quality attributes of whole grain, flatbread, sweet dough, or culturally specific products. This can disadvantage smaller market segments and reduce product diversity. Fairness in food systems is not only about access to technology; it is also about whose preferences and practices are represented in the training data. Participatory design, inclusive data collection, and explicit review of objective functions can help ensure that intelligent optimization does not narrow the range of acceptable products. The goal should be to expand the space of high-quality outcomes rather than to enforce a single industrial standard.

## **6. Deployment, Governance, and Accountability**

Deployment of intelligent optimization in frozen dough production raises governance questions that cannot be resolved by engineering alone. Who is accountable if an automated recommendation leads to a failed batch or a food safety incident? How are model updates approved? What data can be shared with equipment vendors or cloud providers? These questions require clear allocation of responsibility among producers, technology suppliers,

regulators, and auditors. Algorithmic accountability literature emphasizes the need for traceability, explanation, and contestability in automated decision systems [20]. In food manufacturing, traceability is already a regulatory expectation, but it often focuses on ingredients and process steps rather than model versions and parameter recommendations. Extending traceability to algorithmic decisions would allow investigators to reconstruct why a particular fermentation or freezing profile was selected.

Ethical frameworks for artificial intelligence stress principles such as transparency, justice, beneficence, non-maleficence, and autonomy [19]. Applying these principles to frozen dough optimization requires translation into operational practices. Transparency might mean documenting training data, model assumptions, and performance limits in language accessible to quality assurance teams. Justice might mean ensuring that smaller producers and diverse product categories are not excluded from the benefits of optimization. Non-maleficence might require conservative behavior when food safety or allergen control is uncertain. Autonomy might preserve meaningful human authority over critical decisions. These principles are not abstract; they shape the design of interfaces, escalation paths, and audit logs. A system that surfaces uncertainty and recommends verification when confidence is low is more governable than one that presents all outputs as equally authoritative.

The ethics of algorithms also highlights the risk of value lock-in [18]. Once a model is embedded in production routines, it may become difficult to change even if social or environmental priorities shift. For example, if a system is optimized primarily for energy cost, it may resist changes that improve worker safety or product nutrition. Governance should therefore include periodic review of objectives, not just performance metrics. It should also include mechanisms for workers, consumers, and regulators to raise concerns. In frozen dough, this could involve cross-functional committees that review optimization outcomes alongside sensory panels, sustainability reports, and customer complaints. Such committees can help prevent narrow technical metrics from displacing broader conceptions of quality.

## **7. Sustainability and Policy Implications**

Sustainability is increasingly central to food system design. Frozen dough can reduce waste by allowing centralized production and long shelf life, but it also depends on continuous refrigeration and long-distance cold chains. The environmental footprint of frozen dough includes agricultural inputs, processing energy, freezing energy, storage energy, transport, and retail display. Intelligent optimization can reduce waste by improving consistency and predicting quality loss, but it can also increase energy use if it prioritizes narrow quality targets. A whole-system approach should consider trade-offs between product quality, energy demand, food waste, and distribution resilience. Food waste research shows that supply chain coordination and demand forecasting are as important as production efficiency [21]. Intelligent optimization can contribute to both, but only if data are shared across organizational boundaries and if incentives reward waste reduction rather than merely throughput.

Policy can shape these outcomes. Public procurement standards could reward producers that use transparent, auditable optimization systems and demonstrate lower environmental impact. Regulatory frameworks could require documentation of algorithmic decision-making in critical food safety areas. Research funding could support open benchmarks, shared data infrastructure, and training programs for small and medium-sized enterprises. Sustainability frameworks such as the EAT-Lancet Commission emphasize the need for integrated approaches to healthy diets and sustainable food systems [22]. Frozen dough is a small part of

that picture, but it illustrates the broader challenge: optimization must be evaluated against multiple public goals, not only private efficiency. Policies that internalize environmental costs, protect data rights, and support equitable technology access can help align intelligent optimization with sustainability.

## **8. Case Illustrations and Cross-Domain Comparisons**

Several cross-domain comparisons illuminate the design space for frozen dough optimization. Smart manufacturing research has developed architectures for predictive maintenance, quality prediction, and adaptive control [12]. These architectures emphasize standardized data models, edge computing, and human-machine interfaces. Frozen dough production can borrow from these advances, but it must accommodate biological variability and food safety regulations that are less prominent in discrete manufacturing. A freezer in an automotive plant does not contain living yeast, and a batch of dough cannot be reworked in the same way as a metal component. This means that optimization must be conservative in ways that are not always required in other sectors.

Digital twin applications in manufacturing provide another reference. Industrial digital twins often focus on asset health, process optimization, and lifecycle management [14]. In food processing, digital twins must also represent microbial growth, enzymatic activity, and structural transformations. The digital twin of a dough batch may need to simulate fermentation kinetics, heat transfer during freezing, and ice recrystallization during storage. These processes operate at different scales and time horizons, making model integration difficult. Yet the potential benefits are significant. A digital twin could help a producer decide whether to divert a batch to a shorter distribution route if storage temperature has fluctuated, or whether to adjust fermentation for a flour shipment with lower protein content. Such decisions require both prediction and governance, because they affect food safety, quality, and commercial commitments.

Agricultural digital twins offer lessons about heterogeneity and equity [16]. Farms vary in size, soil, climate, and technology adoption. Digital twin systems in agriculture often rely on modular sensors, open data standards, and cooperative extension services. Frozen dough production is more centralized, but it still involves heterogeneous suppliers, bakeries, retailers, and consumers. A cooperative model for data and models could reduce duplication and improve learning across the sector. However, it also raises questions about competition, privacy, and market power. If a few firms control the most valuable training data, they may gain an entrenched advantage. Public institutions may need to play a role in creating neutral data trusts or benchmarks. These arrangements are not purely technical; they are institutional designs that determine who benefits from intelligent optimization.

## **9. Future Directions**

Future research should address several unresolved issues. First, hybrid models that combine mechanistic understanding of dough rheology and ice crystal formation with data-driven learning may improve extrapolation beyond historical conditions [10]. Second, uncertainty quantification should become a standard feature of optimization systems so that operators know when to trust recommendations and when to intervene. Third, human factors research is needed to understand how bakers and line operators interact with automated recommendations, especially when the system contradicts experience. Fourth, lifecycle assessment should be integrated into optimization objectives so that quality improvements are evaluated alongside energy and water use. Fifth, governance experiments should test how

audit logs, model cards, and participatory review affect trust and accountability [20]. These directions require collaboration among food scientists, engineers, computer scientists, social scientists, and policymakers.

Another priority is the development of open, representative datasets. Proprietary data may drive incremental improvements, but they can also fragment knowledge and perpetuate biases. Anonymized, curated datasets that cover diverse flours, dough formulations, freezer designs, and storage conditions would enable more robust model development. Such datasets must respect commercial confidentiality and intellectual property while providing enough detail for reproducibility. Public-private partnerships, pre-competitive consortia, and academic repositories could host these resources. Standards for metadata, sensor calibration, and quality reporting would further improve comparability. Without such infrastructure, intelligent optimization will remain a patchwork of isolated solutions rather than a shared capability.

Finally, the field should resist the temptation to treat optimization as an end in itself. The purpose of intelligent fermentation and freezing control is not to maximize a single metric but to support reliable, nutritious, affordable, and sustainable frozen dough products. That purpose requires ongoing deliberation about values. What level of quality is worth the energy cost? How much automation is compatible with meaningful work? Who bears the risk when models fail? These questions cannot be answered by algorithms alone. They require institutional spaces where technical evidence, stakeholder interests, and public values can be debated. The most advanced optimization system will be one that is not only accurate and efficient but also legitimate and adaptable.

## **10. Conclusion**

Intelligent optimization of fermentation and freezing parameters offers significant potential for improving frozen dough quality, consistency, and supply chain performance. By integrating sensing, predictive modeling, digital twins, and adaptive control, producers can respond more effectively to raw material variability, equipment constraints, and distribution uncertainty. However, the analysis in this paper shows that optimization is not merely a technical exercise. It is embedded in a socio-technical system that includes infrastructure, data governance, labor, regulation, and sustainability commitments. The trade-offs between robustness and performance, throughput and quality, automation and human expertise, and private efficiency and public interest must be made explicit. If these trade-offs are ignored, intelligent optimization may increase fragility, concentrate market power, or narrow the definition of quality. If they are addressed deliberately, it can contribute to more resilient, equitable, and sustainable frozen dough production. The path forward requires hybrid models, transparent governance, shared infrastructure, and inclusive deliberation. High-quality frozen dough products should be understood as the outcome of well-designed systems, not merely well-tuned parameters.

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