Software Reliability Models: An In-depth Review of Fault Detection and Correction Processes

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ABSTRACT
The evaluation of software quality relies significantly on software reliability growth modeling (SRGM), where reliability quantifies the probability of uninterrupted system operation within a predetermined duration. Throughout the last four decades, researchers have introduced numerous Software Reliability Growth Models, predominantly utilizing the "Non-homogeneous Poisson process" as their mathematical foundation. These analytical frameworks play an indispensable role in guiding strategic decisions during software development processes, including financial planning, optimization of testing resource deployment, selection of appropriate release timelines, and change point analysis. This paper offers a wide-ranging review of research on SRGMs, addressing techniques for predicting software reliability through Fault Detection Processes and Fault Correction Processes, both crucial for thoughtful and forecasting software performance. Starting with Schneidewind's pioneering work [1] in 1975, various models have been proposed incorporating different delay functions and statistical approaches for analyzing FDP and FCP. Modern approaches account for the relationship between identifying bugs and fixing them, the lag time involved in these processes, and the resources required for testing activities. This creates more accurate forecasts and dependable assessments of system stability. The primary aim is to consolidate key contributions in the field, offering new researchers a valuable reference point for understanding the progression and nuances of SRGM. This review emphasizes fault detection and correction processes, time delay distributions, testing effort functions, and parameter estimation methods. By presenting this body of work cohesively, the review enables a clearer perspective on integrating FDP and FCP within reliability models and discusses recent developments and future directions for enhancing SRGMs.

Keywords
Software reliability growth model (SRGM); fault detection process (FCP); fault correction process (FDP); mean value function (MVF); maximum likelihood estimation (MLE); least squares estimation (LSE).

1. INTRODUCTION
Software reliability analysis constitutes a fundamental aspect of software quality assessment. It facilitates the identification of potential system vulnerabilities and verifies compliance with established reliability standards prior to software deployment. The concept of software reliability refers to the likelihood concerning software system performance and its intended functions without experiencing failure over a designated time interval [2-3]. In the past 40 years, researchers have developed a substantial number of SRGMs, and the majority being formulated within the NHPP framework [2-8]. Such models offer valuable perspectives that inform critical decisions throughout the software development lifecycle, encompassing cost analysis [9-17], testing resource/effort consumption [18-27], optimum release time determination [8, 16, 28-33], change point perspective [34-40], etc.

An essential aspect of software development, decision-making involves the temporal aspects of fault correction [16, 41-42]. Prolonged delays in addressing detected faults can result in escalating development costs and elevated project risks, consequently affecting the overall dependability of the software system. Effective modeling of fault correction processes enables better resource optimization and reduces the adverse effects of software defects on the development lifecycle. Consequently, there has been growing scholarly interest in the simultaneous modeling of fault corrections and fault detection mechanisms. These integrated approaches seek to furnish more thorough intuitions into software testing dynamics by integrating supplementary evidence dimensions and enhancing the precision of software reliability predictions [43-44].

The current work emphasizes modeling the fault detection process (FDP) and fault correction process (FCP) for software reliability analysis. It examines FDP and FCP characteristics, SRGMs formulated under the NHPP framework, numerous fault detection rate functions, mathematical representations of FDP and FCP, diverse testing effort consumption (TEC), and time-delay distributions—each incorporating corresponding mean value functions. Subsequently, the paper discusses methodologies employed for parameter estimation in relation to FDP and FCP. The concluding section presents an evaluation of the contemporary research landscape and delineates prospective research directions intended to advance the development of SRGMs for enhanced software reliability estimation.

2. REVIEW OF SOFTWARE RELIABILITY MODELING OF FDP & FCP
SRGMs serve as fundamental instruments for forecasting and assessing diverse SRM. These models represent critical tools for guaranteeing stable software performance and decreasing

failure occurrences throughout operational periods. The potential to model both the FDP and FCP has catalyzed substantial progress in software reliability research. The present section provides a comprehensive examination of seminal research contributions addressing the modeling of these processes. A thorough identification of the interrelationships between FDP and FCP proves critical for enhancing software quality, reducing system downtime, and establishing optimal software release strategies.

Schneidewind [1] established the pioneering framework for modeling the FCP while simultaneously proposing an FDP model incorporating a constant time lag parameter. This initial procedure underwent subsequent refinement by Xie and Zhao [45], who substituted the constant time lag with a time-dependent delay function, thereby rendering the model continuous in nature. This modification enabled a more accurate representation of temporal dynamics in fault correction activities. Building upon this foundation, Schneidewind [46] further advanced the methodology by evolving a fault correction model wherein the time delay was characterized as a random variable following an exponential distribution, thus introducing a more flexible probabilistic framework for fault correction modeling.

Subsequently, Lo and Huang [47] presented a generalized framework for modeling both FDP and FCP within software systems. Their structure demonstrated the capability to subsume numerous existing SRGMs, thereby establishing its versatility and broad applicability across diverse contexts. Validation studies confirmed the framework's robustness in accommodating various fault-related datasets, while contributing significantly to enhanced comprehension of software development lifecycle dynamics. This foundational work established a conceptual basis for subsequent research endeavors aimed at improving the precision and reliability of software reliability forecasting.

Wu *et al.* [48-49] examined techniques to address time-related interdependencies between fault correction and detection processes, a dimension previously underexplored in existing models. They derived maximum likelihood estimates for combined models under numerous time delay assumptions, enhancing the precision of fault modeling. Additionally, the research concentrated on the classic challenge of deciding when software should be launched, providing valuable insights into when a software product should be released based on both fault detection and correction considerations. Their contributions helped align theoretical models with practical, real-world software release strategies.

Xie *et al.* [50] proposed alternative methods for modeling FDP and FCP, contributing approaches that demonstrated ease of practical deployment. In their analysis of optimal release timing, they incorporated models for both detecting and fixing faults, thereby establishing a holistic framework for launching reliable software systems. The simplicity of their proposed methods made them particularly useful for practitioners seeking effective, user-friendly tools for managing software reliability.

Hu *et al.* [51] applied recurrent neural networks to model the FDP and FCP jointly, marking a shift towards enhanced analytical techniques in predicting software quality. Their approach utilized genetic algorithms to configure network structures, resulting in models that were capable of making robust predictions. By including a factor that captured the dispersion of prediction repetitions, their model became more resilient to variability, improving its overall reliability. This innovative approach supported the potential of machine learning techniques in enhancing traditional software reliability models.

In 2008, Lo [52] refined existing SRGMs by identifying and correcting unrealistic constraints inherent in prior models. His work produced a more thorough approach to representing the FDP and FCP, which provided improved accuracy and versatility. By refining these models, Lo contributed to more precise software reliability assessments, paving the way for future advancements in the field. His work underscored the importance of continually revising and improving reliability models to keep pace with the evolving complexity of software systems.

Shu *et al.* [53] investigated the correlation between the FDP and FCP by analyzing the number of faults involved. They used the ratio of corrected faults to detected faults, modeling this relationship as an S-shaped function. This approach allowed for a more precise representation of the relationship between detection and correction. By modeling both processes based on this function, the authors provided a deeper understanding of the dynamics between fault detection and correction, offering a useful tool for improving software reliability.

Wu *et al.* [54] introduced two new software reliability growth models (SRGMs): one that includes repeated faults and another that excludes repeated faults. These frameworks were designed to calculate both the cumulative number of detected faults and the number of corrected faults over time. The dual models provided a more nuanced analysis of software reliability, allowing developers to better understand how fault repetition impacts overall software stability. Moreover, they derived two distinct reliability models that excludes repeated faults, reflecting differences in the detection and correction processes.

Building on prior findings, Shu *et al.* [55] explored the interconnection of FDP and FCP using a dual-method approach. First, they proposed that the ratio of corrected faults to detected faults follows an S-shaped curve, and second, they introduced a Bell-shaped function to describe the difference between the number of detected and corrected faults. These insights led to the development of two software reliability models that could simultaneously address fault detection and correction. This dual-model approach allowed for more comprehensive fault analysis and more precise reliability forecasting.

Kapur *et al.* [56] proposed a general SRGM that incorporated different learning functions to reflect the experience gained by the testing team. Their model accounted for the time delays between fault detection, isolation, and correction during software testing. This learning-based approach provided a more realistic understanding of the testing process, as it acknowledged the impact of tester expertise and time delays in improving software reliability. The model offered a valuable framework for improving testing efficiency and optimizing resource allocation.

Jia *et al.* [57] introduced a Markovian SRGM that considered the fault correction process. They established a method for parameter estimation and software reliability prediction based on this model. Jia et al. utilized Markov processes to develop a systematic framework for examining how fault correction evolves temporally. This work contributed significantly to the body of knowledge by offering a model that could be applied in practical scenarios to predict and improve software reliability.

Lin [58] simulated both the FDP and FCP to explore the effects

of imperfect debugging using a single queue multichannel queuing model. They compared it with perfect debugging under a similar queuing theory framework. This research highlighted the influence of imperfect debugging on software reliability, offering insights into how debugging strategies can be optimized for better fault resolution. By simulating these processes, Lin provided a valuable tool for understanding the real-world impact of debugging practices.

Here's a more academically standard version:

Rafi and Akhtar [59] advanced the field by proposing an SRGM that integrated correction lag and error dependency while incorporating the influence of testing effort. Their model enhanced fault prediction accuracy through explicit consideration of temporal delays between fault detection and correction activities, coupled with recognition of interdependencies among various error categories. This methodological approach provided a more faithful representation of the testing process dynamics, enabling development teams to formulate more effective testing strategies and elevate overall system reliability.

Peng *et al*. [43, 60] implemented TEC and a defect introduction mechanism within the fault detection framework, then constructed the FCP as a temporally delayed FDP that included remediation effort. By modifying assumptions about defect introduction behaviors and correction resource distribution, they developed several corresponding FDP and FCP model pairs. These models were subsequently employed to establish optimal release policies under diverse decision criteria, thereby making substantial contributions to release management frameworks. Their approach represented a comprehensive methodology for software reliability analysis by simultaneously addressing both fault detection and correction efforts.

Peng and Shahrzad [61] introduced a simulation-based methodology for modeling FDP and FCP that accounted for heterogeneous skill levels among debugging personnel. Their research underscored the significance of identifying optimal debugger combinations to maximize both fault detection and correction efficiency. Additionally, they examined optimal release timing, illustrating how debugging team composition and scheduling decisions influence software reliability outcomes. This work emphasized the critical role of human factors in fault management processes and demonstrated opportunities for their systematic optimization.

Liu *et al.* [62] developed a defect elimination modeling approach for software reliability based on semi-grouped data, later expanding this approach to handle multiple-release software environments. Parameter estimation within this framework was executed using the Maximum Likelihood Estimation (MLE) methodology. Their framework established a systematic approach for addressing software reliability across successive releases, facilitating more effective fault tracking and remediation throughout the software lifecycle. The incorporation of semi-grouped data enhanced model accuracy and provided a robust mechanism for continuous reliability assessment.

Wang *et al.* [63] developed parameter estimation algorithms grounded in a Bayesian framework applicable to both the FDP individually and the combined detection-correction processes. The Bayesian approach enhanced the precision of reliability predictions while increasing model adaptability to practical software development contexts. Their comparative analysis of Maximum Likelihood Estimation (MLE) and Least Squares Estimation (LSE) methodologies yielded valuable insights regarding the relative advantages and constraints of each technique, thereby furnishing practitioners with diverse analytical instruments for reliability evaluation.

Chen and Chen [64] introduced a software-oriented redundant execution approach targeting the detection and correction of transient faults. Their method leveraged multi-threading to achieve redundant execution at the thread level for identifying defects, while employing majority voting to facilitate error correction. A watchdog thread was employed to manage non-responsive threads, adding another layer of fault management. This model enhanced the reliability of fault detection and correction in multi-threaded systems, offering a more resilient approach to handling transient faults.

Liu *et al.* [65] derived a software reliability model structure that combined information from both the FDP and FCP using a Markov model, as opposed to the traditional non-homogeneous Poisson process. They applied the weighted least-square estimation method for parameter estimation. By leveraging the Markov model, this framework provided a more dynamic view of the FDP and FCP, offering greater flexibility in modeling and improving accuracy in prediction.

Saraf *et al*. [66] introduced a comprehensive SRGM framework designed for systems with multiple releases, integrating both fault detection and correction workflows to support frequent software update schedules. The proposed framework underwent validation through application to empirical datasets, demonstrating its practical utility.

Xiao *et al*. [67] developed a stepwise prediction model for characterizing FDP and FCP utilizing artificial neural network (ANN) architectures. Through analysis of real-world data, the authors conducted comparative performance assessments between analytical models and various neural network configurations, providing insights into the relative efficacy of different modeling approaches.

Li and Pham [68] incorporated testing effort functions to formulate a model examining the interrelationship between FDP and FCP. Their analytical framework was validated using empirical data from an actual software project, elucidating the dynamics governing these interconnected processes.

Kumar *et al.* [69] introduced two distinct paired FDP and FCP models employing the Burr Type-X Testing Effort Function (BTXTEF) under imperfect debugging conditions. Parameter optimization was accomplished through Particle Swarm Optimization (PSO) applied to empirical datasets. Furthermore, the authors conducted comparative analyses evaluating the proposed SRGM models against existing models documented in the literature, demonstrating enhanced predictive capabilities.

The literature reviewed in this paper spans 48 publications, including journals and conference proceedings, from which 75 articles were identified. These sources, distributed across several major publishers, reflect decades of ongoing work in software reliability modeling. We examine how contributions are spread across these outlets, highlighting the dominant venues in fault detection and correction research.

Table 1: Aggregated Article Count by Publisher

No.	Publisher	Articles	% Share
1	IEEE	30	40.00%
2	ELSEVIER	20	26.70%

3	Taylor & Francis	4	5.30%
4	Emerald Publishing	3	4.00%
5	McGrow-Hill	2	2.70%
6	Wiley Online Library	2	2.70%
7	Journal Itself	2	2.70%
8	Others (11 publishers)	12	16.00%
Total		**75**	**100%**

IEEE emerges as the most dominant publisher, contributing 30 articles out of 75, largely through its transactions and conference proceedings dedicated to reliability and software engineering. ELSEVIER accounts for 20 articles, with the Journal of Systems and Software serving as the highest-contributing single journal in the dataset with 11 articles. IEEE Transactions on Reliability further consolidates IEEE's prominence by contributing 8 articles on its own. Secondary publishers including Taylor & Francis, Emerald Publishing, Wiley Online Library, and McGrow-Hill together represent about 14.7% of the literature, reflecting a moderately diverse publishing base. It is also worth noting that nearly two-thirds of the 48 identified sources contributed no more than one article each, underscoring the wide spread of research activity rather than its concentration in a handful of venues. Conference proceedings, especially those under IEEE's aegis, form a meaningful segment of the dataset, indicating the important role of international conferences in shaping and disseminating advances in this field. The reviewed literature collectively spans the period from 1992 to 2016, representing over two decades of progressive research in software fault detection and correction modeling

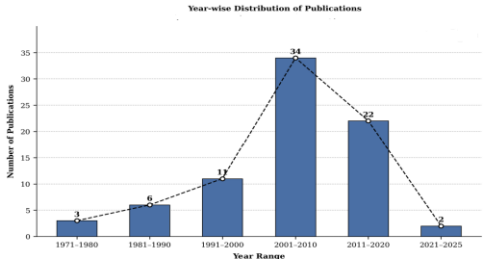

Fig 1: Year wise Distributions of Publications

The chronological distribution of reviewed publications traces a clear arc of growing and then stabilizing research interest in software reliability modeling. Work from the 1971–1990 period contributed nine articles combined, representing the foundational phase during which early probabilistic models, Research output grew through the 1990s, with 11 publications appearing between 1991 and 2000 as awareness of software reliability as a critical engineering concern became more widespread. The most concentrated phase of publication activity falls within the 2001–2010 window, which accounts for 34 articles or nearly 44% of the entire reviewed dataset, driven largely by the proliferation of complex software-intensive systems and the corresponding demand for more rigorous fault modeling methods. The 2011–2020 period follows with 22 publications, reflecting continued engagement with the topic even as the classical SRGM framework matured and alternative computational approaches began attracting attention. Only two articles fall within the 2021–2025 range.

3. REVIEW OF METHODOLOGY

Let $\{N(t), t \geq 0\}$ denote an NHPP counting process representing the cumulative number of faults detected by time t. The mean value function (MVF) $m(t)$ represents the expected number of faults detected in time $(0, t]$, and $\lambda(t)$, denotes the corresponding failure intensity function. The associated NHPP counting process is given by:

$$P\{N(t) = n\} = \frac{m(t)^n}{n!} e^{-m(t)} \quad n = 0,1,2,3 \ldots \qquad (1)$$

and

$$m(t) = \int_0^t \lambda(x)dx \qquad (2)$$

3.1 FDP and FCP Modeling

In this sub-section, a software reliability model that accounts for both the FDP and FCP is presented. The MVF of FDP, $m_d(t)$ and FDP, $m_c(t)$, are formulated using the following system of differential equations [47]:

$$\frac{dm_d(t)}{dt} = \emptyset(t) \times (a - m_d(t)), \qquad (3)$$

$$\frac{dm_c(t)}{dt} = \varphi(t) \times (m_d(t) - m_c(t)). \qquad (4)$$

Different SRGMs for the FDP and FCP can be derived from the above differential equations by specifying different forms of $\emptyset(t)$ & $\varphi(t)$. For instance, when $\emptyset(t) = \varphi(t) = r$, the corresponding MVFs are given by $m_d(t) = a[1 - e^{-rt}]$ and $m_c(t) = a\left[1 - (1 + rt)e^{(-rt)}\right]$; similarly when $\emptyset(t) = r$ & $\varphi(t) = c$, the MVFs are given by $m_d(t) = a[1 - e^{-rt}]$ and $m_c(t) = a\left[1 + \frac{c}{r-c}e^{-rt} - \frac{r}{r-c}e^{-ct}\right]$.

3.2 FDP and FCP modeling with time delay

In this sub-section, a software reliability model that incorporates both the FDP and FCP with time delay is presented. The MVF of FDP $m_d(t)$ satisfies [49, 70].

$$m_d(t) = \int_0^t \lambda_d(s)ds \qquad (5)$$

The FCP model can be characterized with MVF $m_c(t)$. The MVF of FCP can be derived from $\lambda_d(t)$ by incorporating the time delay Δt, and is expressed as

$$m_c(t) = \int_0^t \lambda_c(\tau)d\tau = \int_0^t E[\lambda_d(\tau - \Delta t)]d\tau, \Delta t < t, \qquad (6)$$

$$m_c(t) = \int_0^t \int_x^t \lambda_d(\tau - x)g(x)dxd\tau, \text{ say } \Delta t = x$$

$$= \int_0^t m_d(t - x)f(x)dx.$$

Table 2: MVFs for FCP based on different random correction time delay

Distribution function $f(x)$ of correction time delay Δt	MVF of FCP, $m_c(t)$
Exponential delay $f(x,\theta) = \theta e^{-\theta x}$	$m_c(t) = \begin{cases} a\,.\,[1 + rt)\mathrm{e}^{-\mathrm{rt}}], & \theta = r \\ a\,.\left[1 - \frac{\theta}{\theta - r}\mathrm{e}^{-\mathrm{rt}} + \frac{\theta}{\theta - r}\mathrm{e}^{-\theta \mathrm{t}}\right], & \theta \neq r \end{cases}$
Weibull time delay $f(x,k,\theta) =$	$m_c(t) = \sum_0^\infty \frac{(\theta r)^t}{t!} \int_0^t are^{-rt}\,\Gamma\left(\frac{i}{k} + 1, t\right)dt$

$\frac{k}{\theta}(\frac{x}{\theta})^{k-1}\exp\{-($	
Erlang time delay $f(x,k,\theta) = \frac{\theta^k x^{k-1} e^{-\theta x}}{(k-1)}$	$m_c(t) = \frac{ar\theta^k}{(\theta-r)^k(k-1)!}\int_0^t \Gamma(k,(\theta - r)t)e^{-rt}dt$
Normally distributed time delay $f(x,\theta,\sigma) = \frac{1}{\sigma\sqrt{2\pi}}\exp(-\frac{(x-\theta}{2\sigma^2}$	$m_c(t) = -ae^{-rt+\theta r+\frac{r\sigma^2}{2}}\big(\Phi(t, r\sigma^2 + \theta, \sigma) - \Phi(0, r\sigma^2+\theta, \sigma)\big) + a(\Phi(t,\theta,\sigma) - \Phi(0,\theta,\sigma))$
Chi-square time delay $f(x,k) = \frac{(1/2)^{k/2}}{\Gamma(k/2)}x^{k/2-1}e^{-x/2}$	$m_c(t) = \frac{ar}{(1-2r)^{k/2}\Gamma(k/2)}\int_0^t e^{-rt}\Gamma(k/2,(1 -$
Gamma time delay $f(x,\alpha,\beta) = x^{\alpha-1}\frac{\beta^\alpha e^{-\beta x}}{\Gamma(\alpha)}$	$m_c(t) = a\Gamma(t,\alpha,\beta) - \frac{ae^{-rt}}{(1-r\beta)^\alpha}\Gamma(t,\alpha,\frac{\beta}{1-r\beta})$

Consider, the mean value function as in [4],

$$m_d(t) = a.(1-e^{-rt}),\ a>0, r>0 \quad (7)$$

Here, three distinct cases for the MVF of FCP depending on nature of fault correction time delay. Case 1. When time delay is constant (i.e. $\Delta(t)=\Delta$), the MVF is $m_c(t) = m_d(t-\Delta) = a.\big(1-e^{-r(t-\Delta)}\big)$; Case 2. When time is dependent, the MVF of $m_c(t) = a[1-(1+ct)e^{-rt}]$; and case 3. When the fault correction time delay is a random variable following a specified probability distribution, the corresponding MVF of the FCP, $m_c(t)$ is derived accordingly. Various forms of the MVF corresponding to different random correction time delay distributions are summarized in Table I.

3.3 FDP and FCP modeling with testing effort

The predicted total number of faults at time t is represented by the fault content rate function $a(t)$. Assuming that the number of faults found during $[t, t+\Delta t)$ is proportionate to the number of faults that remain at time t, current testing effort usage $x(t)$ follows. The differential equation that follows can then be used to formulate SRGM [39, 43,60]:

$$\lambda_d(t) = \frac{dm_d(t)}{dt} = b(t).x(t).\big(a(t)-m_d(t)\big), \quad (8)$$

where $x(t)$or $X(t)$ is the current or cumulative TE consumption, $b(t)$ is the fault detection rate per unit TE at time t. In a particular instance, if $b(t) = \mathrm{r}$ and $a(t) = a$, the solution of the above differential equation is

$$m_d(t) = a(1-e^{-rX(t)}) \quad (9)$$

From above differential equation, under the initial condition, $m_d(0)=0$, the MVF of FDP models with TE can be obtained as

$$m_d(t) = a(t) - ae^{-\int_0^t b(s).x(s)ds} -$$

$$e^{-\int_0^t b(s).x(s)ds}.\int_0^t a'(s)e^{\int_0^s b(y).x(y)dy}\,ds. \quad (10)$$

It is evident that different MVF $m_d(t)$ can be obtained by considering different, $a(t)$, $b(t)$, and, $X(t)$.

Additionally, the intensity function for fault detection $\lambda_d(t)$, is obtained as

$$\lambda_d(t) = ab(t)w(t)e^{-\int_0^t b(s).x(s)ds}.(1 + \int_0^t \frac{a'(s)}{a}e^{\int_0^s b(y).x(y)dy}\,ds) \quad (11)$$

Note that if a fault corrected at time t requires a correction effort of duration s, then the expected number of faults corrected during the interval $[t, t+\Delta t)$ equals the expected number of faults detected during $[X^{-1}(X(t)-s), X^{-1}(X(t+\Delta t)-s)]$. Since different faults require different correction efforts, the correction effort is modeled by a pdf $f(s)$ with corresponding cdf $F(s)$. Accordingly, the MVF of the FCP, $m_c(t)$ can be derived as

$$m_c(t) = \int_0^t \lambda_d(s)F(X(t)-X(s))ds, \quad (12)$$

where, $F(X(t)-X(s))$ denotes the probability that a fault detected at time s is corrected before time t. By choosing different correction efforts distributions $f(s)$ from Table I and different TEFs $X(t)$, various forms of the MVF $m_c(t)$ can be derived from $m_d(t)$. The corresponding fault correction intensity function $\lambda_c(t)$ is given by

$$\lambda_c(t) = \int_0^{X(t)} \lambda_d\big(X^{-1}(X(t)-s)\big)f(s)x(t)\frac{ds}{x(X^{-1}(X(t)-s))}. \quad (13)$$

3.4 Parameters Estimation Methods

In this subsection, some estimation methods of parameters are presented.

3.4.1 Least Square Method

Under this parameter estimation technique, the parameters are estimated by minimizing the sum of squared residuals, where the residuals represent the difference between the MVFs of fault detection and fault correction.

$$\sum_{i=1}^n [(m_d(t_i)-d_i)^2 + (m_c(t_i)-c_i)^2] \quad (14)$$

where d_i and c_i represent the cumulative detected and corrected faults up to time t_i, and t_i, $i = 1,2,3\ldots$, denotes the elapsed testing time.

3.4.2 Maximum Likelihood Method

The chance of detecting n_i faults and correcting m_i faults by time t_i is represented by $P(n_i, m_1)$. Denoting $\theta_0 \in \Theta \subset R^m$, the joint density, and parameters of the detected and corrected fault counts over the specified partition can be determined, and likelihood function can be derived with θ_0 substituted by θ as

$$L = \prod_{i=1\ldots k, m_i > n_{i-1}} e^{[m_d(t_i)-m_d(t_i-1)\theta]}\frac{[m_d(t_i)-m_c(t_i)|\theta]^{n_i-m_i}}{(n_i-m_i)!} \times \frac{[m_c(t_i)-m_d(t_{i-1})|\theta]^{m_i-n_{i-1}}}{(m_i-n_{i-1})!} \times$$

$$\prod_{i=1\ldots k, m_i < n_{i-1}} e^{-[m_d(t_i)-m_d(t_i-1)\theta]}\frac{[m_d(t_i)-m_d(t_{i-1})|\theta]^{n_i-n_{i-1}}}{(n_i-n_{i-1})!} \times$$

$$e^{-[m_c(t_i)-m_c(t_i-1)\theta]}\frac{[m_c(t_i)-m_d(t_{i-1})|\theta]^{m_i-m_{i-1}}}{(m_i-m_{i-1})!}$$

3.4.3 Soft Computing Methods

Throughout the last twenty years, soft computing approaches have become increasingly significant in software reliability assessment. Techniques including genetic algorithms (GA), real-valued genetic algorithms (RGA), artificial neural networks (ANN), fuzzy logic (FL), particle swarm optimization (PSO), and quantum particle swarm optimization (QPSO) have been widely applied for parameter estimation in SRGMs. These methodologies provide adaptable and flexible frameworks for addressing intricate optimization challenges, proving valuable in the evolving and unpredictable context of software reliability evaluation. Researchers have increasingly turned to these methods to improve the accuracy and efficiency of parameter estimation in SRGMs, driving innovation in the field. Minohara and Tohma [71] were among the pioneers who applied genetic algorithms to estimate the parameters of the "Hyper-geometric distribution software reliability growth model" (HGSRGM). This early application demonstrated the potential of GA in solving parameter estimation problems in software reliability models. Building on this, Sheta [72] employed GA to estimate parameters for the COCOMO model, a widely used model for software cost estimation, further proving the versatility of GA in different areas of software engineering. These studies laid the groundwork for the widespread adoption of GAs in software reliability research. Hsu and Huang [73] introduced a modified genetic algorithm (MGA) to estimate SRGM parameters, refining earlier techniques by enhancing the optimization process. Their work showcased how modifying traditional genetic algorithms could yield more accurate and efficient results. Later, Kim et al. [74] proposed a real-valued genetic algorithm (RGA) for SRGM parameter estimation, which they found to be more effective than traditional GAs. This advancement highlighted the evolving nature of genetic algorithms, where continuous refinements lead to better performance in reliability analysis. Particle swarm optimization (PSO) also found its place in software reliability analysis, as demonstrated by Sheta [75] and Zhang *et al*. [76], who applied the PSO algorithm to estimate SRGM parameters. PSO, inspired by the social behavior of birds flocking or fish schooling, provided an efficient mechanism for solving complex optimization problems. Building on this, Jin and Jin [77] developed an improved version of swarm intelligence optimization known as quantum particle swarm optimization (QPSO), specifically designed to estimate parameters in testing effort-dependent SRGMs. QPSO further enhanced the performance of traditional PSO by incorporating quantum mechanics principles, demonstrating the potential of hybrid approaches in improving software reliability predictions.

4. DISCUSSION

Researchers spanning multiple disciplines, including stochastic modeling, reliability engineering, operations research, and computer science, have contributed substantially to the advancement of reliability growth models. Their collective efforts have expanded the theoretical understanding of software reliability through the integration of diverse methodological frameworks and the exploration of dynamic characteristics inherent in real-world testing environments. These models have proven instrumental in addressing the multifaceted challenges associated with predicting and enhancing software reliability, thereby establishing a robust foundation for both theoretical inquiry and practical implementation. The formulation of these models typically entails systematic investigation of various assumptions and conditions characterizing actual testing processes. Researchers have concentrated on modeling the intricate interactions among fault detection, fault correction, and additional variables influencing software reliability outcomes. Through rigorous examination of these factors, they have progressively refined their modeling frameworks to more accurately capture the complexities inherent in authentic testing environments, consequently improving the precision of reliability forecasts. A broad spectrum of methodological approaches has been employed in the development of reliability growth models. While certain methods draw upon traditional statistical techniques, others leverage contemporary computational approaches, including soft computing paradigms such as genetic algorithms, artificial neural networks, fuzzy logic systems, and particle swarm optimization. This methodological diversity has enriched the field considerably, facilitating more flexible, adaptive, and accurate modeling of reliability growth phenomena, with models that can be tailored to the distinctive requirements of individual software development initiatives.

Moving forward, soft computing techniques warrant continued emphasis in future research endeavors. The inherent flexibility and adaptability of methodologies such as genetic algorithms, neural networks, and fuzzy logic systems provide powerful mechanisms for addressing the increasing complexity of contemporary software systems. These approaches hold considerable promise for advancing the development of more robust and precise software reliability models, thereby contributing to enhanced software quality assurance practices.

- Incorporation of dynamic testing conditions: Models could account for real-time variations in testing environments, such as fluctuating workloads, to reflect actual operational conditions.
- Exploration of hybrid models: Combining traditional statistical methods with soft computing approaches like neural networks or genetic algorithms could enhance model robustness and flexibility.
- Impact of software architecture: Research could investigate the influence of software architectural patterns on fault detection and correction processes, providing more targeted reliability models.
- Multi-objective optimization: Researcher could explore trade-offs between reliability, performance, and cost, using multi-objective optimization techniques for balanced decision-making in software release planning.

Automated parameter tuning: Techniques like machine learning could be employed to automatically optimize the parameters of reliability models based on historical data, reducing the manual effort and improving model precision.

5. CONCLUSION AND FUTURE WORKS

This study examined the modeling approaches for software fault detection and fault correction mechanisms within the context of software reliability analysis, presenting a comprehensive synthesis of significant scholarly contributions in this domain. The discussion encompasses multiple mathematical formulations for the fault detection process (FDP) and fault correction process (FCP), along with methodologies for estimating critical model parameters. Furthermore, the paper has investigated the concepts of correction time delay and testing effort consumption, elucidating their influence on software reliability assessment. The authors posit that this review may serve as a substantive reference for the development of advanced methodologies in software reliability growth model analysis.

Based upon the findings and analytical perspectives presented

throughout this review, multiple opportunities for further study have emerged. First, the explicit incorporation of testing effort functions into the modeling frameworks for both fault detection and fault correction processes represents a significant opportunity for enhancing model realism and predictive accuracy. Such integration would more faithfully reflect the actual resource allocation during testing phases, thereby yielding improved software reliability forecasts. Second, the application of statistical distribution functions for characterizing correction time delay constitutes another promising research direction. This approach could substantially enhance model precision by more effectively capturing the inherent stochastic variability associated with fault correction activities, addressing limitations in current deterministic or simplified probabilistic representations.

Additionally, the integration of change point analysis into fault detection and correction modeling frameworks represents a significant opportunity for enhancing the flexibility of reliability growth models, particularly in testing characterized by temporal shifts in dynamics. Weighted least squares estimation methodology could serve as a viable alternative approach for parameter estimation, especially in scenarios where conventional estimation techniques exhibit limitations or convergence difficulties. Beyond the widely adopted Goel-Okumoto Non-Homogeneous Poisson Process (NHPP) model, calendar-time-based modeling approaches merit consideration, as they offer expanded perspectives on the temporal evolution of fault detection and correction processes.

Establishing ideal deployment timing through cost-reliability analysis forms a vital research direction, helping practitioners harmonize budget considerations with system performance targets. Moreover, explicit consideration of the correlation structure between fault detection and correction processes, as well as the dependencies among failure occurrence times, could yield more sophisticated understanding of the interdependencies among various reliability factors. Future research endeavors could also address reliability modeling for networked systems and integrated software-hardware platforms, as these configurations present distinctive challenges in fault detection and correction owing to their inherent complexity and interdependence.

Finally, soft computing methodologies warrant sustained attention in future research initiatives. The inherent flexibility and adaptability of techniques such as genetic algorithms, artificial neural networks, and fuzzy logic systems provide powerful analytical frameworks for addressing the increasing complexity characteristic of contemporary software systems. These computational intelligence approaches hold substantial promise for advancing the development of more robust and accurate software reliability models, thereby contributing to enhanced predictive capabilities and more effective quality assurance practices in software engineering.

6. CONFLICTS OF INTEREST

The authors declare no conflict of interest.

7. AUTHOR CONTRIBUTIONS

Kaushal Kumar contributed to resource collection, literature review, and manuscript revision. **Jitendra Kumar** contributed to the conceptualization, development of the review framework, literature identification, and writing of the original draft. **Anil Kumar Singh** contributed to the methodology, literature analysis, and original draft preparation. **Md Shahid Iqbal** (corresponding author) contributed to supervision and review of the manuscript. All authors have read and agreed to the published version of the manuscript.

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