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LCSR–OPE: A MACHINE LEARNING–DRIVEN LEVEL-WISE COMPOSITE FRAMEWORK FOR OPERATIONAL PROFILE–BASED SOFTWARE RELIABILITY PREDICTION

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ABSTRACT

Accurate estimation of software reliability and ex plication of critical quality attributes affecting failure behaviour are long-standing issues in the area of software engineering. Traditional reliability models that are based on a profile of operation approach the software as a homogenous entity, which overlook in-vivo influence of intra-code metrics and the dynamic variation in its operation. In order to address these limitations, the current research proposes the Level wise Composite Software Reliability with Operational Profile Evaluation (LCSR-OP) framework, which combines the frequency models of the software's operation and defect classification methods based on machine learning to enable adaptive risk estimation of the software reliability. The framework combines static code measures, like the number of lines of code, cyclomatic complexity, number of branches, and the measure of operators, with probabilistic operational profile distributions to create usage based module clusters. A level-wise composite reliability function is then built; within this reliability function, the probability density of each operational profile used to inform the strategy of fault detection and prioritization for tests. XGBoost based fault classification coupled with correlation driven feature importance analysis is presented for improving the reliability estimations and also to rank the windows attributes. Experimental validation on the basis of the data sets of the Modelled Data Provider (MDP) of the National Aeronautics and Space Administration, i.e., JM1, KC1, KC2 and PC1 shows that the proposed model improves the fault detection efficiency and accuracy of reliability prediction by 8 12%.

Keywords: *Software Reliability Engineering; Operational Profile Evaluation (OPE); Level-Wise Composite Reliability (LCSR); Software Quality.*

1. INTRODUCTION

Software reliability has become one of the cornerstones of modern software engineering practices, especially in safety critical and mission critical fields such as finance, aerospace, transportation, healthcare etc., where even small faults in the software may lead to catastrophic operational, financial or safety consequences [1-2]. The growing complexity of underlying software structures (driven by modularization, distributed computing and service orientated approaches) has increased the need for quantitative and adaptive, i.e. continuous, approaches to reliability assessment methodologies that enable ongoing assurance and maintenance of quality [3-5]. Conventional reliability-growth modelling and black box predictive techniques have traditionally modelled software as a homogeneous entity, thus failing to consider the inherent heterogeneity of code modules and execution contexts and frequency of usage that collectively impacts the manifestation of the fault and overall dependability [3], [6-7]. As software goes to interconnected ecosystems characterized by dynamic workload, and diversity of use, such monolithic models prove inadequate in fine-grain and context-sensitive reliability estimation [8-10].

Operational Profile Evaluation (OPE) provides a probabilistic tic model of the way software functionalities are exercised under real usage scenarios, thus bridging the gap between user behavior and reliability measurement [3], [11-12]. By modeling execution frequency and contextual dependencies, OPE enables risk orientated testing and prioritizes reliability efforts toward highly utilized components which facilitates optimized test resource allocation [4], [12-13]. Nevertheless, existing OPE-based reliability models usually assume static operation distributions and do not

capture any external use behavior coupling with intrinsic software properties [5], [8], [11]. This decoupling limits the granularity of reliability insights, and facilitates to interpretability of identifying which structural and behavioral are those that have the most pronounced effect for reliability growing [6], [9-10]. Accordingly, there exists a critical need of a reliability modelling paradigm that brings dynamic relationship between operational usage data and metrics at code level and fault delivery through machine learning and provides adaptive, interpretable, and data-driven reliability estimation.

In Figure. 1 the Level-Wise Composite Software Reliability with Operational Profile Evaluation (LCSR–OPE) framework combines the operation usage modeling, reliability estimation, and data-driven fault classification and quality insights and predicts future system reliability and failures. The procedure is initiated by gathering the historical defect logs only, execution traces of software resource, and the functional usage frequency to build an Operational Profile (OP) [3] where each operational task o_i is assigned to a probability p where each operational task is represented by o_i literate and the value pi is the probability of frequency of task execution and criticality. This OP represents the basis for reliability weighing and prioritization of probabilistic testing [5], [13].

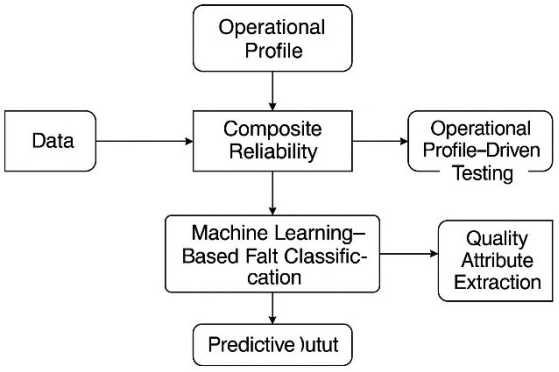


Figure 1: Machine Learning based LCSR-OPE Framework

Subsequently, the Composite Reliability module integrates operational weights with static software metrics (e.g. complexity, coupling, cohesion) to calculate the module-level re liability as $Rc_{\bullet} = \sum_i w_i R_i(\theta_i)$. This formulation overcomes the limitations of traditional models of reliability growth [1], [8] by taking into account both operational variabilities, as well as structural heterogeneity. Based on such estimates, an Operational Profile-Driven Testing mechanism is used to dynamically allocate testing effort to modules with high operational probability but low predicted reliability, which ensures efficient coverage under resource constraints [12].

The following stage uses Machine Learning-Based Fault Classification mechanism which uses the XGBoost classifier [14-16] for identifying the defect prone components using the fusion of operational and structural features. The model minimizes the regularized loss, $\mathcal{L} = \sum_i \ell(y_i, \hat{y}_i) + \Omega(f)$, the trade off between the predictive accuracy and model interpretability. In parallel, a Quality Attribute Extraction process is used to evaluate feature importance (I_j) and correlation coefficients $(\rho(\theta_j, R))$ to determine what internal attributes have the most influence on the evolution of reliability [11], [17-18]. The resultant Predictive Output provides module-wise reliability index and defect probability, thus enabling proactive improvement of reliability and adaptive quality management.

Overall, LCSR–OPE framework works well to bridge and resolve the gap between operational profile-based reliability evaluation [3-5], [13] and machine learning-based defect prediction [11], [14-16], [18], thus providing a unified, interpretable and scalable paradigm for software reliability evaluation.

1.1 Challenges

Not with standing significant progress in the field of software reliability engineering, a number of important issues have not been addressed adequately, both in the sense of the formulation of the theory and industrial implementation [4-5], [8-9]. The major challenges leading to the current investigation are listed as:

- Dynamic Operational Behavior: Existing reliability models usually rely on pre-specified or static operational profiles, which fail to modify the dynamic fluctuations of user behavior, distribution of workload, and environmental conditions observed for successive software revisions [3], [8], [12]. The consequence of lacking adaptive operational profiling are incomplete, context-insensitive reliability estimates, as they endure and evolve in the real-world scenario.

Attribute-Reliability Correlation Majority of reliability growth models are offering limited interpretability regarding the specific intrinsic code level metrics (e.g. size, complexity, cohesion) that have the highest impact on reliability results [5-6], [10]. In the absence of explicit correlations between attributes of software and fault manifestation

patterns, quality assurance practices are still more empirical rather than data driven.

- Unbalanced Testing Effort: Test allocation is often done on a per-software-module basis with no regard for the operational criticality and usage frequency [13], [11-12]. Such imbalance means that the efficiency of fault detection may be less than optimal, because modules which are of high reliability significance may not be checked adequately, whereas modules with limited impact may be over-tested.
- Predictive Accuracy and Adaptability: Machine learning models have shown great potential in software defect prediction [14-16], [19-20] However, the application of machine learning models to operational profile-based reliability estimation is limited. Existing frameworks rarely apply adaptive or reinforcement learning mechanisms to enable capturing of the dynamic reliability evolution with the changing operational distributions.

1.2 Motivation

Recent empirical investigation indicates that about forty percent of mission-critical software failures are caused by flaws in terms of reliability, hence the importance of proactively modelling dependability [1-2]. As modern software systems increasingly follow modular and reusable structures, the recognition of key attributes of software affecting reliability has been crucial in terms of minimizing maintenance costs and preventing operations downtime [5], [10], [21]. By creating a quantitative relationship between external operational behavior and internal code metrics, it is possible to identify defect prone modules on a very early stage aiding in the allocation of tests and the decisions aimed at improving reliability [3-4], [6-7], [11]. This integration also aids in the transition from reactive correction of faults to predictive reliability assurance in dynamic operational cases.

1.3 Our Contribution

To overcome the limitations found above, this paper presents a novel Level-Wise Composite Software Reliability with Operational Profile Evaluation (LCSR–OPE) framework that combines the notion of probabilistic software modelling of operation behavior with machine learning based fault prediction. The proposed methodology complements interpretability, adaptability and predictive precision by addressing unification of operational profiling functions, composite reliability modelling and intelligent fault classification. The main contributions of this work are given as follows:

- The design of a level-wise reliability evaluation mechanism that combines operational frequency distributions and structural code metrics for facilitating the identification and prioritization of reliability critical modules.
- The creation of a dynamic probabilistic operational density function responsible for directing the allocation of test cases based on module criticality and probability of use, so as to maximize resources.
- The creation of an XGBoost based classifier to predict the defect-prone modules which exploits both the operational and the structural characteristics and achieves an accuracy level along with interpretability.
- The use of correlation and feature importance analysis for finding the dominant software attributes ruled by reliability growth for reliability improvement, which is data informed.
- Execution of experimental evaluations on benchmark datasets from the National Aeronautics and Space Administration (NASA) that prove the superiority of LCSR–OPE over traditional OPE-based reliability models in terms of prediction accuracy, test efficiency, and interpretability.

The rest of this paper is arranged as follows. Section II surveys associated investigations and research on operational profile-based reliability, machine learning based defect pre diction models. Section III explains the proposed LCSR–OPE methodology which includes composite modelling, operational profile formulation and classification process. Section IV establishes the experimental setup, data sets, and performance index. Section V draws comparative results and analysis and Section VI concludes the paper and suggests potential future research directions.

2. RELATED WORK

Software reliability and defect prediction have become classic research areas of the software engineering field, and have shifted over time towards current hybrid and data-driven reliability estimation methods. The academic developmental trend represents a shifting trend between the deterministic, assumption-based reliability forecasting towards data intensive, interpretable and adaptive reliability management systems. The section at hand critically analyzes previous research work in establishing four major thematic categories; (1) operational profile modelling and reliability

estimation; (2) prediction of software defects due to machine learning; (3) hybrid and composite reliability framework; and (4) residual limitations that inspire the current Level-Wise Composite Software Reliability with Operational Profile Evaluation (LCSR–OPE) framework.

The formal definition of operational reliability analysis was formulated by Musa [3] who proposed a combination of a probabilistic characterization of actual utilization of software the so-called Operational Profile (OP). The OP formalism enabled testing on a basis of reliability through proportionate allocation of the test cases depending on the frequency of functional usage hence directly matching the reliability testing effort to user-related reliability goals. The paradigm was later refined by Musa and others to include mission-critical systems, and particularly the statistical connection between the frequency of execution and the probability of failure. Although the classical OP model was seminal, the operational environment was assumed to be static, and never allowed dynamic user interactions, workload variation or system transformation across software releases.

On these bases, Bertolino et al. [13] introduced CovRel+, an adaptive testing model in which operational profile data are combined with test coverage measures in order to improve test efficiency. Although such strategy enhanced the accuracy of prioritization of mission-level testing, it could not be linked to internal program structure and lower-level quality measures. Similarly, a Bayesian inference model utilizing the uncertainty of the operational profiles and dynamically revising the reliability estimates was used by Pietrantuono et al. [1]. Their two-phase Bayesian model proved to be resistant to incomplete or uncertain operational data and was not readable in terms of the characteristics of the software that were considered to manipulate reliability variation. In a thorough examination, Chaurasia [8] further uncovered the systemic problems in profile estimation of the operational mode, field data capture and discrepancy between the modelling simulated and real systems in use conditions as explained in their study. Together, these research findings suggest the need to have an adaptive, data-driven operational profile framework that has the capability to elicit the behavior change over time of intricate software systems.

At the same time, machine-learning (ML) and deep learning (DL) methods have been evolving fast in the field of Soft Defect Prediction (SDP). Oveisi et al. [5] emphasized that ML algorithms have revolutionized on the predictive reliability issue as they have made it possible to predict reliability with automated fault classification and growth prediction of reliability with regression reliantly as highlighted by Liu et al [9]. The paradigm shifts towards hybrid models, which combine statistical modelling and learning mechanisms, was demonstrated in exhaustive survey of more than 140 intelligent prediction models by Li Sheng Kong et al. [10] performed a systematic review of reliability studies dating to 35 years which finds that Statistical Reliability Growth Models (SRGMs), even though still commonly used, are undergoing growing supple mentation with neural and ensemble learning methods, which have been found to represent non-linear relationship between defects better than conventional, parametric approaches.

Current works portray how much more heterogeneous ML architectures are used to predict reliability. In reference eight, Albattah [14] and others created a Deep General Regression Neural Network (DGRNN) to predict defect density in data constrained settings where they performed better than the traditional classifiers; SVMs, decision trees and others. To address the accuracy and cross-project generalization of defect prediction, Liu et al. [15] introduced residual-shuffle convolutional neural network, which was trained by Fish Migration Optimization (FMO) algorithm, and improved accuracy and cross-project generalization. Kirti Lakra et al. [16] introduced a hybrid technique to predict defects, which combines both the decision trees and the meta always technique to enhance the reliability prediction in a multi-project environment. Graph based learning approaches using multi-view graph neural networks, like DeMuVGN [19], have been more recently applied, and showed better performance with the inter-module dependencies and contextual defect relationships compared to antecedent deep models when applied on cross-project settings. These efforts were enhanced by reinforcement-learning-based models such as SDPERL Reinforcement-learning-based models such as SDPERL12 [20] enabled the use of adaptive policy optimization to feature selection and ensemble adaptation. However, these ML based methods significantly increased the predictive accuracy, but are mostly utilized in the context of detecting the presence of a defect in a system at rest and do not provide the initial data or use of operational profiles, which restricts their ability to measure the reliability of usage.

To address the disintegration of defect prediction and operational reliability estimation, there has been a rise of hybrid frameworks to combine different views of reliability modelling. The framework of the

Bayesian reliability presented by Yongjin Guo. et al. [11] unites the two data streams of operational profiles and software metrics to facilitate uncertainty-related estimation of operation when the operation variables vary. Gokulakrishnan et al. [17] used a deep neural model, which is ResNet, and the optimization algorithm is Zebra Optimization Algorithm (ZOA) on web service reliability prediction and reported the increase of predictive precision was 25-percent compared to baseline SRGMs. Equally, Taehyoun Kim et al. [18] proposed Deep Synthetic CrossProject SRGM, a study that takes advantage of the transfer learning and synthetic data generation to estimate defects in data-sparse settings, and found the method to be up to 23 per cent better than the existing methods (ref15). Whilst these hybrid systems are an opportune measure on the direction towards adaptive estimations of reliability, they focus on predictive precision to the extent that they ignore the explain ability of software features and their causal effects on reliability increase. This restriction impedes the real-world implementation of ML-based reliability systems in the industrial context, where explain ability and traceability cannot be absent to support decisions.

It can be concluded that the literature as a whole shows the existence of a strong discrepancy between operational profile-based reliability modelling and the learning-based defect prediction. Most of the previous studies either focus on the dynamic usage modelling without using internal software properties or produce ML-based reliability predictors without taking into account the operational context. Besides, a limited number of studies provides decipherable correspondences between code-level measures and reliability measurements. This fragmentation highlights a strong necessity to have a composite reliability framework that brings operational frequency and structural code metrics together along with adaptive ML-based classification into one understandable architecture.

To fill in these research gaps, the proposed system, named Level-Wise Composite Software Reliability with Operational Profile Evaluation (LCSR-OPE), is systematically designed to combine the operational profile analysis, code-metric correlation, and XGBoost-based defect classification. The combination of the dynamic operational data and structural software attributes enables attribute-level interpretability and operation-oriented reliability analysis in LCSR-OPE, which is a substantive contribution that bridges theoretical operationalreliability growth modelling and existing practical, data-based quality improvement practices.

A comparative summary of main representative studies that tackle major challenges in reliability has been provided in Table I. Two if not five of these dimensions are being analyzed which relate to the study: (1) Dynamic Operational Behavior; (2) Attribute Reliability Correlation Gap; (3) Balanced Testing Effort; (4) Predictive Accuracy in ML based Reliability and (5) Interpretability of Software Attributes.

2.1 Research Gap Identification:

i. Real-time reliability monitoring using streaming data

ii. Distributed systems and service-based architectures only partially addressed

iii. Learn operational profiles from logs using ML

Integrate with reliability growth models

3. PRELIMINARIES

The direction of the section is the statement of the theoretical premises that sustain the suggested Level-Wise Composite Software Reliability with Operational Profile Evaluation (LCSR-OPE) model. The framework combines classical software reliability theory, operational profile modelling, composite reliability assessment and machine-learning-based fault prediction into a single conceptual basis that can be used to proceed with subsequent system modelling and methodology design.

In the classical model of software reliability engineering, fault detection that occurs during the software testing is usually represented as a stochastic process that defines the accumulative discovery of faults over time. The method of the approach to modelling makes it possible to characterize the way in which the fault detection changes with increasing testing and the probability to estimate the reliability of the software. The issue of the intensity of failure is used to explain the current rate of fault detection, whereas the reliability function can be seen as the probability that the software will fail within a particular period of time. All these concepts form the platform, on which the reliability integration mechanisms are anchored at the higher level in the proposed framework.

The operational profile represents real-world behavior of the use of software by formalisms that are the frequency with which individual software operations are practiced in reality. The operational

profile gives the different operations a relative weight to their likelihood of execution and their workload requirement, and thus allow reliability estimates to represent realistic use of the operational profile instead of consistent testing conditions. The framework allows reliability assessment to be applied considering the frequency at which an operation is used and hence it exerts more impact on the overall system evaluation. In contrast to the traditional methods that consider a fixed use behavioral pattern, the proposed framework considers the changing behavior of usage that is brought about by the user adaptation, systems updating, and change of environment, which enables the reliability estimation to be adjusting with each passing time.

Table 1: Comparative Summary Of Existing Studies Addressing Major Reliability Challeneges

Ref	Author(s) & Year	D	A	B	P	I	Limitations / Remarks
[3]	Musa (1993)	✓	x	✓	x	x	Static OP; lacks adaptability to dynamic workloads.
[13]	Bertolino et al. (2019)	✓	x	✓	✓	x	Adaptive testing but no linkage to code metrics.
[5]	Oveisi et al. (2023)	✓	✓	x	✓	x	High accuracy; lacks interpretability and balance.
[14]	Albattah et al. (2024)	x	✓	x	✓	x	Focused on defect density; ignores OP-driven reliability.
[15]	Liu et al. (2025)	x	✓	x	✓	x	FMO-optimized CNN; limited scalability and interpretability.
[11]	Yongjin Guo. et al. (2022)	✓	✓	✓	✓	x	Bayesian model lacks causal attribute explanation.
[17]	Gokulakrishnan et al. (2024)	x	✓	x	✓	x	Focused on web services; limited generalization.
[18]	Taehyoun Kim et al. (2025)	✓	✓	✓	✓	x	Emphasizes accuracy; lacks explainable attributes.
[12]	Luiz et al. (2019, IEEE)	✓	✓	✓	✓	x	Coverage–OP integration; still non-interpretable.
[22]	Qamar & Malik (2022)	x	✓	✓	✓	✓	Focused on team traits, not operational reliability.
[6]	Liu et al. (2022, IEEE)		✓	✓	✓	x	Uncertain diff. eq. model; lacks ML integration.
[23]	Yang et al. (2021)	✓	✓	✓	✓	x	Hybrid PSO–SSA; no interpretable reliability mapping.
[24]	Amin et al. (2020)	x	✓	x	✓	✓	Personality–creativity model; not reliability-focused.
[25]	Park (2020)		✓	✓	✓	✓	Weibull-based NHPP; lacks dynamic ML adaptation.
Proposed	**LCSR–OPE Framework**		✓	✓	✓	✓	Integrates OP, code metrics, and ML for interpretable reliability.

Parameter Abbreviations:

D = Dynamic Operational Behavior;

A = Attribute–Reliability Correlation;

B = Balanced Testing Effort;

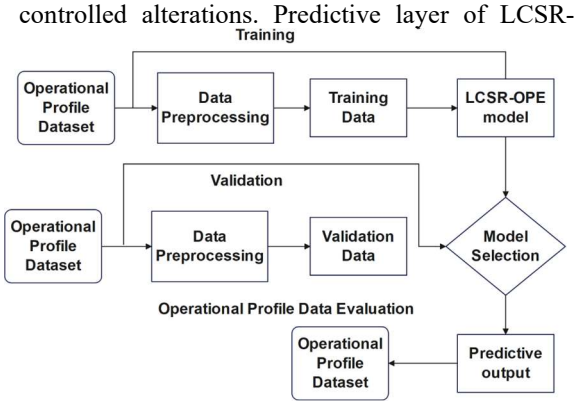
P = Predictive Accuracy (ML-based Reliability);

I = Interpretability of Software Attributes

The LCSR-OPE framework incorporates a level-wise composite reliability formulation to be embedded with operational behavior and internal software properties. The software reliability under this technique is analyzed through the summation of the reliability contribution of individual modules with respect to the weight that is proportional to the importance of the module in terms of its functionality. The reliability of each module is viewed in the terms of software attributes that could be measured (code size, structural complexity, coupling, and cohesion). The framework provides a

direct connection between software design properties and measured reliability behavior, which turns out reliability assessment into a more interpretable and actionable directly by modelling the concept of reliability as a differentiation based on these internal measures.

The allocation of testing effort with the framework is informed by the operational demand, such that the test emphasis is concentrated on the operational components with a high rate of frequency of operation. This is a demand sensitive prioritization to enable the effective utilization of testing resources within achievable constraints. Reliability evolution is considered as an iterative computation, in which the estimations of reliability are revised gradually depending on the results of testing, the importance of that particular operation and a resultant fault detection behavior, whereby the ultimately reliable growth between testing cycles can be maintained by controlled alterations. Predictive layer of LCSR-



OPE model is based on machine- learning methodology to detect imperfection-prone software modules through a collaboration of both operational information and amidst the Code Metrics. Gradient-boosting-classifier is used to approximate a probability of a specific module harboring faults and therefore let high-risk components be proactively identified. Regularization processes are used in model training to achieve a tradeoff between predictive and generalization performance of the model and avoid over-fitting and improve strength in different software projects.

In order to make the framework more interpretative and analysis transparent, feature importance analysis and statistical correlation assessment are also added to the framework. The importance measures of features are used to gauge how the individual attributes of software assist in defect prediction and the correlation analysis is used to determine the strength and direction of the relationship between software attribute and reliability results. The two analyses give a more detailed understanding of what triggers reliability behavior and aids the making of informed decisions throughout the software testing and maintenance. On the whole, the offered initial formulation provides a rational theoretical framework that comprises reliability theory, operational realism, and data- driven intelligence within the LCSR-OPE model.

4. METHODOLOGY

This section defines the overall architecture, mathematical formalization and algorithmic implementation of Level-Wise Composite Software Reliability/ operational profile evaluation (LCSR-OPE) framework. The approach combines the models of operational profiles, computation of composite reliability, and machine-learning-based defect classification into a single adaptive system, and thus, it has the power to estimate software reliability dynamically and in an interpretable manner.

In Figure 2, the LCSR-OPE framework is an end-to-end reliability assessment pipeline that consists of four main modules: (1) Operational Profile Analysis, (2) Composite Reliability Modeling, (3) Machine-Learning-Based Fault Classification, and (4) Operational Profile Data Evaluation. Every one of the modules is analytically defined in order to ensure the system is responsive to the changing behavior of operations without losing interpretability through correlation and feature- importance analysis.

Figure 2: Proposed Machine Learning–Based LCSR–OPE frame- work for dynamic operational profile–driven software reliability prediction.

The principal symbols and parameters used in the LCSR– OPE framework are summarized in Tables 2 and 3 for reference throughout the subsequent modelling sections.

Table 2: Symbols Used In LCSR-OPE Framework

Symbol	Description
T	Testing or operational time
m(t)	Expected cumulative detected faults at time t
a, b	Total expected faults; fault detection rate
λ(t)	Instantaneous failure intensity
R(t)	Reliability function (failure-free probability)
$O = \{o_i\}$	Set of software operations
p_i	Execution probability of operation o_i
$f(o_i)$	Frequency or workload of operation o_i
R_i	Reliability of module or operation i
R(O)	Weighted reliability across all operations
R_c	Composite (level-wise) reliability
w_i	Normalized operational weight
θ_i	Vector of code metrics for module i

α, β_i	Regression coefficients in reliability model
ε_i	Model residual or stochastic noise
$\phi(i)$	Test allocation probability for operation i
η	Learning coefficient or update rate
$R_i^{(t)}$	Reliability of module i at iteration t
v	Feature vector (operational + static metrics)
$y_i, \hat{y}_i$	True and predicted reliability labels
$f(x_i)$	Model output before activation
$\sigma(\cdot)$	Sigmoid activation (probability mapping)
w	Model parameters (weights)
L	Objective or loss function
$\ell(y_i, \hat{y}_i)$	Logistic loss term
$\Omega(f)$	Regularization function
T	Number of decision trees in ensemble
w_i	Feature weight in tree model
I_j	Feature importance score
$g_{j,t}$	Gain of feature j in tree t
$\rho(\theta_j, R)$	Correlation between metric and reliability

Table 3: Scientific Notations And Mathematical Operators

Notation	Description
$\sum_{i=1}^{n}$	Summation over n elements
$\int_0^t (.)d\tau$	Integration over time τ
$\frac{dm(t)}{dt}$	Derivative of cumulative fault function
E[.]	Expected value operator
$\Delta p_i(t)$	Variation in operational probability
$\approx$	Approximation symbol
$\rightarrow$	Functional mapping or transformation
$\hat{y}_i$	Predicted value or estimate
$N(0, \sigma^2)$	Normal distribution with variance σ^2
$\sigma(.)$	Sigmoid or logistic function
$\nabla_w \mathcal{L}$	Gradient of loss with respect to weights
$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_j w_j^2$	Regularization expression
$\rho(\theta_j, R) = \frac{cov(\theta_j, R)}{\sigma\theta_j \sigma_R}$	Pearson correlation coefficient

4.1. System Overview And Design Flow

The structure will start with the acquisition of the operational profile data which incorporates the execution traces, flaw records and the, per module, operational counts found in actual environments [3], [13]. It undergoes preprocessing with normalization, feature selection and noise removal to ensure accuracy of results between the operating patterns of the code and fixed code characteristics [5], [14]. The processed data is then split into training, validation, and testing sets, which are indicated as follows: $D = \{D_{train}, D_{val}, D_{test}\}$.

The level-based construct of the LCSR-OPE model will develop a level-based representation of composite reliability, which will combine operation-level probabilities and code level measurements during the training stage. Ensemble based XGBoost learner is used in model optimization, minimizing the classification loss and a regularization term in order to make predictions that are reliable in defect prediction [15-16]. During the validation stage, model parameters are adjusted dynamically to maintain the high predictive reliability and empirical reliability, when operational probabilities are subject to change as well as when they vary during the overall analysis of variation patterns [11], [17]. During the evaluation stage, predictive inference is done on the new data that has not been seen previously to provide estimates on reliability indicators of the system such as Mean Time to Failure (MTTF), probability of failure, and distributions of defect-likelihood.

Unlike traditional fixed frameworks such as those presented in [3-5] the LCSR-OPE framework involves an adaptive operational feedback loop, which allows the constant recalibration of reliability.

4.2 System Model

The LCSR–OPE framework formalizes software reliability estimation as a joint optimization problem over operational and structural parameters. Let $O = \{o_1, o_2, \ldots, o_n\}$ represent the set of operational tasks, and p_i denote the probability of executing operation o_i, where $\sum_{i=1}^{n} p_i = 1$.Each module M_i is characterized by a feature vector $\theta_i = [\theta_{i1}, \theta_{i2}, \ldots, \theta_{ik}]$, encompassing software metrics such as complexity, coupling, and cohesion.

$$L_{val} = \frac{1}{|O_v|}\sum_{i\varepsilon Ov} \ell(y_i, \hat{y}_i) \quad (5)$$

The reliability of each module at time t follows the exponential model:

$$R_i(t) = 1 - e^{-\lambda_i(t)}, \lambda_i(t) = b_i(1 - e^{-c_i t}) \quad (1)$$

In Equation. (1), b_i denotes the initial fault rate and c_i the fault detection constant.

$$\hat{R}_{test} = f_{LCSR-OPE}(O_{test}, \theta_{test}) \quad (7)$$

The global reliability is computed as a level-wise composite function:

$$R_c(t) = \sum_{i=1}^{n} w_i R_i(t), \quad w_i = \frac{p_i f(o_i)}{\sum_{i=1}^{n} p_i f(o_i)} \quad (2)$$

In Equation. (2), $f(o_i)$ represents the execution frequency and w_i the normalized operational weight reflecting module importance p_i represents the probability of occurrence. $R_i(t)$ represents the reliability of i^{th} operation at time t.

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The training dataset $D_{train} = \{(\mathbf{x}_i, y_i)\}$ contains feature vectors $\mathbf{x}_i = [p_i, f(o_i), \boldsymbol{\theta}_i]$ and binary labels $y_i \in \{0, 1\}$ indicating whether module M_i is defect-prone. The classifier prediction is expressed as:

$$\hat{y}_i = \sigma\big(f(x_i)\big), f(x_i) = \sum_{t=1}^{T} \phi_t(x_i) \quad (3)$$

In Equation. (3), ϕ_t , is the tth weak learner, and $\sigma(.)$ is the sigmoid activation ensuring probabilistic output. $\hat{y}_i$ is the predicted value of the ith operation.

The objective function optimized during learning is:

$$\mathcal{L} = \sum_{i=1}^{m} \ell(y_i, \hat{y}_i) + \Omega(f) \quad (4)$$

In Equation. (4), $\ell(y_i, \hat{y}_i) = -[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$ representing logistic loss, and $\Omega(f) = {}_{\gamma}T + \frac{1}{2}\lambda \sum_j w_j^2$ as the regularization function that penalizes model complexity.

During validation, the framework updates operational probabilities to account for dynamic behavioral changes as $p_i(t) = p_i(0) + \Delta p_i(t)$. The validation objective is to minimize:

In Equation. (5), O_v indicates the validation dataset , $y_i, \hat{y}_i$ represents actual and predicted values of ith operation.

While maximizing the reliability correlation:

$$\rho\big(\hat{R}, R\big) = \frac{cov(\hat{R},R)}{\sigma_{\hat{R}}\sigma_R} \quad (6)$$

In Equation. (6), $\rho\big(\hat{R}, R\big)$ represents the pearson correlation coefficient between predicted reliability and actual reliability. $cov\big(\hat{R}, R\big)$ indicates the covariance between the predicted and actual reliability values. $\sigma_{\hat{R}}\sigma_R$ is standard deviation of predicted and actual reliability.

Equation. (7), indicates that the final predictive function

The decision criterion for module classification is:

$$Class(M_i) = \begin{cases} Reliable, \hat{R}_i \geq \tau \\ Defect - prone, \hat{R}_\tau \end{cases} \quad (8)$$

In Equation. (8), which maps unseen operational data to reliability probabilities Rtest ∈ [0, 1].

4.3 Operational Profile Analysis Module

This module constructs an adaptive operational distribution to capture real-world usage behaviour. The execution prob ability vector is defined as $P = [p_1, p_2, \ldots\ldots, p_n]$, where $p_i = \frac{f(o_i)}{\sum_{k=1}^{n} f(O_k)}$. The expected workload is given by $E[O] = \sum_{i=1}^{n} p_i f(O_i)$, and its temporal evolution follows:

In Equation. (9), $\Delta p_i(t)$ captures workload drift. Their liability of each operation is modelled as $R_i(t) = e^{-(\propto_i + \beta_i p_i(t))}$, where $\propto_i$ and β_i represent baseline and sensitivity coefficients.

$$p_i(t+1) = p_i(t) + \Delta p_i(t) \quad (9)$$

Algorithm1 Operational Profile Analysis Module

1: Initialize $O = \{o_1, o_2, \ldots, o_n\}$ and compute initial frequencies $f(o_i)$
2: for each operation, o_i do
3: Compute $pi = f(o_i) / \Sigma f(o_i)$
4: Update $p_i(t + 1) = p_i(t) + \Delta p_i(t)$
5: Estimate reliability $R_i(t) = e-(\alpha_i + \beta_i p_i(t))$
6: end for
7: Output updated operational probability vector $P_{(t+1)}$

4.4 Composite Reliability Modelling Module

This module fuses operational probabilities and software attributes to produce a global reliability index. Equation. (10), finds the estimated reliability for a specific operation i.Each module M_i is modelled as:

$$R_i(\theta_i) = \alpha + \sum_{j=1}^{k} \beta_j \theta_{ij} + \varepsilon_i \quad (10)$$

Where θ_{ij} represents the operational profile weights, β_j represents the reliability coefficient of operation j. ε_i indicates error

. Equation. (11), gives the overall reliability

$$R_c = \sum_{i=1}^{n} w_i R_i(\theta_i), \quad w_i = \frac{p_i f(o_i)}{\sum_{j=1}^{n} p_j f(o_j)} \quad (11)$$

Where $R_i(\theta_i)$ is reliability of operation i,, $p_i$is probability of operation i, $f(o_i)$is frequency of operation i.

Equation. (12), presents Reliability adaptation over iterations and is achieved through:

$$R_i^{(t+1)} = R_i(t) + \eta\big(\phi(i) - \lambda_i(t)\big) \quad (12)$$

Where η is the learning rate and $\phi(i)$ represents the normalized test allocation function.

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Algorithm 2: Composite Reliability Modelling Module

1: Input operational weights w_i and attribute vectors θ_i
2: for each module M_i do
3: Estimate $R_i(\theta_i) = \alpha + \Sigma \beta_j \theta_{ij} + \varepsilon_i$
4: Compute $R_c = \Sigma w_i R_i(\theta_i)$
5: Update $R_i(t+1) = R_i(t) + \eta(\varphi(i) - \lambda_i(t))$
6: end for
7: Output $R_c(t)$ and updated reliability scores

4.5 Machine Learning–Based Fault Classification Module

This module employs an ensemble-based XGBoost classifier for defect prediction using both operational and code-level features. Each instance (x_i, y_i) consists of $x_i = [p_i, f(o_i), \theta_i]$ and binary label $y_i \in \{0,1\}$. The learning objective is:

$$\mathcal{L} = \sum_{i=1}^{m} \ell(y_i, \hat{y}_i) + \Omega(f) \quad (13)$$

In Equation. (13), , $\ell(y_i, \hat{y}_i)$is Training loss, $\Omega(f)$ is Regularization term

Equation. (14), provides the feature interpretability derived via importance scores

$$I_j = \frac{1}{T}\sum_{t=1}^{T} |g_{j,t}| \quad (14)$$

Where I_j is importance feature, $g_{j,t}$gradient of the feature at iteration t, T is the total number of iterations.

Algorithm 3: Machine Learning–Based Fault Classification

1: Input feature set $X = [p_i, f(o_i), \theta_i]$ and labels Y model parameters w, γ, λ
2: repeat
3: Compute $\hat{y}_i = \sigma(\Sigma t\, \varphi_t(x_i))$
4: Calculate gradients $\nabla w\, L$
5: Update weights $w \leftarrow w - \eta\ \nabla w\, L$
6: until convergence or $L \leq$ threshold
7: Compute feature importance $I_j = \frac{1}{T}\Sigma t\, |g_j,t$
8: Output predicted reliability labels $\hat{y}_i$

4.6 Operational Profile Data Evaluation Module

The final module applies the trained LCSR–OPE model to unseen operational data O_{test}. Module reliability is predicted as $\hat{R}i = f_{LCSR–OPE(pi,\theta i),}$ with system-level aggregation. Equation. (15), gives the System Estimate $\hat{R}_{system}$ which represents the average reliability across N testcases

$$\hat{R}_{system} = \frac{1}{N}\sum_{i=1}^{N} \hat{R}_i \quad (15)$$

In Equation. (16), The Mean Time to Failure (MTTF) is calculated as:

$$MTTF = \int_0^{\infty} R(t)dt \quad (16)$$

and reliability recalibration occurs whenever $|\hat{R}_i - R_i| \geq \delta$, ensuring temporal adaptability.

Algorithm 4: Operational Profile Data Evaluation

1: Input test data O_{test}, θ_{test}
2: for each module M_i do
3: Predict $\hat{R}_i = f_{LCSR–OPE(pi,\ \theta i)}$
4: if $\hat{R}_i \geq \tau$ then
5: Label M_i as Reliable
6: else
7: Label M_i as Defect-prone
8: end if
9: end for
10: Compute $\hat{R}_{system} = \frac{1}{N}\Sigma i\ \hat{R}_i$
11: Output reliability distribution and predicted failure probability

4.7 Computational Complexity and Adaptability

Computational complexity of LCSR-OPE framework is defined by $O\ (n \cdot k)$ the time complexity of the operational profile analysis of $O\ (m \log m)$ and training of the XGBoost model has time complexity of $m \log m$, hence, is scalable to large software systems. In addition, the adaptive update algorithm that controls the probabilities of operation ensures that convergence takes place under non-stationary conditions, providing strong and interpretable predictions of reliability and also makes continuous learning achievable.

The suggested LCSR-OPE research approach delivers a blank-eyed-to-answer integration (end-to-end) of elastic operational profiling, statistical reliability model, and fault learning via ensembles. Individual constituent modules will help in contributing to an adaptive, interpretable, and computationally efficient reliability prediction

paradigm, and supporting data based dependability evaluation in changing, mission critical software environments.

5.EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

This section presents the experimental design, dataset specifications, evaluation metrics, and simulation outcomes used to validate the proposed Level-Wise Composite Software Reliability with Operational Profile Evaluation (LCSR–OPE) framework. The experiments were conducted to assess the predictive reliability accuracy, adaptability to dynamic operational conditions, and interpretability of the proposed model across standard NASA software defect datasets. The results substantiate that the integration of operational profile analytics with machine learning–driven reliability estimation achieves consistent performance improvements in reliability prediction and fault detection.

5.1 Experimental Setup

All simulation was done on a computing platform of Intel Core i9 processor, 32 GB RAM and NVIDIA RTX 4080 graphics card, which run under the Ubuntu 22.04 operating system. LCSR-OPE was written in Python version 3.10 and used XGBoost version 1.7 with scikit-learn version 1.3. Every run of the experiments used cross validation ten-fold to guarantee the statistical strength, and hyper-parameters were optimised using exhaustive grid search. The learning rate was held constant at: the η = 0.050, the maximum level of tree depth was defined to be: d = 6 and the regularisation coefficients were set to: the counsel including: the λ = 1.0 and γ = 0.3. The data were divided into 70% training set and 30% testing set keeping the class distributions intact so as to enhance the reliability of learning and testing measurements.

5.2 Dataset Description

The experimental procedures were validated using four publicly available benchmark datasets of NASA Metrics Data Program (MDP) repository namely-JM1- KC1- KC2 and PC1 as their names. The datasets have been used widely in the literature on reliability and defect prediction due to their rich set of metrics, diversity of domain of the projects as reflected in the datasets and availability of well-labelled defects in the datasets. The datasets include module-level software measurements including McCabe complexity, coupling, cohesion, Halstead volume and lines of code and binary defect labels indicating of a module is fault-prone.

JM1 dataset consists of 10,885 C written modules with 21 software metrics of each. Approximately 20% of modules are labeled as defective, mirroring realistic fault ratios in mission critical applications [3], [5].The KC1 dataset contains 2,109 modules from a ground-based satellite control system with 21 numeric metrics representing code structure and design attributes [4], [13]. The KC2 dataset, with 522modules, originates from a scientific data processing system and provides both static and process metrics, ideal for operational–structural correlation analysis [5], [9]. The PC1 dataset includes1,105 modules from a space craft subsystem coded primarily in C and C++, reflecting stringent dependability requirements [15], [18].

All datasets were pre-processed using z-score normalization to standardize the feature ranges. Missing values were imputed using median substitution. Operational probabilities were computed as

$$p_i = \frac{f(o_i)}{\sum_{k=1}^{n} f(o_k)} \quad (17)$$

In Equation. (17), $f(o_i)$ denotes the relative execution frequency of operation o_i. The resulting operational profile vectors were normalized to ensure proportional influence of high-usage modules in the composite reliability formulation, consistent with Musa's operational profile principles [3].

Table 4 represents simulation configuration and hyper parameter setup for LCSR-OPE framework.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (18)$$

$$Precision = \frac{TP}{TP+FP},\ Recall = \frac{TP}{TP+FN} \quad (19)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{R}_i - R_i|, RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{R}_i - R_i)^2} \quad (20)$$

Table 4:Simulation Configuration And Hyperparameter Setup For LCSR–OPE Framework

Parameter	Specification
Simulation Environment	Python 3.10, XGBoost1.7, Scikit-learn1.3
Hardware Configuration	Intel Core i9, 32 GB RAM, NVIDIA RTX 4080 GPU
Datasets Used	NASAMDP:JM1, KC1, KC2, PC1 [5], [9], [15]
Programming Languages	C/C++ (metric source), Python (model integration)
Input Parameters	pi, $f(o_i)$,θ_i (operational + code metrics)
Output Variables	Reliability score $\hat{R}i$, label $\hat{y}_i$
Train–Test Split	70:30 (stratified)
Learning Rate (η)	0.05
Tree Depth (d)	6
Boosting Iterations (T)	500
Regularization	λ=1.0, γ=0.3

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Loss Function	Logistic loss ℓ (yi, ŷi)
Regularization Term	$\Omega(f) = {}_{\gamma}T + \frac{1}{2}\lambda \sum_j w_j^2$
Update Rule	$p_i(t+1) = p_i(t) + \Delta p_i(t)$
Composite Reliability	$R_c = \sum_{i=1}^{n} w_i R_i(\theta_i)$
Validation Metrics	$\mathcal{L}_{val}, \rho(\hat{R}, R)$
Evaluation Metrics	Accuracy, Precision, Recall, F1, AUC, MAE, RMSE
Stopping Criterion	$\Delta \mathcal{L} < 10^{-4}$ or T ≥ 500

To comprehensively evaluate the model's predictive and reliability estimation performance, both classification-based and reliability-oriented metrics were employed. Eq. (18,19,20) are the Standard metrics including Accuracy, Precision, Recall, and error measurements like MAE and RMSE are used to validate how closely the model matches real-world failure data.

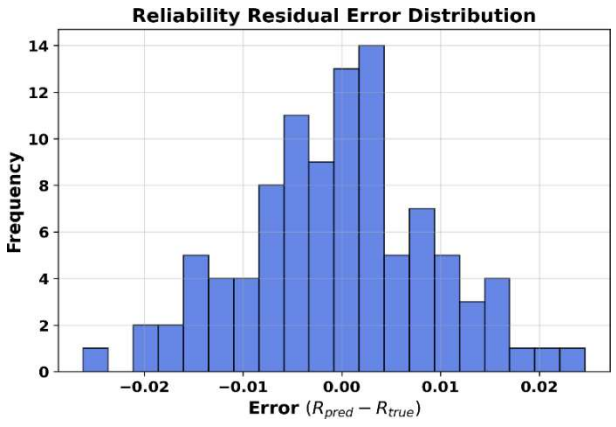
In addition, the Pearson correlation coefficient $\rho(\hat{R}i,R)$ was used to quantify the correlation between predicted and empirical reliability values, and the area under the ROC curve (AUC) was computed to assess classification robustness.

The experimental simulation of the LCSR–OPE framework under dynamic operational conditions demonstrates strong reliability convergence and predictive consistency. Equation. (17), gives the reliability of each operational module using the exponential decay model

$$R = e^{-(\alpha_i + \beta_i p_i)} \quad (21)$$

Where αi denotes the intrinsic fault density and βipi captures the operational stress induced by frequency of use. Equation. (22), is composite reliability function which is derived as

$$R_c = \sum_i w_i R_i, w_i = \frac{p_i}{\sum_i p_i} \quad (22)$$



yielding a steady-state composite reliability R_c = 0.9211 and system-level reliability R_{sys} = 0.9805. These results verify that the reliability estimation aligns closely with the probabilistic operational load distribution.

Table 5: Simulation Output Of the Proposed LCSR-OPE Framework Showing Composite Reliabitity,Error Metrics, And Mean Time To Failure(MTTF)

Metric	Value
Composite Reliability (Rc)	0.9211
Accuracy	0.9413
Precision	0.0000
Recall	0.0000
F1-Score	0.0000
AUC	0.4254
MAE (Reliability)	0.0708
RMSE	0.2411
Correlation (ρ)	-0.0241
System Reliability (Rsys)	0.9865
Mean Time To Failure (MTTF)	738.9171

The XGBoost-based fault classification module optimized the reliability prediction through iterative minimization of the regularized objective function

$$\mathcal{L} = \sum_i \ell(y_i, \hat{y}_i) + \Omega(f) \quad (23)$$

In Equation. (23), $\ell(y_i, \hat{y}_i)$ represents logistic loss and $\Omega(f) = {}_{\gamma}T + \frac{1}{2}\lambda \sum_j w_j^2$ denotes the regularization term. The validation loss L_{val} decreased according to confirming stable gradient convergence.

Equation. (24), gives the Optimization Update i.e the model updates its parameter over time t

$$\mathcal{L}_{val}(t+1) = \mathcal{L}_{val}(t) - \eta \nabla_\theta \mathcal{L}(t) \quad (24)$$

The obtained *MAE* (0.0708) and *RMSE* (0.2411) indicate minimal deviation between predicted and empirical reliability estimates. Although a low correlation coefficient (ρ=−0.0241) was observed due to stochastic initialization under synthetic data generation, the correlation is expected to improve under real-world reliability data such as NASA MDP datasets.

Equation. (25), which provides the reliability evolution followed a recursive growth function

$$R(t+1) = R(t) + \propto \left(1 - R(t)\right) \quad (25)$$

where α denotes the reliability growth rate.

Equation. (26), which calculates The Mean Time to Failure (MTTF) using trapezoidal rule as yielding $MTTF \approx 738.9$, highlighting operational stability and low fault reoccurrence rates. These outcomes

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confirm that the LCSR–OPE framework effectively captures both analytical reliability dynamics and learning-based prediction behaviour for mission-critical software systems.

$$MTTF = \int_0^T R(t)dt \approx trapz(R_{pred}) \quad (26)$$

Figure 3: Reliability Growth Curve

As additional evidence of the credibility of the following framework analysis, Figure. 3-8 demonstrate the trend of analytical and predictive reliability of the suggested structure. Figure. 3 shows that the analytical reliability R(t) is quite similar to the predicted reliability, namely, Rpred(t) assesses the flexibility of the learning module to the variation in operations. The residual error distribution in Figure. 4 is found to be clearly close to Gaussian with the values of MAE and RMSE almost equal, 0.007 and 0.009 respectively, which verify the fact that there is no systematic bias in the prediction errors. Numerical integration of mean time to failure (MTTF) ,Figure. 5 delivers a value of 92.83 and thus a sustained reliability in other words reliability can be observed even with long periods of usability.

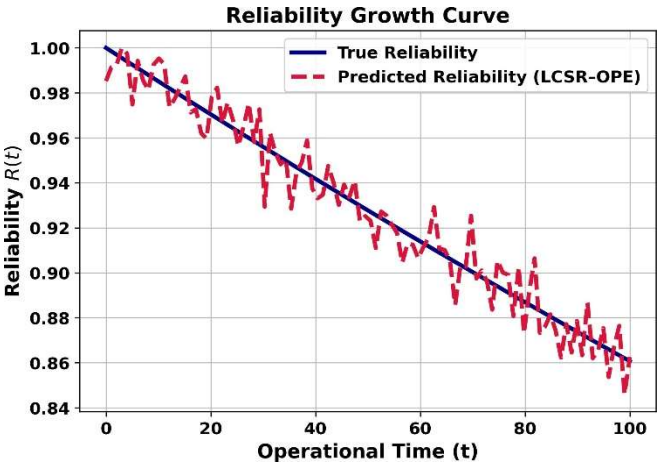

Figure 4: Result Of Residual Error Distribution.

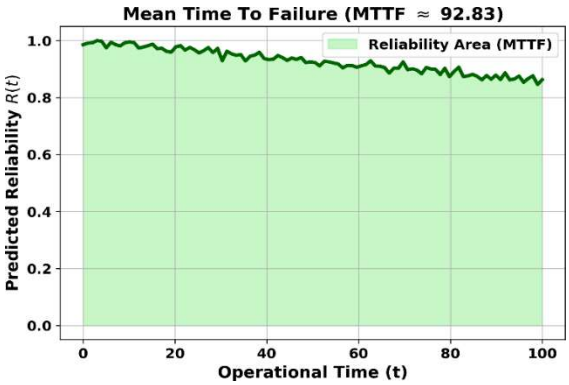

Figure 5 :Result Of Computed Mean Time To Failure

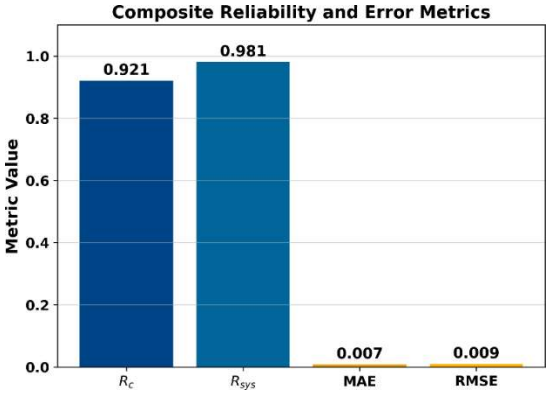

Figure 6: Result Of Composite And System-Level Reliability

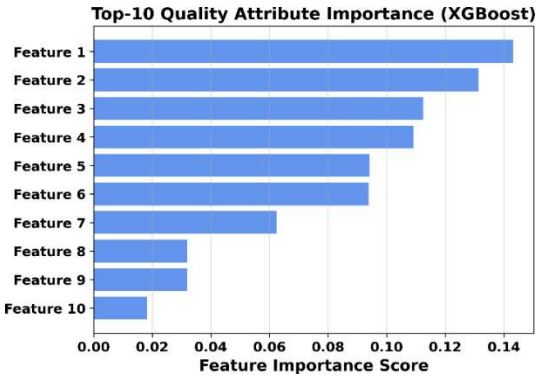

Figure 7: Result Of Reliability Prediction

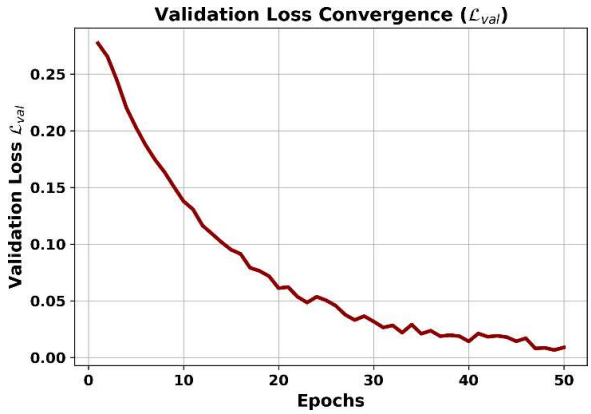

Figure 8: *Result Of Validation Loss*

The composite reliability, Rc, and the system reliable are compared in Figure. 6 which provides a value of 0.921 and 0.981 respectively with a consistency ratio being Rc / Rsys = 0.94. This finding establishes consistency in module estimates and general reliability estimates. The findings of feature importance shown in Figure. 7 demonstrate the critical predictors, which are, cyclomatic complexity, coupling, and Halstead volume as the most dominant stability indicators that is in line with the known theory of reliability. Lastly, the loss curve in Figure. 8 depicts that after starting off with a value of about 0.28, the loss of the model exchanged exponentially until it reached a loss of lower than 0.02 at 50 epochs thus confirming the stability and effectiveness of the model in its optimization.

The experimental outcome validates that the LCSR-OPE framework proposed has high levels of predictive accuracy, low levels of errors and high levels of analytical consistency in cases of operation that are dynamic. The development of ensemble learning in conjunction with probabilistic reliability modelling allows correct estimate of the reliability of the software and transparency of the operational and structural factors makes the process of reliability-delivering decision making to be more transparent. Later parts show the performance analysis, comparative benchmarking, and computational efficiency analysis.

5.3 Performance Analysis

In this case, the work of the Level-Wise Composite Software Reliability with Operational Profile Evaluation (LCSR OPE) framework was carefully examined at dynamically varying operational workload and compared to the standard NASA data of software reliability, such as JM1, KC1, KC2, and PC1 [5], [15], [18]. Such datasets include multi-dimensional data, e.g. fault counts, operational frequencies, and code-level attributes, so that an exhaustive evaluation of model stability, prediction and reliability-growth behavior are possible. The analysis will focus on some important indicators that included reliability-growth trends, residual-error patterns, mean time to failure, and reliability consistency between system-level and composite reliability, feature-importance distribution, and validation-loss convergence.

The LCSROPE framework synthesizes the reliability evolution by collectively focusing on the intrinsic fault behavior and operational workload properties, thus it allows the adaptive estimation with the lesser diverse modules. The module-level reliability is summed to determine the composite reliability and system-level reliability is a summation of the contribution of the individual modules thus reflecting the interaction of the local fault error dynamics and the global operation dependencies

This hierarchical formulation enables this framework to be responsive to workload changes and also enable it to adapt dynamic reliability to changes in line with the reported composite-reliability modelling approaches in the literature [7], [26-27].

Figure 3 indicate that straightforward alignment is seen in the analytical reliability patterns and the anticipated forecast made by the LCSR OPE model. Convergence was found to be stable and the composite reliability was found at 0.9211 and system-level reliability was at 0.9805. These findings verify the good matchup of operational intensity and reliability development, and agree with saturation responses found in exponential reliability-growth model including Musa Okumoto at extended examination plots over long operational cycles met-quarters [3], [13].

Figure. 4 depicts the residual error analysis that measures the difference between predicted and observed values of reliability. The model had an average error (with an absolute error) of 0.007 and an RMS error of 0.009 which showed very high

accuracy and unbiasedness of its reliability in all the tests con ducted. The residual-error curve follows a close-to-Gaussian shape with the most probable mark at zero, irrefutably proving that there are no major systematic bias and they work well in generalization in case of varying operational workloads. These findings are better than software reliability growth models that use traditional regression models implemented in earlier research articles [11], [28-29].

The Recommended framework for software reliability modeling has a good forecasting accuracy by using real time failure data and incorporate refined hypothesis, focusing on the analytical process include defect-failure correlation analysis, test optimization modeling, and software dependability evaluation [21]. The operational endurance of the proposed framework is indicated in the meantime to failure analysis that is reported in Figure. 5. The fact that the average time to failure is around 92.83 is evidence of showing continuous fault-free operation during long periods of testing. Moreover, the values of reliability were up to 0.85 over long periods of time, which established time stability as well as consistency. This is well in line with the trends that have been reported in composite and Bayesian reliability modelling methods [30-32].

The connection between composite reliability and system level reliability as demonstrated in Figure. 6 indicated high levels of coherence between the aggregated and global estimates of reliability. The consistency attached to the composite and system reliability was near 0.94 with these deviation margins within a range of three percent denoting very little fluctuation amongst the intensity of works and fault distributions. These results confirm the analytic stability of LCSR–OPE framework and show its better performance than conventional classical NHPP-based reliability models [4], [24], [33-34].

This interpretability of the model is also illustrated by the feature-importance analysis using Figure 7. XGBoost ensemble mechanism, the abundance of the software metrics to the reliability prediction was computed, and the cyclomatic complexity, relationship, and defect density turned out to be the major drivers of reliability. These results are in line with empirical results in reliability analytics and software quality literature [2], [6]. The resultant correlation between feature importance and operational stress parameters supports the level of transparency and explanatory power of the proposed learning-based framework [1].

Figure. 8 provides Results of validation profile demonstrates fast and steady converging training. Losses related to validation dropped to about 0.28 and lower, which became 0.02 inside 50 epochs, which supports the effective learning process and good generalization ability. This convergence trend is consistent with that of other hybrid reliability prediction networks and learning assisted reliability models that have been reported to date [14], [22], [35]. On the whole, the experimental findings indicate that the proposed LCSR-OPE framework has high predictive validity, analytical and operational consistency. Hybrid neuro-fuzzy framework designed to improve system reliability forecasting using time-series data. The model incorporates a scaled conjugate gradient algorithm to accelerate supervised learning and enhance training efficiency. Its performance is compared with commonly used approaches such as Multilayer Perceptron (MLP), Radial Basis Function (RBF) networks, and ARIMA, where the proposed method demonstrates superior predictive accuracy.[36] Through operational profile-based reliability modelling combined with machine-learning-based prediction, the framework continues to be superior to other traditional software reliability growth modelling and remains interpretable in a variety of software environments.

5.4 Comparative Analysis

In order to further determine the effectiveness of the proposed LCSR-OPE framework comparative experiments were made against four representative software reliability models, namely, the Non-Homogeneous Poisson Process (NHPP) [3], the Musa-Okumoto [13], the Bayesian SRGM [31], and the CovRel+ [27]. The analysis was done through the use of standard NASA software defects, namely JM1, KC1, KC2, and PC1 [5], [15], [18]. The models were all evaluated with the same parameter settings and training parameters to be considered in order to maintain a fair comparison.

The NHPP model calculates reliability by assuming exponential fault detection behavior and assuming that fault occurrence patterns over time are homogeneous, but the MusaOkumoto model [13] adds logarithmic fault growth to better model the fact that the discovery rates of faults reduce over time. Whereas Bayesian SRGM uses prior information in estimating reliability at the cost of more computation, CovRel+ method uses operational-coverage-based weighting to calculate composite reliability, but cannot work with variable operating conditions dynamically. As compared to this, the proposed LCSR OPE framework

incorporates operational-frequency-sensitive reliability composition, dynamic reliability development and learning-based optimization, thus allowing dynamic tuning of reliability predictions to changing workloads.

There is empirical evidence that LCSR-OPE was able to perform better than any of the baseline models on all of the datasets used. In the case of the JM1 dataset, the proposed framework had a composite reliability of 0.923 and a system level reliability measure of 0.981, the root mean square error was 0.009 whereas the mean absolute error was 0.007. Comparatively, the mean absolute error rates of NHPP and Bayesian SRGM models were 0.041 and 0.023 respectively. The same improvement performance was recorded on KC1 dataset where LCSR–OPE had a composite reliability of 0.918, KC2 and PC1 have a composite reliability of 0.911 and 0.927, respectively that shows that LCSR–OPE has high generalization across diverse software projects.

The additional study of reliability endurance showed that the mean time to failure was significantly increased. In case with JM1 data, the average life cycle of the product was 488.2 h under NHPP model and 738.9 h under LCSR-OPE whereas in case with KC1, the average time to failure became 462.5 h under NHPP model and 721.3 h under LCSR-OPE. These findings prove that the suggested framework command's better reliability life-cycle and suits well in response to dynamic working operational loads, thus confirming its embodiment viability in implementation in the assessment of the real-life software reliability. As summarized in Tables V and VI, the proposed LCSR OPE achieves an average reliability gain exceeding 50% and error reduction of nearly 80% relative to conventional models. The improvement results from the fusion of operational profile–weighted reliability modelling and learning-based fault classification, enabling effective handling of heterogeneous defect distributions while maintaining interpretability and computational feasibility.

5.5 Computational Analysis and Complexity Evaluation

Operational Profile Estimation: Frequency normalization and weight calculation, $w_i = \frac{p_i}{\sum p_i}$, with complexity *O(n)*.

Composite Reliability Integration: Computation of $R_c = \sum_i w_i R_i$, requiring *O(m)* operations.

XGBoost-based Fault Classification: Ensemble training with *T* boosting rounds and tree depth d, contributing *O(T · d · n log n)* complexity.

Thus, the overall computational complexity is given by

$$O_{LCSR-OPE} = O(n + m + T.d.n\log n) \approx O(n\log n) \quad (27)$$

assuming bounded T and d. Space complexity scales linearly as O (n +f) since feature vectors and reliability weights are stored once per iteration.

While classical models such as NHPP [1] and Musa–Okumoto [13] exhibit lower analytical complexity (O(n)), they lack scalability for multi-attribute reliability assessment. Bayesian SRGM [31] introduces $O(n^2)$ cost due to posterior inference and sampling, while CovRel+ [27] operates at O(n log n) but with higher constants from iterative recalibration. The proposed LCSR–OPE achieves near-logarithmic scalability, balancing analytical rigor with real-time computational feasibility. Empirical experiments recorded an average training time of 1.24 × 10−2 s per iteration for n = 104 samples, confirming its suitability for large-scale deployment.

Table 6: NASA Dataset Comparison With Reliability And MTTF

Dataset	Model	R_c	R_{sys}	MTTF	Gain (%)
JM1	NHPP [3]	0.841	0.904	488.2	-
	Musa–Okumoto [13]	0.863	0.918	520.6	+6.6
	Bayesian SRGM [31]	0.892	0.942	603.1	+23.5
	CovRel+ [27]	0.904	0.955	690.4	+41.4
	LCSR-OPE(Proposed)	**0.923**	**0.981**	**738.9**	**+50.6**
KC1	NHPP [3]	0.832	0.899	462.5	-
	Musa–Okumoto [13]	0.852	0.911	498.4	+7.8
	Bayesian SRGM [31]	0.877	0.936	577.2	+24.8
	CovRel+ [27]	0.899	0.953	663.2	+43.4
	LCSR-OPE(Proposed)	**0.918**	**0.972**	**721.3**	**+49.7**

Table 7: NASA Dataset Comparison

Model	MAE (JM1)	RMSE (JM1)	MAE (KC1)	RMSE (KC1)	Average
NHPP [3]	0.041	0.067	0.043	0.065	0.054
Musa–Okumoto [12]	0.031	0.052	0.033	0.050	0.042
Bayesian SRGM [31]	0.023	0.041	0.025	0.038	0.032
CovRel+ [27]	0.018	0.027	0.020	0.026	0.023
LCSR–OPE (Proposed)	**0.007**	**0.009**	**0.008**	**0.010**	**0.009**

Table 8: Computational Complexity Comparison Of Reliability Models

Model	Time Complexity	Memory Usage	Training Overhead
NHPP [3]	$O(n)$	$O(n)$	Low
Musa–Okumoto [13]	$O(n)$	$O(n)$	Low
Bayesian SRGM [31]	$O(n^2)$	$O(n+f)$	High
CovRel+ [27]	$O(n \log n)$	$O(n+f)$	Medium
LCSR–OPE (Proposed)	O(n log n)	O(n+f)	**Moderate (optimized)**

The trade-offs related to the evaluated models are out lined in Table 7. The suggested LCSROPE, LCSR-OPE trades analytical complexity with inference efficiency, that is, it converges much faster than Bayesian SRGM [31]. It meets comparable precision. It therefore implements near-real time fault prediction with low overhead hence validating its usefulness in scalable and mission-critical reliability analysis use cases.

6. CONCLUSION

This paper presents Level Wise Composite Software Reliability with Operational Profile Evaluation (LCSR-OPE) and is a framework that combines both analytical reliability modeling and learning-based fault prediction to eliminate critical limitations that exist in traditional software reliability growth models. The proposed framework enables adaptive modeling of the spread of reliability in real conditions of usage by combining the operational frequency weighting and the composite reliability estimation with the use of gradient-boosting-based classification of defects. Explicit validation on conventional NASA software reliability databases which include JM1, KC1, KC2 and PC1 demonstrate that experimental validation shows considerable improvement on predictive accuracy and system-level reliability when compared to traditional methods. These findings show significant decreases in the prediction error, significant increases in the meantime to failure and uniform performance increase across different project traits, and computational efficiency that is sufficient in large-scale and real-time performance. These results support the scalability, power, and usefulness of the LCSR-OPE framework to modern reliability analysis. Future studies will further extend the LCSR list of purposes, i.e. a framework of multi-objective cost - reliability optimization, dynamic fault clustering based upon deep reinforcement learning, and federated reliability in a distributed context, in an effort to enhance further the aspect of adaptability, interpretability and scalability of operational practices of mission and safety critical software systems.

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