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Leveraging usage distributions for reliability design in home appliances

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Abstract: Understanding the load history is fundamental step of Design for Reliability (DfR) approach. Specifically, reliability analysis requires detailed knowledge of both the magnitude and duration/frequency of loads applied to a component. While the magnitude of loads can be measured using sensors or estimated via simulation tools, determining the duration and frequency of loads poses a significant challenge, as it directly influences business-critical decisions such as market positioning and product differentiation. This challenge is particularly relevant in the home appliance industry, where reliability is a key attribute valued by consumers. The increasing availability of high-end connected devices, equipped with integrated hardware connectivity, enables the direct collection of real-world usage data from the field. This paper examines the usage distributions of multiple home appliances, considering the user interaction patterns. A structured approach is presented to analyze field usage data, establishing a connection between usage distributions and Design for Reliability (DfR) strategies.

Keywords: reliability, home appliance, usage distribution.

1. Introduction

Reliability is a key attribute of home appliances, influencing consumer purchasing decisions (Dickson et al., 1983). Beyond consumer preference, reliability has become a central element in sustainability efforts, playing a crucial role in circular economy strategies. Extending product lifespan reduces waste and resource consumption, making reliability essential for sustainable development.

A fundamental aspect of Design for Reliability (DfR) is understanding real-world product usage. Traditionally, reliability decisions—such as defining reliability requirements and designing verification tests—have relied on assumptions, expert judgment, or survey-based data. These methods, while useful, are inherently limited by small sample sizes and potential biases. Several studies have attempted to quantify consumer behavior through indirect methods. For example Tecchio et al. 2019), analyzed consumer behavior using datasets from independent repair centers, identifying common failure modes in washing machines and dishwashers. In (Hennies et al. 2016), the authors collected data through a questionnaire survey, analyzing participant responses to identify correlations between washing-up behavior and socio-demographic factors. In (Prakash et al. 2016), the authors investigated the usage frequency of dishwashers and washing machines based on survey data.

The emergence of connected appliances offers a paradigm shift in studying product usage. These devices generate continuous data, allowing manufacturers to analyze real-world operating conditions at scale. However, a gap remains in systematically integrating large-scale, direct usage data into reliability engineering practices. This study addresses this gap by analyzing real-world usage distributions from connected appliances. Specifically, it examines cycle usage distributions for dishwashers, washing machines, and ovens. The findings bridge traditional reliability assumptions with data-driven insights, supporting the integration of field usage data into the DfR process.

2. Data collection and processing for connected appliances

Customers voluntarily connect their appliances to the internet through a smartphone application. During registration, explicit consent is provided for data collection and processing. Appliances transmit real-time operational data to an IoT cloud infrastructure, enabling remote control and monitoring functionalities.

Due to inherent noise associated with IoT data, issues such as intermittent connectivity, network disruptions, and data packet loss can occur (reference needed). To mitigate these issues, appliances exhibiting extensive data gaps or poor connectivity were excluded from the analysis. Additionally, the initial and final months of data collection per appliance were removed to ensure dataset consistency.

The resulting dataset comprises monthly usage data, aggregated per appliance and further categorized by operational parameters such as program and temperature settings. Each aggregated data point, referred to as a Machine Month, represents normalized monthly appliance usage, ensuring both data integrity and user privacy. Dataset sizes per appliance category are summarized in Table 1.

Table 1. Total machine months recorded by appliance category

Category	Machine Months
Dishwasher	~400,000
Washing Machine	~2,400,000
Oven	~1,000,000

3. Methodology

The methodology encompasses three distinct phases: (a) systematic data collection from connected appliances, (b) statistical analysis of usage distributions, and (c) interpretation of results. For each appliance category, empirical monthly usage distributions were analyzed, calculating critical statistical metrics, including mean, median, standard deviation, and specific percentiles. Theoretical distributions were fitted to empirical data using Maximum Likelihood Estimation (MLE), following methodologies outlined by Myung (2003). Furthermore, scatter plots and correlation coefficients were utilized to examine relationships between the number of operational cycles and cycle durations. Such analyses provided insights into differing usage patterns among appliance categories characterized by varying user interactions.

Potential biases inherent in this research have been identified. One limitation is sampling bias, as the analyzed appliances primarily belong to the connected segment, which typically represents higher-end market categories. This may restrict the generalizability of the findings, and future research will quantitatively assess the extent of this bias. Another limitation concerns data aggregation, as monthly usage aggregation may overlook intra-month variability, potentially reducing the granularity of insights.

4. Analysis of results

The analysis in this paper focuses on appliance usage distributions, categorized based on operational characteristics and user interaction levels (Table 1). Five appliance categories are identified, with key parameters influencing their operational behavior.

Table 1. Categorization of home appliances based on operation and user interaction patterns

Appliance Category	Description	Example Appliances	Interaction Level	Key Parameters
Fixed-Operation	Continuous/cyclic operation, minimal user input	Refrigerators, Dehumidifiers	Very Low	Internal temperature, humidity
Fixed-Program	Fixed, predefined programs with limited customization	Dishwashers	Low	Program selection
Parameter-Driven	User-defined parameters (e.g., load size, temperature)	Washing Machines	Medium	Load size, temperature, mode
Time-Variable	User adjusts session duration based on needs	Ovens, Air Conditioners	High	Recipe type, comfort settings
Multi-Parameter	High flexibility with multiple adjustable settings	Induction Hobs	High	Power level, timer, zones

Fixed-Operation appliances: this category includes automated devices requiring minimal consumer interaction. Refrigerators are a prime example, operating continuously with limited user input.

Fixed-Program appliances: this category includes appliances that are characterized by limited consumer interaction and predefined operational settings. Dishwashers are an example of this category. Their primary use involves selecting one of several predefined washing programs, each with a fixed duration. In automatic washing programs, the cycle duration adjusts dynamically based on the load size, such as the quantity of cutlery. Users can also customize operation by selecting additional options, providing some flexibility while maintaining simplicity in operation.

Figure 1 illustrates the number of washing cycles per month for the dishwasher. The histogram is right-skewed. Most users operate dishwasher at moderate levels, peaking at 17 cycles per month. A small group of heavy users extends the right tail with significantly higher usage. The distribution has a natural floor at zero, preventing a long left tail.

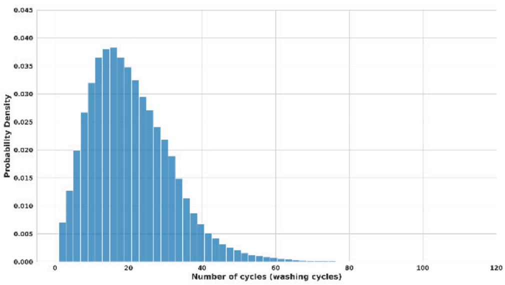

Figure 1. Distribution of monthly washing cycles for a dishwasher (~400.000 Machine Month).

Parameter-driven appliances operate based on user-defined settings that directly affect component loads. Washing machines are a prime example. Unlike dishwashers, their mechanical loads depend on the interaction between selected parameters and laundry conditions.

When using a washing machine, consumers typically set the program and temperature. Additional parameters, such as spin speed, soil level, pre-wash, or extra rinse, can also be adjusted. The laundry load significantly impacts mechanical components. Water absorption by fabrics further increases the load, amplifying its influence. Figure 2 illustrates the monthly distribution of washing machine cycles. Simple one-dimensional data distributions are insufficient to capture this complexity. For example, the median washing duration may not correspond to the median number of cycles or laundry load. A multivariate approach is essential for comprehensively analysing these interactions.

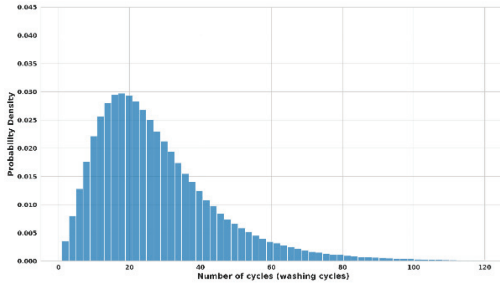

Figure 2. Distribution of monthly washing cycles for a washing machine (2.400.000 Machine Month).

Time-variable appliances are those where the consumer determines the operating duration, with ovens being a key example. Cooking time is entirely dependent on user input. The cooking cycle distribution of ovens (Figure 3) is similar to that of less interactive appliances, such as dishwashers and washing machines. The prominent left section of the distribution suggests that ovens are commonly used at low frequencies.

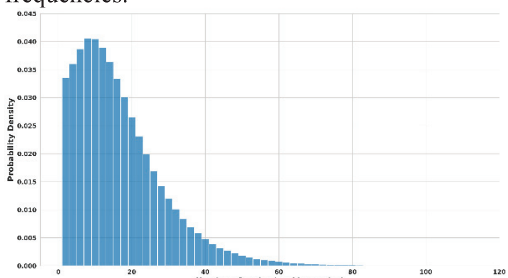

Figure 3. Distribution of monthly cycles for an oven (1.000.000 Machine Month).

Multi-Parameter Appliances: This category encompasses home appliances that require the highest level of user interaction and customization. Induction hobs are a prime example of this category, as they rely heavily on user input to determine operational parameters. Unlike fully automated appliances, the cooking cycle on an induction hob is not predefined but instead is dictated by the consumer. The user actively sets the power level, adjusts temperature settings, and controls the duration of the cooking process based on their specific needs and preferences.

5. Limitations of cycle count as a usage indicator

The distribution of the number of operational cycles may be a sufficient indicator for describing the behavior of low-interaction appliances. However, it is inadequate for high-interaction products. For example, in dishwashers, the cycle duration and number of cycles are closely related, as consumers have limited ability to customize washing parameters. The points for specific washing programs of a dishwasher in Figure 4a appear to cluster around lines that indicate a positive association between number of washing cycles and cycles duration. Conversely, for appliances such as ovens, usage behavior is influenced by multiple user-defined parameters, including the type of cooking cycle, temperature, and duration, in addition to the number of cycles. Consequently, no correlation is observed between the number of cycles and their duration (Figure 4b). A comprehensive analysis of these distributions is essential for accurately defining test profiles, necessitating the use of multivariate approaches rather than relying on a single-variable approach.

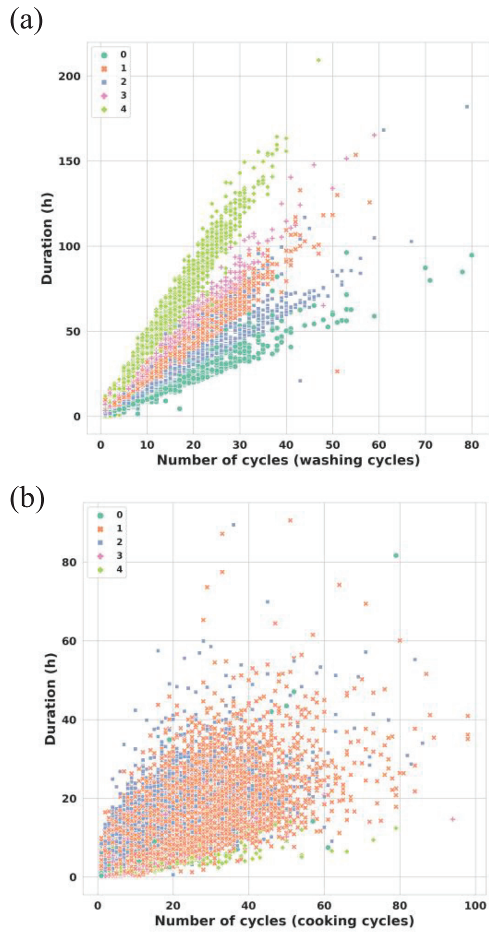

Figure 4. Relationship between cycle duration and number of cycles for a specific month; (a) Dishwashers (44542 data points); (b) Ovens (147674 data points).

6. Practical implications of usage distributions

Design Considerations: A comprehensive understanding of consumer usage behavior is fundamental to optimizing design decisions. By accurately characterizing real-world operating conditions, engineering teams can mitigate the risks of both under-design, which may lead to premature failures, and over-design, which results in unnecessary cost increases. This data-driven approach ensures that products are tailored to meet the expectations of the majority of consumers while maintaining cost-effectiveness and long-term reliability. Additionally, connected devices still represent a small fraction of home appliances, primarily in the higher price range. As a result, their usage patterns may not fully reflect the behaviors of the broader user base. This potential bias in representation will be further investigated in a future study to assess its impact on reliability analyses and user behavior insights.

Reliability verification: Reliability verification tests constitute a significant portion of product development, often extending time to market, consuming substantial energy, and driving up costs. Balancing thorough testing with efficiency is crucial to optimizing resources and accelerating product launches. To achieve this, the testing strategy can be divided into two key components. First, reliability verification should focus on covering the median user, ensuring the product meets standard performance expectations under typical usage conditions. Second, the impact of heavy users—those who subject the product to extreme or prolonged use—can be assessed through targeted extreme condition testing or supplemented by field data collection. This dual approach allows for a more efficient allocation of testing efforts while still addressing critical reliability concerns across diverse user profiles.

7. Conclusions

Home appliances can be categorized based on the level of user interaction. Regardless of this interaction level, the monthly cycle distributions consistently exhibit a right-skewed pattern. Most users cluster around typical usage levels, while a small group of heavy users extends the right tail, operating appliances significantly more frequently.

For appliances with multiple usage parameters—such as washing machines, ovens, and induction hobs—multivariate statistical analysis is essential to accurately capture the complexity of user behavior. Finally, data from connected devices enhances the Design for Reliability (DfR) approach by providing insights into real-world usage. This helps optimize design decisions, balancing reliability and cost while preventing under- or over-design. It also enables more efficient reliability verification testing by focusing on representative appliance usage.

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