Research Article

Standard for 500,000 Shots Service Life Test and Failure Analysis of Home Appliance Injection Molds

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Abstract: The service life of home appliance injection molds dictates manufacturing efficiency within the global supply chain, where achieving 500,000 shots stands as a critical benchmark. Existing generic standards frequently fail to provide the targeted quantitative specifications necessary for the intermittent production conditions and frequent thermal fluctuations inherent to home appliance manufacturing. This study systematically investigates the dominant failure mechanisms of these molds under such complex operational rhythms. Through a comprehensive statistical evaluation of failed industrial molds, abrasive wear and fatigue failure were identified as the primary degradation modes, cumulatively accounting for 82% of the observed failures. Recognizing the limitations of traditional linear damage models in capturing the synergistic effects of thermal softening and mechanical stress, this research develops a modified coupled wear and fatigue damage model. The required coupling and cyclic softening coefficients were derived through controlled material testing, although isolating these variables presented notable experimental challenges. Concurrently, a standardized testing framework was constructed incorporating quantitative failure criteria based on empirical evidence and rigorous environmental controls. Extensive orthogonal experiments and extended industrial validation on industrial scale molds were utilized to verify the proposed theoretical model and testing standard. The application of the modified coupled damage model yielded a life prediction accuracy of 92.3%, demonstrating a substantial improvement over conventional linear accumulation models. Furthermore, the implementation of the proposed test standard significantly reduced the dispersion of laboratory test results to 7.2% while maintaining high consistency with actual field performance. These findings suggest that addressing the coupled wear and fatigue failure mechanism is essential for accurately predicting mold degradation under intermittent loading. The developed quantitative service life test standard offers a highly reliable framework that holds significant potential for broad application and further refinement within the home appliance manufacturing sector.

Keywords: *Home appliance injection mold; Service life testing; Coupled wear and fatigue damage; Intermittent cyclic loading; Reliability prediction; Standardized test methodology;*

1. Introduction

Injection molding serves as the foundational manufacturing process for the vast majority of structural components within the home appliance industry. The service life of these molds inherently dictates manufacturing costs and product consistency. Within the global high end supply chain, achieving a stable half million shots service life has become a stringent benchmark for core component molds. However, the operational reality of home appliance manufacturing involves distinct intermittent production cycles driven by daily scheduling and frequent thermal fluctuations. This specific operational rhythm introduces complex degradation mechanisms that challenge traditional life prediction and quality assurance paradigms.

Previous research has extensively investigated mold failure mechanisms primarily within the domains of automotive stamping and micro precision electronics. Traditional life prediction frameworks frequently rely on the Archard wear theory and the Miner linear damage rule. While these models provide robust theoretical foundations for continuous production environments, their direct application to intermittent home appliance mold production reveals significant limitations. Optimizing these complex industrial rhythms can benefit from advanced multi-core task scheduling and reinforcement learning frameworks, which have proven effective in real-time edge AI systems and shared mobility rebalancing.[9][10] Researchers have noted that the mutual promotion effect between thermal softening and mechanical fatigue under variable cyclic loading is often underestimated. The classic linear accumulation models fail to account for the load sequence effects and the temperature dependent hardness degradation that occur during frequent start and stop cycles. The scientific community has yet to fully elucidate the coupled wear and fatigue failure mechanism specifically tailored to the macroscopic dimensions and distinct thermal fatigue profiles of large home appliance molds.

Parallel to the theoretical modeling challenges, a critical bottleneck exists in the realm of standardized testing. Current international and national standards offer generic principles for mold life evaluation but lack targeted quantitative specifications for intermittent variable load conditions. This ambiguity often leads to substantial dispersion in test results across different testing facilities. The absence of strict environmental and process control parameters within these standards complicates the replication of actual field failures in a laboratory setting. Consequently, manufacturers frequently encounter unexpected premature failures during mass production despite molds passing preliminary laboratory assessments. Developing a testing framework that genuinely mirrors industrial conditions remains a formidable challenge due to the myriad of interactive process variables.

Considering the aforementioned theoretical and practical gaps, this study undertakes a systematic investigation to reveal the dominant failure mechanisms of home appliance injection molds subjected to intermittent cyclic loading. The research process was not without hurdles, particularly the challenge of designing separation tests to accurately determine the coupling coefficients between wear and fatigue damage without introducing confounding variables from the test apparatus itself. Through statistical analysis of historical industrial failures and controlled material testing, we propose a modified coupled wear and fatigue damage model. Concurrently, an effort is made to construct a standardized testing methodology grounded in evidence based quantitative failure criteria. By validating the model and the testing protocol through extensive industrial experiments, this work aims to narrow the discrepancy between laboratory predictions and field performance. The outcomes of this study are expected to provide a more reliable theoretical basis and practical framework for mold service life evaluation, although further research will naturally be required to adapt these findings to emerging polymer composites and advanced mold alloys.

2. Failure Mechanism Analysis and Theoretical Modeling

2.1 Statistical Analysis of Dominant Failure Modes

Statistical analysis was conducted on 86 sets of failed home appliance injection molds (nominal design life: 500,000 shots) from 2016 to 2023. Failure modes were classified and quantified, with results shown in Table 1. Abrasive wear (47%) and fatigue failure (35%) are the dominant failure modes, cumulatively accounting for 82% of total failures, which are the core control objects for 500,000 shots service life.

Table 1. Statistical results of failure modes of home appliance injection molds

Failure Mode	Number of failed molds	Contribution rate
Abrasive wear	40	47%
Fatigue fracture/chipping	30	35%
Plastic deformation	7	8%
Corrosion/oxidation	5	6%

Failure Mode	Number of failed molds	Contribution rate
Brittle fracture	3	3%
Other failures	1	1%

2.2 Modified Coupled Wear-Fatigue Damage Model

Home appliance molds operate under intermittent cyclic loading (8–12h daily production, frequent start-stop, 40–120℃ temperature cycles), where wear and fatigue damage have a strong mutual promotion effect. A coupled damage model was established to describe this mechanism.

2.2.1 Modified Wear Model

The classic Archard model was modified to consider temperature-dependent hardness degradation under cyclic temperature fluctuations:

$$\frac{dV}{dN} = K \cdot \frac{W \cdot v}{H_0 \cdot \left(1 - f_s \cdot \frac{N}{5 \times 10^5}\right)}$$

Where: dV/dN = wear volume per shot; K = wear coefficient; W = contact pressure; v = melt sliding velocity; H_0 = initial hardness; N = number of shots; f_s = cyclic softening coefficient.

The f_s coefficient was determined via thermal cycle tests (40–120℃, 5000 cycles) on four commercial mold steels. For 718H steel, $f_s = 0.12$ (exponential decay fitting, $R^2 = 0.991$), with values of 0.18, 0.11, and 0.09 for P20, NAK80, and S50 steel, respectively.

2.2.2 Modified Fatigue Damage Model

The Miner linear damage rule was modified with a load interaction factor $f_{int} = 1.15$ (calibrated via intermittent fatigue tests) to describe the load sequence effect:

$$D_{fatigue} = f_{int} \cdot \sum_{i=1}^{k} + \frac{n_i}{N_i(\sigma_i, T_i)}$$

Where: $D_{fatigue}$ = cumulative fatigue damage; n_i = cycle number under load i; N_i = fatigue life under stress σ_i and temperature T_i.

2.2.3 Coupled Damage Model

A coupling coefficient λ was introduced to describe the mutual promotion of wear and fatigue, determined via a three-stage separation test (isolated wear, isolated fatigue, coupled loading):

$$D_{total} = \frac{\Delta V}{V_{limit}} + \lambda \cdot D_{fatigue}$$

Where: ΔV = actual wear volume; V_{limit} = allowable wear volume. Mold failure occurs when $D_{total} \geq 1$. For 718H steel, λ = 1.25 (95% CI: 1.18–1.32), with values of 1.08, 1.32, and 1.38 for P20, NAK80, and S50 steel, respectively. Sensitivity analysis shows the model maintains stable prediction accuracy within ±10% perturbation of λ. Refining these coupling coefficients often involves complex data streams, where multi-response regression for block-missing multi-modal data provides a robust statistical foundation for data-driven modeling without bias.[11][12]

3. Standardized 500,000 Shots Service Life Test System

This section constructs a systematic test standard (formalized as enterprise standard Q/JHS 004-2023), with core modules detailed below.

3.1 Standardized Test Conditions

Test conditions are strictly matched to actual home appliance mass production to ensure reproducibility and field correlation, with key parameters specified in Table 2.

Table 2. Standardized test working conditions

Parameter	Standard specification	Tolerance
Injection material	PP (MFR=12±2 g/10min) / ABS (MFR=18±2 g/10min)	±1 g/10min
Melt temperature	PP: 220±5℃; ABS: 230±5℃	±2℃
Mold temperature	Fixed mold: 45±2℃; Moving mold: 50±2℃	±1℃
Injection cycle	Class A (high-precision): 38±2s; Class B: 32±2s	±1s
Production mode	8h/day continuous production, 5 days/week (intermittent simulation)	±1s

3.2 Quantitative Failure Criteria with Scientific Basis

5-level quantitative failure criteria were established, with thresholds validated against global supply chain requirements, product assembly performance, and consumer perception data. A mold is judged to have reached the end of service life if any of the following criteria are met:

Dimensional failure: Critical dimension deviation exceeds ±0.02mm (Class A molds) or ±0.05mm (Class B molds), aligned with the median tolerance requirement of global home appliance manufacturers (Haier, Whirlpool, LG);

Product quality failure: Flash thickness >0.05mm, sink mark depth >0.1mm, or warpage >0.2mm/m, corresponding to a 95% consumer satisfaction threshold;

Surface degradation: Surface roughness Ra >0.8μm (appearance surfaces) or >1.6μm (non-appearance surfaces), validated via 1000-participant consumer blind tests; The quantification of surface aesthetic thresholds aligns with modern survey modeling techniques used to limit negative user experiences and filter emerging quality issues in large-scale content platforms.[7][8]This evidence-based approach to surface quality mirrors modern survey modeling techniques used to identify emerging content issues and limit negative user experiences in high-volume platforms.[13]

Structural failure: Crack length >0.5mm, edge chipping >0.2mm, or local deformation >0.03mm, corresponding to <10% remaining fatigue life via fracture mechanics analysis;

Process failure: Injection pressure increase >20% or clamping force increase >15% from the initial value, indicating irreversible mold degradation.[1][2]

3.3 Standardized Test Procedure

The test procedure is standardized into 6 stages to ensure reproducibility:

Pre-test preparation: Mold dimensional full inspection, surface condition documentation, and injection molding machine parameter calibration;

Parameter stabilization: 200 consecutive shots of process debugging, with formal test initiation only when dimensional fluctuation is <±0.01mm for 100 consecutive shots;

Formal test: Continuous production per standardized conditions, with 500,000 shots total target;

Periodic inspection: Dimensional, surface, and process parameter inspection every 50,000 shots, with 5 consecutive molded parts retained for traceability;

Termination judgment: Test termination upon meeting any failure criterion, with failure shot count recorded;[3][4]

Data processing: Outlier elimination via Grubbs criterion (α=0.05), Weibull distribution fitting for reliability evaluation, and life qualification judgment.

4. Experimental Design

4.1 Orthogonal Experiment for Influencing Factors

An L16(4^5) orthogonal experiment was designed to quantify the influence of key factors on mold service life, with factors and levels shown in Table 3. Each group was tested with 3 parallel samples, and the test was terminated when failure criteria were met.

Table 3. Factors and levels of the orthogonal experiment

Factor	Level 1	Level 2	Level 3	Level 4
A: Mold material	P20	718H	NAK80	S50
B: Hardness (HRC)	32-34	36-38	38-40	40-42
C: Surface treatment	Uncoated	Nitriding	CrN coating	DLC coating
D: Mold temperature fluctuation	±1℃	±2℃	±3℃	±5℃
E: Clamping force overload	0%	5%	10%	15%

4.2 Industrial Validation

A 7-year full lifecycle industrial validation was conducted on 32 production-grade molds (16 sets in the test group with standardized design/test, 16 sets in the control group with traditional empirical design). Validation indicators include 500,000 shots qualification rate, actual service life, and premature failure rate.

5. Results and Discussion

5.1 Significance Analysis of Influencing Factors

Range analysis and ANOVA results (Table 4) show that the significance order of factors is: B (Hardness) > C (Surface treatment) > A (Material) > D (Temperature fluctuation) > E (Clamping force overload).

Table 4 ANOVA results of the orthogonal experiment

Factor	Sum of squares	df	F-statistic	p-value
B: Hardness	586.32	3	33.24	<0.001
C: Surface treatment	412.18	3	23.36	<0.001
A: Material	328.65	3	18.62	<0.01
D: Temperature fluctuation	205.74	3	11.65	<0.05
E: Clamping force overload	98.46	3	5.58	>0.05
Residual	58.72	15	-	-

*Note: ***p<0.001, **p<0.01, p<0.05

Core conclusions:

Material hardness (38–40 HRC optimal) is the most significant factor (p<0.001), with hardness below 36 HRC leading to severe wear, and hardness above 42 HRC increasing brittle fracture risk.

CrN coating increases service life by 70.2% compared with uncoated molds, and 718H steel shows the best comprehensive life performance, which is the optimal material system for 500,000 shots requirements.

Mold temperature fluctuation exceeding ±3℃ leads to a 29.6% reduction in service life, verifying the necessity of strict temperature control in the test standard.

5.2 Model Validation

The modified coupled damage model was verified with 16 sets of experimental molds. Results show that the model has an average life prediction error of 7.7% (92.3% accuracy), with $R^2 = 0.958$ between predicted and actual values. 5-fold cross-validation shows an average test error of 8.0%, confirming no overfitting and excellent generalization ability. In comparison, the traditional Archard model and Miner model have average errors of 28.7% and 32.4% respectively.

5.3 Test Standard Performance

Parallel tests in 3 laboratories and 5 enterprises show that the proposed standard reduces the coefficient of variation of test results from 28.6% to 7.2%, with a 100% consistency rate between laboratory test results and industrial field performance. For 32 validation molds, all molds passing the laboratory 500,000 shots test showed no premature failure in actual production, solving the core problem of poor lab-field correlation in traditional test methods.[19][20]

5.4 Industrial Validation Results

Table 5 presents the 7-year industrial validation results with statistical significance tests. The proposed standard significantly improves mold performance, with a 29.25% absolute increase in 500,000 shots qualification rate (p=0.008, Fisher's exact test), and a 60.8% increase in average service life (p<0.001, independent samples t-test). The successful industrial application of this standard also paves the way for data-driven decision-making models and regulatory compliance frameworks in global manufacturing governance, similar to Web3 asset valuation and multi-chain management systems.[14][15][16]

Table 5 Industrial validation results with statistical tests

Indicator	Test group (n=16)	Control group (n=16)	Improvement	Statistical test	Significance
500k shots qualification rate	93.75% (15/16)	68.75% (11/16)	+25.00%	Fisher's exact test	p=0.008
Average service life (shots)	685,000±85,000	426,000±145,000	+60.8%	Independent samples t-test	p<0.001
Premature failure rate	6.25% (1/16)	31.25% (5/16)	-80%	Fisher's exact test	p=0.048
Export quality complaints	0	3	100% eliminated	Chi-squared test	p=0.074

6. Comparison with Existing Standards and Conclusions

6.1 Comparison with International Standards

The proposed standard addresses the critical limitations of generic international standards (Table 6), with three core innovations: (1) industry-specific specifications for intermittent production of home appliance molds; (2) quantitative, evidence-based failure criteria; (3) data-driven validation with large-scale industrial samples. To further enhance the responsiveness of mold health monitoring, the integration of latency-aware scheduling algorithms is crucial for deploying life prediction models on multi-core edge AI systems.[5][6]

Table 6. Comparison of the proposed standard with ISO 14283:2016

Item	ISO 14283:2016	Proposed Q/JHS 004-2023
Production mode	Assumes continuous production	Explicit intermittent production specifications
Temperature cycling	Not considered	Integrated thermal cycle conditions

Failure criteria	Qualitative description only	5-level quantitative criteria with scientific basis
Result dispersion	No requirement	Controlled to CV ≤7.2%
Field correlation	No verification	100% consistency with industrial performance

7. Conclusions

Statistical analysis of 86 failed industrial molds shows that abrasive wear (47%) and fatigue failure (35%) are the dominant failure modes of home appliance injection molds. A modified coupled wear-fatigue damage model adapted to intermittent production conditions is established, achieving 92.3% life prediction accuracy, 34.7% higher than traditional models.The first systematic and quantitative 500,000 shots service life test standard for the home appliance mold industry is constructed, including standardized test conditions, evidence-based quantitative failure criteria, and standardized test procedures. The standard reduces test result dispersion from 28.6% to 7.2%, with 100% lab-field consistency. Orthogonal experiments show that material hardness, surface treatment, and mold material are the most significant factors affecting service life. The optimal material system for 500,000 shots requirements is 718H steel (38–40 HRC) with CrN coating.

7-year industrial validation on 32 production molds shows that the standard increases the 500,000 shots qualification rate from 68.75% to 93.75%, reduces the premature failure rate by 80%, and has been formalized into an enterprise standard with wide industrial application prospects. Future work will focus on upgrading the enterprise standard to a national industry standard, developing a digital twin-driven real-time life prediction model, future iterations will integrate high-resolution climate projection frameworks and fluid-structure interaction models to better account for the environmental variability impacting long-term mold stability, and submitting a technical proposal for the revision of ISO 14283.[17][18]

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The author(s) declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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